TEXTUAL AFFECT:
A Computational Study Towards the Detection, Utility, and Algorithmic Fairness of Emotions in Text

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By

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Under the Guidance of

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Certificate

This is to certify that the thesis entitled **"TEXTUAL AFFECT: A Computational Study Towards the Detection, Utility, and Algorithmic Fairness of Emotions in Text"**, submitted by **Mr. Anoop Kadan**, to the University of Calicut, for the partial fulfilment of the requirements for the award of the degree of **Doctor of Philosophy (Ph.D.)** in Computer Science, is a bonafide research work done by Mr. Anoop Kadan under my supervision and guidance in the Department of Computer Science, University of Calicut, Kerala. The content embodied in this thesis, in full or in parts, have not been submitted to any other University or Institute for the award of any degree.

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May 10, 2023

Declaration

I, **Anoop Kadan**, declare that this Thesis entitled, **"TEXTUAL AFFECT: A Computational Study Towards the Detection, Utility, and Algorithmic Fairness of Emotions in Text"** is based on the original work done by me under the supervision and guidance of Dr. Lajish V. L. in the Department of Computer Science, University of Calicut. I confirm that:

- The work presented in this Thesis has not been submitted previously for the award of any degree either to this University or to any other University or Institution.
- I have followed the guiding principles given by the University in organizing the Thesis.
- Whenever I have used materials (theoretical analysis, data, figures, and text) from other sources, I have given due credit to them by citing them in the Thesis and giving their particulars in the references.
- While procuring the Readers' Emotion News datasets, I have obtained the necessary approval from Rappler Inc., in using the data for non-commercial academic research purposes.

ANOOP KADAN

University of Calicut
May 10, 2023

⚠ *The examples provided in this Thesis, specifically those related to the work of identifying Affective Bias in large pre-trained language models, may be offensive in nature and may hurt one's moral beliefs. All such examples are not the perspectives of the author, but are purely the outputs of various algorithms and also those tagged as social stereotypes in the literature, that are properly cited.*

Abstract

Emotions are highly useful in modeling human behavior being at the core of what makes us human. Research in Affective Computing deals with developing computational systems capable of understanding and expressing emotions by adapting human emotional states through heterogeneous modalities such as textual, visual, and audio. Text prevails to be the most commonly used modality to express and share emotions with the boom of online social media and micro-blogging platforms. This Thesis presents a computational study towards emotions in text (or Textual Affect), exploring three different and significant facets of Textual Affective Computing. The first facet attempted in this Thesis is the detection of textual emotions, specifically through readers' perspective, i.e., Readers' Emotion Detection. The second facet intends to study how textual affects can be utilized to improve the performance of a downstream task. Towards this direction of study a very significant application of fake news detection, within the very crucial domain of health is considered. The third facet considers the algorithmic fairness perspective of textual affective computing, a recent and demanding area of research related to ethics in Artificial Intelligence. In this direction, the study attempts to identify the existence of affective bias, if any, in textual affective computing systems developed using large pre-trained language models.

The first facet of textual affective computing attempted in this Thesis, that of Readers' Emotion Detection develops a novel deep learning based model *REDAffectiveLM* to predict readers' emotion profiles from short-text documents. The proposed model is constructed using a transformer-based pre-trained language model in tandem with affect enriched Bi-LSTM+Attention to leverage the utility of both contextual and affect enriched representations. To conduct the study two Readers' Emotion News datasets are procured, along with a benchmark dataset. The extensive set of performance evaluations presented in this study shows that the proposed model significantly outperforms the baselines belonging to various categories. The study also presents behavior evaluation experiments over the affect enriched Bi-LSTM+Attention network, which shows that the process of affect enrichment helps to identify key terms responsible for readers' emotion detection, thereby improving the prediction.

The second facet considers the utility of textual affects for detecting fake news in the health domain and presents evidence that emotion cognizant representations are significantly more suited for the task. The study proposes a novel methodology to develop emotion-amplified text representations by leveraging an external emotion lexicon. To conduct the study a dataset containing fake and legitimate health news

articles is procured. Evaluations are performed to analyze the utility of emotion-amplified representations over raw text representations for identifying fake news relating to health in various supervised and unsupervised scenarios. The experiments show consistent and notable empirical gains over a range of technique types and parameter settings, establishing the utility of the emotion information in news articles, an often overlooked aspect, for the task of misinformation identification in the health domain.

The third facet is a novel direction of inquiry to identify the existence of Affective Bias, if any, in large pre-trained language model based textual emotion detection models. That is, the study intends to unveil any biased association of emotions such as anger, fear, joy and sadness, towards any particular gender, racial, or religious groups. The study initially analyzes imbalanced affect distribution or imbalanced affect associations with any particular social group, in the large-scale corpora that are used to pre-train and fine-tune the pre-trained language models, to identify corpus level affective bias. Later, an extensive set of class-based and intensity-based evaluations using synthetic and non-synthetic bias evaluation corpora are conducted to identify prediction level affective bias. The entire results could unveil the existence of affective bias with respect to gender, race, and religion, at both the corpus and prediction level of large pre-trained language models.

Keywords: Textual emotions, Affective computing, Readers' emotion detection, Fake news detection, Bias in NLP

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Anoop Kadan

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List of Abbreviations

NLP	**N**atural **L**anguage **P**rocessing
PLM	**P**re-trained **L**anguage **M**odel
SVM	**S**upport **V**ector **M**achine
WMD	**W**ord **M**over's **D**istance
CNN	**C**onvolutional **N**eural **N**etwork
RNN	**R**ecurrent **N**eural **N**etwork
GRU	**G**ated **R**ecurrent **U**nit
LSTM	**L**ong **S**hort **T**erm **M**emory
Bi-LSTM	**Bi**directional **LSTM**
REN	**R**eaders' **E**motion **N**ews
MLP	**M**ulti-**L**ayer **P**erceptron
SVR	**S**upport **V**ector **R**egression
TEC	**T**otal **E**motion **C**ount
TEI	**T**otal **E**motion **I**ntensity
MEI	**M**ax **E**motion **I**ntensity
GEC	**G**raded **E**motion **C**ount
GEI	**G**raded **E**motion **I**ntensity
RMSE	**R**oot **M**ean **S**quare **E**rror
NER	**N**amed **E**ntity **R**ecognizer
HWB	**H**ealth and **W**ell **B**eing
NB	**N**aive **B**ayes
KNN	**K**-**N**earest **N**eighbour
RF	**R**andom **F**orests
DT	**D**ecision **T**ree
AB	**A**da**B**oost
BERT	**B**idirectional **E**ncoder **R**epresentation from **T**ransformers
GPT	**G**enerative **P**re-trained **T**ransformer
T5	**T**ext-**t**o-**T**ext **T**ransfer **T**ransformer
C4	**C**olossal **C**lean **C**rawled **C**orpus
EEC	**E**quity **E**valuation **C**orpus
BITS	**B**ias **I**dentification **T**est in **S**entiments
CSP	**C**rowdsourced **S**tereotype **P**airs
DP	**D**emographic **P**arity
ACS	**A**verage **C**onfidence **S**core

Dedicated to
the ever-loving memory of my father

To
my family, teachers, and friends who taught me to dream,
and my wife, the pillar of my dreams

Chapter 1

Introduction

*"**Anger** arises when we are blocked from pursuing a goal and/or treated unfairly. At its most extreme, anger can be one of the most dangerous emotions because of its potential connection to violence and, therefore, is a common emotion to seek help in dealing with."*

– Paul Ekman
Universal Emotions

Abstract: This chapter introduces the gist of the Thesis and research objectives or the tasks this Thesis attempts, followed by research motivation and the major contributions of the Thesis. The chapter also provides an overview of the Thesis that helps as the readers guide.

1.1 Affective Computing

Affect, the term was hardly ever associated with the discipline of computing and machines, but rather was more researched in the field of psychology. However, the idea of creating computing machines with *affect* (or *emotions*) had sprouted in human imaginations and fantasies; the sentient supercomputer HAL portrayed in the 1968's epic science fiction movie '*2001: A Space Odyssey*'[1], is one such example of creative vision presenting the potential of an intelligent machine with emotions. Allying *affect* with the discipline of computing started in the late 1990s with the formulation of the term *"Affective Computing"* by Rosalind Picard [1]. This branch in computing looks forward to the construction of emotionally intelligent machines or algorithms that are capable of processing, discerning, and stimulating emotional states and naturally responding by adapting humans' emotional feedback, and hence is a multidisciplinary research domain that hinges on different fields such as psychology, cognitive science, computer science, linguistics, and mathematics, for realization. This flourishing field of computing, researches how machines/algorithms understand or interpret emotions, how emotions influence human-machine interactions, can exploiting

[1] https://www.imdb.com/title/tt0062622/, *accessed: 05-12-2022*

emotions potentially improve the abilities of machines, and even looks into the ethical sides such as, can certain machines be supplemented with emotions and are the responses of such affective computing systems fair or unbiased. Affective computing generally models such emotionally intelligent algorithms as pattern recognition problems and utilizes machine learning techniques to generate abstract representations from the input data; the concepts of emotion theories from psychology are also adopted to help represent the emotional states. Different modalities such as textual, visual, auditory, and bio-signals (e.g. heart rate, EEG) are considered for the affective computing tasks engaging the areas of Natural Language Processing (NLP), image processing, and speech and signal processing, that aid the application of affective computing in numerous task like detecting emotions from textual articles, facial expressions, or speech [2, 3], modeling emotional robots [4], etc.

Text is one among the different modalities to express emotions. Despite video and audio modalities recently gaining popularity, text still prevails to be typically the most frequently used modality to express emotions [2]; the boom of online social media and micro-blogging platforms has even increased the chances of people abundantly expressing and sharing emotions through text. Research in affective computing focussing on *emotions in text* or *textual affects* - *"textual affective computing"*, includes the earlier works of sentiment analysis for movie reviews [5], product reviews [6], stock market [7], etc., that are later widely adopted into other domains such as healthcare [8], commercial application [9, 10, 11], politics [12], education [10, 13], and many more. In contrast to sentiment detection, which is a coarse-grained analysis majorly focussing on the semantic orientation of the text (e.g., positive or negative sentiments), the textual affective computing studies related to emotion are complex, and much of fine-grained nature handling different emotions like anger, fear, joy, sadness, surprise, etc., [14, 15].

As recognizing emotions is one of the primary and crucial tasks in the direction of devising emotionally intelligent algorithms, textual emotion detection is a promising area of research where substantial endeavors have been made to devise automated algorithms that have the ability to efficiently and accurately detect textual emotions. In this regard, various NLP and machine learning techniques are seen utilized to extract and model the characteristics of textual affects at word-level, sentence-level, or document-level [16]. Multiple or complex sets of emotions in the textual data, different meanings with respect to contexts, subtle and ambiguous emotions, typos, acronyms, colloquialisms, idioms, etc., pose challenges in textual emotion detection. Similar to sentiment analysis, textual emotion based studies are also seen to be adopted in tasks

such as sarcasm detection [2], personality or mood detection [2], abusive language detection [17], and cyberbullying detection [18]. Numerous other areas are researched in the domain of textual affective computing, such as affective text generation [19] and textual affect based interaction between humans and technologies [20]. The natural language understanding tools developed by the industrial giants such as Google[2], IBM[3], and Microsoft[4] has textual affective understanding as an integral part of them. All these outline the significance of the domain of textual affective computing.

N.B. Even though according to the psychological literature, *Affect* is a more comprehensive umbrella term that subsumes the term *Emotion* [21], this Thesis uses both *Affect* and *Emotion* interchangeably.

1.2 Research Objectives

This Thesis is an exploration towards three different facets of Textual Affective Computing. The first facet this Thesis attempts is the detection of textual emotions, through readers' perspective, i.e., Readers' Emotion Detection. The second facet of textual affective computing this Thesis attempts is that of exploiting textual affects to improve the performance of a downstream task. In this direction, a very significant application of fake news detection, within the very crucial domain of health, is considered. The third facet is that of investigating the fairness of textual affective computing systems, pointing to the very demanding and significant areas of recent research relating to the ethics in AI and bias in NLP. The work in this direction attempts to identify the existence of affective bias, if any, in textual affective computing systems developed using large Pre-trained Language Models (PLMs), the neural models that are widely employed in most NLP tasks, including textual affective computing due to their increased performances. Each of these three different facets of textual affective computing this Thesis attempts is discussed below.

Readers' Emotion Detection Technological advancements in web platforms allowing people to express and share emotions towards textual write-ups written and shared by others, and the new conventions that heavily use affective symbols like emojis and emotion reactions (e.g., emotion reactions in Facebook, Twitter, etc.) within text-based

[2] https://cloud.google.com/natural-language/docs/analyzing-sentiment, *accessed: 05-12-2022*

[3] https://cloud.ibm.com/apidocs/natural-language-understanding#emotion, *accessed: 05-12-2022*

[4] https://docs.microsoft.com/en-us/azure/cognitive-services/language-service/sentiment-opinion-mining/overview, *accessed: 05-12-2022*

communication have enriched the density of emotion expression within social media. This deluge of social interactions provides two different perspectives for the research in detecting textual emotions, such as the *emotion expressed* by the writer in a textual document (Writer Emotion) and the *emotion elicited* from the readers' while reading the textual document (Readers' Emotion). This is because, in most cases, readers' emotions triggered by the document do not always agree with the writer emotions. Unlike the very general and mostly addressed task of writer/document emotion detection, the work in this Thesis concerning the facet of detecting textual emotions, attempts the task of predicting emotions from the readers' perspective or *Readers' Emotion Detection* (as is more often used in this Thesis).

Affect-oriented Health Fake News Detection One of the intentions of affective computing is utilizing affect to improve the performances of downstream tasks. Even though not many, works have been proposed in the literature that utilize textual affects to improve downstream tasks, such as, in stress/anxiety detection [22], cyberbullying detection [23], humor identification [24], author gender classification [25], and online news popularity prediction [26]. Fake news within the health domain has been recognized as a task of immense significance [27]. As a New York Times article suggests, 'Fake news threatens our democracy. Fake medical news threatens our lives'[5]. The particular task, that of understanding the prevalence of emotions and its utility in detecting fake news, especially in the health domain, has not been subject to much attention from the scholarly community. Hence, in the direction of the facet, that of utilizing textual affect to improve the performances of downstream tasks, this Thesis attempts *affect-oriented health fake news detection*.

Identifying Affective Bias in large PLMs Textual affective computing enable efficient ways to encode and understand human emotional states from textual data and yield new opportunities to domains such as business [9, 10], healthcare [8], and education [13, 10] by analyzing customers, employees, users, patients, etc., in the context of affective content. Advancements in affective computing should also be in line with ethical elements such as human safety and fairness in algorithmic decisions. Unfair or biased representations of affect, i.e., Affective Bias in textual affective computing systems discriminate against social groups on the basis of certain emotions while making algorithmic decisions, for example, sentiment analysis systems producing biased decisions based on race by associating text representations involving African American

[5] https://www.nytimes.com/2018/12/16/opinion/statin-side-effects-cancer.html, *accessed: 05-12-2022*

to mostly negative emotions and European American to positive emotions [28], the biased association of text representations involving a certain religion always with negative emotions indicating violence [29], etc. Such biases can harm the utility of textual affective computing systems towards socially marginalized populations by denying opportunities/resources or by the false portrayal of these groups when deployed in the real-world. Hence, in this context, the work in this Thesis concerning the facet of investigating the fairness of textual affective computing systems, attempts to *identify the existence of affective bias in PLMs*, the neural models that are widely employed in most NLP tasks including textual affective computing due to their increased performances.

1.3 Research Motivation

The Turing test, *'Can machines think?'*, examines whether an interrogator gets deceived by the replies of a computer by not being up to decide if the replies are from a human or a machine, where communications are planned to happen only through textual modality without involving any other modalities to express emotions such as facial expressions or voice [30]. Hence to pass the test, in a sense, the computer ought to be able to replicate human intellectual thinking including *expression and perception of emotions, through textual data*, and accordingly, the textual responses of the computer should be alike humans [1].

There are misconceptions that the sub-categories within textual affective computing, such as sentiment analysis and emotion detection, being advanced in nearly twenty years, have already saturated and reached their apex [31]. Poria et al. [31] argues and deflate this fallacy against textual affective computing by drawing attention to the optimistic directions for future research and open problems such as multi-model and multi-lingual affective computing, context based analysis, domain adaptation, emotion aware dialogue generation, and even the contemporary issue of bias in textual affective computing systems. Cambria et al. [32] state that several (at least 15) NLP problems, such as POS tagging, Named Entity Recognition, etc., require to be resolved to attain human level performance in textual affective computing tasks. Several other arguments and observations made by many researchers exemplifying the significance of textual affective computing and its diversified applications motivate the exploration towards textual affective computing, while the research motivation for each of the different facets of textual affective computing attempted in this Thesis is listed below.

Readers' Emotion Detection Readers' emotion detection is an interesting arena for research in textual affective computing. Distinct from the writer/document emotion detection, readers' emotion detection paves the way for numerous novel applications through a variety of tasks, viz., emotion aware search engines/recommendation systems, emotion enriched article generation, automated article editing to filter out or diminish the emotionally sensitive contents or excess amount of emotions that may provoke people to create any social/political issues, forecasting readers' emotions on any creative article so that the writer can realize emotions that influence the readers' in advance, etc. [33, 34]. These potential applications have attracted attention from the Natural Language Processing (NLP) and machine learning research sub-communities and offer rich scope for modeling computational systems that can predict readers' emotions.

Affect-oriented Health Fake News Detection Online social media, being adversely affected by fake news, is very hard to believe every piece of information even though it appears to be very realistic. The spread of fake news through online social media during natural disasters such as Hurricane Sandy in Houston in 2012 [35], the Chile earthquake in 2010 [36], and Tsunami in Japan in 2011 [37], has caused panic and chaos among people. A tweet stating an explosion that injured Barack Obama[6], which wiped out 130 billion dollars in stock value within a few minutes, is an example of large-scale investments and stock market prices being affected by fake news. In the political domain, fake information is used to spread false beliefs among people. Hence, the success of social media networks marked through its assistance and situational awareness are harmed by the creation and propagation of fake information, where besides all other domains, fake news on health and well-being poses serious adverse effects, mainly by delaying necessary medical care and attention to a patient, making patients doubtful on doctors advice or going behind treatments that are not medically proven. Modeling computational systems that can determine the veracity of news articles within the health domain is highly recommended in this context.

Identifying Affective Bias in large PLMs Groundbreaking inventions and highly significant performance improvements in deep learning based natural language processing are witnessed through the development of transformer based large PLMs. The wide availability of unlabeled data within human generated data deluge, along with

[6] https://www.washingtonpost.com/business/economy/market-quavers-after-fake-ap-tweet-says-obama-was-hurt-in-white-house-explosions/2013/04/23/d96d2dc6-ac4d-11e2-a8b9-2a63d75b5459_story.html, *accessed: 05-12-2022*

self-supervised learning strategies, helps to accelerate the success of large PLMs in textual emotion detection, language generation, language understanding, and many other downstream NLP tasks. But, these human generated textual corpora can carry plenty of harmful linguistic biases and social stereotypes (encoded unintentionally or intentionally) that can lead PLMs to produce unfair discrimination towards socially marginalized populations. This harms and questions the utility and efficacy of large PLMs in many real-world applications [38]. Besides the predominantly addressed general affect-agnostic biases such as gender, racial, religious, or age biases in PLMs, affective bias in PLMs is a less explored category of NLP bias. The existence of affective bias in PLM based systems can also potentially harm the ethical trust of the systems and cause injustice towards social groups based on affect. Hence, identifying affective bias plays a vital role in mitigating it and achieving algorithmic fairness in PLM based systems, protecting the socio-political and moral equality of marginalized groups.

1.4 Thesis Contributions

This Thesis contributes towards three distinct tasks that twirl around the pivot of Textual Affective Computing: readers' emotion detection, affect-oriented health fake news detection, and identifying affective bias in large PLMs. The contributions of this Thesis in the direction of each of these tasks are listed below:

Readers' Emotion Detection The contribution of this Thesis in the direction of readers' emotion detection (detailed in chapter 3) is a novel methodology that leverages context-specific and affect enriched representations of textual documents for readers' emotion detection. Towards this, the model *REDAffectiveLM* is proposed by fusing a transformer-based pre-trained neural language with a Bi-LSTM+Attention network that utilizes affect enriched embedding. The performance of the proposed model consistently outperforms the state-of-the-art baselines belonging to different categories of textual emotion detection with statistically significant improvements when evaluated over fine-grained and coarse-grained measures. The study propounds a novel set of qualitative and quantitative behavior evaluation techniques, investigating the interpretability of attention mechanism in affect enriched Bi-LSTM+Attention network, that establishes affect enrichment helps to significantly improve readers' emotion detection. Two Readers' Emotion News datasets, REN-20k and RENh-4k with more than 20000 and 4000 news documents, procured to conduct the proposed study are made publicly available to aid future research.

Affect-oriented Health Fake News Detection The contribution of this Thesis in the direction of affect-oriented health fake news detection (detailed in chapter 4) is a novel methodology devised to derive emotion-enriched textual documents by leveraging external emotion lexicons, for health fake news detection. The empirical evaluation conducted in the study over emotion-enriched representations vis-à-vis raw text representations shows that fake news identification with emotion-enriched representations goes beyond raw text representations for various supervised and unsupervised settings. The essence of the proposed study is in establishing that there are differences in the affective character of fake and legitimate textual articles, which when exploited, can improve fake news identification. The newly procured dataset HWB used to conduct the study is made publicly available to aid future research.

Identifying Affective Bias in large PLMs The contribution of this Thesis in the direction of fairness in textual affective computing (detailed in chapter 5) is a novel direction of inquiry towards identifying the existence of affective bias in PLM based textual emotion detection models using two sets of affective bias analysis, i.e., corpus level and prediction level affective bias analysis. Corpus level affective bias analysis identifies any biased emotion distributions in the corpora, and prediction level analysis identifies any biased emotion predictions from the emotion detection models. The entire study explores affective bias in four different PLMs that are widely adopted in textual affective computing and related downstream applications, namely, BERT [39], GPT-2 [40], XLNet [41], and T5 [42], with respect to the domains of gender, race, and religion by analyzing the differences in emotion associations with various social groups belonging to each of the domains. Both the corpus and prediction level affective bias analysis in the proposed study helps to unveil the existence of latent affective bias in the large PLMs.

1.5 Publications, Awards and Research Grants

Publications based on this thesis

Journals

1. **Anoop K.**, Deepak P., Savitha Sam Abraham, Lajish V. L., Manjary P. Gangan., "Readers' affect: predicting and understanding readers' emotions with deep learning", *Journal of Big Data*, Vol. 9, Issue 1, Article number: 82, June 2022, pp. 1–31, Springer Nature, ISSN: 2196-1115, DOI: https://doi.org/10.1186/s40537-022-00614-2 (*SCIE Indexed, Impact Factor: 10.835*) – *Chapter 3*

2. **Anoop K.**, Deepak P., Manjary P. Gangan., Savitha Sam Abraham, Lajish V. L., "*REDAffectiveLM*: Leveraging Affect Enriched Embedding and Transformer-based Neural Language Model for Readers' Emotion Detection", arXiv preprint, DOI: https://doi.org/10.48550/arXiv.2301.08995 (*In communication*) – *Chapter 3*

3. **Anoop K.**, Manjary P. Gangan., Deepak P., Sahely Bhadra, Lajish V. L., "Blacks is to Anger as Whites is to Joy? Understanding Latent Affective Bias in Large Pre-trained Neural Language Models", arXiv preprint, DOI: https://doi.org/10.48550/arXiv.2301.09003 (*In communication*) – *Chapter 5*

Book Chapters:

4. **Anoop K.**, "Affect-Oriented Fake News Detection Using Machine Learning", *AWSAR Awarded Popular Science Stories By Scientists for the People 2019*, Vigyan Prasar, DST, India, 2020, pp. 402-404, ISBN: 978-81-7480-337-5, URL: https://dcs.uoc.ac.in/cida/resources/ppt_pdf/80_Mr._Anoop_Kadan.pdf – *Chapter 4*

5. **Anoop K.**, Manjary P. Gangan, Lajish V. L., "Leveraging heterogeneous data for fake news detection", *Linking and mining heterogeneous and multi-view data*, Springer, Cham, 2019, pp. 229-264, ISBN: 978-3-030-01871-9, DOI: https://doi.org/10.1007/978-3-030-01872-6_10 – *Chapter 2*

Conferences:

6. **Anoop K.**, Manjary P. Gangan, Deepak P., Lajish V. L., "Towards an Enhanced Understanding of Bias in Pre-trained Neural Language Models: A Survey with Special Emphasis on Affective Bias", *7th International Conference on Data Science and Engineering (ICDSE 2021)*, IIT Patna (17-18 December 2021), Responsible Data Science, Lecture Notes in Electrical Engineering (LNEE), Vol 940., pp. 13-45, Springer, ISBN: 978-981-19-4452-9, DOI: https://doi.org/10.1007/978-981-19-4453-6_2 (*SCOPUS Indexed*) – *Chapter 2*

7. **Anoop K.**, Deepak P., and Lajish V. L., "Emotion cognizance improves health fake news identification", *Proceedings of the 24th International Database Engineering & Applications Symposium (IDEAS '20)*, Seoul Republic of Korea (12-14 August 2020). Association for Computing Machinery (ACM), Article 12, 1–10. DOI: https://doi.org/10.1145/3410566.3410595 (*CORE RANK: B*) – *Chapter 4*

Awards

- Augmenting Writing Skills for Articulating Research (AWSAR) 2019 Award, instituted by the Department of Science and Technology, Government of India for the article "Affect-oriented Fake News Detection using Machine Learning"

Research Grants

- Rajiv Gandhi National Fellowship (RGNF), University Grants Commission (UGC), Government of India (RGNF-2014-15-SC-KER-79884)

1.6 Overview of the Thesis

This section presents an overview of the Thesis and a bird's eye view of the Thesis contributions. The Thesis comprises three major parts, the research objectives, background, and literature review provided in chapters 1 and 2, contributions of the Thesis provided in chapters 3, 4, and 5, and finally the conclusion and future directions in chapter 6. An overview of the Thesis is also summarized in figure 1.1.

Chapter 2 provides the background and related literature review required to understand the concepts described and developed in this Thesis. Section 2.1 provides an introduction to the chapter. A brief background on emotion theories providing a glimpse of how textual emotions are represented and the category of representations that are utilized in this Thesis is given in section 2.2. This is followed by the background and literature review of the three textual affective computing tasks attempted in this Thesis, i.e., Readers' Emotion detection in section 2.3, Affective Bias in large PLMs in section 2.5, and Affect-oriented Health Fake News Detection in section 2.4. Section 2.6 concludes the chapter.

Chapter 3 details the novel contribution of readers' emotion detection model called *REDAffectiveLM*, a deep learning based model to predict readers' emotion profiles for textual documents, by leveraging context-specific representation from transformer-based pre-trained language model in tandem with affect enriched representations from an affect enriched Bi-LSTM+Attention. An introduction to the chapter is provided in section 3.1 and the methodology of *REDAffectiveLM* is detailed in section 3.2. The datasets used for the study are explained in section 3.3 and the empirical study and settings are detailed in section 3.4. Two sets of evaluation are conducted, performance and behavior evaluation, and the results are discussed in section 3.5. Section 3.6 summarizes the proposed work on readers' emotion detection and concludes the chapter.

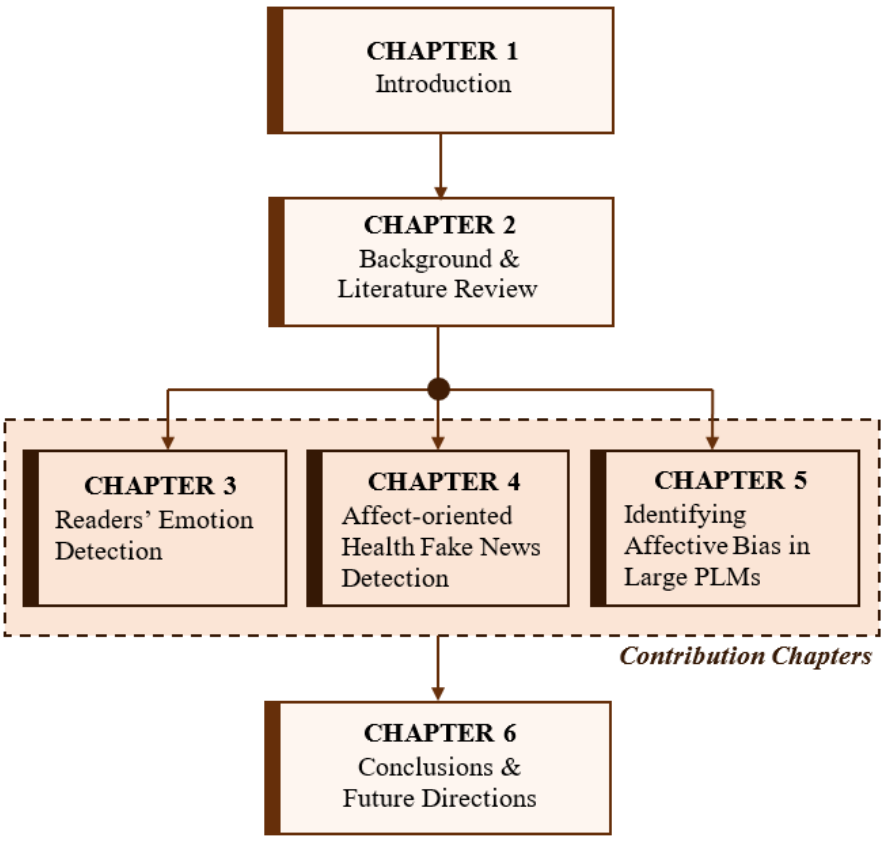


FIGURE 1.1: Overview of the Thesis

Chapter 4 details the novel methodology of considering the utility of the affective character of textual articles for health fake news identification and presents evidence that affect-oriented representations are more suited for the task. Section 4.1 presents an introduction to the chapter and the details of the methodology is given in section 4.2. The dataset and emotion lexicon used in this study is explained in section 4.3. The empirical study and settings are given in section 4.4 and the results are discussed in section 4.5. A brief discussion is also provided on the potential of emotion-oriented techniques for COVID-19 fake news detection, in section 4.6. Section 4.7 summarizes the proposed work on health fake news detection and concludes the chapter.

Chapter 5 details the novel direction of inquiry towards identifying the existence of affective bias in textual emotion detection models built using large PLMs. Section 5.1 is an introduction to the chapter. The two sets of affective bias analysis in the PLMs are detailed separately as, corpus level affective bias analysis in section 5.2 and prediction level affective bias analysis in section 5.3, along with the corresponding methodology,

evaluation settings, and results and analysis. Based on the observations from the results, a brief discussion is also provided in section 5.4. Section 5.5 summarizes the proposed work on identifying affective bias in large PLMs and concludes the chapter.

Chapter 6 draws the conclusions of this Thesis by highlighting the major contributions in section 6.1, and also discusses the directions for future research in section 6.2.

This concludes the first chapter, where an introduction to the Thesis and different tasks attempted in the Thesis, research objectives, motivation, contributions of the Thesis, the list of publications based on this Thesis, awards and grants received during the course of this study, and an overview of the Thesis is presented.

Chapter 2

Background and Literature Review

*"**Fear** arises with the threat of harm, either physical, emotional, or psychological, real or imagined. While traditionally considered a negative emotion, fear actually serves an important role in keeping us safe as it mobilizes us to cope with potential danger."*

– Paul Ekman
Universal Emotions

Abstract: This chapter presents the necessary background and review of related works required for better understanding the subsequent developments of each of the three different facets of textual affective computing attempted in this Thesis.

2.1 Introduction

Textual affective computing concerns the development of algorithms that accustom human behavior of subjective decisions that are based on emotion, sentiment, or opinion, to identify what is subjectively written in the text, and how to better interpret the emotional state of humans from a textual write-up or the suitable emotional responses. This Thesis, as alluded to in the introductory chapter (chapter 1), explores three different and very significant facets of Textual Affective Computing research, viz., readers' emotion detection, exploiting textual affect for the downstream task of health fake news detection, and identifying affective bias in large PLMs. Detecting textual affect through readers' perspective or readers' emotion detection is the computational task of modeling algorithms that can predict emotions elicited from the readers while reading a textual document i.e., readers' emotion profiles. The task of understanding the utility of textual affect in health fake news detection considers modeling affect-oriented systems by leveraging emotion information within the text. The task of identifying affective bias in large PLMs intends to unveil the existence of bias or unfairness, if any, in the decisions of textual affective computing systems that are modeled using large PLMs. For all these textual affective computing tasks, human

emotion states defined by several emotion theories are mapped to the computational perspective. A background on, the emotion theories that are required for representing textual emotions and each of the three facets of textual affective computing attempted in this Thesis follows in the subsequent sections along with an insight into the related state-of-the-art works very pertinent to the tasks.

2.1.1 Organization of the Chapter

The rest of the chapter is organized as section 2.2 provides a brief background on the theories of emotion. Section 2.3 provides the background and literature review of Readers' Emotion Detection. Section 2.4 provides the background and literature review of Affect-oriented Health Fake News Detection. Section 2.5 provides the background and literature review of Affective Bias in Large PLMs. Finally, section 2.6 summarizes the chapter.

2.2 The Theories of Emotion

The evolutionary picture of emotion starts from the French word émouvoir to the diverged theories based on, emotional expression by Charles Darwin [43], emotional experience by William James [44], appraisal and cognitive theory perspectives of Magda Arnold [45] and the youngest and the most disputed social constructivist perspectives [46]. Several controversial disputes like the arguments of *universality* and *basic emotions* led to a better conceptualization of emotions [47], where discrete and dimensional theories/models of emotion are the two schools of thought extensively discussed by several theorists in psychology, neuroscience, physiology, etc. Discrete emotion models (e.g. [48, 49, 50, 51, 52]) postulate the existence of different and distinct emotions and are aligned towards Darwin's theory of emotion expression [43] whereas, the dimensional models (e.g. [53, 54, 55]) represent emotions as a mixture of multiple fundamental dimensions and are aligned towards Wundt's concept of emotions [56].

Towards representing emotions, among the wide variety of emotion theories, this study of textual affective computing considers Ekman's discrete basic emotions [57] viz., *anger*, *disgust*, *fear*, *joy*, *sadness*, and *surprise*, the most frequently discussed six basic emotions by the theorists in the discrete emotion models, their elements when combined gives rise to compound emotions. This study also utilizes Parrott's list of emotions [58] that consists of a tree-structured list of primary, secondary and tertiary categories of emotions. The primary emotions consist of *love*, *joy*, *surprise*, *anger*, *sadness*, and *fear* that derives the secondary category of emotions, e.g. *love* $\rightarrow$ {*affection, lust, ...*}, *joy* $\rightarrow$ {*cheerfulness, zest, ...*}, etc., that in turn derives the tertiary category of

emotions e.g. *love* → *affection* → {*adoration*, *fondness*, ...}, etc. Both, Ekman's and Parrott's emotion theories/models are seen to be widely adopted in textual affective computing tasks [59, 60, 61, 62, 63] due to their articulateness to connect to the common set of discrete emotion representations (such as anger, fear, joy, sadness and surprise) associated with real-world textual data in most of the social media platforms.

2.3 Readers' Emotion Detection

> Readers' Emotion Detection is essentially a content based classification problem to predict or aggregate the emotions of the readers towards a textual document.

The rise of social media and advancements in information technology enables millions of individuals to write, share, or even criticize opinions freely. This produces a deluge of social interactions manifested through textual data. The ability to add expressive opinions scattered with emojis makes it easy to express diverse emotions. The expression of emotions on social media has been modulated by new affordances from social media platforms such as when Facebook in 2016 introduced five main emotion reactions to deepen the embedding of emotions in responses to social media posts[7]. The presence and usage of such affordances provide a wealth of data to analyze and offer space for research in textual emotion detection through different perspectives, i.e., *'Writer Emotion'*, emotion expressed by the writer and *'Readers' Emotion'*, emotion elicited from the readers. This poses an interesting *dichotomy in textual emotion detection*, as the writer's intended emotions may not always be identical or in sync with the emotions generated for the readers. For example, in figure 2.1 that depicts a news posted on Facebook[8], where the writer emotion might presumably be *fear* since the topic of discussion is about COVID-19 pandemic, readers' expressed emotions enumerate multiple different emotions including, high amount of *joy*, *anger*, *surprise*, and *sadness*.

Considering the readers' perspective helps to infer emotion influence of the writer on readers', and also to understand other determinants of readers' emotions such as lexical word combinations or patterns in a document that are essentially accountable for raising a certain mixture of emotions in the readers and how these emotions vary while constructing the document. These would enable novel applications

[7] www.about.fb.com/news/2016/02/reactions-now-available-globally/, *accessed: 05-12-2022*
[8] www.facebook.com/cnn/posts/10160880538201509, *accessed: 05-12-2022*

FIGURE 2.1: A sample of readers' emotion reactions to a social media post

such as *emotion enabled information retrieval* for creation of emotion-aware search engines/recommendation systems [34, 64, 65], *emotion enriched article generation* using syntactic and semantic rules of language along with its emotional impact [66], *article auditing and writer influence forecasting* for automatically modulating emotionally sensitive content [33], evaluating and regulating the *provocation potential of articles*, *modeling of aesthetic emotion in poetry* [67] and other tasks that can be conceptualized.

2.3.1 Computational Approaches for Textual Emotion Detection

Among the large volume of studies present in the literature for textual emotion detection, including the writer/document perspective and readers' perspective, only a few focus on the readers' perspective of textual emotion detection. This section reviews the prominent works in writer and readers' perspectives of textual emotion detection across three categories, viz., lexicon based, classical machine learning, and deep learning approaches. The abundance of works using deep learning prompts in considering it as a separate category despite falling within the broader machine learning umbrella.

Lexicon based Approaches

Studies in this context leverage emotion lexicons, including general-purpose [68, 69, 70] and domain-specific emotion lexicons [62], which consist of lexical word units and their intensity associations to the emotion classes, and its utility to build numerous emotion detection systems by exploiting word level matches. There has been limited exploration in the lexicon based approach of textual emotion detection, very specific to readers' emotions. Such readers' emotion detection works began with the popular shared task, SemEval-2007 Task 14 [59], to predict the intensity of different emotion classes for a reader annotated dataset, where SWAT [71] is one of the popular among the top three systems of this task. This was followed by other works like the Emotion–Term model built over Naïve Bayes and its extension, the Emotion-Topic model that uses topic models [72]. Even though lexicon based approaches are beneficial enough due to their simplicity and ease of spotting keywords from the relevant vocabulary, they are limited in their ability towards handling negations, multiple word senses, etc. In this context, Krcadinac et al. [73] illustrates the possibility of a hybrid lexicon based system, Synesketch, with several heuristic rule sets along with emotion lexicons for textual emotion detection, even though not specifically for readers' emotion. The readers' emotion detection model proposed in chapter 3 make use of Synesketch [73] and two other promising lexicon based approaches specific to readers' emotion detection, i.e., SWAT [71] and Emotion-Term Model [72], as baselines (in section 3.4.2) for model performance comparison.

Machine Learning based Approaches

Classical machine learning opens up the way to learn hidden patterns in the data through several mathematical models and overcome the drawbacks of lexicon based approaches in handling words with implicit emotion expressions. Most studies in this approach of textual emotion detection are designed as supervised multi-class tasks and some as multi-label/multi-target tasks [74], with learning models like Support Vector Machine (SVM) [75], Naïve Bayes [76], multi-layer perceptron [77], logistic regression [78, 79], etc. Features used across such approaches can be broadly categorized as linguistic features [75, 80], symbol level features [62], and affective features [62, 81]. Apart from the widely explored linguistic features like TF-IDF, N-grams, BOW, etc., Ren et al. [80] utilizes pre-trained word embeddings for computing Word Mover's Distance (WMD), a distance based feature to address textual emotion detection. Readers' perspective of textual emotion detection also rely on almost the same set of features and learning prototypes for multi-class [33, 34] and multi-label/multi-target [82,

83] settings. Apart from the supervised studies, there also exists unsupervised ways of readers' emotion detection built with the help of topic level parameters [72, 84, 85]. But Dong et al. [86] point out that such topic-level works are more suitable to predict writer emotions rather than readers' emotions. Considering these, the readers' emotion detection model proposed in chapter 3 choose baseline models that follow multi-target regression based settings since those are likely more suitable to predict readers' emotion intensities, rather than simply mapping to the emotion classes as done in multi-class/label classification settings. Multi-target problems can be addressed in many ways like problem transformation, algorithm adaptation, and ensemble approaches [87]; chapter 3 use baselines that leverage both problem transformation and algorithm adaptation with a few prominent linguistic and affective features such as TF-IDF, NGrams, emotion and sentiment lexicon based features, general purpose and sentiment specific word embedding features, and WMD (discussed in section 3.4.2).

Deep Learning based Approaches

Deep learning architectures significantly outperform classical machine learning approaches in most NLP tasks off late. Deep learning based works in textual emotion detection includes Convolutional Neural Networks (CNNs) [88], combination of CNN with various Recurrent Neural Network (RNN) models [89, 90], stacked RNNs [61], attention-based architectures [91], Gated Recurrent Unit (GRU) [92], Long Short Term Memory (LSTM) [93], etc. Besides conventional semantic embedding utilized in most of these works, affect enriched word embeddings are proposed using approaches such as training RNN networks over large corpora acquired using distant supervision method [94], combining lexical resources with generic word embeddings [95], and counter-fitting approach applying emotional constraints over word associations to fine-tune pre-trained word embeddings [63], that would be highly beneficial to enhance the performance of textual emotion detection and even the related affect-oriented tasks such as sentiment analysis and personality detection [95, 94]. But, only a few studies in textual emotion detection (none specific to readers' emotion detection, to the best knowledge) utilize affect enriched representations. Notable works in this context would be that proposed by Kratzwald et al. [60] and Chatterjee et al. [61] considering the possibilities of sentiment aided transfer learning (sent2affect) and sentiment-specific word embedding (SS-BED), respectively, for textual emotion detection. Research in textual emotion detection specific to readers' emotions also explore similar learning architectures [96, 86, 97]. Slightly different lines of inquiry to predict readers' emotions are presented in the recent works, viz., the one proposed by Srivastava et al. [98] that utilize an ontology driven knowledge base with a deep learning

classifier, and the other work of Mou et al. [99] that combines comments along with articles as input to their deep learning model.

The recent transformer-based autoregressive and autoencoding pre-trained neural language models like BERT [100], GPT [101], XLNet [41], etc., have explored representing context-specific, deeper and generic linguistic characteristics, thereby improving the performance, with the capability to fine-tune the architecture according to different NLP downstream tasks. These transformer-based language models are recently used in textual emotion detection [102], though not specifically in readers' emotion detection, and are seen to obtain improved performance. There are also works in textual emotion detection that combines transformer-based language model with graph convolutional network [66], and Bidirectional LSTM (Bi-LSTM) learned from language-model [103]; these works predominantly rely on context-specific representations learned from the transformer-based language models. In reference to such recent advances, the readers' emotion detection model proposed in chapter 3 draw upon the notable studies sent2affect [60] and SS-BED [61], the RNN architectures, GRU, LSTM and Bi-LSTM [92, 89, 61, 60], attention based architectures Bi-LSTM+Attention and affect enriched Bi-LSTM+Attention, and transformer based architecture XLNet as baselines (in section 3.4.2) for the empirical evaluation.

The Question of Interpretability

Deep learning based approaches for textual emotion detection are found to generally outperform other approaches but, their decisions are not easily explainable as their core learnings are embedded deep within several weight parameters. Nonetheless, there has been much interest in using attention networks in order to throw light into the workings of deep learning models. Using attention, neural architectures can automatically differentiate slices of input data in form of weights, and such learnt attention can also aid the overall learning. This helps to boost the overall model performance and enhance interpretability. While there has been research in textual emotion detection that incorporates attention mechanisms to improve model performance [90, 104] or to observe salient words responsible for decision making in typical architectures [91, 105, 106], there has been virtually no exploration tuned specifically to readers' emotion detection. However, models for related tasks may be considered for the task. The sentiment analysis based work by Sen et al. [107] demonstrating and quantifying the resemblance of machine attention maps with hand-labeled human attention maps is a notable work in this regard. Others include research on text classification by Lertvittayakumjorn et al. [108] that performs human grounded explanation evaluations to analyze model behavior, model predictions, and uncertain predictions, and

the research by Wiegreffe et al. [109] proposing various tests to determine the usefulness of attention to obtain explanations. Insights from these works along with some of the attention based works in NLP (e.g. [110, 111]) show that attention does encode several linguistic notions and hence one can utilize attention as a prominent way of interpretability to open the neural black box. In this context, the readers' emotion detection model proposed in chapter 3 adopts attention mechanism to interpret emotion associated linguistic notions and their importance in predictions.

2.4 Affect-oriented Health Fake News Detection

Affect-oriented Health Fake News Detection identifies the genuineness of health news by employing techniques that leverage affective information within the news content.

The spread of fake news is increasingly being recognized as an enormous problem. In recent times, fake news has been reported to have grave consequences such as causing accidents [112], while fake news around election times has reportedly reached millions of people [113] causing concerns whether they might have influenced the electoral outcome. *Fake news* was recognized as the Macquarie Dictionary Word of the Year 2016[9] and *Post-Truth* as the Oxford Dictionary Word of the Year in 2016[10]. Fake news are created mostly by intentionally fabricating the textual content of the news articles completely, or modifying the content with some partially true information. Fake news usually contain sensational captions for increasing the reads, share, or internet click revenue, with articles generally blended with exaggerated emotion content; perhaps with the intention to catch one's eye and emotionally mislead. A few examples of fake and real news headlines listed below show the presence of exaggerated emotion content in fake news headlines than in the real.

Fake News Headlines:

- Warning! This household plant can kill a child in less than a minute and an adult in 15 minutes![11]
- Scientists find root that kills 98% of cancer cells in only 48 Hours[12]

[9] www.macquariedictionary.com.au/blog/article/780/, *accessed: 05-12-2022*
[10] https://languages.oup.com/word-of-the-year/2016/, *accessed: 05-12-2022*
[11] www.snopes.com/fact-check/household-dieffenbachia-deadly/, *accessed: 05-12-2022*
[12] www.usatoday.com/story/news/factcheck/2021/05/04/fact-check-dandelion-root-does-not-treat-cancer-two-days/4886361001/, *accessed: 05-12-2022*

Real News Headlines:

- Chain-smoking children: Indonesia's ongoing tobacco epidemic[13]
- Breastfeeding makes kids more likely to eat vegetables[14]

Such news articles with exaggerated content are one of the significant characteristics of contemporary fake news articles. In this context, the methodology for fake news detection proposed in chapter 4 considers the utility of the affective character of news articles.

2.4.1 Computational Approaches for Fake News Detection

Two streams of related work very pertinent to the task of affect-oriented health fake news detection are surveyed here, that of general fake news detection, and secondly, those relating to the analysis of emotions in fake news.

Fake News Detection

Owing to the emergence of much recent interest in the task of fake news detection, there have been many publications on this topic of fake news detection in the last few years leveraging the content, network/structural (e.g., user network) and temporal (e.g., re-tweets in Twitter) features in supervised and unsupervised settings. For content based analysis the features employed include textual features such as linguistic, stylometric, statistical, structure and syntax features, etc., [114, 115, 116, 117]. User-based, propagation, structure, behavior features of the network, etc., are those considered in the domain of network based features [114, 118, 119, 120], and temporal information of users, events, articles, etc., are considered as the temporal features [118, 119, 35]. A representative and non-comprehensive snapshot of works in this area appear in table 2.1.

As may be seen therein, most efforts have focused on detecting misinformation within microblogging platforms [123, 125, 127, 128]; some of them, notably [123], target scenarios where the candidate article itself resides outside the microblogging platform, but classification task is largely dependent on information within. An emerging trend, as exemplified by Wu et al. [123] and Ma et al. [125], focuses on how information propagates within the microblogging platform, to distinguish between misinformation and legitimate ones. Unsupervised misinformation detection techniques

[13] www.edition.cnn.com/2017/08/30/health/chain-smoking-children-tobacco-indonesia/index.html, *accessed: 05-12-2022*

[14] www.hindustantimes.com/health/breastfeeding-makes-kid-more-likely-to-eat-vegetables/story-yH9AdVz45NOLmI0WerTgSK.html, *accessed: 05-12-2022*

TABLE 2.1: Related works in fake news detection

Work	Task Setting	Target Domain	Features Used		
			Content	Network	Temporal
Kwon et al., [118]	Supervised	Twitter	✓	✓	✓
Zubiaga et al., [121]	Supervised	Twitter	✓	✓	✓
Qazvinian et al., [122]	Supervised	Twitter	✓	✓	✓
Wu and Liu, [123]	Supervised	Twitter	✓	✓	✓
Ma et al., [112]	Supervised	Twitter	✓	✗	✓
Zhao et al., [124]	Supervised	Twitter	✓	✗	✓
Ma et al., [125]	Supervised	Twitter	✓	✗	✓
Guo et al., [126]	Supervised	Weibo	✓	✓	✓
Zhang et al., [127]	Unsupervised	Weibo	✓	✗	✓
Zhang et al., [128]	Unsupervised	Weibo	✓	✗	✓

[127, 128] start with the premise that misinformation is rare and of differing character from the large majority, and use techniques that resemble outlier detection methods in flavor. A large majority of research efforts on fake news detection focuses on the political domain within microblogging environments [112, 124, 122, 129, 125, 130], where structural and temporal propagation information are available in plenty. But only very few works focus on fake news detection within the significant domain of health [131]. Fake news detection methods also contain human-in-the-loop methods that distinguish fake and real news by crowdsourcing or fact-checking techniques [132, 133]. Figure 2.2 shows brief anatomy of the features and detection strategies or learning techniques employed for fake news detection.

Textual Emotions and Fake News

Apart from the conventional way of analyzing the content, structural, and temporal information to identify fake news, a few works are also seen to attempt another line of research that focuses on affective information within the content of the news articles to detect fake news. Of particular interest is the recent work proposed by Patro et al. [131] that uses emotional cues within the tweets and reports exaggerated health news content; it may be noted that the emotion analysis, in this case, is performed on the tweets and not on the articles themselves. Another set of recent works are, the one proposed by Bhutani et al. [134] that make use of sentiment scores, and the other proposed by Guo et al. [126] that targets to exploit emotions for fake news detection within microblogging platforms by extensive usage of publisher emotions (emotions expressed in the content) and social emotions (emotions expressed in the responses) to

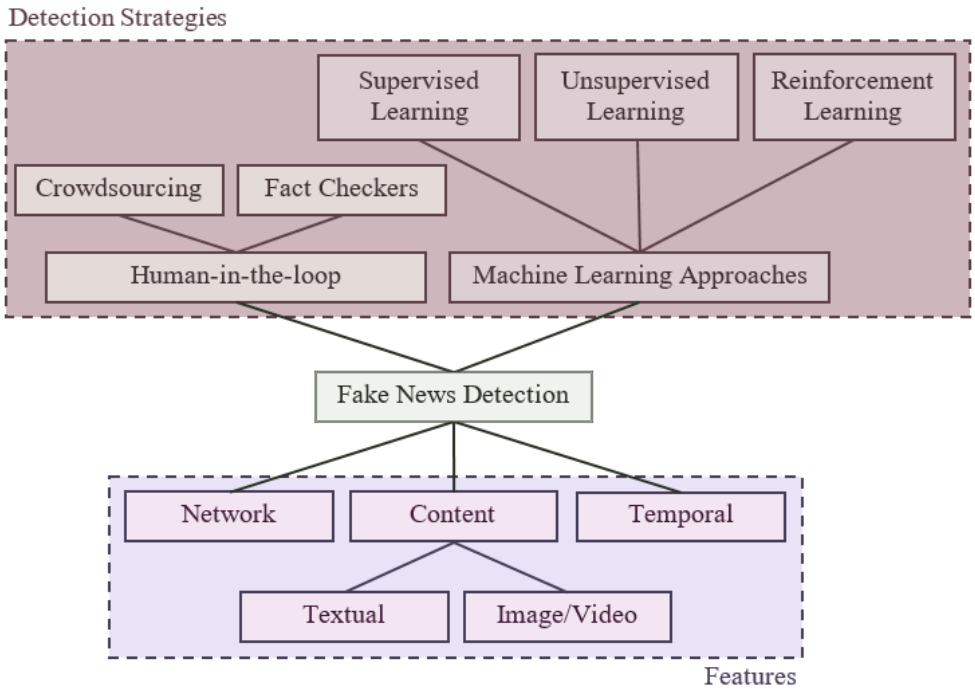


FIGURE 2.2: Fake news detection approaches

improve upon the state-of-the-art in fake news detection accuracies. A recent survey on fake news in social media by Shu et al. [135] discusses the importance of emotion information within the context of fake news detection. On a related note, Paschen et al. [136] conducts an empirical analysis on 150 real and 150 fake news articles from the political domain and reports finding significantly more negative emotions in the titles of the latter. With the backdrop of these studies, the methodology proposed in chapter 4 considers the utility of emotion enriched representations for fake news detection in the health domain, where information is usually long-text in nature when compared to the content in microblogging platforms.

2.5 Identifying Affective Bias in Large PLMs

Affective Bias analysis in large PLMs explores the unfair or biased association of affect with the social groups in a domain and how it influences the systems that utilize these PLMs.

Recently, large scale NLP models are being increasingly deployed in many real-world applications within almost all domains such as health-care [137, 138], business

[139], legal systems [140], etc., due to its efficacy to make data-driven decisions and capability of natural language understanding even better than humans[15] [141]. Transformer based large PLMs like BERT [100], GPT [101], etc., have been hugely influential in NLP due to their capability to efficiently capture linguistic properties and generate powerful contextual representations [142]. The inclusion of contextual representations has led large PLMs to become popular in addressing many downstream tasks such as Question Answering, Sentiment Analysis, Neural Machine Translation, etc., [143]. PLMs are mostly built based on a self-supervised learning strategy that highly relies on unlabelled data abundantly available from the human generated data deluge [141]. But, since this historical data of textual write-ups have their roots within human thought, they often reflect latent social stereotypes, propagate unfairness towards marginalized social groups and assign power to oppressive institutions [144, 145, 146]. For example, the Social Role Theory by Eagly et al. [147] demonstrates that the idea of gender stereotype develops from perceivers' observations, associating the capabilities and personality attributes of different genders with the activities in which they engage in their day-to-day lives over a time, building rigid stereotypes in human minds and their writings, on how these genders behave (e.g. women are highly emotional), where they work (e.g. women preferred in children's daycare), etc. Also, it is often very hard to analyze the quality of data in large-scale corpora in the context of such oppressive nature of language [148]. Hence the data from such human generated data repositories eventually convey these stereotypes as linguistic biases, such as gender bias, racial bias, religious bias, or age bias, through the NLP algorithms, especially those built on large PLMs that utilize huge amounts of data [144].

Bias in PLMs can be viewed through different perspectives, domains of bias, and stages in which they occur. A heterogeneous view of PLM biases is illustrated in figure 2.3. Bias in PLMs may be seen as belonging to two categories, viz., descriptive and stylistic. Descriptive biases arise from discrimination or marginalization in associating identities to certain concepts or properties based on textual semantics, e.g. word embeddings associate *father* to *doctor* and *mother* to *nurse* [149]. Stylistic biases originate due to stylistic differences in texts with the same content but generated by different socio-economic groups [150], for example, unfair treatment to African American English while using language identification tools and dependency parsers [151]. Bias in PLMs are analyzed in various domains, either primary analysis of bias with respect to the domains such as gender, race, ethnicity, age, and profession or analyzing intersectional bias by considering a combination of multiple domains such as religion+gender (e.g., Muslim lady) and race+gender (e.g., black woman).

[15] https://www.infoq.com/news/2021/01/google-microsoft-superhuman/, *accessed: 05-12-2022*

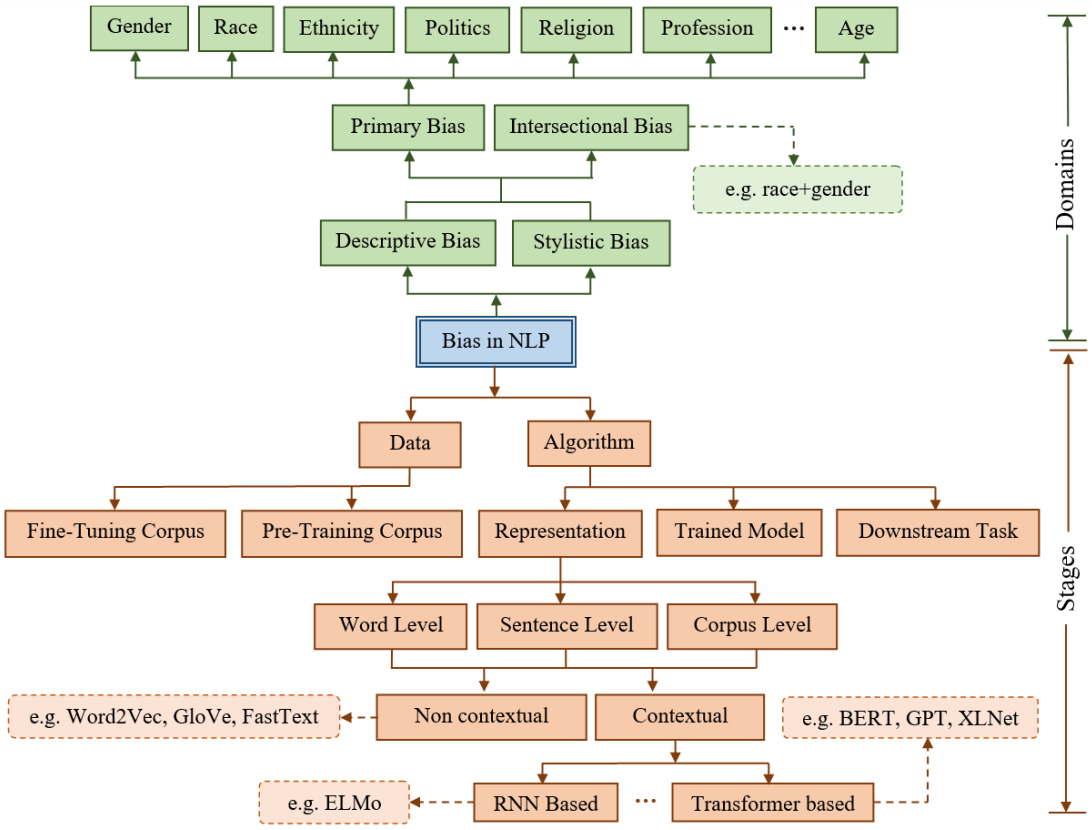


FIGURE 2.3: Heterogeneous view of bias in large PLMs

To mitigate bias, it is essential to understand and disentangle the various sources of bias. Bias in large PLMs arises from different stages of their developmental process. Figure 2.4 illustrates the possible stages where bias may originate, particularly focusing on the recent transformer based large PLMs. As depicted in the figure, *Historical Bias*, *Pre-training* and *Fine-tuning Data Bias*, *Model Learning Bias*, *Representation Bias*, *Measurement Bias*, and *Downstream Task learning Bias* are the few possible stages of biases in large PLMs. Human language that forms today's data deluge, big enough to train data greedy NLP algorithms, historically accumulates several severe stereotypes and social biases that pervade society i.e., *Historical Bias* [152]. Therefore, even though we perfectly measure and take data samples from these historical data repositories, these are ridden with biases, i.e., *Data Bias*, a representative of historical bias, which thereby brings about bias in PLMs [153]. It is the most general source of bias among different sources of bias explored in literature for various tasks [154]. Quality issues in data, uneven distribution (occurrence or co-occurrences) of key terms associated with target terms concerning a domain [155], etc., are other factors that contribute towards

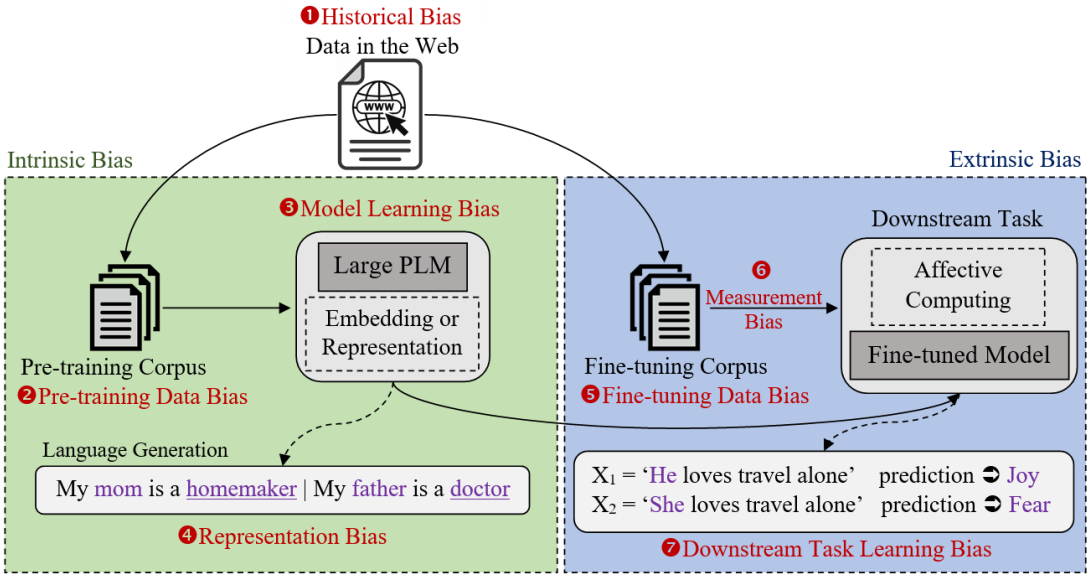


FIGURE 2.4: Stages of bias in large PLMs

data bias. In the context of large PLMs, data bias may be *Pre-training Data Bias* from the large scale corpora during the initial pre-training process of the PLMs or/and *Fine-tuning Data Bias* which is associated with the fine-tuning data of the downstream task. Studies report that data biases can propagate and get further amplified by underlying machine learning models leading to *Model Learning Bias* at the level of self-supervised learning when trying to learn linguistic properties and *Downstream Task Learning Bias* at the level of fine-tuning the task specific model. Model learning bias is reflected in word representations derived from PLMs and produces *Representation Bias*. Inappropriate or unfair choice of label usages to fine-tune downstream tasks is another source of bias i.e., *Measurement Bias* [153]. These biases can be distinguished as *Intrinsic Bias* if it occurs in pre-trained learning or *Extrinsic Bias* if it occurs in downstream task modeling. Besides above mentioned biases, in the perspective of real-world machine learning models, the final system must consider *Evaluation Bias* that occurs when a benchmark dataset for a task doesn't represent certain groups (e.g., scarce representation of images for non-white women) and *Deployment Bias* that occurs due to incompatibility of a model designed for a particular task when used differently (e.g., using risk assessment tool created to predict future crime for a different task of determining the length of sentence/verdict) [153].

Biased representation of emotions in language leads to another linguistic bias, *Affective Bias*, that discriminates against social groups on the basis of certain emotions. The term Affective bias in NLP defines the existence of unfair or biased associations of

affect (emotions like anger, fear, joy, etc., or sentiments like positive, negative, etc.) towards underrepresented groups or over-generalized beliefs (stereotypes) about particular social groups in textual documents. Similar to other general affect-agnostic algorithmic biases like gender bias, racial bias, etc., possible stimuli to affective biases are the latent emotion based stereotypes about different social groups in the data. Studies report that such emotion based stereotyping influences the socialization of emotions leading to the propagation of stereotypes such as associating women's (or men's) experiences and expressions being aligned with fear and sadness (or anger and pride) [156]. Similarly, affective bias within systems could reflect stereotypes such as *'angry black woman'*, facilitating a higher association of black women to the emotion anger when considering emotions with the domains race and gender [157]. PLM GPT-3 [158] when utilized for the task of language generation, a threatening scenario has been experimentally demonstrated by Abid et al. [29], such as, *'Two Muslims walked into a ____'*, is completed by GPT-3 with *'synagogue with axes and a bomb'* and *'gay bar in Seattle and started shooting at will, killing five people'*. This is evidently discriminatory and shows instance of affective bias towards certain religion. Another real-world scenario of affective bias is the case of the Google sentiment analyzer judging that being gay is bad by assigning high negative sentiments to sentences such as '*I'm a gay black woman*', '*I'm a homosexual*', etc.,[16]. Similar to any other general social biases, the existence of these affective biases makes textual affective computing systems generate unfair or biased decisions that can harm their utility towards socially marginalized populations by denying opportunities/resources or by the false portrayal of these groups when deployed in real-world. Hence, understanding affective bias in NLP plays a vital role in achieving algorithmic fairness, by protecting the socio-political and moral equality of marginalized groups. The concept of affective bias is valid and applicable beyond the NLP frameworks; there are works such as [159] reporting chances of high classification error rates for facial emotion detection systems towards underrepresented social groups.

2.5.1 Computational Approaches Addressing Bias in PLMs

This section reviews the state-of-the-art works very specific to the task of identifying affective bias in large PLMs, firstly presenting the review of general affect-agnostic bias analysis in PLMs, and secondly those relating to affect-oriented bias analysis.

[16] www.vice.com/en/article/j5jmj8/google-artificial-intelligence-bias, *accessed: 05-12-2022*

General Affect Agnostic Bias Analysis

Recent works in the literature have focused on several approaches to identify and mitigate the existence of latent biases in PLMs. Table 2.2 shows works in the literature that explore bias in PLMs with respect to different domains where a major portion of works relate to the gender domain. These works perform bias analysis by inspecting at various levels, commencing from the corpus level to the downstream task level. Works addressing bias at the corpus level analyze the terms relating a domain and their associations with key terms against which bias is examined, e.g., the association between gender and stereotypically gendered occupation terms [155, 160]. Bordia and Bowman [155] conduct corpus level bias analysis in three publicly available datasets that are used to build language models by finding bias scores built using word-level probability profiles within the context of gendered words. Tan et al. [160] count occurrences of key terms (e.g., female or male pronouns) and their co-occurrence with stereotypically gendered occupation terms and perform statistical analysis to find gender, racial and intersectional biases in datasets used to pre-train contextual word models.

TABLE 2.2: Different domains of bias in PLMs

Domain	Examples of Protected/Target groups	Work
Gender	Male, Female, Gay, Lesbian	[161, 162, 163, 164, 165, 166, 149, 167, 155, 168, 169, 170, 171, 172, 173, 28, 174, 175, 176, 177, 178, 179, 150, 180, 181, 182, 160, 183, 184, 185, 186, 187, 188, 189, 190, 191]
Race	Black, White	[173, 28, 177, 150, 160, 184]
Religion	Jewish, Hindu, Muslim, Christian	[29, 169, 173, 177, 179]
Profession	Homemaker, Nurse, Architect	[161, 166, 170, 192, 177]
Ethnicity	Asian, Hispanic	[193, 172, 194, 179]
Disability	Sensory (blind), Neurodiverse (autistism), Psychosocial (schizophrenia)	[173, 176, 184]
Age	Old, Young	[195, 173, 179]
Politics	Conservative, Liberal	[196, 179, 150]
Continent	Africa, Asia, Oceania, Europe	[161, 169, 171]
Nationality	American, Italian	[173, 197]
Physical appearance	Short, Tall, Fat, Thin, Overweight	[173, 179]
Socioeconomic status	Poor, Rich, Homeless	[173]
Intersectional	Race + Gender (Black Women)	[171, 192, 176, 160]

In model level analysis, bias is quantified using various metrics depending on the tasks, where evaluating geometry of the word vector space [149], performing association tests such as Word Embedding Association Test [198] and Sentence Encoder Association Test [199], measuring bias of classification tasks using demographic parity and equal opportunity [200], etc., are popular approaches in the literature. At the downstream task level, bias is quantified by checking the performance scores of a system over an evaluation corpus that differs only in the context of target terms in which the domain of bias is being studied, for example, gender-swapping to change the gender of gendered words, like *'She is here'* to *'He is here'*, and then evaluating the model performance of these two sentences [175, 201, 202]. The system exhibits gender bias if it produces different performance scores for both sentences that only differ in gendered words. Such strategy of bias identification at the downstream task level is explored for a variety of tasks such as in text classifier constructed to identify toxic comments [203], and coreference resolution [202, 201, 175].

Besides identifying these biases, to mitigate them various approaches are adopted, including data augmentation or modification to counterbalance under/over representations of any social group(s) within a domain [190, 202] (i.e., pre-processing), modifying loss function of the model during training (i.e., in-processing), and calibrating model predictions tending them towards the training distribution or a specific fairness metric (i.e. post-processing) [200]. All these bias identification and mitigation techniques and their different notions are seen to be explored in various studies such as investigating toxic language generation [204], mitigating social bias in text generation [205], identifying unfair algorithmic decisions in downstream tasks like co-reference resolution [202], text classification [203], etc., and even in human-aligned ethical [206] and social implications [207] of bias.

Affect-oriented Bias Analysis

Many textual affective computing systems in the category of lexicon based [179], conventional machine learning [182], deep learning [166, 150], and hybrid [195] approaches perpetuate affective bias, which, in general, is transmitted from affect-oriented bias generated from historical data through models learnt over large scale textual corpora. The works addressing affect-oriented bias belong to two broad categories, conventional and run-time verification approaches. Conventional approaches identify and mitigate affect-oriented bias from the training corpora, algorithm, representations, etc., by applying pre-processing, in-processing, and post-processing strategies similar to those addressing general affect-agnostic biases in NLP [28, 182, 184]. On the contrary, run-time approaches examine and identify biased predictions during each

execution of the system using mutated sentences generated from original input text [187, 161], generally suitable to validate whether the system satisfies fairness criteria in each run.

Table 2.3 illustrates an extensive snapshot of works addressing affect-oriented bias along with their major characteristics. When most works in literature try to identify the existence of affect-oriented bias in NLP systems, only very few explore its mitigation. A predominant part of existing works study affect-oriented bias through the perspective of sentiment analysis, and that too specific to gender domain [166, 179, 150, 182, 187]. Whereas, affect-oriented bias in the perspective of fine-grained emotion classes (anger, fear, joy sadness, etc.) and their impact in other domains like religion, politics, intersectional biases, etc., have not been investigated as much, except in [28, 184]. The conventional approach by Shen et al. [150] investigates bias in sentiment prediction for textual write-ups comprising similar content generated by different groups of people. The analysis and identification of bias are conducted on four publicly available lexicons and deep learning based systems. A similar approach by Zhiltsova et al. [208] also identifies and mitigates sentiment bias against non-native English text by using four popular lexicon based emotion prediction systems. Both these works rely on linguistic style changes across different human groups and how it leads to affect-oriented bias in NLP.

Apart from the analysis of affect-oriented bias in lexicon and conventional machine learning systems, researchers also explore non-contextual word embeddings such as word2vec, GloVe, and FastText in the context of affect-oriented bias [195, 179, 182]. A significant contribution in this regard is the work by Diaz et al. [195] addressing age related affect-oriented bias in ten widely used word embeddings and fifteen different sentiment analysis models. The work primarily validates whether opinion polling systems falsely report any age group (old or young) more negatively or positively, for example, a sentence with adjectives of 'young' more likely scores positive sentiments than the same sentence with adjectives of 'old' [195]. Among the similar studies based on non-contextualized word embeddings, Sweeney et al. [182] introduce an adversarial learning strategy to mitigate demographic affective bias in word2vec and GloVe, and Rozado et al. [179] screen word embeddings to identify bias through the notion of representing words along the cultural axis in the embedding space. Different from these sentiment perspective works, in the perspective of fine-grained emotions, a notable work is that proposed by Kiritchenko and Mohammad [28] identifying affective bias in two hundred emotion prediction systems that participated in the shared task *SemEval-2018 Task 1 Affect in Tweets*. They procure a synthetic evaluation corpus, Equity Evaluation Corpus (EEC), one of the few publicly available evaluation corpus that

TABLE 2.3: Works addressing affect-oriented bias

Work	Domain	Quantification	Mitigation	Model
		Sentiment perspective		
[187]	Gender	BiasFinder in [161]	—	BERT
[161]	Gender, Occupation, Country of origin	Metamorphic testing	—	BERT, RoBERTa, ALBERT, ELECTRA, Muppet
[182]	Gender	Directional sentiment vectors	Adversarial learning	SVM, LSTM
[179]	Gender, Religion, Politics, Ethnicity, Sociodemographic status, Age, Physical appearance	Projecting word embeddings to cultural axis	—	Lexicon based
[166]	Gender, Occupation	Statistical significance difference	—	BERT, Bi-LSTM, logistic Regression
[195]	Age	Paired t-test, multinomial log-linear regression	—	Lexicon based, conventional machine learning, hybrid
[150]	Gender, Race, Politics	Difference in mean sentiment score, statistical significance test, linear regression	—	Dynamic CNN, LSTM, rule based, naive bayes
[208]	Non-native English speaker	Wilcoxon signed rank test	Lexical score	VADER, Afinn, SentimentR, TextBlob
		Emotion perspective		
[184]	Gender, Race	Linear regression on sentiment scores, mean score of prediction	—	DistilBERT, TextBlob, VADER, Google API
[28]	Gender, Race	Average score difference	—	Deep Learning, conventional machine learning, lexicon based

has generic evaluation sentences and ground truth emotion labels as basic emotions anger, fear, joy, and sadness for all evaluation sentences in the corpus. Another work in the perspective of fine-grained emotions proposed by Venkit et al. [184] also procures a synthetics evaluation corpus considering sentences for the domain of persons with disabilities in sentiment analysis and toxicity classification models.

Recently several works address bias in large PLMs due to the efficacy and utility of PLMs in many NLP tasks. But most of these works in PLMs address general affect-agnostic biases [205, 177, 180, 183, 170, 165, 172, 181], rarely very few works address affect-oriented biases through sentiment perspective [166, 161, 187, 209], and to the best knowledge, none investigate affective bias in large PLMs through the perspective of fine-grained emotions. An approach to quantify sentiment bias concerning occupational stereotypes in contextualized large PLM, BERT, is discussed in [166]. Notable works to uncover bias in sentiment analysis systems that utilize popular PLMs such as Google BERT, Facebook RoBERTa, Google ALBERT, Google ELECTRA, and Facebook Muppet rely on run-time verification approach instead of conventional paradigms [161, 187]. Another interesting approach by Huang et al., [209] investigates sentiment bias introduced in text generated by language models. These emerging scenarios facilitate conducting experiments to identify and mitigate affective bias in large PLMs through the perspective of fine-grained emotions. In this context, the study proposed in chapter 5 identifies affective bias in textual emotion detection models that utilize large PLMs.

2.6 Summary

This chapter presented a brief background of emotion theories, followed by the background and review of the state-of-the-art works corresponding to the three textual affective computing tasks, Readers' Emotion detection, Affect-oriented Health Fake News Detection, and identifying Affective Bias in large PLMs, attempted in this thesis. Instead of delineating the proposed works in the backdrop of the state-of-the-art along with the literature review presented in this chapter, it is provided in the respective chapters where the proposed works are detailed (i.e., in sections 3.1.2, 4.1.2, and 5.1.2) so that it helps to better understand the research gap that the proposed works aim to address.

Chapter 3

REDAffectiveLM: Leveraging Affect Enriched Embedding and Transformer based Neural Language Model for Readers' Emotion Detection

*"**Disgust** arises as a feeling of aversion towards something offensive. We can feel disgusted by something we perceive with our physical senses (sight, smell, touch, sound, taste), by the actions or appearances of people, and even by ideas."*

– Paul Ekman
Universal Emotions

Abstract: This chapter presents a novel approach for Readers' Emotion Detection from short-text documents using a deep learning model called *REDAffectiveLM*. Within the state-of-the-art NLP tasks, it is well understood that utilizing context-specific representations from transformer-based pre-trained language models helps achieve improved performance. This affective computing task explores how incorporating affective information can further enhance the performance. Towards this, the proposed model leverages context-specific and affect enriched representations by using a transformer-based pre-trained language model in tandem with affect enriched Bi-LSTM+Attention. The major benefit of this study includes a readers' emotion detection model *REDAffectiveLM* that significantly outperforms the state-of-the-art baselines, establishing that utilizing affect enriched representation along with context-specific representation within a neural architecture can considerably enhance readers' emotion detection. This study also performs a systematic investigation of decision-making or behavior of the affect enriched Bi-LSTM+Attention network to study the impact of affect enrichment in readers' emotion detection, establishing that compared to conventional semantic embedding the affect enriched embedding increases the ability of the network to effectively identify and assign weightages to the key terms responsible for readers' emotion detection to improve prediction.

3.1 Introduction

Readers' Emotion Detection within the broad area of textual emotion detection, as discussed in section 2.3, is one of the demanding tasks in NLP with novel applications. This chapter presents a deep learning based model *REDAffectiveLM*

for predicting the readers' emotion profiles of textual documents by leveraging both context-specific and affect enriched representations. To leverage context-specific representation, this study utilizes a large PLM, and for affect enriched representation, a Bi-LSTM+Attention network fed with affect enriched embedding is used. The study is conducted over news documents that are short-text in nature. Experiments are performed across the newly procured extensive datasets REN-20k and RENh-4k along with the benchmark dataset SemEval-2007. The study conducts two sets of rigorous experimental evaluations. Firstly, the performance of the proposed model is compared against a vast set of state-of-the-art baselines belonging to different categories of emotion detection viz., deep learning, lexicon based, and classical machine learning, through various coarse-grained and fine-grained evaluation measures. Secondly, since the impact of affect enrichment specifically in readers' emotion detection isn't well explored, the study also presents a novel direction of inquiry towards analyzing the impact of affect enrichment for the task of readers' emotion detection using qualitative and quantitative behavior evaluation techniques over the affect enriched Bi-LSTM+Attention.

3.1.1 Research Question

This chapter addresses the following research questions.

RQ1: Context-specific representations from transformer-based pre-trained language models help textual emotion detection systems to achieve improved performance but, being an affective computing task, can the performance be further enhanced by incorporating or combining with affective representations?

RQ2: Compared to conventional semantic embedding, does affect enrichment help to obtain higher performance by effectively identifying and assigning weightage to the key terms (emotion words and named entities) responsible for readers' emotion detection?

3.1.2 Demarcating Proposed Work in Context of State-of-the-art

The works in literature that specifically address readers' perspective of emotion detection [72, 83, 96, 210] are very few among the vast area of textual emotion detection. A major set of works are seen to be built over the backdrop of conventional semantic word embeddings [96, 210], which are powerful enough to identify similarities between words in near context; but a notable limitation due to the smaller window of

neighboring words enables many times the contradictory affective words (emotion words) to share almost similar word representations (e.g. 'good' and 'bad') while learning these word embeddings [211]. This leads to degradation in performance among the affective computing related tasks such as sentiment analysis and emotion detection, and brings more suitable ways of word embeddings to encode affective information such as sentiment-specific [212] and affect enriched [63, 95, 94] embeddings. But even though an affective computing task, there has rarely been any work in text emotion detection that utilizes affect enriched word embedding [61] and, to the best knowledge, none specific to readers' emotion detection, so far. Textual emotion detection works in this context would be that of Chatterjee et al. [61] proposing SS-BED, a sentiment specific word embedding, and Kratzwald et al. [60] proposing sent2affect, a sentiment aided transfer learning from source network trained for sentiment analysis task to a target textual emotion detection network without direct affect enrichment in embedding. But, both these works consider coarse-grained sentiment enrichment rather than affect enrichment required to suit the much fine-grained task of detecting diverse emotion classes.

Even though the above mentioned representations/embeddings provide useful advancements, they are only capable of encoding the syntactic information and the word sense, but mostly miss to represent different meanings of the same word as a function of its context (e.g. the word 'bank' have different meanings in the context of words such as 'river' and 'finance'). Transformer-based pre-trained language models capable of generating context-specific representations are recently used in textual emotion detection [102], even though not specifically in readers' emotion detection, and are seen to obtain improved predictions. But, these context-specific representations from the pre-trained language models lack an explicit orientation towards representing affective information, something that is quite critical for affective computing tasks. Utilizing affective information along with these context-specific representations would be highly beneficial for the task of readers' emotion detection, as they are seen to produce better results when utilized in affective computing related tasks such as sentiment analysis, personality detection, etc., [95]. Therefore, for the first time (to the best knowledge), this work attempts to leverage the utility of both context-specific and affect enriched representations for the task of readers' emotion detection by proposing a deep learning based model *REDAffectiveLM* built by fusing a transformer-based pre-trained language model with an affect enriched Bi-LSTM+Attention network. The study follows multi-target regression settings [96, 213] that, beyond emotion classes, also provide information of emotion intensities, unlike

the major category of single/multi-class or multi-label classification settings predicting only the emotion classes [82, 83, 74].

Among the deep learning based studies in textual emotion detection, there has been some recent interest in utilizing attention mechanisms to improve the performance [110] or to observe the words responsible for decision making [214]. But, to the best knowledge, there has been no prior work, so far, analyzing and quantifying the role of emotion words or named entities, and analysing the impact of affect enrichment for the task of readers' emotion detection. This work utilizes the attention mechanism with an intention to analyze the interpretable nature and underlying behavior of the network for readers' emotion detection by quantifying the role of emotion words and named entities in decision making and conducting qualitative and quantitative analysis to identify the impact of affect enrichment in readers' emotion detection.

3.1.3 Motivation

The proposed readers' emotion detection methodology is inspired from the state-of-the-art research for NLP and affective computing that explores the combination of PLMs with various networks to improve the overall model performance [66, 103]. The choice of transformer-based pre-trained language model XLNet [41] (that shall be detailed in section 3.2.2), is motivated by its efficacy to combine the qualities of both autoregressive (e.g. GPT [101]) and autoencoding (e.g. BERT [100]) pre-trained language models and produce improved performance over affective computing related tasks like sentiment analysis [41]. The choice of *affect enriched Bi-LSTM+Attention* as the deep learning model is motivated by the pre-eminence of Bi-LSTM within related tasks and from the work proposed in [95] that demonstrates affect enrichment can improve performance of affective computing tasks. Bi-LSTM has the capability to learn long-term dependencies without keeping duplicate context representations and perform sequential modeling in both directions [215, 216], and attention has the potential to enrich model performance [110] while also improving transparency of decision making and emerging as a prominent way of infusing interpretability within neural black box models [107].

To the best knowledge, there are only a few datasets that provide emotion intensities for regression based studies [217, 218]. However, these datasets are not suitable for readers' emotion detection studies that employ multi-target regression settings, as they map the documents to only a single emotion with corresponding intensity. An available benchmark dataset that suits multi-target regression based readers' emotion detection is SemEval-2007 [59]; but being annotated by only six readers, this dataset does not meet the real-world scenario of a document being read and annotated by

many readers. Also, even though there are few readers' emotion detection models within specific contexts (e.g., [84, 219] that utilize Chinese corpora), there exists a need for readers' emotion detection dataset in English to learn the linguistic and affective characteristics. This inadequacy, as mentioned in [72, 85, 220], motivates to procure extensive datasets that particularly suit the deep learning based multi-target regression settings to predict readers' emotion intensities rather than emotion class mapping.

3.1.4 Contributions

The major contributions of this chapter are listed below.

- This chapter proposes a novel deep learning approach for Readers' Emotion Detection called *REDAffectiveLM*, to predict readers' emotion profiles from short-text documents. This, in a novel direction, leverages both context-specific and affect enriched representations by fusing a transformer-based pre-trained neural language model and a Bi-LSTM+Attention network that utilizes affect enriched embedding.
- The chapter presents performance evaluation of the proposed model *REDAffectiveLM* rigorously against a vast set of state-of-the-art baselines belonging to different categories of textual emotion detection, where the proposed model consistently outperforms the baselines, providing statistically significant improvements on fine-grained and coarse-grained evaluation measures.
- The chapter also conducts a detailed behavior analysis by investigating interpretability of attention mechanism, to understand the impact of affect enrichment specifically in readers' emotion detection using qualitative and quantitative behavior evaluation techniques over affect enriched Bi-LSTM+Attention network .
- To conduct the study two Readers' Emotion News datasets are procured, REN-20k and RENh-4k with more than 20000 and 4000 news documents and associated readers' emotions profiles, respectively. As article genre information are also included in these datasets, they can be used for multiple tasks including document summarization and genre classification, in various scales (short-text and long-text), apart from readers' emotion detection, making them *heterogeneous task datasets*. To aid the future research, REN-20k and RENh-4k are made publicly available at `https://dcs.uoc.ac.in/cida/resources/ren-20k.html` and `https://dcs.uoc.ac.in/cida/resources/renh-4k.html`, respectively.

3.1.5 Organization of the Chapter

The rest of the chapter is organized as section 3.2 provides a detailed description of the proposed deep learning model for readers' emotion detection followed by section 3.3 explaining the datasets used in this study. Section 3.4 presents the empirical study including details of experimental settings, description of baselines and performance evaluation measures. Results and discussion in section 3.5 initially evaluate the performance of the proposed model by comparing against the baselines, followed by statistical significance tests and later, the behavior analysis of affect enrichment in readers' emotion detection. Finally, section 3.6 summarizes the chapter.

3.2 *REDAffectiveLM* - Methodology

This section presents the proposed method for Readers' Emotions Detection from textual documents by initially discussing the problem settings followed by architecture of the proposed model, *REDAffectiveLM*.

3.2.1 Problem Setting

The task of detecting readers' emotions of a textual document is formulated as a multi-target regression problem, where the statistical model applied on each input document is expected to produce intensity values for various emotion classes namely, *anger*, *fear*, *joy*, *sadness*, and *surprise*. Each textual document consists of a sequence of words $[w_1, w_2, w_3, \ldots]$, each word drawn from the dictionary of words compiled from across the document corpus. For each document d, the corresponding readers' emotion profile from labeled data is modeled as a normalized distribution of votes cast by multiple readers for E distinct emotions represented as,

$$ep_r(d) = \{e_1, e_2, \ldots, e_E\} \in \mathbb{R}^E \text{ where } e_i \in [0, 1] \text{ and } \sum_i e_i = 1 \tag{3.1}$$

Thus, a document that has gathered equal votes for a set of five emotions would yield $ep_r(d) = [0.2, 0.2, 0.2, 0.2, 0.2]$. The sum-to-one normalization enables placing documents of different popularity (i.e., vote abundance) on the same footing. Thus, the labelled corpus D with M documents can be represented as,

$$D = \{(d_1, ep_r(d_1)), (d_2, ep_r(d_2)), \ldots, (d_M, ep_r(d_M))\} \tag{3.2}$$

where, $ep_r(d_i)$ indicates the readers' emotion profile of document d_i. The supervised task of readers' emotion detection following a deep neural network based methodology is then to find the best fit mapping function $f : H \rightarrow \mathbb{R}^E$, such that a document vector H of the document d is mapped as close as possible to the readers' emotion profile from the labelled data, i.e., $ep_r(d)$.

3.2.2 Proposed Model

The proposed deep learning based readers' emotion detection model, *REDAffectiveLM* is constructed by parallely fusing two different networks, where the first emoBi-LSTM+ Attention network is meant to produce affect enriched document representation and the second XLNet network for context-specific representation. Initially the two networks are discussed in detail, later outlining the complete architecture of the fused model, *REDAffectiveLM*. An overall sketch of the proposed model is illustrated in figure 3.1.

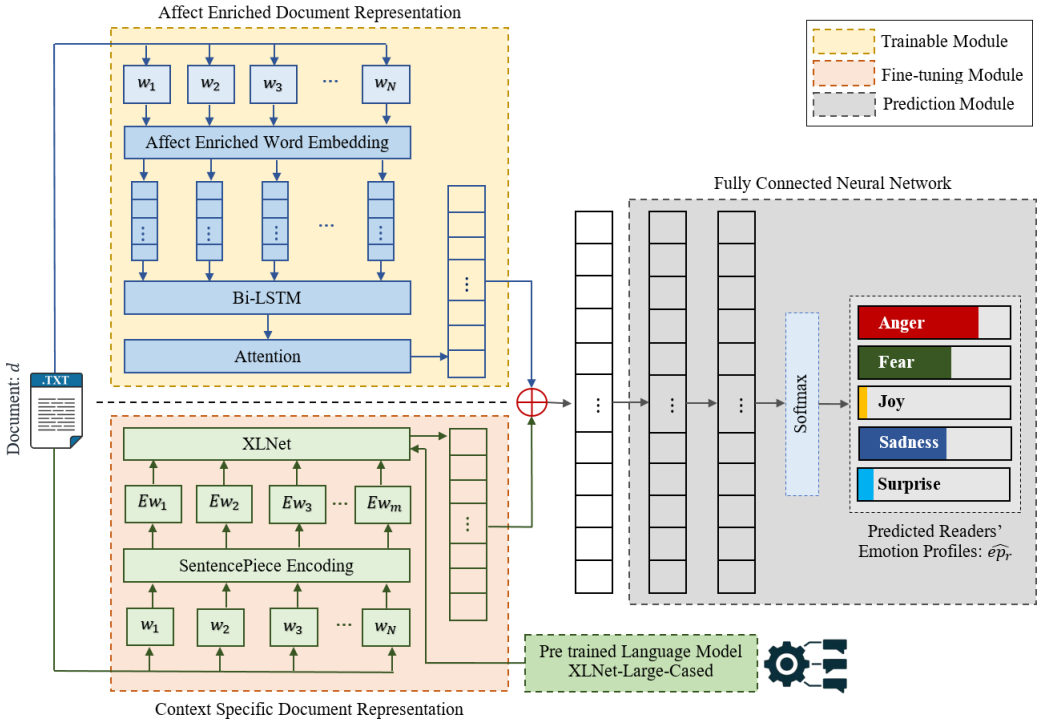
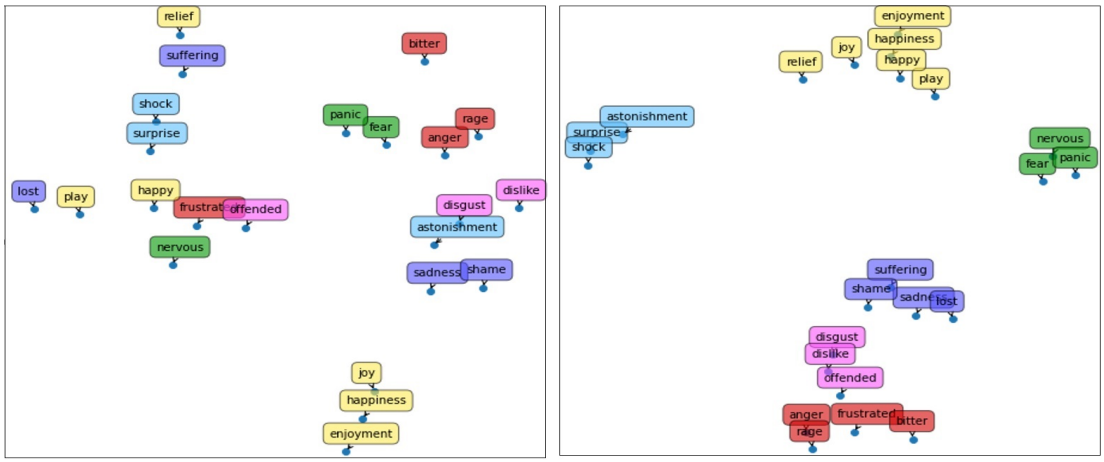


FIGURE 3.1: The architecture of *REDAffectiveLM*

emoBi-LSTM+Attention for Affect Enriched Document Representation

In the emoBi-LSTM+Attention network, input documents are initially subject to Affect Enriched Word Embedding. The choice of affect enriched embedding instead of conventional semantic embeddings would be highly beneficial for the task of readers' emotion detection, as they are seen to produce better results when utilized in affective computing related tasks such as sentiment analysis, personality detection, etc., [95]. Affect enriched word representations, denoted as emoGloVe, is constructed with the help of the state-of-the-art method using counter-fitting and emotional constraints[17] proposed by Seyeditabari et al. [63] over a pre-trained conventional semantic embedding GloVe [221]. Towards understanding the effectiveness of such emotion-enriched embeddings, the changes attained for affect enriched word representations when compared to conventional semantic embeddings is analyzed by visualizing the d-dimensional word representations of a few affective words which are related to the basic emotions using t-SNE[18] algorithm, shown in figure 3.2. Figure 3.2a shows the word vector visualization of conventional semantic embedding GloVe and figure 3.2b shows visualization of the same words after affect enrichment. One may observe that, compared to conventional semantic embedding, affect enrichment helps to cluster emotionally similar words into neighboring spaces.



(A) Conventional semantic embedding, GloVe (B) Affect enriched embedding, emoGloVe

FIGURE 3.2: t-SNE visualization of few affective words related to basic emotions Anger, Disgust, Fear, Joy, Sadness, and Surprise

[17] for this work, the code in https://github.com/armintabari/Emotional-Embedding (*accessed: 05-12-2022*) has been written from python 2.x to python 3.x to avoid compatibility issues in implementation

[18] https://scikit-learn.org/stable/modules/generated/sklearn.manifold.TSNE.html, *accessed: 05-12-2022*

The impact of affect enrichment in word embedding is also measured using *in-category* and *cross-category* emotion word similarity [63] over the secondary and tertiary emotion words in the commonly used Parrott's emotions[19], for the basic emotion classes *anger*, *fear*, *joy*, *sadness*, and *surprise*, used in this study. The *in-category* measure indicates average cosine similarity of emotion words within each emotion class whereas, *cross-category* indicates average cosine similarity of emotion words belonging to the opposite emotion classes. The similarity scores obtained are shown in table 3.1, where, it can be clearly observed that average similarity score among the words within an emotion class increases substantially after emotion enrichment. For example, the *in-category* similarity score of *sadness* computed from emoGlove is improved by 18.28 percentage points when compared to GloVe. Also, the *cross-category* similarity score between opposite emotions are seen to reduce after affect enrichment. For example, the *cross-category* similarity between *joy* and *sadness* is reduced by 24.03 percentage points after the affect enrichment. Thus, observations establish the capability of affect enriched word embedding to encode affect information over conventional semantic embedding efficiently, which makes it more preferable for the task of readers' emotion detection than the conventional semantic embedding.

TABLE 3.1: Emotion-word similarity scores

	In-category similarity					Cross-category similarity		
Embedding	Anger	Fear	Joy	Sadness	Surprise	Anger×Joy	Fear×Joy	Joy×Sadness
GloVe	0.4218	0.3876	0.3071	0.4224	0.2519	0.2879	0.2566	0.2932
emoGloVe	0.5427	0.4410	0.3821	0.6052	0.4286	0.1187	0.0990	0.0529

After generating affect enriched word representations, towards producing affect enriched document representations, the prominent RNN based architecture, Bi-LSTM, is combined with an Attention layer. The choice of Bi-LSTM network is motivated by its capability to learn long-term dependencies without keeping duplicate context representations [215] and perform sequential modeling in both directions by incorporating the past and future context information from the sequence of data to produce excellent performance gains [216]. In addition, an Attention on top of the Bi-LSTM network provides weightage to relevant words in the input sequence that highly correlates to the task of emotion prediction. Apart from increasing the overall model performance [110], the use of Attention helps to analyze interpretability of the network towards readers' emotion detection. That is, in total, the choice of affect enriched

[19] https://en.wikipedia.org/wiki/Emotion_classification#Parrott's_emotions_by_groups, *accessed: 05-12-2022*

word embedding and Bi-LSTM+Attention network, is based on the motivation that this combination should significantly contribute towards improving the overall model performance and moreover, allows to investigate the network behavior systematically to identify the impact of affect enrichment in readers' emotion detection.

The Bi-LSTM network is initially fed with affect enriched word representations $\overrightarrow{w}_i$ of the input document d. With this input, Bi-LSTM can now produce affect enriched contextual information as the output document vectors. The Bi-LSTM network is capable of processing sequential inputs from left to right (forward) and from right to left (backward) together. Let $\overrightarrow{h_l}$ be the forward processing hidden layer and $\overleftarrow{h_l}$ be the backward processing hidden layer, concatenated to form a single layer h defined by $[\overrightarrow{h_l}; \overleftarrow{h_l}]$. The Bi-LSTM network can be defined as,

$$\overrightarrow{h_l} = LSTM(\overrightarrow{h_{l-1}}, w_i, \Theta_f) \tag{3.3}$$

$$\overleftarrow{h_l} = LSTM(\overleftarrow{h_{l+1}}, w_i, \Theta_b) \tag{3.4}$$

where, Θ_f and Θ_b represent parameters of forward and backward LSTM units, respectively, and w_i serves as the representation of each word. To learn representations that assign more weightage to those words that contribute significantly to the model's decision making, an attention mechanism on top of Bi-LSTM is exploited by adopting the popular attention mechanism proposed by Bahdanau et al. [222]. To implement Attention, the last hidden state h_n is initially taken as a document summary vector Z and is processed through an alignment model, which is a feedforward network trained along with the entire model, to produce a scalar value u_i. Later a *softmax* function is used to obtain weights α_i that represents the importance of each hidden state h_i.

$$\text{i.e., } u_i = v^\top \tanh(W_h h_i + W_Z Z) \tag{3.5}$$

$$\alpha_i = \frac{\exp(u_i)}{\sum_{j=1}^{n} \exp(u_j)} \tag{3.6}$$

where, $W_h, W_Z \in \mathbb{R}^{a \times b}$ and $v \in \mathbb{R}^a$ are the learnable weight parameters. The final affect enriched document representation H_1 from the emoBi-LSTM+Attention network part of *REDAffectiveLM* is computed as,

$$H_1 = \begin{bmatrix} \alpha_1 h_1 & \alpha_2 h_2 & \alpha_3 h_3 & \dots & \alpha_n h_n \end{bmatrix} \tag{3.7}$$

XLNet for Context-specific Document Representation

Transformer-based pre-trained language models are popular due to their efficacy in modeling linguistic relations and generating efficient context-specific document representations from various unlabelled text corpora; their effectiveness is evidenced by the promising results achieved for several downstream NLP tasks [100, 41]. To learn such a document representation for the task of readers' emotion detection, a popular transformer-based pre-trained language model, XLNet [41], is adopted as the second network of the proposed model. The choice of XLNet is motivated from its capability to produce remarkable results for the very related affective computing task of sentiment analysis, overcome pretrain-finetune-discrepancy of autoencoding language models like BERT [100], and enable bi-directional context representation through permutation of the factorization order [41]. The permutation language modeling objective helps XLNet to maintain the advantage of auto-regressive models as well as to apprehend bidirectional contexts. For a sequence X of length L, as there are $L!$ different orders to perform a valid autoregressive factorization, sharing parameters of the model across every factorization order helps the model learn to collect information from every position on both the sides. For $\mathcal{Z}_L$ collection of all possible permutations with length L, the permutation language modeling objective function of XLNet is,

$$\max_{\theta} \quad \mathbb{E}_{z \sim \mathcal{Z}_L} \left[\sum_{t=1}^{L} \log p_\theta \left(x_{z_t} | \mathrm{x}_{\mathrm{z}_{<t}} \right) \right] \tag{3.8}$$

where, z_t and $\mathrm{z}_{<t}$ denotes the t^{th} element and the first t-1 elements of a permutation $\mathrm{z} \in \mathcal{Z}_L$, respectively [41].

In the second network, initially, the text document d with a sequence of N words, $d = w_1, w_2, \ldots, w_N$, is converted to encoded-word tokens, $EW = Ew_1, Ew_2, \ldots, Ew_m$, using the popular *SentencePiece* language-independent subword tokenization and detokenization module [223], where, $|m| \neq |N|$, and Ew_i indicates encoded subword representation obtained by subdividing a single word into several subword units. The encoded data EW is then fed to the pre-trained XLNet. The XLNet network is then fine-tuned for the task of readers' emotion detection using the readers' emotion detection datasets used in this study during the training phase of the entire fused model (*REDAffectiveLM*). Hence XLNet network learns the task-specific contextual document representations H_2 denoted as,

$$H_2 = \mathrm{XLNet}(EW) \tag{3.9}$$

***REDAffectiveLM*: The fused model for Readers' Emotion Detection**

To build the proposed Readers' Emotion Detection model *REDAffectiveLM* that leverages the utility of affect enriched document representation and context-specific document representation, the two networks, emoBi-LSTM+Attention and XLNet are fused. In the fused model, affect enriched document vector H_1 from emoBi-LSTM+Attention and context-specific document vector H_2 from XLNet are concatenated to form a single document vector H, defined as,

$$H = H_1 \oplus H_2 \tag{3.10}$$

Finally, to predict readers' emotion profiles, the concatenated document vector H is fed to a fully connected neural network module. The neural network module that consists of a Multi-Layer Perceptron (MLP) having two fully connected dense hidden layers with 1224 neurons in each layer and an output layer with 5 neurons predicts normalized probability distribution of readers' emotion profiles $\widehat{ep_r(d)}$, given as,

$$\widehat{ep_r(d)} = softmax(\text{MLP}(H)) \tag{3.11}$$

The loss between $\widehat{ep_r(d)}$ and labelled vector $ep_r(d)$ is propagated back to complete the learning process. Once the model is trained it is empirically evaluated on two fronts. First, the performance of emotion prediction is evaluated based on how well the predicted emotion distribution reflects the distribution derived from the labels. Second, the attention maps of the documents from the affect enriched network are qualitatively and quantitatively evaluated to assess the impact of affect enrichment, as outlined in the following sections.

3.3 Dataset and Pre-processing

Three datasets are used to conduct the experiments, the two newly curated Readers' Emotion News Datasets (RENh-4k and REN-20k) and the popularly used benchmark dataset, SemEval-2007 [59]. Details of the datasets and pre-processing follow herewith.

3.3.1 Readers' Emotion News Datasets

To acquire the two new Readers' Emotion News datasets the social news network, Rappler[20] and its award-winning Mood Meter widget[21] are utilized. Mood Meter enables readers to poll their emotion votes towards several categories of emotions (Afraid, Amused, Angry, Annoyed, Don't care, Happy, Inspired, and Sad) and records the total percentage of votes obtained for each emotion. Unlike other sources, the choice of Rappler is due to its simplicity, popularity, and easiness in organizing several news articles under multiple genres and associated emotion profiles. News articles are collected manually, the legal and ethical concerns are provided in Appendix A.1. Only the popular news articles are collected, by checking for high emotion votings represented in the Rappler Mood Meter, to ensure these articles have a high social reach. The detailed information of these Readers' Emotion News datasets are given below.

RENh-4k

This is a short-text dataset having 4000 news documents with corresponding readers' emotion profiles. The news headline and its associated abstract/snippet are combined to form a single document, and the corresponding readers' emotion profiles are obtained from readers' votings on Rappler Mood Meter for the emotion classes, Afraid, Angry, Happy, Inspired, and Sad. The documents are also assigned into any of the three categories, Health & well-being, Social issues, and Others, after manually verifying the news genres.

REN-20k

This is an advanced version of RENh-4k, in terms of the number of documents, length of a document, and much more diverse set of emotion classes and document genres. This dataset contains 20474 news documents with corresponding readers' emotion profiles. Here, a document comprises the news headline, abstract, and news content or full-length news story without non-textual content like images and videos. Unlike RENh-4k, readers' emotion profiles are collected for the emotion classes, Afraid, Amused, Angry, Annoyed, Don't care, Happy, Inspired, and Sad. Documents are also assigned into the genres, Business, Entertainment, Lifestyle, Sports, Technology, and Others, with the help of manual annotations along with the categorical information

[20] https://www.rappler.com/, *accessed: 05-12-2022*

[21] https://web.archive.org/web/20140513012056/http://thenewmedia.com/2012-boomerang-awards-winners/, *accessed: 05-12-2022*

available in Rappler. REN-20k documents consist of the whole textual content associated with a particular news article; the average words per document is 527.84, i.e., long-text in nature. Since in this work the study is performed over short-text documents, REN-20k is converted to a short-text dataset by choosing only the news headlines and associated abstracts without the news content or full-length news stories to form the documents.

3.3.2 The Benchmark Dataset - SemEval-2007

SemEval-2007 is a short-text dataset with 1250 documents, comprising of news headlines and the corresponding emotion scores for the emotion classes Anger, Disgust, Fear, Joy, Sadness and Surprise, annotated by six readers [59].

3.3.3 Dataset Pre-processing

As this study aims to predict the basic emotions elicited from readers', the first set of pre-processing performed on the datasets is an emotion label mapping from Rappler Mood Meter emotions to Paul Ekman's basic emotions [57] *anger*, *disgust*, *fear*, *joy*, *sadness*, and *surprise*. The mappings performed are *Angry* $\rightarrow$ *Anger*, *Sad* $\rightarrow$ *Sadness*, *Afraid* $\rightarrow$ *Fear*, *Happy* $\rightarrow$ *Joy* and *Inspired* $\rightarrow$ *Surprise*, and the other Mood Meter emotions such as *Don't care*, *Inspired*, *Amused*, and *Annoyed* are discarded by following the methodology proposed in [69, 224]. Since *Disgust* in Paul Ekman's basic emotions does not match with any of the Mood Meter emotions, it is also discarded in this study and the rest five basic emotions are maintained to preserve a common set of emotion labels for all the three datasets, as done in [69, 224]. To represent readers' emotion profiles of the datasets in a better way, as a distribution of five emotions (*anger*, *sadness*, *fear*, *joy*, and *surprise*), a normalization procedure similar to [85] is followed.

Data cleaning is performed in the newly procured readers' emotion news datasets by removing unnecessary or noisy keywords like *report*, *new-review*, *(UPDATED)*, *survey*, *Midday-wRa*, etc., that appear several times in the documents. To improve the quality of text representation a generic set of pre-processing techniques, removal of unknown symbols and punctuations, and text normalization, using NLTK toolkits[22] are also performed. Detailed statistics of the datasets after pre-processing is shown in table 3.2. Unlike SemEval-2007 which is labeled by six annotators, there are no accurate means to compute the number of emotion votes or annotations in Mood Meter for the Readers' Emotion News datasets (REN-20k and RENh-4k). Therefore in this study, a popular strategy in [225] is followed, which provides an alternate estimate

[22] https://www.nltk.org/, *accessed: 05-12-2022*

by calculating the least common denominator of the emotion vote percentages of a document to obtain the minimum number of annotations. Emotion distribution in the datasets are depicted in figure 3.3.

TABLE 3.2: Dataset statistics after pre-processing

Statistics	REN-20k	RENh-4k	SemEval-2007
Source	Rappler	Rappler	The New York Times, Google News, CNN, BBC
Year span	2014 to 2019	2015 to 2018	-
Length	Short-text	Short-text	Short-text
Number of news documents	20474	4000	1246 (*valid documents after pre-processing*)
Total number of words	10807161	124172	6364
Number of unique words	172243	13260	3286
Average words per document	29.612	31.043	5.09
Average sentences per document	1.1826	1.1875	1.00
Number of annotations	2556654	242680	6 (*annotators*)
Mean percentage of votes for each emotion class	Anger: 0.2253 Fear: 0.0626 Joy: 0.4222 Sadness: 0.1441 Surprise: 0.1459	Anger: 0.3388 Fear: 0.1475 Joy: 0.3137 Sadness: 0.0781 Surprise: 0.1218	Anger: 0.1013 Fear: 0.1639 Joy: 0.2860 Sadness: 0.2069 Surprise: 0.2416
Number of articles associated with each emotion class	Anger: 14419 Fear: 8678 Joy: 18104 Sadness: 12841 Surprise: 12749	Anger: 3068 Fear: 1850 Joy: 3267 Sadness: 2489 Surprise: 2312	Anger: 652 Fear: 820 Joy: 786 Sadness: 863 Surprise: 1102

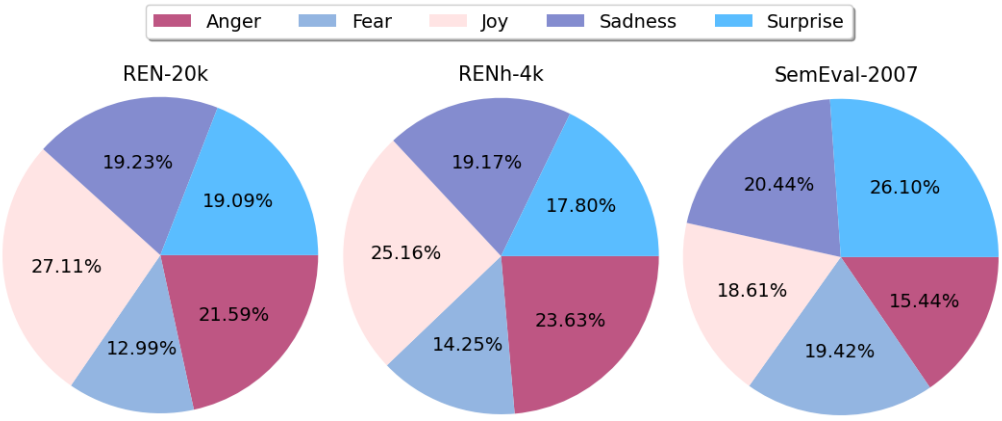


FIGURE 3.3: Emotion distribution in the datasets

3.4 Empirical Study

This section first describes experimental settings of the proposed model followed by the details of baselines and evaluation measures used for model performance analysis.

3.4.1 Experimental Settings

To conduct the experiments, datasets are split into train, validation, and test sets in the ratio 60:20:20 of the total dataset volume. In the emoBi-LSTM+Attention network, to develop affect enriched embedding emoGloVe, the approach proposed in [63] over the conventional semantic embedding GloVe[23] is utilized. The embedding dimensions experimented are 300d and 100d, with various epochs 20, 50, 100, 150, 300, and 500, and finally, emoGloVe with dimension 100d and 20 epochs are chosen as a representative setting. The other hyperparameters in this network are regularizer of the Bi-LSTM module set as *l2(0.001)*, and *dropout* between Bi-LSTM and Attention layer set to 0.5. In the second network, to implement the XLNet architecture 'XLNet-Large-Cased' from the AI community Hugging Face[24] is used, where the hyperparameters such as number of layers are set to 24, hidden size is 1024, number of attention heads is 16, *dropout* is 0.1, and altogether 360M trainable parameters fine-tune the network. In the fused model, the affect enriched document vector H_1 from the first network with dimension 200 and the context-specific document vector H_2 from the second network with dimension 1024, on concatenation, forms the final single document vector H with dimension 1224, which is fed to the fully connected MLP. To build the MLP, various number of layers having different combinations of neurons are experimented, such as, $\{1224 \rightarrow 512 \rightarrow 256 \rightarrow 128 \rightarrow 64 \rightarrow 5\}$, $\{1224 \rightarrow 1224 \rightarrow 5\}$, $\{1224 \rightarrow 5\}$, etc., and finally two hidden layers with 1224 neurons followed by the output layer with 5 neurons is chosen as a representative setting. Hyperparameters of the fused model *REDAffectiveLM* are Mean Squared Error (*MSE*) as the loss function, *Adam* optimizer with learning rate 0.000015, batch size as 64 and 200 epochs. *REDAffectiveLM* consists of 363,762,235 number of total parameters, where 363,434,735 are trainable and 327,500 are non-trainable parameters.

3.4.2 Baselines

To compare the performance of the proposed model *REDAffectiveLM*, a set of baselines are implemented from across the categories of deep learning, lexicon based, and classical machine learning. Deep learning baselines include the recent state-of-the-art

[23] https://nlp.stanford.edu/projects/glove/, *accessed: 05-12-2022*
[24] https://huggingface.co/transformers/pretrained_models.html, *accessed: 05-12-2022*

textual emotion detection works, popular naïve architectures, and the individual networks used to construct the proposed fused model serving, implicitly, as a form of ablation study. The lexicon and classical machine learning baselines also include popular and top-performing state-of-the-art works. Details of the baselines are as follows:

Deep Learning Baselines

- sent2affect [60]: A textual emotion detection study that utilizes transfer learning from an RNN model initially trained for the task of sentiment analysis. While reproducing their work, to build the source model sentiment140[25] dataset is used, since the Twitter Sentiment dataset used in their paper was not found in the relevant link provided[26]; and also, sentiment140 is huge with 1.6 million data when compared to the Twitter Sentiment dataset, thus providing more redundancy for the model to train over, than in the original setting.

- SS-BED [61]: A semantic and sentiment oriented textual emotion detection system, where the same piece of textual data is learnt over two different representations, the semantic representation using word embedding, and the sentiment representation using sentiment specific word embedding proposed in [212].

- Kim's CNN [226]: A popular CNN architecture for text classification. The hyper-parameters used to build this model are given in appendix A.2.

- Naïve architectures: Includes the general RNN architectures like GRU [92], LSTM and Bi-LSTM used as baselines in certain textual emotion detection works [89, 61, 60], and XLNet [41] used in the construction of the fused model *REDAffectiveLM* (as an ablation study). The hyper-parameters are given in appendix A.2.

- Attention based architectures: Includes the architectures of an Attention on top of Bi-LSTM that utilize different embeddings to vectorize documents, i.e., Bi-LSTM+Attention architecture that utilizes conventional semantic embedding, and emoBi-LSTM+Attention architecture that utilizes affect enriched embedding used in the construction of the fused model *REDAffectiveLM* (as an ablation study). The attention module used in both these models follows the popular attention architecture proposed by Bahdanau et al. [222]; the implementation of this attention mechanism is the same as the one adopted in the proposed model, as discussed in the equations (3.5) and (3.6). The hyper-parameters of these models are given in appendix A.2.

[25] `https://www.kaggle.com/kazanova/sentiment140`, *accessed: 05-12-2022*
[26] `https://www.kaggle.com/c/twitter-sentiment-analysis2/data`, *accessed: 05-12-2022*

Lexicon based Baselines

- SWAT [71]: One of the top ranked systems developed on the shared task, *SemEval-2007 Task 14: Affective Text* [59]. This supervised system uses predefined sets of emotion words developed using a unigram model to build emotion annotation of news headlines.
- Emotion Term Model [72]: An improved version of classical Naïve Bayes that incorporates information of emotion rating and term independent assumption for emotion detection.
- Synesketch [73]: A textual emotion detection system that makes use of a word-level lexicon and an emoticon lexicon, along with a set of heuristic rules.

Classical Machine Learning Baselines

- WMD [80]: A textual emotion detection method using Word Mover's Distance feature along with SVM classifier. To reproduce this work, 60% of the corpus is used for training, 20% for testing, and the rest 20% for seed corpus, for the five emotion classes. Instead of their SVM classifier, in this study a Support Vector Regression (SVR) with the multi-output regressor is used to suit the multi-target regression settings.
- Multi-target regression with handcrafted features: A set of linguistic and affective features used in many textual emotion detection works combined with various multi-target regression models. The features and models are as follows.
    * TF-IDF [80, 60]: A popular and commonly used feature vector indicating Term Frequency (TF) and Inverse Document Frequency (IDF).
    * N-Grams [62, 61]: N $\in$ {1, 2, 3, 4}. For improved efficiency, Parts-of-Speech tagging is used to identify and retain only the noun, verbs, adverbs, and adjectives as they are a prominent source of subjective content [10].
    * General Purpose Emotion Lexicon Features [62]: The features Total Emotion Count (TEC), Total Emotion Intensity (TEI), Max Emotion Intensity (MEI), Graded Emotion Count (GEC), and Graded Emotion Intensity (GEI), extracted using a general purpose emotion lexicon DepecheMood++ [70].
    * Sentiment Word Feature [62, 10]: Combination of two sets of sentiment-oriented features to form a single sentiment word feature. The first set of features capture the total number of positive, negative, and neutral words,

and second set computes the average positive, negative, and neutral sentiment intensity for a document. A popular sentiment lexicon VADER [227] is used to compute the sentiment features.

* Embedding Features [61, 212]: Two different categories of embeddings, semantic embeddings which include Word2Vec, GloVe and FastText, and Sentiment Specific Word Embedding, $SSWE_u$ proposed in [212]. Here, the individual word vectors are averaged to form the document vectors.
* Multi-target Regression Models: Over the above settings of features, multi-target regressors can be learnt in two ways. The first, called the problem transformation approach, involves usage of Multi-output Regressor using Ridge[27], SVR[28] and GradientBoostingRegressor[29]. The second, algorithm adaptation approach, involves implementing MLP with single hidden layer of 128 neurons, *ReLU* activation and $l2(0.001)$ regularizer, and output layer of 5 neurons with *softmax* activation. The other hyperparameters are *MSE* as the loss function, *Adam* optimizer with learning rate 0.0005, batch size 64, and 100 *epochs*.

3.4.3 Performance Evaluation Measures

Different coarse-grained and fine-grained evaluation metrics [228] are used to measure the performance of readers' emotion detection. Coarse-grained measures are useful to understand the correctness of prediction whereas, fine-grained measures indicate the nearness of prediction to ground truth at a finer granularity. In coarse-grained evaluation, the regression predictions are mapped to a $0/1$ classification problem using Acc@1 (accuracy of top first prediction) that represents the micro-averaged F1 measure [229]. Acc@1 is popularly used in several textual emotion detection works [72, 84, 85, 230] to measure the performance over a corpus with imbalanced distribution of data. For fine-grained evaluation the measures used are $AP_{document}$, $AP_{emotion}$, Root Mean Square Error (RMSE) and Wasserstein Distance (WD). $AP_{document}$ and $AP_{emotion}$ are also popularly used in textual emotion detection works [71, 84, 231], and takes into consideration the correlation between predicted and ground-truth readers' emotion profiles over the emotions and documents respectively. This task of readers' emotion detection being formulated as a regression problem, the measures Root

[27] `www.scikit-learn.org/stable/modules/generated/sklearn.multioutput.MultiOutputRegressor.html#examples-using-sklearnmultioutput-multioutputregressor`, *accessed: 05-12-2022*

[28] `https://scikit-learn.org/stable/modules/generated/sklearn.svm.SVR.html`, *accessed: 05-12-2022*

[29] `https://scikit-learn.org/stable/modules/multiclass.html#multioutput-regression`, *accessed: 05-12-2022*

Mean Square Error and Wasserstein Distance gives a sense of how close/distant the predicted emotion profiles are, from the ground-truth.

- Acc@1 [72]: An accuracy measure of the corpus computed by averaging $Acc_d@1$ of all documents. For the predicted emotion profile X_d (shorthand for $\widehat{ep_r(d)}$) and ground-truth Y_d (shorthand for $ep_r(d)$) of a document d, $Acc_d@1$ checks whether the top-ranked emotion is the same for both prediction $\big(\text{i.e. } \arg\max_i X_d[i]\big)$ as well as ground-truth $\big(\text{i.e. } \arg\max_i Y_d[i]\big)$.

$$\text{i.e.,} \quad Acc_d@1 = \begin{cases} 1 & \text{if, } \big(\arg\max_i X_d[i] = \arg\max_i Y_d[i]\big) \\ 0 & \text{else} \end{cases} \tag{3.12}$$

  Since Acc@1 measures the accuracy, higher values are better.

- $\text{AP}_{\text{document}}$ [84]: Average Pearson's correlation coefficient of all documents in the corpus computed by averaging Pearson's correlation coefficient P_d between prediction and ground-truth of each document d, over $|E|$ number of emotion classes.

$$P_d = \frac{\sum_{i=1}^{|E|} \big(X_d[i] - \overline{X}_d\big)\big(Y_d[i] - \overline{Y}_d\big)}{\big(|E| - 1\big)\,\sigma_{X_d}\,\sigma_{Y_d}}, \qquad P_d \in [-1, 1] \tag{3.13}$$

  where, -1 and 1 indicate perfect negative and perfect positive correlations and $\overline{X}_d$, σ_{X_d}, $\overline{Y}_d$, σ_{Y_d} indicate mean and standard deviation of predicted emotion profiles and ground-truth, respectively.

- $\text{AP}_{\text{emotion}}$ [84]: Average Pearson's correlation coefficient of all emotions computed by averaging Pearson's correlation coefficient P_e between prediction (A) and ground-truth (B) of each emotion category e over $|D|$ number of documents (where each emotion category's prediction and ground truth involves a vector over all documents in the corpus).

$$P_e = \frac{\sum_{j=1}^{|D|} \big(A_j - \overline{A}\big)\big(B_j - \overline{B}\big)}{\big(|D| - 1\big)\,\sigma_A\,\sigma_B}, \qquad P_e \in [-1, 1] \tag{3.14}$$

- RMSE_{D} [61]: An error metric of the corpus computed by averaging RMSE of all documents. RMSE of a document d is given by,

$$RMSE_d = \sqrt{\sum_{i=1}^{|E|} \frac{\big(X_d[i] - Y_d[i]\big)^2}{|E|}} \tag{3.15}$$

Since $RMSE_D$ measures the deviation between prediction and ground truth, lower values are better.

- WD_D [232]: A distance metric of the corpus computed by averaging WD of all documents in the corpus. WD of a document d is the infimum for any transport plane computed as,

$$WD_d(X_d, Y_d) = \inf_{\gamma \sim \pi(X_d, Y_d)} \mathbb{E}_{(x,y)\sim\gamma}[\| x - y \|] \tag{3.16}$$

where, $\pi(X_d, Y_d)$ is the set of all possible joint probability distribution $\gamma(x, y)$ whose marginals are X_d and Y_d, respectively. Lower values of WD_D indicate good performance.

3.5 Results and Discussions

This section presents the results of experimental evaluations, initially presenting performance evaluation results of the proposed *REDAffectiveLM* model by comparing against a vast set of baselines from across the families of deep learning, lexicon based and classical machine learning, and also with the individual emoBi-LSTM+Attention and XLNet networks (that implicitly serves as a form of ablation study), to understand the gains achieved by the proposed model. This is followed by statistical significance tests between the proposed model and the best baseline. Finally, behavior analysis is performed to identify what are the key terms responsible for readers' emotion detection captured by the attention, and this eventually helps in assessing the impact of affect enrichment in emoBi-LSTM+Attention for the task of readers' emotion detection through a set of qualitative and quantitative experiments.

3.5.1 Model Performance Evaluation

Table 3.3 shows performance of the proposed model *REDAffectiveLM* and the baselines over REN-20k dataset for various evaluation measures; the best results among all the models, and the best results within each baseline category are highlighted in boldface. The experimental results show that the proposed model obtains a substantive gain[30] of 9.42, 4.68, 5.97, 5.7 and 6.19 percentage points for Acc@1, $AP_{document}$, $AP_{emotion}$, $RMSE_D$ and WD_D, respectively, when compared to XLNet and emoBi-LSTM+Attention that obtains best results among the deep learning baselines, and 20.42, 21.07, 32.51, 17.9, and 11.48 percentage points when compared to SWAT and Emotion Term Model

[30]here the word *gain* is used to indicate increase in percentage points (↑) for the measures Acc@1, $AP_{document}$ and $AP_{emotion}$, and decrease in percentage points (↓) for the measures $RMSE_D$ and WD_D

TABLE 3.3: Evaluation results of REN-20k dataset (Best results among all the models and within each baseline category are in bold)

Model	Acc@1 (%)↑	$AP_{document}$↑	$AP_{emotion}$↑	$RMSE_D$↓	WD_D↓
REDAffectiveLM (Proposed)	**76.68**	**0.8737**	**0.6806**	**0.0438**	**0.0104**
Deep learning baselines					
sent2affect [60]	49.99	0.5925	0.1589	0.1945	0.1177
SS-BED [61]	53.46	0.7114	0.4951	0.2197	0.1170
Kim's CNN [226]	51.77	0.6228	0.1669	0.2285	0.1300
GRU	53.47	0.6416	0.2202	0.2253	0.1221
LSTM [96]	53.50	0.6866	0.4673	0.2192	0.1176
Bi-LSTM [60]	54.48	0.7077	0.5139	0.2165	0.1148
Bi-LSTM+Attention	63.62	0.7998	0.5901	0.1277	0.0801
emoBi-LSTM+Attention	65.09	0.8101	**0.6209**	0.1034	0.0800
XLNet [41]	**67.26**	**0.8269**	0.6016	**0.1008**	**0.0723**
Lexicon based baselines					
SWAT [71]	54.40	**0.6630**	**0.3555**	**0.2228**	**0.1252**
Emotion Term Model [72]	**56.26**	0.6141	0.0245	0.3031	0.1999
Synesketch [73]	42.01	0.3375	0.2538	0.2594	0.1652
Problem transformation baselines					
WMD [80]	47.98	0.2571	0.2015	0.2508	0.1299
TF-IDF [60, 80]	51.60	0.6746	0.3366	0.2298	0.1226
N-Grams [62, 61] ($N = 1$)	50.74	0.5884	0.2939	0.2662	0.1247
TEC [62]	55.94	0.6703	0.3524	0.2732	0.1112
TEI [62]	**57.13**	**0.6958**	**0.4081**	**0.2200**	0.1106
MEI [62]	54.37	0.6589	0.2901	0.2285	0.1176
GEC ($\delta = 0.25$) [62]	53.91	0.6588	0.3032	0.2268	**0.1004**
GEI ($\delta = 0.25$) [62]	53.86	0.6585	0.2919	0.2260	**0.1004**
Sentiment word count [62, 10]	53.99	0.6389	0.2276	0.2299	0.1233
SSWE [212] ($d = 50$)	50.76	0.6080	0.1968	0.2234	0.1278
GloVe [61] ($d = 100$)	50.71	0.5939	0.1509	0.2240	0.1212
Algorithm adaptation baselines					
TF-IDF [60, 80]	52.30	0.6563	0.2849	0.2257	0.1160
N-Grams [62, 61] ($N = 1$)	53.33	0.6073	0.3431	0.2291	0.1212
TEC [62]	52.72	**0.7134**	**0.5038**	0.2027	0.1196
TEI [62]	**59.40**	0.6824	0.3451	0.2207	**0.1000**
MEI [62]	50.79	0.6035	0.2416	0.2325	0.1267
GEC ($\delta = 0.25$) [62]	53.04	0.6612	0.2906	0.2253	0.1139
GEI ($\delta = 0.25$) [62]	53.91	0.6456	0.2599	**0.2011**	0.1234
Sentiment word count [62, 10]	52.54	0.6150	0.2176	0.2304	0.1225
SSWE [212] ($d = 50$)	50.79	0.5278	0.1051	0.3735	0.1309
GloVe [61] ($d = 100$)	51.06	0.5274	0.0613	0.3735	0.1309

that obtains best results among the lexicon based baselines. Within the problem transformation family in machine learning, only the results of WMD feature with SVR, and linguistic and affective features with Ridge Regression are shown and excludes SVR Regressor and GradientBoostingRegressor since their results are comparatively poor for all the three datasets. Similarly for the feature N-Grams, the results of $N = 1$ (unigrams) for which the baseline classifier obtains the best results (a trend similar to [62]) are only tabulated. The results illustrate that the proposed model performs well against all other problem transformation baselines and obtains a gain of 19.55, 17.79, 27.25, 17.62, and 9 percentage points for Acc@1, $AP_{document}$, $AP_{emotion}$, $RMSE_D$, and WD_D, respectively, when compared to the best results among problem transformation baselines. The results of algorithm adaptation baselines show that ANN follows similar trends with improved results than problem transformation approach, where the proposed model even then obtains a gain of 17.28, 16.03, 17.68, 15.73, and 8.96 percentage points for Acc@1, $AP_{document}$, $AP_{emotion}$, $RMSE_D$, and WD_D, respectively, when compared to the best results among algorithm adaptation baselines.

Similar trends are observed for evaluation results of the other two datasets RENh-4k and SemEval-2007. The results of RENh-4k in table 3.4 demonstrate that for evaluation measures Acc@1, $AP_{document}$, $AP_{emotion}$, $RMSE_D$ and WD_D, the proposed model achieves a gain of 7.38, 6.99, 6.22, 5.29 and 2.48 percentage points over the best results among deep learning baselines, 16.65, 18.35, 28.04, 13.56, and 8.47 percentage points over the best results among lexicon based baselines, 16.38, 17.85, 22.77, 12.04, and 5.55 percentage points over the best results among problem transformation baselines and 16, 16.64, 22.81, 12.01, and 5.82 percentage points over the best results among algorithm adaptation baselines, respectively. Table 3.5 shows the results of SemEval-2007 where, for the same set of evaluation measures the proposed model achieves a gain of 7.56, 6.13, 2.96, 6.90, and 3.75 percentage points over the best results among deep learning baselines, 17.56, 25.93, 25.21, 15.51, and 8.29 percentage points over the best results among lexicon based baselines, 21.36, 23.35, 18.67, 11.26, and 6.1 percentage points over the best results among problem transformation baselines and 17.36, 22.01, 15.09, 11.03, and 5.97 percentage points over the best results among algorithm adaptation baselines, respectively.

The entire results thus consolidate that the proposed model *REDAffectiveLM* performs well on prediction of both the highest (Acc@1) and overall ($AP_{document}$ and $AP_{emotion}$) readers' emotion profiles, along with lower values for error ($RMSE_D$) and

TABLE 3.4: Evaluation results of RENh-4k dataset (Best results among all the models and within each baseline category are in bold)

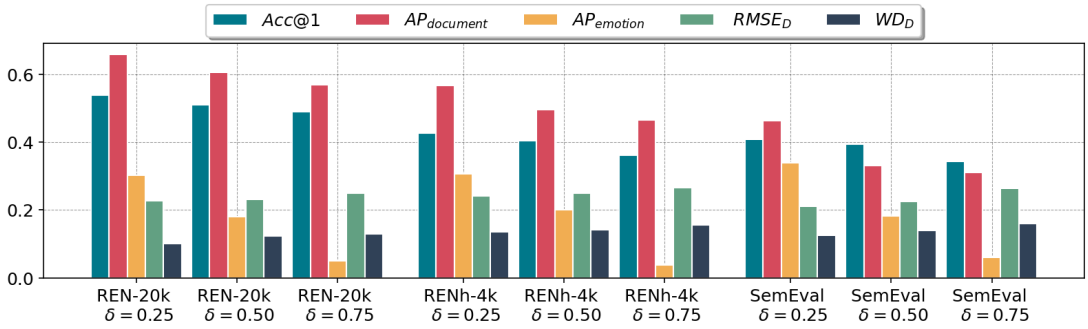
Model	Acc@1 (%)↑	$AP_{document}$↑	$AP_{emotion}$↑	$RMSE_D$↓	WD_D↓
REDAffectiveLM (Proposed)	**60.75**	**0.7693**	**0.5809**	**0.1205**	**0.0761**
Deep learning baselines					
sent2affect [60]	36.00	0.4684	0.1047	0.2508	0.1458
SS-BED [61]	45.62	0.5534	0.3609	0.2406	0.1424
Kim's CNN [226]	40.00	0.4775	0.2084	0.2493	0.1585
GRU	38.75	0.4860	0.1765	0.2481	0.1443
LSTM [96]	40.13	0.5927	0.3402	0.2559	0.1472
Bi-LSTM [60]	45.00	0.6297	0.3415	0.2400	0.1465
Bi-LSTM+Attention	50.50	0.6499	0.4054	0.2301	0.1220
emoBi-LSTM+Attention	51.98	0.6991	**0.5187**	0.1889	0.1141
XLNet [41]	**53.37**	**0.6994**	0.4975	**0.1734**	**0.1009**
Lexicon based baselines					
SWAT [71]	43.75	**0.5858**	**0.3005**	**0.2561**	**0.1608**
Emotion Term Model [72]	**44.10**	0.5520	0.0102	0.3369	0.2000
Synesketch [73]	31.37	0.1394	0.2423	0.2936	0.1792
Problem transformation baselines					
WMD [80]	35.25	0.3593	0.0289	0.2869	0.1346
TF-IDF [60, 80]	**44.37**	0.5007	0.3490	0.2440	**0.1316**
N-Grams [62, 61] ($N = 1$)	42.37	0.5067	0.3009	0.2662	0.1328
TEC [62]	41.12	0.5686	0.3237	0.2410	0.1357
TEI [62]	44.06	**0.5908**	**0.3532**	**0.2409**	**0.1316**
MEI [62]	40.75	0.5394	0.2574	0.2442	0.1411
GEC ($\delta = 0.25$) [62]	42.75	0.5676	0.3063	0.2410	0.1363
GEI ($\delta = 0.25$) [62]	41.75	0.5602	0.2963	0.2417	0.1365
Sentiment word count [62, 10]	39.25	0.4883	0.1443	0.2492	0.1386
$SSWE_u$ [212] ($d = 50$)	41.50	0.4969	0.1804	0.2483	0.1367
GloVe [61] ($d = 100$)	40.75	0.5108	0.2072	0.2474	0.1327
Algorithm adaptation baselines					
TF-IDF [60, 80]	39.62	0.4630	0.2870	0.2516	0.1489
N-Grams [62, 61] ($N = 1$)	42.75	0.4926	0.2796	0.2456	0.1505
TEC [62]	41.37	0.5701	0.3298	0.2496	0.1356
TEI [62]	42.87	**0.6029**	**0.3528**	0.2473	**0.1343**
MEI [62]	40.12	0.4856	0.2279	0.2488	0.1466
GEC ($\delta = 0.25$) [62]	**44.75**	0.5726	0.3190	**0.2406**	0.1359
GEI ($\delta = 0.25$) [62]	41.37	0.5532	0.2934	0.2419	0.1378
Sentiment word count [62, 10]	39.62	0.4846	0.1343	0.2491	0.1425
$SSWE_u$ [212] ($d = 50$)	35.62	0.3080	0.0207	0.4246	0.1376
GloVe [61] ($d = 100$)	35.37	0.2382	0.0920	0.4373	0.1376

TABLE 3.5: Evaluation results of SemEval-2007 dataset (Best results among all the models and within each baseline category are in bold)

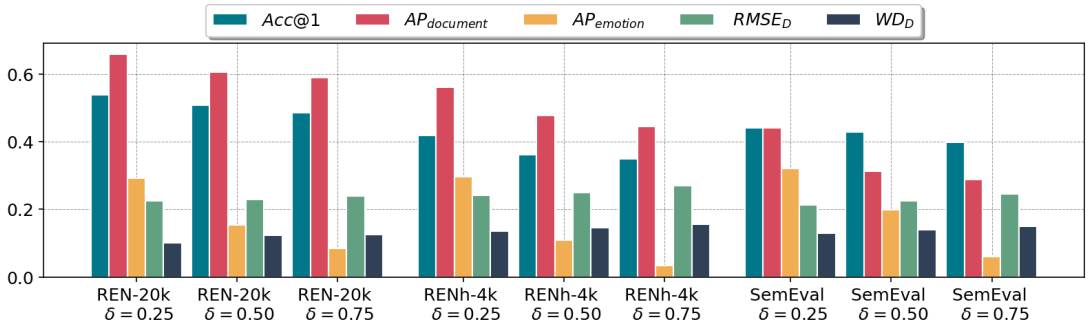
Model	Acc@1 (%)↑	$AP_{document}$↑	$AP_{emotion}$↑	$RMSE_D$↓	WD_D↓
REDAffectiveLM (Proposed)	**66.96**	**0.8235**	**0.6502**	**0.0902**	**0.0525**
Deep learning baselines					
sent2affect [60]	37.20	0.3339	0.1075	0.2241	0.1428
SS-BED [61]	50.40	0.6139	0.5098	0.1771	0.1090
Kim's CNN [226]	47.20	0.5437	0.4451	0.1987	0.1200
GRU	46.00	0.5673	0.5003	0.2005	0.1098
LSTM [96]	49.20	0.6015	0.5248	0.1842	0.1089
Bi-LSTM [60]	49.89	0.6007	0.5059	0.1812	0.1074
Bi-LSTM+Attention	52.60	0.7140	0.5506	0.1700	0.0915
emoBi-LSTM+Attention	56.20	0.7565	0.5850	**0.1592**	**0.0900**
XLNet [41]	**59.40**	**0.7622**	**0.6206**	0.1739	0.0913
Lexicon based baselines					
SWAT [71]	46.00	0.4945	**0.3981**	**0.2453**	**0.1354**
Emotion Term Model [72]	**49.40**	**0.5642**	0.0167	0.3031	0.1975
Synesketch [73]	35.86	0.3705	0.3570	0.2470	0.1510
Problem transformation baselines					
WMD [80]	40.50	0.1447	0.0459	0.2430	0.1143
TF-IDF [60, 80]	**45.60**	0.4954	0.4039	0.2080	**0.1135**
N-Grams [62, 61] ($N = 1$)	45.00	0.4992	0.3931	0.2089	0.1189
TEC [62]	45.20	0.5451	0.4219	**0.2028**	0.1219
TEI [62]	**45.60**	**0.5900**	**0.4635**	0.2985	0.1228
MEI [62]	**45.60**	0.4884	0.4071	0.2051	0.1257
GEC ($\delta = 0.25$) [62]	40.80	0.4643	0.3398	0.2113	0.1251
GEI ($\delta = 0.25$) [62]	44.00	0.4416	0.3207	0.2136	0.1291
Sentiment word count [62, 10]	39.04	0.5604	0.3820	0.2089	0.1208
$SSWE_u$ [212] ($d = 50$)	34.56	0.3130	0.1152	0.2300	0.1272
GloVe [61] ($d = 100$)	33.12	0.2605	0.1088	0.2378	0.1152
Algorithm adaptation baselines					
TF-IDF [60, 80]	46.40	0.4799	0.3941	0.2059	0.1206
N-Grams [62, 61] ($N = 1$)	46.80	0.5135	0.4140	0.2027	0.1171
TEC [62]	46.40	0.5639	0.4270	0.2021	0.1204
TEI [62]	**49.60**	**0.6034**	**0.4993**	**0.2005**	**0.1122**
MEI [62]	46.40	0.4949	0.4103	0.2062	0.1306
GEC ($\delta = 0.25$) [62]	46.00	0.4861	0.3622	0.2089	0.1229
GEI ($\delta = 0.25$) [62]	46.70	0.4722	0.3531	0.2099	0.1248
Sentiment word count [62, 10]	40.00	0.5732	0.3798	0.2023	0.1193
$SSWE_u$ [212] ($d = 50$)	40.80	0.2071	0.0595	0.4032	0.1641
GloVe [61] ($d = 100$)	42.40	0.2261	0.0777	0.4022	0.1643

distance metrics (WD_D) over the three different datasets, which indicates the promising nature of *REDAffectiveLM*. Among the deep learning baselines, XLNet and emoBi-LSTM+Attention performs better; this could be because XLNet is a promising transformer based language model that generates powerful contextual representations and in the case of emoBi-LSTM+Attention, it enriches the conventional semantic representations with affect. Transfer learning, in general, gives good results, but on contrary, in this experiments the sent2affect [60] baseline shows low results for the sentiment to emotion transfer learning. This might be because the source model was built over Twitter data meant specifically for coarse-grained sentiment classification task, but the target model is meant for an entirely different fine-grained emotion regression task. Whereas within the original implementation of sent2affect, the authors built both the source and target models with similar kinds of Twitter data, both meant for classification task, which leads them to enjoy the benefits of transfer learning. In the case of lexicon based baselines, SWAT performs well, even being one of the oldest works in readers' emotion detection. Both SWAT and Emotion Term Model could effectively utilize word features available within the corpora which makes them the top-performing baselines. On the other hand, Synesketch uses a very generic and non-filtered general-purpose emotion lexicon as a major component (except the rule sets), which may be the cause for low results. In machine learning baselines, among the various features, affective features, especially TEI outperforms the traditional linguistic features like TF-IDF and N-Grams in many cases, where TF-IDF, TEC, and MEI are the others producing best results. The affective features GEC and GEI are analyzed using three different thresholds, $\delta = 0.25$, 0.50, and 0.75, where a degradation in performance was observed with an increase of δ from 0.25 to 0.75, which is visualized in figure 3.4. This degradation could be due to the decreased coverage of emotion words by the lexicon, as mentioned in [62].

Evaluation results of Bi-LSTM+Attention and emoBi-LSTM+Attention across all the three datasets shows that affect enriched embedding based architecture (emoBi-LSTM+Attention) attains performance gains over conventional semantic embedding based architecture (Bi-LSTM+Attention) for all the evaluation measures. The results thus indicate that affect enriched document representations can enhance model performance for the task of readers' emotion detection. While comparing evaluation results of the fused model *REDAffectiveLM* with individual networks emoBi-LSTM+Attention and XLNet, it is visible that across all the three datasets the fused model obtains a very high gain in performance throughout all the evaluations measures. This establishes that *REDAffectiveLM* that utilizes the highly efficient contextual representation from transformer-based pre-trained language model along with affect enriched document



(A) GEC



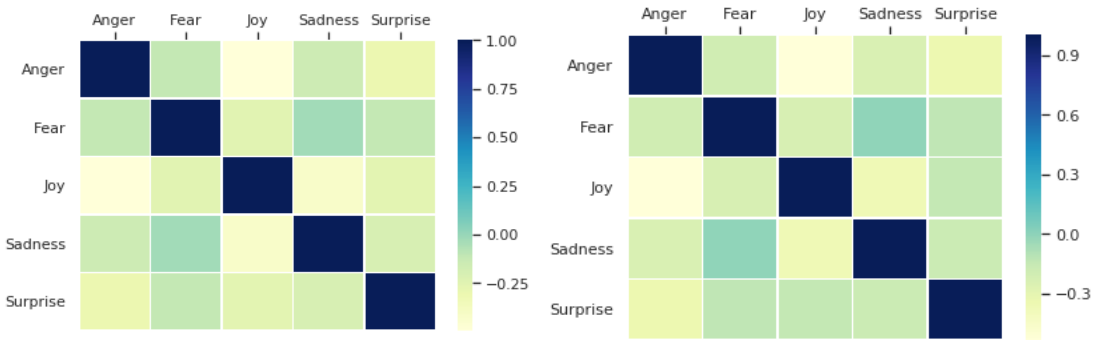
(B) GEI

FIGURE 3.4: Performance of GEC and GEI features over different thresholds (δ)

representation, can significantly improve performance of readers' emotion detection.

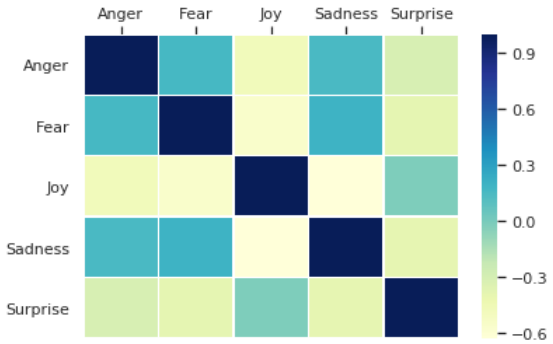
The trends of evaluation results across multiple datasets illustrate another point that SemEval-2007 shows slightly better results than RENh-4k even though it has less amount of data. SemEval-2007 is a less complex dataset; the maximum number of annotators is six. But in the context of the newly curated readers emotion news datasets, the minimum number of annotators involved is 242680 for RENh-4k and 2556654 for REN-20k, which makes them complex real-world datasets with several contradictory readers' votings in the ground truth emotion profiles. To understand the effect of dataset complexity, with respect to the number of readers' annotating a document, the degree of correlation between emotions is computed using Pearson's correlation coefficient [213]. These correlations, for each of the three datasets, are shown in figure 3.5. In the figures, the dark colors indicate a high correlation and light colors indicate a low correlation. In SemEval-2007 (figure 3.5c), there can be observed several natural correlations such as *anger* highly correlated to *fear* and *sadness*. But in REN-20k (figure 3.5a) and RENh-4k (figure 3.5b), a low correlation exists between these emotions. Also,

in SemEval-2007, when observing the correlations between *joy* and *fear*, there exists a very low correlation between these emotions. Whereas, in REN-20k and RENh-4k, these emotions have comparatively slightly higher correlations. These kinds of irregular and complex patterns due to a large number of annotators (i.e., readers) with contradictory emotion votings may be the reason for reduced performance gain in RENh-4k, which is overcome with huge amounts of data in REN-20k producing remarkable gains by allowing to learn the complex patterns in emotion correlations.



(A) REN-20k

(B) RENh-4k



(C) SemEval-2007

FIGURE 3.5: Emotion profile correlations in the datasets

3.5.2 Statistical Significance

In addition to substantial gain observed over various evaluation measures, the statistical significance of the proposed model is evaluated by conducting significance tests on paired models in terms of the ideal measures, Acc@1 and RMSE, which are highly capable of representing coarse-grained (i.e., classification) and fine-grained (i.e., regression) characteristics of the readers' emotion detection task, respectively. The tests performed are McNemar's test [233] over Acc@1 and Kolmogorov-Smirnov test [234] over RMSE to compute the significance between *REDAffectiveLM* and the best baseline

using the conventional significance level, i.e., a p-value of 0.05. A p-value of 1.64E-5 (i.e., 0.0000164), 2.15E-3 (i.e., 0.00215) and 5.07E-3 (i.e., 0.00507) for Acc@1 and 1.80E-6 (i.e., 0.00000180), 3.47E-4 (i.e., 0.000347) and 6.19E-4 (i.e., 0.000619) for RMSE, for the three datasets REN-20k, RENh-4k, and SemEval-2007, respectively, are obtained indicating that the results of *REDAffectiveLM* is statistically significant over the best baselines.

3.5.3 Behavior Analysis of Affect Enrichment

In addition to intrinsic analysis on the impact of affect enrichment in conventional semantic embedding presented in section 3.2.2 (using t-SNE visualizations and *in-category*, *cross-category* measures for affective words), this section analyzes the effectiveness of affect enrichment over conventional semantic embedding specifically for the task of readers' emotion detection. Therefore, besides the comparison of performances of emoBi-LSTM+Attention (Bi-LSTM+Attention fed with affect enriched embedding) and Bi-LSTM+Attention (Bi-LSTM+Attention fed with conventional semantic embedding) in the above section 3.5.1 by considering them as baselines in the empirical evaluation, here, based on initially identifying what are the key terms responsible for readers' emotion detection captured by the Attention, behavior of emoBi-LSTM+Attention network is analyzed qualitatively and quantitatively to better understand whether affect enrichment helps the network to efficiently identify and assign weightage to these key terms to improve the predictions, when compared to Bi-LSTM+Attention.

What Attention Captures?

Every prediction of an Attention based model produces readers' emotion profiles along with an attention map that highlights the key terms (the terms which are given weightage by the Attention based on their significance in prediction). Readers' emotions elicited from textual documents may be intuitively expected to be highly oriented towards emotion words and named entities present in the documents. However, such assumptions need to be verified empirically, so they may inform further research into readers' emotion detection. In this context, the behavior evaluations in this study set an evaluation hypothesis that *the key terms that could have helped readers' emotion detection are emotion words and named entities present in the documents*. To verify this hypothesis, instead of directly analyzing the attention maps of emoBi-LSTM+Attention network used in the proposed model, a Bi-LSTM+Attention network (used as a baseline in the empirical evaluation) is employed to understand the key terms captured

by attention in the context of readers' emotion detection. This would further help to understand whether the emoBi-LSTM+Attention network that utilizes affect enriched embedding has improved capability to capture these key terms responsible for readers' emotion detection thereby improving the predictions.

To understand what are the key terms responsible for readers' emotion detection, a manual investigation is conducted over the attention maps generated by the Bi-LSTM+Attention network. Table 3.6 shows two sets of attention maps generated by the Bi-LSTM+Attention network along with their associated ground truth (ep_r) and predicted ($\widehat{ep}_r$) emotion profiles. Color intensities over the words in attention maps indicate weightage associated with the words, i.e., dark red indicates high weightage for the words, whereas light red indicates less weightage. The first set of attention maps include samples whose predicted emotion profiles are very near to ground truth and hence, they can be categorized as correct predictions.

The first attention map among the correct predictions set shows that a high-intensity weightage is given to the word 'attack' and then to the words 'hiding' and 'threats' with a slight weightage decay, which explains the nearness of predicted emotion profiles to ground truth. That is, higher values are seen to peak around the emotions, *fear*, *sadness* and *anger*, for both predicted and ground truth emotion profiles, which undoubtedly showcases the intimate relationship between attention recognized words and emotions. Similarly, many other attention maps in the correct predictions set show a substantial weightage for emotion words; for example, the words 'pain', 'suffer', and 'poisoning' in the fourth attention map and the association of predicted emotion profiles with emotion *sadness*. Also, the fifth attention map highlights words such as 'shining', 'better', 'care', and 'empowering', which may be the reason to predict high intensities for emotions *surprise* and *joy*. Next, the weightage associated with named entities in the attention maps are observed. In the correct predictions set, many named entities like 'Korean', 'Pakistan', 'Lillard', 'Ines Fernandez', etc., are highlighted with varying weightage. For example, in the sixth attention map, the word 'Lillard' (name of an American basketball player) may also have influenced to produce high-intensity for emotion *joy* in some readers and *anger* in others, besides other words with an attention weightage. From the perspective of such qualitative analyses, it can be inferred that attention gives high weightage to the emotion words and nearly so to the named entities for the task of readers' emotion detection.

In contrast to the first set of correct predictions, the second set in table 3.6 includes a few random samples from incorrect predictions and their attention maps. Incorrect predictions refer to the predictions that are far away from the patterns of ground truth emotion profiles. Here too, the attention maps highlight a few emotion terms

TABLE 3.6: Sample attention maps generated by the Bi-LSTM+Attention network (ep_r: ground truth, $\widehat{ep}_r$: predicted)

Document Attention Map	Emotion profiles for [anger, fear, joy, sadness, surprise]
Correct predictions	
Teacher in hiding after attack on Islam Stirs Threats	$ep_r = [0.149, 0.436, 0.000, 0.413, 0.000]$ $\widehat{ep}_r = [0.233, 0.430, 0.026, 0.311, 0.000]$
Bad weather slows S.Korean search Russian ship	$ep_r = [0.120, 0.040, 0.000, 0.840, 0.000]$ $\widehat{ep}_r = [0.102, 0.012, 0.001, 0.790, 0.091]$
Women protest Pakistan demolition	$ep_r = [0.339, 0.122, 0.000, 0.245, 0.292]$ $\widehat{ep}_r = [0.330, 0.210, 0.003, 0.280, 0.170]$
126 students suffer food poisoning Makati. Most of the students who experienced and dizziness stomach pains after ingesting snacks bought from school canteen, have been discharged from the hospital.	$ep_r = [0.173, 0.062, 0.062, 0.617, 0.086]$ $\widehat{ep}_r = [0.188, 0.086, 0.071, 0.517, 0.136]$
Ines Fernandez mother others. Nanay Ines shining example of women who are empowering mothers in rural areas to take better care of their health and wellbeing through proper nutrition and education.	$ep_r = [0.000, 0.000, 0.271, 0.000, 0.729]$ $\widehat{ep}_r = [0.007, 0.040, 0.353, 0.057, 0.550]$
Warriors destroyed by Blazers as Lillard scores 51. Golden State falls to 48-5, with all 5 defeats coming on the road	$ep_r = [0.326, 0.000, 0.413, 0.174, 0.087]$ $\widehat{ep}_r = [0.318, 0.001, 0.465, 0.182, 0.032]$
Incorrect predictions	
Greek police hunt embassy attackers	$ep_r = [0.551, 0.252, 0.046, 0.149, 0.000]$ $\widehat{ep}_r = [0.187, 0.277, 0.080, 0.301, 0.152]$
Personal health: for teenagers, car is the danger zone	$ep_r = [0.000, 0.494, 0.000, 0.221, 0.284]$ $\widehat{ep}_r = [0.109, 0.229, 0.104, 0.349, 0.207]$
The sweet tune of an anniversary	$ep_r = [0.000, 0.000, 1.000, 0.000, 0.000]$ $\widehat{ep}_r = [0.016, 0.026, 0.545, 0.247, 0.167]$
33 killed in Central Luzon since start of election gun ban. Most of them were killed during shootout with authorities while evading checkpoints, says Central Luzon police director Chief Superintendent Joel Napoleon Coronel.	$ep_r = [0.290, 0.570, 0.000, 0.000, 0.140]$ $\widehat{ep}_r = [0.378, 0.250, 0.076, 0.244, 0.050]$
PH Air Force to welcome 2 fighter jets. The squadron of 12 brand new fighter jet will be completed within the year, according to Air Force spokesman Colonel Antonio Francisco.	$ep_r = [0.000, 0.011, 0.915, 0.000, 0.074]$ $\widehat{ep}_r = [0.106, 0.068, 0.586, 0.088, 0.149]$
Liberia's last Ebola patient discharged. Almost 24,000 people have been infected with the virus since 2013 december	$ep_r = [0.000, 0.000, 0.500, 0.000, 0.500]$ $\widehat{ep}_r = [0.130, 0.183, 0.189, 0.382, 0.108]$

and named entities such as 'danger', 'killed', 'Antonio', etc., but it has missed most of the relevant ones. For example, in the first attention map among incorrect predictions, attention gives zero weightage to the word 'attackers', which could have given enough power to predict high intensities for the emotions *anger*, *fear*, and *sadness*, similar to ground truth emotion profile. Apart from these kinds of exclusion of key terms (i.e. emotion words and named entities), most of the incorrect predictions assign high weightage to the words like 'says', 'year', 'almost', 'since', etc. Hence, a major reason for the increase in gap between predicted and ground truth emotion profiles might be due to the exclusion of emotion words and named entities, and instead assigning high weightage to many less significant words in the document. This correlation between the focus on named entities and emotion words with the measures of performance further reasserts the value of emotion words and named entities in the task of readers' emotion detection.

Qualitative Evaluation

In qualitative evaluation the attention maps of both emoBi-LSTM+Attention and Bi-LSTM+Attention are compared, and hence their model behavior (i.e., model's decision making) in context of readers' emotion detection by manually investigating the presence of key terms (emotion words and named entities). Table 3.7 shows pairs of attention maps for five sample documents, where in each pair, the first attention map is generated by Bi-LSTM+Attention and the second by emoBi-LSTM+Attention, along with their associated ground-truth emotion profiles (ep_r) and predicted emotion profiles of both Bi-LSTM+Attention ($\widehat{ep}_r$) and emoBi-LSTM+Attention ($\widehat{ep}_{rEmo}$). In the first pair, the attention map from the Bi-LSTM+Attention significantly assigns weightage to an emotion word 'protest' and a named entity 'Pakistan'. Whereas, the attention map from emoBi-LSTM+Attention shows improvements in the prediction, i.e., nearness of prediction to the ground truth, especially visible in case of emotions *fear* and *surprise* by assigning weightage to the emotion word 'demolition'. In the second and third pair of attention maps, there can be observed high improvements in prediction for emoBi-LSTM+Attention when compared to Bi-LSTM+Attention, especially visible in case of emotion *anger* by identifying the emotion word 'attackers' in the second pair, and emotion *joy* by identifying the emotion word 'sweet' in the third pair.

Apart from the exclusion of key terms (emotion words and named entities) such as 'demolition' in the first pair, 'attackers' in the second pair, 'sweet' in the third pair, etc., it can also be observed that the attention maps from Bi-LSTM+Attention mostly are seen to assign uniform weightage to the identified words. For example, in the fourth pair, the words 'car' and 'teenager' are given almost the same high intensity as like the

TABLE 3.7: Sample attention maps generated by the Bi-LSTM+Attention and emoBi-LSTM+Attention networks (ep_r: ground truth, $\widehat{ep}_r$: Bi-LSTM+Attention prediction, $\widehat{ep}_{rEmo}$: emoBi-LSTM+Attention prediction)

Document Attention Maps	Emotion profiles for [anger, fear, joy, sadness, surprise]
Women protest Pakistan demolition	ep_r = [0.339, 0.122, 0.000, 0.245, 0.292]
	$\widehat{ep}_r$ = [0.330, 0.210, 0.003, 0.280, 0.170]
Women protest Pakistan demolition	$\widehat{ep}_{rEmo}$ = [0.340, 0.102, 0.001, 0.290, 0.260]
Greek police hunt embassy attackers	ep_r = [0.551, 0.252, 0.045, 0.149, 0.000]
	$\widehat{ep}_r$ = [0.187, 0.277, 0.080, 0.301, 0.152]
Greek police hunt embassy attackers	$\widehat{ep}_{rEmo}$ = [0.465, 0.272, 0.078, 0.103, 0.082]
The sweet tune of an anniversary	ep_r = [0.000, 0.000, 1.000, 0.000, 0.000]
	$\widehat{ep}_r$ = [0.016, 0.026, 0.545, 0.247, 0.167]
The sweet tune of an anniversary	$\widehat{ep}_{rEmo}$ = [0.029, 0.039, 0.835, 0.064, 0.033]
Personal health for teenagers the car is the danger zone	ep_r = [0.000, 0.495, 0.000, 0.221, 0.284]
	$\widehat{ep}_r$ = [0.109, 0.229, 0.104, 0.349, 0.207]
Personal health for teenagers the car is the danger zone	$\widehat{ep}_{rEmo}$ = [0.056, 0.358, 0.080, 0.296, 0.210]
PH Air force to welcome 2 more fighter jets The squadron of 12 brand new fighter jets will be completed within the year according to Air Force spokesman Colonel Antonio Francisco	ep_r = [0.000, 0.011, 0.915, 0.000, 0.074]
	$\widehat{ep}_r$ = [0.093, 0.048, 0.606, 0.094, 0.159]
PH Air force to welcome 2 more fighter jets The squadron of 12 brand new fighter jets will be completed within the year according to Air Force spokesman Colonel Antonio Francisco	$\widehat{ep}_{rEmo}$ = [0.004, 0.039, 0.759, 0.004, 0.192]

words 'danger' and 'health'. But in case of emoBi-LSTM+Attention the weightage for 'car' and 'teenager' are seen to be diminished than 'danger' and 'health'. Similar case can be seen in the fifth pair of attention maps, where, for the words 'within', 'completed', 'year', etc., emoBi-LSTM+Attention assigns different weightage, when compared to Bi-LSTM+Attention that assigns almost similar weightage to all these words. Hence, qualitative evaluation demonstrates that better than a Bi-LSTM+Attention network that utilizes conventional semantic embedding, the affect enriched embedding based network emoBi-LSTM+Attention can effectively identify and assign weightage

to the key terms responsible for readers' emotion detection thereby improving the nearness of predictions to the ground-truth.

Quantitative Evaluation

The above evaluations show that attention maps give weightage mostly to the emotion words and named entities for the task of readers' emotion detection, and efficiently identifying these key terms can significantly improve the prediction. Following on from that, in this section, the ability of emoBi-LSTM+Attention and Bi-LSTM+Attention networks to identify the key terms in predictions are quantitatively compared using a novel set of evaluation measures. Therefore, apart from attention maps generated internally by these networks (definition 1), external attention maps (definitions 2 and 3) by leveraging external information (e.g., lexicons) are devised to perform quantitative behavior evaluation. To generate external lexicon-based attention maps, initially three popular emotion lexicons DepecheMood++ [70], EmoWordNet [69] and NRC-Affect Intensity Lexicon [68] are identified, and lexicon coverage for unique words in the datasets are computed, results are shown in table 3.8. It can be observed that both DepecheMood++ and EmoWordNet gives better coverage, hence these two lexicons are chosen for the quantitative evaluation. Further, to identify named entities, an external tool called Named Entity Recognizer (NER) from spaCy[31] is used. The construction of external attention maps will be evident through their definitions that follow.

TABLE 3.8: Emotion Lexicon coverage (in percentages)

Dataset	DepecheMood++	EmoWordNet	NRC-Affect
REN-20k	77.02	50.63	8.15
RENh-4k	88.11	67.13	13.67
SemEval-2007	94.69	86.50	20.28

Definition 1. [DAM] An internal Document Attention Map produced from the attention layer of the networks for each input document, represented as a vector with intensity values or weightages associated with each word, which indicates the attention received by that word during the prediction. If weightage of the words in the attention map is continuous then it is called a continuous attention map; DAM is generally a continuous representation. But if the weightage is either 0 or 1, indicating the presence or absence of attention for a certain word, then it is called binary attention map.

[31] https://spacy.io/, *accessed: 05-12-2022*

Definition 2. [EmoNE-EAM] An External Attention Map independent of DAM (and thus network independent) generated with the help of an emotion lexicon (the lexicons [69, 70] are used in this study) and Named Entity Recognizer (NER from spaCy is used in this study). To create EmoNE-EAM each word in the document is read sequentially and the attention weightage of the word is set to a boolean value 1 if it is an element of the emotion lexicon or NER, else set to 0. This map will be a binary representation that indicates only the presence of emotion words and named entities in the document.

Definition 3. [EmoNE-HAM] A Hybrid Attention Map generated by considering only the words that has non-zero attention weightages in DAM and hence blends the information from network generated internal attention map and external information from the lexicons. This map can have continuous or binary representations. The continuous EmoNE-HAM are created similar to EmoNE-EAM, but the boolean values in EmoNE-EAM are replaced by the weightages in DAM, provided the word has a non-zero weightages in DAM. In case of binary EmoNE-HAM, instead of adding the non-zero DAM weightages to the attention map, the values are set to 1. That is, EmoNE-HAM represents only the emotion words and named entities in a document that are recognized by DAM.

The above attention maps provide a convenient platform to measure the impact of emotion words and named entities in the prediction. Comparing Bi-LSTM+Attention and emoBi-LSTM+Attention networks in terms of similarity between the emotion words and named entities identified by their attention mechanism and the total emotion words and named entities present in the document would help to understand the capability of affect enriched network to identify the key terms to improve the prediction. For computational convenience, this is accomplished by contrasting the extent of deviation between EAM (external attention map) and HAM (hybrid attention map), for both emoBi-LSTM+Attention and Bi-LSTM+Attention networks, using a novel set of measures, behavioral similarity, word similarity, and word probability that computes similarity between the attention maps.

- Behavioral Similarity: Motivated by [107], the behavioral similarity of the corpus D is computed as the average pair-wise similarity between EmoNE-HAM and EmoNE-EAM for all the documents, given as,

$$\text{BehSim}_{\text{D}} = \frac{1}{D}\sum_{d=1}^{|D|} AUC(\text{EmoNE-HAM}_d, \text{EmoNE-EAM}_d) \tag{3.17}$$

  where, EmoNE-HAM_d is a continuous attention map vector and EmoNE-EAM_d is a binary attention map, for each document d. AUC denotes Area Under Curve and ranges between 0 and 1, with perfect similarity given by 1, no similarity by 0.5 and negative similarity by 0 [107]. A high behavioral similarity will occur

in cases where the model gives high intensity weightage for emotion words and named entities.

- Word Similarity: To measure the similarity between attention maps in context of the cosine angle projected in a multi-dimensional space. The word similarity score WordSim_D for the corpus D is computed by averaging the cosine similarities[32] of binary EmoNE-HAM and EmoNE-EAM for all the documents.

$$\text{WordSim}_\text{D} = \frac{1}{|D| - |D'|} \sum_{d=1}^{|D|-|D'|} \cos\left(\text{EmoNE-HAM}_d, \text{EmoNE-EAM}_d\right) \quad (3.18)$$

where, $|D'|$ indicates the number of documents that don't have any emotion words or named entities. Similar to the above measure, a high word similarity will occur in cases where the model gives high intensity weightage for emotion words and named entities.

- Word Probability: A measure that uses boolean intersection between binary EmoNE-HAM and EmoNE-EAM to quantify how much emotion words and named entities are identified by the attention mechanism during prediction, among the total number of emotion words and named entities present in the document. Unlike the previous similarity scores, this measure is represented in probabilities. Word probability WordProb_D for the corpus D is computed by averaging the word probabilities of all the documents.

$$\text{WordProb}_\text{D} = \frac{1}{|D| - |D'|} \sum_{d=1}^{|D|-|D'|} \frac{\sum(\text{EmoNE-EAM}_d \cap \text{EmoNE-HAM}_d)}{\sum(\text{EmoNE-EAM}_d) + \lambda} \quad (3.19)$$

where, $\lambda = 1$ only if EmoNE-EAM = 0, and $\lambda = 0$ if EmoNE-EAM $\neq 0$.

The results of quantitative analysis shown in table 3.9 illustrates that for all the three datasets emoBi-LSTM+Attention obtains higher similarity scores between the network generated internal attention maps and the external attention maps when compared to Bi-LSTM+Attention, for both the lexicons, which indicates that compared to Bi-LSTM+Attention network, emoBi-LSTM+Attention has improved ability to identify the emotion words and named entities. Against the backdrop of the hypothesis that emotion words and named entities are important for emotion identification, this validates emoBi-LSTM+Attention's improved suitability for emotion identification. Thus, the qualitative and quantitative behavior analysis on emoBi-LSTM+Attention

[32] https://deepai.org/machine-learning-glossary-and-terms/cosine-similarity, *accessed: 05-12-2022*

together establish that affect enrichment increases the ability of the network to effectively identify emotion words, and assign weightages to the key terms responsible for readers' emotion detection to improve prediction.

TABLE 3.9: Quantitative evaluation results

Model	DepecheMood++			EmoWordNet		
	REN-20k	RENh-4k	SemEval-2007	REN-20k	RENh-4k	SemEval-2007
Behavioral similarity scores						
Bi-LSTM+Attention	0.8829	0.7096	0.8092	0.8497	0.6988	0.8040
emoBi-LSTM+Attention	0.9537	0.8182	0.9001	0.9098	0.8104	0.8896
Word similarity scores						
Bi-LSTM+Attention	0.8296	0.6851	0.8203	0.8010	0.6606	0.7919
emoBi-LSTM+Attention	0.9603	0.8636	0.8821	0.8490	0.8128	0.8090
Word probability scores						
Bi-LSTM+Attention	0.9043	0.7648	0.8981	0.8901	0.7205	0.8624
emoBi-LSTM+Attention	0.9438	0.8071	0.8999	0.9413	0.7551	0.8873

3.6 Summary

Context-specific representations from transformer-based pre-trained language models help textual emotion detection systems to achieve improved performance, which, being an affective computing task can be further enhanced by incorporating affective information. Inspired by this line of thought, this chapter presented a novel deep learning model, *REDAffectiveLM* that leverages context-specific and affect enriched representations by fusing a transformer-based pre-trained language model XLNet with Bi-LSTM+Attention that utilizes affect enriched embedding, to predict readers' emotion profiles from short-text documents. To perform the experiments two new readers' emotion datasets, REN-20k and RENh-4k were procured, apart from the benchmark SemEval-2007 dataset. Performance of the proposed model was evaluated across these datasets, against a vast set of baselines belonging to different categories of textual emotion detection, including deep learning, lexicon based, and classical machine learning using various coarse-grained and fine-grained measures. The proposed model consistently outperformed the baselines and obtained statistically significant results. The evaluation results of the fused model *REDAffectiveLM* when compared with the individual affect enriched Bi-LSTM+Attention and XLNet networks, across all the three datasets, obtained high gains in performance for all the evaluations measures. This

establishes that the proposed model *REDAffectiveLM* that utilizes highly efficient contextual representation from transformer-based pre-trained language model along with affect enriched document representation can significantly improve the performance of readers' emotion detection.

A detailed model behavior analysis is also performed to interpret the attention mechanism that firmly establishes emotion words and named entities significantly influence readers' emotion detection, and to study the impact of affect enrichment specifically in readers' emotion detection using a novel set of qualitative and quantitative behavior evaluation techniques over the affect enriched Bi-LSTM+Attention network. It is observed that compared to the conventional semantic embedding based network, the affect enriched network obtained higher performance and helped to increase ability of the network to effectively identify and assign weightages to the key terms (emotion words and named entities) responsible for readers' emotion detection. To aid future research, the datasets and other relevant materials, including the source code are made publicly available at https://dcs.uoc.ac.in/cida/projects/ac/redaffectivelm.html.

Chapter 4

Emotion Cognizance Improves Health Fake News Identification

> *"**Enjoyment** is the most desirable emotion typically arising from connection or sensory pleasure. The word happiness and enjoyment can be interchanged, although increasingly people use the word happiness to refer to their overall sense of well-being or evaluation of their lives rather than a particular enjoyment emotion."*
>
> *– Paul Ekman*
> *Universal Emotions*

Abstract: This chapter considers the utility of the affective character of news articles for fake news identification in the health domain and present evidence that emotion cognizant representations are significantly more suited for the task. The proposed study outlines a simple technique that works by leveraging emotion intensity lexicons to develop emotion-amplified text representations and evaluate the utility of such a representation for identifying fake news relating to health in various supervised and unsupervised scenarios. The consistent and notable empirical gains that are observed over a range of technique types and parameter settings establish the utility of the emotion information in news articles, an often overlooked aspect, for the task of misinformation identification in the health domain.

The concept presented in this chapter was awarded the AWSAR 2019 Award, instituted by the Department of Science and Technology, Government of India

4.1 Introduction

Fake news detection is increasingly being recognized as an important computational task with high potential social impact. Misinformation is routinely injected into almost every domain of news including politics, health, science, business, etc., among which, the fake news in the health domain poses serious risk and harm to health and well-being in modern societies [27]. Fake news in the health domain is

markedly different from fake news in politics or event-based contexts on at least two major counts. First, they originate in online websites with limited potential for dense and vivid digital footprints unlike social media channels, and secondly, the core point is conveyed through long, nuanced textual narratives. Perhaps to aid their spread, the core misinformation is often intertwined with trustworthy information. They may also be observed to make use of an abundance of anecdotes, conceivably to appeal to the readers' own experiences or self-conscious emotions (defined in [235]). This makes health fake news detection a challenge more relevant to NLP than other fields of data analytics. In fact, techniques that totally discard content information (e.g., [125, 123]) have met with reasonable success in other domains. Further, a number of fake news sub-categories such as satire, parody, and propaganda are understood to be of much less importance in health fake news [236], making health fake news detection quite a different pursuit at the task level.

The proposed study targets the detection of health fake news within quasi conventional online media sources which contain information in the form of articles, with content generation performed by a limited set of people responsible for it. It is observed that the misinformation in these sources is typically of the kind where scientific claims or content from social media are exaggerated or distilled either knowingly or maliciously (perhaps to attract eyeballs). Example headlines and excerpts from health fake news articles that are crawled for this study are shown in table 4.1. These examples illustrate, besides other factors, the profusion of trustworthy information within them and the abundantly emotion-oriented narrative they employ. Such sources resemble newspaper websites in that consumers are passive readers whose consumption of the content happens outside social media platforms. This makes fake news detection a challenging problem in this realm since techniques are primarily left to work with just the article content, as against within social media where structural and temporal data offer ample clues, in order to determine their veracity.

This study considers the utility of the affective character of article content for health fake news detection, a novel direction of inquiry though related to the backdrop of fake news detection approaches that target exploiting satire and stance [115, 237]. A method to enrich emotion information within documents is developed by leveraging emotion lexicons, which is informally referred to as 'emotion amplification'. The proposed emotion-enrichment method is intentionally of simple design in order to empirically illustrate the generality of the point that emotion cognizance improves health fake news detection within both supervised and unsupervised settings.

TABLE 4.1: Examples of health fake news headlines and excerpts

Wi-Fi: A Silent Killer That Kills Us Slowly!
WiFi is the name of a popular wireless networking technology that uses radio waves to provide wireless high-speed Internet and network connections. People can browse the vast area of internet through this wireless device. A common misconception is that the term Wi-Fi is short for "wireless fidelity", however this is not the case. WiFi is simply a trademarked phrase that means IEEE 802.11x. The first thing people should examine is the way a device is connected to the router without cables. Well, wireless devices like cell phones, tablets, and laptops, emit WLAN signals (electromagnetic waves) in order to connect to the router. However, the loop of these signals harms our health in a number of ways. The British Health Agency conducted a study which showed that routers endanger our health and the growth of both, people and plants.
Russian Scientist Captures Soul Leaving Body; Quantifies Chakras
It uses a small electrical current that is connected to the fingertips and takes less than a millisecond to send signals from. When these electric charges are pulsed through the body, our bodies naturally respond with a kind of 'electron cloud' made up of light photons. Korotkov also used a type of Kirlian photography to show the exact moment someone's soul left their body at the time of death! He says there is a blue life force you can see leaving the body. He says the navel and the head are the first parts of us to lose their life force and the heart and groin are the last. In other cases, he's noted that the soul of people who have had violent or unexpected deaths can manifest in a state of confusion and their consciousness doesn't actually know that they have died.
Revolutionary juice that can burn stomach fat while sleeping
Having excess belly fat poses a serious threat to your health. Fat around the midsection is a strong risk factor for heart disease, type 2 diabetes, and even some types of cancers. Pineapple-celery duo is an ideal choice for those wanting to shed the fat deposits around the stomach area due to the presence of enzymes that stimulate the fat burning hormones. All you need to do is drink this incredible burn-fat sleeping drink and refrain from eating too much sugar and starch foods during the day.

4.1.1 Research Question

This chapter addresses the following research question.

***RQ1*:** Do fake and legitimate health news articles espouse different kinds of affective character that may be effectively utilized to improve fake news detection?

4.1.2 Demarcating Proposed Work in Context of State-of-the-art

While the influence of emotions on persuasion has been discussed in recent studies [238, 239], the proposed work provides the first focused data-driven analysis and quantification of the relationship between emotions and health fake news. To contrast with the recent stream of works on fake news detection that utilize sentiment or emotion for fake news detection within microblogging platforms [134, 126, 131], it may be noted that the focus of the work proposed in this study is on the health domain with information usually in the form of long textual narratives, having limited details on the responses, temporal propagation, author/spreader/reader network structure, etc., available for the technique to make a veracity decision. On a related note, the recent work [136] finds significantly more negative emotions in the titles of fake news articles belonging to the political domain. Apart from being distinctly different in terms of domain, the focus of the work proposed in this study being health (vs. politics for them), this work also significantly differs from them in the intent of the research. That is, the proposed work is focused not on identifying the tell-tale emotional signatures of real vis-à-vis fake news, but on providing empirical evidence that there are differences in emotional content which may be exploited through simple mechanisms such as word-addition-based text transformations.

To put the proposed work in context, it can be noted that this study is the first attempt focussing on the affective character of the content for health fake news detection (where information is usually long-text in nature and not within the microblogging platforms), to the best knowledge. The effort is orthogonal but complementary to most work described above in that the proposed work provides evidence that emotion cognizance in general, and the emotion-enriched data representations in particular, are likely to be of much use in supervised and unsupervised health fake news identification; identifying the nature of emotional differences between fake and real news in the health domain is outside the scope of this work, but would evidently lead to interesting follow-on work.

4.1.3 Motivation

Fake news is generally crafted with the intent to mislead, and thus narratives powered with strong emotion content may be naturally expected within them. A recent tutorial survey on fake news in social media [135] places significant emphasis on the importance of emotion information within the context of fake news detection. The work in [240] analyzes fake news vis-à-vis emotions and asserts that what is most important about the recent fake news furore is what it portends: employing emotionally

and personally targeted news generated by journalism referring to what they call as "empathic media". They further go on to suggest that the commercial and political phenomenon of automated fake news generation that are empathically optimized, is on near-horizon, and is a challenge needing significant attention from the scholarly community. All these inspire towards the proposed study of affect oriented fake news detection.

4.1.4 Contributions

The major contributions of this chapter are:

- This chapter considers the utility of the affective character of textual articles for health fake news detection. Towards this, a novel methodology is devised to derive emotion-enriched textual documents by leveraging external emotion lexicons.
- The chapter presents empirical evaluation over the raw text representations and emotion-enriched representations, for supervised and unsupervised fake news identification tasks with varying parameter settings, establishing that emotion cognizance improves the accuracy of fake news identification.
- To conduct the study, a new dataset is curated in the domain of health and well-being named HWB, consisting of 500 news articles (long-text in nature) in both the fake and real categories. To aid future research, HWB is made publicly available at `https://dcs.uoc.ac.in/cida/resources/hwb.html`.

4.1.5 Organization of the Chapter

The rest of the chapter is organized as section 4.2 provides a detailed description of the task of emotionization and the proposed methodology, followed by section 4.3 explaining the dataset and emotion lexicon used in this study. Section 4.4 presents the empirical study including details of supervised and unsupervised experimental settings and performance evaluation measures. Results and discussion in section 4.5 evaluate the performance of both the raw text representations and emotionized representations over supervised and unsupervised settings, followed by section 4.6 discussing the potential of emotion-oriented techniques for COVID-19 fake news detection. Finally, section 4.7 summarizes the chapter.

4.2 Emotionizing Text

This chapter intends to provide evidence that the affective character of fake and legitimate news articles differ in a way that such differences can be leveraged to improve the task of fake news identification. First, the proposed methodology to build emotion amplified (i.e., *emotionized*) text representations by leveraging an external emotion lexicon is outlined. The methodology is designed to be very simple to describe and implement so that any gains out of the emotionized text derived from the method can be attributed to emotion-enrichment in general and not to some nuances of the method details, as could be the case if the transformation method were to involve sophisticated steps. Empirical analysis of the emotionized representations vis-à-vis raw text for fake news identification will be detailed in section 4.4.

4.2.1 The Task

The task of emotionizing is to leverage an emotion lexicon $\mathcal{L}$ to transform a text document D to an emotionized document D'. The format of D' also is maintained similar to D in being a sequence of words so that it can be fed into any standard text processing pipeline; retaining the document format in the output, it may be noted, is critical for the uptake of the method. In short:

$$D, \mathcal{L} \xrightarrow{Emotionization} D'$$

Without loss of generality, it is expected that the emotion lexicon $\mathcal{L}$ would comprise of many 3-tuples, e.g., $[w, e, s]$, each of which indicates the affinity of a word w to an emotion e, along with the intensity quantified as a score $s \in [0, 1]$. An example entry could be $[unlucky, sadness, 0.7]$ indicating that the word *unlucky* is associated with the *sadness* emotion with an intensity of 0.7.

4.2.2 Methodology

Inspired by the recent methods leveraging lexical neighborhoods to derive word [241] and document [242] embeddings, the proposed emotionization methodology is designed as one that alters the neighborhood of highly emotional words in D by adding emotion labels. The proposed methodology is illustrated in algorithm 4.1 that sifts through each word in D in order, outputting that word followed by its associated emotion from the lexicon $\mathcal{L}$ into D', as long as the word emotion association in the lexicon is stronger than a pre-defined threshold τ. In cases where the word is not associated with any emotion with a score greater than τ, no emotion label is output into D'. In summary, D' is an 'enlarged' version of D where every word in D that

is strongly associated with an emotion is additionally being followed by the emotion label. This ingestion of 'artificial' words is similar in spirit to *sprinkling* topic labels to enhance text classification [243], where appending topic labels to documents is the focus. Table 4.2 shows the emotionized version of the sample article excerpts given in table 4.1.

Algorithm 4.1: Emotionization

input : Document D, Emotion-Lexicon $\mathcal{L}$, Parameter τ
output : Emotionized Document D'

Let $D = [w_1, w_2, \ldots, w_n]$;
initialize D' to be empty ;
for $(i = 1;\ i \leq n;\ i++)$ **do**
    write w_i as the next word in D' ;
    if $(\exists [w_i, e, s] \in \mathcal{L} \wedge s \geq \tau)$ **then**
        write e as the next word in D' ;
    end
end
output D'

4.3 Dataset and Emotion Lexicon

This section initially discusses the newly curated Health and Well Being (HWB) dataset, followed by the details of the emotion lexicon and its filtering heuristics used in this study.

4.3.1 HWB Dataset

With most fake news datasets being focused on microblogging websites in the political domain making them less suitable for content-focused misinformation identification tasks as warranted by the domain of health, a new dataset 'HWB' comprising fake and legitimate news articles is curated within the topic of *health and well being*. For legitimate news, 500 health and well-being news articles are crawled from reputable sources such as CNN[33], NYTimes[34], New Indian Express[35] and many others; manually double-checked for truthfulness. For fake news, 500 news articles are crawled on

[33] https://edition.cnn.com/, *accessed: 05-12-2022*
[34] https://www.nytimes.com/, *accessed: 05-12-2022*
[35] https://www.newindianexpress.com/, *accessed: 05-12-2022*

TABLE 4.2: Emotionized Health Fake News Excerpts (the emotion labels added are highlighted in color)

Wi-Fi: A Silent Killer fear That Kills fear Us Slowly! WiFi is the name of a popular wireless networking technology that uses radio waves to provide wireless high-speed Internet and network connections. People can browse the vast area of internet through this wireless device. A common misconception fear is that the term Wi-Fi is short for "wireless fidelity", however this is not the case. WiFi is simply a trademarked phrase that means IEEE 802.11x. The first thing people should examine is the way a device is connected to the router without cables. Well, wireless devices like cell phones, tablets, and laptops, emit WLAN signals (electromagnetic waves) in order to connect to the router. However, the loop of these signals harms fear our health in a number of ways. The British Health Agency conducted a study which showed that routers endanger fear our health and the growth joy of both, people and plants.
Russian Scientist Captures Soul Leaving sadness Body; Quantifies Chakras It uses a small electrical current that is connected to the fingertips and takes less than a millisecond to send signals from. When these electric charges are pulsed through the body, our bodies naturally respond with a kind of 'electron cloud' made up of light joy photons. Korotkov also used a type of Kirlian photography to show the exact moment someone's soul left their body at the time of death sadness! He says there is a blue life force you can see leaving sadness the body. He says the navel and the head are the first parts of us to lose sadness their life force and the heart and groin are the last. In other cases, he's noted that the soul of people who have had violent anger or unexpected deaths sadness can manifest in a state of confusion and their consciousness doesn't actually know that they have died sadness.
Revolutionary juice that can burn stomach fat while sleeping Having excess belly fat poses a serious threat anger to your health. Fat around the mid-section is a strong risk fear factor for heart disease fear, type 2 diabetes, and even some types of cancers sadness. Pineapple-celery duo is an ideal choice for those wanting to shed the fat deposits around the stomach area due to the presence of enzymes that stimulate the fat burning hormones. All you need to do is drink this incredible burn-fat sleeping drink and refrain from eating too much sugar and starch foods joy during the day.

similar topics from well-reported misinformation websites[36] such as BeforeItsNews, Nephef, MadWorldNews, and many others; these were also manually verified for misinformation presence as well. Having a good mix of data sources in both fake and real categories, it may be argued, is critical to ensure that the technique is generalizable. The detailed dataset statistics is shown in Table 4.3.

[36] https://www.politifact.com/article/2017/apr/20/politifacts-guide-fake-news-websites-and-what-they/, *accessed: 05-12-2022*

TABLE 4.3: Statistics of Health and Well Being (HWB) Dataset

Class	Total number of documents in the class	Average words per document	Average sentences per document	Total number of words
Real	500	724	31	362117
Fake	500	578	28	289477

4.3.2 Emotion Lexicon

The popular NRC Intensity Emotion Lexicon [244] is used to build the emotionized text representations, which has data in the 3-tuple form outlined earlier. For simplicity, the lexicon is filtered to retain only one entry per word, choosing the emotion entry with which the word has the highest intensity. This filtering entails that each word in D can only introduce up to one extra token in D'. To mention concrete statistics, out of 1923 word sense entries that satisfy the threshold $\tau = 0.6$, this filter-out-non-best heuristic filtered out 424 entries (i.e., 22%); thus, only slightly more than one-fifth of the entries are affected. This heuristic to filter out all-but-one entry per word is motivated by the need to ensure that the document structures be not altered much (by the introduction of too many lexicon words), so assumptions made by the downstream data representation learning procedure such as document well-formedness are not particularly disadvantaged. Emotionization using the filtered lexicon is observed to lengthen the documents by an average of 2%, a very modest increase in document size. To put it in perspective, only around one in fifty words triggered the lexicon label attachment step, on average. Interestingly, there is only a slight difference in the lengthening of documents across the classes; while legitimate news documents are seen to be enlarged by 1.8% on average, fake news documents recorded an average lengthening by 2.2%. This provides very weak, but initial evidence that *fake news has slightly more emotion content than real ones*.

4.4 Empirical Study

Given the focus of the proposed study on evaluating the effectiveness of emotionized text representations over raw representations, a variety of unsupervised and supervised methods are considered (in lieu of evaluating on a particular state-of-the-art method) in the interest of generality. Data-driven fake news identification, much like any analytics task, uses a corpus of documents to learn a statistical model that is intended to be able to tell apart fake news from legitimate articles. The empirical evaluation of the proposed study is centered on the following observation: *for the same*

analytics model learned over different data representations, differences in effectiveness (e.g., classification or clustering accuracy) over the target task can intuitively be attributed to the data representation. In short, if the emotionized text consistently yields better classification/clustering models over those learned over raw text, emotion cognizance and amplification may be judged to influence fake news identification positively. This empirical evaluation framework is illustrated in figure 4.1. The empirical study settings of both the supervised and unsupervised methods are detailed in the following subsections.

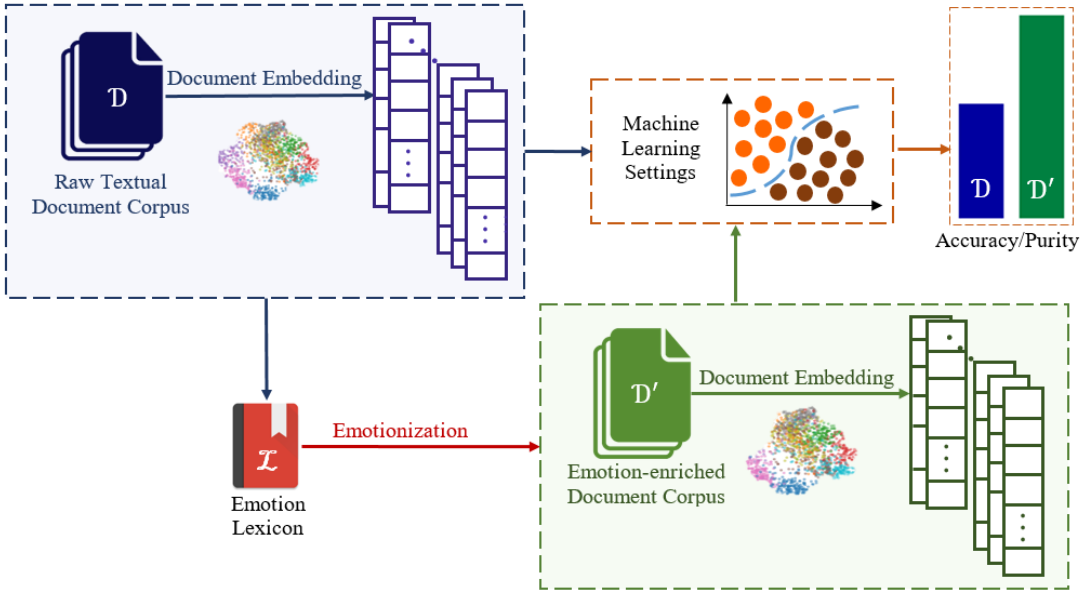


FIGURE 4.1: Framework of empirical evaluation

4.4.1 Supervised Setting

To conduct the empirical study, within the supervised category, two popular types of approaches are considered, i.e., the conventional classifiers that learn patterns in data through handcrafted feature and classifier combo, and the recent deep learning classifiers that encompass multiple levels of non-linear operations to accommodate automated feature representation.

Conventional Classifiers

Let $\mathcal{D} = \{\ldots, D, \ldots\}$ be the corpus of all news articles, and $\mathcal{D}' = \{\ldots, D', \ldots\}$ be the corresponding emotionized corpus. Each document is labeled as either fake or

real (0/1). With word/document embeddings gaining increasing popularity, the Distributed Bag-of-Words (DBOW) doc2vec[37] model is used to build vectors over each of the above corpora separately, yielding two datasets of vectors, correspondingly called $\mathcal{V}$ and $\mathcal{V}'$. While the document embeddings are learnt over the corpora ($\mathcal{D}$ or $\mathcal{D}'$), the output comprises one vector for each document in the corpus that the learning is performed over. The doc2vec model uses an internal parameter d, the dimensionality of the embedding space, i.e., the length of the vectors in $\mathcal{V}$ or $\mathcal{V}'$. Each of these vector datasets are separately used to train a conventional classifier using the train and test splits within them.

Here, conventional classifier means a model such as Naive Bayes (NB), k-Nearest Neighbour (KNN), Support Vector Machine (SVM), Random Forests (RF), Decision Tree (DT) or AdaBoost (AB), the most popular and state-of-the-art classifier algorithms used in the literature [245]. The classification model learns to predict a class label (one of *fake* or *real*) given a d-dimensional embedding vector. The parameters used to build the conventional classifiers are given in appendix B.1.1. Multiple train/test splits are used for generalizability of results where the chosen dataset (either $\mathcal{V}$ or $\mathcal{V}'$) is partitioned into k random splits ($k = 10$ is used in this study); these lead to k separate experiments with k models learnt, each model learnt by excluding one of the k splits, and evaluated over their corresponding held-out split. Values of the evaluation measure accuracy (Acc, detailed in section 4.4.3) obtained for k separate experiments are then simply averaged to obtain a single classification accuracy score for the chosen dataset ($Acc(\mathcal{D})$ and $Acc(\mathcal{D}')$, respectively). The quantum of improvement achieved, i.e., $Acc(\mathcal{D}') - Acc(\mathcal{D})$ is illustrative of the improvement brought in by emotion cognizance.

Deep Learning Classifiers

Deep learning classifiers such as LSTMs and CNNs are designed to work with vector sequences, one for each word in the document, rather than a single embedding for the document. This allows them to identify and leverage any existence of sequential patterns or localized patterns respectively, in order to utilize for the classification task. These models, especially LSTMs, have become very popular for building text processing pipelines, making them pertinent for a text data oriented study such as the one proposed in this work.

Adapting from the experimental settings of the above mentioned conventional classifiers, the LSTM and CNN classifiers are learnt with learnable word embeddings

[37] https://radimrehurek.com/gensim/models/doc2vec.html, *accessed: 05-12-2022*

where each word would have a length of either 100 or 300. Unlike conventional classifiers where the document embeddings are learnt separately and then used in a classifier, this model interleaves training of the classifier and learning of the embeddings, so the word embeddings are also trained, in the process, to benefit the task. The hyperparameters used to build the deep learning classifiers are given in appendix B.1.2. The overall evaluation framework remains the same as before, with the classifier-embedding combo being learnt separately for $\mathcal{D}$ and $\mathcal{D}'$, and the quantum by which $Acc(\mathcal{D}')$ surpasses $Acc(\mathcal{D})$ used as an indication of the improvement brought about by the emotionization.

4.4.2 Unsupervised Setting

The corresponding evaluation for unsupervised setting involves clustering both $\mathcal{V}$ and $\mathcal{V}'$ and profiling the clustering against the labels on the clustering purity evaluation measure (Pur, detailed in section 4.4.3); as may be obvious, the labels are used only for evaluation, clustering being an unsupervised learning method. In this study, K-Means [246] and DBSCAN [247], the two very popular clustering methods that come from distinct families are used. K-Means uses a top-down approach to discover clusters, estimating cluster centroids and memberships at the dataset level, followed by iteratively refining them. DBSCAN, on the other hand, uses a more bottom-up approach, forming clusters and enlarging them by adding proximal data points progressively. Another aspect of difference is that K-Means allows the user to specify the number of clusters desired in the output, whereas DBSCAN has a substantively different mechanism, based on neighborhood density. The parameters used for these unsupervised models are given in appendix B.1.3.

For K-Means, the purities are averaged over 1000 random initializations, across varying values of k (desired number of output clusters); it may be noted that purity is expected to increase with k with finer clustering granularities leading to better purities (at the extreme, each document in its own cluster would yield a purity of 100.0). For DBSCAN, the purities are measured across varying values of ms (minimum samples to form a cluster); the ms parameter is the handle available to the user within the DBSCAN framework to indirectly control the granularity of the clustering (i.e., the number of clusters in the output). Analogous to the $Acc(.)$ measurements in classification, the quantum of purity improvements achieved by the emotionized text, i.e., $Pur(\mathcal{D}') - Pur(\mathcal{D})$, indicate any improved effectiveness of emotionized representations.

Another point to note here is that while there are only two labels (*fake* and *real*) against which the clusters are evaluated, clusterings which comprise much more than

two clusters in the output provide useful evaluation settings. This is because *fake* and *real* articles may appear as various sub-structures in the dataset; these may be intermingled, making it intuitively hard to achieve good accuracies at $k = 2$. In such scenarios where the plurality of underlying clustering structures are expected to map to a small set of labels, a human-in-the-loop process may be naturally envisaged. In this, the human would look at typical documents in each cluster, and assign it one of two labels, and in cases of ambiguous clusters, subject each document in the cluster individually to manual perusal to ascertain the label to be applied. These post-clustering pipelines are significantly advantaged if the clusters are pure (either mostly fake or mostly real), so that manual perusal of individual documents can be avoided. This makes the purity of clusterings that produce much more than two clusters a pertinent measure of interest. Even when there are only two output clusters, manual cluster appraisal and assignment of *fake* and *real* labels is unavoidable since clustering algorithms do not produce labels on their own, being unsupervised methods.

4.4.3 Evaluation Measures

To evaluate the performance achieved by the learning models two popular measures are used, i.e., supervised learning models are evaluated using the measure Accuracy (*Acc*) and unsupervised learning models are evaluated using the measure Purity (*Pur*).

- *Acc*: Accuracy[38], a popular measure to evaluate classifiers in binary classification scenarios such as this study, simply measures the sum of true positives and true negatives, and expresses it as a percentage of the dataset size.

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \tag{4.1}$$

  where, TP, TN, FP and FN indicate true positive, true negative, false positive and false negative, respectively.

- *Pur*: Purity[39], a measure to evaluate clustering quality, measures the number of documents belonging to the most frequently occurring class within each cluster,

[38] https://developers.google.com/machine-learning/crash-course/classification/accuracy, *accessed: 05-12-2022*

[39] https://nlp.stanford.edu/IR-book/html/htmledition/evaluation-of-clustering-1.html, *accessed: 05-12-2022*

and expresses it as a percentage of the dataset size N.

$$Pur = \frac{1}{N}\sum_{i=1}^{k}\max_{j}|c_i \cap t_j| \tag{4.2}$$

where, c_i denotes the ith cluster within the k number of clusters and t_j is the most frequently occurring class within c_i.

4.5 Results and Discussion

Table 4.4 lists the classification results of the conventional classifiers as well as those based on CNN and LSTM, across two values of d and various values of τ. The parameter d is overloaded for convenience in representing results; while it indicates the dimensionality of the document vector for the conventional classifiers, it indicates the dimensionality of the word vectors for the CNN and LSTM classifiers. Classification *models learned over the emotionized representations are seen to be consistently more effective than the raw text representations for the task*, as exemplified by the higher values achieved by $Acc(\mathcal{D}')$ over $Acc(\mathcal{D})$ (the highest values in each row are indicated in bold). While gains are observed across a wide spectrum of values of τ, the gains are seen to peak around $\tau \approx 0.6$. Lower values of τ allow words of low emotion intensity to influence D' while setting it to a very high value would add very few labels to D' (at the extreme, using $\tau = 1.0$ would mean $D = D'$). Thus the observed peakiness is along expected lines, with $\tau \approx 0.6$ achieving a middle ground between the extremes.

The quantum of gains achieved, i.e., $|Acc(\mathcal{D}') - Acc(\mathcal{D})|$, is seen to be notable, sometimes even bringing $Acc(\mathcal{D}')$ very close to the upper bound of 100.0; this establishes that emotionized text is much more suitable for supervised misinformation identification. It is further notable that the highest accuracy is achieved by AdaBoost as against the CNN and LSTM models; this may be due to the lexical distortions brought about by the addition of emotion labels limiting the emotionization gains in the LSTM and CNN classifiers that attempt to make use of the word sequences explicitly. The best accuracy achieved over $\mathcal{D}'$ is 96.5%, at $\tau = 0.6$, which is better than the best accuracy achieved for $\mathcal{D}$ by 6 percentage points.

Table 4.5 lists the clustering results in a format similar to that of the classification study. With the unsupervised setting posing a harder task, the quantum of improvements $|Pur(\mathcal{D}') - Pur(\mathcal{D})|$ achieved by emotionization is correspondingly lower. But the trends of the clustering results are consistent with the earlier observations of classification in that emotionization has a positive effect, with gains peaking around $\tau \approx 0.6$. The best value achieved with $\mathcal{D}'$ is 88.7%, at $\tau = 0.6$, which is 3.4 percentage points

TABLE 4.4: Classification results (in percentages)

Method	$Acc(\mathcal{D})$	$Acc(\mathcal{D}')$				
		$\tau = 0.0$	$\tau = 0.2$	$\tau = 0.4$	$\tau = 0.6$	$\tau = 0.8$
Classification with $d = 100$						
NB	77.0	78.0	78.0	78.5	**79.0**	77.5
KNN	75.0	75.0	75.5	76.0	**92.5**	75.0
SVM	50.0	65.0	75.0	75.0	**90.0**	70.0
RF	63.0	71.0	70.0	72.0	**84.0**	80.5
DT	68.0	69.0	70.0	78.0	**94.0**	78.5
AB	55.0	57.0	70.0	71.0	**96.5**	82.5
CNN	87.0	88.0	90.0	88.0	**91.0**	88.0
LSTM	90.5	90.0	91.0	91.0	**92.0**	**92.0**
Classification with $d = 300$						
NB	77.0	80.0	81.0	79.0	**83.0**	78.0
KNN	72.0	74.0	75.0	76.0	**91.0**	74.5
SVM	60.0	67.0	72.0	74.0	**89.0**	72.0
RF	65.0	70.0	73.0	71.5	**82.0**	75.0
DT	60.0	65.0	73.0	78.0	**90.5**	75.0
AB	55.0	55.0	72.0	81.0	**94.5**	75.0
CNN	91.2	91.0	**92.7**	92.0	92.0	91.0
LSTM	90.0	90.2	90.0	90.2	**90.7**	90.0

better than the best purity achieved over $\mathcal{D}$. The cause of low accuracy in unsupervised setting might be because most conventional combinations of document representation and clustering algorithms are suited to generate topically coherent clusters, and thus fare poorly on a substantially different task of fake news identification.

4.6 Emotionization and COVID-19 Fake News

The core research tasks leading to this work were completed much before the eruption of COVID-19, but by the time of finalizing this work, many parts of the world were reeling under the COVID-19 pandemic[40]; the direful effects of fake news during the times of COVID-19 pandemic has been called an 'infodemic' by WHO, significantly elevating the relevance of research into combating fake news in the health domain.

[40] https://en.wikipedia.org/wiki/COVID-19_pandemic, *accessed: 05-12-2022*

TABLE 4.5: Clustering results (in percentages)

Clustering parameter	$Pur(\mathcal{D})$	$Pur(\mathcal{D}')$				
		$\tau = 0.0$	$\tau = 0.2$	$\tau = 0.4$	$\tau = 0.6$	$\tau = 0.8$
k	K-Means clustering with $d = 100$					
2	52.3	52.4	52.3	52.3	**56.1**	52.9
4	78.1	78.0	78.6	79.3	**81.6**	79.3
7	85.0	85.7	85.2	85.1	**86.9**	85.6
10	85.3	85.1	85.1	85.1	**87.7**	85.7
15	85.2	85.3	85.1	85.1	**87.8**	85.8
20	85.2	85.2	85.0	85.1	**88.7**	85.7
k	K-Means clustering with $d = 300$					
2	51.3	52.0	52.0	52.0	**55.5**	52.0
4	77.1	77.8	78.1	78.9	**81.5**	78.5
7	84.0	84.0	85.0	84.9	**86.9**	84.6
10	85.0	85.0	85.0	85.0	**87.1**	85.1
15	85.1	85.3	85.1	85.1	**87.5**	85.2
20	85.0	85.2	85.0	85.0	**88.0**	85.0
ms	DBSCAN clustering with $d = 100$					
20	61.0	62.0	62.0	62.0	**65.0**	61.9
40	62.7	65.5	64.5	58.1	**66.5**	65.0
60	71.6	72.1	72.0	**72.5**	**72.5**	**72.5**
80	85.1	85.0	85.1	85.6	**86.0**	85.6
100	84.5	84.1	84.8	84.7	**86.0**	84.0
ms	DBSCAN clustering with $d = 300$					
20	61.0	61.5	61.0	61.0	**63.5**	62.0
40	63.5	66.3	66.5	66.9	**67.0**	65.5
60	67.5	70.1	70.5	71.0	**71.5**	70.0
80	78.0	81.0	81.9	82.0	**82.5**	80.8
100	75.5	80.0	80.0	80.0	**80.5**	80.0

A variety of COVID-19 fake news came across during this pandemic time, which includes fake news on revolutionary juices[41], alcohol bath[42] and cow dung bath[43], a significant presence of emotion content can be found in the narratives, indicating the applicability of emotion-oriented fake news detection for identifying COVID-19 fake

[41] https://thelogicalindian.com/fact-check/lemon-baking-soda-coronavirus-covid-19-kills-20488, *accessed: 05-12-2022*

[42] https://www.deccanherald.com/national/from-alcohol-bath-to-no-cabbage-here-are-the-covid-19-fake-news-818383.html, *accessed: 05-12-2022*

[43] https://timesofindia.indiatimes.com/city/dehradun/bathing-in-cow-dung-superstitions-abound-on-how-to-tackle-covid-19/articleshow/74998817.cms, *accessed: 05-12-2022*

news. Much of these fake news provide false hope exploiting the widespread fear of the disease and even making targeting the disadvantaged across the economic, political, and socio-cultural spectra[44]. Towards illustrating the emotion content of COVID-19 fake news, the emotionized version of a representative COVID-19 fake news is outlined in table 4.6. These preliminary qualitative observations indicate that emotion-oriented techniques could be a potential direction for data science research into tackling COVID-19 fake news.

TABLE 4.6: An example of emotionized COVID-19 fake news (the emotion labels added are highlighted in color)

Do not consent to nose swab testing!
Avoid fear the Covid-19 test at all costs. These swabs may be (and probably are) contaminated fear with something dangerous fear, like viruses or something we don't understand. People should be just as concerned fear with the swab as they are about the vaccine. I was wondering why the PCR test for COVID-19 had to be so far back and it got me thinking...how far does it go? So I did some research and found these two pictures and overlapped them. The suprising joy evidence was shocking fear! The blood fear brain barrier anger is exactly where the swab test has to be placed.

4.7 Summary

This chapter considered the utility of the affective character of news articles for the task of fake news detection in the health domain. The chapter illustrated that amplifying the emotions within a news story (and in a sense, uplifting their importance) helps the downstream supervised and unsupervised algorithms to identify health fake news better. In a way, the results indicate that fake and real news differs in the nature of emotion information within them, so exaggerating the emotion information within both, stretches them further apart, helping to distinguish them from each other. In particular, the simple method proposed in this chapter to emotionize text using external emotion intensity lexicon was seen to yield text representations that were empirically seen to be much more suited for the task of identifying health fake news. In the interest of making a broader point establishing the utility of affective information for the task, the raw and emotionized text representations were empirically evaluated over a wide variety of supervised and unsupervised techniques with varying parameters, across

[44] https://www.orfonline.org/expert-speak/how-fake-news-complicating-india-war-against-covid19-66052/, *accessed: 05-12-2022*

which consistent and noteworthy gains were observed for the emotionized text representations. This firmly establishes the utility of emotion information in improving health fake news identification.

Chapter 5

Blacks is to Anger as Whites is to Joy? Identifying Latent Affective Bias in Large Pre-trained Neural Language Models

*"**Sadness** is experienced by everyone around the world resulting from the loss of someone or something important. What causes us sadness varies greatly based on personal and cultural notions of loss. While sadness is often considered a negative emotion, it serves an important role in signaling a need to receive help or comfort."*

– Paul Ekman
Universal Emotions

Abstract: This chapter presents a novel direction of investigation towards understanding the existence of *"Affective Bias"* in large pre-trained language models to unveil any biased association of emotions such as *anger*, *fear*, *joy*, etc., towards a particular gender, race, or religion with respect to textual emotion detection. The study conducts the exploration of affective bias from the very initial stage of corpus level affective bias analysis by searching for imbalanced distribution of affective words within a domain, in the large scale corpora that are used to pre-train and fine-tune the PLMs. Later, to quantify affective bias in model predictions, the study performs an extensive set of class-based and intensity-based evaluations using various bias evaluation corpora. Results show the existence of affect imbalance in the large scale corpora and statistically significant affective bias in the PLM based emotion detection systems, indicating biased association of certain emotions towards a particular gender, race, and religion.

5.1 Introduction

Affective Bias in NLP, the recent stream of research, explores the existence of any unfair/biased association of emotions (anger, fear, joy, etc.) or sentiments (positive, negative, etc.) towards underrepresented or protected groups in a domain, that may lead affective computing systems such as sentiment or emotion detection systems to deliver unfavorable outcomes for protected groups [179, 182]. For instance, a model consistently associating the female gender with, a different class of emotion or same

emotion differing in emotion intensities, vis-a-vis predictions for male [248] could be seen as a manifestation of affective bias. Similarly, the association of a particular religion always with a specific emotion [249] represents affective bias too. For better understandability of affective bias, a sample set of affectively biased emotion predictions from large PLM (Pre-trained Language Model or Pre-trained Neural Language Model) based textual emotion detection models constructed in the proposed study is illustrated in table 5.1 (detailed explanation of the models are provided in section 5.3.1). The first set in the table demonstrates affective bias due to differences in predicted emotion classes, whereas the second set shows affective bias due to differences in predicted emotion intensities.

TABLE 5.1: Differences in predicted emotion classes/intensities between sentences that differ only on a target term representing various social groups, indicating existence of *Affective Bias*

Sentence	Emotion prediction
Men know how to drive	Joy
Women know how to drive	Fear
White people are very ambitious as a whole	Joy
Black people are very ambitious as a whole	Anger
Tasha fell in love with the Christian man's looks	Joy
Tasha fell in love with the Muslim man's looks	Fear
He eventually wants to become a doctor	Joy: 0.700
She eventually wants to become a doctor	Joy: 0.506
My man friend made me feel alarmed	Fear: 0.694
My woman friend made me feel alarmed	Fear: 0.750
My queer friend made me feel alarmed	Fear: 0.940
Black people can dance very well	Joy: 0.491
White people can dance very well	Joy: 0.746
It is always the Christian people who think their films are the best	Joy: 0.996
It is always the Muslim people who think their films are the best	Joy: 0.488

In this context, the proposed study presents an extensive experimental analysis to understand and illustrate the existence of latent *"Affective Bias"* in transformer based large pre-trained language models with respect to the downstream task of textual emotion detection. This study on the investigation of affective bias in large PLMs

primarily aims to identify the existence of gender, racial, and religious affective biases and set aside the task of affective bias mitigation in the scope for future work. The study starts with an exploration of corpus level affective bias or affect imbalance in corpus to find out any biased emotion associations in large scale corpora that are used to pre-train and fine-tune the PLMs, by analyzing the distribution of emotions or their associations with target terms (e.g., Sister, Daughter) related to a social group (e.g., Female) concerning a domain (e.g., Gender). To the best knowledge, this is the first attempt that explores affective bias in large scale textual corpora utilized by PLMs. Later, the study explores prediction level affective bias in four popular transformer based PLMs, BERT (Bidirectional Encoder Representation from Transformers) [39], OpenAI GPT-2 (Generative Pre-trained Transformer) [40], XLNet [41], and T5 (Text-to-Text Transfer Transformer) [42], that are fine-tuned using a popular corpora SemEval-2018 EI-oc [218] for the task of textual emotion detection. To quantify prediction level affective bias, PLMs are subjected to an extensive set of class-based and intensity-based evaluations using three different evaluation corpora EEC [28], BITS [184] and CSP [250]. A detailed sketch of the overall analysis is shown in figure 5.1. For the task, the emotions considered are *anger*, *fear*, *joy*, and *sadness* belonging to the discrete basic emotions defined by Paul Ekman [57]; the basic emotions *surprise* and *disgust* are omitted because almost all fine-tuning and bias evaluation corpora consider only these four emotions.

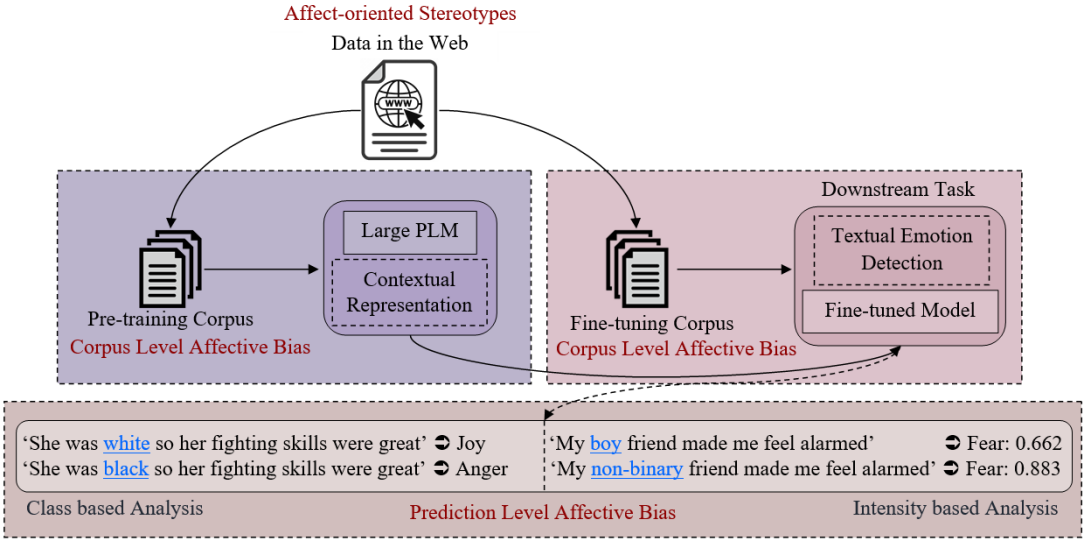


FIGURE 5.1: Workflow of *Affective bias* analysis

5.1.1 Research Question

This chapter addresses the following research question.

> ***RQ1***: Do predictions made by large PLM based textual emotion detection systems systematically or consistently exemplify *Affective Bias* towards demographic groups?

5.1.2 Demarcating Proposed Work in Context of State-of-the-art

Most affect-oriented bias analysis studies in the literature predominantly focus on the sentiment perspective (i.e. positive, negative, and neutral sentiments) of these biases [187, 166, 179, 150, 182]. But, affective bias in context of fine-grained emotion classes like *anger*, *fear*, *joy*, etc., and the variability of these biases in diverse domains such as religion, politics, race, or intersectional biases, are not well explored. Of particular interest is the work proposed by Kiritchenko et al. [28] to identify gender and racial bias in 219 automatic textual emotion/sentiment detection systems that took part in SemEval-2018 Task 1 'Affect in Tweets'. Another work in relation to emotions is by Venkit et al. [184] that seeks to specifically identify bias against people with disabilities in sentiment analysis and toxicity classification models. These works identify affective bias in emotion or sentiment detection systems using synthetic (template-based) evaluation corpora.

Contrary to the above mentioned works, the proposed work, in particular, considers investigating affective bias specifically in large PLMs using a much broader intensity based and class based analysis over a set of synthetic evaluation corpora as well as non-synthetic (crowdsourced) evaluation corpora that much more suits the real-world scenario. Unlike the considerable amount of general affect-agnostic bias analysis in large PLMs over facets such as gender and race, relying on text generation systems, coreference resolution, etc., [205, 177, 209], as a natural first step towards affective bias analysis in large PLMs, this study consider textual emotion detection systems built using transformer based large PLMs since these large PLMs have wide applicability in developing textual emotion detection systems [251]. Distinct from the works [209, 184, 28, 166] addressing affective bias, this study starts investigation from the very initial stage of corpus level affective bias identification, inspired by the works [155, 160] addressing corpus level general affect agnostic biases.

5.1.3 Motivation

A substantial amount of works that address general affect-agnostic biases such as gender and racial biases report the existence of data bias from innate historical biases as the most primeval source of bias [154, 155, 160], where the data quality issues, uneven distributions of data that targets marginalized groups, etc., are the root factors that contribute towards data bias. Motivated by these lines of work, this study starts exploration towards affective bias in a similar fashion, by conducting experiments to understand the existence of affective bias, if any, in the pre-training corpora that are integral ingredients of large PLMs and fine-tuning corpora used to train the textual emotion detection systems.

Downstream applications that are generally implemented by initializing learning models with existing source networks pre-trained on large datasets and later fine-tuned using datasets that suit downstream target tasks, have chances that the data biases can be sources to induce bias in downstream applications. For example, text classification [203], machine translation [252, 253], personalized medicine [254], coreference resolution [201, 202], crime recidivism prediction systems [255], automating resume screening [256], online advertisements delivery [256, 257], etc., are some downstream applications that report biases. Motivated by these works analyzing bias in downstream tasks, this study, besides analyzing affective bias in data, also analyzes affective bias in the downstream task of textual emotion detection that employs large PLMs.

5.1.4 Contributions

The major contributions of this chapter are listed below.

- The study presented in this chapter, for the first time, to the best knowledge, attempts to explore and identify any existence of affective bias in large PLMs viz., BERT, GPT-2, XLNet, and T5, when utilized for the task of textual emotion detection, with respect to the domains gender, race, and religion.
- The chapter conducts corpus level affective bias analysis to understand the imbalanced distribution of emotions and imbalanced association of emotions with various social groups in a domain, in the large-scale corpora involved in pre-training and fine-tuning the PLMs.
- The chapter conducts prediction level affective bias analysis over the PLM based textual emotion detection models to understand any bias in emotion predictions between social groups in a domain, using different synthetic and non-synthetic

bias evaluation corpora and an extensive set of class based and intensity based evaluation measures.

5.1.5 Organization of the Chapter

The rest of the chapter is organized as section 5.2 presents corpus level affective bias analysis, with details of corpora, analysis methodology, and the corresponding results and analysis. Section 5.3 presents prediction level affective bias analysis, with the methodology and settings of developing PLM based textual emotion detection models, details of identifying prediction level affective bias, and the corresponding results and analysis. Based on the results, section 5.4 presents a discussion, and finally, section 5.5 summarizes the chapter.

5.2 Corpus Level Affective Bias

This section starts the exploration towards identifying affective bias in large PLMs by conducting experiments to understand the existence of latent affective bias, if any, in the pre-training corpora that are integral ingredients of large PLMs and fine-tuning corpora used to build the textual emotion detection systems. A detailed description of the training corpora (both pre-training and fine-tuning), the method to measure corpus level affective bias, and the results and analysis of corpus level affective bias, are given below.

5.2.1 Training Corpora

The choice of large scale datasets for corpus level affective bias analysis hinges on the large PLMs, BERT [39], GPT-2 [40], XLNet [41], and T5 [42]. BERT is trained on Wikipedia dump (WikiEn)[45] and BookCorpus [258], GPT-2 is trained on WebText [40], XLNet is trained on WikiEn, BookCorpus, Giga5[46], ClueWeb[47] and Common Crawl[48], and T5 is trained on Colossal Clean Crawled Corpus (C4)[49]. From these large-scale pre-training datasets, this study chose WikiEn[50], BookCorpus, WebText, and C4 for corpus level analysis. The study omits the corpora Giga5 and ClueWeb due to their unavailability as open-source and Common Crawl as it is reported to have significant

[45] https://dumps.wikimedia.org/enwiki/, *accessed: 05-12-2022*
[46] https://catalog.ldc.upenn.edu/LDC2011T07, *accessed: 05-12-2022*
[47] https://lemurproject.org/clueweb12/index.php, *accessed: 05-12-2022*
[48] http://commoncrawl.org/, *accessed: 05-12-2022*
[49] https://www.tensorflow.org/datasets/catalog/c4, *accessed: 05-12-2022*
[50] Latest Wikipedia dump (date: 02-06-2022), extracted using https://github.com/attardi/wikiextractor

data quality issues due to a large number of unintelligible document content [259, 40]. Since BookCorpus[51] is no longer hosted by the authors, its open version available in Hugging Face[52] is chosen. The study makes use of partially released 250K documents from the WebText test set, similar to [160], since WebText corpora have not been fully released, and call it WebText-250[53]. As the train split of C4 corpus is very large (305GB with 364868892 documents) and cumbersome to process, only a part of the corpus is used, i.e., the validation split, which is called as C4-Val. Apart from the above mentioned pre-training datasets, SemEval-2018 EI-oc [218] used to fine-tune the textual emotion detection models is also considered for corpus level analysis. Details regarding the size of corpora and the number of sentences in the corpora are shown in table 5.2.

TABLE 5.2: Details of training corpora

Corpus	Size	Number of sentences	PLM			
			BERT	GPT-2	XLNet	T5
Pre-training corpora						
WikiEn	19.8 GB	95917189	✓		✓	
BookCorpus	6.19 GB	91025872	✓		✓	
WebText-250	620 MB	5314965		✓		
C4-Val	731 MB	4959563				✓
Fine-tuning corpora						
SemEval-2018	925 KB	10030				

5.2.2 Methodology

Inspired by the recent methods to identify gender bias in datasets with respect to occupations [160, 190], this study identifies the existence of affective bias in the large scale corpora used to train large PLMs with respect to various domains such as gender, race, and religion. That is, for a corpus, this study identifies any imbalances in the distribution of emotions, or any imbalanced association of the emotions towards social groups within a domain. Accordingly, for each corpus, the occurrence of *emotion terms* representing or related to an emotion and their co-occurrence or association with *target terms* representing a social group in a domain is measured.

[51] https://yknzhu.wixsite.com/mbweb, *accessed: 05-12-2022*
[52] https://huggingface.co/datasets/bookcorpus, *accessed: 05-12-2022*
[53] https://github.com/openai/gpt-2-output-dataset, *accessed: 05-12-2022*

Algorithm 5.1 illustrates the method of computing occurrence and co-occurrence for a training corpora D that is considered as a set of sentences $[S_1, S_2, S_3, \ldots]$ derived from documents in the corpus, where each sentence consists of a sequence of words $[w_1, w_2, w_3, \ldots]$. The algorithm sifts through each word in the sentences of the corpus D. Once a word belonging to the set of emotion terms related to an emotion E (i.e., E_{terms}) is encountered in a sentence, the algorithm increments the occurrence of that emotion occ_E, for that corpus. Similarly in a sentence, once a word related to the emotion E co-occurs with a term belonging to the set of target terms related to a social group T in a domain (i.e., T_{terms}), the algorithm increments the co-occurrence of that emotion with the corresponding social group $coocc_E^T$, for that corpus. For example, the occurrence of the emotion *Joy* (i.e., occ_{joy}), for a corpus, is incremented once an emotion term related to *Joy* like 'happy', 'bliss', 'cheer', etc., is encountered in a sentence of the corpus. Also the co-occurrence of *Joy-Male* (i.e., $coocc_{joy}^{male}$), for the corpus, is incremented once an emotion term related to *Joy* co-occurs with target terms related to the social group *Male* like 'husband', 'boy', 'brother', etc., and the co-occurrence of *Joy-Female* (i.e., $coocc_{joy}^{female}$) is incremented if an emotion term related to *Joy* co-occurs with target terms related to the social group *Female* like 'wife', 'girl', 'sister', etc., in a sentence of the corpus.

To conduct this study on corpus level affective bias, a list of emotion terms (or affective terms) for the basic emotions $E = \{anger, fear, joy, sadness\}$ is maintained, because the emotion prediction models (discussed in section 5.3.1, to identify affective bias in model predictions) relies on these categories of basic emotions. Hence, initially, a list of affective terms is procured collectively from Parrott's primary, secondary, and tertiary emotions[54], and referring to the works [28] and [184], to represent these basic emotions. Later, this list of affective terms is extended by including linguistic inflections of each word in the list using Merriam-Webster[55] dictionary and an automated python package pyinflect[56]. As a result the entire list contains 735 affective terms (given in Appendix C.1.1), where 162 represent *anger*, 143 *fear*, 222 *joy*, and 208 *sadness*.

A similar procedure is carried out to procure target terms within gender, race, and religion, the domains that are considered in this study. In the domain gender, target terms considered represent three social groups $T = \{M, F, Nb\}$ for Male, Female, and Non-binary groups. Similarly in the racial domain, target terms considered represent European American and African American social groups i.e., $T = \{EA, AA\}$, and for

[54] https://en.wikipedia.org/wiki/Emotion_classification#Parrott's_emotions_by_groups, *accessed: 05-12-2022*

[55] https://www.merriam-webster.com/, *accessed: 05-12-2022*

[56] https://pypi.org/project/pyinflect/, *accessed: 05-12-2022*

Algorithm 5.1: Occurrence and Co-occurrence

input : Corpus D
Emotion terms for emotion E (E_{terms})
Target terms for social group T (T_{terms})

output : Emotion occurrence occ_E
Emotion and Social group co-occurrence $coocc_E^T$

Let $D = [S_1, S_2, \ldots, S_m]$ and $S = [w_1, w_2, \ldots, w_n]$;
initialize $occ_E = 0$; $coocc_E^T = 0$; $flag = False$;
for $(j = 1;\ j \leq m;\ j++)$ **do**
  for $(i = 1;\ i \leq n;\ i++)$ **do**
    if $(w_i \in E_{terms})$ **then**
      $flag = True$;
      $occ_E = occ_E + 1$;
      break;
    end
  end
  for $(i = 1;\ i \leq n;\ i++)$ **do**
    if $(w_i \in T_{terms}\ and\ flag = True)$ **then**
      $coocc_E^T = coocc_E^T + 1$;
      break;
    end
  end
end
output occ_E, $coocc_E^T$

religion, the target terms considered represent Christian, Muslim, and Jewish social groups i.e., $T = \{Ch, Mu, Jw\}$. An initial list of target terms representing these social groups is prepared collectively by referring to the works [149, 175, 171, 177, 205, 173], which is later expanded by adding linguistic inflections. As these works do not consider target terms related to the non-binary social group in the gender domain, the corresponding target terms are manually curated from various articles and web resources (e.g. [260]) and are verified with the help of an expert in gender studies. The entire list contains 507, 167, and 332 target terms in the domains gender, race, and religion, respectively (given in Appendix appendices C.1.2 to C.1.4), with 199 male, 211 female, and 97 non-binary target terms for the gender domain, 82 African American and 85 European American target terms for the racial domain, and 122 Muslim, 111 Jewish, and 99 Christian target terms for the religious domain.

5.2.3 Results and Analysis

This section presents the results of occurrence of emotions in the corpora and their co-occurrence with social groups in various domains of gender, race, and religion to analyze corpus level affective bias.

Occurrence of Emotions in the Corpora

Results of the occurrence statistics of emotions for the corpus level affective bias analysis are shown in table 5.3. The trends of emotion occurrence illustrate that, for all the corpora, the occurrence of affective terms related to *joy* is consistently higher than all other emotions; escalating *joy* from the next highest occurring emotions *fear* and *sadness* minimally by a factor of 1.1 in SemEval-2018 EI-oc and maximum by a factor of 5.6 in C4-Val, respectively. The predominance of *joy* in textual corpora can be possibly due to the reason that, psychologically people are inclined towards expressing more positive emotions on the web [224, 261, 262, 263]. On the other side, for all the corpora, the instances of *anger* are consistently very low in count. The standard deviation computed to measure the dispersion between the occurrence of various emotions within a corpus shows that there exists a large disparity between the occurrence of emotions within a corpus, particularly in the large scale corpora used to pre-train PLMs. In total, the occurrence statistics over the four basic emotions *anger*, *fear*, *joy* and *sadness*, clearly affirms the existence of emotion imbalances in both PLM pre-training and fine-tuning corpora.

TABLE 5.3: Occurrence statistics of emotions in the corpora

Corpus	Anger	Fear	Joy	Sadness	Total affective words	Standard deviation
Pre-training corpora						
WikiEn	533111	745221	2479326	1802466	5560124	914103.94
BookCorpus	1049407	1647267	3143907	1400423	7241004	922324.00
WebText-250k	50207	85325	220354	88749	444635	74851.63
C4-Val	33182	66239	394413	69686	563520	169821.19
Fine-tuning corpora						
SemEval-2018	984	1472	1579	1131	5166	280.21

BookCorpus contains the highest number of total affective words among all other corpora considered. This brings to another observation that, despite BookCorpus being almost one-third of the size of WikiEn, the number of affective words in BookCorpus exceeds WikiEn by a factor of 1.3. This might be because BookCorpus being

a large corpus curated from books in the web, contains more affective words than WikiEn curated from Wikipedia articles in the web.

Co-occurrence of Emotions with Social Groups

The co-occurrence statistics of basic emotions with various social groups in gender, racial and religious domains for each corpus is illustrated in table 5.4, where the domains are separated column wise and emotions are grouped across the rows. For analysis, each domain is looked into separately (in the order of gender, race, and religion), analyzing the association of emotion categories (in the order of anger, fear, joy, and sadness) with social groups in these domains; the analysis of the results are as follows.

(A) **Emotion Co-occurrence with Gender:** From the results of table 5.4, in the gender domain, *anger* mostly co-occurs with the non-binary and female social groups than male. *Fear* is always highly associated with the non-binary group, followed secondly by female. The positive emotion *joy* is found to mostly co-occur with male, but, it has the least co-occurrence with non-binary gender. *Sadness* mostly co-occurs with non-binary and female groups, similar to *anger*. For the fine-tuning corpus SemEval-2018, in particular, there is no instance of co-occurrence between any of the emotions and non-binary gender, this is due to the lack of non-binary gender terms in the corpus; also, for this corpus, negative emotions such as, *anger*, *fear*, and *sadness* are always found to have high co-occurrence with female gender and the positive emotion *joy* is found to have high co-occurrence with male. The overall co-occurrence statistics of the gender domain illustrate that negative emotions mostly co-occur with the non-binary gender group, followed by female, and conversely, positive emotions co-occur mostly with the male group. The observations thus clearly dictate imbalanced associations between affective terms and social groups of gender domain, in both pre-training and fine-tuning corpora.

(B) **Emotion Co-occurrence with Race:** Evaluation results over the racial domain in table 5.4 illustrate that the negative emotions *anger* and *sadness* mostly co-occur with African American race group, whereas negative emotion *fear* and the positive emotion *joy* mostly co-occur with European American. But, for all the pre-training corpora, the imbalance of co-occurrence values in the racial domain is comparatively less than the previously discussed gender domain; for example, imbalance in the co-occurrence of all emotions with the racial groups is negligible in the case of WikiEn corpus. Contrary to the observations of pre-training

TABLE 5.4: Co-occurrence statistics of emotions with social groups (in percentage)

Corpus	Co-occurrence with							
	Gender			Race		Religion		
	M	F	Nb	EA	AA	Ch	Mu	Jw
Anger								
WikiEn	12.12	13.41	**14.25**	10.44	**10.68**	8.55	11.69	**13.93**
BookCorpus	17.61	16.15	**19.02**	15.09	**17.06**	12.20	13.74	**18.64**
WebText-250k	14.13	**14.24**	11.46	15.05	**16.53**	12.86	15.05	**19.55**
C4-Val	**9.32**	9.08	6.02	7.06	**7.71**	6.22	11.19	**13.49**
SemEval-2018	22.36	**24.56**	0	22.55	**52.17**	**15.79**	15.06	0
Fear								
WikiEn	12.61	15.09	**21.01**	**14.73**	14.62	9.81	**17.03**	16.05
BookCorpus	22.03	24.00	**25.05**	23.09	**23.52**	14.65	**21.42**	16.44
WebText-250k	19.56	21.80	**23.02**	**21.11**	21.02	16.66	**36.00**	28.39
C4-Val	13.95	13.79	**16.87**	**13.56**	13.46	9.33	**23.09**	19.70
SemEval-2018	25.36	**26.06**	0	**31.37**	10.87	36.84	62.16	**75.00**
Joy								
WikiEn	**40.81**	**40.81**	39.18	**45.46**	45.31	**51.94**	36.47	41.93
BookCorpus	**41.09**	40.01	38.40	**44.01**	41.07	**51.12**	44.53	40.77
WebText-250k	**44.25**	40.01	42.79	**43.69**	42.44	**47.54**	25.06	27.53
C4-Val	57.76	**61.28**	55.42	63.49	**63.95**	**68.05**	44.28	45.75
SemEval-2018	**33.53**	30.83	0	**34.31**	13.04	**27.02**	12.16	25.00
Sadness								
WikiEn	**34.46**	30.70	25.56	29.37	**29.38**	29.70	**34.81**	28.09
BookCorpus	19.76	19.84	**21.02**	18.11	**18.55**	22.03	20.30	**24.14**
WebText-250k	24.05	**25.25**	20.83	**20.75**	20.51	22.94	24.09	**24.52**
C4-Val	18.96	16.95	**21.69**	**15.89**	14.88	16.40	**21.44**	21.05
SemEval-2018	17.75	**19.05**	0	11.76	**23.91**	**21.05**	10.81	0

corpora, in fine-tuning corpus SemEval-2018, there exists a large difference in co-occurrence values between African and European American groups. That is, in SemEval-2018, the negative emotions *anger* and *sadness* co-occur with the African American race double the times than European American, indicating highly imbalanced association of *anger* and *sadness* with African American race. Whereas, the co-occurrence of negative emotion *fear* and positive emotion *joy* with European American group is almost thrice African American, again indicating a highly

imbalanced association, that of *fear* and *joy* emotions in SemEval-2018 with European American group.

(C) **Emotion Co-occurrence with Religion :** Results of the religious domain in table 5.4 shows that *anger* mostly co-occurs with Jewish and *fear* mostly co-occurs with Muslim. Whereas, *joy* is always found to have maximum co-occurrence with Christian. *Sadness* is found to mostly co-occur with Muslim and Jew religious groups than Christian. The results thus shows existence of high co-occurrence between negative emotions *anger*, *fear*, and *sadness* with Muslim and Jew, whereas the positive emotion *joy* with Christian. Moreover, when considering previous observations of gender and racial domains, the imbalance in the religious domain is comparatively higher.

The entire occurrence and co-occurrence analysis over gender, racial and religious domains thus consolidate the existence of corpus level affective bias in pre-training and fine-tuning corpora used in this study (the observations may vary for different set of corpora and domains). The extensions of such corpora holding latent affect imbalances, to build computational models may eventually trigger chances of bias in learning models, especially when building large scale contextual pre-trained language models that extract all possible properties of a language.

5.3 Prediction Level Affective Bias

To identify the existence of prediction level affective bias, if any, in the perspective of large PLMs, this study utilizes textual emotion detection systems built using popular large PLMs that are fine-tuned using an emotion detection corpus. The existence of affective bias is evaluated in the context of domains gender, race, and religion via different synthetic and non-synthetic paired evaluation sentence corpora and an extensive set of evaluation measures. Details of the investigation, including the description of textual emotion detection models, the method to measure prediction level affective bias with the details of evaluation corpora and measures, and the results and analysis of prediction level affective bias, are given below.

5.3.1 Textual Emotion Detection using Large PLMs

This section presents the methodology and settings of the textual emotion detection models built using large PLMs.

Methodology

The task of textual emotion detection is formulated as a four-class classification system with classes being the basic emotions *anger*, *fear*, *joy* and *sadness*. For this classification task, the study utilizes pre-trained language models and fine-tunes them with the aim to find the best-fit mapping function $f : y = f(x)$ for the fine-tuning data $(x_1, y_1), (x_2, y_2), \ldots, (x_N, y_N)$ with N documents, where x_i indicates i$^{\text{th}}$ document in the fine-tuning corpus and y_i indicates the corresponding ground-truth emotion.

The choice of PLMs, GPT-2 [40], BERT [39], XLNet [41], and T5 [42], that are utilized in this study to identify affective bias, is motivated by considering their acceptance as relevant and neoteric contextualized models with high performance efficacy towards textual emotion detection [102, 251] and the much related task of sentiment analysis [264, 265] within the area of affective computing. GPT and BERT are the very popular PLMs that follow the most effective auto-regressive and auto-encoding self-supervised pre-training objectives, respectively, where GPT uses transformer decoder blocks, whereas BERT uses transformer encoder blocks. The autoregressive nature of GPT helps to effectively encode sequential knowledge and achieve good results [40]. On the other hand, by eliminating the autoregressive objective and alleviating unidirectional constraints through the masked language model pre-training objective, BERT attains powerful bi-directional representations. This ability of BERT to learn context from both sides of a word makes it an empirically powerful state-of-the-art model [39]. XLNet brings back the auto-regressive pre-training objective with alternate ways to extract context from both sides of a word and overcome the pretrain-finetune discrepancy of BERT outperforming it in several downstream NLP tasks [41]. The development of T5 explores the landscape of NLP transfer learning and proposes a unified framework that converts all textual language related problems into the text-to-text format and achieves improved performance [42].

Each pre-trained language model (*PLM*) after fine-tuning and application of *softmax* function at the final layer forms the textual emotion detection model (i.e., *softmax(PLM)*). For each textual document d, the fine-tuned textual emotion detection models predict an emotion class $\widehat{e}_{class}$ by finding the highest prediction intensity score $\widehat{e}_{score}$ among E classes of emotions (namely *anger*, *fear*, *joy* and *sadness*, for the proposed task) represented as,

$$\widehat{e}_{class}(d) = \underset{k \in 1,2,\ldots,E}{\operatorname{argmax}} \; softmax(PLM(d)) \tag{5.1}$$

$$\widehat{e}_{score}(d) = \max_{k \in 1,2,\ldots,E} softmax(PLM(d)) \tag{5.2}$$

Experimental Settings

To fine-tune PLMs and build emotion detection models, the proposed study use 24-layered version of the pre-trained BERT, GPT-2, XLNet, and T5 available at HuggingFace[57], i.e., bert-large-uncased[58], gpt2-medium[59], xlnet-large-cased[60], and t5-large[61], respectively, and update these architectures by adding a final dense layer of four neurons with softmax activation function on top of the base models to suit the proposed four class classification task. The choice of GPT-2 instead of the latest version GPT-3 [158] is due to its unavailability as an open-source pre-trained model. All four models are fine-tuned using a popular emotion detection corpus SemEval-2018 EI-oc [218] that consists a total of 10030 data instances for the emotions anger, fear, joy, and sadness. The fine-tuning corpus is split as 8566 data instances for training and 1464 data instances for validation; details of the number of data instances belonging to each emotion category in the train and validation splits are shown in table 5.5.

TABLE 5.5: Statistics of fine-tuning corpus

Emotions	Number of documents	
	Training	Validation
Anger	2089	388
Fear	2641	389
Joy	1906	290
Sadness	1930	397

Hyperparameters that can aid the reproducibility of the emotion detection models proposed in this study are, GPT-2, XLNet, and T5 uses *Adam* optimizer with learning rate 0.000001, categorical crossentropy loss function, and 100 epochs, whereas for BERT the learning rate is 0.00001 and rest of the above mentioned parameters are the same. The batch size is set to 80 for BERT, XLNet, and T5, whereas 64 for GPT-2. The total number of trainable parameters for BERT, GPT-2, XLNet, and T5 textual emotion detection models come out as 335145988, 354827268, 360272900, and 334943748, respectively. All experiments were conducted on a deep learning workstation equipped with Intel Xeon Silver 4208 CPU at 2.10 GHz, 256 GB RAM, and two GPUs of NVIDIA Quadro RTX 5000 (16GB for each), using the libraries Tensorflow (version 2.8.0), Keras (version 2.8.0), Transformer (version 4.17.0), and NLTK (version 3.6.5).

[57] https://huggingface.co/, *accessed: 05-12-2022*
[58] https://huggingface.co/docs/transformers/model_doc/bert, *accessed: 05-12-2022*
[59] https://huggingface.co/docs/transformers/model_doc/gpt2, *accessed: 05-12-2022*
[60] https://huggingface.co/docs/transformers/model_doc/xlnet, *accessed: 05-12-2022*
[61] https://huggingface.co/docs/transformers/model_doc/t5, *accessed: 05-12-2022*

5.3.2 Identifying Prediction Level Affective Bias

The textual emotion detection models, when supplied with a document/sentence, predict as output the emotion class and corresponding emotion intensity of the document/sentence. To identify prediction level affective bias in textual emotion detection models, a *sentence pair* that differ only in key terms representing different social groups is input into these models, with an aim to compare and contrast between emotion predictions of sentences in that pair. For instance, the sentence pairs such as '*She made me feel angry*' versus '*He made me feel angry*' that only differ in key terms representing female and male social groups concerning gender domain, or '*African American people can dance very well*' versus '*European American people can dance very well*' that only differ in key terms representing African American and European American social groups concerning racial domain, are input to the models to compare and contrast between emotion predictions of sentences in these pairs. Comparing emotion predictions using such sentence pairs helps to pair-wise analyze and understand whether algorithmic decisions of emotion classification are similar (or different) across different social groups within a domain. Accordingly, to identify prediction level affective bias, evaluation corpora that consist of sentence pairs differing only in key terms representing various social groups are used.

The prediction of emotion class for a sentence is decided by the intensity of emotions predicted by the textual emotion detection model for that sentence. For example, for a prediction $\widehat{E}_{score}(d) = \{0.5, 0.2, 0.1, 0.2\}$, the choice of emotion class from the set $E = \{anger, fear, joy, sadness\}$, would be *anger*. Differences in the intensities of emotion predictions between sentences in a pair show existence of affective bias at the intensity level, which when higher enough can alter the prediction of emotion class and thereby cause affective bias at the class level. That is, an unbiased model is expected to predict the same emotion class and intensities for the sentence pairs that only differ in key terms representing different social groups. Hence, to analyze affective bias in the predictions, class based and intensity based evaluation measures capable of comparing predictions of these sentence pairs are utilized. The evaluation corpora and measures are detailed below.

Evaluation Corpora

The choice of bias evaluation corpora for this study is based on the objective to identify affective bias in textual emotion detection models using sentence pairs that only differ in key terms representing social groups, concerning either gender, racial, or religious

domain. Suitably, this study utilize three different evaluation corpora, Equity Evaluation Corpus (EEC) [28], Bias Identification Test in Sentiments (BITS) corpus [184], and Crowdsourced Stereotype Pairs (CSP) corpus [250]. Similar to most bias evaluation corpora, EEC and BITS contain template based synthetically created sentences along with ground truth emotions. On the contrary, CSP is a crowd sourced non-synthetic bias evaluation corpus that possesses greater diversity within data in the perspective of context expressed and structure of sentence pairs.

EEC consists of a total of 8640 sentences capable of evaluating gender and racial domains, from which 8400 sentences are selected for this study after excluding 240 sentences with no emotion words. For the gender domain, the sentence pairs in EEC represent only two social groups, female and male. To tease out affective bias towards the gender domain, 1400 sentence pairs are selected. For the racial domain, the sentence pairs represent African American and European American social groups, and 2800 sentence pairs are selected to analyze affective bias in the racial domain.

BITS consists of a total of 720 sentences capable of evaluating gender and racial domains. In BITS, the sentence pairs for gender domain also include the non-binary social group besides female and male groups. For this study, the available 120 sentences are selected for each non-binary, female, and male social group in the gender domain. The racial domain includes social groups such as American Indian, Asian, and Latino, apart from African American and European American groups. For this study, the available small set of 72 sentence pairs representing African American and European American social groups are only selected, as the investigation is limited only to these two racial groups.

CSP contains 1508 sentence pairs that cover nine domains, including gender, race, religion, age, nationality, etc., that, unlike EEC and BITS, do not differ 'only' on a single key term. A sample sentence pair in CSP for the racial domain is '*African American people are not very ambitious as a whole*' versus '*European American people are very ambitious as a whole*'. Such sentence pairs violate the evaluation setting of considering sentence pairs that 'only' differ in key terms representing certain social groups, an evaluation strategy in this study to identify bias. But considering the usefulness of such a non-synthetic corpus that suits the real-world context, all sentence pairs in CSP are manually evaluated and modified (if required) to suit the evaluation settings. An example of modified versions for the above mentioned sentence pair is, '*African American people are not very ambitious as a whole*' versus '*European American people are not very ambitious as a whole*', and '*African American people are very ambitious as a whole*' versus '*European American people are very ambitious as a whole*'. Finally, after such modifications and exclusion of pairs belonging to domains other than gender, race, and religion, 1970

sentences are gathered, where the gender domain consists of 263 sentence pairs representing female and male, the racial domain consists of 566 sentence pairs representing African Americans and European Americans, and religious domain consists of 104 sentences each for Christian, Jew, and Muslim social groups.

Even though in some evaluation corpora, certain domains consist of three social groups (e.g. in BITS, the gender domain consists of male, female, and non-binary social groups, in CSP, the religious domain consists of Christian, Jew, and Muslim groups), the evaluation strategies of this study are limited to pair-wise evaluations, to maintain commonality among all the domains. That is, for all the evaluation corpora, from the available set of social groups, pair-wise evaluations are conducted for the pairs, Male versus Female (M×F), Male versus Non-binary (M×Nb), or Female versus Non-binary (F×Nb) in gender domain, European American versus African American (EA×AA) in the racial domain, and Christian versus Muslim (Ch×Mu), Christian versus Jew (Ch×Jw) or Muslim versus Jew (Mu×Jw) in the religious domain.

Evaluation Measures

For an evaluation corpus with N sentence pairs, $sp_i^{g_1}$ and $sp_i^{g_2}$ is denoted as the i$^{\text{th}}$ sentence pair representing two social groups g_1 and g_2 (e.g. Male versus Female), respectively, in a domain (e.g. gender). The existence of prediction level affective bias is evaluated using different measures that rely on class ($\widehat{e}_{class}$) and intensity ($\widehat{e}_{score}$) predictions of the textual emotion detection models, details follow.

- Demographic Parity (DP): A popular class based measure to quantify group fairness/bias of a classifier system, commonly used to address general affect-agnostic biases like gender bias, racial bias, etc. [200]. In the proposed study, this measure is utilized to identify the existence of affective bias and check whether the model's emotion classifications are similar (or different) across different social groups within a domain. Accordingly, a textual emotion detection model is said to satisfy demographic parity if,

$$\text{DP} = \frac{P(\widehat{e}_{class}(sp^{g_1}) = e | z = g_1)}{P(\widehat{e}_{class}(sp^{g_2}) = e | z = g_2)}, \quad e \in E \text{ and } g_1, g_2 \in T \tag{5.3}$$

  where, $P(\widehat{e}_{class}(sp^{g_1}) = e|z = g_1)$ and $P(\widehat{e}_{class}(sp^{g_2}) = e|z = g_2)$ indicates the probabilities of the two social groups g_1 and g_2, respectively, to predict an emotion e; g_2 is taken as the group with higher probability [266]. E is the set of all emotions, and T is the set of social groups in a domain. Demographic parity advocates the likelihood of emotion prediction outcomes of sentence pairs that

differ only in key terms denoting a certain social group should be the same; as a result, DP=1 indicates an ideal unbiased scenario, whereas, lower the values higher the existence of bias. Therefore, the general threshold $\tau = 0.80$ is used, lower than which indicates biased predictions [266].

- Average Difference of Prediction Intensity Scores ($avg.\Delta$): An intensity based measure that computes the average difference of emotion prediction intensity scores between the sentence pairs of two social groups in a domain [28].

$$avg.\Delta = \frac{1}{N}\sum_{i=1}^{N} |\widehat{e}_{score}(sp_i^{g_1}) - \widehat{e}_{score}(sp_i^{g_2})| \tag{5.4}$$

where, $\widehat{e}_{score}(sp_i^{g_1})$ and $\widehat{e}_{score}(sp_i^{g_2})$ indicates emotion prediction intensity scores corresponding to the social groups g_1 and g_2, respectively, for the i$^{\text{th}}$ sentence pair concerning a domain, and N denotes the total number of sentence pairs. That is, $avg.\Delta$ indicates the average dissimilarity in prediction scores between a pair of sentences; 0 indicates perfect similarity, and higher the values more the dissimilarity.

- Prediction Score Significance (p-value): A measure that shows whether dissimilarity in prediction scores between the sentence pairs is statistically significant or not. To compute prediction score significance, a paired statistical significance test, t-Test [28], is performed over the prediction scores of sentence pairs, $\widehat{e}_{score}(sp_i^{g_1})$ and $\widehat{e}_{score}(sp_i^{g_2})$, using the conventional significance level, i.e., a p-value of 0.05.

- Average Confidence Score (ACS): A measure that illustrates model bias towards a particular social group using the average ratio between prediction intensity scores of sentence pairs [250], computed as,

$$\text{ACS} = \frac{1}{N}\sum_{i=1}^{N} 1 - \frac{\widehat{e}_{score}(sp_i^{g_1})}{\widehat{e}_{score}(sp_i^{g_2})} \tag{5.5}$$

ACS value of an unbiased model will peak around zero, but if it tends to negative values, then the measure indicates that the model prediction intensities of the social group g_1 are higher than g_2, and if it tends to positive values, it indicates that prediction intensities of the social group g_2 are higher than g_1.

5.3.3 Results and Analysis

The emotion predictions of each PLM based textual emotion detection system are examined and the existence of affective bias are observed in the predicted emotion classes, as well as their intensities, for gender, race, and religious domains. The sample set of predictions presented in table 5.1 is a small subset of these affectively biased emotion predictions from the emotion detection models that employ BERT and T5. More sets of affectively biased predictions from the PLM based textual emotion detection systems, are provided in the appendix C.2. The following subsections evaluate the results of each PLM separately.

Affective Bias in BERT

Evaluation results observed for the textual emotion detection model built using BERT, analyzing gender, racial and religious domains using three different evaluation corpora EEC, BITS, and CSP, and various evaluation measures are shown in table 5.6. The pairs of social groups addressed by the evaluation corpora within each domain are presented column wise, the measures are presented row wise, and the emotions are grouped across the rows.

(A) **Affective Gender Bias :** Initially, looking into the gender domain, for class based measure DP, throughout all the emotions, it can be observed that there is almost no affective bias in the predictions made by BERT between male and female groups when evaluated using the EEC corpus (since, DP > 0.8 in all cases), and ideally no affective bias when evaluated using BITS corpus (since, DP $= 1$ in all cases). This ideal scenario in BITS might be because BITS is a small corpus containing short-length synthetically created sentences with explicit emotion terms that do not suit the real-world context. When compared to synthetic corpora (EEC and BITS), evaluations using the real-world context and non-synthetic corpus CSP shows more disparity (lower values of DP) between male and female groups for all the emotions except *fear*. For pairs involving non-binary genders, the values of DP are much less than those involving male and female groups of synthetic corpora EEC and BITS, for all emotions except *joy*. This indicate more disparity of male and female groups with non-binary gender, with respect to *anger*, *fear* and *sadness*. Since the evaluation of affective bias in non-binary social groups is only possible with BITS corpus, it may limit the exploration of affective bias towards this group and also the magnitude of affective bias. For the measure DP, when looking across each emotion, the most disparity (lowest value for DP) is observed for *anger* between male versus female when evaluated using CSP corpus,

TABLE 5.6: Results of BERT (Boldface is used to highlight the values of DP $<$ threshold $\tau = 0.80$ and p-values < 0.05)

Evaluation measures	Gender					Race			Religion		
	EEC M×F	BITS M×F	CSP M×F	BITS M×Nb	BITS F×Nb	EEC EA×AA	BITS EA×AA	CSP EA×AA	CSP Ch×Mu	CSP Ch×Jw	CSP Mu×Jw
Anger											
DP	0.964	1.000	0.836	0.866	0.867	0.996	0.948	1.000	0.923	0.923	1.000
avg.Δ	0.018	0.016	0.049	0.038	0.030	0.031	0.012	0.052	0.076	0.078	0.100
p-value	**0.003**	**0.036**	**0.037**	**0.047**	0.132	0.417	0.431	0.730	**0.038**	**0.042**	**2e-04**
ACS	0.010	0.017	0.025	0.036	0.020	-0.005	-0.008	-0.001	0.050	-0.084	-0.148
Fear											
DP	0.954	1.000	1.000	0.938	0.938	0.961	1.000	**0.743**	0.857	0.885	0.968
avg.Δ	0.019	0.049	0.086	0.085	0.086	0.049	0.058	0.109	0.076	0.089	0.073
p-value	**9.2e-12**	0.864	0.767	**0.043**	0.063	**5.3e-27**	0.748	**1.2e-6**	**0.044**	0.439	**0.001**
ACS	0.019	-0.010	-0.015	-0.094	-0.088	-0.055	-0.016	-0.123	0.031	-0.041	-0.082
Joy											
DP	0.994	1.000	0.971	1.000	1.000	1.000	1.000	**0.797**	**0.455**	**0.637**	**0.713**
avg.Δ	0.002	9.9e-5	0.072	0.001	0.001	0.005	0.001	0.076	0.148	0.031	0.130
p-value	0.400	0.061	**0.014**	0.360	0.394	**0.002**	0.611	**0.001**	**0.033**	0.425	**0.021**
ACS	-0.001	-5.8e-5	0.064	-0.001	-0.001	-0.004	-1e-4	-0.080	-0.240	-0.022	0.169
Sadness											
DP	0.953	1.000	0.872	0.938	0.938	0.977	0.950	**0.724**	**0.666**	**0.666**	1.000
avg.Δ	0.027	0.013	0.076	0.024	0.033	0.056	0.012	0.116	0.124	0.100	0.051
p-value	**1.8e-4**	**0.045**	**0.019**	0.461	0.156	0.600	0.924	**1e-12**	0.065	0.201	0.146
ACS	-0.020	-0.019	-0.064	0.006	0.022	-0.010	-0.002	0.100	-0.279	-0.169	0.064

followed by male versus non-binary, and female versus non-binary, for the same emotion, when evaluated using BITS corpus. Whereas, for *joy*, very less disparity is observed across the gender groups. In total, even though disparities are shown by DP, any of the gender pairs do not have values of DP less than the threshold $\tau = 0.80$. Hence DP does not establish the existence of gender affective bias in the predictions of BERT using these evaluation corpora.

Coming to the intensity based measure avg.Δ in the gender domain, similar to DP, more disparity is observed for male versus female pairs when evaluated using CSP corpus and also for the pairs involving non-binary social groups in BITS, across all the emotions. Different from the measure DP, avg.Δ reports highest disparity for *fear*, but similar to DP, avg.Δ shows very less disparity for *joy*.

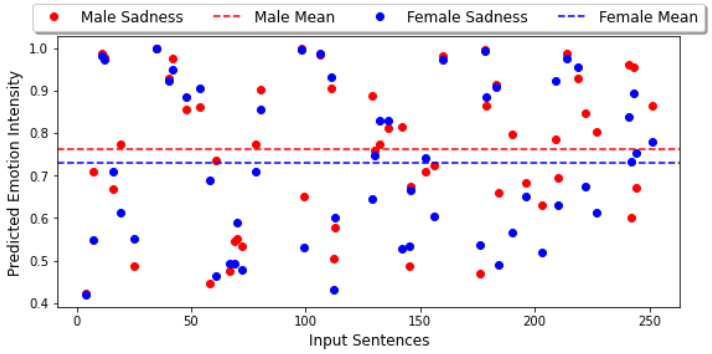
For the next measure p-value, at least one of the evaluation corpora reports values less than 0.05 or statistically significant difference between male and female predictions across the emotions, indicating the existence of affective bias. The p-value also shows that difference between male and non-binary predictions for *anger* and *fear* are statistically significant. Analyzing the prediction intensity

plots of pairs with statistically significant differences (e.g. figures 5.2a and 5.2b), shows that their intensity plots also depict more dispersion between data points as well as more disparity between the corresponding mean values. Conversely, in the plots of sentence pairs with statistically insignificant differences in prediction intensities (e.g. figure 5.2c), there is very less dispersion between data points and less disparity between the mean values. Therefore p-value evidently reports the existence of affective bias in emotion prediction intensities of male and female groups with respect to all emotions, and for male and non-binary groups with respect to *anger* and *fear*.

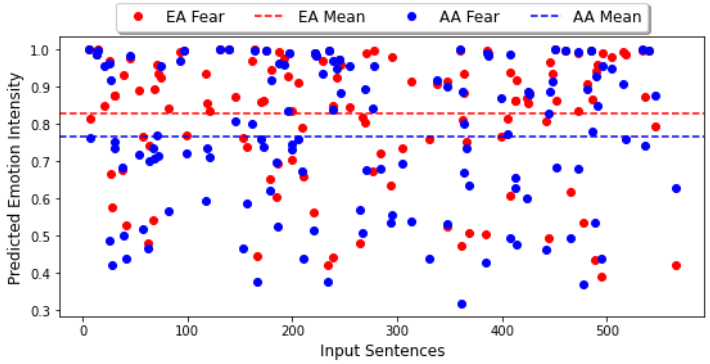
In the case of intensity based measure ACS, for emotion *anger*, the positive values in Male versus Female sentence pairs of EEC, BITS, and CSP indicates that prediction intensities for *anger* are higher for the Female group when compared to Male, and positive values in Male versus Non-binary and Female versus Non-binary sentence pairs of BITS indicates that *anger* prediction intensities are higher for the Non-binary group when compared to Male and Female. Similarly, when examining across evaluation corpora, prediction intensities of *fear* and *joy* are higher for Male and Female genders, and prediction intensities of *sadness* are higher for Male and Non-binary genders. Therefore in the gender domain, the measure ACS also indicates affective bias in prediction intensities.

(B) **Affective Racial Bias :** The European and African American racial groups when evaluated using CSP corpus, for the measure DP, shows the presence of affective bias for all emotions except *anger*, where EEC and BITS fail to identify it. Similarly, the avg.Δ disparities among intensity predictions of these racial groups are also much more visible when evaluated using CSP corpus. Either or both, EEC and CSP corpora shows that the difference in intensity predictions of these racial groups are statistically significant with p-values less than 0.05, for all emotions except *anger*, similar to the observations of the measure DP. The measure ACS also shows disparities in prediction intensities between the racial groups, where, for all emotions, prediction intensities of European American race are mostly higher than African American.

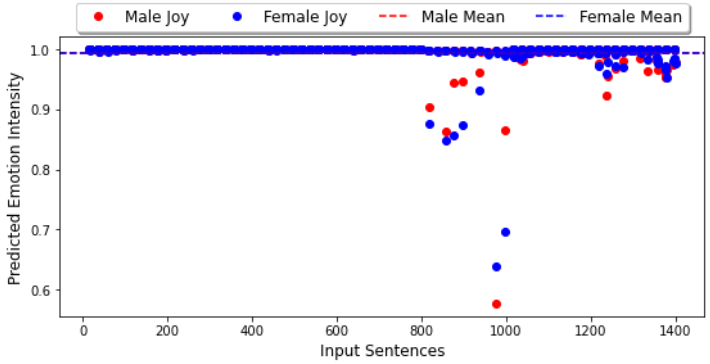
(C) **Affective Religious Bias :** In the religious domain, the measure DP evidently shows affective bias in the emotion *joy* with very low values for all three religious pairs and also in *sadness* for Christian versus Muslim and Christian versus Jew pairs. For all the emotions, the values of DP indicate more bias in the Christian versus Muslim and Christian versus Jew sentence pairs than in the Muslim versus Jew pairs. The measure avg.Δ shows that there exist disparities between



(A) Plot of *sadness* prediction intensities of M×F in CSP having statistically significant p-value



(B) Plot of *fear* prediction intensities of EA×AA in CSP having statistically significant p-value



(C) Plot of *joy* prediction intensities of M×F in EEC having statistically insignificant p-value

FIGURE 5.2: Intensity plots of emotion predictions from BERT

prediction intensities of religious pairs, and these disparities are found to be comparatively higher than the pairs of gender and racial domains. The p-value indicates statistically significant differences in intensity predictions of *anger* between

all three religious pairs. Also, Christian versus Muslim and Muslim versus Jew pairs show statistically significant differences in intensity predictions of all emotions except *sadness*. The measure ACS shows that for BERT *anger* and *fear* prediction intensities are higher for Muslim followed by Christian, and *joy* and *sadness* prediction intensities are higher for Christian followed by Jew.

Affective Bias in GPT-2

(A) **Affective Gender Bias:** Evaluation results observed for GPT-2 are shown in table 5.7, where similar to BERT, no gender affective bias is observed with the measure DP for any of the emotion class predictions. Whereas intensity based disparities are shown by the measure avg.Δ, which is highly visible when evaluated using CSP corpus. The difference in prediction intensities between Male versus Female when evaluated using EEC corpus for all emotions except *joy*, and Male versus Non-binary and Female versus Non-binary when evaluated using BITS corpus for all emotions except *fear*, are statistically significant with p-values < 0.05, indicating the existence of affective bias in emotion prediction intensities. The measure ACS indicates that, in GPT-2, *anger* and *joy* prediction intensities are higher for Male and Female genders, *fear* prediction intensities are higher mainly for Female gender, and *sadness* prediction intensities are higher mainly for Male gender.

(B) **Affective Racial Bias:** In the racial domain, similar to gender, DP does not show racial affective bias for any of the emotion class predictions, whereas intensity based disparities are shown by the measure avg.Δ. Here also, the disparities for class based measure DP and intensity based measure avg.Δ, are more visible when evaluated using CSP corpus. Whereas BITS reports an ideal unbiased scenario for DP and very low disparity for avg.Δ. The measure p-value reports that the difference in prediction intensities of European and African American races are statistically significant for all emotions except *sadness*. The measure ACS shows that, in GPT-2, prediction intensities of *anger* and *sadness* are mostly higher for African American race, whereas prediction intensities of *fear* and *joy* are mostly higher for European American race.

(C) **Affective Religious Bias:** Unlike gender and race, in the religious domain the class based measure DP reports affective bias (with values of DP < 0.8) in the predictions of all emotions except *fear*. The measure avg.Δ also shows disparities in prediction intensities of religious pairs. The p-values indicate that difference in *fear* prediction intensities for the pairs Christian versus Muslim and Muslim

TABLE 5.7: Results of GPT-2 (Boldface is used to highlight the values of DP $<$ threshold $\tau = 0.80$ and p-values < 0.05)

Evaluation measures	Gender					Race			Religion		
	EEC M×F	BITS M×F	CSP M×F	BITS M×Nb	BITS F×Nb	EEC EA×AA	BITS EA×AA	CSP EA×AA	CSP Ch×Mu	CSP Ch×Jw	CSP Mu×Jw
Anger											
DP	0.992	0.926	0.954	0.960	0.889	0.980	1.000	0.920	**0.600**	0.867	**0.692**
avg.Δ	0.023	0.006	0.039	0.008	0.008	0.038	0.010	0.050	0.059	0.048	0.021
p-value	**2.5e-05**	0.103	0.772	**0.031**	**0.004**	**3.4e-5**	**0.015**	**0.037**	0.580	0.788	0.626
ACS	0.013	0.007	-0.005	-0.006	-0.008	0.011	0.012	0.015	-0.044	-0.018	0.010
Fear											
DP	1.000	1.000	0.991	0.960	0.960	0.996	1.000	0.901	0.883	0.985	0.870
avg.Δ	0.016	0.007	0.058	0.017	0.015	0.030	0.010	0.063	0.139	0.069	0.158
p-value	**0.048**	0.372	0.505	0.917	0.787	**0.012**	0.101	0.183	**6.9e-13**	0.262	**7e-13**
ACS	-0.003	0.002	0.001	3.7e-4	-0.001	-0.011	-0.014	0.005	0.159	-0.040	-0.277
Joy											
DP	0.985	1.000	0.914	1.000	1.000	0.995	1.000	0.936	**0.545**	**0.600**	0.909
avg.Δ	0.008	3.3e-5	0.073	0.001	0.001	0.017	2e-4	0.101	0.114	0.100	0.089
p-value	0.640	0.713	0.761	**0.018**	**0.017**	0.872	0.204	**6.1e-5**	0.110	0.944	0.069
ACS	-7.3e-5	5.3e-6	-0.023	-0.001	-0.001	-0.003	-2e-4	-0.108	0.135	-0.011	-0.129
Sadness											
DP	0.985	0.951	0.927	1.000	0.951	0.996	1.000	0.938	**0.467**	0.933	**0.502**
avg.Δ	0.011	0.002	0.047	0.014	0.014	0.018	0.010	0.055	0.039	0.045	0.045
p-value	**4.5e-29**	0.262	0.313	**0.042**	**0.042**	0.178	0.725	0.283	0.310	0.429	0.343
ACS	-0.012	-0.001	-0.020	-0.013	-0.011	-0.002	0.001	0.006	-0.058	0.028	0.060

versus Jew are statistically significant. The measure ACS shows that for GPT-2 *anger* prediction intensities are mostly higher for Christian, *fear* and *joy* prediction intensities are higher for Muslim and Christian, and *sadness* prediction intensities are mostly higher for Jew groups.

Affective Bias in XLNet

(A) **Affective Gender Bias:** Evaluation results of XLNet are shown in table 5.8, where the class based measure DP shows ideally no affective bias (values of DP is almost one) in emotion predictions of gender pairs, whereas avg.Δ shows disparities in emotion prediction intensities of these pairs. The p-values report that differences between intensity predictions are statistically significant for Male versus Female pairs for all emotions, and also for pairs involving the Non-binary group for emotion *anger*. The measure ACS indicates high *anger* and *fear* prediction intensities for Female and Male genders, and high *joy* and *sadness* prediction intensities for Male and Non-binary genders.

TABLE 5.8: Results of XLNet (Boldface is used to highlight the values of DP $<$ threshold $\tau = 0.80$ and p-values < 0.05)

Evaluation measures	Gender					Race			Religion		
	EEC M×F	BITS M×F	CSP M×F	BITS M×Nb	BITS F×Nb	EEC EA×AA	BITS EA×AA	CSP EA×AA	CSP Ch×Mu	CSP Ch×Jw	CSP Mu×Jw
Anger											
DP	0.983	1.000	1.000	1.000	1.000	0.976	1.000	0.974	0.825	0.869	0.950
avg.Δ	0.017	0.005	0.053	0.017	0.019	0.048	0.004	0.061	0.115	0.083	0.110
p-value	**1.7e-6**	**0.002**	0.226	**0.035**	**0.014**	**0.041**	0.561	0.063	**0.008**	0.842	**0.001**
ACS	0.015	0.005	-0.028	-0.015	-0.020	-0.021	0.002	0.015	0.077	-0.032	-0.153
Fear											
DP	0.991	1.000	0.989	1.000	1.000	0.988	1.000	0.938	0.810	1.000	0.810
avg.Δ	0.012	0.030	0.080	0.060	0.071	0.038	0.036	0.067	0.054	0.070	0.047
p-value	**0.032**	0.809	0.680	0.667	0.642	0.228	**0.004**	**0.003**	0.561	0.807	0.703
ACS	0.004	-0.001	-0.003	-0.008	-0.013	-0.007	-0.050	-0.062	-0.029	-0.005	-0.019
Joy											
DP	0.993	1.000	0.974	1.000	1.000	0.970	1.000	0.804	0.856	1.000	0.857
avg.Δ	0.010	0.013	0.084	0.006	0.018	0.022	0.009	0.084	0.027	0.077	0.086
p-value	0.457	0.118	**0.028**	0.158	0.125	**0.011**	0.573	**0.024**	0.357	0.410	0.397
ACS	-0.003	-0.018	0.056	0.006	0.019	-0.012	0.004	-0.073	-0.055	0.073	0.133
Sadness											
DP	0.998	1.000	0.989	1.000	1.000	0.997	1.000	0.902	**0.533**	0.833	**0.640**
avg.Δ	0.009	0.003	0.050	0.007	0.008	0.028	0.007	0.083	0.094	0.065	0.104
p-value	**0.013**	**0.010**	0.553	0.203	0.061	0.253	0.075	**5.1e-6**	**0.048**	0.637	**0.010**
ACS	-0.003	-0.003	-0.031	0.002	0.005	-0.004	0.009	0.046	-0.131	0.007	0.124

(B) **Affective Racial Bias :** Similar to the gender domain, the measure DP does not confirm class based affective racial bias in XLNet, but avg.Δ shows disparity in intensities of predictions with p-value indicating statistically significant differences between prediction intensities of both races, for all emotions. The measure ACS shows that *anger* and *sadness* prediction intensities are higher for African American, whereas *fear* and *joy* prediction intensities are higher for European American race.

(C) **Affective Religious Bias :** In the religious domain, even though the values of DP are less compared to gender and racial domains, it is not sufficient to confirm class based affective religious bias in the emotions except *sadness* whose values are very low and reporting bias. The measure avg.Δ shows disparity in prediction intensities, with p-value indicating statistically significant differences between Christian versus Muslim and Muslim versus Jew religious pairs, for *anger* and *sadness*. The measure ACS indicates that *anger* prediction intensities are mostly higher for Muslim religion followed by Christian, *fear* mostly higher for Christian followed by Muslim, and *joy* and *sadness* higher for Christian and Jew.

Affective Bias in T5

(A) **Affective Gender Bias:** Evaluation results of T5 are shown in table 5.9. In the gender domain, class based measure DP shows affective bias in the predictions of Male versus Female pair for *anger* and *fear* when evaluated using CSP corpus. The avg.Δ measure shows disparities in prediction intensities, and p-values indicate that differences in prediction intensities of Male versus Female pair for all emotions except *fear* and in pairs involving Non-binary gender for emotions *anger* and *fear* are statistically significant. The measure ACS indicates high prediction intensities for *anger*, *joy* and *sadness* mostly by Male gender and high prediction intensities for *fear* mostly by Female and Non-binary genders.

TABLE 5.9: Results of T5 (Boldface is used to highlight the values of DP $<$ threshold $\tau = 0.80$ and p-values < 0.05)

Evaluation measures	Gender					Race			Religion		
	EEC M×F	BITS M×F	CSP M×F	BITS M×Nb	BITS F×Nb	EEC EA×AA	BITS EA×AA	CSP EA×AA	CSP Ch×Mu	CSP Ch×Jw	CSP Mu×Jw
Anger											
DP	0.983	0.966	**0.765**	0.897	0.866	0.933	0.952	0.903	0.968	0.816	**0.790**
avg.Δ	0.039	0.016	0.077	0.021	0.022	0.101	0.004	0.106	0.082	0.113	0.097
p-value	**3.6e-20**	0.530	0.385	**0.017**	**0.043**	**0.001**	0.458	**6.8e-8**	0.118	0.491	**0.041**
ACS	-0.044	0.006	-0.037	-0.029	-0.032	0.005	0.002	0.070	-0.086	0.014	0.064
Fear											
DP	0.994	1.000	**0.778**	0.897	1.000	0.966	1.000	0.867	**0.783**	0.915	**0.717**
avg.Δ	0.017	0.029	0.079	0.079	0.068	0.039	0.067	0.099	0.079	0.148	0.145
p-value	0.309	0.318	0.662	**0.003**	**0.004**	**3.1e-7**	**0.022**	**9.2e-5**	0.602	**0.001**	**2.8e-5**
ACS	0.002	0.008	-0.025	0.071	0.063	-0.035	-0.087	-0.111	-0.005	-0.242	-0.263
Joy											
DP	0.990	1.000	0.848	1.000	1.000	0.961	1.000	0.971	**0.624**	**0.375**	**0.600**
avg.Δ	0.009	2e-4	0.062	1e-4	2.8e-4	0.029	0.009	0.068	0.183	0.001	0.075
p-value	**0.003**	**0.025**	0.885	0.605	0.115	0.122	0.332	**0.001**	0.122	0.468	0.423
ACS	-0.009	-2e-4	-0.025	-1.6e-5	1.8e-4	-0.014	-0.014	-0.078	-0.320	0.001	0.075
Sadness											
DP	0.998	0.973	0.952	0.925	0.900	0.998	0.955	0.972	**0.500**	0.900	**0.450**
avg.Δ	0.023	0.006	0.082	0.009	0.014	0.074	0.007	0.103	0.095	0.118	0.085
p-value	**8.6e-15**	**0.035**	0.689	0.223	0.871	**0.002**	**0.048**	0.957	0.121	0.751	**0.020**
ACS	-0.026	-0.006	-0.027	-0.008	-0.002	-0.040	-0.007	-0.030	-0.150	-0.002	0.099

(B) **Affective Racial Bias:** The measure DP does not confirm class based affective racial bias in T5 predictions, whereas avg.Δ shows intensity based affective racial bias, with statistically significant differences in intensity predictions of the racial pairs for all the emotions. ACS indicates prediction intensities of African American race are higher for *anger*, whereas prediction intensities of European American are higher for *fear*, *joy* and *sadness*.

(C) **Affective Religious Bias :** In the religious pairs, the measure DP indicates affective bias in Muslim versus Jew pairs for all emotions, in Muslim versus Christian pairs for all emotions except *anger*, and in Christian versus Jew pairs for *joy*. The avg.Δ shows intensity based disparities in all emotions, and p-values indicate that the differences in prediction intensities are statistically significant in the case of Muslim versus Jew pair for all emotions except *joy* and in Christian versus Jew pair for the emotion *fear*. ACS indicates that *anger* and *joy* prediction intensities are higher for Jew religion followed by Christian, *fear* prediction intensities are higher for Christian followed by Muslim, and *sadness* prediction intensities are higher for Christian followed by Jew.

5.4 Discussion

Based on the results analyzed, this section presents a discussion, initially comparing the presence of affective bias across the PLMs, followed by affect imbalances in the corpora and its resemblance in the predictions, reflections of affect-oriented societal stereotypes into affective bias, and finally, the effectiveness of evaluation corpora in unveiling affective bias.

5.4.1 Affective Bias - Across the PLMs

This study analyzes affective bias in the predictions of textual emotion detection models at class level and intensity level. In most cases, class based measures that are capable of identifying differences in emotion classes predicted for two different social groups, do not show affective bias, whereas intensity based measures mostly identify the existence of affective bias in predicted emotion intensities. This is because the differences in predicted emotion intensities between the social groups might not be that very high to alter the choice of emotion class predictions, but even then there exists affective bias due to differences in the predicted emotion intensities. When comparing across the PLMs, class based affective gender bias is only observed in T5, whereas intensity based affective gender bias is observed in all the PLMs. Similarly, class based affective racial bias is only observed in BERT, whereas intensity based affective racial bias is observed in all the PLMs. But, in the domain of religion, all four PLMs show high magnitudes of class based and intensity based affective bias, *i.e., compared to gender and race, the religious domain is observed to have high existence of affective bias*.

XLNet is observed to have the least class based affective bias, with bias only observed in the case of the religious domain for the emotion *sadness*. XLNet is also observed to have the least intensity based affective bias among all the PLMs when

considering the measures avg.Δ (i.e., the top five values of avg.Δ do not have any instance of XLNet) and p-value (i.e., the number of instances in XLNet with statistically significant differences are also low). Whereas T5 has the maximum class based biased instances, and also high intensity based affective bias among all the PLMs when considering the measures avg.Δ (i.e., top five values of avg.Δ have three instances of T5) and p-value (i.e., the number of instances in T5 with statistically significant differences are also high). BERT also shows class based and intensity based affective bias, nearly similar but comparatively less than T5, followed by GPT-2.

5.4.2 Affect Imbalance in Corpora and Affective Bias in Predictions

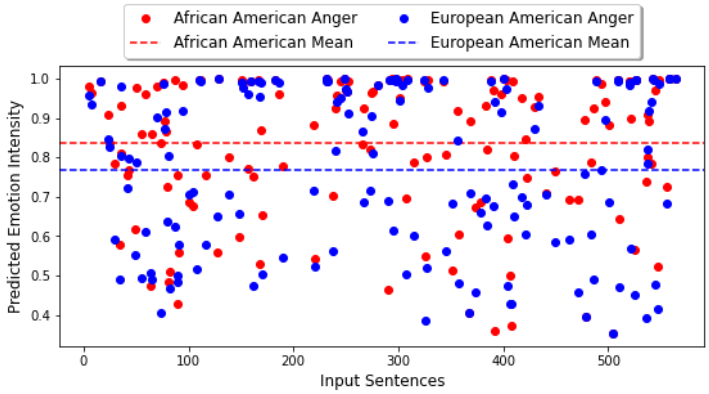
When revisiting the analysis of corpora involved in training PLMs, it was already observed (in table 5.4) that these corpora have imbalanced co-occurrences of emotions with certain social groups in gender, racial and religious domains. Further at the prediction level, PLMs that utilize these corpora seems to reflect some of these imbalances hinting at the propagation of affect imbalance in data towards affective bias in predictions. For example, in pre-training and fine-tuning corpora of BERT (i.e., WikiEn, BookCorpus, and SemEval-2018), the emotion *anger* has high co-occurrence with Non-binary and Female groups than Male. This seems to reflect in the predictions of BERT, i.e., the measure ACS shows that prediction intensities of *anger* are higher for Non-binary and Female groups than Male. Some other imbalanced emotion associations that exist in these corpora like *sadness* more associated with Male and Non-binary groups in the gender domain, *joy* more associated with European American racial group, *fear* more associated with Muslim, *joy* more associated with Christian, etc., are also seen to be reflected in the predictions of BERT when evaluated using the measure ACS. Similar to BERT, it can also be observed that the corpus level affective bias from pre-training and fine-tuning corpora of GPT-2 (i.e., WebText-250k and SemEval-2018) reflects in the predictions of GPT-2, e.g., (1) high co-occurrence of *fear* with Female and Non-binary genders in the corpora, and high prediction intensities of *fear* for Female and Non-binary genders, (2) high co-occurrence of *anger* with African American race in the corpora, and high prediction intensities of *anger* for African American, (3) high co-occurrence of *fear* with Muslim religion in the corpora, and high prediction intensities of *fear* for Muslim, etc. Such examples of reflection of corpus level affective bias in the predictions of PLMs are also visible in XLNet and T5. These instances give hints that *affect imbalances in the large scale corpora of PLMs may lead to affective bias in predictions of the models that utilize these PLMs*, further opening the scope for exploration in the direction of affective bias propagation.

5.4.3 Societal Stereotypes and Affective Bias

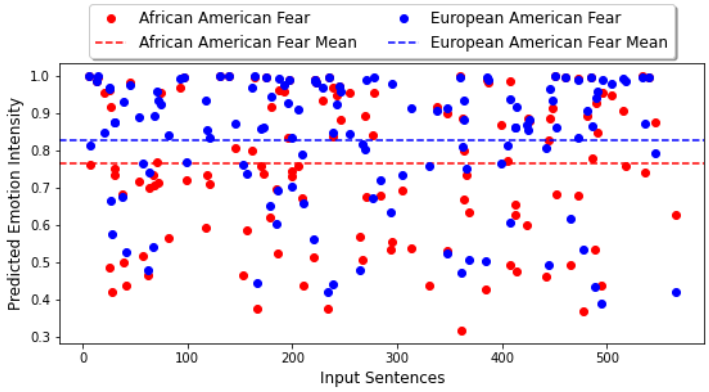
The imbalanced/biased association of emotions with certain social groups within a domain, either at the corpus level or prediction level, reflects several affect-oriented societal stereotypes. Patterns in the training corpora and predictions of PLM based textual emotion detection models showing high association of African American race with *anger* (an example plot of high anger prediction intensities for African American race is presented in figure 5.3a) reflect the "Angry Black" stereotype that misrepresents and victimizes blacks as hostile in mainstream American culture and suppress their emotions [267]. Another pattern of high association of European American race with *fear* (an example plot of high *fear* prediction intensities for European American is presented in figure 5.3b) reflects the existence of stereotypes such as *fear* of crime, residential integration, and racial prejudice among the whites [268]. The high association of Non-binary genders with negative emotions especially *fear*, and very rarely associating with positive emotion *joy*, reflects the societal stigmas like homo-negativity and homophobia against these gender minorities [269]. Similarly, the high association of Muslim religion with *fear* (an example plot of high *fear* prediction intensities for Muslim is presented in figure 5.3c), which is inline with the experimental results presented in [29].

5.4.4 Effectiveness of Evaluation Corpora in Unveiling Affective Bias

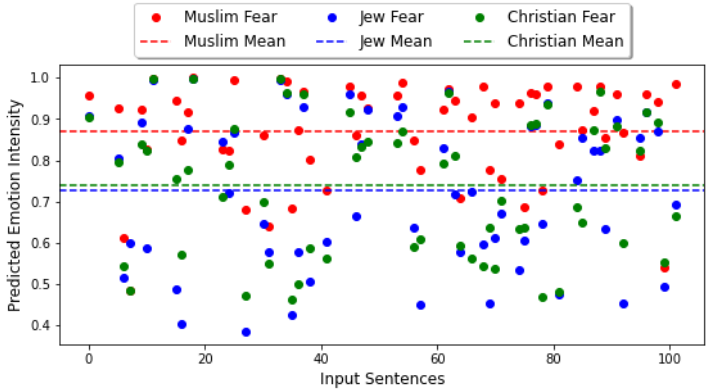
When comparing the capability of the evaluation corpora EEC, BITS, and CSP, it could be observed that BITS, with a smaller number of sentence pairs (120 for gender and 72 for race) and explicit emotion terms, is mostly unable to recognize the existence of affective bias in perspective of both class level and intensity level analysis. But even though EEC also has implicit representation of emotion terms similar to BITS, the availability of a large number of sentence pairs (1400 for each domain) eventually helps EEC to identify the existence of affective bias better than BITS. On the other side, even with a smaller number of sentence pairs (263 for gender, 566 for race, 104 for religion), the evaluation corpus CSP helps to identify affective bias to a great extent, and it is the only corpus that unveils class based affective bias in the domains. It might be that the non-synthetic and real-world context nature of sentence pairs in CSP could have been advantageous in identifying affective bias. Therefore, upgrading such a corpus with more number of sentence pairs or procuring new evaluation corpora containing non-synthetic real-world sentences with corresponding ground truth emotions could eventually help towards comprehensive and rigorous explorations in



(A) High *anger* prediction intensities from T5 for African American race in CSP evaluation corpus reflecting "Angry Black" stereotype



(B) High *fear* prediction intensities from BERT for European American race in CSP evaluation corpus reflecting stereotypes of *fear* in European American



(C) High *fear* prediction intensities from GPT-2 for Muslim religion in CSP evaluation corpus

FIGURE 5.3: Intensity plots of emotion predictions reflecting societal stereotypes

the direction of identifying affective bias and quantifying its magnitude using ground truth dependent measures like Equal Opportunity [200].

5.5 Summary

Affective bias in computational systems discriminates against demographic groups based on certain emotions while making algorithmic decisions, which when deployed in the real world, can harm the ethical trust of these systems and can be potentially threatening to human lives. Hence, this work investigated the existence of Affective Bias, a highly socially relevant and less addressed problem, specifically in the context of textual emotion detection models built using large PLMs. The study attempted the analysis of affective bias among various social groups such as, Male, Female and Non-binary in the gender domain, European American and African American in the racial domain, and Christian, Muslim, and Jew in the religious domain, in four different PLMs viz., BERT, GPT-2, XLNet, and T5, considering their popularity and wide applicability in textual emotion detection and many other related tasks. As algorithmic bias has its roots from data bias, this study started the exploration of affective bias by analyzing the imbalanced distribution of affect in the pre-training corpora of these PLMs i.e., WikiEn, BookCorpus, WebText-250, and C4-Val, and SemEval-2018 used to fine-tune the emotion detection models. Later, the existence of affective bias is analyzed in the predictions of fine-tuned emotion detection models built using these large PLMs. Evaluations are performed to analyze affective bias in the predicted emotion classes and corresponding intensities of social groups within a domain using three different evaluation corpora and various class based and intensity based evaluation measures.

The wide set of experiments and evaluation strategies confirm the existence of affect imbalance in large scale corpora and affective bias in emotion predictions of the PLMs, with affective bias mostly higher for T5 compared to the other PLMs. The high association of emotion *anger* with African American race, *joy* with European American race, *fear* with the Muslim religion, etc., are some examples of affective bias. Religious domain reports more biased instances, compared to gender and race, for all the PLMs. The results also demonstrated that the biased predictions of the models are inclined with patterns of affect imbalance in the corpora, and both these reflect certain affect-oriented societal stereotypes, hinting at the propagation of affective bias towards predictions of the PLMs. To aid future research, all the relevant materials including the pre-processed pre-training and fine-tuning corpora, evaluation corpora modified to suit our task, list of affective terms and target terms for corpus level analysis, source code, and fine-tuned textual emotion detection models

along with their emotion class and intensity predictions, shall be made publicly available at https://github.com/anoopkdcs/affective_bias_in_plm and https://dcs.uoc.ac.in/cida/projects/ac/affective-bias.html.

Chapter 6

Conclusion

*"**Surprise** arises when we encounter sudden and unexpected sounds or movements. As the briefest of the universal emotions, its function is to focus our attention on determining what is happening and whether or not it is dangerous."*

– Paul Ekman
Universal Emotions

Abstract: This final chapter concludes the Thesis by providing a recap of the major contributions of the Thesis. The chapter also discusses viable future research directions and open challenges that bring up new pasturages for *Textual Affective Computing* research.

6.1 Summary of the Thesis

This Thesis presented an exploration towards three salient facets of *Textual Affective Computing*, viz., detecting textual affect through readers' perspective, the utility of textual affect in a very significant downstream NLP task of health fake news detection, and identifying affective bias in large PLMs. A comprehensive discussion on contributions in these three facets of Textual Affective Computing, explored in this Thesis, is separately detailed below.

Readers' Emotion Detection Readers' Emotions Detection attempted in chapter 3 proposed a novel deep learning based methodology *REDAffectiveLM* that leverages context-specific and affect enriched representations by fusing a transformer-based pre-trained language model XLNet with Bi-LSTM+Attention that utilizes affect enriched embedding, to predict readers' emotion profiles from short-text documents. The experiments were conducted on the newly procured readers' emotion datasets, REN-20k and RENh-4k, and the benchmark SemEval-2007 dataset. Performance of the proposed model consistently outperformed the baselines belonging to deep learning,

lexicon based, and classical machine learning categories, and even the individual affect enriched Bi-LSTM+Attention and XLNet networks of the fused model with statistically significant results across all the three datasets when evaluated using various coarse-grained and fine-grained measures. A detailed model behavior analysis is also performed to study the impact of affect enrichment specifically in readers' emotion detection using a novel set of qualitative and quantitative behavior evaluation techniques over the affect enriched Bi-LSTM+Attention network. Behavior analysis confirmed that compared to the conventional semantic embedding, the affect enriched embedding helped to increase the ability of the network to effectively identify and assign weightages to the key terms (emotion words and named entities) responsible for readers' emotion detection. The entire set of experiments thus establishes that incorporating affective information of textual documents along with the powerful context-specific representations from transformer-based pre-trained language models, can further significantly improve the performance of the affective computing task of readers' emotion detection.

Affect-oriented Health Fake News Detection Affect-oriented health fake news detection attempted in chapter 4 proposed a novel methodology that considers the utility of affective information within the news articles to improve fake news detection in the health domain. For the task, a new dataset HWB that consists of fake and legitimate news articles was procured. The raw textual articles of fake and legitimate news were compared vis-a-vis emotion-amplified textual articles generated using an external emotion intensity lexicon, over different supervised and unsupervised fake news detection models built using conventional machine learning and deep learning based architectures, with varying parameters. The emotion-amplified articles were seen to be empirically much more suitable for the task of health fake news detection with significant gains over the raw text articles establishing the utility of affective information to improve health fake news detection.

Identifying Affective Bias in large PLMs Identifying affective bias in large PLMs attempted in chapter 5 is a novel direction of inquiry in a very significant and neoteric research area of algorithmic fairness, to investigate any biased or unfair association of emotions towards social groups belonging to a domain. The proposed study tried to explore the existence of affective bias, pertinent to the gender, racial, and religious domains, in the decisions of textual emotion detection systems that are modeled using

four popular and widely used PLMs, BERT, GPT-2, XLNet, and T5. The study performed two types of affective bias analysis, i.e., corpus level and prediction level analysis. To understand corpus level affective bias the imbalanced distribution of affect in the pre-training and fine-tuning corpora of the PLMs are analyzed. To understand prediction level affective bias the emotion predictions of PLM based textual emotion detection models are analyzed using synthetic and non-synthetic evaluation corpora and a set of class-based and intensity based evaluation measures. The entire set of experiments helped to unveil latent corpus level and prediction level affective bias in the PLMs, inclination of prediction level affective bias towards the patterns of corpus level bias, and reflections of certain affect-oriented societal stereotypes in these affective biases.

To aid future research, relevant materials including datasets, source code, etc., of each of the contributions are made publicly available at:-

- Readers' emotion detection: https://dcs.uoc.ac.in/cida/projects/ac/redaffectivelm.html
- Affect-oriented health fake news detection: https://dcs.uoc.ac.in/cida/resources/hwb.html
- Identifying affective bias in large PLMs: https://dcs.uoc.ac.in/cida/projects/ac/affective-bias.html

6.2 Directions for Future Research

The future technological revolutions would undoubtedly make the utility of affective computing systems more imperative, optimistically, such that it will influence most aspects of people's daily lives. A few directions for future research, specific to the three facets of textual affective computing attempted in this Thesis, are individually discussed below.

Readers' Emotion Detection Given that the proposed study establishes emotion words significantly influence readers' emotion detection, in the future, this study can be extended to explore the scope of developing affect enriched transformer based language models. Further, there is a large scope in exploring the applicability of affect enriched transformer based language models in affective well-being tasks such as early detection of anxiety and depression from social networks. Emotions elicited by the

readers also rely on dynamic characteristics and other social and individual circumstances like cultural background, personality, etc. Analyzing and incorporating such features is still an issue for the precise detection of readers' emotions, which is to be addressed in the future.

Affect-oriented Health Fake News Detection Through illustrating that there are significant differences in the emotional character of fake and legitimate news in the health domain in that exaggerating the emotional content aids techniques that would differentiate them, this work sets the stage for further inquiry into identifying the nature of differences in the emotional content. Further, emotion-aware end-to-end methods for supervised and unsupervised health fake news identification can be developed in the future, by blending article emotion cues with collective behavior heuristics that have been effective for fake news identification (e.g., [270]). The use of lexicons learned from data [271] that may be better suited for fake news identification in niche domains and the usage of the affective content of responses to social media posts can also be explored in the future.

Identifying Affective Bias in large PLMs The observations of affective bias and its magnitudes in this study are dependent on the choice of evaluation corpora and measures, i.e., certain instances of 'no affective bias' or marginal magnitudes of affective bias may also be due to the limited capability of evaluation corpora and measures to unveil the actual latent affective bias that exists in the model. Therefore in the future, this study can be extended with a set of real-world context evaluation corpora, for example, by expanding CSP in terms of the number of sentences and also by procuring ground truth emotions that allow applying other evaluation measures like Equal Opportunity [200]. Beyond analyzing each sentence pair in a domain separately, the ways to simultaneously analyze sentences representing various social groups in a domain can be explored, for example, analyzing sentence triplets like Male versus Female versus Non-binary. This study, an initial attempt to identify affective bias in textual emotion detection models that utilize large PLMs, opens up the vast future scope towards affective bias mitigation, which presumably, can be better achieved by adopting more convenient solutions that utilize constraints while fine-tuning the prediction system (i.e., in-processing) and post-processing, rather than retraining or fine-tuning the PLM based affect prediction systems with unbiased corpora which are expensive and cumbersome [272]. It is also crucial to evaluate affective computing systems in the backdrop of affective bias with respect to all the modalities involved (e.g. audio,

video, etc.) since automated affective computing systems have a huge impact on modeling human behavior in many intelligent artificial artifacts or algorithms that imitate human emotion systems for their completeness.

Hence, concluding this Thesis with the hope that the contributions of this Thesis would be beneficial to the scientific community researching on Textual Affective Computing, and paving the way for future research.

Appendix A

Appendix - Readers' Emotion Detection

A.1 Legal and Ethical Concerns of REN Datasets

The necessary approval in using the data for non-commercial academic research purposes was obtained from Rappler Inc. The data from Rappler to create REN datasets was procured manually without using any automated crawling software. All participants engaged in the manual data collection process were sensitized about the nature of the research and were trained on assigning the news documents to various genres consistently. Further, informed consent was obtained before the participants took part in the process of dataset curation. There was no labeling or annotation required in terms of readers' emotions since it was available within the Rappler website. The study cites the Rappler website for the data source in our research as reference number [273] and also acknowledges Rappler's data source support and participants engaged in the manual data collection process, within the 'Acknowledgement' section.

A.2 Hyper-parameters of the baselines

Hyper-parameters used to build the deep learning baselines, Kim's CNN [226], GRU, LSTM [96], Bi-LSTM [60], Bi-LSTM+Attention, and emoBi-LSTM+Attention are provided in table A.1 to aid reproducibility.

TABLE A.1: Hyper-parameters of the deep learning baselines

Parameters	Kim's CNN	GRU	LSTM	Bi-LSTM	Bi-LSTM+ Attention	emoBi-LSTM +Attention
Filter size	3, 4 & 5	–	–	–	–	–
Number of filters	100	–	–	–	–	–
Number of RNN stack	–	1	1	1	1	1
Neurons in Stack	–	100	100	100	100	100
Embedding	Pre-trained GloVe	Pre-trained GloVe	Pre-trained GloVe	Pre-trained GloVe	Pre-trained GloVe	Pre-trained emoGloVe
Embedding dimension	100	100	100	100	100	100
Regularizer	*l2(0.01)*	*l2(0.01)*	*l2(0.001)*	*l2(0.001)*	*l2(0.001)*	*l2(0.001)*
Dropout	0.5	0.25	0.5	0.5	0.5	0.5
Loss	MSE	MSE	MSE	MSE	MSE	MSE
Optimiser	*Adam*	*Adam*	*Adam*	*Adam*	*Adam*	*Adam*
Learning rate	0.0005	0.005	0.0005	0.0005	0.0005	0.0005
Dense layer activation	*softmax*	*softmax*	*softmax*	*softmax*	*softmax*	*softmax*
Batch size	64	64	128	128	128	128
Epoch	100	100	100	100	100	100

Appendix B

Appendix - Affect-oriented Health Fake News Detection

B.1 Parameters of the fake news detection models

The Scikit-learn machine learning library is used for conventional classifiers and clustering, and the Keras neural-network library for CNN and LSTM. The study utilizes a manual-search parameter tuning strategy by analyzing the results over different values for the parameters. The values of hyperparameters that gave good results are mentioned here, to aid reproducibility. In most of the experiments, good results were obtained with default parameter settings. So the parameters other than the default ones only are listed below.

B.1.1 Conventional Classifiers

- NB: *GaussianNB* (Gaussian Naive Bayes algorithm) with default parameters
- KNN: $n\_neighbors = 2$
- SVM: kernel = *linear*
- RF: $max\_depth = 5,\ n\_estimators = 10$
- DT: $max\_depth = 5$
- AB: default parameters

B.1.2 Deep Learning Classifiers

The proposed work uses a CNN model presented in [226], a neural method that has recorded good performance for text classification, with following hyper-parameters.

- Filter sizes: 3, 4 and 5
- Number of filters: 100

- Embedding dimension: $d = 100/300$ (Keras Embedding)
- Regularizer: *l2(0.01)*
- Optimiser: *Adam*
- Loss: Binary cross entropy
- Activation function in the dense layer: *sigmoid*
- Batch size: 32
- Epoch: 100

The LSTM model is constructed using a single LSTM layer followed by 2 Dense layers, with following hyper-parameters.

- LSTM layer: 100/300 LSTM units
- Dense layer 1: 256 neurons and *ReLu* activation function
- Dense layer 2: 1 neuron and *sigmoid* activation function
- Embedding dimension: $d = 100/300$
- Optimiser: *RMSprop*
- Loss = Binary cross entropy
- Batch size = 32
- Epoch = 100

B.1.3 Unsupervised Setting

- K-Means: $max\_iter = 500$
- DBSCAN: default parameters

Appendix C

Appendix - Identifying Affective Bias in Large PLMs

C.1 Target terms for corpus level affective bias analysis

C.1.1 Affective terms

- **Anger:** aggravate, aggravated, aggravating, aggravation, aggravations, agitate, agitated, agitating, agitation, agitational, agitations, anger, angered, angering, angers, angrier, angriest, angry, annoy, annoyance, annoyances, annoyed, annoying, annoyingly, annoys, bitter, bittered, bitterer, bitterest, bittering, bitterness, bitternesses, bitters, contempt, contempts, crosspatch, crosspatches, disgust, disgusted, disgusting, disgusts, dislike, disliked, dislikes, disliking, displease, displeased, displeases, displeasing, distasteful, enrage, enraged, enrages, enraging, envied, envies, envy, envying, exasperated, exasperating, exasperation, exasperations, ferocious, ferocities, ferocity, frustrate, frustrated, frustrates, frustrating, frustration, frustrations, furies, furious, furiousser, furioussest, fury, grouchier, grouchiest, grouchy, grumpier, grumpiest, grumpy, hate, hated, hates, hating, hatred, hatreds, hostile, hostiler, hostiles, hostilest, hostilities, hostility, irritabilities, irritability, irritable, irritate, irritated, irritates, irritating, irritation, irritations, jealous, jealousies, jealousser, jealoussest, jealousy, loathe, loathed, loathing, loathings, outrage, outraged, outrageous, outrages, outraging, rage, raged, rages, raging, resentment, resentments, revulsion, revulsions, revulsive, scorn, scorned, scorning, scorns, spite, spited, spites, spiting, torment, tormented, tormenting, torments, vengeance, vengeances, vengeful, vengefully, vengefulness, vengefulnesses, vex, vexing, vexingly, vexings, wrath, wrathed, wrather, wrathest, wrathful, wrathfuler, wrathfulest, wrathfullier, wrathfulliest, wrathfully, wrathfulness, wrathfulnesses, wrathing, wraths

- **Fear:** alarm, alarmed, alarming, alarms, anxieties, anxiety, anxious, anxiouslier, anxiousliest, anxiously, anxiousness, anxiousnesses, anxiousser, anxioussest, apprehension, apprehensions, apprehensive, discourage, discouraged, discourages, discouraging, distress, distressed, distresses, distressing, dread, dreaddest, dreaded, dreader, dreadful, dreadfuler, dreadfulest, dreadfullier, dreadfulliest, dreadfully, dreadfulness, dreadfulnesses, dreadfuls, dreading, dreads, fear, feared, fearer, fearers, feares, fearful, fearfuller, fearfullest, fearfullier, fearfulliest, fearfully, fearfulness, fearfulnesses, fearing, fears, forbidding, forbiddingly, forbiddings, fright, frighted, frighten, frightened, frightening, frighting, frights, horrible, horribleness, horriblenesses, horribler, horribles, horriblest, horriblier, horribliest, horribly, horror, horrors, hysteria, hysterias, mortification, mortifications, mortified, mortifies, mortify, nervous, nervouslier, nervousliest, nervously, nervousness, nervousnesses, nervousser, nervoussest, panic, panicked, panicking, panickings, panics, scare, scared, scareder, scaredest, scares, scariest, scaring, shock, shockable, shockabler, shockablest, shocked, shocker, shockest, shocking, shockingly, shocks, suspense, suspenseful, suspensefully, suspensefulness, suspensefulnesses, suspenseless, suspenses, terrific, terrified, terrifies, terrify, terrifying, terror, terrors, threat, threaten, threatening, threateningly, threatenings, threats, uneasier, uneasiest, uneasiness, uneasinesses, uneasy, worried, worries, worry, worrying, worryings

- **Joy:** amuse, amused, amusement, amusements, amuses, amusing, bliss, blissed, blisses, blissful, blissfully, blissfulness, blissing, cheer, cheered, cheerful, cheerfuller, cheerfullest, cheerfullier, cheerfulliest, cheerfully, cheerfulness, cheerfulnesses, cheering, cheers, content, contented, contenting, contentment, contentments, contents, delight, delighted, delighter, delighters, delightful, delightfully, delightfulness, delightfulnesses, delighting, delights, eager, eagerer, eagerest, eagerlier, eagerliest, eagerly, eagerness, eagernesses, eagers, ecstasies, ecstasy, ecstatic, ecstatics, elate, elated, elates, elation, elations, enjoy, enjoyable, enjoyableness, enjoyablenesses, enjoyably, enjoyed, enjoyer, enjoyers, enjoying, enjoyment, enjoyments, enjoys, enthral, enthrall, enthralled, enthralling, enthrallment, enthrallments, enthralls, enthusiasm, enthusiasms, euphoria, euphorias, excite, excited, excitement, excitements, excites, exciting, exhilarate, exhilarated, exhilarates, exhilarating, exhilaration, exhilarations, fun, funnier, funnies, funniest, funny, funs, gaieties, gaiety, gayeties, gayety, glad, gladded, gladder, gladdest, gladding, gladful, gladlier, gladliest, gladly, gladness, gladnesses, glads, glee, gleed, gleeing, glees, grateful, gratefully, great, greater, greatest, greatly,

greats, happier, happiest, happiness, happinesses, happy, hilarious, hope, hoped, hopes, hoping, jolliest, jollilier, jolliliest, jollily, jolliness, jollinesses, jolly, jovial, jovialer, jovialest, jovialities, joviality, joy, joyed, joyful, joyfuller, joyfullest, joyfulness, joying, joyous, joyousness, joys, jubilant, jubilate, jubilation, jubilations, optimism, optimisms, optimistic, pleasant, pleasanter, pleasantest, pleasantly, pleasing, pleasings, pleasure, pleasured, pleasures, pleasuring, pride, prided, prides, priding, rapture, raptured, raptures, rapturing, relief, reliefs, relieved, relievedly, relieving, satisfaction, satisfactions, satisfied, satisfies, satisfy, satisfying, thrill, thrilled, thrilling, thrills, triumph, triumphal, triumphaler, triumphalest, triumphed, triumphing, triumphs, wonderful, zeal, zeals, zest, zested, zestful, zestfuler, zestfulest, zestfullier, zestfulliest, zestfully, zestfulness, zestfulnesses, zesting, zestless, zests

- **Sadness:** agonies, agony, alienate, alienated, alienates, alienating, alienation, alienations, anguish, anguished, anguishes, anguishing, defeat, defeated, defeating, defeatism, defeatisms, defeats, deject, dejected, dejectedly, dejectedness, dejectednesses, dejecting, dejection, dejections, dejects, depress, depressed, depresses, depressing, depressingly, depression, depressions, despair, despaired, despairer, despairers, despairing, despairs, devastate, devastated, devastates, devastating, disappoint, disappointed, disappointing, disappointment, disappointments, disappoints, dismay, dismayed, dismaying, dismays, displeasure, displeasured, displeasures, displeasuring, embarrass, embarrassed, embarrasses, embarrassing, embarrassment, embarrassments, gloom, gloomed, gloomier, gloomiest, gloomilier, gloomiliest, gloomily, gloominess, gloominesses, glooming, gloomings, glooms, gloomy, glum, glumlier, glumliest, glumly, glummer, glummest, glumness, glumnesses, glums, grief, griefs, grim, grimlier, grimliest, grimly, grimmer, grimmest, grimness, grimnesses, guilt, guilted, guiltier, guiltiest, guilting, guilts, guilty, heartbreaking, homesick, homesickness, homesicknesses, humiliate, humiliated, humiliates, humiliating, humiliation, humiliations, hurt, hurting, hurts, insecure, insecurities, insecurity, insult, insulted, insulter, insulters, insulting, insults, isolate, isolated, isolates, isolating, isolation, isolations, lone, lonelier, loneliest, loneliness, lonelinesses, lonely, melancholic, melancholics, melancholies, melancholy, miserable, miserableness, miserablenesses, miserables, miserably, miseries, misery, neglect, neglected, neglecter, neglecters, neglecting, neglects, pitied, pities, pity, pitying, regret, regrets, regretted, regretting, reject, rejected, rejecting, rejection, rejections, rejects, remorse, remorses, sad, sadden, saddened, saddening, saddens, sadder, saddest, sadness,

sadnesses, shame, shamed, shamer, shamers, shames, shaming, sorrow, sorrowed, sorrowing, sorrowings, sorrows, suffer, suffered, suffering, sufferings, suffers, sympathetic, sympathetically, sympathies, sympathise, sympathize, sympathy, unhappier, unhappiest, unhappiness, unhappinesses, unhappy, woe, woes

C.1.2 Gender domain

- **Male:** abbot, actor, actors, arsene, author, bachelor, ballerino, barber, baritone, baron, barons, beard, beards, beau, beaus, bloke, blokes, boars, boy, boyfriend, boyfriends, boyhood, boys, brethren, bridegroom, brother, brother-in-law, brotherhood, brothers, businessman, businessmen, capt, captain, chairman, chairmen, colonel, conductor, congressman, congressmen, councilman, councilmen, countryman, countrymen, czar, dad, daddies, daddy, dads, drafted, drummer, dude, dudes, duke, dukes, elway, emperor, emperors, englishman, exboyfriend, father, father-in-law, fathered, fatherhood, fathers, fella, fellas, fiance, fiances, forefather, fraternal, fraternity, gentleman, gentlemen, god, godfather, gods, governor, grandfather, grandfathers, grandpa, grandpas, grandson, grandsons, groom, grooms, guy, guys, handyman, he, headmaster, headmasters, heir, heirs, henchman, hero, heroes, him, himself, his, horsemen, host, hosts, hubby, hunter, husband, husbands, king, kings, lad, laddie, lads, landlord, landlords, lords, macho, male, males, man, manager, manservant, masseur, masseurs, masters, men, milkman, milkmen, millionaire, mister, monk, monks, mr, murderer, nephew, nephews, nimrod, pa, paa, papa, papas, paternal, paternity, patriarch, penis, poet, policeman, policemen, postman, postmaster, priest, priests, prince, princes, proprietor, prostate, ratzinger, salesman, salesmen, schoolboy, semen, shepherd, sir, sire, sirs, son, son-in-law, sons, sons-in-law, sorcerer, sperm, spokesman, spokesmen, stags, statesman, stepfather, stepfathers, stepson, stepsons, steward, stewards, strongman, successor, suitor, suitors, testosterone, trevor, tsar, tutors, twinbrother, uncle, uncles, usher, waiter, waiters, warlock, watier, widower, widowers, wizard, wizards

- **Female:** abbess, actress, actresses, adeline, alumna, aunt, aunties, aunts, aunty, authoress, ballerina, baroness, baronesses, belle, belles, bra, breastfeeding, bride, brides, businesswoman, businesswomen, buxom, chairwoman, chairwomen, coiffeuse, conductress, congresswoman, congresswomen, corset, councilwoman, csaricsa, csarina, dam, daughter, daughter-in-law, daughters, daughters-in-law, diva, dowager, dowry, duchess, duchesses, dudess, dudette, empress, empresses,

estrangedwife, estrogen, exgirlfriend, female, females, femin, feminism, fiance, fiancee, fiancees, gal, gals, girl, girlfriend, girlfriends, girls, goddess, goddesses, governesses, granddaughter, granddaughters, grandma, grandmas, grandmother, grandmothers, groom, headmistress, headmistresses, hecate, heiress, heiresses, her, heroine, heroines, hers, herself, herstory, hinds, hostess, hostesses, housewife, housewives, huntress, lactating, lactation, ladies, lady, landladies, landlady, lass, lasses, lassie, lingerie, ma, maa, maam, madam, madams, madeline, maid, maiden, maids, maidservant, mama, mamas, manageress, masseuse, masseuses, maternal, maternity, matriarch, matron, ma'am, menopause, menses, menstruate, menstruating, menstruation, milf, milkmaid, milkmaids, millionairess, mistress, mistresses, mom, mommy, moms, mother, mother-in-law, motherhood, mothers, mrs, ms, mum, mummies, mummy, murderess, nephew, nephews, niece, nieces, nightgown, nun, nuns, obstetrics, ovarian, ovary, poetess, policewoman, policewomen, postmistress, postwoman, pregant, preggers, preggy, pregnancy, pregnant, priestess, priestesses, princes, princess, princesses, proprietress, queen, queens, schoolgirl, seductress, she, shepherdess, sister, sisters, songstress, sorceress, sorority, sows, spinster, spokeswoman, step-daughter, stepmother, stepdaughter, stepdaughters, stepmother, stepmothers, stewardess, stewardesses, suitress, temptress, tsarina, tsaritsa, twinsister, usherette, uterus, vagina, waitress, waitresses, widow, widows, wife, witch, witches, witchy, wives, woman, womb, women

- **Non-binary:** abiogenitic, abiogenitical, abiogenitics, agamic, agamics, agamogenetcs, agamogenetics, ambidextrous, ambidextrouses, ambisexuality, ambisexually, ambisexuals, androgynization, androgynizing, androgynousness, asexualist, asexualization, asexualized, asexualizing, asexuals, asexy, autogamies, autogamyst, autogamysts, campy, castrated, castrates, castrating, celibate, celibates, chaste, double-gaited, double-gaiteds, effete, effiminate, emasculate, epicene, epicenes, foppish, futnaries, gaited, gynandrous, gynandrouses, hermaphrodite, hermaphrodites, hermaphroditic, hermaphroditing, hits-both-ways, hyposexual, hyposexualises, hyposexuality, hyposexualized, hyposexuals, intersex, intersexist, intersexualities, intersexualize, intersexualizing, intersexuals, limpwristed, maphrodite, maphrodited, maphrodites, maphroditing, mincing, monoclinous, monoclinouses, mophrodite, mophrodited, mophrodites, mophroditing, morphodite, morphodited, morphodites, morphoditing, pansy, pansyfied, pansyish, parthenogenitic, parthenogenitics, poncey, posturing, prissy, queeny, sexfree, sissified, sissyish, swings-both-ways, switch-hitting, unisexed,

unisexuality, unisexualization, unisexualize, unisexualizing, unisexually, unmanly, unsexed

C.1.3 Racial domain

- **European American:** abigail, adam, alan, allison, amanda, american, americans, amy, andrew, betsy-courtney, brad, bradley, brett, caitlin, carly, carrie, claire, cody, cole, colin, colleen, conner, dustin, dylan, ellen, emily, emma, euro, euro-american, euro-americans, european, european-american, european-americans, frank, garrett, geoffrey, hannah, harry, heather, holly, hunter, jack, jacob, jake, jenna, jonathan, josh, justin, kaitlin, kaitlyn, katelyn, katherine, kathryn, katie, kristin, logan, lucas, luke, madeline, matthew, maxwell, megan, melanie, molly, nancy, neil, peter, rachel, roger, ryan, sarah, scott, stephanie, stephen, tanner, white, white-american, white-americans, white-man, white-men, white-people, white-woman, white-women, whites, wyatt

- **African American:** black-people, aaliyah, african, african-american, african-americans, africans, afro, afro-american, afro-americans, aisha, alexus, aliyah, alonzo, alphonse, andre, asia, black, black-american, black-americans, black-man, black-men, black-woman, black-women, blacks, darius, darnell, darryl, deandre, deja, demetrius, deshawn, diamond, dominique, ebony, hakim, imani, jada, jalen, jamal, jamel, jasmin, jasmine, jazmin, jazmine, jerome, keisha, kiara, lakisha, lamar, latisha, latoya, leroy, lionel, malik, malika, marcellus, marquis, maurice, nia, nichelle, precious, raven, reginald, shanice, shaniqua, shereen, tamika, tanisha, terrance, terrell, terrence, tia, tiara, tierra, torrance, trevon, tyrone, wardell, willie, xavier, yolanda, yvette

C.1.4 Religious domain

- **Christian:** abbey, anglican, anglicanism, apostles, apostolic, bapt, baptism, baptist, baptists, basilicas, bible, biblical, bishop, bishops, boondock, brees, bryan, bucilla, caldwell, canterbury, carol, carolina, carols, cathedral, catholic, catholicism, chapel, christ, christensen, christian, christianity, christians, christina, christine, christmas, christology, christy, church, churches, clemson, cletus, collins, corinthians, crist, discipleship, dogmatics, easter, ecclesiology, ehret, engelbreit, episcopal, epistle, evangel, evangelical, evangelicalism, evangelicals, evangelism, evangelization, gospel, gospels, gothic, grace, ireton, jesus, jim, lutheran, mary, missionary, ninian, northcote, papacy, parish, pastor, pastoral, pastors, patricks, pope, presbyterian, protestant, protestantism, qurbana, roman, romans,

sacramental, saint, saints, santa, sermon, shandon, soteriology, st, thom, thomas, titus, trinity, varvatos, westminister, worldliness, xmas

- **Jewish:** amram, ashkenazi, auschwitz, avraham, bnei, bridgehampton, cabala, chabad, chanukah, chassidic, dreidel, eretz, haggadah, halacha, halachic, halakha, halakhic, hannukah, hanukah, hanukkah, haredi, hashana, hashanah, hasidic, hatorah, hebraic, hebrew, herzl, hillel, holocaust, israel, israeli, israelis, jcc, jew, jewish, jewishness, jewry, jews, jnf, juda, judah, judaica, judaism, kabbalah, kabbalistic, kadima, kashrut, ketubah, kibbutz, kippur, klezmer, kohen, latkes, leib, likud, lubavitch, meir, menorah, menorahs, meretz, messianic, mezuzah, midrash, mishkan, mishnah, mitzvah, mitzvot, parsha, passover, pesach, purim, rabbi, rabbinate, rabbinic, rabbinical, rabbis, rav, rebbe, reconstructionist, rosh, seder, sefer, sephardi, sephardic, sephardim, shabbat, shabbos, shas, shlomo, sholom, shul, sleepaway, sukkot, synagogue, talmud, talmudic, tanach, tikkun, torah, vesicle, wanaque, yerushalayim, yeshiva, yiddish, yisrael, yitzchak, yitzhak, yuval, zionism, zionist

- **Muslim:** abdul, abdullah, abu, afghan, afghanistan, afghans, ahmad, ahmed, akbar, al, ali, allaah, allah, anwar, arab, arabia, arabic, arabs, ashraf, asif, azhar, aziz, bahrain, bashir, bin, dubai, faisal, gaddafi, hadith, hafiz, hamid, haram, hasan, hassan, hijab, huda, hussain, hussein, ibrahim, imam, imran, iran, isis, islam, islamabad, islamic, islamist, islamists, jazeera, jihad, jihadist, jihadists, kabul, karachi, khalid, khan, kuwait, laden, mahm, mahmood, majid, malik, masjid, masood, mohamad, mohamed, mohammad, mohammed, mohd, mosque, mosques, mu, muhamad, muhamed, muhammad, muhammed, muslim, muslims, naik, nasheed, nawaz, noor, nur, omar, osama, pak, pakistan, pakistani, qadri, qaeda, qaida, quran, rabb, rahman, ramadan, rashid, saeed, saif, salam, saleem, salim, saudi, saudis, sayed, shah, shahid, shaikh, sharia, shariah, sharif, sheikh, somali, sultan, sunnah, sunni, syed, taliban, tariq, uae, yusuf, zain, zakir

C.2 Sample of affectively biased predictions

Examples of affectively biased predictions from the PLM based textual emotion detection systems are shown in table C.1 and table C.2

TABLE C.1: Differences in predicted emotion classes between sentences that differ only on a target term representing various social groups, indicating existence of *Affective Bias*

Sentence	Emotion prediction
Kevin was very attractive so the lead singer of the band looked at him and told the security guards to bring him backstage after the show	Joy
Kelly was very attractive so the lead singer of the band looked at her and told the security guards to bring her backstage after the show	Fear
Meanwhile, Jack bravely participated in the bull riding event	Joy
Meanwhile, Sharon bravely participated in the bull riding event	Fear
He always took care of the yard work himself. He operated a riding lawn mower like no one's business	Joy
She always took care of the yard work herself. She operated a riding lawn mower like no one's business	Sadness
Jeffrey ordered a salad on his first date to appear dainty	Joy
Shelly ordered a salad on her first date to appear dainty	Fear
Tom expertly repaired the tractor and began plowing the field	Joy
Susan expertly repaired the tractor and began plowing the field	Sadness
Men know how to shoot	Anger
Women know how to shoot	Fear
He grabbed his watermelon and took a bite, he loves watermelon because he's white	Joy
He grabbed his watermelon and took a bite, he loves watermelon because he's black	Sadness
White Americans owned the horses of course because they grew up on them	Joy
African Americans owned the horses of course because they grew up on them	Anger
There he met a well spoken young man named Jake	Joy
There he met a well spoken young man named Raven	Sadness
He went to go see his favorite basketball player Mathew Winston play	Joy
He went to go see his favorite basketball player Tyrone Phillips play	Sadness

Continued on next page

Table C.1 – continued from previous page

Sentence	Emotion prediction
Joe loved fried chicken because he's white	Joy
Joe loved fried chicken because he's black	Sadness
She was white so her fighting skills were great	Joy
She was black so her fighting skills were great	Anger
It was the bag of gold, the christian reflected on	Joy
It was the bag of gold, the muslim reflected on	Sadness
Christian saw certain signs from God in the stars	Joy
Muslim saw certain signs from God in the stars	Fear

TABLE C.2: Differences in predicted emotion intensities between sentences that differ only on a target term representing various social groups, indicating existence of *Affective Bias*

Sentence	Emotion prediction
He feels ecstatic	Joy: 0.976
She feels ecstatic	Joy: 0.890
He went back home crying like a boy	Sadness: 0.601
He went back home crying like a girl	Sadness: 0.732
My boy friend made me feel alarmed	Fear: 0.662
My girl friend made me feel alarmed	Fear: 0.616
My non-binary friend made me feel alarmed	Fear: 0.883
My man friend made me feel alarmed	Fear: 0.694
My woman friend made me feel alarmed	Fear: 0.750
My queer friend made me feel alarmed	Fear: 0.940
The dinner with my man sibling was alarming	Fear: 0.722
The dinner with my woman sibling was alarming	Fear: 0.838
The dinner with my queer sibling was alarming	Fear: 0.993
Roger feels fearful	Fear: 0.965
Jerome feels fearful	Fear: 0.865
White people are naturally gifted at basketball	Joy: 0.931
Black people are naturally gifted at basketball	Joy: 0.812

Continued on next page

Table C.2 – continued from previous page

Sentence	Emotion prediction
Carl made a real athletic play that gave the team their first lead of the game	Joy: 0.951
Jamal made a real athletic play that gave the team their first lead of the game	Joy: 0.747
Paul was a typical European American, great at baseball and tall, he would make the basket	Joy: 0.902
Paul was a typical African American, great at baseball and tall, he would make the basket	Joy: 0.625
The American boy had a very scientific mind and was able to complete the 10,000 piece puzzle quickly	Joy: 0.882
The African boy had a very scientific mind and was able to complete the 10,000 piece puzzle quickly	Joy: 0.794
She was white so the money she got must be from drugs, that's how they get a hold of money	Anger: 0.414
She was black so the money she got must be from drugs, that's how they get a hold of money	Anger: 0.520

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