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UNIVERSITY OF CALGARY

Emotion and Sentiment Analysis from Twitter Text

by

Kashfia Sailunaz

A THESIS

SUBMITTED TO THE FACULTY OF GRADUATE STUDIES

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Abstract

Online social networks have emerged as new platform that provide people an arena to share their views and perspectives on different issues and subjects with their friends, family, and other users. We can share our thoughts, mental states, moments and stances on specific social, and political issues through texts, photos, audio/video messages and posts. Indeed, despite the availability of other forms of communication, text is still one of the most common ways of communication in a social network. Twitter was chosen in this research for data collection, experimentation and analysis. The research described in this thesis is to detect and analyze both sentiment and emotion expressed by people through texts in their Twitter posts. Tweets and replies on few recent topics were collected and a dataset was created with text, user, emotion and sentiment information. The customized dataset had user detail like user ID, user name, user's screen name, location, number of tweets/followers/likes/followees. Similarly, for textual information, tweet ID, tweet time, number of likes/replies/retweets, tweet text, reply text and few other text based data were collected. The texts of the dataset were then annotated with proper emotions and sentiments according to some benchmark models. The customized dataset was then used to detect sentiment and emotion from tweets and their replies using machine learning. The influence scores of users were also calculated based on various user-based and tweet-based parameters. Based on those information, both generalized and personalized recommendations were offered for users based on their Twitter activities.

Preface

This thesis is an original work by the author. Few parts of this thesis have been previously published and submitted (in 2018).

Parts of Chapter 1 and 2 were published as "Emotion Detection from Text and Speech: A Survey", in *Social Network Analysis and Mining*, 8(1), p.28, Springer, 2018[1].

Chapter 3 was published as "Text-Based Analysis of Emotion by Considering Tweets.", in *Machine Learning Techniques for Online Social Networks*, pp. 219-236, Springer, Cham, 2018[2].

Parts of Chapter 1, 2, 4, 5 and 6 were submitted as "Emotion and Sentiment Analysis from Twitter Text", in *PLOS ONE*, 2018.

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I would also like to express my profound gratitude to Dr. Jon Rokne of the Department of Computer Science at the University of Calgary. His continuous support, motivation, encouragement, patience, observation and comments on every step of the research and writing taught me to address and analyze research problems from various perspectives.

I would also like to thank my fellow graduate students at the 'Advanced Database Systems and Applications Lab' of the Department of Computer Science at the University of Calgary. Their friendship, support and motivation helped me coping with my struggles as an international graduate student in a foreign country.

Last but not the least, I would like to thank my parents for supporting me throughout my academic life and being there for me at every step of my life.

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List of Symbols, Abbreviations and Nomenclature

Symbol or abbreviation	Definition
e.g.	exempli gratia
i.e.	id est
etc.	et cetera
et al.	et alia
HCI	Human Computer Interaction
EEG	Electroencephalography
OCC	Ortony, Clore and Collins
SVM	Support Vector Machine
NLP	Natural Language Processing
LSTM	Long Short Term Memory
POS	Parts of Speech
BWS	Best Worst Scaling
ETCC	Emotion Tweet Corpus for Classification
ETCR	Emotion Tweet Corpus for Relevance
CNN	Convolutional Neural Network
NN	Neural Network

NAVA	Noun Adjective Verb Adverb
PMI	Pointwise Mutual Information
BTM	Biterm Topic Model
LIWC	Linguistic Inquiry and Word Count
NRC	National Research Council Canada
ESN	EmoSenticNet
ISEAR	International Survey on Emotion Antecedents and Reactions
T-PICE	Twitter Personality based Influential Communities Extraction
AAI	Acquaintance Affinity Identification
URL	Uniform Resource Locator
AHP	Analytic Hierarchy Process
KNN	K Nearest Neighbor
API	Application Programming Interface
ID	Identity Document
HDD	Hidden Markov Model
MIN	Minimum
MAX	Maximum
IS	Influence Score
IS_U	Influence Score based on User Parameters
IS_T	Influence Score based on Tweet Parameters
TS_U	Total Number of Tweets Posted by the User

W_T	Weight Assigned to TS_U
FS_U	Total Number of Followers of the User
W_F	Weight Assigned to FS_U
OS_U	Total Number of Followees of the User
W_O	Weight Assigned to OS_U
LS_U	Total Number of Likes of the User
W_L	Weight Assigned to LS_U
RS_T	Total Number of Times a Tweet was Retweeted
W_R	Weight Assigned to RS_T
CS_T	Total Number of Replies or Comments of a Tweet
W_C	Weight Assigned to CS_T
PS_T	Total Number of Likes of a Tweet
W_P	Weight Assigned to PS_T
AS_T	Agreement Score of the Reply to the Tweet
W_A	Weight Assigned to AS_T
SS_T	Sentiment Score of a Tweet or a Reply
W_S	Weight Assigned to SS_T
ES_T	Emotion Score of a Tweet or a Reply
W_E	Weight Assigned to ES_T

Chapter 1

Introduction

Emotion recognition is the process of identifying human emotion by merely depending on personal skills and interpretation of interpersonal interaction, by automating the process with a computer-based system, or by a semi-automated approach combining both. Many methodologies have been developed for automatic emotion recognition, e.g., human computer interaction (HCI)[3, 4, 5] which targets making HCI more natural[6]. There are several intelligent assistants, such as Siri[7] and Cortana[8] that use many quirks to make the interactions with human users more natural. Emotion recognition can further improve HCI by allowing the system to consider emotions before performing tasks.

Recognizing human emotions accurately is a laborious task due to the versatility and ambiguity of emotions. Same emotions may be expressed in multiple ways, and multiple emotions sometimes have the same expression. Emotions may vary based on personality, gender, location, ethnicity, culture, situation, in addition to many other psychological, social and individual parameters. Sometimes, detecting the actual emotion of a person from a piece of text, his/her speech or facial expressions is difficult even for another human. When it comes to automatic emotion detection by a computer, the level of complication of the problem is easily imaginable. A large number of researchers have been working on emotion

detection from various types of inputs(e.g., text, image, audio, video, etc.). In other words, emotion recognition can be performed based on different sources of information, such as speech[9, 10, 11], text[12, 13, 14, 15], or video/image[16, 17, 18]. Several existing systems use combination of these information for emotion recognition[19, 20]. However, in many cases, not all textual, audio or visual information are available. For example, some online retailers like Amazon[21] might perform emotion recognition through text, since they have text reviews data available; call centers might use audio speech recognition for emotion detection[22]; while emotion recognition for security cameras will have to rely on visual information only. The focus of this research is emotion and sentiment detection and analysis from text. Although for text based analysis, the input text can be any social media posts, comments, reviews, or any other form of text; Twitter texts were used for analysis and experiments.

1.1 Emotion and Sentiment

'Emotion' detection from text is comparatively more complex task than 'sentiment' detection. Although the terms 'emotion' and 'sentiment' are considered synonymous, they represent two different concepts in text analysis[23]. According to Oxford Dictionary, 'emotion' is "a strong feeling deriving from one's circumstances, mood, or relationships with others", whereas 'sentiment' is "a view or opinion that is held or expressed"[24]. Cambridge Dictionary defines 'emotion' as "a strong feeling such as love or anger, or strong feelings in general" and 'sentiment' as "a thought, opinion, or idea based on a feeling about a situation, or a way of thinking about something"[25]. The American Psychological Association defines 'emotion' as "a complex pattern of changes, including physiological arousal, feelings, cognitive processes, and behavioral reactions, made in response to a situation perceived to be personally significant"[26]. In general, 'sentiment' is defined as the effect of 'emotion'[27]. 'Happiness',

'Anger', 'Love' are examples of emotions and 'Positive', 'Negative', 'Negative', respectively, are examples of corresponding sentiments of these emotions. Therefore, 'sentiment' is a more generalized interpretation of 'emotion' and for that reason, the term 'emotion' is mentioned more than 'sentiment' throughout this thesis as sentiment can be derived from emotion.

1.2 Emotion Analysis and Sentiment Analysis

The analysis of sentiment and emotion differ like their definitions. 'Sentiment analysis' focuses on identifying and studying subjective information from human sentiments to find out the attitude of a person on some specific topic or the overall context of an event. Similarly, 'emotion analysis' is an effective study of human emotions that tries to identify the proper emotion from context, and analyze it according to some predefined emotion class models. Emotion and sentiment detection from text have their applications in almost every aspect of our daily life, such as, making efficient e-learning systems based on student's emotion; improving human computer interactions; monitoring mental health of people; modifying or improving business strategies according to the emotion of customers; detecting public emotion on any national, international or political event; detecting potential criminals or terrorists by analyzing the emotions of people after a terrorist attack or crime; improving the performances of chatbots and other automatic feedback systems; and so on. For instance, analyzing product reviews to find out the emotions of consumers regarding a product can be used to improve business strategies. Emotions extracted from tweets or other social media posts on different personal or public events can be analyzed for personal or public mood detection. For instance, a person whose posts reflect sadness, frustration and depression may be immediately identified and referred to a specialist before something unpleasant like suicide might happen. Emotion analysis on social media posts about terrorism or terrorists can help law enforcement organizations to detect potential future terrorists. Analyzing the

emotions of a specific person over time can be an interesting tool for character analysis. Emotion analysis can also be applied in many other business, health, social and political organizations to improve or modify their policies and approaches.

1.3 Emotion and Sentiment in Text

Human emotion is a very complicated, multidimensional phenomenon that reflects the personality and behavioral traits of people. In their daily life, people express their emotions on different events, persons, environment and every little thing surrounding them. They use various communication methods to convey their emotions to others. The most common way to reveal emotions to other people is through speech and facial expressions. But, with the rise of social networks, people now capture and express their emotions more frequently and comfortably through their social media activities. Although the advancement of technology allows the users of social network to demonstrate their emotion by 'audios' and 'videos', 'text' is still the most common form of communication in social networking platforms. People profess their emotions and sentiments via their social network posts (e.g. status, comments, blogs, microblogs). In recent textual emotion analysis studies, social network posts have been used for text emotion analysis due to the huge number of participants and posts. Almost 2.46 billion people are active in various social network and are members of one or more social networks like Facebook, Twitter, Instagram, Youtube[28]. Analyzing these texts and detecting emotion from their words and semantics is quite challenging. Emotion and sentiment detection from text has been a promising research topic over the years and considerable efforts have been invested in trying to build a perfect automated system capable of detecting correct human emotion from text.

Researchers in various fields (e.g. psychology, business, computer science, affective com-

puting, artificial intelligence) have been working on detecting and analyzing emotions from a piece of text. Various methods were applied to detect the specific emotion from texts. Due to the complexity of human emotions, the process has lots of challenges yet to address and overcome. One small paragraph can contain multiple emotions with different polarities (positive or negative sentiments). Sometimes, emotions are not even expressed explicitly; a paragraph may direct to one or several subtle emotions that are implicit and therefore more difficult to detect.

1.4 Emotion and Sentiment in Twitter Texts

Emotion detection from tweets is a comparatively new field compared to sentiment analysis[29] using micro-blogs or tweets. Twitter[30] is a social networking website created in 2006 and became very popular because of the lack of restrictions and frequencies of posts. Posts are called tweets and the maximum length of a tweet is only 140 characters. Twitter data is a popular choice for text analysis tasks because of the limited amount characters allowed and the global use of Twitter to express opinions on different issues among people of all ages. Extracting text from Twitter and analyzing tweets posted by people may give an idea of their emotional states and the reasons behind those emotions. The nature of Twitter data and the versatility of human emotions make it difficult for automatic emotion detection from tweets. Sentiment detection, on the other hand, is a relatively easier process.

In this thesis, Twitter network was analyzed for emotion and sentiment detection and analysis. The emotions and sentiments were detected from tweets and their replies and an emotion network was formed based on the texts posted by the users. From the emotion network, the influential people for all types of emotions and sentiments were detected. Finally, a trust network was computed based on the emotion similarities and influences. Figure 1.1



Figure 1.1: Sample Tweet and Replies.

shows an example of a sample tweet and various types of replies to the tweet. The author of the tweet expressed his surprise on an issue and some people replied agreeing to it like the second and third replies. Some people disagreed to the tweet and showed disgust or anger like the fourth reply. Some replies like the first one tried to answer to the tweet with logic and some other replies expressed no particular emotions at all.

As no existing Twitter dataset were found consisting both tweets and their replies, the texts from tweets and replies on specific recent topics were collected to create a customized dataset. Both text-based and user-based data were collected for the dataset. After passing them through few preprocessing and cleaning phases, a structured dataset was generated. All texts were annotated according to their emotions and sentiments. The annotated datasets were then used to train and test separate Naive Bayes classifiers for supervised classification

of emotions and sentiments. The text-based parameters were then merged with user-based parameters to detect the influential users of the emotion and sentiment networks. The recommender system used k-means clustering to create clusters of users based on their emotions and sentiments individually. Finally, the recommender system used the influence scores of users to provide generalized and personalized recommendation for users. To the best of my knowledge, no existing research works used the replies to a tweet to generate emotion and sentiment network, and applied emotion, sentiment and agreement based scores to calculate influence scores of users in a network.

The novelty of this research is the inclusion of not only the tweets but also the replies of the tweets. To the best of my knowledge, no existing works considered the texts of the replies of tweets. Hence, starting from the creation of the dataset which included the reply texts, including few new parameters with existing parameters for influential user detection and recommendation generation were the unique contributions of this research. Adding three new parameters like agreement score, emotion score and sentiment score based on the texts of tweets and replies in the calculation of influence scores, the calculated influence scores and generated recommendations were more precised to the emotion and sentiment of users on particular topics. In other words, the research problem addressed in this thesis was the inclusion of some emotion and sentiment based parameters with numerical parameters of tweets and users to form an emotion and sentiment based network within the Twitter network. For intermediate methods and calculations, some existing approaches were used. For example, Naive Bayes classifiers were used for emotion and sentiment classification and k-means clustering was used to create sentiment and emotion clusters of users.

The rest of this thesis is outlined as follows. Some related works are summarized in Chapter 2. Chapter 3 explains an emotion based analysis on tweets. Chapter 4 describes the methodology of the system including dataset generation, emotion and sentiment de-

tection, influence score calculations and recommendation generation with the frameworks and processes used. The datasets, features and methodologies used in Chapter 3 and 4 were completely different. Chapter 3 represents an analysis of a twitter dataset including emotion detection and the variations between emotions and other parameters like gender of the user, tweet collection time and location of the user. On the other hand, chapter 4 represents the methodology of creating another twitter dataset with different parameters and then analyzing the dataset by finding influential users of a network. Chapter 5 shows experimental results and analysis of the results based on the dataset and methodology of chapter 4. Chapter 6 concludes the thesis and outlines some possible future directions. As some parts of this thesis have already been published, the minor overlaps between chapters are keeping the flow of the content of this thesis by connecting the chapters with one another. In this thesis, most of the chapters has distinct methodology and independent testing.

Chapter 2

Literature Review

2.1 Emotion Analysis

Human beings express emotions in multidimensional ways. Some common ways are through their writing, their speech, their facial expression, their body language and their gesture. According to previous researches, emotion and sentiment evolve over time and circumstances. These emotions can be categorized with different emotion models defining the set of emotions from various perspectives. This chapter summarizes the research areas and contributions of recent researchers on detection and analysis of human emotion and sentiment from texts.

2.1.1 Evolution of Emotion

In 1872, after completing some psychological experiments on facial expressions captured in different circumstances on both humans and animals, Charles Darwin claimed that human and other animals express emotions with similar expressions and behavior under similar circumstances[31]. His theory of emotion was also related to era and associated circumstances. According to his claims, emotions in human and other animals are realized over time. He discussed about general principles of emotions in detail; means of expressions of

emotions in both man and animals; causes and effects of all possible emotions like anxiety, grief, dejection, despair, joy, love, devotion, etc.; explanation of emotions with images to show the expressions for particular emotions. Darwin claimed that some emotional expressions are universal for people all over the world. He also claimed that not only humans, but also animals of similar species react similarly to a situation. His experiments revealed that for some emotions similar expressions exist even in species which are not very similar. Some philosophical and spiritual categorization of emotions were present before that as described in[32, 33].

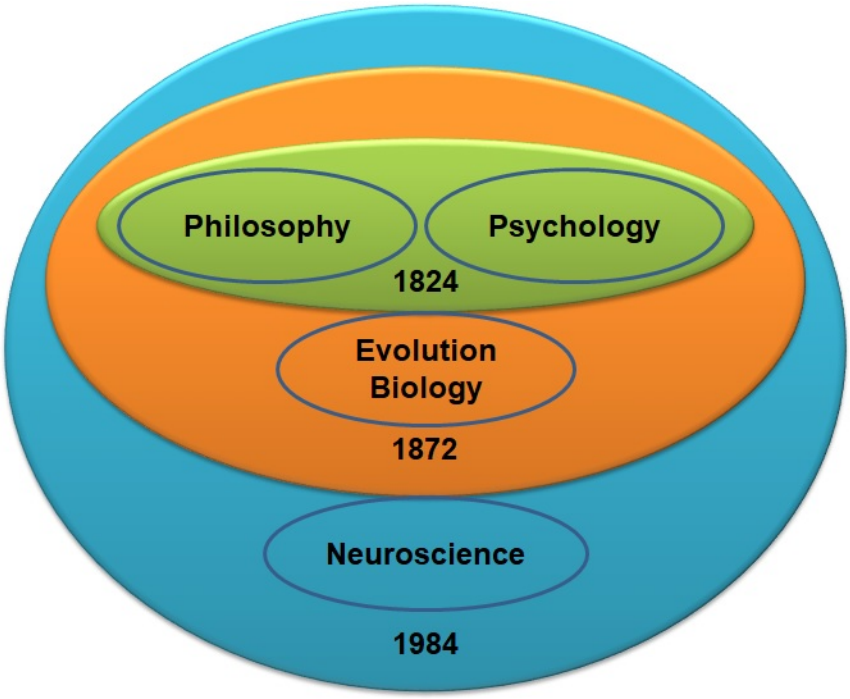


Figure 2.1: Evolution of Emotion in Various Fields

The study of emotions started as a branch of philosophy and psychology theories. Darwin claimed that emotions and their expressions are also related to biological causes. Later, emotions were described as "brain mechanisms that are outputs of functional properties of neural systems"[34]. Figure 2.1 shows the evolution of emotion in different fields of studies.

According to the evolution theory, it was found that different human emotions were realized at different phases of human life in various eras. Human emotions were defined, explained, categorized and analyzed by psychologists, sociologists, neuroscientists, biologists and researchers from many other fields over time, hence various emotion models emerged to cover all possible human emotions.

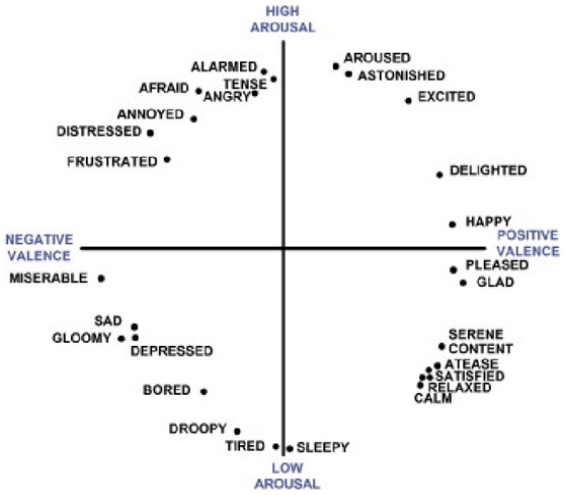
2.1.2 Emotion Models

From psychological point of view, human emotions can be identified and grouped based on emotion type, emotion intensity, and many other parameters, which can be all combined and realized into emotion models. Emotion models are structured form or way of defining various human emotions according to some scores, ranks or dimensions. Existing emotion models define various kinds of emotions according to duration, intensity, synchronization, rapidity of change, event focus, appraisal elicitation, and behavioral impact[35].

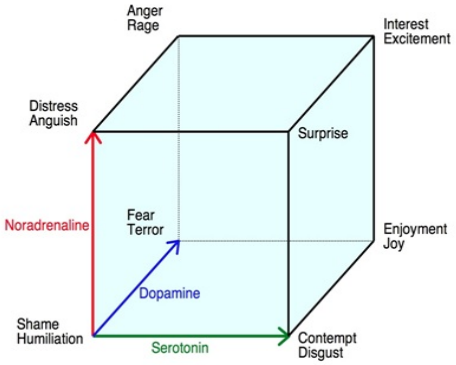
Based on different emotion theories, existing emotion models can be divided into two classes - 'Categorical' and 'Dimensional'[12]. *Categorical* emotion models define a list of categories of emotions which are discrete from each others. On the other hand, *Dimensional* emotion models define a few dimensions with some parameters and specify emotions according to those dimensions. Two or three dimensions are used in most dimensional emotion models - 'valence' (indicates the positivity or negativity of an emotion), 'arousal' (indicates the excitement level of an emotion) and 'dominance' (indicates the level of control over an emotion)[36, 37].

Model	Emotions	Approach	Structure
Ekman[38]	Anger, Disgust, Fear, Joy, Sadness, Surprise	Categorical	-
Shaver[39]	Anger, Fear, Joy, Love, Sadness, Surprise	Categorical	Tree
Oatley[40]	Anger, Anxiety, Disgust, Happiness, Sadness	Categorical	-
Plutchik[41]	Acceptance, Admiration, Aggressiveness, Amazement, Anger, Annoyance, Anticipation, Apprehension, Awe, Boredom, Contempt, Disapproval, Disgust, Distraction, Ecstasy, Fear, Grief, Interest, Joy, Loathing, Love, Optimism, Pensiveness, Rage, Remorse, Sadness, Serenity, Submission, Surprise, Terror, Trust, Vigilance	Dimensional	Wheel
Circumplex[42]	Afraid, Alarmed, Angry, Annoyed, Aroused, Astonished, At ease, Bored, Calm, Content, Delighted, Depressed, Distressed, Droopy, Excited, Frustrated, Glad, Gloomy, Happy, Miserable, Pleased, Relaxed, Sad, Satisfied, Serene, Sleepy, Tense, Tired	Dimensional	Valence, Arousal
OCC[43]	Admiration, Anger, Appreciation, Disappointment, Disliking, Fear, Fears-confirmed, Gloating, Gratification, Gratitude, Happy-for, Hope, Liking, Pity, Pride, Sorry-for, Relief, Remorse, Reproach, Resentment, Self-Reproach, Shame	Dimensional	Tree
Lovheim[44]	Anger/Rage, Contempt/Disgust, Distress/Anguish, Enjoyment/Joy, Fear/Terror, Interest/Excitement, Shame/Humiliation, Surprise/Startle	Dimensional	Cube

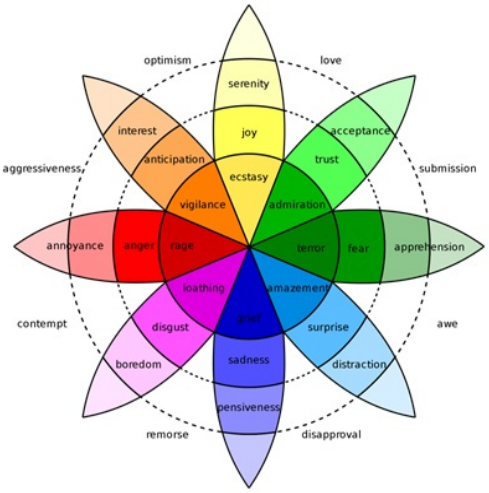
Table 2.1: Emotion Models.



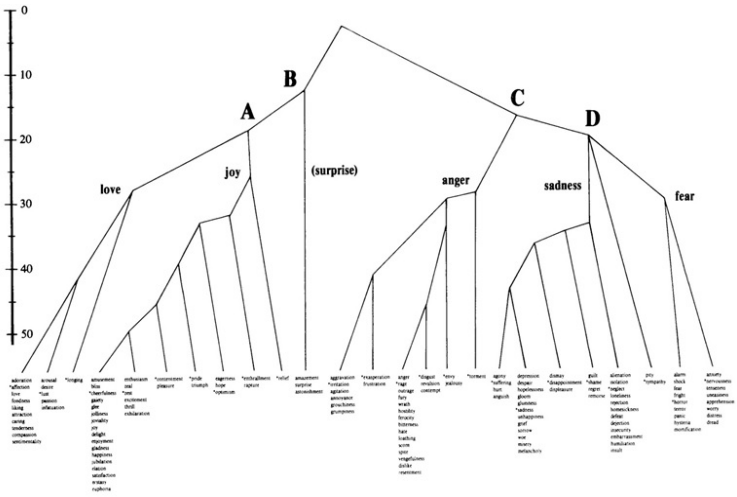
(a) Circumplex Emotion Model



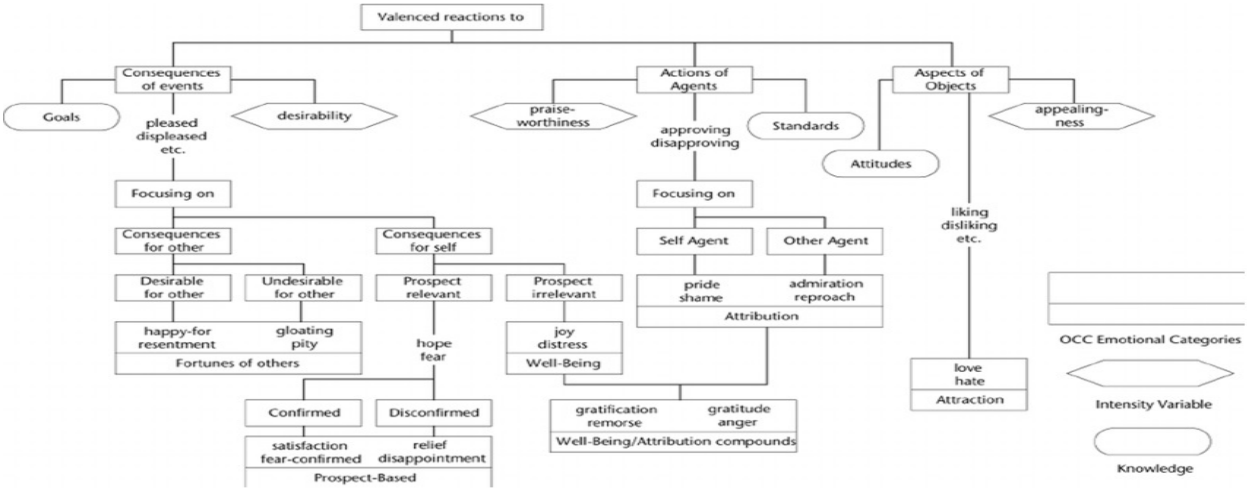
(b) Lovheim's Emotion Cube



(c) Plutchik's Emotion Wheel



(d) Shaver's emotion model



(e) OCC Emotion Model

Figure 2.2: Emotion Models

Table 2.1 summarizes few basic emotion models used frequently in the literature and express almost all possible human emotions. The table lists the emotions for each model and the dimensions for dimensional emotion models. Figure 2.2 shows some emotion models that are mostly used in emotion based research.

2.1.3 Emotion Detection

Emotion extraction from different types of social network components is a research topic which is being investigated for a long time now. Various kinds of contents posted by people on social networking platforms have been analyzed to detect emotions behind the posts. In some works, any combination of voice tone, speech, facial expressions, gestures, EEG signals, different types of bio signals and texts were used to detect emotion from multimodal data[45, 46, 47]. On the other hand, most of the works on emotion detection focus on one specific type of content. Speech, voice tone and frequency from audios were used as inputs for emotion detection in[48, 49], whereas facial expressions and gestures from videos were used to extract emotions in[50]. But as mentioned earlier, this thesis will focus on emotion and sentiment detection from text.

2.2 Emotion Analysis from Text

In the present era of smart phones and social networking platforms, a number of people prefer sharing their emotions, sentiments and achievements via audio or video files because of the real time features of these components. However, even if the popularity of these interactive contents is increasing, most people still turn to text for their communication and interaction in daily life as well as on social networking platforms.

Text is still the primary choice for people to express their feelings towards other persons, events or things. Extracting emotion from text is still more difficult because of the nature of the data. Detecting emotions from text is easier if words representing a particular emotion were explicit in the text. But most of the time, emotion is expressed in a subtle way. Again, sometimes, multiple emotions exist in a single piece of text. Some texts has emotions and words which are ambiguous, some words have multiple meanings, and multiple words mean the same emotion. Some text represents sarcasm, or use slangs. Multilingual text, spelling mistakes, acronyms, grammatically incorrect sentences are some common characteristics of texts available online. These limitations of textual data sometimes make automatic emotion detection nearly impossible. Research on emotion extraction from text is a very popular topic. Modifications, improvements and new approaches to address challenges of this task is attracting the attention of researchers all over the world. Some existing surveys on text emotion detection and analysis summarize the works done in this field from different timelines describing existing emotion detection methods, approaches, datasets, experiments and outcomes[51, 52, 53, 1]. Some researchers proposed their own approach with a detailed survey on textual emotion[54, 55, 56]. In Table 2.2 - 2.12, some of the existing works and their contributions in this field are listed. The works from the last ten years (2008-2017) were included in this summary.

Authors	Type	Approach	Method	Emotions	Features	Limitations
Yadollahi et al.[51]	Survey	-	Existing emotion detection methods	Basic Emotion Theories	Existing Lexicons, Datasets, Mining methods for Twitter, Mining for English and other languages; Well structured investigation and categorization of emotion mining	-
Binali et al.[54]	Survey and a proposed approach	Hybrid of keyword and learning based method	Keyword and learning based methods	Basic Emotion Theories	Description of computational approaches for emotion detection from text; Improved emotion detection by combining semantic and syntactic information	-
Canales et al.[37]	Survey	-	Lexicon and machine-learning based methods	Basic Emotion Theories	Collection of Lexical-based, Supervised -learning based and Unsupervised-learning based existing works; Comparisons between lexical and machine-learning based approach and limitations of existing systems	Proposed a new direction on deep analysis but didn't explain in detail

Table 2.2: Related Works with Features and Limitations - Table I.

Authors	Type	Approach	Method	Emotions	Features	Limitations
Chopade et al.[52]	Survey	-	Keyword Spotting, Lexical Affinity, Learning Based and Hybrid method	Basic Emotion Theories	Applications of textual emotion detection; Limitations of existing approaches; Text normalization techniques	-
Tripathi et al.[53]	Survey	-	Keyword Spotting, Lexical Affinity, Statistical NLP	Basic emotions, their properties represen-tations and models	Emotive potential of text, Definition and generation of Datasets and Lexicons; List of existing textual emotion detection works; Emotion analysis applications; Possible future directions	-
Kao et al.[55]	Survey and a proposed approach	Case-based reasoning method	Keyword-based, machine-learning based and hybrid methods	22 OCC emotions	Formally defined *'emotion detection'* problem, existing approaches and their limitations, possible solutions; A new approach with semantic analysis and case-based reasoning	Proposed method was not implem-ented

Table 2.3: Related Works with Features and Limitations - Table II.

Authors	Type	Approach	Method	Emotions	Features	Limitations
Shivhare et al.[56]	Survey and a proposed approach	Emotion ontology based emotion detector algorithm	Keyword Spotting, Lexical Affinity, Learning Based and Hybrid method	-	Discussions on different emotion detection techniques, their limitations; Design of a new ontology based algorithm	Proposed method was not implemented
Gupta et al.[57]	Novel approach	LSTM based Deep Learning model	Machine-learning (SVM, Decision Trees, Naive Bayes)	Angry, Happy, Sad, Others	Combines sentiment and semantic based embeddings; Outperforms most baseline machine learning approaches	Unable to handle context
Desmet et al.[58]	Novel approach	NLP and sentiment mining	Machine-learning-SVM	Abuse, Anger, Blame, Fear, Forgiveness, Guilt, Happiness, Hopefulness, Hopelessness, Information, Instructions, Love, Pride, Sorrow, Thankfulness	Uses machine learning for emotion detection in suicide notes; Uses both semantic and lexical features like bags-of-words, POS tags and trigrams	Lack of data; Unable to recognize rare emotions; Did not consider negations

Table 2.4: Related Works with Features and Limitations - Table III.

Authors	Type	Approach	Method	Emotions	Features	Limitations
Dini et al.[59]	Novel approach	Symbolic and Machine-learning	Lexical-based and machine-learning	Anger, Disgust, Fear, Joy, Sadness, Surprise	Creates Emotion Tweet Corpus for Classification (ETCC) and Emotion Tweet Corpus for Relevance (ETCR); Uses word, lemma, noun phrase, dependencies between POS as feature set	Quality verification needed for two new corpora
Mohammad et al.[60]	Novel approach	Best Worst Scaling (BWS)	Regression	Anger, Fear, Joy, Sadness	Detects emotion intensity; Creates four tweet datasets; Shows correlations between emotion pairs; Uses word n-grams, character n-grams, word embeddings and affect lexicons for regression	Accuracy not verified
Summa et al.[61]	Novel approach	Interdis-ciplinary method	Graph-based semi-supervised learning, NLP	Anger, Happiness, Disgust, Fear, Sadness, Surprise, None	Combines linguistic, temporal, and spatial information; Computes similarity between tweet nodes	Accuracy was not very high; Parameters selection was random

Table 2.5: Related Works with Features and Limitations - Table IV.

Authors	Type	Approach	Method	Emotions	Features	Limitations
Sen et al.[62]	Novel approach	Jointly learnt model for emotion and sentiment	Machine-learning (SVM, CNN)	Emotion - Anger, Amusement, Excitement, Happiness, Hope, Love, Sadness; Sentiment - Positive, Negative, Neutral, None	Uses sentiments as auxiliary input for textual emotion detection; Uses multi-tasking NN for embedding learning	-
Jain et al.[63]	Survey and a proposed approach	Machine-learning (SVM, Naive Bayes)	Intelligent text processing	Basic Emotion Theories, Ekman (for framework)	Compilation of different emotion detection methods in existing researches; Detail survey on election prediction tweets; Combines corpus-based features and emotion related features for multilingual text emotion detection	Proposed framework focuses on only political, health and sports domain
Kang et. al.[64]	Novel approach	Bayesian Model	Bayesian Inference Method	Anger, Anxiety, Expect, Hate, Joy, Love, Sorrow, Surprise	Works with contextual information to get the latent semantic dimensions; Predicts emotion for both word and document text; Two Bayesian models DWET and HDWET were applied; DWET outperforms all baseline methods.	Bayesian model will never converge if the semantic dimensions increase much; Works with Chinese language only

Table 2.6: Related Works with Features and Limitations - Table V.

Authors	Type	Approach	Method	Emotions	Features	Limitations
Perikos et. al.[13]	Ensemble Approach	Machine Learning	Ensemble of Naive Bayes, Maximum Entropy learner, Knowledge-based Tool	Circum-plex Model	A sentence-level emotion and polarity detector; Analyzes each sentence for feature extraction and inserts them into three classifiers; Output is decided by a voting system	Lack of lexical resources; Accuracy is not better than all baseline methods
Nahin et. al.[14]	Novel approach	Machine Learning (SVM with Jaccard Similarity)	Combin-ation of keystroke and text pattern analysis	Anger, Disgust, Fear, Guilt, Joy, Sadness, Shame	Collects user keystrokes and emotions with and without some specific texts; Uses this data to train and test the classifiers	Lack of proper user participation; Time consuming data collection; Lack of adequate words in dataset
Moha-mmad et al.[15]	Novel approach	Machine Learning (Majority classifier, SVM)	Machine Learning with combin-ations of 11 feature sets containing different features	Anger, Disgust, Fear, Joy, Sadness, Surprise	Collection of emotion tweets labeled with hashtag emotion words; Generation of a large word-emotion association lexicon; Detection of both emotion and personality; Calculation of extroversion, neuroticism, agreeably, conscientiousness and openness	-

Table 2.7: Related Works with Features and Limitations - Table VI.

Authors	Type	Approach	Method	Emotions	Features	Limitations
Agrawal et. al.[65]	Novel approach	Machine Learning	Unsupervised Context-based Method	Ekman's Model	Unsupervised approach classifies emotions based on the semantic relationships of Noun, Verb, Adjective and Adverb; Generates emotion vectors with NAVA; Uses a few emotion representative words to start; Does not need any annotated dataset or lexicon; Accurate than other unsupervised and some supervised method; Can work with any emotion model	Semantic relatedness is dependent on the corpus
Tiwari et. al.[66]	Novel Approach	Hybrid Approach	Hybrid of Machine Learning and Rule based methods	Ekman's Model	Detail explanations about emotion, emotion models, emotion detection methods and their limitations; Uses a combination of machine learning and rule based method; Uses emotion vectors with NAVA extracted by POS tagger	Uses a small dataset which effects the general-ization and standards of the results
Lee et. al.[67]	Novel Approach	Emotion-Cause Detection	Rule-based emotion-cause detection	Anger, Fear, Happiness, Sadness, Surprise	Generated a Chinese annotated emotion-cause corpus; Linguistic analysis was done to find out the correlation between emotion and cause; Linguistic rules used for cause detection	Works with Chinese language only

Table 2.8: Related Works with Features and Limitations - Table VII.

Authors	Type	Approach	Method	Emotions	Features	Limitations
Li et. al.[68]	Novel Approach	Emotion and Cause Detection and analysis	Rule-based emotion-cause detection and machine learning based emotion detection	Ekman's Model	Works with Chinese micro-blog data; Emotion-cause extraction system was used to extract the features; System was trained with that data; SVM was used to detect emotion	Works with Chinese language only; Do not work well with complicated linguistic patterns
An et. al.[69]	Novel Approach	Machine Learning based approach for emotion detection in song lyrics	Machine Learning (Naive Bayes)	Comfortable, Happy, Inspirational, Joyful, Lonely, Miss, Nostalgic, Passionate, Quiet, Relaxed, Romantic, Sad, Soulful, Sweet, Yearning	Naive Bayes classifier was used for emotion classifications from music lyrics; Positivity and negativity of emotions were also analyzed; Four different dataset of English and Chinese music lyrics were used for classification	The result for English lyrics were not as accurate as Chinese lyrics
Hajar et. al.[70]	Novel Approach	Machine Learning	Unsuper-vised Machine Learning Approach	Ekman's Model	You tube comments texts were used for emotion detection; NAVA words were extracted from the sentences; PMI for each emotion word against NAVA words were calculated for measuring the correlations	-

Table 2.9: Related Works with Features and Limitations - Table VIII.

Authors	Type	Approach	Method	Emotions	Features	Limitations
Li et. al.[71]	Novel Approach	Machine Learning	Hybrid of Neural Networks (Biterm Topic Model and Convolution Neural Network)	Ekman's Model	Uses Biterm Topic Model(BTM) which uses probabilistic latent semantic analysis on the words of a text to find out the co-occurrence patterns; BTM is used to learn the layers of a neural network; Back-propagation method is used to fine-tune the network	User context was not considered
Strapparava et. al.[72]	Comparative Study	Existing Methods	Keyword-based, Lexicon-based, Supervised and Unsupervised Machine Learning based Methods	Ekman's Model	A comparative study to find out which method is better for annotating datasets	No decision was made after the comparisons; Not a complete survey on emotion detection; No new approach was proposed
Ghazi et. al.[73]	Novel Approach	Hybrid Method	Hybrid of keyword-based, lexicon-based and machine learning based approaches with logical regression	Ekman's Model	Uses keywords to find to match with the sentences; Extracts syntactic and semantic features from the sentences; Applies machine learning to classify the sentences according to their emotions by using the extracted features	Lack of generalization of features; Indirect dependencies between emotion word and other words of the sentence was ignored

Table 2.10: Related Works with Features and Limitations - Table IX.

Authors	Type	Approach	Method	Emotions	Features	Limitations
Hasan et. al.[74]	Novel Approach	Machine Learning	Naive Bayes, Support Vector Machine, Decision Tree, K Nearest Neighbor	Circum-plex Model	Uses hashtag words, punctuations, emoticons and negations as features; Uses hashtags to label the tweets automatically	-
Hasan et. al.[75]	Novel Approach	Machine Learning	Emotex Classifier	Angry, Happy, Sad	Filters tweets with a binary classifier to find out the tweets with emotion; Applies Emotex to extract features; Classifies tweets about a public event; Generates decision about public mood on an event; Tracks temporal changes in public emotions	Considers only three emotions
Kanger et. al.[76]	Novel Approach	Machine Learning	Combination of fuzzy logic and Neural Network	Anger, Happy, Sad	Applies hybrid of fuzzy logic and neural network; Creates fuzzy rules and extracts features from the input data	Absence of results on benchmark data; Lack of generalization for any domain; Lack of detail of some steps of the approach; Works with three emotions only

Table 2.11: Related Works with Features and Limitations - Table X.

Authors	Type	Approach	Method	Emotions	Features	Limitations
Grover et. al.[77]	Hybrid Approach	Hybrid of Keyword-based and Machine Learning	Keyword-based and Machine-Learning (Naive Bayes and SVM)	Ekman's Model	Tokenizes the data; After removing stop words applies stemming steps; Extracts features and applies rule-based engine to filter data with emotions; Uses classifiers to classify the filtered data	Works with Punjabi language only
Joshi et. al.[78]	Novel Approach	Lexicon-based Approach	Lexicon (LIWC and Emo-Lex) based Emotion Tracker	Angry, Anxious, Happy, Sad	Develops an emotion tracker; Downloads tweets, predicts emotion, predicts overall emotion in a time -period; Generates and shows emotion time-sequence graphs; Computes the excitement levels of a cricket match, emotions between characters of a play and emotions towards a product accurately	Lack of detection of subjectivity and emotion interactions

Table 2.12: Related Works with Features and Limitations - Table XI.

Features	Binali et al. [54]	Kao et al. [55]	Shivhare et al. [56]	Gupta et al. [57]	Desmet et al. [58]	Dini et al. [59]
Keyword-based	X					
Lexicon-based						X
Learning-based	X			X	X	X
Supervised Machine Learning-based				X	X	
Support Vector Machine					X	
Naive Bayes				X		
Bayesian Models						
Decision Tree				X		
K-Nearest Neighbor						
Neural Networks						
Maximum Entropy						
Majority Classifier						
Unsupervised Machine Learning-based						
Semi-supervised Machine Learning-based						
Hybrid Method	X					
Ensemble Method						
Fuzzy-Logic						
Rule-based Method						
Reasoning Method		X				
Semantic-based Method		X		X	X	
Ontology-based Method			X			
Regression-based Method						
Uses Sentiment			X	X		
Generation of new Data Corpus						X
Generation of new Lexicon						
Works with English Language	X	X	X	X	X	X
Works with Other Languages						
Detects Single Emotion	X	X	X	X	X	X
Detects Multiple Emotions						
Word-level Detection	X		X	X	X	X
Sentence-level Detection		X				
Document-level Detection						
Emotion Intensity Detection						
Personality Detection						
Emotion-Cause Detection						
Public Mood Detection						
Temporal Effect						

Table 2.13: Features used in Existing Works - Table I.

Features	Kang et. al. [64]	Perikos et. al. [13]	Nahin et. al. [14]	Moha-mmad et al. [15]	Agrawal et. al. [65]	Tiwari et. al. [66]
Keyword-based						
Lexicon-based						
Learning-based	X	X	X	X	X	X
Supervised Machine Learning-based	X	X	X	X		
Support Vector Machine				X		
Naive Bayes		X				
Bayesian Models	X					
Decision Tree						
K-Nearest Neighbor						
Neural Networks						
Maximum Entropy		X				
Majority Classifier				X		
Unsupervised Machine Learning-based					X	
Semi-supervised Machine Learning-based						
Hybrid Method						X
Ensemble Method		X				
Fuzzy-Logic						
Rule-based Method						X
Reasoning Method						
Semantic-based Method	X				X	
Ontology-based Method						
Regression-based Method						
Uses Sentiment		X				
Generation of new Data Corpus						
Generation of new Lexicon				X		
Works with English Language			X	X	X	X
Works with Other Languages	X	X				
Detects Single Emotion	X	X	X	X	X	X
Detects Multiple Emotions						
Word-level Detection	X		X	X	X	X
Sentence-level Detection		X				
Document-level Detection	X					
Emotion Intensity Detection						
Personality Detection				X		
Emotion-Cause Detection						
Public Mood Detection						
Temporal Effect						

Table 2.14: Features used in Existing Works - Table II.

Features	Hajar et. al. [70]	Li et. al. [71]	Strapparava et. al. [72]	Ghazi et. al. [73]	Hasan et. al. [74]	Hasan et. al. [75]
Keyword-based			X	X		
Lexicon-based			X	X	X	X
Learning-based	X	X	X	X	X	X
Supervised Machine Learning-based		X	X	X	X	X
Support Vector Machine				X	X	X
Naive Bayes			X		X	X
Bayesian Models						
Decision Tree					X	X
K-Nearest Neighbor					X	X
Neural Networks		X				
Maximum Entropy						
Majority Classifier						
Unsupervised Machine Learning-based	X					
Semi-supervised Machine Learning-based						
Hybrid Method		X		X		
Ensemble Method						
Fuzzy-Logic						
Rule-based Method						
Reasoning Method						
Semantic-based Method		X		X		
Ontology-based Method						
Regression-based Method				X		
Uses Sentiment						
Generation of new Data Corpus			X			
Generation of new Lexicon						
Works with English Language	X	X	X	X	X	X
Works with Other Languages						
Detects Single Emotion	X	X	X	X	X	X
Detects Multiple Emotions						
Word-level Detection			X		X	X
Sentence-level Detection	X	X		X		
Document-level Detection						
Emotion Intensity Detection						
Personality Detection						
Emotion-Cause Detection						
Public Mood Detection						X
Temporal Effect					X	X

Table 2.15: Features used in Existing Works - Table III.

Features	Mohammad et al. [60]	Summa et al. [61]	Sen et al. [62]	Jain et al. [63]	Lee et. al. [67]	Li et. al. [68]
Keyword-based						
Lexicon-based	X					
Learning-based		X	X	X		X
Supervised Machine Learning-based			X	X		X
Support Vector Machine			X	X		
Naive Bayes				X		X
Bayesian Models						
Decision Tree						
K-Nearest Neighbor						
Neural Networks			X			
Maximum Entropy						
Majority Classifier						
Unsupervised Machine Learning-based						
Semi-supervised Machine Learning-based		X				
Hybrid Method						
Ensemble Method						
Fuzzy-Logic						
Rule-based Method					X	
Reasoning Method						
Semantic-based Method						
Ontology-based Method						
Regression-based Method	X					
Uses Sentiment			X			
Generation of new Data Corpus	X					
Generation of new Lexicon						
Works with English Language	X	X	X	X		
Works with Other Languages				X	X	X
Detects Single Emotion	X	X	X	X	X	X
Detects Multiple Emotions						
Word-level Detection	X	X	X	X	X	X
Sentence-level Detection						
Document-level Detection						
Emotion Intensity Detection	X					
Personality Detection						
Emotion-Cause Detection					X	X
Public Mood Detection						
Temporal Effect						

Table 2.16: Features used in Existing Works - Table IV.

Features	An et. al. [69]	Kanger et. al. [76]	Grover et. al. [77]	Joshi et. al. [78]
Keyword-based			X	
Lexicon-based				X
Learning-based	X	X	X	
Supervised Machine Learning-based	X	X		
Support Vector Machine			X	
Naive Bayes	X		X	
Bayesian Models				
Decision Tree				
K-Nearest Neighbor				
Neural Networks		X		
Maximum Entropy				
Majority Classifier				
Unsupervised Machine Learning-based				
Semi-supervised Machine Learning-based				
Hybrid Method			X	
Ensemble Method				
Fuzzy-Logic		X		
Rule-based Method		X	X	X
Reasoning Method				
Semantic-based Method				
Ontology-based Method				
Regression-based Method				
Uses Sentiment				
Generation of new Data Corpus				
Generation of new Lexicon				
Works with English Language	X	X		X
Works with Other Languages	X		X	
Detects Single Emotion	X	X	X	X
Detects Multiple Emotions				
Word-level Detection	X	X	X	X
Sentence-level Detection				X
Document-level Detection				
Emotion Intensity Detection				
Personality Detection				
Emotion-Cause Detection				
Public Mood Detection				
Temporal Effect				X

Table 2.17: Features used in Existing Works - Table V.

2.2.1 Emotion and Sentiment Detection Methods

Several approaches exist for textual emotion and sentiment detection. Emotion and sentiment recognition task is a part of *Affective Computing* and the computational methods used in this area have been classified into several categories by various researchers. The methods defined by these researchers can be generalized into four categories - 'Keyword-based Method', 'Lexicon-based Method', 'Machine learning Method' and 'Hybrid Method'. Existing works utilized unigrams (one word), n-grams (multiple words), emotiocons, hashtag words, punctuations, negations as features for the emotion detection task. Approaches for textual emotion detection are defined as described in the following subsections.

Keyword-based Method

Keyword-based emotion detection is the most intuitive and straightforward approach. The idea is to find out patterns similar to emotion keywords and match them. The first task is to find out the word which expresses the emotion in a sentence. This is normally done by tagging the words of a sentence with Parts-Of-Speech tagger and then extracting the Noun, Verb, Adjective and Adverb (NAVA) words. Most linguistic and emotion based researches mentioned that these are the most probable emotion carrying words[65, 66, 70]. Then these words are matched against a list of words representing emotions according to a specific emotion model. Whichever emotion matches with the keyword is considered as the emotion of the specific sentence. If the word matches with multiple emotions from the list, then different approaches can be applied. In some keyword-dictionaries, each word has a probability score for each emotion and the emotion with the highest probability is picked as the emotion of the word. In some other works, the first emotion matched with the word is picked as the primary emotion of the word. For the reference list of keyword or the keyword dictionary, it differs depending on the researcher. The keyword dictionary is normally made by the researchers based on the emotions and the words they are working with. There are online

tools and programs like WordNet[74] which can find synonyms and antonyms of words which can be used to make the dictionary.

Lexicon-based Method

Lexicon-based emotion detection approach classifies text using a lexicon (a knowledge-base with text labeled according to emotions) appropriate for the input dataset[59, 60]. Emotion detection is similar to the previous method, but in this case, an emotion lexicon is used instead of the word list. National Research Council Canada(NRC), EmoSenticNet(ESN) are some mostly used emotion and sentiment lexicons[75].

Machine learning Method

Both 'supervised'[57, 62] and 'unsupervised'[65, 70] machine learning methods are used for textual emotion detection in which a model is designed to train a classifier with a part of the dataset and then test the classifier with the rest of the data. For supervised method, an annotated emotion dataset is used for training and testing the supervised classifier. Naive Bayes, Support Vector Machine, and Decision Tree may be named as the mostly used classifiers. By the definition of 'Unsupervised Classification', the data used is not labeled with the classes. The classifier starts with several seed words for each emotion which are then cross-referenced to the sentences, thus classifying the sentences to corresponding emotions. This trains the classifier model which is then further used to label the testing data. Unsupervised method is a more generalized one but in most cases, supervised classification achieves better accuracy.

Hybrid Method

Hybrid approach for emotion detection in text combines any two or all three methods defined to achieve the benefit of multiple methods and reach the maximum level of accuracy. In some previous works, it was proved that applying a combination of multiple emotion detection methods gives better results than individual methods[54, 66].

According to the previous surveys[37, 51, 54, 52, 53] done on comparison between the accuracy of emotion detection using *Keyword-based Method*, *Lexicon-based Method*, *Machine learning Method* and *Hybrid Method*, it was mentioned that *Keyword-based Method* and *Lexicon-based Method* worked better. *Machine learning Method* worked better with larger datasets and *Hybrid Method* had similar accuracy to *Machine learning Method*. Although these methods are the benchmark approaches for textual emotion detection, some researchers tried natural language processing[58], linguistic rule-based methods[76], ensemble of multiple methods[13] or some novel methods almost completely unique and achieved some good results. Modifications to those novel methods may lead to an improved and highly accurate automatic emotion detection system from text input.

2.2.2 Datasets

In the literature, different existing or customized datasets have been used for emotion detection according to the types of the experiments of different researchers. The annotated datasets are annotated with particular emotion models, hence bearing only those emotions that exist in the specific emotion model. A small number of emotion labeled datasets are available. Some researchers contributed some data corpus that they built to utilized in their experiments. But still the number of available datasets for emotion analysis is not enough. Further, there is no generalized dataset which can be used for any emotion model. Researchers are either bound to use the emotion model that exists in the datasets or to

Dataset	Datasize	Description
EmoBank[79]	10K Sentences	Double annotation with valence, arousal and dominance were used from the perspectives of both writer and reader
The Valence and Arousal Facebook Posts[80]	2895 Facebook posts	Double annotation with valence and arousal values
The Emotion in Text data set[81]	40000 Tweets	Annotated with Anger, Boredom, Empty, Enthusiasm, Fun, Happiness, Hate, Love, Relief, Sadness, Surprise, Worry, Neutral
EmoLex[82]	14182 Unigrams	Annotated with Sentiments- Negative, Positive and Emotions- Anger, Anticipation, Disgust, Fear, Joy, Sadness, Surprise, Trust
ISEAR[83]	7666 Sentences	Contains responses of questionnaires on seven emotions (Joy, Fear, Anger, Sadness, Disgust, Shame, and Guilt) from 37 countries from 5 continents
Affective Text[84]	1200 News Headlines	Annotated with 6 basic emotions from Ekman's model and polarity

Table 2.18: Datasets

generate a data corpus and then manually annotate the data according to emotion labels. The latter task is time consuming. Some of the most commonly used datasets in recent works are listed in Table 2.18 together with a brief description of the amount of data that exists in each dataset.

2.2.3 Influential Users in Social Network

Finding influential people and groups in any social network can be significant to detect and control the information flow. Haewoon et. al[85] analyzed Twitter and generated the first quantitative study on Twitter. They crawled Twitter on July 2009 and got more than 41 million user information along with the following/follower relations. They computed the distributions of users, their followers, the people they were following, the recent trends, separation, homophily and diffusion of information in Twitter. Their analysis showed noticeable differences between Twitter and other social networks. Because of the one directional relation

between users in Twitter, it defied the power law and the distributions were not very structured. The list of top ranked users also differed according to the method of the computation-number of followers, page rank, number of retweets. They also mentioned and calculated the active periods of trends which was less than a week in most cases. Their retweet trees and temporal analysis of retweets showed the diffusion of information and it's difference from other media. Vosoughi et. al[86] showed how both true and false news spread in Twitter network. According to their observation, false news spread more than true news and false news tend to be unique. Among various kinds of false news, rumors regarding political issues spread quickly among huge number of people rather than other types of rumors.

Riquelme et. al[87] conducted a detailed survey on Twitter activities, influences and popularity of the users. They showed a classification of different measures of Twitter data based on various metrics and contents. The relationships between users and tweets was discussed in detail. Twitter metrics and their time complexity were explained with detail anatomy of Twitter. They mentioned existing methods of finding influential users and experiments done on Twitter data. Finally, some open research problems were stated for researchers to analyze. T-PICE[88] is an influential community extraction system which identifies influential people by classifying people into some personality classes based on their tweets on a specific topic. NavigTweet[89] is a visualization tool which finds the influential people from the friend list of an user by analyzing the contents of tweets that are common between them. An analysis on the tweets about two car companies to find out the influential users led to some hypotheses in [90]. It represented some interesting patterns of influential people of a social network and some of the textual characteristics like their use of words, hashtags, links, expressions etc. Emotion contagion in Facebook was analyzed by Coviello et. al[91]. Facebook posts were analyzed using instrumental variable regression method to detect positive and negative emotions of people in rainy days and the effect of one's emotion on his/her friends' emotion. Detecting influential people from a social network is a very lucrative research area for referral

marketing to spread the information of any product and reach highest possible nodes of a network[92].

In most of the previous works, researchers counted the number of followers to find out the influential users from Twitter. The idea was that "the more follower a person has, the more influential he/she is". Some researchers ranked the users based on their total number of tweets[93] or summation of total number of tweets and the number of retweets of those tweets[94]. To find the most influential users on a specific topic, the number of tweets, the number of replies by the author, the number of retweets on a specific topic were used and normalized with the total number of tweets on that topic[95]. Followers and following counts were also used to find the influential users. The ratio of number of followers and followees[96], ratio of followers and summation of followers and followees[93, 87] were used to compute how influential a user is in Twitter. In [97], the reciprocal relationship between users were also counted in case the user had less followers than the number of people the user followed.

Acquaintance Affinity Identification(AAI) score was calculated with the number of followers, number of users mentioning the author, number of users replied to that author's tweets, number of users retweeted the author's tweets[98]. Various common centrality measures like betweenness and closeness centrality were used by researchers to find influential users from a network[99], whereas few researchers found their own centrality indexes like H-index which considered a maximum h value for replies, retweets, likes for the calculations[100, 101]. Google's page rank algorithm was modified as TunkRank[102] and UserRank[103] using followers, followees and tweets to rank Twitter users. Lahuerta-Otero et. al[90] used regression model with lexical diversities in tweets, average number of characters used in tweets, hashtags, user mentions, URLs, followees, positive and negative sentiments to extract influential users from Twitter. Exponential of number of followers was used in [104] to find the popular users from Twitter. Users were ranked using both tweet-based and user-based scores by

Francalanci et. al[89]. They used favorites, followers, following, listed, tweets for user-based score and favorited, retweets, urls, hashtags, mentions for tweets-based score. Each parameter was assigned with weights based on Analytic Hierarchy Process (AHP).

2.3 Few Challenges or Open Problems

Emotion and sentiment analysis is a research field with lots of unturned stones and possibilities. Due to the diverse nature of human emotions, there are still lots of scopes for developing unique systems or improving and enriching existing systems with effective modifications and capabilities. Some possible future directions in the research of emotion and sentiments detection and analysis from texts are listed as follows.

2.3.1 Text-based Emotion Network Detection

The existing research works based on textual emotion in social networks mostly focused on the post by a user. The emotions of the comments or replies to those posts can give us an idea about the similarity and dissimilarity between emotions of users in a network. This can be used to detect emotion networks within the social networks and the propagation of particular emotions.

2.3.2 Emotion Intensity Detection

Considering the amount of research going on about emotion detection, a very small number of researchers are concentrating on intensity of the detected emotion[60]. Each emotion may have different intensity level and detecting the intensity of an emotion can be beneficial for emotion analysis. For example, if a person writes “I am sad” or “I want to end my life, there

is nothing left for me", then the existing systems will label both of these declarations as 'sad' emotions. However, in reality, the intensity of sadness in both statements is different - the former represents normal sadness while the other reflects severe depression or suicidal emotion.

2.3.3 Sarcasm Detection

Sarcasm detection from text is a very complex task and the maximum accuracy achieved so far is not very much. Correct sarcasm detection depends on correctly using sentence structure, detecting accurate emotion behind the sentence, understanding the context of the sentence, and many other parameters. For example, "I'm trying to imagine you with a personality"[105] represents a sarcasm which is very implicit and hard to detect for an existing automatic sarcasm detection system.

2.3.4 Multiple Emotion Detection

In most of the emotion detection efforts, researchers concentrate on the primary emotion in the text. Sentences expressing multiple emotions are either discarded or labeled with the first emotion that was detected. For example, if a person writes "I was sad this morning but now I am happy" or "This makes me happy and sad at the same time", then the system should be able to recognize both emotions with a temporal and/or spatial dimension.

2.3.5 Emotion-Cause Detection

A limited number of works focus on the cause of the emotion that was expressed by a person[67, 68]. Sometimes, detecting the cause can increase the accuracy of the detection

of the correct emotion in a text or even speech. For example, if a person expresses "I am so happy!!! It is raining!!", then the system should recognize that the reason of his/her happiness is rain. This can also be applied to personalized systems where the system has knowledge of the likes and dislikes of a person and can detect the cause of an emotion even if the cause is not directly stated in the same sentence.

2.3.6 Personality or Mood Detection

By detecting the emotion from text for a particular person, his/her personality or mood can be detected and analyzed[15]. Personality or mood detection can be integrated into existing social networking platforms and other applications for personalized suggestions. For example, if a person is angry and is expressing anger in his/her text, then an application may suggest to him/her different things he/she likes (i.e. a nearby restaurant which serves his/her favorite food, a nearby movie theater where a new movie is playing which is of his/her favorite genre, and so on).

2.3.7 Emotion versus Individual or Social Parameters

Human emotions can be related to their age, gender, time, location, ethnicity, political views, educational qualifications, in addition to some other individual, social, temporal and spatial parameters. The connection between emotion and these parameters can present some new dimensions for emotion analysis based research[2]. For example, adult people are in general more concerned about political issues than teenagers. Issues in one country may effect people of neighbor countries and other countries of the world in different ways.

In this research, the problems of detecting the emotions and sentiments of Twitter users from their tweets and replies and finding their influence score in the network was addressed.

One of the mostly used supervised classifier, 'Naive Bayes' was applied for classifying the emotions and sentiments of texts. Then the influential users on a specific topic were extracted by combining the parameters of user and his/her tweets and replies. Few parameters from the existing works were included and at the same time, few new parameters were introduced that were applicable for the calculations.

Chapter 3

Text-Based Analysis of Emotion by Considering Tweets

This chapter is based on the emotion detection and analysis work in [2]. In this work, after extracting tweets on various topics, they were preprocessed and each tweet was divided into words and then corresponding parts-of-speeches were identified for those words. After analyzing the words, they were classified into 32 emotion classes according to Robert Plutchik's emotion classification model[41]. Emotions were then analyzed with respect to gender and location of the user and the time of the tweet. The analysis revealed some interesting outcomes and some new challenges. The rest of this chapter is outlined as follows. Subsection 3.1 describes the methodology of the emotion classification process. Subsection 3.2 shows experimental results and analysis of the results. Subsection 3.3 concludes the work and outlines some possible future directions.

3.1 Tweet Emotion Detection

The process for detecting emotions from tweets and analyzing them with respect to user's gender and location involves several sequential steps. Tweets should be preprocessed before

using them in the emotion analysis model. After that, parts-of-speech tagging is necessary to find out which words from the tweets to focus on. An emotion dictionary is required according to the chosen emotion class model. After detecting emotion unigrams, they should be classified into corresponding emotion classes.

3.1.1 Preprocessing

Collected tweets contained considerable amount of noises (e.g., extra and missing symbols, characters, spelling mistakes). The dataset was preprocessed by removing unnecessary parts in order to have more usability. First, @username (e.g., @mary), URLs (e.g., `http://a.com/`) and emoticons (e.g., ':-)') were removed from the dataset. Then, multiple dots (e.g., ...), symbols (e.g., !!!), characters (e.g., happyyyyy) were also removed. Hashtag symbols were removed without removing the words associated with them (e.g., in the hashtag #sad - only # was removed, not 'sad'). After removing these symbols, the dataset was checked for redundancy. Finally, the filtered dataset had tweets with no emoticons, hashtags, unnecessary multiple occurrences of one symbol or illegible words.

3.1.2 POS Tagging

A 'parts-of-speech tagger' was used to tag each word of the tweets into corresponding parts-of-speech. In total, 36 parts-of-speech classes were used. They were- *Coordinating conjunction, Cardinal number, Determiner, Existential there, Foreign word, Preposition or subordinating conjunction, Adjective, Adjective - comparative, Adjective - superlative, List item marker, Modal, Noun - singular or mass, Noun - plural, Proper noun - singular, Proper noun - plural, Predeterminer, Possessive ending, Personal pronoun, Possessive pronoun, Adverb, Adverb - comparative, Adverb - superlative, Particle, Symbol, to, Interjection, Verb - base form, Verb - past tense, Verb - gerund or present participle, Verb - past participle, Verb -*

non 3rd person singular present, Verb - 3rd person singular present, Wh determiner, Wh pronoun, Possessive wh pronoun), Wh adverb and *Others*. Tweet words were tagged and each word was stored in one of those 37 (36 POS and Others) classes against user IDs.

3.1.3 Emotion Dictionary

Existing emotion detection systems use different emotion models according to their requirements. As described in the literature, Ekman's model[38], Johnson-laird and Oatley model[40] and Circumplex model[42] are the mostly used emotion classification models. But the limitation of these models is that they focus on only few basic emotions. The Circumplex model works with 28 emotions and it is a widely used emotion model. Another emotion model called 'Plutchik's Wheel of Emotion'[41] defined 32 emotions. Emotion classification used in this work was Plutchik's model with 32 emotions (as shown in Fig.3.1) - *Acceptance, Admiration, Aggressiveness, Amazement, Anger, Annoyance, Anticipation, Apprehension, Awe, Boredom, Contempt, Disapproval, Disgust, Distraction, Ecstasy, Fear, Grief, Interest, Joy, Loathing, Love, Optimism, Pensiveness, Rage, Remorse, Sadness, Serenity, Submission, Surprise, Terror, Trust,* and *Vigilance.*

An interesting observation about tweets is that some of them did not express any specific emotion; they just expressed some facts or asked some questions. Some tweets represented taunts, requests, advises, suggestions or sarcasms. Some tweets had words from multiple languages. Some tweets did not make any sense, they looked like just some random words put together. Those tweets were classified as *Others*.

The emotion dictionary was built based on these 32 emotions. Synonyms for each emotion word were collected from various online English dictionaries[106, 25, 107, 108, 109]. After inserting the synonyms from English dictionaries, some common synonymous words

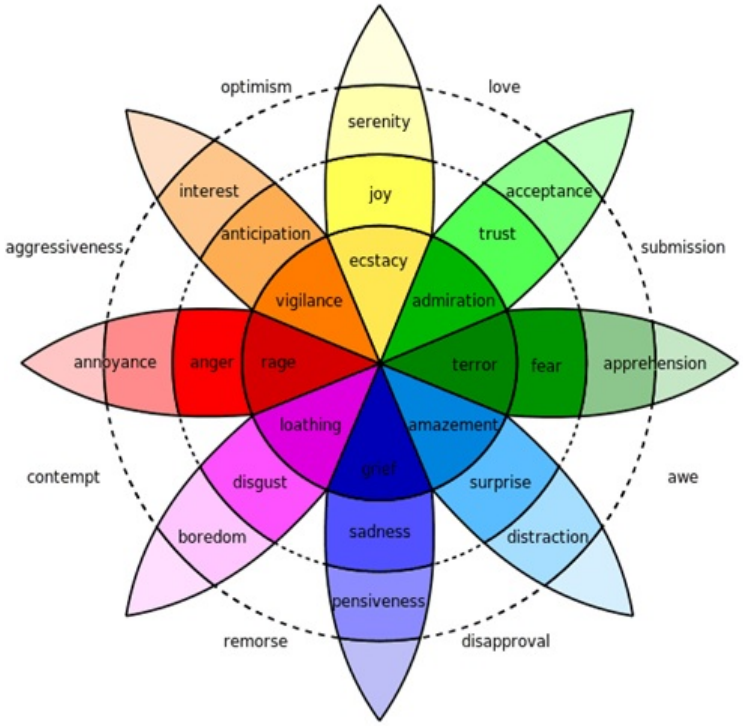


Figure 3.1: Plutchik's Wheel of Emotion.

used in tweets were collected from some dictionaries based on tweet words only[110, 111]. Those words were also inserted into the emotion dictionary for each emotion. Finally some common acronyms used nowadays were extracted from different sources and were inserted for each emotion. After merging all these synonymous words and acronyms, the emotion dictionary had more than 20 synonyms for each emotion.

3.1.4 Unigram Selection and Dataset Annotation

After building the emotion dictionary, the dataset was annotated with emotions. To select emotion unigrams (one word), all unnecessary POSs were removed from the dataset (i.e., articles, prepositions, etc.) and the concentration was on the rest of the words to annotate each tweet with an emotion. Nouns, adjectives and adverbs were the POSs that were used. For tweets in which multiple emotions existed, the primary emotion was considered and

the tweet was annotated accordingly. The emotion model used in this work has not been previously applied in any other work, so no automated system for data annotation exists according to this model. Therefore, the dataset annotation was done manually.

3.1.5 Emotion Classification

The final step for emotion detection was emotion classification by a classifier using the emotion dictionary. Different supervised classifiers like KNN, Naive Bayes classifier, and Decision Tree have been used in literature for emotion classification. In most cases, the Naive Bayes classifier produced the most accurate results, hence was used for this work.

$$p(C_k|x_1, ..., x_n) = \frac{p(C_k)}{p(x)} \prod_{i=1}^{n} p(x_i|C_k) \tag{3.1}$$

$$L = \arg \max_{k \in \{1,....,K\}} p(C_k) \prod_{i=1}^{n} p(x_i|C_k) \tag{3.2}$$

Equations 1 and 2 represent the Naive Bayes classifier. Here C_k is the emotion class. This research used 32 emotion classes. So for this case, k varied from 1 to 32 and x_i's are the unigrams used for emotion detection from each tweet. Finally, 70% of the annotated data was used as the training set and the rest 30% data acted as the test set for the classifier.

3.2 Experimental Results

Every step of the methodology- preprocessing, parts-of-speech tagging, creating emotion dictionary, implementing Naive Bayes classifier, classifying tweets according to their emotions and analyzing the results were implemented and tested using different packages of R

for networks, graphs, matrices, Natural Language Processing, words, parts-of-speech, and synonyms. Several data matrices and data frames were used for the intermediate calculations.

3.2.1 Dataset

The dataset used in this experiment was collected from the tweets of 26 October 2015[112]. The user ID, tweet location (city or some local information), user gender and time the tweets were created were extracted from the dataset. The time zone of the tweets were not considered while including the tweet creation time in the analysis. Almost 30% of the tweets had to be removed because those tweets were advertisement tweets for different products or websites. Retweets and illegible tweets were deleted from the rest of the tweets. The location of each tweet was replaced with corresponding country name based on the given city name or local information. Finally, each data in the dataset had a user ID, tweet text, gender of the user, location of the user (country) and time of the tweet expressed in 'hh:mm' format.

3.2.2 Results

Tweets were classified into 32 emotion classes with their corresponding ID, gender, location and time of each tweet. Users were then classified according to these parameters and analyzed based on their emotions.

Emotion Network

Shown in Figure 3.2 is the emotion network for all the 32 emotions. The network could be divided into clusters of nodes based on different emotions and nodes represent users. People who shared the same emotion are connected to each other and form one cluster. So, for each emotion, a cluster was formed with people who expressed the same emotion via their tweets.

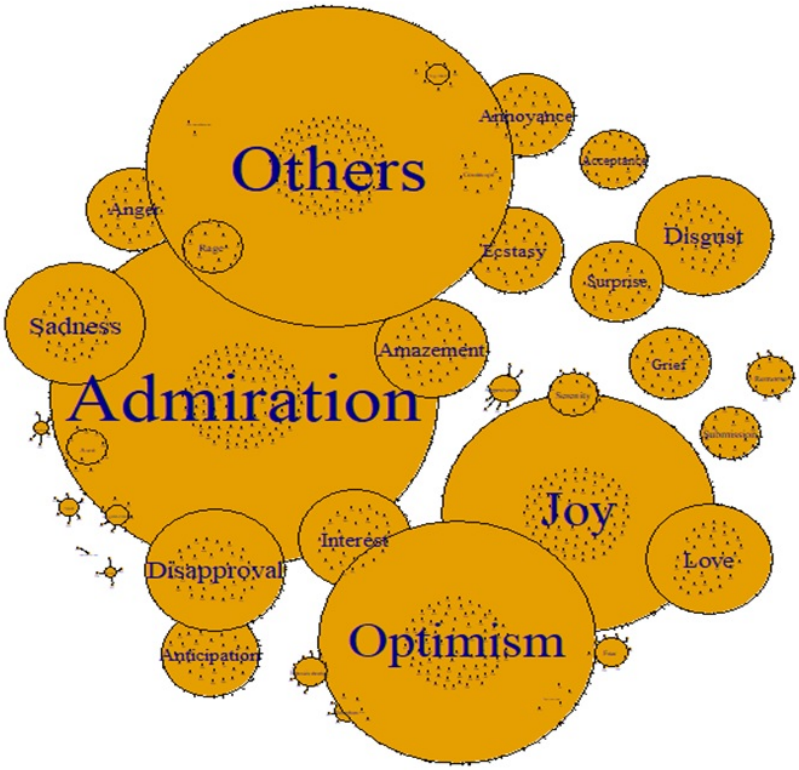


Figure 3.2: Emotion Network.

Some emotions were used more than others in tweets and this is the reason for different sized clusters. From Figure 3.2, it can be clearly realized that majority of the tweets represented *Admiration*, *Joy, Optimism, Others*. Some other notable emotions appeared in the dataset where quite a lot of users expressed *Sadness, Disgust, Love, Disapproval*. The rest of the emotions were encountered as well, but were not that much prominent in the dataset.

Gender versus Emotion

Gender information which was collected from the tweets was divided into two classes, namely *male* and *female*. In Figure 3.3, the X-axis represents emotions and the Y-axis represents percentages of tweets of that emotion from a gender. Blue bars show *Female* tweets, and red bars show *Male* tweets.

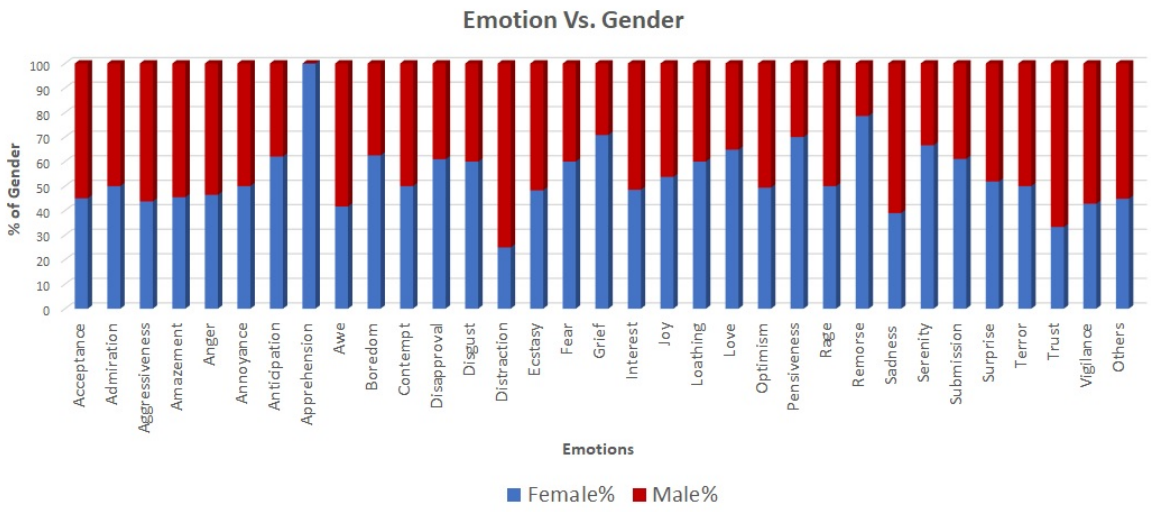


Figure 3.3: Gender Vs. Emotion.

Female users had the majority in positive emotions like *Anticipation, Joy, Love, Pensiveness, Serenity*, but they were also the major contributors to negative emotions like *Boredom, Disgust, Disapproval, Fear, Grief, Loathing, Remorse*, and *Submission*. In contrast, *Male* users expressed positive emotions like *Acceptance, Amazement, Awe*, and *Trust* and negative emotions like *Aggressiveness, Anger, Distraction, Sadness*, and *Vigilance* more than *Females*. Other emotions were mentioned in tweets from both *Male* and *Female* almost equally. Surprisingly, *Apprehension* was expressed by *Females* only.

Time versus Emotion

Temporal information collected from the tweets was divided into two classes. Tweets which were posted until 12:00 noon were classified as *Morning* tweets, and tweets that were posted after 12:00 noon were classified as *Afternoon* tweets. In Figure 3.4, the X-axis represents emotions and the Y-axis represents corresponding percentages of tweets based on their temporal classes. Blue bars show *Afternoon* tweets and red bars show *Morning* tweets.

From the graph shown in Figure 3.4, it is easily visible that negative emotions like

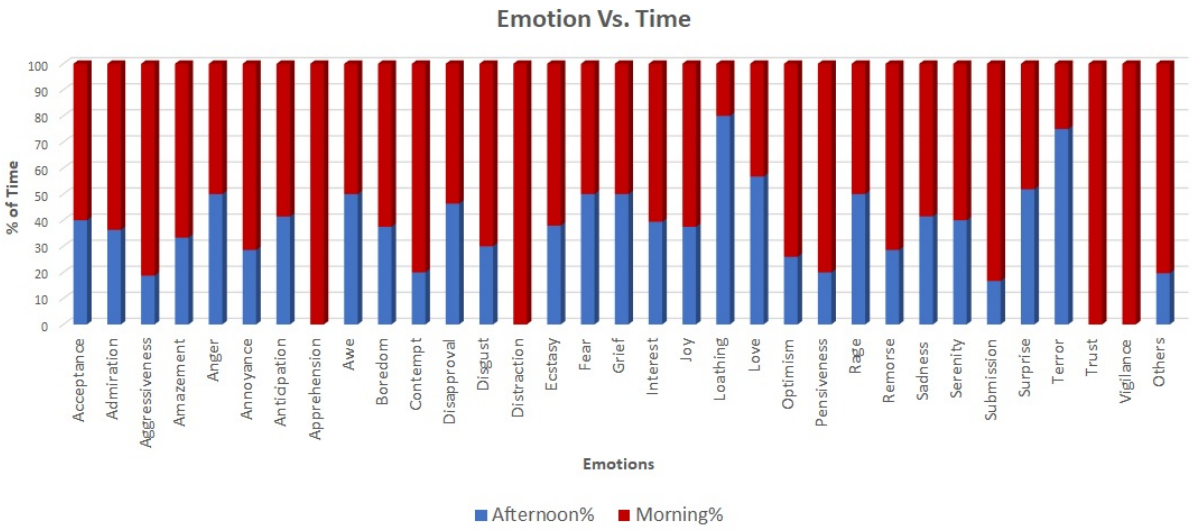


Figure 3.4: Time Vs. Emotion.

Loathing, and *Terror* were prominent in *Afternoon* tweets with one exception, namely *Love*. On the other hand, positive emotions like *Acceptance, Admiration, Amazement, Anticipation, Ecstasy, Interest, Joy, Optimism, Pensiveness*, and *Serenity*; and negative emotions like *Aggressiveness, Annoyance, Boredom, Contempt, Disgust, Remorse, Sadness*, and *Submission* mostly occurred in *Morning* tweets. *Apprehension, Distraction, Trust*, and *Vigilance* have been encountered only in *Morning* tweets.

Location versus Emotion

The relationship between emotion and user location (country) is shown in Figures 3.5, 3.6, 3.7 and 3.8. In Figure 3.5, all the 32 emotions are shown in the map with different colors according to their locations. The pie charts shown in Figures 3.6-3.8 were generated based on 33 emotion classes (32 emotions and others) according to 63 countries (*Africa, Argentina, Armenia, Australia, Austria, Belgium, Brazil, Canada, Chile, China, Colombia, Croatia, Czech Republic, Denmark, Dominican Republic, Ecuador, Egypt, Europe, France, Germany, Greece, Greenland, India, Indonesia, Iraq, Ireland, Israel, Italy, Japan, Kenya, Korea, Kuwait, Lebanon, Malaysia, Mexico, Morocco, Netherlands, New Zealand, Nigeria,*

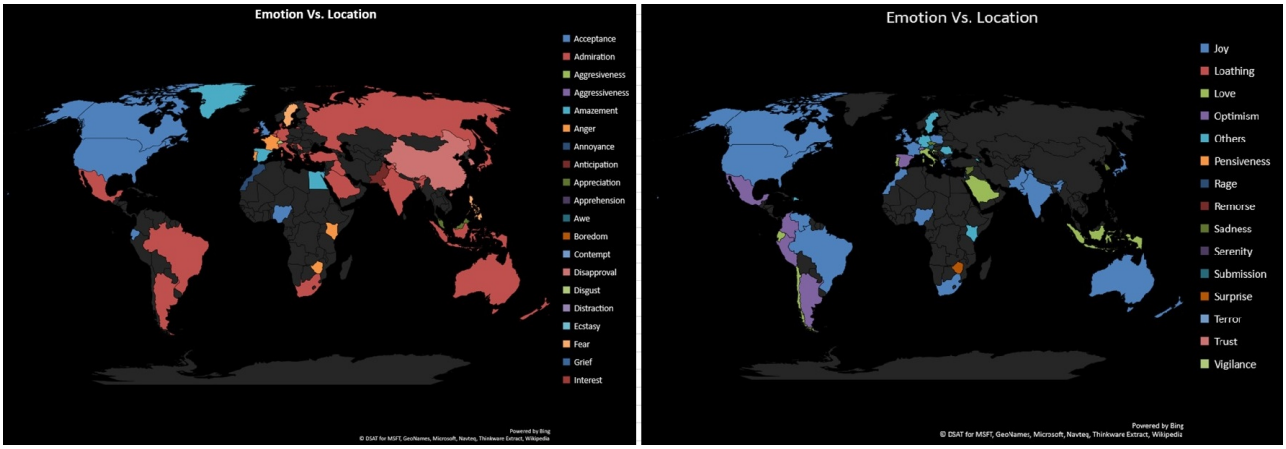


Figure 3.5: Location Vs. Emotion - Map.

Pakistan, Pennsylvania, Peru, Philippines, Poland, Polynesia, Portugal, Romania, Rome, Russia, Saudi Arabia, Serbia, Singapore, Spain, Sweden, Switzerland, Syria, Trinidad and Tobago, Turkey, UK, USA, Venezuela, Zimbabwe) which were detected from the dataset. Each circle represents an emotion and countries which contributed to that particular emotion. As most tweets were from USA and UK, these two countries were the two major contributors to all emotions.

For positive emotions like *Ecstasy, Joy, Admiration, Acceptance, Anticipation, Interest, Amazement, Surprise, Pensiveness, Love*, and *Optimism*, in addition to *USA* and *UK*, tweets from countries like *Canada, Greece, Netherlands, Australia, India*, and *Nigeria* are some major participators. Similarly, other than *USA* and *UK*, countries like *Canada, Netherlands, Germany, New Zealand, Mexico, Australia, Ecuador, Europe, Indonesia, Sweden, Kenya*, and *Africa* expressed negative emotions like *Grief, Sadness, Loathing, Disgust, Boredom, Rage, Anger, Annoyance, Terror, Fear, Submission, Disapproval, Remorse*, and *Aggressiveness* more than other countries.

Experimental result reflected some interesting aspects regarding emotions of a person with respect to his/her gender, location and time. But these results can not be generalized

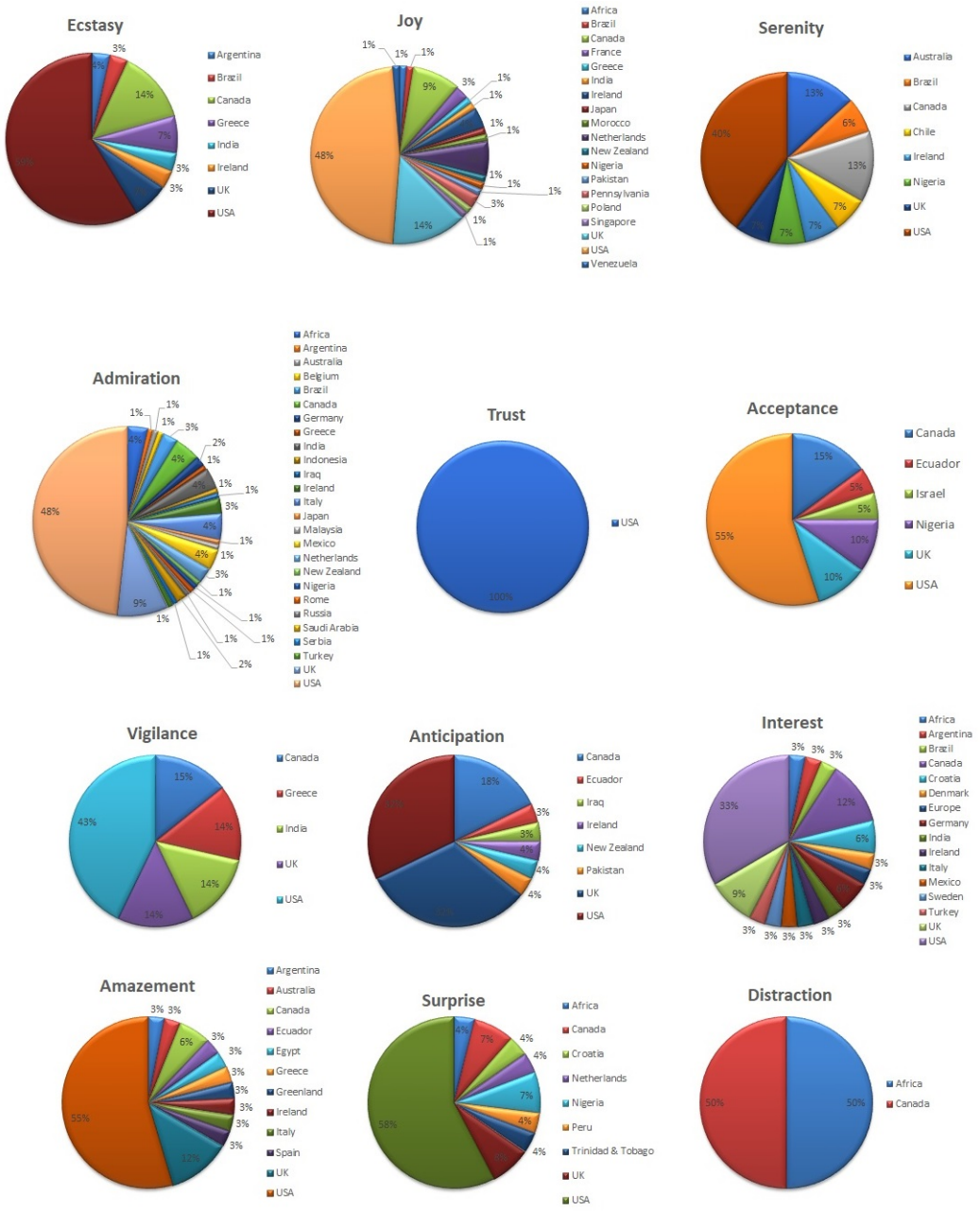


Figure 3.6: Location Vs. Emotion - Pie Chart 1.

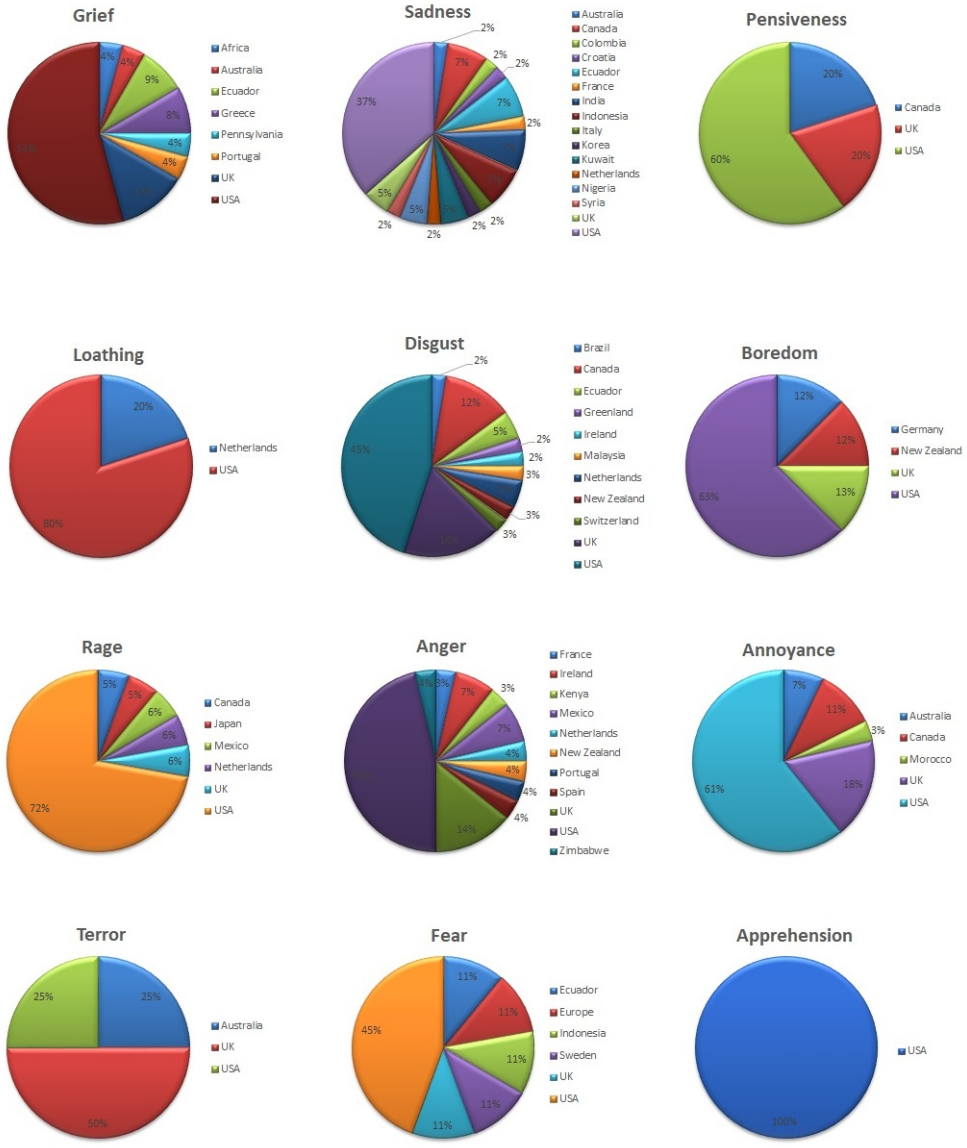


Figure 3.7: Location Vs. Emotion - Pie Chart 2.

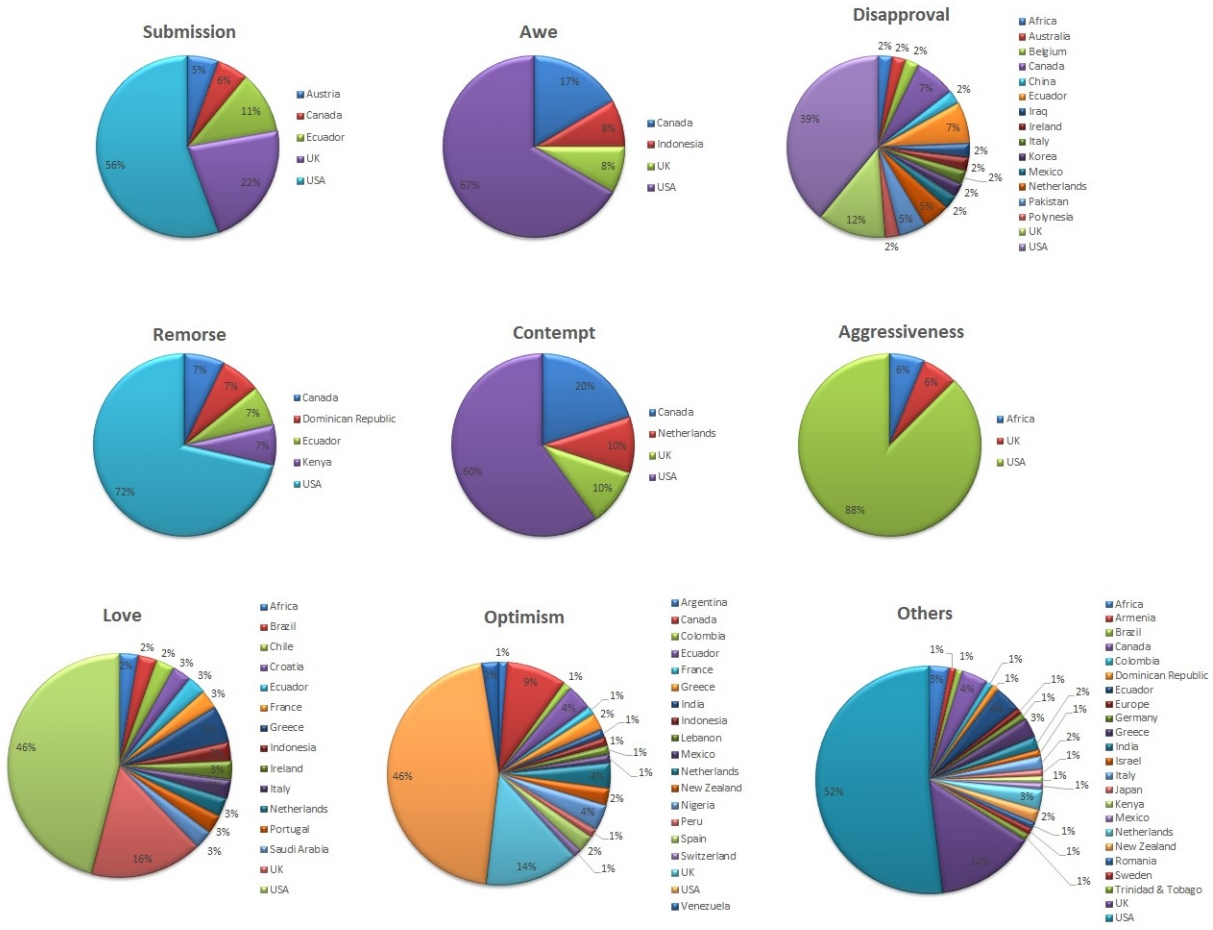


Figure 3.8: Location Vs. Emotion - Pie Chart 3.

for all human beings and their emotions because they are completely based on a specific dataset containing tweets collected on a random day from different people scattered almost all over the world. It is important to investigate whether emotions were directly reflecting personal feelings related to any particular events associated with the time period during which the tweets were posted.

3.3 Conclusion

Emotion detection and analysis is an important research area for analyzing both individual and public emotions on various events. The diversity and multiple dimensions of human emotions make the process complicated and reduce the accuracy. The emotion model that was used in this work covered almost all basic human emotions. A larger emotion dictionary built by collecting words from different sources made emotion detection more sparse and accurate. Acronyms of common tweet words and some common words used in tweets only were considered in this work which made the emotion detection process easier and more efficient. After detecting emotions from the text, the analysis on the emotion with respect to gender, location and time represented some interesting human characteristics.

Chapter 4

Emotion Detection : From Data Collection to Recommendation

Twitter is one of the most popular social network nowadays with 330 million monthly active users[113]. People express their opinions about their daily lives, different social or national or international issues. They share their views within 140 characters of text and sometimes also share audio or video files. Posts are called tweets and they are public. Other people can like posts, reply to them or retweet them. People can follow each other or can be friends with each other in Twitter. Unlike most other social networking platforms, Twitter allows one directional links, which means one user can follow another user without the latter user reciprocating the communication. These interactions lead to a network of communication containing both one-directional and bi-directional connections between the Twitter users. Hashtags(#) and emojis(i.e., :) , :(, etc.) are used in tweets to enhance the sentiment of a tweet.

In this chapter, the methodology of the implementation of emotion and sentiment based recommender system is explained in detail. The methodology is different than the methodology mentioned in chapter 3. The dataset created for this procedure including both tweets

and replies was a new dataset which had nothing in common with the dataset that was used in chapter 3 for experiments. For emotion detection in both chapter 3 and 4, Naive Bayes classifier was used. But the features used for the classifiers in both chapters were different. In chapter 3, for Naive Bayes classification, only NAVA words of the dataset of chapter 3 were considered whereas both the full texts and NAVA words of the new dataset of chapter 4 were considered for Naive Bayes classification features in this chapter. The methodology followed from data collection to recommendation generation were explained in the following sections.

4.1 Data Collection

The dataset used for this experiments contains a collection of tweets, replies, retweets and their user information. The existing datasets of Twitter couldn't be used for this work, because most existing datasets have either the tweets or the friend/follower connections between users. For this specific experiment, an emotion network based on the text of the users including the user data was needed, not just the information about who is following whom. For the emotion network, the connections between users were required based on their emotion on a specific issue. So, few recent events and issues were selected to collect tweets with various emotions with search keywords - #Syria, #DonaldTrump, #SchoolShooting, #Christmas2017, #NewYear, #ValentinesDay2018, #Terrorism, #olympicgames2018, #WomensDay, #Oscars2018.

The dataset was prepared in few steps - (i) collecting random tweets on a keyword; (ii) collecting user information like user ID(unique ID generated by Twitter), user name(the full name of the user), screen name(the name that the user can be addressed by), location(location of the user), number of posts(number of tweets), number of followers(the peo-

ple who are following the particular user), number of followees(all the people the particular user is following), number of likes; (iii) collecting replies on each tweet; (iv) collecting user information of the repliers; (v) collecting retweets on the tweet; and (vi) collecting user information of each retweeter. These steps were repeated for all search keywords.

Few challenges emerged while collecting data from Twitter that included: (i) Some tweets shared photos and videos and didn't mention much in the text. (ii) Even for tweets which were expressed as text in English, lots of comments were in other languages. (iii) Lots of comments had no text, they just shared photos or videos. (iv) In some cases, lots of replies were posted by persons who tweeted as reply to repliers. Some people replied to each reply on their tweet making the number of replies on their tweets double. (v) Some replies on some tweets were not from another regular user, but from some accounts of news channels or business persons. Those replies were basically advertisements of some news or product. For example, in the replies of #WomensDay tweets, few advertisement replies were from some news media which work for gender equity, few replies were from business accounts with advertisement of their beauty products, and so on. (vi) Few people had thousands of tweets, but none of them were original. They just retweeted others tweets. (vii) Few replies didn't have any text other than few mentions of some accounts. (viii) Few replies just had the same hashtagged word as the original tweet and nothing else. (ix) Few tweets and replies just stated some facts without expressing any sentiments or emotions. (x) Few replies just had emojis and no text. (xi) Some repliers responded by asking questions which didn't express any emotion. (xii) Some responses were totally random and out of context.

Both Twitter API and web-page scraping were used for data collection from Twitter. Table 4.1 shows attributes of the tweets and Table 4.2 shows the attributes of a user object that can be extracted using Twitter API. There are few profile images and background images attributes available which were not mentioned in the tables. Due to the rate limit of

created_at	id	id_str	text
source truncated	in_reply_to_status_id	in_reply_to_status_id_str	in_reply_to_user_id
in_reply_to_user_id_str	in_reply_to_screen_name	user	coordinates
place	quoted_status_id_str	is_quote_status	quoted_status
retweeted_status	quote_count	reply_count	retweet_count
favorite_count	entities	extended_entities	favorited
retweeted	possibly_sensitive	filter_level	lang

Table 4.1: Tweet Attributes

id	id_str	name	screen_name	location
url	description	derived	protected	verified
followers_count	friends_count	listed_count	favourites_count	statuses_count
created_at	utc_offset	time_zone	geo_enabled	lang

Table 4.2: User Attributes

Twitter API, 15 API calls are allowed in every 15 minutes and this restricted the amount of data collected for the research.

4.2 Pre-processing

Figure 4.1 shows the work-flow of creating the dataset. First, a crawler was used to find original tweets on a specific topic. The tweets were filtered while collecting tweets and only original tweets (not retweets) were accepted on the topic. The first crawling operation returned unique tweet ID and tweet text which were applied on another crawler to find the number of likes, retweets and time of tweet. Another crawler returned retweeters user IDs. No direct functions exist for extracting replies to a tweet using the Twitter API. Thus, replies to a tweet were collected using a different crawler. The latter crawler took the tweet ID and user ID and checked the texts directed to the user since the time of the tweet. It collected only texts which were true for the parameter 'in_reply_to_status_id'. As this was not using any direct function, collecting replies of a tweet took most of the time.

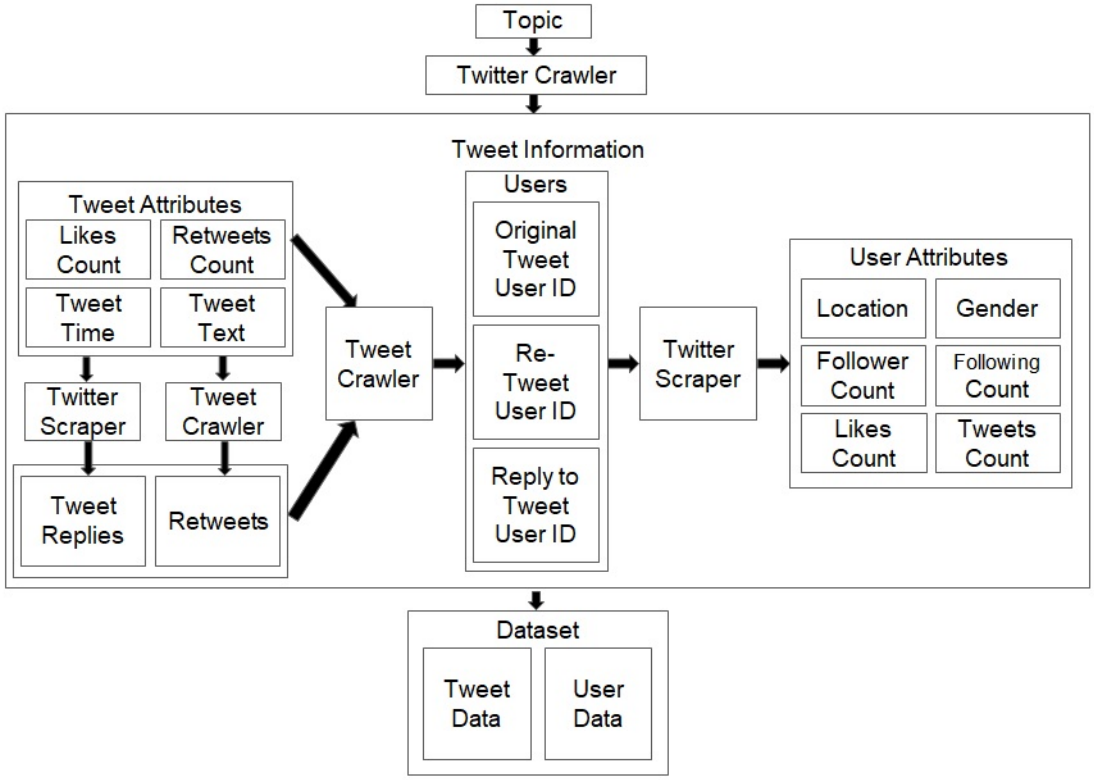


Figure 4.1: Dataset Creation Workflow.

To enhance the speed of collecting replies of tweets, a Web page scraper was used where replies were collected by scraping the tweet page. User information was collected as well for this research. A Web page scraper was used to extract users' data from their Twitter Web page for original tweet users, retweeters and repliers. User attributes collected were the number of tweets, likes, follower, followee and location (when available). In the final dataset, all user data and tweet data were combined. Figure 4.3, Figure 4.4, Figure 4.5 and Figure 4.6 are samples of tweet, reply, retweet and user datasets consecutively.

Data preprocessing included cleaning the collected data and annotating the data according to sentiments and emotions. Tweets and comments had lots of unnecessary symbols and noise. Figure 4.2 shows the steps of preprocessing. The data cleansing process followed these steps: (i) all user mentions (i.e., @alice) were removed from the text and added as a connec-

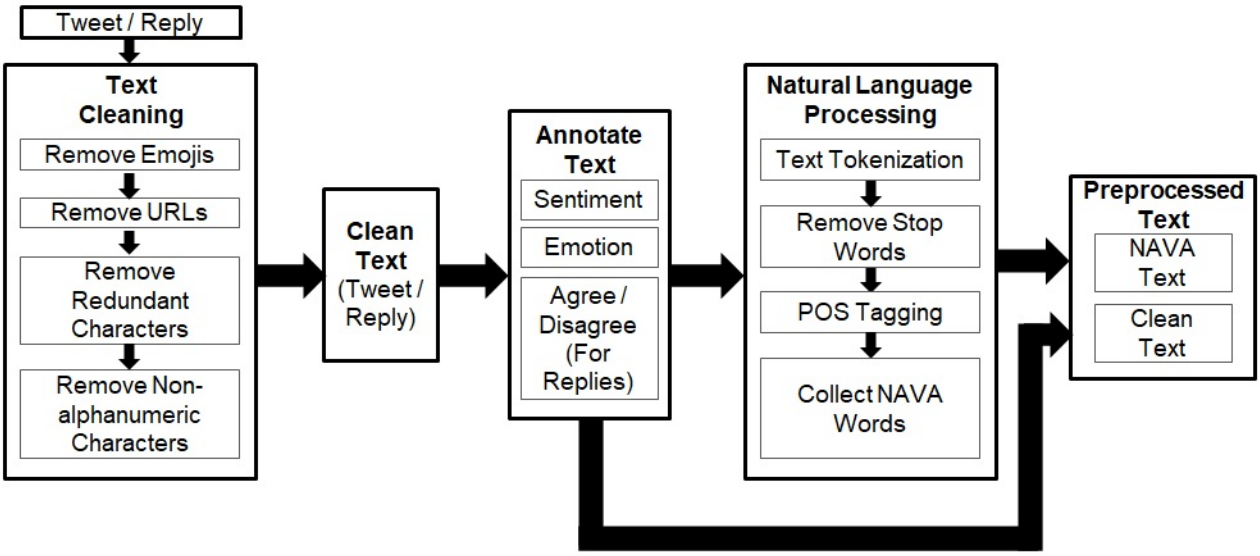


Figure 4.2: Preprocessing Workflow.

UserID	TweetID	Retweets	Likes	Replies	TweetTime	Tweet	Topic	Sentiment	Emotion
1173863894'	968177563439857664'	463	768	31	9:34 AM - 26 Feb 2018	Killing of innocent children and women in #Syria is strongly condemnable. UN and all other human rights organizations must play their role to save humanity and	#syria	Negative	Disgust
126384734'	968009367168536576'	925	848	66	10:26 PM - 25 Feb 2018	OUR MEDIA IS FAILING TO REPORT THE FULL TRU	#syria	Negative	Disgust
1561077758'	971929948410793984'	1995	5988	375	6:05 PM - 8 Mar 2018	I salute all the conservative women today who fight for ou	#WomensDay	Positive	Joy
17980523'	970673331035955200'	215	515	35	6:52 AM - 5 Mar 2018	If America hates Trump, why don't they love the shows tha	#Oscars2018	Negative	Surprise
19397785'	970514262832463872'	1178	15755	274	8:20 PM - 4 Mar 2018	So happy and proud for you @JordanPeele ! Thanks again	#Oscars2018	Positive	Joy
2400907280'	971979563528896517'	63	776	12	9:22 PM - 8 Mar 2018	The sign of a beautiful woman is they always see the beau	#WomensDay	Positive	Joy
2820265567'	968005032367988736'	128	581	14	10:09 PM - 25 Feb 2018	What a pathetic world we're living on? What did these po	#syria	Negative	Disgust
312696314'	970969985345400834'	205	193	19	2:30 AM - 6 Mar 2018	A year before the war began #Syria had plans to produce	#syria	Negative	Anger
48038539'	969422253757812737'	110	179	11	8:00 PM - 1 Mar 2018	#Syria: We know that that defending our country will cost	#syria	Negative	Sadness
739784130'	971865392279777280'	8904	35307	2500	1:49 PM - 8 Mar 2018	This #womensday I'd like to thank my mama who's my best friend; i love u. Who inspires u? #pressforprogress	#WomensDay	Positive	Joy
25058809676075010'	970777015652581376'	674	661	61	1:44 PM - 5 Mar 2018	Heavy bombing in #EastGhouta. Noor's Arabic teacher ha	#syria	Negative	Fear

Figure 4.3: Sample Tweet Dataset.

OTUserID	Topic	OTSentiment	OTEmotion	OTweetID	ReplyUserID	Reply Date	ReplyTime	Reply	A/D	Sentiment	Emotion
940536029953499141'	#syria	Negative	Sadness	967810695638212613'	1652128214'	26 Feb 2018	7:27 AM	God will punish the world, and its leaders for such pain and	Agree	Negative	Anger
1173863894'	#syria	Negative	Disgust	968177563439857664'	286166105'	26 Feb 2018	11:08 AM	ms r killed by terrorism.why these so called terrorist not att	Agree	Negative	Disgust
1173863894'	#syria	Negative	Disgust	968177563439857664'	863848771465220096'	26 Feb 2018	10:52 PM	We expect from u ppl to raise the voice strongly	Agree	Negative	Anger
1173863894'	#syria	Negative	Disgust	968177563439857664'	319305957'	27 Feb 2018	11:17 AM	It's a shame that this has gone on tooo looong!!!!!!	Agree	Negative	Disgust
1173863894'	#syria	Negative	Disgust	968177563439857664'	721516312246231041'	26 Feb 2018	3:11 PM	tect innocent civilians anywhere in the world. UN is a powe	Agree	Negative	Disgust
1173863894'	#syria	Negative	Disgust	968177563439857664'	810395293820784640'	26 Feb 2018	11:26 AM	The killing of a human is the murder of all humanity	Agree	Negative	Disgust
1173863894'	#syria	Negative	Disgust	968177563439857664'	2203132478'	27 Feb 2018	11:09 AM	Atleast try to find some genuine images	Disagree	Negative	Anger
1173863894'	#syria	Negative	Disgust	968177563439857664'	865644050942017538'	26 Feb 2018	9:45 AM	To whom you are saying?? Imran khan is still silent .	Agree	Negative	Anger
126384734'	#syria	Negative	Disgust	968009367168536576'	852902730763046912'	26 Feb 2018	1:03 AM	rest you reporting this? Why are you failing to tell the full	Agree	Negative	Anger
126384734'	#syria	Negative	Disgust	968009367168536576'	25960696'	25 Feb 2018	11:21 PM	So I wonder if you come from Mars or another planet? Anyv	Agree	Positive	Joy
126384734'	#syria	Negative	Disgust	968009367168536576'	743135039416733697'	26 Feb 2018	10:43 AM	left... notice how ghouta is totally destroyed while Damasc	Disagree	Negative	Anger
126384734'	#syria	Negative	Disgust	968009367168536576'	813386974602137600'	26 Feb 2018	4:32 AM	Carla for helping to show the world what really is happenin	Agree	Positive	Joy
126384734'	#syria	Negative	Disgust	968009367168536576'	3304752681'	26 Feb 2018	3:35 AM	Sickening	Agree	Negative	Disgust
126384734'	#syria	Negative	Disgust	968009367168536576'	1725156751'	26 Feb 2018	1:07 AM	Nice video telling the truth	Agree	Positive	Joy
126384734'	#syria	Negative	Disgust	968009367168536576'	1470586742'	26 Feb 2018	12:43 AM	ressed, who created this video. So well done and sound exa	Disagree	Positive	Joy
126384734'	#syria	Negative	Disgust	968009367168536576'	4427337886'	26 Feb 2018	12:41 AM	to share the truth. So few are willing to even investigate th	Agree	Positive	Joy
126384734'	#syria	Negative	Disgust	968009367168536576'	1129300921'	25 Feb 2018	11:36 PM	for being the truth and the light within all the darkness. Than	Agree	Positive	Joy
126384734'	#syria	Negative	Disgust	968009367168536576'	410734320'	26 Feb 2018	3:32 PM	Raqqa were destroyed, not liberated. ISIS forces were re-di	Agree	Negative	Anger
312696314'	#syria	Negative	Anger	970969985345400834'	970003379287220224'	6 Mar 2018	3:49 AM	Look here below and don't spread propoganda	Disagree	Negative	Anger
312696314'	#syria	Negative	Anger	970969985345400834'	791284563091791873'	6 Mar 2018	3:09 AM	ost of Syria is safe now and Syria woll be strong again and w	Agree	Positive	Joy
312696314'	#syria	Negative	Anger	970969985345400834'	1621053301'	6 Mar 2018	9:16 PM	punish the innocent. Which way do you think our evolutiona	Agree	Negative	Sadness
312696314'	#syria	Negative	Anger	970969985345400834'	827912555687391232'	6 Mar 2018	4:58 PM	onestly heartbreaking to know what's being done in our name	Agree	Negative	Sadness
312696314'	#syria	Negative	Anger	970969985345400834'	79343069'	6 Mar 2018	7:01 AM	trikes on hospitals that eviscerate babies and leave them as r	Disagree	Negative	Anger
312696314'	#syria	Negative	Anger	970969985345400834'	2477324378'	6 Mar 2018	4:14 AM	Get with the program, Partisangirl. You don't want the NY	Agree	Negative	Anger
312696314'	#syria	Negative	Anger	970969985345400834'	826748803277484033'	6 Mar 2018	2:47 AM	it, is a bit of a battle...even if they could get drugs, it would	Agree	Negative	Disgust
312696314'	#syria	Negative	Anger	970969985345400834'	3398870566'	6 Mar 2018	1:22 PM	nctions can be applied to life saving drugs. That itself is su	Agree	Negative	Disgust
312696314'	#syria	Negative	Anger	970969985345400834'	891083329'	6 Mar 2018	11:33 AM	same thing is happening in Gaza thanks to these hypocrites a	Agree	Negative	Disgust
312696314'	#syria	Negative	Anger	970969985345400834'	959941287435583488'	6 Mar 2018	3:10 AM	ps the rich richer while all of our family members have to g	Agree	Negative	Disgust

Figure 4.4: Sample Reply Dataset.

'OTUserID'	'TweetID'	'RetweeterID'	Topic
'767104070280630272'	'978652593546252288'	'830964611205718016'	#SchoolShooting
'767104070280630272'	'978652593546252288'	'732078408'	#SchoolShooting
'4899575941'	'978718074990944257'	'846190758696673280'	#SchoolShooting
'4899575941'	'978718074990944257'	'946358671067570176'	#SchoolShooting
'4899575941'	'978718074990944257'	'2265799817'	#SchoolShooting
'4899575941'	'978718074990944257'	'792425445929078788'	#SchoolShooting
'4899575941'	'978718074990944257'	'826867021086343169'	#SchoolShooting
'4899575941'	'978718074990944257'	'459471568'	#SchoolShooting
'4899575941'	'978718074990944257'	'919722437616418816'	#SchoolShooting
'4899575941'	'978718074990944257'	'607371255'	#SchoolShooting
'4899575941'	'978718074990944257'	'874074353889140736'	#SchoolShooting
'4899575941'	'978718074990944257'	'799605330200186880'	#SchoolShooting
'4899575941'	'978718074990944257'	'558607687'	#SchoolShooting
'4899575941'	'978718074990944257'	'1607390360'	#SchoolShooting
'4899575941'	'978718074990944257'	'826124051869528065'	#SchoolShooting
'4899575941'	'978718074990944257'	'256321188'	#SchoolShooting
'4899575941'	'978718074990944257'	'4248009076'	#SchoolShooting
'4899575941'	'978718074990944257'	'768166136106057729'	#SchoolShooting
'4899575941'	'978718074990944257'	'818290710730379265'	#SchoolShooting
'4899575941'	'978718074990944257'	'856923191926824961'	#SchoolShooting
'4899575941'	'978718074990944257'	'947293112774389760'	#SchoolShooting
'4899575941'	'978718074990944257'	'821037202968870912'	#SchoolShooting
'911222120050544645'	'978793645854863360'	'788011598657032192'	#SchoolShooting
'911222120050544645'	'978793645854863360'	'816037443468197892'	#SchoolShooting

Figure 4.5: Sample Retweet Dataset.

UserID	TweetLocation	#Tweets	#Followers	#Likes	#Following
2820265567	Hyderabad, India	1363	390000	391	18
940536029953499141	Los Angeles, USA	7817	1159	16500	665
1173863894	Punjab, Pakistan	6766	235000	485	55
126384734	Los Angeles, USA	9050	80900	10300	387
312696314	Syria	46600	71900	15100	974
48038539	Syria	40200	5695	1430	189
932954218406617088	USA	2412	4365	3067	4991
925058809676075010	Syria	232	8590	791	70
19397785	USA	12400	41900000	149	290
17980523	Florida, USA	112000	340000	19800	8762
1561077758	Spartanburg, USA	11200	77300	51200	38600
2400907280	Philippines	477	16300	7983	409
739784130	Mexico	11500	647000	19900	16800

Figure 4.6: Sample User Dataset.

tion between users in the network; (ii) all hashtags (only the # symbol) were removed; (iii) all emoticons were removed (i.e., :-), :-(etc.); (iv) all multiple occurrences of the same letter were removed (i.e., 'wowwwwwww' became 'wow'); (v) all non-alphanumeric characters (not in A-Z or a-z or 0-9) were removed (i.e., ?, ,, ., ;, ! etc.); (vi) all URLs were removed (i.e., `http://a.com`). Clean tweets and replies were then annotated.

All tweets and replies were annotated with 'positive', 'negative' or 'neutral' sentiments. For emotion annotations, Ekman's emotion model[38] was used which lists six basic human emotions - 'Anger', 'Disgust', 'Fear', 'Joy', 'Sadness' and 'Surprise'. All tweets and replies were annotated using these six emotions. Replies on tweets were also annotated with 'agreed' or 'disagreed' based on their agreement or difference on the original tweet text. This version of texts was stored as 'Clean Text'. After annotating tweets and replies, Natural Language

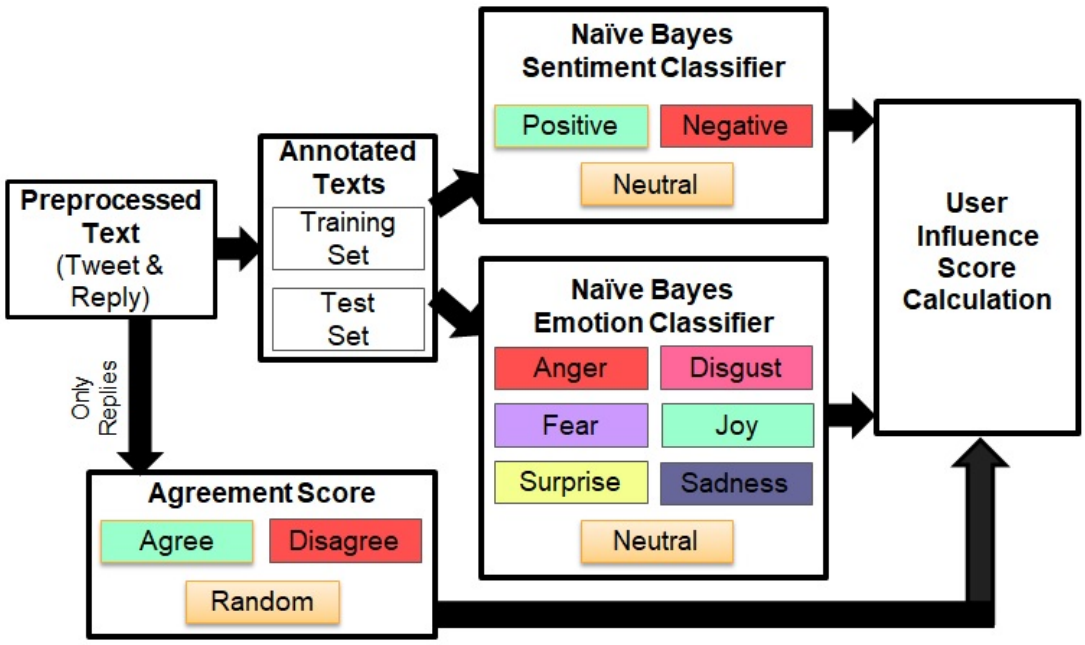


Figure 4.7: Classification & Recommender System Workflow.

Processing (NLP) was used to process the texts. Words of the sentences were tokenized. Then common English stop words (i.e., am, as, the, etc.) were removed from the text and words were tagged according to their corresponding Parts-of-Speeches(POS) using a POS tagger. Among all words, only Noun, Adjective, Verb and Adverb(NAVA) words were collected as they contribute most in a sentence. These texts were stored as 'NAVA Text' and finally, the preprocessed text were extracted that had two versions of the texts - the cleaned texts and only the NAVA words of each piece of text.

4.3 Emotion Detection

In previous studies of emotion detection from text, different methods were used by various researchers. In most recent researches, machine learning was used with both supervised[57, 62] and unsupervised[70, 65] classifiers. Machine learning is a better option for a larger dataset and the training of the classifier is a more generalized approach than creating emotion word dictionaries. Naive Bayes worked better than other machine learning approaches described

in the literature with sentiment and emotion detection from text. Therefore, Naive Bayes algorithm was chosen to classify tweets and replies into their corresponding sentiment and emotion classes.

Figure 4.7 shows a work flow of classification of preprocessed text and calculation of influence score to generate recommendation. The preprocessed text (both tweets and replies) were divided into training and test sets for emotion and sentiment classifications. Then, emotion and sentiment were fed into the calculation of "user influence score" which also used the agreement score for replies (i.e., if the reply agreed to the original tweet or not). The influence score used all these values along with the number of tweets, retweets, follower and followees to generate the final influence score. The recommender system took the score and generated a list of users as a recommendation who shared similar emotion and sentiment on a specific topic.

The Naive Bayes algorithm was applied with 3-fold, 5-fold and 10-fold cross validation on the preprocessed text (tweets and replies). The feature set used for Naive Bayes were NAVA words for *'NAVA Text'* and all the words for *'Clean Text'* from each tweet and reply. The classifier was applied on the same data set twice - (i) for classifying them according to their sentiments and (ii) for classifying them according to their corresponding emotions.

4.4 Influential Users Detection

In literature, researchers applied only the numeric scores like number of followers, followees to detect the influential users from a network. But, in this research, few other factors were considered for the calculations. One person can influence another person in both positive and negative ways. Normally, when someone likes or retweets a tweet from another person,

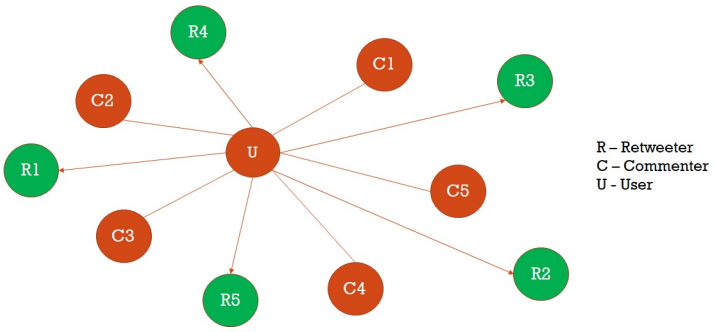


Figure 4.8: Connections between a Tweeter and the Retweeters and Repliers.

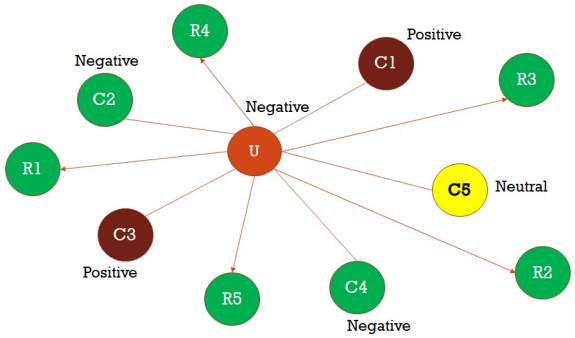


Figure 4.9: Sentiments of Nodes.

he/she agrees to that tweet. But a person can reply on another person's tweet and express either his/her support or disagreement to that tweet. This was addressed while calculating the influence score based on all the factors - (i) Number of retweets, (ii) Number of likes, (iii) Number of comments that agree to the tweet or show similar sentiment/emotion, (iv) Number of comments that disagree to the tweet or show opposite sentiment/emotion, and (v) Number of people who follow the person.

Figure 4.8 represents a sample of connections between the user of the tweet (U) and the retweeters (R) and repliers (C) of that tweet. The retweeters are influenced by the tweeter and are shown in green nodes; U influences R nodes. In Figure 4.9, the sentiments of the replies are shown as positive, negative or neutral. It shows people having similar sentiments to the user. Even if some nodes are expressing same sentiments on a certain issue, they still can have different emotions. For example, on some horrific incident, one person can express

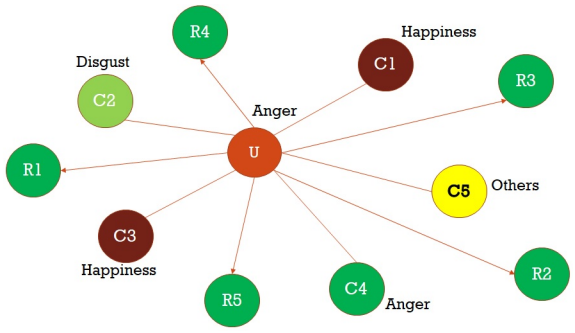


Figure 4.10: Emotions of Nodes.

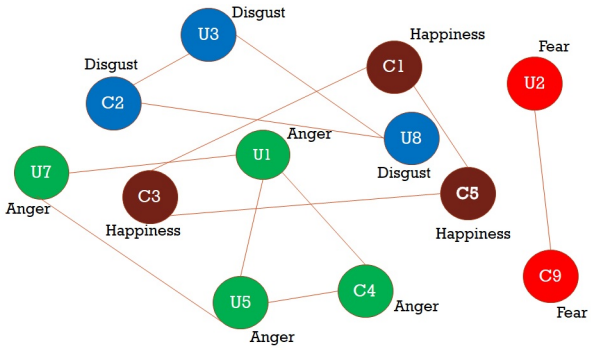


Figure 4.11: Suggestions of Connections between Similar Emotion Nodes.

anger whereas another person can express disgust, but anger and disgust both are negative sentiments. Figure 4.10 represents emotions of the nodes. Figure 4.11 represents possible suggestions for users to let them know people who are not directly connected, but have the same emotion regarding any social, national or international issue.

Due to the variety of parameters and metrics of Twitter data, there is no one standard equation to measure influential users in Twitter. Various researchers used different measurements based on different perspectives and statements of their research problems.

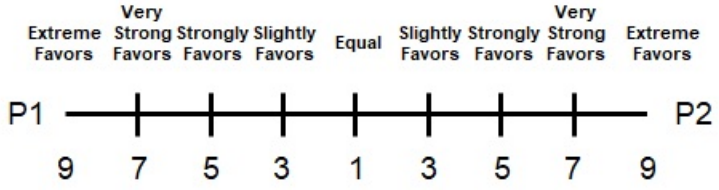


Figure 4.12: Pairwise Comparison Scale in AHP.

Existing measurements were modified according to the problem statement and two types of influence scores (IS) of a user were measured using the following values. W values are the weights assigned to each parameter. These weights were calculated using Analytical Hierarchy Process(AHP)[114]. Weight calculation was done using the following steps. (i) Parameters were divided into two groups: (a) user-based parameters (Number of tweets, followers, followees and likes), (b) tweet-based parameters (number of retweets, replies, likes, agreement, sentiment and emotion scores). (ii) For each group of parameters, a pairwise comparison was done between every combination of two parameters using the scale shown in Figure 4.12. P1 and P2 are any two parameters and values from 1 to 9 are measurements of their comparison. (iii) Two different comparison matrix for two groups were created. (iv) After creating the Eigen vectors for both matrices, normalized Eigen vectors were used as priority matrices for weight vectors. A general influence score (IS_G) for each user was calculated based on user-based parameters. Another topic specific influence score (IS_T) was computed by merging user-based and tweet-based parameters.

User-based Parameters:

$TS_U(Tweet_Score) = W_T * \#Tweets$

$FS_U(Follower_Score) = W_F * \#Followers$

$OS_U(Followee_Score) = W_O * \#Followees$

$LS_U(Like_Score) = W_L * \#Likes$

Tweet-based Parameters:

$RS_T(Retweet_Score) = W_R * \#Retweets$

$CS_T(Comment_Score) = W_C * \#Comments$

$PS_T(Like_Score) = W_P * \#Likes$

$AS_T(Agreement_Score) = W_A * Agreement_Value$

$SS_T(Sentiment_Score) = W_S * Sentiment_Value$

$$ES_T(Emotion_Score) = W_E * Emotion_Value$$

$$Agreement_Value = \begin{cases} 1 & \text{if reply agrees with tweet} \\ \text{-1} & \text{if reply disagrees with tweet} \end{cases}$$

$$Sentiment_Value = \begin{cases} 1 & \text{similar sentiment} \\ \text{-1} & \text{different sentiment} \end{cases}$$

$$Emotion_Value = \begin{cases} 1 & \text{similar emotion} \\ \text{-1} & \text{different emotion} \end{cases}$$

The two Influence_Scores (IS) are,

$$IS_U = TS_U + FS_U + OS_U + LS_U$$

$$IS_T = IS_U + RS_T + CS_T + PS_T + AS_T + SS_T + ES_T$$

To normalize IS values, the values were converted into percentage using the following formula, where MIN and MAX are the minimum and maximum values of IS (Influence Score) among all users in the dataset.

$$\frac{IS - MIN}{MAX - MIN} * 100$$

4.5 Recommendation

The recommender system provided two different types of recommendation on both emotion and sentiment. (i) General Recommendation: A common recommendation based on a specific topic which recommended top ten user IDs on each sentiment and emotion. (ii) Personalized Recommendation: For each user, a recommendation which recommended top ten

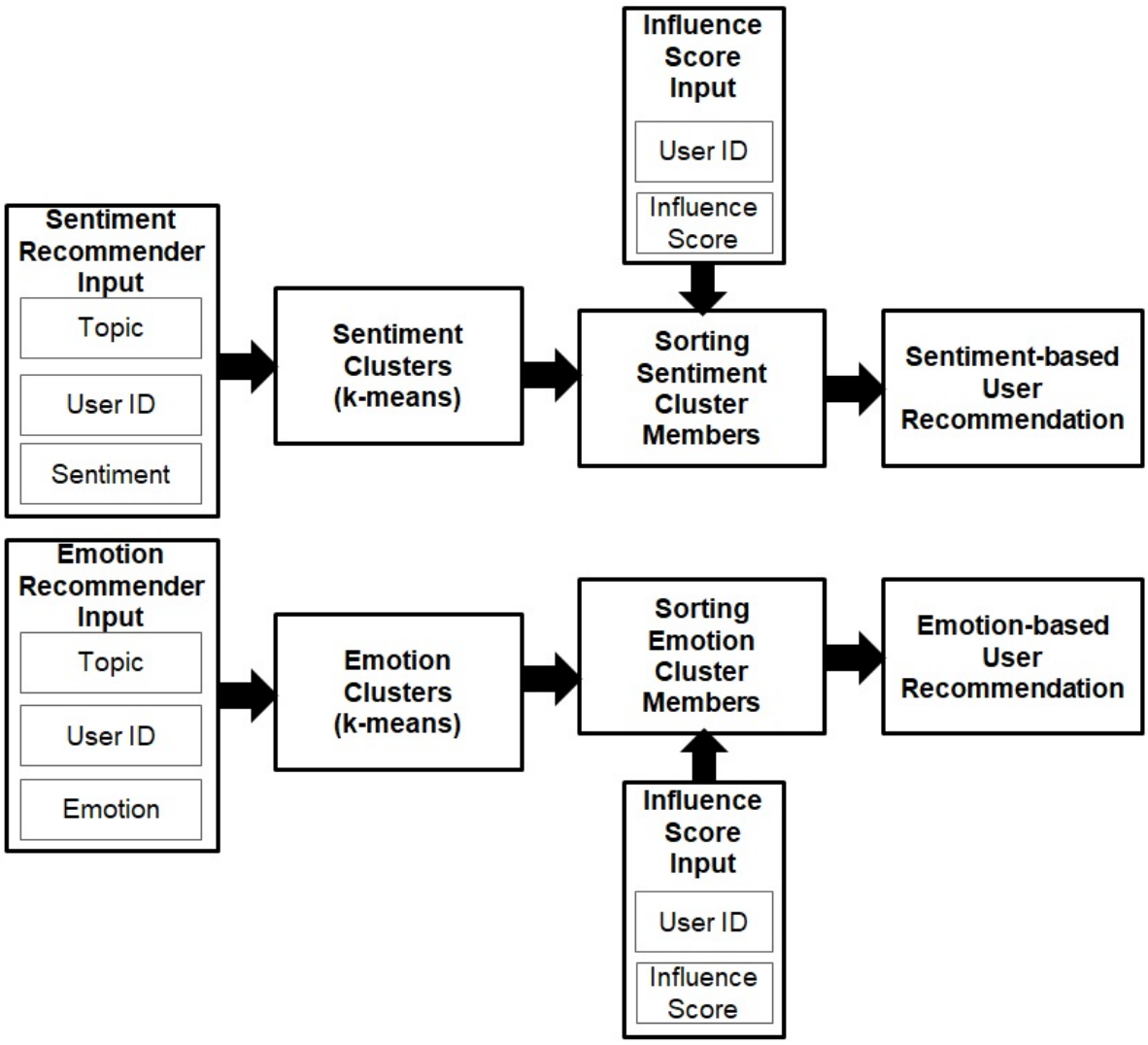


Figure 4.13: Recommender System Workflow.

user IDs who shared similar emotion and sentiment on a specific topic. The general recommender found users who interacted (tweeted, replied, retweeted) on a specific topic. Each of those users expressed some emotion and sentiment regarding that particular topic. Therefore, k-means clustering was applied individually based on sentiment and emotion to create individual clusters for each emotion and sentiment. As each user had a corresponding emotion and a sentiment regarding a specific topic, for each topic, k-means clustering method created clusters of users according to their emotion and sentiment towards that topic. Since k-means clustering needs the number of clusters prior to any calculation, the method worked

well for this procedure. The number of clusters of sentiment and emotion recommender were equal to the number of sentiments and emotions considered. For sentiment, three clusters (positive, negative and neutral) were formed. Each user was assigned to a cluster according to his/her sentiment on the topic. Then, all users of each cluster were sorted according to their influence score and the first ten users with highest influence scores were recommended. The same process was repeated for emotion as well. Seven clusters for emotion were formed, namely anger, disgust, fear, joy, sadness, surprise and neutral. Figure 4.13 shows the workflow of the recommender system. For the personalized recommendation, for each user of a cluster, a highest influence score ranked list of users from the same cluster was generated as a customized recommendation to that user to suggest him/her about other people sharing similar emotion or sentiment on a topic.

The framework for the data collection, annotation, classification and recommendation used few existing ideas and parameters from literature and combined them with some new framework units and calculation parameters. The workflow diagrams of each unit showed the process in detail with all the considered features. The equations used included parameters with proper definition and reasoning behind the calculations for experimental setup.

Chapter 5

Experimental Results

The experiments and results discussed in this chapter were the outcomes of the methodology and procedures explained in chapter 5. As the dataset and methodology of chapter 4 differ from the dataset and procedure of chapter 3, chapter 5 has nothing in common with the experimental results of chapter 3. The experiments for this research were conducted in multiple steps. The data collection process with sample results were described in Chapter 4. In this chapter, all the preprocessing done on the collected data are mentioned with classification accuracy scores, sample influence scores, sample general and personalized recommendations for both sentiments and emotions.

5.1 Emotion and Sentiment Classification

After collecting the data, the texts were cleaned and preprocessed. Then Naive Bayes classifier was applied to classify the text according to corresponding sentiment and emotion classes using 3-fold, 5-fold and 10-fold cross validation. The sentiment and emotion classifiers were applied on the cleaned text and on only the NAVA words individually to measure the classification accuracy. Table 5.1 shows accuracy results in percentage for sentiment and emotion classification for both full text and text with only NAVA words. The table

also shows the accuracy of emotion classification accuracy of Naive Bayes on the benchmark ISEAR dataset[83]. The emotion classes in the new dataset and the ISEAR dataset had five emotions in common. Instead of 'surprise', ISEAR included 'shame' and 'guilt'. The accuracy of emotion classification of ISEAR dataset were included to show variation in results of the same classifier with two different datasets with slightly varying emotions.

According to the results, using full text for classification increased accuracy by at least 5% than using only NAVA words. Also, as the number of folds were increased for the k-fold cross validation, classification accuracy increased gradually. Another interesting observation was the differences between accuracies in sentiment and emotion classifications. For sentiment classification, 3 classes (positive, negative, neutral) existed whereas there were 7 classes for emotion (anger, disgust, fear, joy, sadness, surprise and neutral). As the number of classes increased for emotion classifier, the accuracy level decreased a little bit compared to the sentiment classifier. As expected from a text based classifier, the accuracy levels were not very high. The reason behind this was the structure of the data. For Twitter data (tweets and replies), finding proper and grammatically correct sentences with appropriate parts-of-speeches was difficult. On the other hand, for the benchmark ISEAR dataset, as the texts were properly formed meaningful sentences, the accuracy level of classification was higher than the Twitter data. The distribution of emotions in the dataset was another reason for the lower accuracy. As the tweets and replies were collected randomly, all the emotions were not very well-distributed in the dataset which resulted lower classification accuracy.

5.2 Influence Score

The next step was measuring the influence score for users. AHP was used to calculate the weight vector. The comparison matrices is shown in Figure 5.1. The priority matrices were

k-fold	Full Text Sentiment	NAVA Sentiment	Full Text Emotion	NAVA Emotion	ISEAR[83] Dataset Full Text Emotion	ISEAR[83] Dataset NAVA Emotion
3-fold	62.69	55.96	44.37	40.45	52.34	53.37
5-fold	63.71	58.33	46.32	41.29	54.01	54.82
10-fold	66.86	61.15	47.34	43.24	55.11	56.51

Table 5.1: Sentiment and Emotion Classification Accuracy (in percentage - %)

	TS_U	FS_U	OS_U	LS_U
TS_U	1	1/5	7	7
FS_U	5	1	7	7
OS_U	1/7	1/7	1	1
LS_U	1/7	1/7	1	1

	RS_T	CS_T	PS_T	AS_T	SS_T	ES_T
RS_T	1	7	3	1/3	7	7
CS_T	1/7	1	1/7	1/7	1	1
PS_T	1/3	7	1	1/3	7	7
AS_T	3	7	3	1	7	7
SS_T	1/7	1	1/7	1/7	1	3
ES_T	1/7	1	1/7	1/7	1/3	1

Figure 5.1: Comparison Matrices for AHP.

calculated by eigen vectors and normalization. Finally, the weight vector had the following weight values -

$W_T = 0.292,\ W_F = 0.586,\ W_O = 0.061,\ W_L = 0.061,\ W_R = 0.272,\ W_C = 0.040,\ W_P = 0.204,\ W_A = 0.395,\ W_S = 0.053,\ and\ W_E = 0.035.$

The agreement score represented if the reply to a tweet agreed or disagreed to the tweet. To apply the influence score formula on the whole dataset (both tweets and replies), 1 (agreement) was assigned as the Agreement_Value for original tweets. This inclusion was logical because the user who tweeted something obviously agreed to his/her own tweet. After the calculation the influence score was normalized between 0 to 100 since the influence scores of users varied from 10 to millions because of the number of tweets, followers etc. Figure 5.2 shows the user IDs with their original and normalized influence scores in a descending

UserID	IS	Normalized IS
19397785'	24557047.58	99.99999991
739784130'	384738.7	1.566705736
17980523'	233686.282	0.951597466
2820265567'	228962.945	0.932363324
'77338274'	219298.639	0.893008809
'749038067747590144'	196021.573	0.798221079
'149296998'	182857.669	0.744615673
1173863894'	160579.121	0.65389406
'251009806'	115090.954	0.46865937
'1713417312'	107508.749	0.437783486
'17235735'	107062.369	0.435965759
'2258357868'	105952.716	0.431447084
'880929493'	105707.38	0.430448039
'253340432'	104023.739	0.423591999
'839099917121511425'	103879.948	0.42300646
'503794853'	102850.474	0.418814286
'2318083470'	101315.387	0.41256318
'3357427702'	98647.878	0.40170068
'2876041031'	98647.878	0.40170068
'805345210557493248'	97451.093	0.396827191
'348780432'	96743.078	0.393944047
'348780432'	96743.078	0.393944047
'624827127'	92965.685	0.378561932

Figure 5.2: Users and their Influence Scores.

order. An interesting observation from the influence scores is that the difference between the highest score and all the other scores is very high. As Twitter does not enforce the bidirectional follow rule like other social networks, few people (i.e. actors, politicians, journalists, etc.) have sometimes 1000 times more followers than a regular user. That difference still existed after normalizing the scores. They were not considered as outliers because there were multiple users with huge amount of followers and this also represented the uniqueness of Twitter over other social networks.

5.3 Recommendations

The influence scores were then used for the recommender system. The general recommender provided top 10 most influential users for each sentiment and emotion. Figure 5.3 and 5.4

UserID	IS	Sentiment
19397785'	100	Positive
407474647'	0.550642859	Positive
'601448080'	0.539985025	Positive
'601448080'	0.539985025	Positive
'601448080'	0.539985025	Positive
20831692'	0.46468827	Positive
413007007'	0.314848707	Positive
90895234'	0.212021002	Positive
150422835'	0.19237308	Positive
'3061826623'	0.15292931	Positive
17980523'	1.146551095	Negative
'29703494'	0.154778385	Negative
477918460'	0.083265675	Negative
368586936'	0.075857442	Negative
54158866'	0.022759141	Negative
'3740444776'	0.014704328	Negative
'3740444776'	0.014704328	Negative
862840407159447552'	0.006537378	Negative
811007544080662532'	0.003154166	Negative
'891708601093562369'	0.001586626	Negative
'938907973279154177'	0.215082117	Neutral
'3555274281'	0.05117049	Neutral

Figure 5.3: General Recommendation according to Sentiment.

show the general sentiment and emotion recommendation on #Oscars2018. Figure 5.5 shows personalized recommendation for one user. The file name shows user ID for whom the recommendation was issued.

5.4 Networks between Users

Figure 5.6 shows the retweet network for tweets on #Oscars2018. The little circles represent users. Larger circles represent clusters of users who retweeted a tweet of the user who is the center of the cluster. The bigger the circle is, the more retweets that tweet has. This is equivalent to the influence of the user. Few tweets were retweeted later by the author of the tweet. This created few loops in the network. Figure 5.7 shows the retweet network for #Oscars2018. Figure 5.8 shows the reply network for #Oscars2018 without considering

UserID	IS	Emotion
'891708601093562369'	0.001586626	Anger
54158866'	0.022759141	Disgust
862840407159447552'	0.006537378	Disgust
811007544080662532'	0.003154166	Disgust
814488110306381825'	0.000212345	Disgust
'29703494'	0.154778385	Fear
19397785'	100	Joy
407474647'	0.550642859	Joy
20831692'	0.46468827	Joy
413007007'	0.314848707	Joy
90895234'	0.212021002	Joy
150422835'	0.19237308	Joy
'820232246904950784'	0.094951834	Joy
89931829'	0.043022627	Joy
750441536848994304'	0.025071083	Joy
279785200'	0.021029361	Joy
'3740444776'	0.014704328	Sadness
'3740444776'	0.014704328	Sadness
17980523'	1.146551095	Surprise
'601448080'	0.539985025	Surprise
'601448080'	0.539985025	Surprise
'601448080'	0.539985025	Surprise
'3061826623'	0.15292931	Surprise
477918460'	0.083265675	Surprise
368586936'	0.075857442	Surprise
'3740444776'	0.014704328	Surprise
'938907973279154177'	0.215082117	Neutral
'3555274281'	0.05117049	Neutral
'882654015284051969'	0.007735102	Neutral

Figure 5.4: General Recommendation according to Emotion.

279785200'_Rec.csv	
UserID	**IS**
19397785'	100
'601448080'	0.539985025
'601448080'	0.539985025
413007007'	0.314848707
150422835'	0.19237308
'820232246904950784'	0.094951834
750441536848994304'	0.025071083
'3296075343'	0.017386085
831982169253937152'	0.016925605
958527409019432960'	0.012621434

Figure 5.5: Personalized Recommendation.

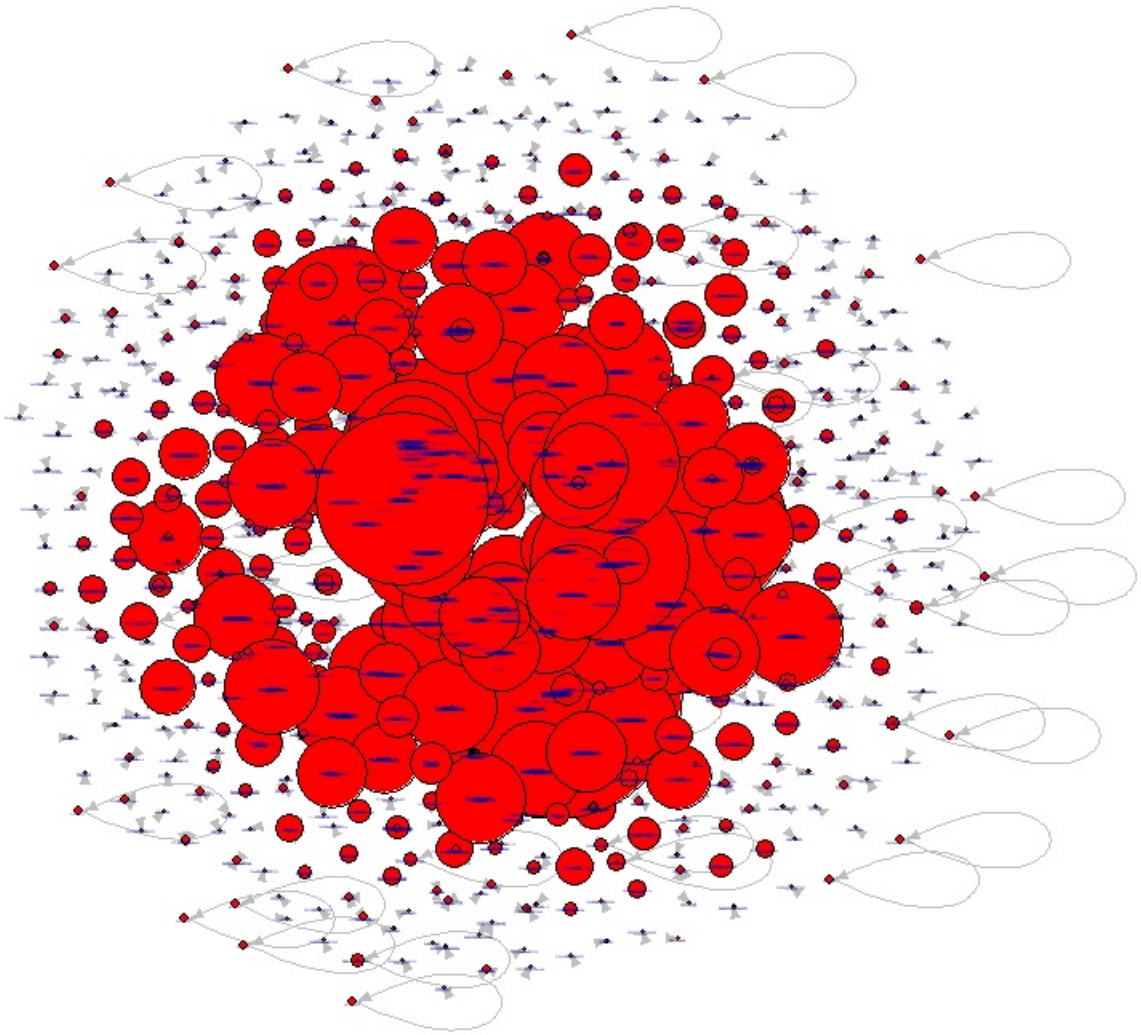


Figure 5.6: Retweet Network based on Degree for #Oscars2018.

emotions or sentiments. Here, a connection from one node to another means the source node replied to a tweet of the destination node. Figure 5.9 and 5.10 show the reply network connections for #Oscars2018. They are color coded according to their sentiments and emotions. For the sentiment network, yellow nodes represent positive sentiment, blue nodes represent negative sentiment and green nodes represent neutral sentiment. In the emotion network, dark blue represents joy, pink represents anger, blue represents disgust, orange represents fear, red represents surprise and yellow represents neutral emotion. This shows how most of the connected users show similar sentiment and emotion on a topic.

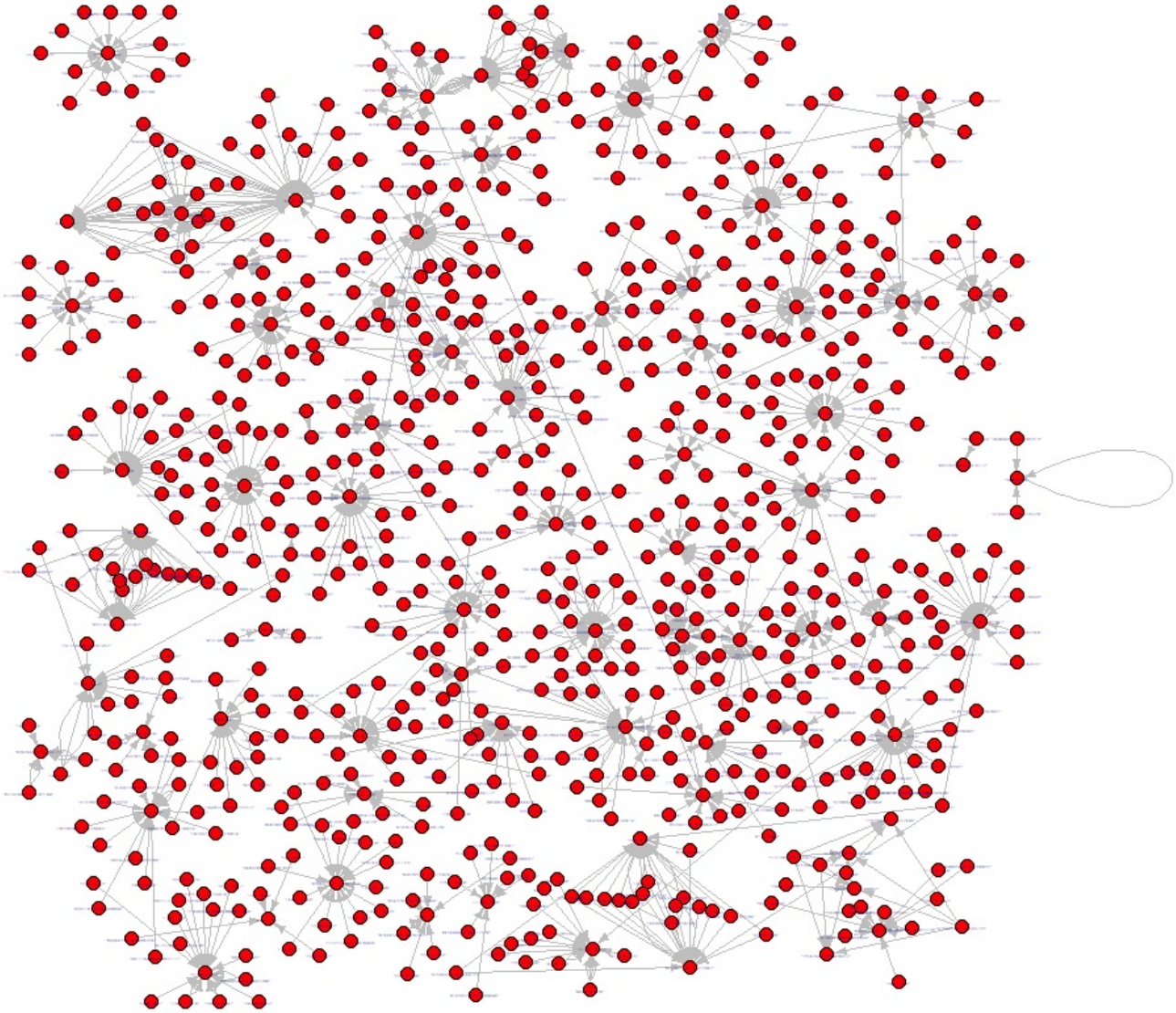


Figure 5.7: Retweet Network for #Oscars2018.

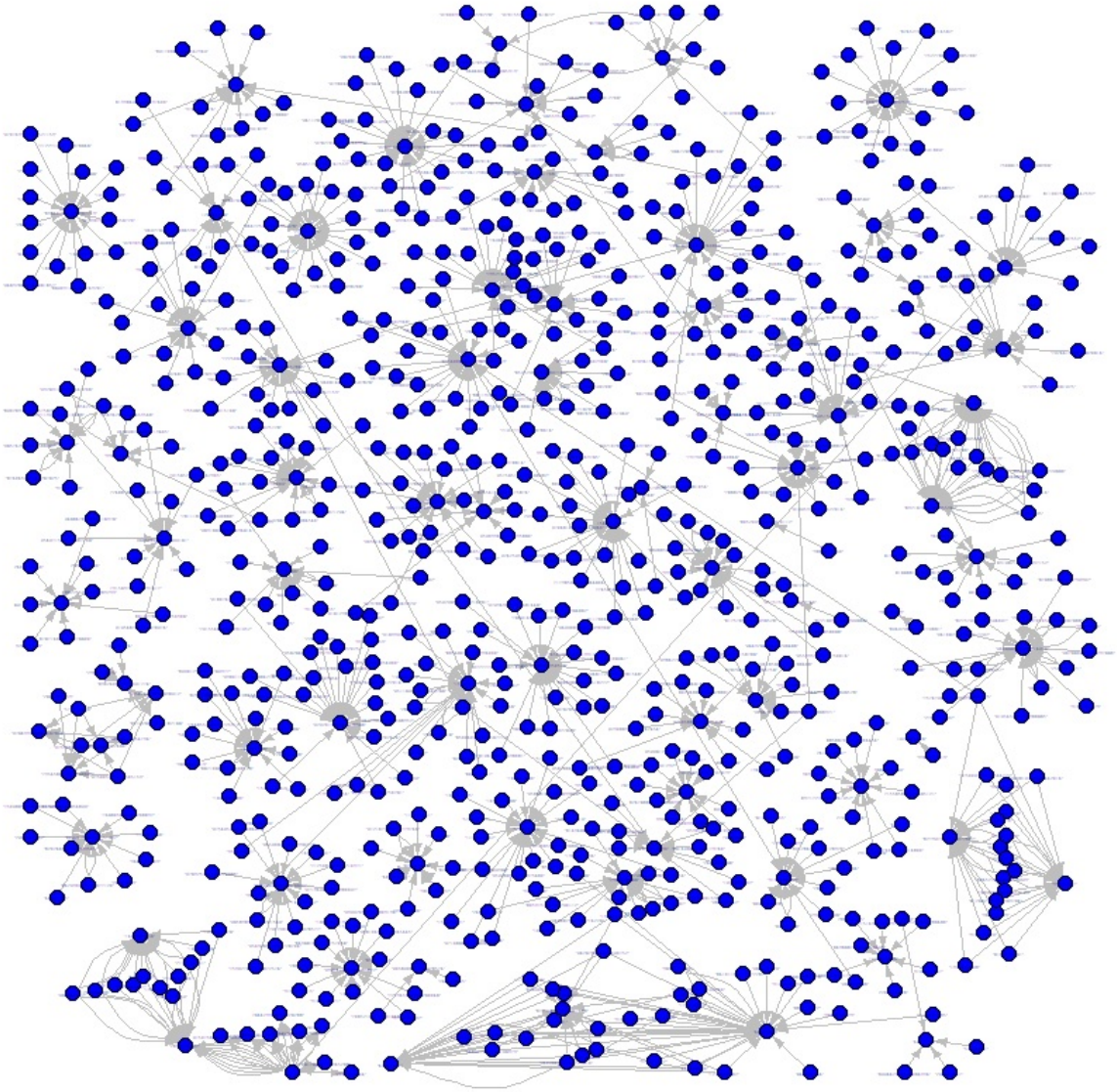


Figure 5.8: Reply Network for #Oscars2018.

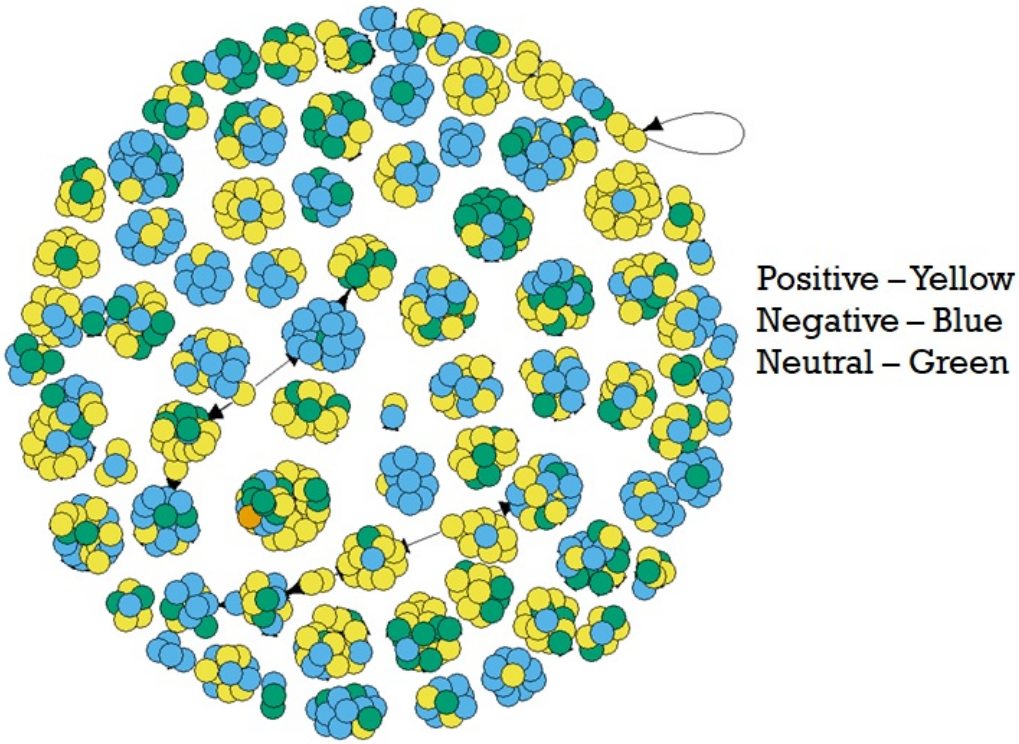


Figure 5.9: Tweet Sentiment Network for #Oscars2018.

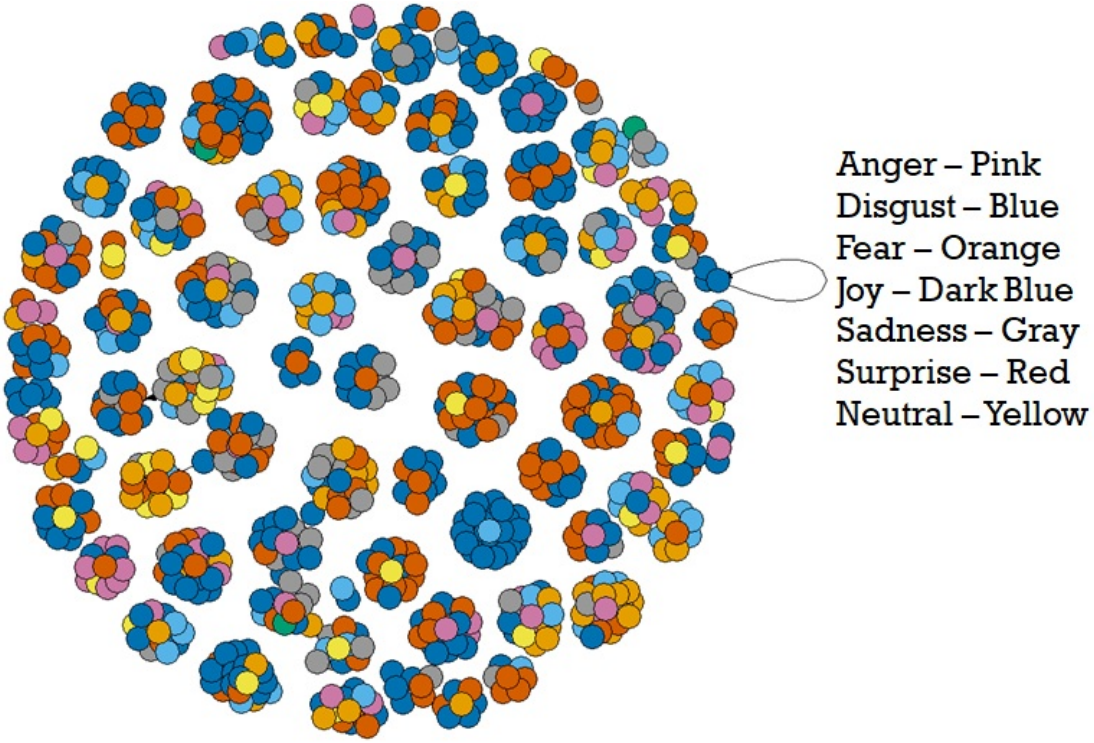


Figure 5.10: Tweet Emotion Network for #Oscars2018.

The experimental results mentioned in this chapter lead us to some interesting realizations. The randomness of Twitter data showed it's affect on most of the scores and results to further prove the claim of the previous researchers, that *"Twitter is different than the other social networks in terms of all measurable characteristics and therefore do not follow any rules that are applicable for other social networks for most scenarios."*

Chapter 6

Conclusion and Future Works

Humans themselves intentionally or unintentionally perform emotion recognition every time they interact with others. Hints may be picked up to classify emotions based on facial expression, speech, and even text. There have been a lot of research works done to categorize emotions and sentiments by considering these information sources. In this thesis, the focus was on reviewing research works performed on categorizing emotions and sentiments based on text and analyzing them. Emotion and sentiment based parameters were used with the other user-based and tweet-based parameters to generate recommendations for users based on emotion and sentiment network.

6.1 Conclusion

In this thesis, some recent works on this topic and some possible areas where improvements are possible and needed were covered. Existing works of different researchers have used novel approaches or hybrids of existing approaches to address text based emotion and sentiment detection. They have used only one word or multiple words from the given sentences, they have applied lexicons, implemented machine learning methods, created new datasets for various domains, described emotions and sentiments with diverse models and tried some unique

ideas. Many different methodologies, such as, SVM, Hybrid systems, Ensemble systems have been used for categorizing emotions and sentiments. Hybrid systems seemed to perform better than systems using just one source of information. Ensemble systems also seemed to perform better than individual classifier. There is a lot of overlap in the methodologies and features used in the research on this topic. Few existing works were summarized to give an idea on the research done on this topic, databases used, features extracted, methodologies used, and the results reported by various researchers.

But despite so many existing works described in the literature, the accuracy of emotion detection from text when the emotion is implicit is not good. Detecting sentiments from texts have better accuracy than detecting emotions due to the fact that sentiments can vary within only three categories- positive, negative or neutral. Detecting sarcasms correctly still needs huge contributions. Classifying emotions according to their intensities is a comparatively new topic. Detecting multiple emotions and sentiments from the same text; realizing the cause behind an emotion or sentiments; detecting the personality of a person; relating emotion and sentiment with different social and individual parameters; detecting the mood of an individual or public in general; predicting the action of a person based on his/her emotion or sentiment - these can be some possible issues to focus on in future. Through the literature review, a better understanding of the research done on this topic, databases used, features extracted, methodologies used, and the results reported by various researchers can be achieved.

The analysis done in this thesis on different emotion and sentiment showed some interesting human characteristics. For all six emotions analyzed, each of them can be characterized by multiple dimensions. For example, 'surprise' is an emotion which can express both 'positive' and 'negative' sentiments. Someone can be surprised by how stupid or disgusting some people are, which is the 'negative' kind of surprise. On the other hand, someone can be

surprised by how beautiful nature is, which is the 'positive' type of surprise. This occurred in the dataset several times. Sometimes, some repliers' emotion about a tweet was 'surprise' even if they disagreed to the tweet because they were surprised about the stupidity of the tweet. For some tweets, few comments expressed opposite sentiment even though the repliers agreed to the tweet. For example, a tweet from a Syrian who tweeted about their sufferings had most of the comments agreeing to the content. Few comments expressed love and support towards them. So, those comments fall into positive sentiment by classification because of their positive words. This shows that even if the tweet and its' comments were showing opposite sentiment, they were actually agreeing on the tweet.

The idea for this research was to analyze Twitter network from a comparatively newer perspective. Users behavior were observed based on their text (tweets, replies) along with numerical scores like number of tweets, followers, likes, followees. All those values were combined with the sentiment and emotion of the users on certain topics to measure the effect. Existing researches focused on the text of the tweets where text from both tweets and replies were considered in this research to find the communication between users in more humane aspects. In most cases, the experiment found that users who reply to tweets normally share similar emotion or sentiment and agree to the tweet content. But there were cases where the reply opposed the original tweet emotion and expressed the disagreement of the replier very clearly. After considering all these factors to find influential users of a network, the result was more specific to a certain issue or topic. The experiment provided a general recommendation to show who are the most influential users expressing a certain emotion or sentiment on an issue. The personalized recommender provided customized recommendation to suggest from the network information about other people in a descending order of similarity who share similar sentiment or emotion on a topic as the user himself/herself.

6.2 Future Works

Based on the study described in this research, a number of aspects were identified that were investigated further with the hope to produce an improved model and hence produce better results. For instance, one of the limitations of this work is that the system can not process tweets containing multiple emotions which can be considered as a possible future work. Detecting sarcasms, slangs, metaphors and implicit emotions can also be some possible fields to focus on in future. In this thesis, all emotions were considered with the same intensity which is not the case in real life. Assigning different weights to different emotions based on their intensity and the involved user would be interesting to investigate. A comparison between the classification accuracies of multiple supervised and unsupervised classifiers can also be a possible future work to detect the most appropriate classifier for the new dataset mentioned in chapter 4 and 5. Also, an automatic emotion and sentiment annotator using unsupervised classifier can accelerate the data preprocessing system.

Another possible topic to focus on in future can be the recommender system. The proposed approach is the first step towards a personalized recommender system for social networks. The system is static and is limited to the range of collected data within a limited time period and lots of missing information on users. A dynamic recommender system to provide suggestions based on any topic on any social network using user emotion and sentiment can be a possible future work which can use this framework to recommend various preferable topics to users. Weights were assigned to different user and tweet based parameters using AHP and the weights were static throughout the experiments. A dynamic weight generation system which can start from initial weight values and can update the weights using machine learning to achieve higher accuracy can be another possible topic for future implementations.

In spite of the use of different audio-visual technologies, people still use text in most of their interactions within their social networks and for their posting on social media forums.

For a long time, various organizations related to business, psychology, health-care, politics, security and other fields have been trying to extract emotion of people from their social network interactions. Due to the necessity of detecting the correct emotion from a piece of text in various socio-economical areas, researchers have developed automatic emotion detection systems using different approaches. Researchers are still working on this topic to optimize existing systems and to increase their accuracy. Since it is nearly impossible to identify all variations of text representing all possible human emotions, the current research described in the literature has a wide range of possibilities for improvement.

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