Sentiment and Emotion Analysis of Text: A Survey on Approaches and Resources

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Abstract

The evolution of internet has given the ability to the users to give their reviews, ratings, and opinions on social media or commercial websites. Sentiment and emotion analysis is an ongoing field of research in text processing, which aims to classify these reviews automatically. This paper presents the survey regarding approaches and resources used for sentiment and emotion analysis of text. We summarize the techniques, datasets, and resources available for text analysis. Additionally, we focus on summarizing literature and resources available for Urdu, a low resource language, along with some open problems for Urdu text analysis. The presented survey can be used effectively to understand challenges and to take future direction for research in sentiment and emotion analysis field, especially for Urdu.

Keywords– Sentiment analysis, Emotion analysis, Lexicon, Urdu natural language processing

1. Introduction

In recent years, technology has been so much enhanced that internet is now an irreplaceable part of our lives. According to Human Computer Interaction (HCI) studies, people are now so addicted and connected to computers and busy in using internet. The accelerated evolution of internet has attracted people from all over the world to social media platforms, micro-blogging websites, and online discussion forums. The sentimental content in form of reviews, opinions, recommendations, ratings, and feedback is generated by users on these platforms. Analysis of these sentiments has spread across many fields such as consumer information, marketing, and social analysis. Sentiment analysis is performed to enhance the quality of products or to understand the public opinion towards different topics [1], [2], [3].

In the field of sentiment analysis, subjectivity analysis of text is done to determine the attitude or polarity of the writer. Such analysis helps in decision making and it is an important human aspect because it tells us “What other people think”. In general, the polarity or sentiment of text is classified into three main classes, i.e., positive, negative, and neutral. Similar to sentiment, emotions can be analyzed computationally. Despite the fact that sentiments and emotions are synonyms and equivalent words, but they don’t express something very similar. Looking into the dictionary shows that sentiment is just an opinion or view while emotion alludes to feeling according to the mood [4]. However, the goal of emotion analysis is a difficult task as differences between emotions are subtler than those between positive and negative class. Additionally, the emotion itself is a universal feeling however different people concerning social context, values, interests, and experience have a different interpretation of text [5].

The approaches for sentiment and emotion analysis for text are categorized into three classes: 1) Lexicon Based, 2) Machine Learning, 3) Hybrid approach. Lexicon based approach classifies textual content utilizing a list of manually labelled words. Machine learning methods use machine learning algorithms along with textual features of content for classification of text. Hybrid method combines lexicon and machine learning approaches to enhance the performance of classifiers. However, the performance of the approach is highly dependent on data quality, size, and content language.

The sentiment and emotion analysis are extensively applied to understand social, political and business behaviours. The sentiment analysis of reviews is done in [1], [2], [6], and [7] to automatically rate the product using user opinion. Similarly, tweets are analyzed to understand the political biases of news channels [8] and to calculate sentiment towards Syrian refugees [9]. The emotion analysis of tweets is done in [10] to predict the outcome of US election 2016 by analyzing public perception towards candidates. Previous studies show that much work has been done on sentiment and emotion analysis for English text. A large research gap is still present in case of Urdu - a resource poor language.

In this paper, we aim to do a survey on sentiment and emotion analysis research efforts, datasets, lexical resources and classification techniques. Besides discussing approaches used for English language, we focus on approaches and challenges for sentiment and emotion analysis of Urdu and Roman Urdu text as well. Additionally, a discussion of available resources and datasets for the Urdu language is provided to facilitate future work.

The rest of the paper is organized as follows: We discuss available lexicons, datasets, and existing approaches for sentiment analysis in Section 2. Next, we present our survey on emotion analysis in Section 3. Before the conclusion, we discuss some open problems related to Urdu text analysis in Section 4. Finally, we conclude our paper in Section 5.

2. Sentiment Analysis

In this section, first, we provide details of publicly available lexicons and datasets to perform sentiment analysis. Next, we discuss different approaches used to perform sentiment analysis.

2.1. Datasets and Lexicons

Table 1 provides a summary of a few online available sentiment analysis lexicons and datasets. AFFIN [11] lexicon consists of 3300+ English words labelled from -5 to +5 scale with an integer variance. Similarly, SentiWordNet [12], and Sentiment lexicon [13] provide English words with sentiment score. However, the Urdu language lacks in lexical resources. An Urdu sentiment lexicon1[3] provides sentiment labels of Urdu words by translating English language lexicon [13] into Urdu using a dictionary lookup. Additionally, all synonyms of translated words are also included in the lexicon. The lexicon consists of 2,607 positive and 4,728 negative sentiment words.

The number of datasets from microblogs, blogs, user comments and review sites are constructed because these platforms provide a good understanding of public opinions. The IMDB review dataset [14] provides 50k movie reviews with even split of 25,000 reviews from positive and negative class. Similarly, Twitter US airline sentiment[4] labelled 14.5k tweets related to six US airlines into three classes of positive, negative, and neutral. Multi-language sentiment analysis[5] provides labelled public opinion from chat logs of WhatsApp, Messenger, and SMS data in English, Mandarin, and Malay language. Additionally, the efforts are made to understand public opinion in Urdu by building Roman Urdu[6] and Urdu language sentiment [15] analysis dataset. Roman Urdu dataset consists of 20,000 roman Urdu sentences labelled into three classes. Urdu language sentiment dataset consists of 999 Urdu language political tweets manually labelled by three judges.

2.2. Approaches

For sentiment detection in textual data, various methods are introduced in the literature. Table 2 provides the summary of research done for sentiment analysis. The work is distributed into three sections of English, Roman Urdu, and Urdu according to language focused in work. The methods used for sentiment analysis of these languages can be categorized into three classes 1) Lexicon-based Method, 2) Machine learning Method, and 3) Hybrid Method.

2.2.1. Lexicon Based Method: Lexicon based recognition approach classifies textual content utilizing a list of labelled positive, negative, and neutral words. In study [9], lexicon is developed for Turkish language. Additionally, sentiment analysis of English and Turkish tweets related to Syrian refugees is performed. The classification of tweets into 5 categories of very negative, negative, neutral, positive, and very positive shows the positive sentiment of Turkish tweets compared to English.

In [18], the Roman Urdu Opinion Mining System (RUOMIS) is built for analysis of comments on mobile review website. The lexicon is built by labelling adjectives in content. The results show 100% recall but the precision value is 27.1% only. The reason for poor precision is noise and failure of POS tagger in identifying adjectives correctly due to the unstructured nature of Roman text.

Study in [20] use English translated Urdu lexicon [15] for analysis of 124 Urdu comments. The experiment shows the accuracy of 66% in sentiment classification. Similarly, study in [21] use Urdu content from blogs to for sentiment analysis. Lexicon is built by identifying and labelling nouns and adjectives using POS tagger. The accuracy of 66% in classification of text shows good results. However, remaining parts of POS-tagged text need to be analyzed and included in lexicon to improve the accuracy. The research is done for identification and labelling of words with sentiment (SentiUnits) in [22]. The authors use POS tagger with grammatical and semantic rules to identify and label SentiUnits in Urdu text. The labelled lexicon is used for sentiment analysis of Urdu corpus containing reviews about movies and products. The results show 72% and 78% accuracy for movies and reviews, respectively. The similar study is done in [1] by using SentiUnits for sentiment classification of Urdu text. The study also shows the improvement in results by applying negation handling during sentiment classification of Urdu text.

The authors use Urdu tweets to determine the political biases of Pakistani news channels in [8]. They

[3]http://chaoticity.com/urdusentimentlexicon/
[4]https://www.kaggle.com/crowdflower/twitter-airline sentiment
[5]https://www.kaggle.com/weywenn/sentiment-analysis-multilanguage
[6]https://archive.ics.uci.edu/ml/datasets/Roman+Urdu+Data+Set

build an Urdu language sentiment lexicon by labelling nouns and adjectives in Urdu tweets. In addition to sentiment analysis, the aspect analysis of sentiment is done to determine the biases of three news channels towards the Pakistani Government. The paper [23] compares the performance of three machine learning algorithms i.e., Support Vector Machine (SVM), Decision Tree, K-Nearest Neighbor (KNN), and lexicon approaches for sentiment classification of Urdu text. The results show that the lexicon approach improves accuracy from 73.88% to 89.03% compared to machine learning algorithms. In addition, the lexicon approach performs better in terms of precision, recall, time-cost. The reason for better performance of lexical approach is that wide coverage of lexicon and an efficient Urdu Sentiment Analyzer is developed that can efficiently handle data from multiple domains.

2.2.2. Machine Learning Method: The study in [16] uses Multinomial Naive Bayes (MNB) model with n-gram and POS tags as features for classification of English tweets into positive, negative, and neutral class. The results describe the best performance of model with bi-gram features. Additionally, the evaluation of model on different size datasets shows the improvement in accuracy of classification on large dataset. However,

Table 1: Summary of publicly available lexicons & datasets for sentiment analysis

	Name	Data Size	Language	Classes
Lexicon	AFINN lexicon [11]	3,300+ words	English	Integer between -5 (negative) and +5 (positive)
	SentiWordNet [12]	-	English	Positive, Negative, and Objectivity
	Sentiment Lexicon [13]	6,800 words	English	Positive and Negative.
	Urdu Sentiment Lexicon[1]	7,335 words	Urdu	Positive and Negative.
Datasets	IMDB reviews [14]	50,000 reviews	English	Positive and Negative
	Twitter US Airline Sentiment [2]	14,500 Tweets	English	Positive, Negative, and Neutral
	Sentiment Analysis Multi-Language[3]	1,531 samples	Multi Language	Very Satisfied, Satisfied, Neutral, Unsatisfied, Very Unsatisfied.
	Roman Urdu Dataset[4]	20,000 records	Roman Urdu	Positive, Negative, and Neutral
	Urdu-Sentiment- Dataset [15]	999 Tweets	Urdu	Positive, Negative, and Objective

Table 2: Summary of sentiment analysis research

Language	Author	Methodology	Data
English	Öztürk and Ayvaz [9]	Lexicon based	1,353,367 English & 1,027,930 Turkish Tweets
	Pak and Paroubek [16]	Machine learning	300,000 Tweets
	Shoeb and Ahmed [17]	Machine learning	489 Tweets
	Mukwazvure and Supreethi [3]	Hybrid Method	333,686 News Comments
	Govindarajan [6]	Hybrid Method	2,000 movie reviews
Roman Urdu	Daud et al. [18]	Lexicon based	1,620 Roman Urdu comments
	Arif et al. [7]	Machine learning	Roman 1,600 Urdu/Hindi hotel reviews
	Noor et al. [2]	Machine learning	20,286 Roman Urdu reviews from Ecommerce site
	Ghulam et al. [19]	Machine learning	Roman Urdu text
Urdu	Rehman and Bajwa [20]	Lexicon Based	Urdu news
	Hashim and Khan [21]	Lexicon Based	Public opinion on news headlines
	Syed et al. [22]	Lexicon Based	1,000 Reviews on Urdu Websites
	Syed et al. [1]	Lexicon Based	Urdu corpus of movie reviews
	Amjad et al. [8]	Lexicon Based	26,614 Urdu news Tweets
	Mukhtar et al. [23]	Lexicon Based	Urdu text from blogs

when the dataset is large enough, the improvement cannot be achieved by only increasing the size of the training data. Similarly, in [17], a study is done to classify English tweets using K Nearest Neighbor (KNN), Naive Bayes (NB), and Decision Tree (DT) classifier. The results describe the Decision Tree as outperforming classifier with 84.66% accuracy and 95.96% precision.

2.2.3. Hybrid Method: The study in [3] combines lexicon and machine learning approach to classify English news comments from technology, business, and political domain. The lexicon is used for polarity detection of text. The output of lexicon is used to train SVM and KNN models. The results describe the negative impact of small training data size and neutral class on the performance of classifiers. In [6] NB and Genetic Algorithms are combined as an ensemble technique for analysis of English documents. Their comparative experiments show the effectiveness of hybrid technique for sentiment classification. The comparison of both models with hybrid approach shows the hybrid approach as the best performing model with 93% accuracy.

Table 3: Summary of emotion models

Model	Proposed Emotions	Approach	Structure
Ekman [24]	Anger, disgust, fear, joy, sadness, surprise	Categorical	-
Shaver et al. [25]	Anger, fear, joy, love, sadness, surprise	Categorical	Tree
Oatley and Johnson-Laird [26]	Anger, anxiety, disgust, happiness, sadness	Categorical	-
Plutchik [27]	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 Russell [28]	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 Ortony et al. [29]	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 [30]	Anger/rage, contempt/disgust, distress/anguish, enjoyment/ joy, fear/terror, interest/excitement, shame/humiliation, surprise/startle	Dimensional	Cube

The sentiment analysis of hotel reviews in Roman Urdu text is done in [7]. The corpus is built by translating English text into Roman Urdu. The translation of English text is done with one translation tool to avoid irregularities in spelling. The SVM classifier shows significant performance with 95% accuracy with Term Frequency (TF)-Inverse Document Frequency (IDF) features. However, the performance is with no spelling inconsistencies which is one of the challenging issues in the analysis of Roman Urdu text. Similarly, [2] uses SVM model with Bag of Word (BoW) features to classify Roman Urdu reviews from an e-commerce site into positive, negative, and neutral classes. In [19] the comparison of baseline machine learning models (NB, Random Forest (RF), and SVM) and deep learning model Long Short Term Memory (LSTM) is done for sentiment classification of Roman Urdu text. The comparison shows the better performance of LSTM model with word embedding.

3. Emotion Analysis

In this section, first, we discuss existing emotion models for categorization of emotions. Next, we present available datasets and lexicons for analysis. Finally, we discuss the approaches which exist in the literature for emotion classification.

2.1. Emotion Models

To detect and analyze the emotions, they are categorized with standard emotion models. Table 3 summarizes the existing emotion models. According to psychology, there are 6 types of basic emotions expressed by human beings [37]. These emotions are 1) Happiness, 2) Sadness, 3) Fear, 4) Disgust, 5) Anger, and 6) Surprise. Variety of emotion models are presented to further classify these basic emotions. Ekman [24] presents six discrete emotions as mentioned in Table 3. Shaver et al. [25] and Oatley and Johnson-Laird [26] define 6 categories of emotions including love, anxiety and happiness. Plutchik [27] and Circumplex Russell [28] provides two dimensional emotion categorization model. Additionally, OCC Ortony et al. [29] and Lovheim [30] distribute emotions in three dimensions to create categories.

2.2. Datasets and Lexicons

Table 4 provides summary of available labelled emotion datasets and lexicons. EmoSenticNet [31] is online available emotion lexicon containing 13,171 words categorized into joy, sadness, disgust, anger, surprise, and fear. Similarly, National Research Council (NRC) Word-Emotion Association Lexicon (EmoLex) [32] categorizes 14,000+ words into eight classes of emotion. Additionally, NRC dataset is translated into 40+ languages including Urdu. Our manual inspection of Urdu translated lexicon reveals that few English terms are not translated to Urdu. Additionally, we note that ATM translates multiple English terms to one Urdu word, i.e., accused, accuser, and accusing are translated to one word "*Alzaam laga*'. In English, these terms are provided different labels, however, translated to one Urdu term creates ambiguity of assigned label. Therefore, manual cleaning of the lexicon is required to use it for Urdu text.

EmoBank [33] dataset consists of 10k English sentences labelled with six Ekman emotions using Valence-Arousal-Dominance scheme. Similarly, International Survey on Emotion Antecedents and Reactions (ISEAR) [34] dataset provides 7,666 labelled English sentences with seven emotions of anger, disgust, fear, sadness, shame, joy, and guilt. Furthermore, the emotion in text dataset5[7] consists of manually label 40k tweets into 13 classes of emotion. Additionally, 2,892 Facebook posts are categorized into six classes using Valence-Arousal-Dominance scheme [35]. Similarly, Affective text [36] classifies 1,200 news headlines into Ekman model categories. Up to our knowledge, there is no publicly available Urdu language emotion labelled dataset. This shows the scarcity of resource and huge research gap in emotion analysis of Urdu content.

Table 4: Summary of publicly available lexicons & datasets for emotion analysis

	Name	Data Size	Language	Classes
Lexicon	EmoSenticNet [31]	13,171 words	English	Joy, Sadness, Disgust, Anger, Surprise, Fear
	NRC-EmoLex [32]	14,000+ words	40+ languages including Urdu	Anger, Fear, Anticipation, Trust, Surprise, Sadness, Joy, and Disgust.
Datasets	EmoBank [33]	10,000 sentences	English	Double annotation with valence, arousal and dominance
	ISEAR [34]	7,666 sentences	English	Joy, Fear, Anger, Sadness, Disgust, Shame, and Guilt
	Emotion in Text[5]	40,000 Tweets	English	Anger, Boredom, Empty, Enthusiasm, Fun, Happiness, Hate, Love, Relief, Sadness, Surprise, Worry, Neutral
	The valence and arousal Facebook posts [35]	2,895 Facebook posts	English	Double annotation with valence and arousal values
	Affective Text [36]	1,200 News Headlines	English	Annotated with 6 basic emotions from Ekman's model

2.3. Approaches

The brief overview of papers on emotion analysis of text is given in Table 5. Keyword based method is used in [39] for classification of English email content into three categories of happy, sad, and angry. Besides keyword spotting, semantic emotions are calculated using a semantic network method for classification of text. The proposed methodology is limited to certain emotion-related texts, e.g., couple's breakup. Therefore, emotion detection from technical writings or scientific

[7] https://www.kaggle.com/c/sa-emotions

papers is not possible because these texts simply do not contain emotions.

Authors in [10] use lexicon based approach for emotion analysis of 25 million English tweets related to Donald Trump and Hillary Clinton. Based on emotion analysis using NRC lexicon, they predicted the outcome of US state election 2016. The proposed approach has extensive applications as it is not only limited to the political domain.

The study in [40] uses machine learning models of SVM and KNN for emotion classification of tweets according to Circumplex Model of Affect. In addition, the authors manually label hashtags to use it as an emotion label of tweet. The comparison of manually labelling of complete tweet and automatic labelling of a tweet using hashtags shows that hashtags can be used as an emotion label of a tweet with 87% accuracy. Additionally, in [41] online health communities (OHCs) comments regarding cancer are classified using a combination of lexicon approach and deep learning models of CNN and LSTM. The analysis shows that hybrid model performance improves because it captures the hidden semantics in OHCs messages. Similarly, Lexicon-based, Keyword based, and machine learning-based emotion classification methods are combined for classification of 15 emotions in suicide notes [42]. The combination of Affective text lexicon with machine learning models of SVM, KNN, and maximum entropy shows that hybrid techniques exhibit a high robust discriminative capability in emotion classification especially when a large number of emotion instances are available.

The little amount of literature is available in emotion analysis of Roman Urdu content. The study in [43] presents knowledge based approach to label Roman Urdu text by developing an emotion ontology of happiness, anger, disgust, surprise, and fear emotions. The approach analyses syntax and the semantic relationship of text to detect the emotion. The testing of the proposed approach on manually labelled data shows the average recall and precision of 85.40% and 92.87%, respectively. The study presented in [44] made an effort to detect joy, fear, anger, sadness, disgust, and shame from Urdu language tweets about smartphones and sports products. The SVM, RF, NB and KNN models are tested on 1,000 sports and 1,200 smartphone tweets.

Table 5: Summary of emotion analysis research

Language	**Author**	**Methodology**	**Data**	
English	Sailunaz [38]	Survey	-	-
	Ling et al. [39]	Keyword based	Emails	Happy, Sad, Angry
	Srinivasan et al. [10]	Lexicon based	English Tweets	Plutchik's Wheel of Emotions [27]
	Hasan et al. [40]	Machine learning	English Tweets	Circumplex Model of Affect
	Khanpour [41]	Hybrid method	Online health Communities' Posts	Anger, Disgust, Fear, Joy, Sadness, Surprise
	Yang et al. [42]	Hybrid method	English Suicide Notes	15 emotion categories
Roman Urdu	Nargis and Jamil [43]	Knowledge based	Roman Urdu Text or Blogs	Happiness, Anger, Hurt, Caring, Fear
Urdu	Rehman and Bajwa [20]	Machine learning	Smartphone and Sports Tweets	غصہ, خوف, خوشی ندامت, نفرت, اداس

4. Open Problems in Urdu Text Analysis

The core approaches (lexicon based, machine learning, and hybrid method), as mentioned in Section 2.2, used to perform text analysis of English can also be used for Urdu but research and development effort is required because of vast differences between English & Urdu grammar, orthography, and morphology. For Urdu language text analysis, first of all, we need a dataset and there are rare datasets & corpora available for sentiment as well as emotion analysis of Urdu text. To use the lexicon based approach either for sentiment or emotion analysis, we need annotated lexicon of Urdu. Few Urdu lexicons have been created so far and most of them are not publicly available while in the case of English, we have a variety of lexicons available. Due to different sentence structure, i.e., Subject-Object-Verb (SOV) and position of preposition, as compared to English, we face difficulty in Urdu text classification [45]. Due to complex morphology and unstructured format of Urdu, English morphological analyzers and POS taggers cannot be exactly used [46].

5. Conclusion

In this paper, we perform a survey on techniques used for sentiment and emotion analysis of text. We explore the literature related to analysis of Urdu text deeply to understand the challenges in analyzing low resource language. We observe that field of sentiment analysis for Urdu is growing despite lack of resources. Additionally, emotion analysis task has more scarcity of literature and resources for Urdu text. Building resources, used in sentiment and emotion analysis tasks, is still needed for the Urdu language. Furthermore, due to the complex nature and challenges of Urdu text, a lot of work is required to understand Urdu text context.

In the future, we will deploy and compare the performance of existing models and resources for sentiment and emotion analysis for Urdu text to provide the benchmark for future research.

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