Predicting the Semantic Orientation of Communication over Social Networking

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Abstract— *Social media has reformed into the digital revolution. Applications like Facebook, Instagram, Twitter, LinkedIn, WhatsApp and lot more, are highly enjoyed by social media users. But where some people are enjoying social media to their full, others are the victims of its negative aspect which includes sending obscene messages to someone. Although blocking is the favourable solution to it, it has a deep impact on one's mind. 81 percent of Internet-initiated crime involves social networking sites, mainly Facebook and Twitter due to unhealthy comments and posts. This paper develops the state of art sentiment analysis that provides the particular channel through which any post, comment, message or any other text scrutinized for the sentiment before getting posted to the concerned web and if any unethical sentiment found, action would be placed through defined protocols of that social media. Different sentimental datasets corpus are revived from the cyberspace. Customized naive Bye's classifier is trained for the prediction of respective sentiments of the text. This paper doesn't motivate to not to write controversial comments but discourage the unhealthy way of controversy.*

Keywords — *Naive Baye's Algorithm, Sentiment Analysis, Semantic Approach, Lexicon Analysis.*

I. INTRODUCTION

One of the key, defining aspects of the present scenario, in reshaping the world as we know it is the worldwide accessibility of the internet. Majorly, world wide web is surrounded by the social media which comes in many forms like blogs, forums, photo-sharing platforms, chats, Social Networks such as Facebook, WhatsApp and more like evenly. As statistics suggest, the number of worldwide users in 2021 would be 3.02 billion that is around the third of Earth's entire population. In this world wide scenario, there are some term which have serious impact on the youth of the world. Yes, I am talking about cyber crimes. These term majorly includes bullying, negative stalking, harassments. Statistics says that 7.5 billion people were stalked in 1year. This includes 61% female and 44% male were found the victims by their current or former intimate partner.

A. Cyberbullying

Cyberbullying is the common crime that can be found among teenagers. Facebook is one of the major via of this serious crime charges. According to the data, it has contributed to the deaths of several teens who either committed suicide or were killed by them. Cyberbullying also involves the hacking the password or any other private items and sending offensive message directly to their IDs. In this the identity theft is punishable under the state and federal law. When all these bullying are done by adults, this is the nomenclatural form and called as cyberstalking.

B. Cyberstalking

The term "stalking" is thrown a lot on different social network, and it is often meant as a joke for regularly peeping at someone's profile. Cyberstalking typically involves harassing a person with messages i.e. threats, non-decent exposures. This generally violate the person's safety and a serious offense in the world of cybernetics. Although, cyberstalking is nothing but an irritating behaviour towards a person but its impact is really nasty and unbearable. This is also punishable under the respective law.

C. Harassment

Harassment happens all the time on every Social Media, either it is Facebook. Twitter, WhatsApp and many more. From sexual harassment to the highly non-decent threats, there has been a significant increase in the number of harassment cases happening on Facebook. It's not uncommon for sex offenders and sexual predators that prey on accept victims on Facebook and even target as a teen or college student. Harassing messages, inappropriate comments and post, and other persistent behaviours made the social network un bearable.

This paper depicts the behaviour of social network by creating a classifier that becomes the mediator channel between sending a comment, post or message and receiving the these stuff. It trains the classifier for the efficient prediction of the sentiment that helps by scrutinizing the messages or post about the sentiment before getting posted or commented to anyone's.

II. LITERATURE REVIEW

Sentiment classification has advanced considerably since the work of Pang et al. (2002), which this paper uses as our baseline. Thomas et al. (2006) use discourse structure present in congressional records to perform more accurate sentiment classification. Pang and Lee (2005) treat sentiment analysis as an ordinal ranking problem. In our work, we only show improvement or the basic model, but all of these new techniques also make use of lexical features. Thus we believe that our adaptation methods could be also applied to those more refined models. While working on domain adaptation for sentiment classifiers are sparse, it is worth noting that other researchers have investigated unsupervised and semi-supervised methods for domain adaptation. The work most similar in spirit to ours that of Turney (2002). He used the difference in mutual information with two human-selected features (the words "excellent" and "poor") to score features in a completely unsupervised manner. Then he classified documents according to various functions of these mutual information scores. We stress that our method improves a supervised baseline. While we do not have a direct comparison, we note that Turney (2002) performs worse on movie reviews than on his other datasets, the same type of data as the polarity dataset. We also note the work of Aue and Gamon (2005), who performed a number of empirical tests on domain adaptation of sentiment classifiers. Most of these tests were unsuccessful. We briefly note their results on combining a number of source domains. They observed that source domains closer to the target helped more. In preliminary experiments, we confirmed these results. Adding more labelled data always helps, but diversifying training data does not When classifying kitchen appliances, for any fixed amount of labelled data, it is always better to draw from electronics as a source then use some combination of all three other domains. Domain adaptation alone is a generally well-studied area and we cannot possibly hope to cover all of it here. As we noted in Section 5, we are able to significantly outperform basic structural correspondence learning (Blitzer et al., 2006). We also note that while Florian et al. (2004) and Blitzer et al. (2006) observe that including the label of a source classified as a feature on small amounts of target data tends to improve over using either the source alone or the target alone, we did not observe that for our data. We believe the most important reason for this is that they explore structured prediction problems, where labels of surrounding words from the source the classifier may be very informative, even if the current the label is not. In contrast our simple binary prediction the problem does not exhibit such behaviour. This may also be the reason that the model of Chelba and Acero (2004) did not aid in adaptation. Finally, we note that while Blitzer et al. (2006) did combine SCL with labelled target domain data, they only compared using the label of SCL or non-SCL source classifiers as features, following the work of Florian et al. (2004). By only adapting the SCL related part of the weight vector v, we are able to make better use of our small amount of unlabeled data than these previous techniques.

III.METHODOLOGY

The development of the program starts by analysing the Datasets that has been collected from cyber net(*). After Analysing phase, this paper describes the customized data structure using Adelson-Velskii and Landis Trees for the datasets to be organised for easy fetching that majorly helps in mathematical computation. This data is then used for computing the probability of the sentiments on any sentence provided as the input.

A. Analysing

The goal of analysing phase is to scrutinize the lexicons for different sentiments in different areas. According to the latest research in this area, the data for categories of the out-of-dictionary token by category for the tweet and SMS test sets.

Category of Tokens	Tweet/ Posts Test Sets	SMS test set
Named entities	31.84%	32.63%
User mentions	21.23%	0.11%
URLs	16.92%	0.84%
Hashtags	10.94%	0.00%
interjections	2.56%	10.32%
emoticons	1.40%	1.89%
nouns	8.52%	25.47%
verbs	3.05%	18.95%
adjectives	1.43%	4.84%
adverbs	0.70%	6.21%
others	4.00%	15.69%

Table 1: The Distribution of the out-of-dictionary tokens by category.

According to the SEM-EVAL 2013 sets, evaluation on a system of datasets of movie review has been excerpted. The major task was to predict the sentiment label (positive or negative) from the reviews of the movies. In this experiment, 4 major category of sentiments i.e. happy, sad, angry, vulgar are getting concerned. About 1200 of the datasets has been taken out for each sentiment of which 70% (~840) sentences are used to train the classifier and rest are used to test it.

The analysis phase also focuses on describing and searching in the stop word list i.e. the word that has no sentiment but used in sentence to make it more efficient for the semantics e.g. "the", "is", "are", "am", "a", "an" etc likewise. To search these words in the sentences, these words are structured in tree. Basically, these words are inserted in the Balanced Binary tree so that words get their sorted position as inorder traversal. As Balancing takes O(1) in the form of rotation for balancing the unbalanced tree. Moreover, O(logn) (where "n" is the number of elements) is the worst case time complexity to insert any element in the AVL tree but as the inserted elements are the words ("Strings") of length say "m" therefore, the total complexity of the element (words) to be inserted would be O(mlogn). This tree helps in easy identification of the non-sentimental words. For achieving the good efficiency to find stop words in the sentences, the unused words are titled as stop words and so inserted into tree. Unused words in the sentences are those words that are found neither in stop words tree nor in sentimental words in the datasets after finding the sentiment for the input sentence.

B. Designing

The designing phase majorly focuses on designing the method for lexicon scoring and bringing the outreach to naive baye's classifier. For lexicon scoring, this paper uses the concept of PMI (Pointwise Mutual Information). In the PMI, frequency of the sentiment decides the Happiness, Sadness, Angriness or the vulgarity of the sentence. Basic Mathematical expression is termed as follows.

where s is the name of the sentiment mentioned above and x is the word under the sentiment that is to be classified. To express PMI, we have calculated the frequency of the word in that sentiment s.

here *freq(x, s)* is the number of times x occurs in that sentiment s corpus. *freq(x)* is the total frequency of term s in the corpus. *freq(s)* is the total number of token in that sentimental post, tweet or message. *N* is the total number of tokens in the corpus. PMI for all the other sentiment is calculated in the same way. Hence by merging two of the equation we get,

By the help of these score we would classify the respective sentiment for the particular word in the sentence. This score is calculated for all the sentences refer to the training set. After resolving the score, we would use the naïve baye's theorem to classify the sentiments. Naïve baye's theorem comes under conditional probability which states the probability of the event A after B as occurred. Here,

This equation states that the probability of occurrence of event A when B has Occurred is the product of probability of B when A has occurred and the probability of occurrence of A itself, divided by the probability of occurrence of B. This equation is used to majorly classify the sentiment by the input value calculated above. In this, we calculate the probability of the sentiment when any sentimental word found in the sentence.

using above equations the respective probability of the sentiments would be calculated and hence would be the required probability. The sentimental scores indicate a greater overall association with the respective sentiments. The magnitude is indicative of the degree of association. Note that there exist numerous other methods to estimate the degree of association of a term with a category (e.g., cross entropy, Chi-squared, and information gain). We have chosen PMI because it is simple and robust and has been successfully applied in a number of NLP tasks (Turney, 2001; Turney & Littman, 2003). The final lexicon, which we will refer to as Hashtags Sentiment Base Lexicon (HS Base) has entries for 39,413 unigrams and 178,851 bigrams. Entries were also generated for unigram{unigram, unigram{bigram, and bigram{bigram pairs that were not necessarily contiguous in the tweets corpus. Pairs where at least one of the terms is punctuation (e.g., \,", \?", \."), a user mention, a URL, or a function word (e.g., \a", \the", \and") were removed. The lexicon has entries for 308,808 non-contiguous pairs. This paper propose an empirical method to determine the sentiment of words in the presence of negation. We create separate data for affirmative and negated contexts. In this way, two sentiment scores for each term w are computed: one for affirmative contexts and another for negated contexts. The lexicons are related as follows. The Hashtags Sentiment Corpus is split into two parts: Affirmative Context Corpus and Negated Context Corpus. Following the work by Pang, Lee, and Vaithyanathan (2002), we define a negated context as a segment of a tweet that starts with a negation word (e.g., no, shouldn't) and ends with one of the punctuation marks: `,', `.', `:', `;', `!', `?'. The list of negation words was adopted from Christopher Potts' sentiment tutorial.11 Thus, part of a tweet that is marked as negated is included into the Negated Context Corpus while the rest of the tweet becomes part of the Affirmative Context Corpus. The sentiment label for the message or post is kept unchanged.

IV. Result Analysis

All the system components are tested independently. At every testing a test data sentence has taken as input and split into words these words got searched in the stop words tree (filtration) and then by getting the frequency of these remaining words in the corpus we would use the probability theorem discussed above. The example of the sentiment score for Happy and Sad.

Computing the scores, we put all the frequencies in the classifier to classify the respective sentiment. The classifier works upon the equation mentioned in the Methodology section. After getting all the frequencies output is mentioned below in the form of picture. This contain the frequency of the sentimental words that has been filtered from the stop words. This frequency is then act as the input for the principle classifier. Fig 1 shows that the frequency of the word "annoying" is highest in "freqInAngry" and same for others. That is why the same sentence is computed as Angry Sentence. In all other figures the thing has been computed as same and results are as found respectively.

Mentioned above lexicons analysis, I have found that in the training set we have 236 frequency of the word "anger" in anger corpus 12 frequency in happy corpus and 8 frequency in the sad corpus. This has been found an efficient data for the sentiment analysis for the messaging corpus

Term	Sentiment Lexicons		
	Angry	**Happy**	**Sad**
Anger	236	12	8
Annoy	144	7	60
Furious	97	21	32
Happy	3	107	7
Beautiful	4	213	1
Glad	8	234	27
Sad	67	5	381
Disappoint	89	11	278
Cheerless	101	23	307

Table 2: Example of the frequency set of the word in the respective sentiment corpus.

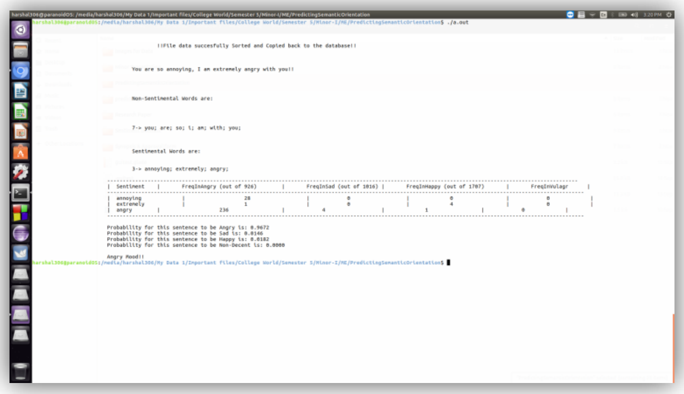

Fig 1: Sample test case sentence for the Angry Mood

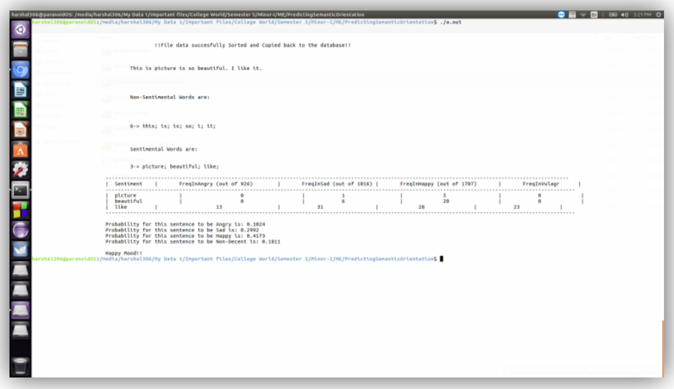

Fig 2: Sample test case sentence for the Happy Mood

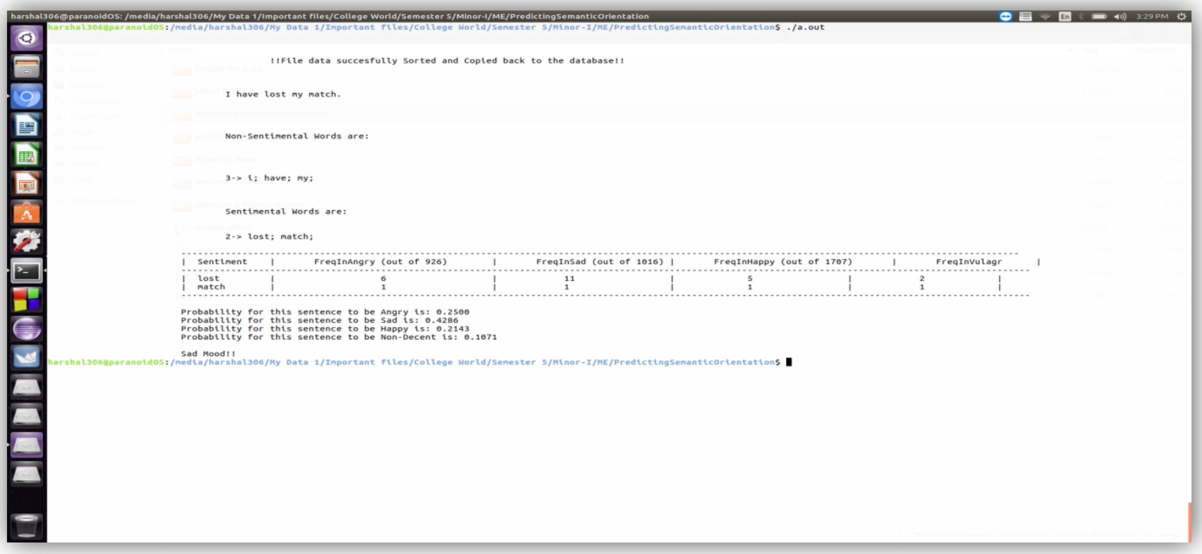

Fig 3: Sample test case sentence for the Sad Mood

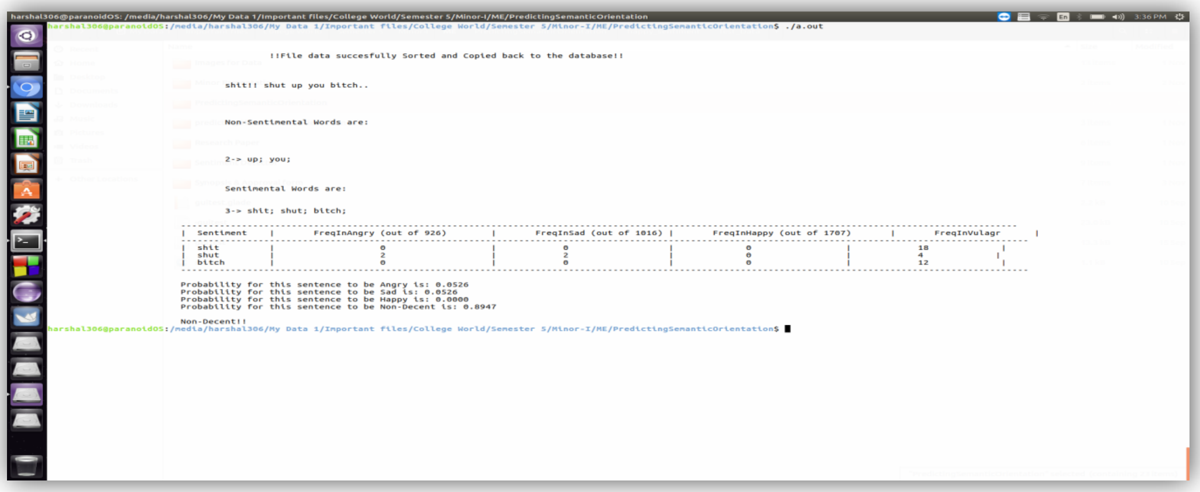

Fig 4: Sample test case sentence for the Non-Decent

V. CONCLUSIONS

This paper has built the state-of-the-art classifiers for sentiment analysis in short text for the social media data like message, post, tweet etc. Here, I study the impact of lexicon-based features on the performance and learned how the performance enhances on adding new stop words to the trash file. I have also constructed my own sentiment classifier using new metric called natural entropy and naive baye's theorem which boosts the terms that unevenly distributed among the classes. This new customized featured classifier seem to improve the results more than the features extracted from the same lexicon but using PMI metric. This PMI metric only states the frequency of the particular sentiment and hence not so efficient. As the probabilistic algorithm features have proved their performance, future work will focus on the commonsense reasoning for the machine translation which we think promising in measuring the association between terms and sentiment labels for many language translations.

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