

Predicting the Semantic Orientation of Communication over Social Networking

Harshal Mittal

School of Computer Science, University of Petroleum and Energy Studies, Dehradun, India

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 Baye'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, $O(\log n)$ (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 $O(m \log n)$. 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, Angriiness or the vulgarity of the sentence. Basic Mathematical expression is termed as follows.

$$SentimentScr_s(x) = PMI(x, s) \quad \dots (1)$$

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.

$$PMI(x, s) = \log_2 \frac{freq(x, s) * N}{freq(x) * freq(s)} \quad \dots (2)$$

$$s \in \{Happy, Sad, Angry, Vulgar\}$$

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,

$$SentimentScr_{happy}(x) = \log_2 \frac{freq(x, Happy) * N}{freq(x) * freq(Happy)}$$

$$SentimentScr_{sad}(x) = \log_2 \frac{freq(x, Sad) * N}{freq(x) * freq(Sad)}$$

$$SentimentScr_{angry}(x) = \log_2 \frac{freq(x, Angry) * N}{freq(x) * freq(Angry)}$$

$$SentimentScr_{vulgar}(x) = \log_2 \frac{freq(x, Vulgar) * N}{freq(x) * freq(Vulgar)}$$

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 naive 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,

$$P\left(\frac{A}{B}\right) = \frac{P\left(\frac{B}{A}\right) * P(A)}{P(B)}$$

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.


```

harshal306@paranoidOS: ~/media/harshal306/My Data 1/important files/College World/Semester 5/Minor-1/ME/PredictingSemanticOrientation
harshal306@paranoidOS: ~/media/harshal306/My Data 1/important files/College World/Semester 5/Minor-1/ME/PredictingSemanticOrientations $ ./a.out

!!File data successfully Sorted and Copied back to the database!!

I have lost my match.

Non-Sentimental Words are:

Sentimental Words are:
3-> I; have; my;
2-> lost; match;

| Sentiment | FreqInAngry (out of 926) | FreqInSad (out of 1016) | FreqInHappy (out of 1707) | FreqInVulgar |
|-----|-----|-----|-----|-----|
| lost | 6 | 11 | 5 | 2 |
| match | 1 | 1 | 1 | 1 |

Probability for this sentence to be Angry is: 0.2500
Probability for this sentence to be Sad is: 0.4286
Probability for this sentence to be Happy is: 0.2143
Probability for this sentence to be Non-Decent is: 0.1071

Sad Mood!!
harshal306@paranoidOS: ~/media/harshal306/My Data 1/important files/College World/Semester 5/Minor-1/ME/PredictingSemanticOrientations

```

Fig 3: Sample test case sentence for the Sad Mood

```

harshal306@paranoidOS: ~/media/harshal306/My Data 1/important files/College World/Semester 5/Minor-1/ME/PredictingSemanticOrientation
harshal306@paranoidOS: ~/media/harshal306/My Data 1/important files/College World/Semester 5/Minor-1/ME/PredictingSemanticOrientations $ ./a.out

!!File data successfully Sorted and Copied back to the database!!

shht!! shut up you btch..

Non-Sentimental Words are:

Sentimental Words are:
2-> up; you;
3-> shht; shut; btch;

| Sentiment | FreqInAngry (out of 926) | FreqInSad (out of 1016) | FreqInHappy (out of 1707) | FreqInVulgar |
|-----|-----|-----|-----|-----|
| shht | 0 | 0 | 0 | 18 |
| shut | 2 | 2 | 0 | 4 |
| btch | 0 | 0 | 0 | 12 |

Probability for this sentence to be Angry is: 0.0526
Probability for this sentence to be Sad is: 0.0526
Probability for this sentence to be Happy is: 0.0000
Probability for this sentence to be Non-Decent is: 0.8947

Non-Decent!!
harshal306@paranoidOS: ~/media/harshal306/My Data 1/important files/College World/Semester 5/Minor-1/ME/PredictingSemanticOrientations

```

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.

ACKNOWLEDGMENT

A great thanks to the UPES faculties, Mr. P.Srikanth, Dr. Ajay Prasad and others who guided me throughout the research project and gave me the opportunity to express myself. I also

thank to my partners Mr. Arpit Ahlawat, Ms. Mansi Sahu, Ms. Shubhangi Srivastava, Mr. Anurag Tripathi who helped me to get datasets for the research and motivated me to write the paper.

REFERENCES

- [1] Agarwal, A., Xie, B., Vovsha, I., Rambow, O., & Passonneau, R. (2011). Sentiment analysis of twitter data. In Proceedings of the Workshop on Languages in Social Media, LSM '11, pp. 30{38, Portland, Oregon.
- [2] Bing Liu. *Sentiment Analysis and Opinion Mining*. Synthesis Lectures on Human Language Technologies. Morgan & Claypool Publishers, 2012.
- [3] Bo Pang, Lillian Lee, and Shivakumar Vaithyanathan. Thumbs up?: Sentiment classification on Empirical Methods in Natural Language processing - Volume 10, EMNLP '02, pages 79-86. Association for Computational Linguistics, 2002.
- [4] Alec Go, Richa Bhayani, and Lei Huang. Twitter Sentiment classification using distant supervision. pages 1-6, 2009.
- [5] Stefano Baccianella, Andrea Esuli, and Fabrizio Sebastianin. SentiWordNet 3.0: An enhanced lexicon resource for Sentiment Analysis and Opinion Mining. In in Proc. of LREC, 2010.

- [6] Er Pak and Patrick Paroubek. Twitter as a corpus for sentiment analysis and opinion mining. In *In Proceedings of the Seventh Conference on International Language Resources and Evaluation*, 2010.
- [7] Saif M. Mohammad, Svetlana Kiritchenko, and Xiadan Zhu. NRCCanada: Building the state-of-art in sentiment analysis of tweets. In *Proceedings of the 8th International Workshop on Semantic Evaluation, SemEval '13*, 2013.
- [8] Yasuhide Miura, Shigeyunki Sakaki, Keigo Hattori, and Tomoko Ohkuma. TeamX: A sentiment analyzer with enhanced lexicon mapping and weight scheme for unbalanced data. In *Proceedings of the 8th International Workshop on Semantic Evaluation*, pages 628-632. Association for Computational Linguistics and Dublin City University, 2014-08.
- [9] Hussam Hamdan, Patrice Bellot, and Frederic Bechet. Lsif: Feature extraction and label weighting for sentiment analysis in twitter. In *In Proceedings of the 9th International Workshop on Semantic Evaluation*, 2015.
- [10] Peter D. Turney and Michael L. Littman. Measuring praise and criticism: Inference of semantic orientation from association. 21(4): 315-346, 2003-10.
- [11] Saif Mohammad. #emotional tweets. In 2012, The first Joint Conference on lexicon and computational semantics- Volume 1: *Proceedings of the main Conference and the shared task*, and Volume 2: *Proceedings of the Sixth International Workshop on Semantic Evaluation*, pages 246-255.
- [12] Preslav Nakov, Sara Rosenthal, Zornitsa Kozareva, Veselin Stoyanov, Alan Ritter, and Theresa Wilson. SemEval-2013 task 2: Sentiment analysis in twitter. In Second Joint Conference on Lexical and Computational Semantics (*SEM), Volume 2: *Proceedings of the Seventh International Workshop on Semantic Evaluation (SemEval 2013)*, pages 312-320. Association for Computational Linguistics, 2013.
- [13] Sara Rosenthal, Preslav Nakov, Svetlana Kiritchenko, Saif M. Mohammad, Alan Ritter, and Veselin Stoyanov. SemEval-2015 task 10: Sentiment analysis in twitter. In *Proceedings of the 9th International Workshop on Semantic Evaluation, SemEval '2015*. Association for Computational Linguistics, 2015-06.
- [14] Maria Pontiki, Dimitrios Galanis, Haris Papageorgiou, Suresh Manandhar, and Ion Androutsopoulos. SemEval-2015 task 12: aspect based sentiment analysis. In *Proceedings of the 9th International Workshop on Semantic Evaluation (SemEval 2015)*, 2015.
- [15] Minqing Hu and Bing Liu. Mining and summarizing customer reviews. In *Proceedings of the Tenth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, KDD '04*, pages 168-177. ACM, 2004.
- [16] Hussam Hamdan, Patrice Bellot, and Frederic Bechet. The impact of z score on twitter sentiment analysis. In *In Proceedings of the Eighth International Workshop on Semantic Evaluation (SemEval 2014)*, page 636, 2014.
- [17] Josef Ruppenhofer and Ines Rehbein. Semantic frames as an anchor representation for sentiment analysis. In *Proceedings of the 3rd Workshop in Computational Approaches to Subjectivity and Sentiment Analysis*, pages 104-109. Association for Computational Linguistics, 2012.
- [18] Rong-En Fan, Kai-Wei Chang, Cho-Jui Hsieh, Xiang-Rui Wang, and Chih-Jen Lin. LIBLINEAR: A library for large linear classification. 9:1871-1874, 2008.
- [19] Hussam Hamdan, Patrice Bellot, and Frederic Bechet. Lsif: CRF and logistic regression for opinion target extraction and sentiment polarity analysis. In *In Proceedings of the 9th International Workshop on Semantic Evaluation (SemEval2015)*, 2015.
- [20] Aisopos, F., Papadakis, G., Tserpes, K., & Varvarigou, T. (2012). Textual and contextual patterns for sentiment analysis over microblogs. In *Proceedings of the 21st International Conference on World Wide Web Companion*, WWW '12 Companion, pp. 453-454, New York, NY, USA.
- [21] Alec Go, Richa Bhayani, and Lei Huang. Twitter Sentiment classification using distant supervision. pages 1-6, 2010.
- [22] Hussam Hamdan, Patrice Bellot, and Frederic Bechet. Lsif: CRF and logistic regression for opinion target extraction and sentiment polarity analysis. In *In Proceedings of the 9th International Workshop on Semantic Evaluation (SemEval2015)*, 2015.
- [23] Bo Pang, Lillian Lee, and Shivakumar Vaithyanathan. Thumbs up?: Sentiment classification on Empirical Methods in Natural Language processing - Volume 10, EMNLP '02, pages 79-86. Association for Computational Linguistics, 2005.
- [24] Gimpel, K., Schneider, N., O'Connor, B., Das, D., Mills, D., Eisenstein, J., Heilman, M., Yogatama, D., Flanigan, J., & Smith, N. A. (2011). Part-of-speech tagging for Twitter: Annotation, features, and experiments. In *Proceedings of the Annual Meeting of the Association for Computational Linguistics, ACL '11*.