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Basic Review of Different Strategies for Sentiment Analysis in Online Social Networks

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Abstract: The growth of different online networks such as MySpace, Twitter, LinkedIn and Face book have been increased in recent years, high amount of data outsource via social media into data sources. This huge amount of data analyzed for research on different types of real time applications. So that analysis of sentiment and mining user opinion is one of aggressive concept to explore meaning of outsourced data. While different types of approaches are implemented to identifying sentiment and opinion in social networks like pattern based classification with respect to parts of speech, emotions and batch model learning while analyzing huge amount of data. In this paper we give brief description of different machine learning approaches to describe utilize sentiment of huge amount data in social networks. We give survey of different approaches with respect to sentiment exploration from online social network. Also describe comparative analysis of different methods used for analysis of sentiment and mining of user opinion in online social networks.

Index Terms: Sentiment analysis, Twitter, online social networks, stream detection, information retrieval, data -processing, concept based approaches and machine learning.

I. INTRODUCTION

The utilization of social communication sites, for example, Twitter and Facebook has been seeing a quick development over the most recent couple of years. Most likely the purpose for this expansion is that individuals feel good communicating with their conclusions and perspectives calmly exhibit on a subjects with respective relative sites. Then again, our basic leadership process is as a rule affected by other individuals' assessments. The greater part of us would look for our companions', relatives', or colleagues' proposals previously settling on essential buy choices, before eating at a particular eatery, or viewing another motion picture. Here and there we even base our choice exclusively on those feelings. To this end, feeling examination has pulled in an immense research intrigue particularly as of late. Specialists dissected in numerous spaces: motion picture surveys, news articles, online journals, gatherings, audits of item things, and all the more as of late internet based life information. Slant investigation of information accessible on the business organization which includes individuals' perspectives is winding up imperative so as to check popular supposition on a specific subject of premium.

It can help assess shopper fulfillment about a few items, clients' interests and inclinations, political perspectives and numerous others. Opinion examination on content is an exceptionally troublesome undertaking without anyone else's input, based on given unstructured best cases badly organized content alongside the setting intricacy [4], not to mention extricating estimation from content as loud as online networking content. There are a few troubles inborn in breaking down assessment from web-based social networking [5]. One precedent is "Negatives False representations" where different words, for example, "poop" and "crying" by and large recommends pessimism, yet they suggest positive feeling when utilized in an analysis of preferred sentiment for example, " Satisfied with crying referral objects" or "Blessed poo! This is extraordinary". Another precedent is "Contingent estimation, for example, "In the event that somebody doesn't get back to me, never work again. Different models define slant investigation of online networking content to be hard. The procedure gets significantly complex with the usage of different things, for example, "・ " ("smiley") & probable hash table, for example, "#happy" to explore emotions unexpectedly or snidely.

II. REVIEW OF LITERATURE

The soonest deal with feeling investigation on Twitter information can be followed back to works of Go et al., (2009) [5] Their way to deal with mockery discovery was to characterize tweets as positive or negative utilizing Naive Bayes, Maximum Entropy or Support Vector Machines calculations for characterization also, unigrams, bigrams, unigrams and bigrams, and unigrams with grammatical form labels as highlight extractors. The paper proposed a grouping model with emoji discovery and examination for order and furthermore considered dreary characters. The calculation demonstrated a precision around 80%. In any case, the paper didn't investigate mockery discovery, and limited the arrangement into just positive and negative classes. The subsequent stage around there of research would make the order ongoing. The continuous nature of tweets have propelled numerous inquires about. One among them being crafted by Bifet et al., (2011) [6]
which utilizes the Twitter Streaming API to acquire tweets in continuous. The paper demonstrates use of MOA (Massive Online Examination); it gathers ongoing information, utilizes an accumulation of calculations and arranges the tweets into two classes, in particular positive and negative tweets. The calculation proposed utilizes a highlight age channel which utilizes a weighting plan and at that point performs change identification to touch base at its outcomes.

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The work, be that as it may, is again constrained to only two class arrangement and does not wander into mockery location. Besides, it utilizes a predefined dataset for preparing. Another inquire about which is similarly is by Bifet. A. what's more, Straightforward E. (2010) [7] which again utilize the twitter spilling Programming interface and a predefined preparing set to order tweets. This work assesses three calculations in particular Multinomial Naive Bayes, Stochastic Gradient Descent and Hoeffding Tree for order and shows consequences of up to 82% on the best fit calculation. Be that as it may, the proposed work neglects to perform mockery recognition, however utilizes emoticon word reference to help in arrangement.Pfitzer, Garas, and Shweitzer [3] gathered twitter posts as serving especially one of two limits. A tweet is either information creation or the unadulterated scattering of information where a customer reposts another's exceptional idea or thought (re-tweet). It was found that energetic distinction influences the probability of a scrap of information being re-tweeted; tweets with higher enthusiastic uniqueness have a higher probability of being re-tweeted. Past work in feeling examination on Twitter has revealed that there is a specific relationship of the swing of the total perspective on account of the ability to re-tweet another customer's post. In an examination by Garas, Garcia, Skowron, and Shweitzer [4] the correspondence structures used transversely over online social environment were explored for instances of both steady information exchange and by and large inclination. Models of online correspondence were used to choose and separate energetic triggers in talk, similarly as a relationship of lead both on the web and as a general rule. It was discovered that people did not change their case of enunciation basically between as of late inspected kinds of correspondence. Likewise, minute talk rooms don't show the proportionate warmed eager models that are normally found in substitute sorts of online correspondence; passing answer visits are progressively balanced in feeling about various subjects. The tongue of tweets is novel as a result of the 140- character limit constrained upon individual posts, making customers routinely utilize shorthand documentation similarly as emoticons in supposition verbalization [5]. Pak and Paroubek [6] have done profound work in the field of short substance examination while gathering tweets subject to the association among emoticons and parts of talk.

III. SENTIMENT ANALYSIS (SA)

Sentiment mining, extremity mining, and sentiment mining or on the other hand notion examination is worried about investigation of course based content, content containing sentiments and feelings. Estimation examination includes numerous undertakings. Four of the essential assignments of notion investigation where most of the exploration exertion is engaged are: pre-processing data, class naming, granularity of comment, distinguishing proof [8]. Information pre-processing is indispensable particularly for the content gathered from web based life sites since it is unstructured and loaded with spelling botches also, characteristics. All scientists in the zone of notion examination play out a few or the majority of the common dialect pre-processing assignments including: spellchecking, and expulsion of stop words, for example, accentuation marks. Also, a few scientists perform stemming previously arrangement [9] [10].In class naming procedure (for example the procedure of commenting on content into marks or classes) some examination centers on ordering content as abstract or goal. In feeling examination, this errand is normally done to start with; on the grounds that it was demonstrated that performing it before extremity grouping enhances the last [4]. In other words, on the off chance that content is recognized as emotional, we can perform extremity grouping to decide if this abstract content is conveying slant or assessment of negative. Then again, a huge collection of research centers on computerizing the procedure of class marking through inaccessible supervision utilizing boisterous names. For example [11] utilized emojis, for example, ":-)" and ":(" to mark +ve or –ve tweets. Be that as it may, [12] contended that utilizing boisterous feeling marks may block the execution of opinion classifiers. Proposed different models to abuse Twitter devotee diagram to move forward opinion characterization and developed a diagram that has clients, no. of tweets, unigram related word, bigrams of words, hash tags, what's more, emojis as its hubs to be associated with connection presence (e.g., clients are associated with tweets they made; tweeted data is associated to unigram of words and so on). At that point they connected a name proliferation technique where slant names were proliferated from a little arrangement of hubs seeded with some underlying name data all through the chart.Having a pre-handled abstract content with class marks, estimation characterization to be archive [13], sentence of word ambiguity [14] or state levels [15] (where an expression is a piece of a sentence sequence of words) which we allude to as the characterization of words. At long last, the objective of a feeling is to be considered the difficulties of feeling investigation that was tended to by number of scientists [16].

3.1. Approaches Used for Sentiment Analysis

After audit of papers referred to in the reference segment, it is discovered that the undertaking of SA can be performed utilizing either the Lexicon/Lexical based techniques, Machine Learning based strategies, Keyword Spotting or Concept based techniques.Lexical /Lexicon based strategies.

Information is grouped dependent on the quantity of "sentiment words" present in the content [3]. Words communicating either a positive/negative supposition are called conclusion words - "incredible", "splendid", "terrible", "costly" are precedents. The semantic introduction of individual words in an audit is utilized to all in all decide the by and large estimation extremity of the survey [4]. These techniques in this way require a corpus [dictionary of words/ notion lexicon], in which each word is commented on with its semantic introduction (positive/negative) [5].

Given a bit of content whose assessment must be resolved, these techniques recognize the supposition words in the content. The corpus is then used to decide the extremity (quality/semantic introduction) of every assessment word. A semantic introduction score of +1 and-1 are relegated to the positive and negative words individually. On the off chance that the all-out extremity score (tops) is certain (i.e., there are more positive supposition words than negative words), the content is delegated positive, else negative. The notion vocabulary is the essential and most critical asset for slant classifiers, which can be made physically/consequently [6].

The slant dictionary comprises of conclusion words and expressions [7].Distinctive strategies that can be utilized to develop an assumption dictionary are – Construction of Manual, Corpus based and the Dictionary based strategies. The upsides of Lexical/ Lexicon based strategies are:

1) The technique is straightforward and productive and gives sensible outcomes,
2) They depend just on named information and needn't bother with any preparation dataset, and
3) The requirement for a corpus may appear to be a downside. The simple accessibility of dictionaries and their extensible contrasted with preparing set, demonstrate something else.

Condensed beneath are the disadvantages of Lexicon based strategies:

1) Context subordinate supposition words can't be managed,
2) Sentences that contain numerous clashing feeling words can't be managed.
3) A solitary sentence may address numerous substances and the sentiment for every element can differ.
4) One noteworthy analysis raised against these techniques is that the word references are problematic as they are hand positioned by people [8],
5) It is difficult to make an exceptional lexical-based word reference to be utilized for various settings [9],
6) Limited words inclusion - may neglect to perceive words that are not as of now in the dictionary,
7) They normally perform less precisely than machine learning approaches [5], and
8) Results could be finished/under broke down prompting a decline in the execution if the word reference is excessively comprehensive/scanty.

Information Machine Learning/Learning based techniques:
Here, feeling recognition is a double arrangement assignment i.e., positive or negative. A given bit of content is grouped based on marked models. A preparation dataset is utilized to separate the applicable highlights and at that point used to prepare the calculation (Naive Bayes, Maximum Entropy, SVM and so on).

Directed, Semi-administered and Unsupervised strategies are distinctive classifications of machine learning based SA techniques [10].

I. Directed - utilizing marked prepared information,
ii. Unsupervised - without marked information, and
iii. Semi-directed - blended of marked and unlabeled information. The upsides of information Machine Learning based techniques are:

1) Machine Learning technique enhance the exactness altogether [3],
2) Ability to adjust and make prepared model for explicit purposes and settings [9],
3) Better outcomes can be acquired utilizing machine learning approaches in limited areas [5], and
4) Machine learning strategies give more exactness [11].

The downsides of information Machine learning techniques are:

1) Supervised strategies require marked contributions as preparing information - the bigger the better,
2) If there is an adjustment in the dialect use, these strategies adjust ineffectively,
3) Availability of named information and thus the low pertinence of the strategy on new information [9],
4) Labeling information is expensive and restrictive for a few undertakings,
5) Machine learning strategies depend on the utilization of a vast dataset of marked archives for preparing [11],
6) When a classifier that has accomplished a high precision is utilized for another area, its execution diminishes [6],
7) Collecting and commenting on a substantial corpus of labeled preparing information can be both, a testing and costly undertaking.

<u>Keyword Spotting</u>

This strategy incorporates building up a rundown of effect words (catchphrases that identify with a specific feeling). These are typically positive/negative descriptive stop words to be solid pointers of feeling [12].

<u>Impediments of this methodology are:</u>

1) When invalidation is included, influence words are inadequately perceived [12]. For instance, the sentence "the present climate was great" will be effectively named having a positive feelings is an attempting to characterize the sentence "the present climate wasn't great", it is prone to fizzle.
2) This strategy depends on the nearness of effect watchwords which are surface component of writing [1, 2]. For eq., the sentence "My significant other petitioned for legal separation today" has no influence words yet passes on forceful feelings. In this way stop words spotting is incapable.

<u>Ideal based approach</u>

Depend on huge semantic learning bases and use web ontology's/semantic systems for semantic content examination [13]. Dissimilar to strategies that utilization keyword(s) and word co-event tallies, they utilize verifiable importance related with normal dialect ideas.

<u>Focal points of this methodology include:</u>

1) Detection of assumptions that are communicated inconspicuously, and
2) Multi-word calculations can be broke down despite the fact that they don't expressly pass on feelings yet are identified with ideas that do [1]. Overwhelming dependence on the profundity and broadness of the learning base utilized is the real downside of this strategy.

IV DESCRIPTION OF DIFFERENT APPROACHES USED IN SA

This section describes about basic usage of different approaches used in earlier work regarding sentiment analysis with respect to features used for real time applications.

S.No	Technique	Tools used	Experiment	dependency of language	M/L based and Laxicon techniques (LB)	Data Source

1	User based prediction	Social ContextMatrix Factorization	Predict unknown user topic prediction	Yes	LB	Twitter
2	Shift of polarity with opinion prediction	Representation of duel Sentiment analysis	Classification of polarity class	No	LB	Amazon and corpos
3	Large scale data matching	Multilabel classification	Student Experienceswithr espect to social media.	Yes	ML	Twitter and social networks
4	Sentiment classification for class-do main	Corpus based	Cross domain sentiment classification wit h sensitive	Yes	LB	Amozon. com
5	Interpretation of sentiment variations	Background latent Dirichlet analysis (LDA)	To preserve possible reasons	Yes	ML	Twitter
6	Detection of Sentiment detection	Weekly preserved sentiment topic analysis	Detection of topic from text	Yes	ML	IMDB movie data set
7	Hashtag-leve l sentiment classification	SVM Classifier	To automatic ally generate the overall sentiment polarity	Yes	ML	Tweets
8	Sentiment classification through detection of sentiment analysis	Hybrid approach(lexicon based +M/clearning	Detection of sentiment strength through polarity of classificati on	Yes	ML and LB*	Reviews of Software and movie reviews

IV. PERFORMANCE EVALUATION METRICS

To evaluate the truth of a classifier, very exercise to make a misunderstandings matrix. Confusion matrix defines table with explains the efficiency of classifier with set of information which are known by user.

The standard conditions showing in the misunderstandings matrix are:

i) True Positives (TP) - the classifier expected yes, and it is actually a yes.

ii) True Negative (TN) - the classifier expected no, and it is actually a no.

iii) False Positives (FP) - the classifier expected yes, but it actually is a no (also known as a “Type I error”).

iv) False Negatives (FN) - the classifier expected no, but it actually is a yes (also known as a “Type II error”).

Accuracy, Perfection, Remember and F Ranking are four measures/indices used to evaluate the efficiency of the feeling classifiers. These spiders are calculated in accordance with the misunderstandings matrix.

1) Accuracy - Overall, how often is the classifier:

$$Acc = (TP + TN)/(TP + TN + FP + FN)$$

2) Precision - When a classifier predicts yes, how often is it correct? This measure shows how accurately the model makes predictions

3) Recall - it is the basic portion of true +ve instances against with actual +ve instances.

4) F1 - is a weighted average of the true positive rate (recall) and precision.

VI. MAJOR CHALLENGES IN SA

The accessibility of a few procedures for SA, makes it is hard to state which strategy is better over the other. To enhance the general execution and precision of SA strategies, it is important to address the following issues and difficulties:

1) An assessment/influence word perhaps viewed as positive in one circumstance and negative in another circumstance,

2) a similar feeling can be communicated contrastingly by various individuals. They can be conflicting in their announcements,

3) People may utilize a solitary sentence that joins distinctive suppositions – which is simple for a human to see yet extraordinary for a PC/machine to parse,

4) When a short bit of content needs setting it winds up troublesome for even human's to comprehend what another person thought,

5) Handling refutations, polysemy (a word with different implications), slangs and area speculation,

6) Identifying concealed feelings (e.g., outrage, appall, happiness) is a testing errand, and

7) Updating/Down-dating Lexicons [13]-Since an

$$p = TP/(TP + FP)$$

assumption analyzer utilizes a vocabulary, its execution depends significantly on the

8) precision of the dictionary. Vocabularies

$$r = TP/(TP + FN)$$

should in this way be refreshed to stifle the words which are never again utilized and to suit new words.

VII. CONCLUSION

Users relate to social network communication based on their emotions defined in public network communications, it defines exploration and monitoring of users feeling. Online social network is one of important platform which describes resource utilization and analysis of sentiment analysis and mining of user opinion with respect to stop words relates to various interested concepts like products, words relates to celebrations etc. Main purpose of this paper gives brief description about different approaches relates to machine learning based classification approaches based on user emotions taken from twitter and other related social networks. We also discuss description of different lexical, machine learning related approaches present in social network communication.

REFERENCES

1. Fuji Ren,Ye Wu," Predicting User-Topic Opinions in Twitter withSocial and Topical Context", IEEE Trans. on affective computing, vol. 4, no. 4, October-December 2013.
2. Rui Xia, Feng Xu, Chengqing Zong, Qianmu Li, Yong Qi, and Tao Li,"Dual Sentiment Analysis:Considering Two Sides of One Review", IEEE Trans.on Knowledge and Data Engineering, 2015
3. Xin Chen,Mihaela Vorvoreanu, and Krishna Madhavan," Mining Social Media Data for Understanding Students' Learning Experiences" IEEE trans. on learning technologies, vol. 7, no. 3, JulySeptember 2014.
4. Danushka Bollegala, David Weir, and John Carroll," Cross-Domain Sentiment Classification Using a Sentiment Sensitive Thesaurus", IEEE trans. on knowledge and data engineering, vol. 25, no. 8, August 2013.
5. Shulong Tan, Yang Li, Huan Sun, Ziyu Guan, Xifeng Yan, Jiajun Bu, ,Chun Chen, and Xiaofei He," Interpreting the Public Sentiment Variations on Twitter", IEEE trans. on knowledge and data engineering, vol. 26, no. 5, May 2014.
6. Chenghua Lin, Yulan He, Richard Everson, Member, IEEE, and Stefan Ru¨ger," Weakly Supervised Joint Sentiment-Topic Detection from Text", IEEE trans. on knowledge and data engineering, vol. 24, no. 6, June 2012.
7. LI Bing, Keith C.C. Chan, Carol OU," Public Sentiment Analysis in Twitter Data for Prediction of A Company's Stock Price Movements", 2014 IEEE, 11th International Conference on e-Business Engineering.
8. DeMers, J., "How Social Media is Changing the SEO Industry," Search Engine Journal, April 2013.
9. Olensky, S., "Are Brands Wielding More Influence In Social Media Than We Thought?," Forbes, May 2012.
10. Jiang, L., Yu, M., Zhou, M., Liu, X., & Zhao, T, "Targetdependent Twitter Sentiment Classification," in Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies, Portland, 2011.
11. Bhuta, S., Doshi, A., Doshi, U., & Narvekar, M, "A Review of Techniques for Sentiment Analysis of Twitter Data," in Issues and Challenges in Intelligent Computing Techniques (ICICT), 2014.
12. Yu, H., & Kim, S., "SVM Tutorial—Classification, Regression and Ranking.," Springer Berlin Heidelberg in Handbook of Natural Computing, 2012.
13. Saif, H., He, Y., & Alani, H, "Alleviating Data Sparsity for Twitter Sentiment Analysis," in CEUR Workshop Proceedings (CEUR-WS. org), Lyon, France., 2012.
14. Sagar Bhuta, Avit Doshi, Uehit Doshi, Meera Narvekar : "A Review of Techniques for Sentiment Analysis " , International Conference on Issues and Challenges in Intelligent Computing Techniques (ICICT) , 978-1-4799- 2900-9/14 2014 IEEE.
15. Alvaro Ortigosa , José M. Martín, Rosa M. Carro: "Sentiment analysis in Facebook and its application to e- learning", Elsevier Journal of Computers in Human Behavior 31 (2014), Published by Elsevier Ltd.
16. Zohreh Madhoushi, Zohreh Madhoushi, Suhaila Zainudin: "Sentiment Analysis Techniques in Recent Works" Science and Information Conference 2015 July 28-30, 2015 - London, UK.
17. Valentina Mazzonello, Salvatore Gaglio, Agnese Augello, Giovanni Pilato: "A Study on Classification Methods Applied to Sentiment Analysis ", 2013 IEEE Seventh International Conference on Semantic Computing,978-0-7695-5119-7/19 DOI 10.1109/ICSC.2013.82
18. Shreya Banker, Rupal Patel: "A brief review of sentiment analysis methods", International Journal of Information Sciences and Techniques (IJIST) Vol.6, No.1/2, March 2016. DOI : 10.5121/ijist.2016.6210 89
19. Ms Kranti Ghag and Dr. Ketan Shah: "Comparative Analysis of the Techniques for Sentiment Analysis", ICATE 2013 Paper Identification Number-124.
20. Neha R. Kasture, Poonam B. Bhilare: "An Approach for sentiment analysis on social networking sites", IEEE International Conference on Computing Communication Control and Automation 2015. 978-1-4799-6892-3/15 2015.
21. Volkova, S., Wilson, T., & Yarowsky, D. Exploring Demographic Language Variations to Improve Multilingual Sentiment Analysis in Social Media. In EMNLP, pp. 1815–1827 (2013).
22. Thelwall, M., Buckley, K., & Paltoglou, G. Sentiment strength detection for the social web Journal of the American Society for Information Science and Technology 63(1), pp. 163–173 (2012).
23. Thomas, K., Fern´andez, M., Brown, S., Alani, H.: OUSocial2 - A Platform for Gathering Students' Feedback from Social Media. Demo at the 13th International Semantic Web Conference (ISWC'14) (2014).
24. Simon, T., Goldberg, A., Aharonson-Daniel, L., Leykin, D., Adini, B.: Twitter in the Cross Fire – The Use of Social Media in the Westgate Mall Terror Attack in Kenya. PloS one 9(8): e104136 (2014).
25. Saif, H., Fern´andez, M., He, Y., Alani, H.: SentiCircles for Contextual and Conceptual Semantic Sentiment Analysis of Twitter. In: Proceedings of the 11th Extended Semantic Web Conference (ESWC'14), pp. 83–98 (2014)
26. Saif, H., Fern´andez, M., He, Y., Alani, H.: On Stopwords, Filtering and Data Sparsity for Sentiment Analysis of Twitter. In: Proceedings of the 9th International Conference on Language Resources and Evaluation (LREC'14), pp. 810–817 (2014)
27. Saif, H., He, Y., Fern´andez, M., Alani, H.: Semantic Patterns for Sentiment Analysis of Twitter. In: Proceedings of the 13th International Semantic Web Conference (ISWC'14) - part 2, pp. 324–340 (2014).
28. Aston, N., Liddle, J. and Hu, W. (2014) Twitter Sentiment in Date Streams with Perceptron. Journal of Computer and Communications, 2, 11-16.
29. Bifet, Albert, and Eibe Frank. (2010) Sentiment Knowledge Discovery in Twitter Streaming Data. Proceedings of 13th International Conference on Discovery Science, Canberra, 6-8 October 2010, 1-15.
30. Perez-Tellez, F., Pinto, D., Cardiff, J., & Rosso, P, "On The Difficulty of Clustering Company tweets," in Proceedings of the 2nd international workshop on Search and mining user-generated contents, New York, 2010.
31. David Bamman and Noah A. Smith., "Contextualized Sarcasm Detection on Twitter", School of Computer Science, Carnegie Mellon University (2016).
32. Bollen, J., Pepe, A., & Mao, H, "Modeling Public Mood and Emotion: Twitter Sentiment and Socio-Economic Phenomena," in International AAAI Conference on Weblogs and Social Media, Barcelona, 2009.

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