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Intensity Weight Factor Based Sentiment Prediction Analysis on Tweets

Manasa K N, M. C. PADMA

***Abstract:** Advances in the field of sentiment analysis are quick and purposeful to explore the views or articles available on various social media platforms through the techniques of machine learning with emotions, topic analysis or polarization calculations. Although employing various machine learning techniques and emotion analysis tools, there is a direct need for modern methods. To address these challenges, the contribution of this paper involves adopting a new approach that includes emotional analysts that integrates emotional intensity and machine learning. In addition, this document also provides a comparison of sentiment analysis techniques in analyzing political views through the application of machine learning algorithms such as Naive Bayes and KNN.*

***Keywords:**Sentiment Analyzer; WordNet; word sequence disambiguation (WSD); Twitter; machine learning; Naïve Bayes*

I. INTRODUCTION

Emotions can be illustrated as emotions, or as judgments, thoughts or ideas, stimulated or colored by emotion [5]. In linguistics, the emphasis is on opinions, not feelings, in addition to the terms "sentiment" and "opinion" are frequently employed interchangeably in this work. Textual data can be separated into two categories: factual and substantive. While facts are an expression of the purpose of the subject, their events, and their properties, a general opinion is an expression of a characteristic that describes a person's feelings, evaluations, or feelings about their subject, events, and properties. Emotional Analysis (Emotional Retrieval, Emotion Classification, Subjective Analysis, Review or Estimation, and, in some cases, Polymorphism) in relation to the treatment of thoughts, emotions, and topics in the text [17] . It aims to shape the behavior or opinion of the speaker or author with respect to a particular subject or purpose. It should also be eminent that in this context, "subject" does not mean that something is not true.

The rest of the paper remains as follows. Section II reviews the work. Steps to develop an emotion analysis model to determine the strength of emotion are mentioned in Section 3. Section 4 illustrates the experimental results of the proposed method. In this section, the proposed method is compared with the existing method to prove the effectiveness of the new method. Conclusions in addition to future work of this work are presented in Section V.

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Manasa K. N., Asst. Professor, Department of Computer Science, St. Philomena's College, Mysuru, Karnataka, India.

M. C. PADMA, Professor and Head Department of Computer Science and Engineering, PES College of Engineering, Mandya, India.

II. RELATED WORK

In [6] Duwairi et. al suggested that sentiment analysis identifies textual biases employing machine learning methods or employing acoustic-based approaches. The classifiers implemented in the dataset were Naive Bayes Support Vector Machine (SVM) and K-Nearest Neighbor (KNN (k = 10)), where SVM provided the maximum accuracy and KNN provided a recall. The maximum . In [8] Kouloumpis et. Al shows the benefits of the existing lexical features and resources employed in small blogs to browse Twitter messages. The model [9] has a new methodology developed by a combination of categorization, control learning, and machine learning demonstrating the improvement of F1 from mean and macro average value.[20], Mudinas et al. Al concluded that sentiment level analysis systems are better than pure lexicons and systems based on pure training due to higher precision in polarization and better readability results.

In [18] Lin et. al defines subject data employing an automated tool and a new validated modeling framework, called an integrated emotion / model that detects emotions and topics together from a text. [10] explored a globally structured model for distinguishing textual feelings at dissimilar levels of detail, as well as making real solutions by means of classification, on which the assumptions of the model rely on Decide on a grade. On the other, the authors in [11] state that when presenting dissimilar perspectives to the public, public opinion polls are taken into account due to various sources in the network, and it classifies comments either positively or negatively. [19] proved that in text classification, dissimilar alternatives to machine learning algorithms prove large differences in their effectiveness. They also suggested that diagrams prove continuous improvement in tasks, and that Naive Bayes (NB) is preferred over SVM for a small portion of emotional tasks.

In [7] sentimental analysis is employed for natural language processing that illustrates the fragility of text documents. Initially, only positive and negative emotions were discriminated, i.e.. The binary classification problem. Fuof et al. [12] proposed a system of tweets based on the vote of the majority of the three aristocracy classifiers: the SVM, NB, and LR. In their work, experiments were conducted to investigate the effect of data acquisition on classification accuracy, And the results proved an improvement in classification accuracy after reducing the size of the vector features.

Employing the data and the aggregation of data proved a clear improvement in the classification accuracy of all data. The average improvement rate is about 15%.

The above studies identified and listed several drawbacks of these methods

1. A sample is needed to analyze emotions to find the intensity of emotion.
2.Data from multiple platforms must be verified for sentiment analysis.
3.Prosecution, ridicule, and misinformation play an important role in reversing the ambiguity of the message.
4.Non-sentimental terms are ignored by existing sentiment analysis methods.
5. An in-depth machine / learning model is required to analyze emotional intensity.

III. SENTIMENT ANALYSIS MODEL CREATION

This journal uses double-blind review process, which means that both the reviewer (s) and author (s) identities concealed from the reviewers, and vice versa, throughout the review process. All submitted manuscripts are reviewed by three reviewer one from India and rest two from overseas. There should be proper comments of the reviewers for the purpose of acceptance/ rejection. There should be minimum 01 to 02 week time window for it.

The overall purpose of this study was to determine the mood of the article, whether positive or negative, which extended to the polarization dynamics. The first step is to create a scientific model of science employing data extracted from social media applications such as facebook, twitter. The second process is to extract the context of emotions as well as words that are not related to tweets or to check out the stereotype. These processes include tasks such as extracting data and cleaning data, defining emotions in text, analyzing patterns, creating scientific models, and finding the intensity of feedback from a sample. The proposed method is keyword-based search in the field of emotion analysis / concept development. After all, the SA / OM problem is a search-focused NLP problem when a sentence expresses its views and receives feedback bias (generally positive or negative). The datasets that will be employed in this work to compare results are usually Twitter datasets, movie review datasets, and Facebook commentary. Emotional analysis can be done based on a tweet or comment. The words in each article were compared to the text in the database, which was previously defined as "positive" or "negative." After considering these terms, the algorithm then calculates whether the text is positive or negative based on the probability of each possibility.

A. Feature Extraction employing Vector Space Model Representation

When you analyze emotions from a topic text employing machine learning techniques, functional extraction becomes an integral elements. In machine learning, functions refer to data that can be extracted from any data model. An attribute describes the properties of the data that are unique. Extensive and informative extracts help improve machine learning productivity and reduce computational complexity. In this work, we employed vector space models [3], [4] to extract features from each file. Each blog post is displayed in vector form. This word vector contains the individual words that appear in the blog post and its relative weight. There are several ways to represent a word vector. The commonly employed objects are tf, tf.idf, and boolean presentations. Frequency word (tf) is the frequency at which a word appears in the document. If the total number of files of interest is N and dft is the number of files containing the word t, then the id for the t word is calculated as idft = log (N / dft). IT A.S. IT E. Rarely high while i. D. The conventional AS is low. The values tf and idf are employed to produce the composite weights for each word in each file defined as tf-idft, d = tft, d X idft. The vector V (d) is derived from file d, so there is one component for each term. The Boolean presence employing values "0" and "1" denotes the absence and presence of words in the document vector. When we have a whole set of declarations representing a vector of documents, their degree of similarity can also be calculated by Jacquard's measure of similarity, as in equation 1

$$J(X,Y)=(|X\cap Y|)/(|X\cup Y|) \quad (1)$$

where X is the document vector1 and Y is the document vector2. $X\cap Y$ is the common vector term among X and Y. $X\cup Y$ is the combination of all vector terms of X and Y.

Jaccard Relation Estimator Algorithm:

1.Collects the conditions for the given data set and creates a list of words
2 Highlight each word with "token_term"Tokens = sent_translate (txt)
for i in tokenized:
wordsList = nltk.word_tokenize(i)
3.Specify the POS markup for each term after classifying the terms
tagged = nltk.pos_tag(wordsList)
4. Change the size by attaching the condition and canceling the unwanted condition.
Produce cluster C1= set of token[i]
Get cluster C1
Produce F = (D,A,C)
5. Commit to the planning process to obtain structured data in the form of topics, estimates and objects.
The generation of object objects and predicted by A.
6. Employing the Jaccard Connection Estimator, determine the similarity of the subject, object, and estimates acquired from the given data set.
Get [i] tokens [i + 1].
Fill j (token [i] tokens {i + 1].
Prove J

B. Parts of Speech Tagging

POS labeling mentions to the assignment of a language category to each term in a document based on syntactic and physical behavior, and a Penbank Tree POS tag Employed [5] are shown in Table 1 below. We cite two consecutive terms that indicate that their POS tags match a pattern.

Tag	Description	Example	Tag	Description	Example
CC	coordin. conjunction	*and, but, or*	SYM	symbol	+,%, &
CD	cardinal number	*one, two*	TO	"to"	*to*
DT	determiner	*a, the*	UH	interjection	*ah, oops*
EX	existential 'there'	*there*	VB	verb base form	*eat*
FW	foreign word	*mea culpa*	VBD	verb past tense	*ate*
IN	preposition/sub-conj	*of, in, by*	VBG	verb gerund	*eating*
JJ	adjective	*yellow*	VBN	verb past participle	*eaten*
JJR	adj., comparative	*bigger*	VBP	verb non-3sg pres	*eat*
JJS	adj., superlative	*wildest*	VBZ	verb 3sg pres	*eats*
LS	list item marker	*1, 2, One*	WDT	wh-determiner	*which, that*
MD	modal	*can, should*	WP	wh-pronoun	*what, who*
NN	noun, sing. or mass	*llama*	WP$	possessive wh-	*whose*
NNS	noun, plural	*llamas*	WRB	wh-adverb	*how, where*
NNP	proper noun, sing.	*IBM*	$	dollar sign	$
NNPS	proper noun, plural	*Carolinas*	#	pound sign	#
PDT	predeterminer	*all, both*	"	left quote	' or "
POS	possessive ending	*'s*	"	right quote	' or "
PRP	personal pronoun	*I, you, he*	(	left parenthesis	[, (, {, <
PRP$	possessive pronoun	*your, one's*	)	right parenthesis	],), }, >
RB	adverb	*quickly, never*	,	comma	,
RBR	adverb, comparative	*faster*	.	sentence-final punc	. ! ?
RBS	adverb, superlative	*fastest*	:	mid-sentence punc	: ; ... – -
RP	particle	*up, off*			

C. Feature Extraction employing Vector Space Model Representation

The Navie Bayes method was employed in this work to analyze emotions. He computed three weight estimates, Obe (S), O and N (Neg), describing the purpose, positive and negative words, in the synchronization. The method is based on a qualitative analysis of the synchronous tone and on the employ of word output vector representations for semi-synchronized. Obj (s), Pos (s) and Neg (for) synset s results from a committee of eight ternary classifiers. The synchronization result is determined by the normal elements of the three classes labeled corresponding to it..

These results correlate with the negative NPN with each interesting period. It is important to note that the sum of the three syringes is always 1. When all POS points are awarded, the total points are employed to calculate the objectives, positive and negative results of the entire document, and Label them accordingly. Algorithms for Weight Coefficients

The following example shows the calculation of intensity.

possize ← pos.size
negsize← neg.size
neusize← neu.size
posper ← (possize/sensize)
negper← (negsize/sensize)
neuper← (neusize/sensize)
if ((posper>negper) and (posper>neuper)) then
polarity← 1/sensize
pospolarity ← polarity * possize
if (pospolarity > polarity) then
classlabel← "Very Positive"
vppolarity += pospolarity
tpolarity← pospolarity
else
classlabel ← "Positive"
ppolarity += pospolarity
tpolarity ← pospolarity
end if
else if (negper>neuper)
polarity← 1/sensize
negpolarity ← (polarity*negsize)
if(negpolarity>polarity) then
classlabel← "Very Negative"
vnpolarity +=negpolarity
tpolarity ← negpolarity
else
classlabel← "Negative"
npolarity += negpolarity
tpolarity ← negpolarity
end if
else
polarity ← 1/sensize
neupolarity ← (polarity*neusize)
classlabel← "Neutral"
nepolarity +=neupolarity
tpolarity ← neupolarity
end if

Naive Bayes text classification scheme was also employed to analyze emotions. We employed the Navigator machine learning method to test the accuracy of our semester orientation method. This classifier based on coastal theory with the assumption of inter-rater reliability. The Naive Bayesian model is easy to construct without complex parameter estimates, which makes it particularly useful for very large datasets. Despite its simplicity, Bayes classifiers often do surprisingly well and are widely employed because they often outperform the ranking method.

Algorithm

Bell's theorem gives way to computing the posterior probabilities P (c | x) of P (c) P (x) and P (x | c). Naive Bayes Classifier assumes that the effect of the predictor value (x) on a given class (c) is independent of the values of the other predictors. This assumption is called conditional independence.

$$P(c \mid x) = \frac{P(x \mid c)P(c)}{P(x)} \tag{2}$$

$$P(c \mid X) = P(x_1 \mid c) \times P(x_2 \mid c) \times \cdots \times P(x_n \mid c) \times P(c) \tag{3}$$

where

- P (c | x) is the posterior probability of the class (target) given by the predictor (attribute).
- P (c) is the primary probability for a class.
- P (x | c) is the probability, which is the probability for a given prediction class.
- P (x) is the preliminary probability of prediction.

Based on the model built for each analyzer, the test instrument was evaluated. After evaluating the test instrument, we recorded the accuracy of the analyzer in each sample.

IV. RESULT AND ANALYSIS

A. Dataset Employed

In this paper, research are accomplished on two sentiment analysis datasets for sentiment analysis: SSTSMD and tweets data collected from tweets. Both datasets include raw text and hand-labeled sentiments.

HCR: This dataset was collected from [49]. It consists of three elements: training set, development tool and test kit. There are five kinds of labels in the dataset: positive, irrelevant, negative and mixed. The case was hand-written by the author. In this document this work only employ tweets labeled positive and negative. We employed the full follower graph, which was developed in 2009 to build HCR customer relationships and acquire non-target graphs. The dataset contains 9 dissimilar topics: health care reform, Obama, Democratic Republicans, conservatives, conservatives, Democrats, the Tea Party and more. Each micro-block meets one of these goals.

OMD: It includes tweets about US presidential candidates Barack Obama and John McCain. This dataset was physically labeled by the Amazon Mechanical Company. Each tweeter is labeled by at least three Turks, and its inter-annotation contract is 0.655, which indicates a excellent contract among the bookkeepers. Four kinds of labels appear in the dataset, they are positive, irrelevant, negative and mixed. The communication graph was created employing a tracker table that was expanded in 2009.

B. Performance Parameters

Several performance indicators are available to evaluate the effectiveness of the proposed sentiment analysis process. This article uses the F-Measure , Precision Rate, Error Rate , Recall Rate, Specificity, Detection Accuracy and Sensitivity to analyze results..

Detection Accuracy

Detection accuracy is a evaluation system that evaluate the degree of closeness among the original labeled text and the correctly labeled text.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \quad (3)$$

Where, TP – True Positive
FN – False Negative
TN – True Negative
FP – False Positive

Error Rate

Error Rate is the evaluation system that evaluate no of falsely recognized sentiment analysis form the given input text.

$$\text{Error Rate} = \frac{\text{No of Datas of Falsely labeled texts}}{\text{Total No of texts}} \quad (4)$$

Precision Rate

The precision is the fraction of retrieved instances that are relevant to the find.

$$\text{Precision} = \frac{TP}{TP+FP} \quad (5)$$

Recall Rate

The recall is the fraction of relevant instances that are retrieved according to the input data.

$$\text{Recall} = \frac{TP}{TP+FN} \quad (6)$$

Sensitivity

Sensitivity also called the true positive rate or the recall rate in some field's measures the proportion of actual positives.

$$\text{Sensitivity} = \frac{TP}{(TP+FN)} \quad (7)$$

Specificity

Specificity measures the proportion of negatives which are correctly identified such as the percentage.

$$\text{Specificity} = \frac{TN}{(FP+TN)} \quad (8)$$

F-Measure

F-measure is the ratio of product of precision and recall to the sum of precision and recall. The f-measure can be calculated as,

$$F_m = (1+\alpha) * \frac{\text{Precision} * \text{Recall}}{\alpha * (\text{Precision} * \text{Recall})} \quad (9)$$

Experiment No #1: Performance Analysis of Sentiment Analysis Approach

This experiment evaluates the contribution of each type of Sentiment Analysis methods. It takes KNN and Navie Bayes as the Sentiment Analysis approaches. Detection accuracy analysis for classification based on HCR and OMD dataset all classifier shown in the Table 1

Table 1 shows that the detection accuracy values employing KNN and Naive Bays, methods. Navie Bayes method is better than KNN.

Test Data	KNN	Naive Bayes
HCR	0.842	0.927
OMD	0.83	0.915

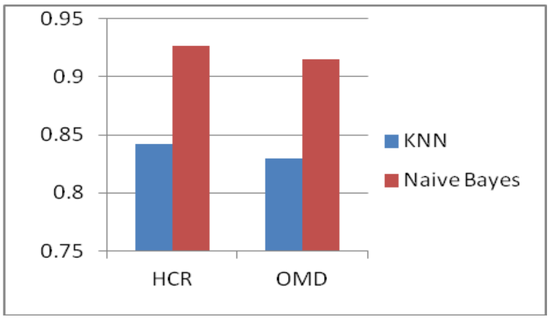

Fig.1 Accuracy Analysis of Sentiment Analysis Method

From the graph shown in figure 3.5 shows that the detection accuracy values employing KNN and Naive Bays, methods. Navie Bayes method is better than KNN .

Table 2 Error Rate Analysis of Sentiment Analysis Method

Test Data	KNN	Naive Bayes
HCR	0.158	0.073
OMD	0.17	0.085

Table 3.2 shows the results of error rate value employing KNN and Naive Bays, methods, gets the best result other than the existing approaches.

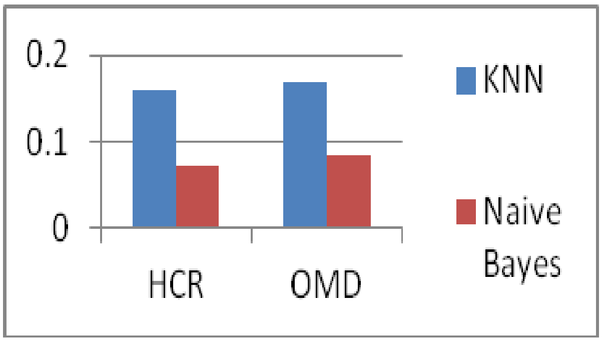

Fig.2 Error Rate Analysis of Sentiment Analysis Method

Fig.2 shows the results of error rate value employing KNN and Naive Bays, methods and Navie Bayes method gets the best result other than KNN.

Table 3 Precision Rate Analysis for Sentiment Analysis Method

Test Data	KNN	Naive Bayes
HCR	0.855	0.94
OMD	0.843	0.928

Table 3 shows precision rate value for sentiment analysis approaches based on KNN and Naive Bays, methods. Navie Bayes method acquired the best results than KNN. Precision rate analysis is shown in Fig.3.

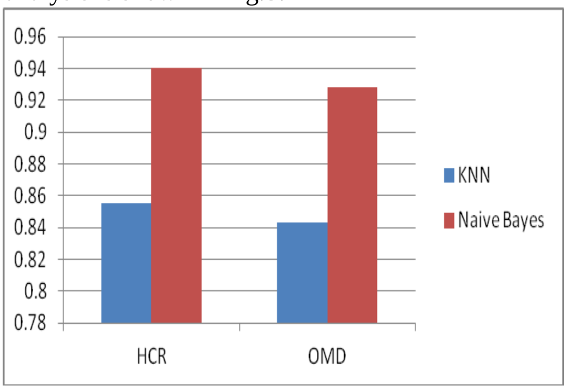

Fig.3 Precision Rate Analysis of Sentiment Analysis Method

Fig.3 shows the precision rate value with KNN and Naive Bays, methods. Navie Bayes method acquired the best results than KNN.

Table 4 Recall Rate Analysis for Sentiment Analysis Method

Test Data	KNN	Naive Bayes
HCR	0.833	0.918
OMD	0.821	0.906

Table 4 shows the recall rate value of KNN and Naive Bays, methods. Navie Bayes method acquired the best results other than KNN that illustrates recall rate analysis is shown in Fig.4

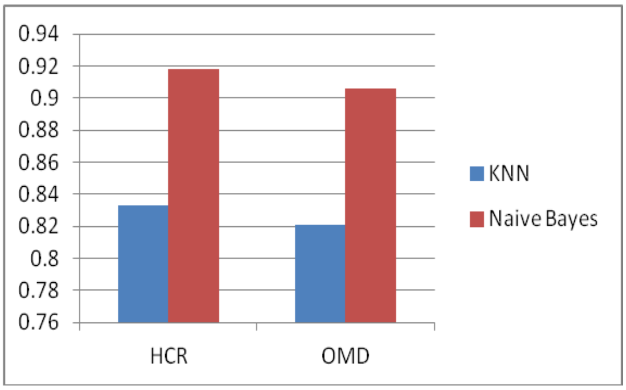

Fig.4. Recall Rate Analysis of Sentiment Analysis Method

Fig.4 shows the recall rate value of Navie Bayes method which acquired the maximum results other than other two existing approaches.
Table 5 illustrates the F-score analysis for sentiment analysis approaches.

Table 5 F-Score Analysis of Sentiment Analysis Method

Test Data	KNN	Naive Bayes
HCR	0.854	0.939
OMD	0.842	0.927

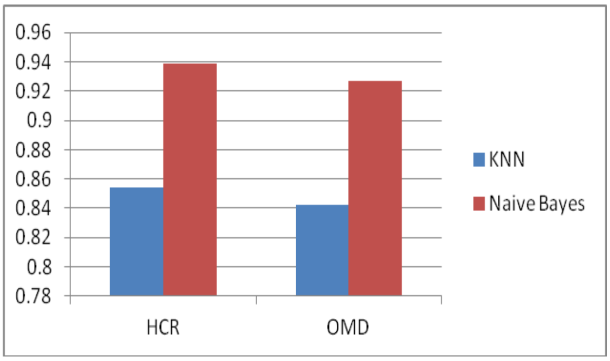

Fig.5 F-Score Analysis of Sentiment Analysis Method

To compare the performance of precision rate analysis it uses KNN and Naive Bays, methods. Navie Bayes method gets best results than KNN. Acquired f-score analysis is shown in Fig5. Fig.5 compares the f-score value employing KNN and Naive Bays method. Navie Bayes method acquired the best results than KNN.

Experiment No #2: Performance Analysis of Sentiment Analysis Approach employing Live Twitter Account

This experiment evaluates the contribution of each type of Sentiment Analysis methods. It takes KNN and Navie Bayes as the Sentiment Analysis approaches. Performance analysis for classification based on Live Twitter account all classifier shown in the Table 6

Table6: Performance Analysis of Sentiment Analysis Approach employing Live Twitter Account

DataSet					
Sentiment Analysis Approaches					
Metrics	Acc	Sen	Spec	F-Score	Error
KNN	97.692	96.332	98.992	98.752	
Navie Bayes	98.326	98.157	98.926	99.824	

Table 6 illustrates the performance analysis for sentiment analysis approaches. To compare the performance of precision rate analysis it uses KNN and Naive Bays, methods. Navie Bayes method gets best results other than the existing approach. Acquired performance analysis is shown in Fig.6.

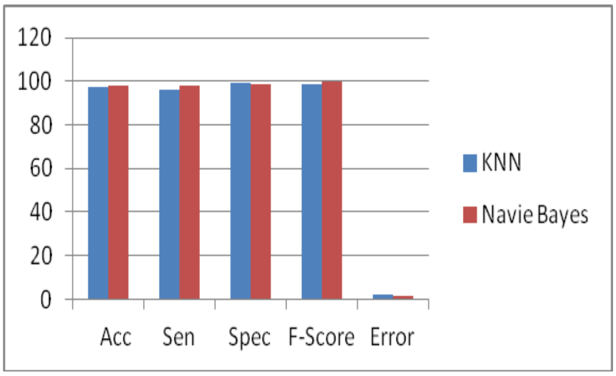

Fig.6 Performance Analysis of Sentiment Analysis Approach employing Live Twitter Account

Fig.6 compares the performance value employing KNN and Naive Bays, methods. Navie Bayes method acquired the best result than KNN.

V. CONCLUSION

In this work, a new methodology is proposed that uses social context to determine emotional clarity. Motivated by consistency, sentiment, and the spread of emotion, we consider three kinds of contexts: user context, structural context, and contextual context. This work introduce structural similarity measures, we construct a structural similarity matrix. This work also established a topic context and create a topic context matrix. This work append all these circumstance to the model employing the Laplace matrix of graphs build by context. This work also tested their results with the Navie Bayes and the KNN engine class, managed by two. Investigational outcome prove that structural similarity is superior than direct customer relationships. In addition, adding context to a topic is useful for improving the accuracy of emotion ratings.

REFERENCES

1. Alomari, K. M., ElSherif, H. M., & Shaalan, K. (2017, June). Arabic Tweets Sentimental Analysis Employing Machine Learning. In International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems (pp. 602- 610). Springer, Cham.
2. Arun, K., Srinagesh, A., & Ramesh, M. (2017). Twitter Sentiment Analysis on Demonetization tweets in India Employing R language. International Journal of Computer Engineering in Research Trends, 4 (6), 252-258.
3. Anta, A. F., Chiroque, L. N., Morere, P., & Santos, A. (2013). Sentiment analysis and topic detection of Spanish tweets: A comparative study of of NLP techniques. Procesamiento del lenguaje natural, 50, 45-52.
4. Basha, S. M., Zhenning, Y., Rajput, D. S., Iyengar, N., & Caytiles, D. R. (2017). Weighted Fuzzy Rule Based Sentiment Prediction Analysis on Tweets. International Journal of Grid and Distributed Computing, 10 (6), 41-54.
5. BOIY, E., HENS, P., DESCHACHT, K. & MOENS, M.-F. (2007), “Automatic Sentiment Analysis in OnLine Text”. In Proceedings of the Conference on Electronic Publishing (ELPUB-2007), p. 349-360.
6. Salloum, S. A., AlHamad, A. Q., Al-Emran, M., & Shaalan, K. (2018). A Survey of Arabic Text Mining. In Intelligent Natural Language Processing: Trends and Applications (pp. 417-431). Springer, Cham.
7. Ng, V., Dasgupta, S., & Arifin, S. M. (2006, July). Examining the role of linguistic knowledge sources in the automatic identification and classification of reviews. In Proceedings of the COLING/ACL on Main conference poster sessions (pp. 611-618). Association for Computational Linguistics.
8. Kouloumpis, E., Wilson, T., & Moore, J. D. (2011). Twitter sentiment analysis: The excellent the bad and the omg!. Icwsm, 11 (538-541), 164.
9. Prabowo, R., & Thelwall, M. (2009). Sentiment analysis: A combined approach. Journal of Informetrics, 3 (2), 143-157.
10. McDonald, R., Hannan, K., Neylon, T., Wells, M., & Reynar, J. (2007). Structured models for fine-to-coarse sentiment analysis. In Proceedings of the 45th annual meeting of the association of computational linguistics (pp. 432-439).
11. Saleh, M. R., Martín-Valdivia, M. T., Montejo-Ráez, A., & Ureña-López, L. A. (2011). Experiments with SVM to classify opinions in dissimilar domains. Expert Systems with Applications, 38 (12), 14799-14804.
12. PANG, B. & LEE, L. (2008), “Opinion Mining and Sentiment Analysis”. In Foundations and Trends in Iformation Retrieval 2 (1-2), p. 1–135.
13. M. M. Fouad, T. F. Gharib, and A. S. Mashat, "Efficient Twitter Sentiment Analysis System with Feature Selection and lassifier Ensemble," in International Conference on Advanced Machine Learning Technologies and Applications, 2018: Springer, pp. 516-527.
14. Law, D., Gruss, R., & Abrahams, A. S. (2017). Automated defect discovery for dishwasher appliances from online consumer reviews. Expert Systems with Applications, 67, 84-94.
15. Nguyen, D. Q., Nguyen, D. Q., Vu, T., & Pham, S. B. (2014). Sentiment classification on polarity reviews: an empirical study employing rating-based features. In Proceedings of the 5th workshop on computational approaches to subjectivity, sentiment and social media analysis (pp. 128-135).
16. Tiwari, P., Mishra, B. K., Kumar, S., & Kumar, V. (2017). Implementation of n-gram methodology for rotten tomatoes review dataset sentiment analysis. International Journal of Knowledge Discovery in Bioinformatics (IJKDB), 7 (1), 30-41.
17. Ng, V., Dasgupta, S., & Arifin, S. M. (2006, July). Examining the role of linguistic knowledge sources in the automatic identification and classification of reviews. In Proceedings of the COLING/ACL on Main conference poster sessions (pp. 611-618). Association for Computational Linguistics.
18. Lin, C., & He, Y. (2009, November). Joint sentiment/topic model for sentiment analysis. In Proceedings of the 18th ACM conference on Data and knowledge management (pp. 375-384). ACM.
19. Wang, S., & Manning, C. D. (2012, July). Baselines and bigrams: Simple, excellent sentiment and topic classification. In Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics: Short Papers-Volume 2 (pp. 90- 94). Association for Computational Linguistics.
20. Mudinas, A., Zhang, D., & Levene, M. (2012, August). Combining lexicon and learning based approaches for concept-level sentiment analysis. In Proceedings of the first international workshop on issues of sentiment discovery and opinion mining (p. 5). ACM.

AUTHORS PROFILE

Manasa K N received her B.E. and M. Tech. in Computer Science and Engineering from Visvesvaraya Technological University, Belgavi. She is pursuing Ph.D., under the guideship of Dr. Padma M C, PET Research Centre (affiliated to University of Mysore), Mandya. She worked as Asst. Professor in PG department of Computer Science, St. Philomena's College, Mysuru. Currently, she is working as Guest faculty in Department of Studies in Computer Science, Manasagangotri.

M. C. PADMA received her B.E. and M. Sc. Tech. by Research degree in Computer Science and Engineering from University of Mysore, Mysore, India. She received her Ph.D. degree from Visvesvaraya Technological Univeresity (VTU), Belgaum, India. Currently, she is Professor and Head of the department of Computer Science and Engineering, PES College of Engineering, Mandya, India. She is a member of IEEE, MISTE, CSI, IEI professional societies and mentor for WIE-PESCE Student Branch. She is actively involved in guiding the students for PhD. Her research areas are Image Processing, Pattern Recognition, Natural Language Processing, Machine Translation, Artificial Intelligence and Expert Systems, Document Image Analysis and Recognition, Data Mining and warehousing and Big Data Analytics. She has published 72 papers in National/International Conferences/Journals. She has conducted many National and International Conferences.

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