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# Emotions Identification by Using Unsupervised Aspect Category Based Sentiment Classification

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***Abstract*: The social media is growing at an astonishing rate; this has resulted in increased online communications. The online communication contains feedbacks, comments, and reviews that are posted on the internet by users. To analyze such data, the paper represents the Aspect-based unsupervised method that applies association rule mining on customer reviews aims to algorithmically identify product aspects, their corresponding opinions from a collection of opinionated reviews. This framework involves four main subtasks: Product aspect identification, Sentiment expression identification, Emotion Detection, Comparison of Products. This paper also represents a Comparative study of sentiment analysis techniques including machine learning technique and lexicon based technique. The comparisons are majorly drawn based on features such as techniques, data source, data scope, and limitations. The proposed framework performs well with F1-Score 76.426%.***

***Keywords:* Aspects, Helpfulness protocol, Machine learning, Sentiment analysis, Spreading activation, Text mining.**

## I. INTRODUCTION

Sentiment analysis (or) opinion mining is next huge thing in the research; it enables us to mine information from online reviews and understand whether they indicate positive conclusion or negative feeling. The information might be either product reviews, client recommendations or even articles. This input encourages individual to purchase an item and furthermore the association building up the item [1].Sentiment analysis isn't a simple assignment because of the unstructured natural language and the multifaceted nature of a machine to translate the significance of a sentence. But the reviews and estimation of the sentiment from the surveys is more prominent than any time in recent memory step by step. For tackling this issue a strategy must be made to understand and translate the human feelings and sentiments. Retail organizations, for example, Amazon [2] [4] consists of their product reviews. These reviews are important assets e. g. Yelp [5] [6] [7] which have buyer's surveys of nearby restaurants, inns, and different organizations. Research has shown these reviews are viewed as huger for buyers than advertisement data. Article recommendations are progressively utilized decision making for buying different products [6].Information which is obtained from online reviews of different items or services isn't just gainful to buyers, yet additionally to respective organizations [6]. Acknowledging what is available on the Web, can lead to revamp their items or services. In spite of only managing available data an automated system to analysis this data is highly required. A basic undertaking for such a framework perceives the topics e.g. attributes of a product or service. These topics can be categorized for doing aspect-level sentiment analysis or all the more by and large on account of aspect categories [5] [6].Even though many people are affected by the obstinate information they get online. This is especially legitimate for thing reviews, which have been seemed to affect acquiring conduct. Besides, data shared by people on the Web is viewed as more reliable than data given by the merchant. From a merchant perspective, each individual is a prospective client. So, understanding individual preferences will be incredible useful in developing new products, and in addition, managing and enhancing existing ones [6] [8] [9]. Online reviews have an important source to be utilized by organizations [10]. Apart from traditional producer/consumer model, it is necessary to perform sentiment analysis across different sectors [11].Researchers have been interested in automatically detecting sentiment in texts for a decade [12]. Sentiment examination is a part of natural language processing in which machine learning, computational linguistic, and information mining are applied.For the most part, it manages the programmed extraction and investigation of sentiment and feelings conveyed in the reviews [13]. Since last few years sentiment analysis has turned into a prominent research area. It can be applied in various real life problem domains such as product reviews, forecasting sales etc.

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The customer's emotions get either on a specific polarity scale, or twofold (positive, negative); different levels such as document level, sentence-level, or aspect-based sentiment.Document level is for the most part applied to various surveys, to choose the general conclusion towards the objective (e.g. Thing or movie). In sentence level analysis the general sentiment in a sentence is identified. In aspect-based sentiment analysis exact features (aspects) of the sentiments are identified. Document and sentence level of sentiment analysis ignores focus on specific aspect categories of interest during sentiment analysis [14]. Aspect-Based Sentiment Analysis (ABSA) models work on reviews (e.g., product or service surveys on different websites) looking at a particular entity (e.g., new model of a mobile). The systems achieve to differentiate (e.g., the most a great part of the time discussed) aspects (features) of product (e.g., display, audio quality of mobile) and to measure the normal sentiment of the text per aspect (e.g., how positive or negative the conclusions are all things considered for every aspect).

## II. RELATED WORK

In the paper [15], authors have proposed a strategy Parallel K-implies utilizing Map-Reduce structure, utilizing bagging and ensemble techniques to conquer the precariousness and the affectability of parallel k-implies utilizing Map-Reduce design. In Map Reduce, the wastefulness issue is resolved. Extensive experiments have been performed to demonstrate that their approach is effective. Their outcomes have demonstrated that their solution outflanks than other methods. Additionally, it demonstrates that it is more heartless to anomalies and furthermore it is effective for abridging substantial dataset.

[16]A Hidden Topic Sentiment Model (HTSM) has been utilized to unequivocally catch topic coherence and sentiment consistency in an obstinate content archive to precisely separate latent aspects and relating supposition polarities. Broad examinations on four classes of item reviews of Amazon and NewEgg approve the viability work.

With consumer surveys turning into a standard piece of web based business, a great technique for distinguishing the item or administration aspect that is examined is attractive.

This work [17] centers on distinguishing aspect that do not have implicit aspects. An improved co-occurrence matrix of synsets from WordNet and implicit aspect is developede. Comparable technique which isn't semantics-driven unmistakably demonstrates the advantage of the proposed strategy. Particularly corpora of constrained size appear to profit by the additional semantic setting.

In this direction [18], researchers have investigated application surveys of 25 applications to remove application highlights, decided contending applications in light of highlight shared characteristic, and after that look at contending applications in view of clients' conclusions with respect to highlights. They have built up a tool prototype that aide’s application engineers in recognizing features which have been seen contrarily by its clients. The tool prototype is also useful to find a set of features loved by users in other similar apps but missing in one’s app. We show the handiness of the tool prototype and offer pointers to future work. In this paper [19], authors have proposed a method for creating Hidden Markov Model-based assumption analyzer which will help in examining on the web client reviews. The goal is to give a Sentiment- based outcome to countless reviews of items sold on the web. Their trial demonstrates that the proposed system is exceptionally encouraging in playing out its undertakings. This paper [20] addresses the issue of multi-perspective assumption investigation of product review. Proposed semantic features mining and lexicon-based techniques to investigate the aspect- level sentiment analysis. The examination item includes separating by LDA demonstrate, relating sentiment. At that point semantic highlights identified with domain- lexicons are chose. Using topics distribution, the weight of different features is learned. Their results demonstrate that their technique outflanks the fundamental machine learning strategy. This paper presents impact of aspect sentiment on analyst’s conclusion. In this work [21], authors have proposed a framework that naturally creates customized survey suggestions utilizing two diverse methodologies. Firstly, drawing inspiration from traditional collaborative filtering systems, the framework creates client rating profiles and tailors the rundown of review to the inclinations of every client. Also, they have utilized aspect-based opinion mining to recognize the imperative highlights featured in each survey. Rather than customary sentiment examination, which gives a general picture of whether a review is certain or negative, aspect-based opinion mining gives a fine-grain investigation of both sentiment and strength of the survey. Given a predetermined set of features for a specific domain, comes about because of aspect-based opinion mining can be utilized to rank/sort the surveys in light of the perspective the clients are most keen on. The proposed framework shows a customized rundown of audits for a similar item/benefit custom- made to the inclinations of every client. In Paper [6] researchers have utilized supervised and unsupervised methods. Algorithm discussed has five-steps as i. Finding seed words for category, ii. Generating a graph, iii. Using spreading activation, iv. Applying mining and v. Mapping the categories.Supervised methods have limitations such as it requires setting multiple parameters, it can’t deal well with miscellaneous categories, and it requires grammatically correct reviews and training data. These methods get a good precision, recall & F1 scores.

[22]SemEval-2014 aspect-based sentiment analysis is used to determine the sentiment and assign the polarity. The system is also very robust for handling generic data by extracting the opinion from the reviews.

Scientists utilized one kind or a greater amount of classifiers to test their work [23]. They introduced a Machine Learning based method to deal with the issue of finding reports conveying positive or negative idealness inside media investigation. The lopsidedness in the dispersion of positive and negative examples, changes in the reports after some time, and compelling training and assessment methods for the models are the difficulties they looked to achieve their objective.

They dealt with three informational collections created by a media-examination organization. They grouped reports in two ways: distinguishing the nearness of idealness, and evaluating negative versus positive idealness. They have utilized five unique sorts of highlights to make the informational collections from the crude content. They tried numerous classifiers to locate the best one which are (SVM, K-closest neighbor, NB, BN, DT, a Rule student and other). They demonstrated that adjusting the class conveyance in preparing information can be gainful in enhancing execution, yet NB can be antagonistically influenced. Chen and Tseng et al. [3] have utilized two multiclass SVM-based methodologies: They proposed a technique for assessing the standard of data in item reviews thinking about it as a classification issue. Their outcomes demonstrated that their technique can precisely order surveys regarding their quality.

## III. MOTIVATION

"The phone has an amazing sound quality it's loud enough to host a club party but in doing so battery gets affected as it does not last for long hours. Camera quality seems to be great for both front and back side. Being a tech savvy I was quite amazed with its processor speed and RAM performance. Overall I assume it's better than the previous version and its peers."

Without referring to this content as it would appear that some other survey you run over on the World Wide Web. The content is a case of a common client survey found on the site of a well-known gadgets item gateway. Like these, a large number of client surveys are composed and distributed on the Web every day. The subjects are complex, running from reviews of electronic items, books, or motion pictures to surveys of inns or restaurants. Surely, every rate-capable item or administration might be tended to, for instance, understudies likewise rate their teachers and speakers.

As a buyer, we get advantage from online client reviews by settling on more educated buy choices. For prevalent items/administrations, we have the various encounters with thousands of different shoppers specifically readily available. These days, in the event that we need to buy another PC, design our next get-away, or look for a decent formula for Chicken Crispy, we normally counsel online surveys and evaluations before settling on our choice. While we ourselves can watch this conduct, economic analysts likewise report that online item looks into has turned into a fundamental piece of the customers "purchase experience ".

As a seller, we are normally inspired by our client's sentiments. In this specific circumstance, web based social networking all in all, and online client surveys, specifically, speak to an inexorably essential wellspring of data. Surveys speak to certified client voices that basically can help us to comprehend our client's different preferences. We can rapidly find out about issues with our items or benefits and respond likewise for instance, by enhancing the item or changing our promoting effort. We additionally realize that client reviews impact the conclusions and at last may influence the buying choice of different customers. We are in this manner emphatically keen on what clients are saying in regards to our items or our image all in all. Having the capacity to screen and break down web-based social networking is in this way a foundation for actualizing an online notoriety administration procedure. Other than finding out about our own clients, we may likewise be occupied with realizing what individuals consider our rival's items. The analysis of contents posted by clients on social networks, online journals, containing client surveys, and so forth, must be viewed as extra sources of information for business insight applications. For instance, contrasted with conventional (structured) overviews the examination of veritable, spontaneous client input accompanies the benefit of being accessible progressively at semi no expenses.

Normally, opinion investigation isn't obliged to the examination of client reviews. Indeed, sentiment examination is considered and connected in altogether different situations and areas, for example, political verbal confrontations, financial news [12], and as a major aspect of recommender frameworks or numerous viewpoints question noting frameworks [22]. As of late, huge scale 3 assumption examination of client remarks in micro blogging services (e.g., Twitter) has gotten expanding consideration.

Applications of sentiment examination are complex, contingent upon the particular domain or situation, distinctive task, and subtasks in assumption investigation wind up imperative. Most clearly, the nature of printed information changes between various domains, for instance, we normally watch more formal dialect in newswire content contrasted with the somewhat casual dialect or slang in smaller scale blogging posts. In outcome, the many-sided quality of investigation, and with that, additionally the solid strategies for sentiment examination may vary generally.

In this work, we unequivocally set a spotlight on the particular application situation of investigating supposition in online client surveys. While we give an exhaustive overview of survey mining, as a rule, we are fundamentally interested in aspect-oriented customer review mining. The assignments primary objective is to consequently decide and survey articulations of estimation towards singular parts of an item. For instance, we may locate that most inn visitors were satisfied with their room as a rule, yet numerous grumbled about the moderate Wi-Fi association and the noisy aerating and cooling framework. A framework able to do such a fine-grained examination permits to create an itemized synopsis of the client's sentiments and along these lines can ease the data over-burden we delineated prior.

This paper finds aspect category by using unsupervised approach and second find out emotions toward this aspect category.

## IV. PROBLEM DEFINITION

Aspect-based pinion mining identifies product aspects and related opinions from the reviews. Fig. 1 represents process for Aspect based Sentiment Analysis.

### A. Aspect Identification

For any product or service review, it is necessary to correctly identify product aspects. After identifying aspects categorize synonyms [18].

## B. Sentiment Expression Identification

Sentiment identification is to identify the corresponding opinions for aspects. After aspect identification step and their grouping system detects sentiments. And then analyses the polarity to be negative or positive. [24]

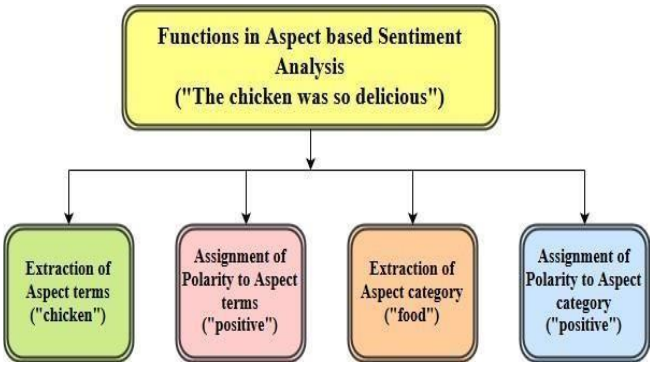


**Fig. 1. Aspect based Sentiment Analysis**

## C. Emotion Detection & Comparison of Products

Besides above two problems we wish to tackle emotion detection and comparison of products as discussed below:
Emotion Detection: Given a product review does not just focus to find its sentiment value in terms of positive or negative but work towards finding what the user feels.

For example "The phone has a too amazing camera quality, it makes the pictures look so realistic". [25] This particular review under sentiment analysis would just hold of being a positive text and if you mine further and use aspect based opinion mining it would still give a thumbs up for the aspect category 'camera quality'. But emotions hold a mandatory part of human nature which needs to be addressed. With the help of emotional data one can track user's feelings such as states of trust, anticipate, joy, surprise, Anxiety, Anger, sadness and disgust to particular external events. Making use of an emotion lexicon developed by an expert overseas and testing the reviews over them builds the aim to handle this problem.
Comparison of Products: Any E-commerce site we visit we have been given a lot of recommendations based on the features provided by the selling company of that particular product. Here we wish to focus on presenting recommendations or comparison among peer products by mining of what customers have to say about them rather than the already known selling company facts. For example, giving a comparison of product A from product B based on what sentiment value they hold for their respective aspects.

# V. DESIGN CONSIDERATIONS AND CHALLENGES

Previously, there are so many approaches by two approaches where first approach find aspect category by using unsupervised approach and second find out emotions toward this aspect category. But there is no work on applying both approaches to get accurate results. So, this is challenging task to combine this two approaches in single model. Example-mine and evaluate opinions from online review is insufficient to purely achieve the overall sentiment regarding a product. Generally, It is necessary to discover detail sentiments with respect to specific feature of reviewed product. Example: "The restaurant has good food quality but less food options/variety." This review analysis will help reader to understand positive as well as negative feeling of customer about food provided in the restaurant and not only the customer's general review conclusion. So, first we need large dataset so that we can find out aspect category and emotions towards each aspect category. There are many datasets available for offline download but Zomato provides large dataset.

# VI. PROPOSED APPROACH

Fig. 2 depicts the complete step by step flow which helps to understand the overall working of proposed approach. Each step in work flow is discussed below in detail:

## A. Load Dataset

This is the first stage of our framework where a standard dataset on which we have to work upon is selected.

## B. Aspect Category and Aspect Term Detection

This stage involves number of sub stages as stated:
i. Identify Category Seed Word Sets
To start with, for each category C an arrangement of seed words Sc which contains the category/equivalent words of respective word by using WorldNet dictionary.

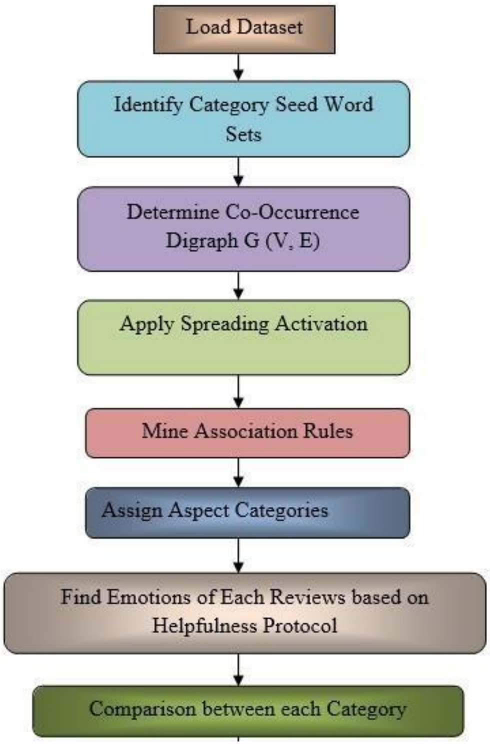


**Fig. 2. workflow of proposed approach**

ii. Determine Co-Occurrence Digraph G (V, E)
For a natural language pre-processing step, to start with, all reviews experience the lemmatize of the Stanford CoreNLP [10]. All lemmas in the content corpus are screened to find their frequencies.

Stop words and lemmas that have an occasion repeat which is lesser α are discarded, remaining lemmas and relating frequencies are stored in an event vector N. α is utilized to sift through low appearing lemmas.

System generates co-occurrence matrix X which represents frequency of word when Ni appears after Nj in a sentence. With the help of co-ocurrance matrix X and event vector N the Co-Occurrence digraph G(V, E) is created with Where V is nodes and E edges. If positive co-occurrence recurrence Xi,j then there exist as edge E from vertex i to j. Each edge (i, j) has a weight represented by Wi,j and shown by conditional probability as below:

W (i,j)= X (i,j) / Nj

Where X (i, j) is the co-occurrence frequency of words i & j, word i occurs after word j

Nj is frequency of word j

## C. Apply Spreading Activation

SPREADING ACTIVATION ALGORITHM

```
input : category c
input : vertices V
input : seed vertices S_c
input : weight matrix W
input : decay factor δ
input : firing threshold τ_c
output: activation values A_{c,i} for category c
foreach s ∈ S_c do
 | A_{c,s} ← 1
end
foreach i ∈ V \ S_c do
 | A_{c,i} ← 0
end
F ← S_c
M ← S_c
while M ≠ ∅ do
 | foreach i ∈ M do
 | | foreach j ∈ V do
 | | | A_{c,j} ← min{A_{c,j} + A_{c,i} · W_{i,j} · δ, 1}
 | | end
 | end
 | M ← ∅
 | foreach i ∈ V \ F do
 | | if A_{c,i} > τ_c then
 | | | add i to F
 | | | add i to M
 | | end
 | end
end
```

DISCRETE EMOTION FEATURES SCORING ALGORITHM

After Step B which generates Co-Occurrence Digraph we perform Spreading Activation for each category C which defines in second sub-step of second step. By applying Spreading Activation algorithm [6] on each vertex of Co-Occurrence Digraph for respective category, we will get activation value Ac,j with respect to that category. If this activation value Ac,j is greater than specified threshold then that node also added as seed word for that category C. activation value lies within range of 0 to 1. Spreading activation begins by relegating vertices which are named as the category seed words which has a place with Sc get the most extreme activation estimation of 1, while whatever is left of the vertices get the minimum activation estimation of 0. The equation (2) calculates the activation value of vertex j connected to i:

$$A_{c,j} = \min(A_{c,j} + A_{c,i} W_{i,j} \delta, 1) \quad \ldots\ldots (2)$$

Where δ represents the activation value decay ranges between values from 0 to 1.

## D. Mining Association Rules

After Step C, for each category, it will get seed word which is other than specified in ‘Identify Category Seed Word Sets’ step. This seed word (vertices) has activation values greater than threshold. Now, for each category, there is notional word and by using this word, Association rule is formed as follows: [notional word i → category c]

## E. Assign Aspect Categories

Now with respect association rule we predict categories for each unprocessed sentences. If any notional word appears in any unprocessed sentence, then category of that notional word is assign to that sentence.

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```
for each review, u_i in U do
    DE_i = [0,0,0,0,0,0,0,0]        // DE_i = [trust, anticipation, joy, surprise, anxiety, anger, sadness, disgust]
    word-count = 0                  // initialize the word count
    for each sentence s_j in u_i do
        for each word w_k in s_j do
            Increment word-count
            for each emotion dimension, e_m in NRC do
                if(w_k belongs to NRC[e_m])
                    Increment the score in DE_i[m]
                end if
            end for
        end for
    end for
    for each element, n in DE_i do
        compute DE_i[n] = (DE_i[n] * 100) / word-count
    end for
end for
Compute mean and standard deviation of DE scores for product category
for each review u_i in U do
Compute z-score to obtain the final DE_i
end for
```

### F. Extraction of Emotion Features from Review Texts

By previous step, under each category C number of unprocessed reviews will come. Now, using NRC emotion lexicon we will find, what kind of emotion is expressed toward each category. Emotional data used by researchers [25] to find out emotions e.g. joy, delight, surprise, excitement, fear and sadness to specific activity. For example If there is some lexicon is associated with joy emotions and that lexicon come in any un-processed sentence then that unprocessed sentence expressed joy.

### G. A Comparison between Each Category

By previous step, each category is explained with trust, anticipate, joy, surprise, Anxiety, Anger, sadness and disgust emotions. But under each category number of sentences can be different so we have to normalized the Matrix [trust, anticipate, joy, surprise, Anxiety, Anger, sadness, disgust] by using Z score and with respect to that Z score each category is compared and recommendation is given to user.

## VII. EXPERIMENTS & RESULTS

### A. Dataset

The proposed framework is tested using dataset SemEval-2014 task 4 [6]. It contains more than 3000 training sentences and 800 test sentence taken from eatery audits. This dataset comprises of more than 3K English sentences from the eatery audits of Ganu et al. (2009). The first dataset of Ganu et al. included comments for coarse viewpoint classifications (Subtask 3) and general sentence polarities; we altered the dataset to incorporate comments for aspect terms happening in the sentences (Subtask 1), perspective term polarities (Subtask 2), and aspect classification particular polarities (Subtask 4). We likewise remedied a few blunders (e.g., sentence part mistakes) of the first dataset. Experienced human annotators distinguished the perspective terms of the sentences and their polarities (Subtasks 1 and 2). Extra eatery surveys, not in the first dataset of Ganu et al. (2009), are being clarified in a similar way, and they will be utilized as test information.

### B. Result Analysis

As discussed in [6], an evaluation of proposed framework is done based on F1- Score as defined below:

$$F_1 = \left(\frac{\text{recall}^{-1} + \text{precision}^{-1}}{2}\right)^{-1} = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

Where

$$\text{Precision} = \frac{tp}{tp + fp}$$

$$\text{Recall} = \frac{tp}{tp + fn}$$

Where tp: true positive
fp: false positive
fn: false negative

Table 1. Shows precision, recall and F1-Score for each aspect category. The final F1-Score of 76.426% the proposed framwork performs very well.

**Table 1. Precision, Recall & F1-Score on Test Data**

| Category | Precision (%) | Recall (%) | F1 Score (%) |
|---|---|---|---|
| Food | 86.74 | 95.23 | 90.78 |
| Price | 49.33 | 75.51 | 59.68 |
| Service | 100 | 90.48 | 95 |
| Ambiance | 100 | 52.94 | 69.23 |
| Miscellaneous | 73.58 | 62.23 | 67.44 |
| All | 81.93 | 75.278 | 76.426 |

## VIII. CONCLUSION & FUTURE DIRECTIONS

This work provides a framework in-order to improve the decision making of consumers which include following subtask:

1. Build a framework to perform aspect based sentiment analysis.
2. Extraction of emotions from reviews using an expert developed emotion lexicon.
3. Produce a comparison among products based on consumer feedback.

In future, one can apply hybrid evolutionary algorithms to improve the accuracy. Other interesting research can be done to work on more emotion types to improve the review helpfulness prediction.

## REFERENCES


1. Tanvi Hardeniya, D. A. Borikar,"An Approach To Sentiment Analysis Using Lexicons With Comparative Analysis of Different Techniques" in IOSR Journal of Computer Engineering (IOSR-JCE) Volume 18, Issue 3, Ver. I (May-Jun. 2016), PP 53-57, 2016.
2. J. Yu, Z. J. Zha, M. Wang, and T. S. Chua, "Aspect Ranking: Identifying Important Product Aspects from Online Consumer Reviews," in Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies (ACL 2011). ACL, 2011, pp. 1496–1505.
3. Chen, C. C., & Tseng, Y. D. (2011). Quality evaluation of product reviews using an information quality framework. Decision Support Systems, 50(4), 755-768.
4. A. Mukherjee and B. Liu, "Modeling Review Comments," in Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics (ACL 2012). ACL, 2012, pp. 320–329.
5. B. Lu, M. Ott, C. Cardie, and B. K. Tsou, "Multi-Aspect Sentiment Analysis with Topic Models," in Proceedings of the 2011 IEEE 11th International Conference on Data Mining Workshops (ICDMW 2011). IEEE, 2011, pp. 81–88.
6. Kim Schouten, Onne van der Weijde, Flavius Frasincar and Rommert Dekker., " Supervised and unsupervised aspect category detection for sentiment analysis with cooccurrence data", 2017, IEEE TRANSACTIONS ON CYBERNETICS,2017 , pages 1–13.
7. Garcıa-Pablos, Aitor, MontseCuadros, and German Rigau. "V3: Unsupervised Aspect Based Sentiment Analysis for SemEval-2015 Task 12."
8. A. Mukherjee and B. Liu, "Modeling Review Comments," in Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics (ACL 2012). ACL, 2012, pp. 320–329.
9. Y. Jo and A. H. Oh, "Aspect and Sentiment Unification Model for Online Review Analysis," in Proceedings of the Forth International Conference on Web Search and Web Data Mining (WSDM 2011). ACM, 2011, pp. 815–824.
10. P. F. Bone, "Word-of-mouth effects on short-term and long-term product judgments," J. Bus. Res., vol. 32, no. 3, pp. 213–223, 1995.
11. G. Qiu, B. Liu, J. Bu, and C. Chen, "Opinion word expansion and target extraction through double propagation," Comput. Linguist, vol. 37, no. 1, pp. 9–27, 2011.
12. Deepa Anand, Deepan Naorem, "Semi-supervised Aspect Based Sentiment Analysis for Movies Using Review Filtering", 7th International conference on Intelligent Human Computer Interaction, IHCI 2015, pp. 86 - 93.
13. W. Medhat, A. Hassan, H. Korashy, "Sentiment analysis algorithms and applications: A survey", 2010, Ain Shams Engineering Journal., Egypt,2014, pp. 1093–1113.
14. Hui Du,Xueke Xu, Xueqi Cheng, Dayong Wu, Yue Liu, Zhihua Yu, "Aspect-specific Sentimental Word Embedding for Sentiment Analysis of Online Reviews", April 11-15, 2016, Montréal, Québec, Canada., WWW 2016: Montreal, Canada - Companion Volume, vol. 29, no. 7, pp. 1645 - 1660.
15. V. Priya and K. Umamaheswari, "Ensemble based Parallel k means using Map Reduce for Aspect Based Summarization", 2016, IEE International Conference on Information and Automation, vol. 1, pp. 158 - 167.
16. Md Mustafizur Rahman and Hongning Wang., "Hidden Topic Sentiment Model", 2013, the International World Wide Web Conference Committee (IW3C2)., April 11–15, 2016, Montréal, Québec, Canada., pp. 1 - 5.
17. Kim Schouten,Nienke de Boer,Tjian Lam,Marijtje van Leeuwen,Ruud van Luijk, "Semantics-Driven Implicit Aspect Detection in Consumer Reviews", May 18–22, 2015, Florence, Italy. 24th International World Wide Web Conference, vol. 4, pp. 1222 - 1242.
18. Faiz Ali Shah,Yevhenii Sabanin,Dietmar Pfahl, "Feature-Based Evaluation of Competing Apps",November 14,2016,Seattle, USA, WAMA 2016- Proceedings of the International Workshop on App Market Analytics, pp. 74 - 75.
19. Swati Soni and Aakansha Shraff, "Sentiment Analysis of Customer Reviews based Hidden Markov Model", 2016 International Conference on Advanced Research in Computer Science Engi- neering Technology (ICARCSET 2015), Unnao, India March 06 - 07, 2015, pp. 1 - 2.
20. Qing Sun , Jianwei Niu , Zhong Yao , Dongmin Qiu , "Research on Semantic Orientation Classification of Chinese Online Product Reviews Based on Multi-aspect Sentiment Analysis", 2017, 2016 IEEE/ACM 3rd International Conference on Big Data Computing, Applications and Technologies, December 06-09, 2016, Shanghai, China., pp. 101 - 106.
21. Vaishak Suresh,Syeda Roohi,Magdalini Eirinaki, "Aspect-Based Opinion Mining and Recommendation System for Restaurant Reviews", 2010,pp. 914 - 917.
22. R. K. Amplayo and M. Song, "An adaptable fine-grained sentiment analysis for summarization of multi- ple short online reviews", 2017, Data Knowledge Engineering,2017, . 110, pp. 54–67.
23. Toqir A. Rana, Yu-N Cheah, "A two-fold rule-based model for aspect extraction", 2016, Expert Systems With Applications, Universiti Sains Malaysia, Malaysia,2017, pp. 21-26.
24. N. U. Pannala, C. P. Nawarathna, J. T. K. Jayakody, L. Rupasinghe, and K. Krishnadeva, "Supervised Learning Based Approach to Aspect Based Sentiment Analysis", 2016 IEEE International Conference on Computer and Information Technology (CIT), 2016, vol. 16, no. 13, pp. 5344 - 5353.
25. M.S.I. Malik and Ayyaz Hussain, "Helpfulness of product reviews as a function of discrete positive and negative emotions", Computers in Human Behavior,2017, vol. 76 ,pp. 290 - 302.
26. Schouten, K., Frasincar, F., & De Jong, F. (2014). Commit-p1wp3: A co-occurrence based approach to aspect-level sentiment analysis. In Proceedings of the 8th International Workshop on Semantic Evaluation (SemEval 2014) (pp. 203-207).
27. Pablos, A. G., Cuadros, M., & Rigau, G. (2014, August). V3: Unsupervised generation of domain aspect terms for aspect based sentiment analysis. In Proceedings of the 8th International Workshop on Semantic Evaluation (SemEval 2014) (pp. 833-837).
28. M. Pontiki et al.,"SemEval-2014 Task 4: Aspect based sentiment analysis", in Proc. 8th Int. Workshop Semantic Eval. (SemEval), Dublin, Ireland, 2014, pp. 27-35.


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