ISSN (Online) 2456 -1304

International Journal of Science, Engineering and Management (IJSEM)
Vol 3, Issue 2, February 2018

Implicit and explicit Association-Based Feature Opinion mining Framework

[1] Sonali Pardeshi, [2] Sugandha Nandedkar
[1] Department of Computer Science and Engineering Marthawada Shikshan Prasark Mandal's Deogiri Institute of Engineering & Management Studies, Aurangabad Maharashtra state, India 2015-16
[2] Associate Professor Department of Computer Science and Engineering Marthawada Shikshan Prasark Mandal's Deogiri Institute of Engineering & Management Studies, Aurangabad Maharashtra state, India 2015-16

Abstract: **A significant advancement in e-commerce has led to the invention of several websites selling products online. These websites also facilitate the buyers to express their opinions about the products & their features in the form of reviews. Knowing these opinions and the related sentiments plays an important role in decision-making processes involving regular customers to executive managers. But these reviews are available in huge numbers hence referring them becomes a practically impossible task to achieve. Thus a new orientation called Opinion Mining & Summarization has emerged to deal with the problem. Aspect-based (Feature-based) Opinion Summarization is one of these summarization techniques which provide brief yet most relevant information about different features related to the target product. Hence the approach is in great demand nowadays because it exactly shows what a customer usually tries to search while referring the reviews. This paper focuses on the extraction of different kinds of features associated with a target entity. The current state of the art suggests that concrete techniques are highly required for identification of those features which are not clearly mentioned. Thus our prime target is to deliver a succinct solution for effective identification of implicit features along with the explicit ones based on the opinion words encountered in user reviews. This is achieved by first extracting and processing the explicit features and then using them for the identification of implicit features. Finally, summarization of sentences containing both kinds of aspects is done.**

Keywords**: Opinion mining, feature, implicit feature, explicit feature, opinion word, association.**

I. INTRODUCTION

Online services play a very crucial role in every individual's day to day schedule. These services include daily news, weather forecast, banking transactions, shopping, social networking, blogging, and much more. With the rapid expansion in web technologies, online buying and selling of products has increased to a great extent. Added to the growth is the capability of users to share their feeling of satisfaction or criticism in the form of reviews. Knowing these opinions and its associated sentiments is important since it greatly affects the decision-making of an individual or an organization management system. Looking at the current scenario, each product sold online nearly receives thousands of opinions from different users across the world. Hence going through this large number of reviews is a laborious task. On the other hand, referring only a few of them would lead to a biased decision. Thus opinion mining, sentiment analysis and summarization become a serious necessity. Summarization is a way of presenting large amount of information using limited words still maintaining its meaning and relevancy. Similarly opinion summarization illustrates a summary for large number of opinionated sentences. It can be performed at various levels of granularity like at document level, sentence level or at aspect level. For document level mining, a document is considered as a single entity to be observed. Similarly for sentence level mining, a single sentence and for aspect level mining, different aspects of an entity are taken into consideration. Initial studies on opinion mining and summarization has focused on classification of all the opinions as either positive or negative and determining the final polarity of the entire document. But the problem at this level occurred since different parts of a document (i.e. different reviews) may deal with different issues. As a solution, researchers tried sentence level mining but still it is error prone because within a single sentence, multiple opinions with different polarities regarding different aspects of the target entity may exist which are necessary to be studied for true knowledge extraction and summary generation. Thus a feature-based approach to opinion mining has become a necessity where target entities and their expressed features are extracted from the text and then the expressed opinions are analyzed for every feature. This summary making procedure primarily involve works like features identification of the target, opinion words (sentences) related to the identified features determination, polarity detection of the obtained opinion words and finally providing a relevant feature-based summary regarding the target product. The final summary generated can play an instrumental role in influencing a buyer's or any managerial decision. Looking at the current scenario, we can observe that major works done so far has focused on identification and extraction of explicit features. But problem persists when the opinionated sentences

IFERP

ISSN (Online) 2456 -1304

International Journal of Science, Engineering and Management (IJSEM)
Vol 3, Issue 2, February 2018

that imply features remain undetected i.e. the sentences that contain opinions for a particular feature of target entity which is not clearly determined. This paper will identify disparate features of target entity so that a legitimately accurate opinion summary can be can be designed and presented to target audience.

Online administrations assume an exceptionally urgent part in each individual's everyday calendar. These administrations incorporate day by day news, climate figure, keeping money exchanges, shopping, interpersonal interaction, blogging, and substantially more. With the fast extension in web innovations, web based purchasing and offering of items has expanded as it were. Added to the development is the capacity of clients to share their sentiment fulfillment or feedback as audits. Knowing these feelings and its related estimations is imperative since it enormously influences the basic leadership of an individual or an association administration framework. Taking a gander at the present situation, every item sold online almost gets a large number of suppositions from various clients over the world. Thus experiencing this vast number of audits is a relentless errand. Then again, alluding just a couple of them would prompt to a one-sided choice. Therefore feeling mining, conclusion investigation and summarization turn into a genuine need. Summarization is a method for displaying expansive measure of data utilizing restricted words as yet keeping up its significance and importance. So also supposition summarization represents an outline for expansive number of obstinate sentences. It can be performed at different levels of granularity like a report level, sentence level or at perspective level. For archive level mining, a record is considered as a solitary substance to be watched. Correspondingly for sentence level mining, a solitary sentence and for perspective level mining, diverse parts of an element are mulled over. Beginning studies on assessment mining and summarization has concentrated on characterization of the considerable number of feelings as either positive or negative and deciding the last extremity of the whole report. Be that as it may, the issue at this level happened since various parts of a record (i.e. diverse surveys) may manage distinctive issues. As an answer, analysts attempted sentence level mining yet at the same time it is mistake inclined in light of the fact that inside a solitary sentence, various conclusions with various polarities in regards to various parts of the objective substance may exist which are important to be considered for genuine information extraction and rundown era. Along these lines a component based way to deal with supposition mining has turned into a need where target substances and their communicated features are separated from the content and after that the communicated sentiments are investigated for each element. This synopsis making technique essentially include works like features distinguishing proof of the objective, conclusion words (sentences) identified with the recognized features assurance, extremity recognition of the acquired sentiment words lastly giving an applicable component based outline in regards to the objective item. The last synopsis created can assume an instrumental part in affecting a purchaser's or any administrative choice. Taking a gander at the present situation, we can watch that significant works done as such far has concentrated on distinguishing proof and extraction of explicit features. Be that as it may, issue continues when the stubborn sentences that infer features stay undetected i.e. the sentences that contains sentiments for a specific component of target element which is not unmistakably decided. This paper will recognize divergent features of target substance so that a truly precise feeling outline can be can be composed and introduced to target crowd.

II. LITERATURE SURVEY

Opinion mining, also called sentiment examination, is the field of study that breaks down clients' appraisals, feelings, influences, and states of mind toward substances, for instance, things, administrations, and their segments or characteristics [22]. For the most part, conclusions and assumptions communicated in a survey archive can be investigated at various levels of granularity. Record level/sentence-level supposition mining arrangements to mastermind the general subjectivity or appraisal introduction of an entire archive/sentence. [23] Proposed to utilize managed learning strategies, credulous Bayes, most noteworthy entropy, and reinforce vector machines, to orchestrate motion picture surveys into positive or negative assessments. To keep a feeling classifier from considering immaterial content [24] proposed to first utilize a subjectivity finder to organize the sentences in a report as either subjective or objective, discarding the objective ones. They then connected a notion classifier to the subsequent subjectivity removes, prompting to enhanced execution. [21] Proposed a ghostly feature (data figure) arrangement count for cross space feeling request at both report and sentence levels. An unsupervised learning technique was proposed to portray a survey report as thumbs up (positive) or thumbs down (negative) in light of the normal opinion introduction of supposition expressions in the audit [22]. [24] Proposed a dictionary based strategy to organize the assessment introduction communicated in content. Maas et al. [36] displayed a blend approach that joins both directed and unsupervised learning strategies for the notion arrange issue as well as feeling mining at the expression level spotlights on anticipating the assessment introductions of supposition phrases. [35] Proposed an administered learning technique to portray the logical estimations of conclusion expressions. To anticipate the expression level slant introductions, [27] presented a key relapse strategy in view of factors, for instance, prior furthest point, lexical expressions, and syntactic constituents. Take note of that supposition mining at the report, sentence, or expression level does not find what precisely individuals like and aversion in surveys. That is, it can't relate the arranged evaluations and feelings with the focused on features in audits. In a general sense, an evaluation without the comparing feature is of constrained esteem by and by [22]. By figuring feature-based evaluation mining as a joint helper naming issue, [27] proposed a directed learning strategy in light of lexicalized concealed Markov models (HMMs). They then utilized the strategy to perceive/tag the explicit features, supposition words, and assumption introductions of conclusion words from thing audits. [21] Built up unexpected sporadic fields (CRFs) - based technique to address the feature-based audit synopsis issue. Notwithstanding, the administered learning strategies can't be utilized to tag/gather implicit features suggested by supposition words in surveys.

Phonetic strategies depend on reliance parsing to create syntactic tenets or reliance designs for feature and feeling word extraction. A reliance parsing-based twofold multiplication (DP) approach was proposed to address the issue [31]. DP first recognizes word conditions using eight physically characterized syntactic standards. It then iteratively separates explicit features and appraisal words using the recognized syntactic reliance relations in light of the removed known words. Other phonetic strategies were proposed for feature-based supposition mining issue [32]. Nonetheless, phonetic techniques have a tendency to experience the ill effects of the poor scope issue of physically ordered syntactic standards. Facilitate the syntactic principles or reliance designs can't be connected to inadequate audit sentences (that don't specify explicit features) for inducing the implicit features for the supposition words without explicit features.

Corpus estimations approaches focus on mining continuous corpus bits of knowledge examples for feature and supposition word extraction. [33] proposed to utilize the association administer mining technique (ARM) to first find an arrangement of continuous thing sets, that is, things or thing phrases every now and again said in audits, as potential features. They then utilize conservativeness and repetition pruning to sift through the superfluous features. Next, the nearby modifiers of the distinguished features will be perceived as feeling words. [34] Employed the point-wise shared information show (PMI) to assess the things (thing phrases) regularly happening in surveys and pruned the incessant however invalid potential features, prompting to enhanced execution.

Regardless of the way that extricating the features and conclusion words that truly show up in audits has been explored, there is little work done on implicit feature deduction in the supposition mining field [22]. [29] Proposed a typical support bunching strategy to manage the feature-based appraisal examination issue. The found shrouded nostalgic relationship between feature classifications and feeling word bunches may be valuable for construing implicit features, yet no trials were directed to assess the implicit feature deduction of the approach. A co-event association administer mining (coARM) approach was proposed for implicit feature induction in [31]. coARM first finds an arrangement of co-event connection governs on a given audit corpus. It then applies the produced connection tenets to the inclination words without explicit features for implicit feature surmising. In any case, coARM needs to precisely prune countless candidate alliance rules.

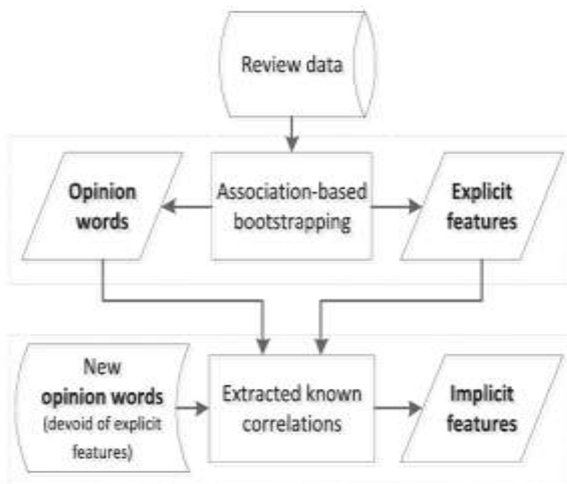

Figure 1: An association-based unified framework for identifying explicit features, opinion words, and implicit features from customer reviews.

As of late, in light of the basic inert Dirichlet designation display (LDA) [25], various probabilistic subject models have been created to address opinion mining issues [26],[27],[28]. The point displaying approaches have been exhibited successful for finding the irregular state idle topics/angles, to be specific, shrouded word groups, from literary data. Along these lines, for the implicit feature ID issue in this article, the topic displaying methodologies are maybe valuable for distinguishing the candidate implicit feature groups to be connected with the perceived opinion words without explicit features.

Opinion target and opinion word extraction are not new errands in opinion mining. There is basic exertion cantered around these assignments [1], [6], [12], [13], [14]. They can be isolated into two classes: sentence-level extraction and corpus

ISSN (Online) 2456 -1304

International Journal of Science, Engineering and Management (IJSEM)
Vol 3, Issue 2, February 2018

level extraction as showed by their extraction focuses. In sentence-level extraction, the task of opinion target/word extraction is to recognize the opinion target notices or opinion expressions in sentences. In this way, these endeavours are typically viewed as arrangement marking issues [13], [14], [15],[16]. Instinctively, logical words are chosen as the features to demonstrate opinion targets/words in sentences. Additionally, conventional grouping naming models are utilized to gather the extractor, for instance, CRFs [13] and HMM [17]. Jin and Huang [17] proposed a lexicalized HMM model to perform opinion mining. Both [13] and [15] utilized CRFs to concentrate opinion focuses from reviews. In any case, these strategies constantly require the marked data to set up the model. If the marked planning data are lacking or originate from the diverse spaces than the present writings, they would have unsatisfied extraction execution. Despite the way that [2] proposed a technique in light of exchange figuring out how to encourage cross range extraction of opinion targets/words, their strategy still required the marked data from out-spaces and the extraction execution intensely relied on upon the significance between in-territory and out-zone.

Similarly, much research concentrated on corpus-level extraction. They didn't recognize the opinion target/word says in sentences, yet intended to remove an once-over of opinion targets or create an assumption word vocabulary from writings. Most past methodologies received an aggregate unsupervised extraction structure. As specified in our first segment, distinguishing opinion relations and learning opinion relationship among words are the key segment of this sort of technique. Wang and Wang [8] received the co-event recurrence of opinion targets and opinion words to demonstrate their opinion affiliations. Hu and Liu [5] abused closest neighbour standards to recognize opinion relations among words. Next, continuous and explicit thing features were extricated using a bootstrapping procedure. Simply the utilization of co-event information or closest neighbour principles to identify opinion relations among words couldn't secure exact outcomes. In this way, [6] abused sentence structure information to concentrate opinion targets, and outlined some syntactic examples to catch the opinion relations among words. The exploratory outcomes demonstrated that their technique performed superior to that of [5]. Additionally, [10] and [7] proposed a technique, named as Double Propagation, which misused syntactic relations among words to expand assumption words and opinion targets iteratively. Their essential hindrance is that the examples in view of the reliance parsing tree couldn't cover all opinion relations. In this manner, Zhang et al. [3] developed the work by [7]. Other than the examples utilized as a part of [7], Zhang et al. additionally outlined particular examples to expand review. Additionally, they utilized a HITS [18] figuring to register opinion target confidences to enhance exactness. Liu et al. [4] concentrated on opinion target extraction in light of the WAM. They utilized a totally unsupervised WAM to catch opinion relations in sentences. Next, opinion targets were extricated in a standard sporadic walk structure. Liu's exploratory outcomes demonstrated that the WAM was compelling for extricating opinion targets. Regardless, they exhibit no confirmation to show the adequacy of the WAM on opinion word extraction. Besides, a review utilized subject demonstrating to recognize implicit topics and conclusion words [19], [20], [21], [22].The purposes of these strategies as a general rule were not to remove an opinion target once-over or opinion word dictionary from reviews.

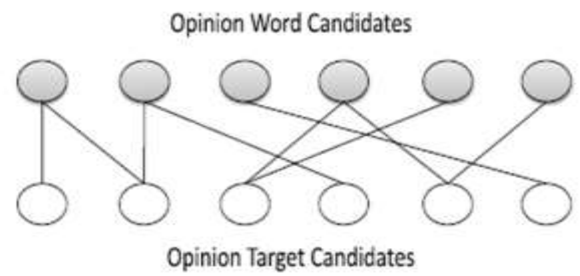

Figure 2: Opinion relation graph

Rather, they were to group for all words into relating viewpoints in reviews, which was not quite the same as the endeavour in this paper. These strategies for the most part embraced coarser methods, for instance, recurrence estimations and expression discovery, to identify the best possible opinion targets/words. They put more accentuation on the most ideal approach to group these words into their relating topics or angles research.

III. PROPOSED SYSTEM

The proposed system has five noteworthy modules. These modules are Input (User Review Sentences), Explicit Feature and Opinion Word extraction, Implicit Feature Identification, Summary Generation and Output (Aspect - based Summary). The figure 3.1 beneath demonstrates a diagrammatic perspective of the proposed system alongside its modules and their stream of communications.

Figure 3: Proposed Framework

International Journal of Science, Engineering and Management (IJSEM)
Vol 3, Issue 2, February 2018

For implicit feature recognizable proof, the procedure include steps like conclusion introduction forecast, feature-opinion combine era, supplanting the equivalent word words with their comparing feature word, checking the recurrence events of each exceptional match and at last the ID of implicit feature. Figure 3.2 underneath depicts the means performed for the recognizable proof of shrouded features in a viewpoint - empty audit proclamation.

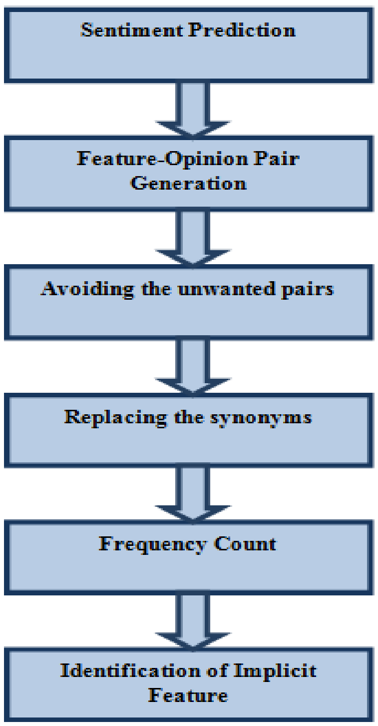

Figure 4: Implicit Feature Identification Process

3.1.1 Sentiment Prediction

This progression predicts the notion connected with a sentence. That is, it tries to distinguish whether the given sentence is certain or negative as for an item considered. It characterizes the score of 1.0 for positive explanation and - 1.0 for the negative proclamation.

3.1.2 Feature-Opinion Pair Generation

In this progression, above all else the given sentence experiences POS labeling where every word is labeled with its particular grammatical form. Next the things and modifiers are separated and put away as feature-opinion match.

3.1.3 Avoiding the undesirable sets

While era of these sets, there are sure things which don't signify the feature words and consequently are to be overlooked. This issue is additionally considered where just the sets containing feature words or the related equivalent words are taken and the rest are disregarded.

3.1.4 Replacing the equivalent words

In this progression, distinctive equivalent words for a perspective are supplanted by their relating feature word. It is required to have consistency and to maintain a strategic distance from feature grouping.

3.1.5 Frequency Count

This progression tallies the event recurrence of every one of a kind combine accessible. The uniqueness is characterized by a opinion word. Henceforth in light of an opinion word, its event recurrence for each feature, if combine is accessible, is figured. This work is proficient utilizing Rapid Miner, an instrument accessible to play out specific information mining undertakings.

3.1.6 Identification of Implicit Feature

In this progression, an implicit feature is recognized by contrasting the recurrence event of the gained opinion word with various features and selecting the one with most elevated number. On the off chance that same recurrence numbers are gotten amid correlation, then aggregate recurrence tally of features is considered as the second check.

3.1.7 Summary Generation

Once the implicit features are distinguished and set to their particular feature add up to tally, an Aspect - based Summary will be produced where add up to number of positive and negative reviews will be shown for each feature contemplated. At first the aggregate check will incorporate just aggregate number of explicit review sentences yet the last aggregate tally will incorporate aggregate number of implicit and explicit sentences.

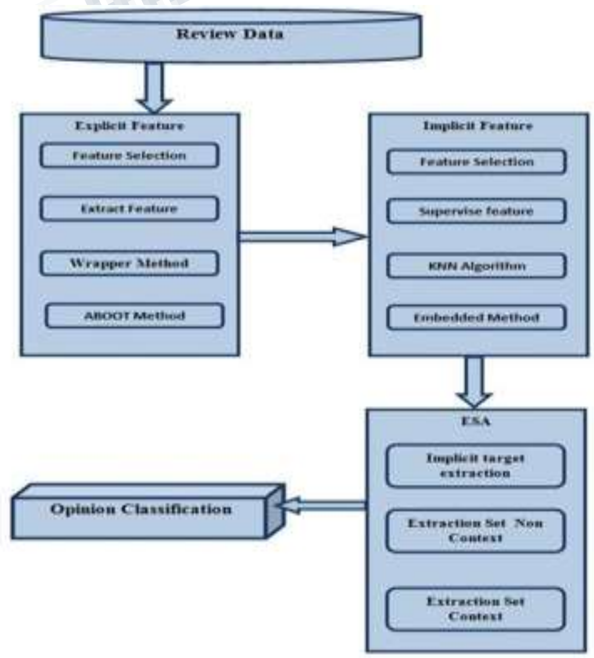

Figure 5: Proposed System architecture

IV. CONCLUSION

Aspect-based Opinion Summarization is one of the recent yet very useful techniques for opinion summarization. This method tries to display the opinions or user reviews related to a product according to its various features (aspects). The current literature shows that existing systems works well with explicit kind of sentences but suffers a great deal of problems for identification and inclusion of implicit statements. The proposed framework identifies implicit features for a given opinion word and summarizes both kinds of sentences effectively. The current system illustrates a statistical summary of the user reviews. A summary by combining statistics with text can be generated making it more productive. The proposed framework can be made suitable for other domains as well by implying some modifications. Finally an enhancement to the system that covers verbs and nouns as well can be made to improve the overall performance of the system. In this paper, we design a system to extract feature targets and opinion targets from online comments and propose a novel approach to extract subjective from implicit sentences. In order to solve the extraction of implicit sentences, we use the Wikipedia to build the associations between words and then use the cosine theorem to compute the words' similarity degree. After all we can get the synonyms and use them to represent the implicit sentence's real subjective word. The experiment results demonstrate that our method is effective.

REFERENCES

[1] Minimum Redundancy Feature Selection from Microarray Gene Expression Data NERSC Division, Lawrence Berkeley National Laboratory, Chris Ding and Hanchuan Peng NERSC Division, Lawrence Berkeley National Laboratory, University of California, Berkeley, CA, 94720, USA, Proceedings of the Computational Systems Bioinformatics (CSB'03) 0-7695-2000-6/03 $17.00 © 2003 IEEE

[2] Hua Wang, "Sparse Multi-Task Regression and Feature Selection to Identify Brain Imaging Predictors for Memory Performance," 2011 IEEE International Conference on Computer Vision978-1-4577-1102-2/11/$26.00c 2011 IEEE.

[3] Jianxin Wu, and James M. Rehg,, "CENTRIST: A Visual Descriptor for Scene Categorization," SUBMITTED TO IEEE TRANS. PAMI.

[4] George Forman, Evan Kirshenbaum, "George Forman, Evan Kirshenbaum," CIKM'08, October 26–30, 2008, Napa Valley California, USA. Copyright 2008 ACM 978-1-59593-991-3/08/10...$5.00.

[5] D. Wang, F. Nie, H. Huang, J. Yan, S. L. Risacher, A. J. Saykin, and L. Shen, "Structural brain network constrained neuroimaging marker identification for predicting cognitive functions," in Proc. 23rd Int. Conf. Inf. Process. Med. Imaging, 2013, pp. 536–547.

[6] H. Wang, F. Nie, H. Huang, S. Kim, K. Nho, S. L. Risacher, A. J. Saykin, and L. Shen, "Identifying quantitative trait loci via group-sparse multitask regression and feature selection: An imaging genetics study of the ADNI cohort," Bioinformatics, vol. 28, no. 2, pp. 229–37, 2012.

[7] D. Wang, L. Yang, Z. Fu, and J. Xia, "Prediction of thermophilic protein with pseudo amino acid composition: An approach from combined feature selection and reduction," Protein Peptide Lett., vol. 18, no. 7, pp. 684–689, 2011.

[8] X. Chang, F. Nie, Y. Yang, and H. Huang, "A convex formulation for semi-supervised multi-label feature selection," in Proc. AAAI Conf. Artif. Intell., 2014, pp. 1171–1177.

[9] D. D. Lewis, "Feature selection and feature extraction for text categorization," in Proc. Workshop Speech Natural Language,Stroudsburg, PA, USA, 1992, pp. 212–217.

[10] H. Liu and H. Motoda, Feature Selection for Knowledge Discovery and Data Mining. New York, NY, USA: Springer, 1998.

[11] G. Forman and E. Kirshenbaum, "Extremely fast text feature extraction for classification and indexing," in Proc. Int. Conf. Inf. Knowl. Manag., 2008, pp. 1221–1230.

[12] H. Peng, F. Long, and C. Ding, "Feature selection based on mutual information criteria of max-dependency, max-relevance, and minredundancy,"IEEE Trans. Pattern Anal. Mach. Intell., vol. 27, no. 8,pp. 1226–1238, Aug. 2005.

[13] Y. Saeys, I. Inza, and P. Larra~naga, "A review of feature selection techniques in bioinformatics," Bioinformatics, vol. 23, no. 19, pp. 2507–2517, 2007.

[14] R. Kohavi and G. H. John, "Wrappers for feature subset selection,"Artif. Intell., vol. 97, no. 1/2, pp. 273–324, 1997.

[15] X. Cai, F. Nie, and H. Huang, "Exact top-k feature selection via l2,0-norm constraint," in Proc. 23rd Int. Joint Conf. Artif. Intell.,2013, pp. 1240–1246.

[16] C. Ding and H. Peng, "Minimum redundancy feature selection from microarray gene expression data," J. Bioinformatics Comput. Biol., vol. 3, no. 02, pp. 185–205, 2005.

[17] D. Wang, F. Nie, and H. Huang, "Unsupervised feature selection via unified trace ratio formulation and k-means clustering (track)." in Proc. Eur. Conf. Mach. Learning Knowl. Discovery Databases,2014, pp. 306–321.

[18] D. Cai, C. Zhang, and X. He, "Unsupervised feature selection for multi-cluster data," in Proc. 16th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining, 2010, pp. 333–342.

[19] Semantic Analysis and Implicit Target Extraction of Comments from E-commerce Websites Hui Song, Jian feng Chu1, Yun Hu, Xiao qiang Liu School of Computer Science and Technology, Donghua University, China Shanghai Key Laboratory of Computer Software Evaluating and Testing, Shanghai, China 2013 IEEEDOI 10.1109/WCSE.2013.62

[20] Y. Freund and R. Schapire, "Experiments with a new boosting algorithm," in Proceedings of the Thirteenth International Conference on Machine Learning, 1996, pp. 148–156.

[21] Wanxiang Che, Zhenghua Li, and Ting Liu. 2010. LTP: A Chinese language technology platform. In Proceedings of the 23rd International Conference on Computational Linguistics: Demonstrations (COLING'10).13–16.

[22]Bing Liu. 2012. Sentiment analysis and opinion mining. Synthesis Lectures on Human Language Technologies 5, 1 (2012), 1–167.

[23] Bo Pang, Lillian Lee, and Shivakumar Vaithyanathan. 2002. Thumbs up?: Sentiment classification using machine learning techniques. In Proceedings of the Conference on Empirical Methods in Natural Language Processing (EMNLP'02). 79–86.

[24] Bo Pang and Lillian Lee. 2004. A sentimental education: Sentiment analysis using subjectivity summarization based on minimum cuts. In Proceedings of the 42nd Annual Meeting on Association for Computational Linguistics (ACL'04). Article 271.

[25]David M. Blei, Andrew Y. Ng, and Michael I. Jordan. 2003. Latent Dirichlet allocation. Journal of Machine Learning Research 3 (March 2003), 993–1022.

[26] Ivan Titov and Ryan McDonald. 2008. Modeling online reviews with multi-grain topic models. In Proceedings of the 17th International Conference on World Wide Web (WWW'08). 111–120.

[27] Dual Sentiment Analysis: Considering Two Sides of One Review Rui Xia, Feng Xu, Cheng qing Zong, Qianmu Li, Yong Qi, and Tao Li IEEE TRANSACTIONS ON KNOWLEDGE AND DATA ENGINEERING, VOL. 27, NO. 8, AUGUST 2015

[28] Yohan Jo and Alice H. Oh. 2011. Aspect and sentiment unification model for online review analysis. In Proceedings of the 4th ACM International Conference on Web Search and Data Mining (WSDM'11). 815–824.

[29] Qi Su, Xinying Xu, Honglei Guo, Zhili Guo, Xian Wu, Xiaoxun Zhang, Bin Swen, and Zhong Su. 2008.Hidden sentiment association in Chinese web opinion mining. In Proceedings of the 17th International Conference on World Wide Web (WWW'08). 959–968.

[30] Zhen Hai, Kuiyu Chang, and Jung-jae Kim. 2011. Implicit feature identification via co-occurrence association rule mining. In Proceedings of the 12th International Conference on Computational Linguistics and Intelligent Text Processing (CICLing'11). 393–404.

[31] Guang Qiu, Bing Liu, Jiajun Bu, and Chun Chen. 2011. Opinion word expansion and target extraction through double propagation. Computational linguistics 37, 1 (March 2011), 9–27.

[32] YuanbinWu, Qi Zhang, Xuanjing Huang, and LideWu. 2009. Phrase dependency parsing for opinion mining. In Proceedings of the Conference on Empirical Methods in Natural Language Processing (EMNLP'09).1533–1541.

[33] Minqing Hu and Bing Liu. 2004. Mining and summarizing customer reviews. In Proceedings of the 10th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD'04). 168–177.

[34] Ana-Maria Popescu and Oren Etzioni. 2005. Extracting product features and opinions from reviews. In Proceedings of the Conference on Human Language Technology and Empirical Methods in Natural Language Processing (HLT&EMNLP'05). 339–346.

[35] Theresa Wilson, Janyce Wiebe, and Paul Hoffmann. 2005. Recognizing contextual polarity in phrase-level sentiment analysis. In Proceedings of the Conference on Human Language Technology and Empirical Methods in Natural Language Processing (HLT&EMNLP'05). 347–354.

[36] Andrew L. Maas, Raymond E. Daly, Peter T. Pham, Dan Huang, Andrew Y. Ng, and Christopher Potts. 2011. Learning word vectors for sentiment analysis. In Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics (ACL'11). 142–150.

