

Using Machine Learning Techniques for Subjectivity Analysis based on Lexical and Non-lexical Features

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Abstract: Machine learning techniques have been used to address various problems and classification of documents is one of the main applications of such techniques. Opinion mining has emerged as an active research domain due to its wide range of applications such as multi-document summarization, opinion mining of documents and users' reviews analysis improving answers of opinion questions in forums. Existing works classify the documents using lexicon-based features only. In this work, four state of the art machine learning techniques have been applied to classify the content into subjective and objective. The subjective content contains opinionative information while objective content contains factual information. The main contribution lies in the introduction of non-lexical features and content based features in addition to the use of a conventional lexicon based feature set. We compare results of four machine learning techniques and discuss performance in diverse categories of lexical and non-lexical features. The comparative analysis has been accomplished using standard performance evaluation measures and experiments have been performed on a real-world dataset of the online forum related to diverse topics. It has been proven that proposed content and non-lexical thread specific features play their role in the classification of subjective and non-subjective content.

Keywords: Machine Learning, classification, opinion mining, lexicon, non-lexical features.

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1. Introduction

Machine learning explores the study and development of algorithms that can learn from data. Machine learning techniques operate on building a model on the input and then model is used for prediction and decision making. Machine learning methods have vast applications in various fields of computer science such as data mining, spam detection [4], detecting unknown scanning and email worms [3]. Such methods have been applied in the field of opinion mining for the problem of classifying documents by accomplishing overall sentiment after its introductory use in which three different machine learning techniques were applied [20].

Opinion mining analyzes people's views, opinions, attitudes and emotions towards various products, brands, companies [19]. It imposes several challenges such as co-reference resolution, relation extraction and natural language processing. In addition to lexicon based features there is need to use non-lexical features as well because user generated content imposes difficulties to detect opinions as it is grammatically incorrect and may include informal writing style, hashtags, emoticons and spelling mistakes that hurdles in the opinion mining task [17]. It lacks contextual information, contains extensive use of sarcasm and irony which leads to dis-orientation [17], is surrounded

by irrelevant data, such as navigational components, advertisements which diverts users' attention and leads to an unrelated topic [22].

Existing works classify the post content using the lexical features for opinion mining. In this work, we explore the use of lexical and content based post features and non-lexical thread specific features for classifying the threads into objective and subjective threads. Our main contributions include:

- Subjective analysis of the forum has been carried out at post and thread level using lexical and content feature sets and compared with non-lexical thread structure based features.
- Four different machine learning techniques have been used for classification using a real-world data set and compared using four standard performance evaluation measures.
- The results analysis confirms that thread specific features are helpful in the categorization of threads into objective and subjective threads.

The rest of the paper is organized as follows: section 2 overviews related works, section 3 provides problem formulation and statement, section 4 describes feature sets and section 5 discusses the experimental setup and then in section 6 results are discussed before concluding the paper.

2. Related Works

Opinion mining has become one of the most active domains of research. We find a lot number of work to find the opinion subjectivity or sentiment polarity of the text or textual content of discussion threads. A brief overview of relevant studies is presented here.

2.1. Subjectivity Analysis

We find various machine learning approaches for subjectivity classification. Rule based classifiers extract labeled sentences for training data. Semi-supervised learning approach learns patterns associated with subjectivity and objectivity [27]. Another work applies the word sense subjectivity classification by applying existing resources without manually creating an annotated training set and proves that their approach performs well as compared to supervised training set [23]. In a recent work, machine learning techniques have been applied using features like words, parts-of-speech tags and their combinations for subjectivity classification. They showed that threads' subjectivity can be better indicated by initial posts and reply posts [7]. We find other work that proposed method to develop tools through application of machine translation on existent subjectivity analysis tools [18]. Banea *et al.* [5] used subjective aspects at sense level for automatic subjectivity transfer across languages. They proposed an automatic framework for multilingual feature space to utilize subjectivity information. A recent work presents subjectivity analysis system for Arabic social media [2].

2.2. Opinion Mining

An important phenomenon of opinion mining is the separation of subjective and objective sentences. A comprehensive survey has been conducted regarding subjectivity and sentiment mining [16]. A recent work aims to identify the positive, neutral or negative polarity of the opinions [9]. Another work summarizes the product reviews of online review sites [11]. A review depicts users' feedback about products while a thread comprises a set of posts from multiple users, which serves multiple roles including feedback, junk, question [24]. A new approach for inter-corpus feature extraction has been introduced for opinion identification across corpus [13]. A feature based sentiment approach classifies web opinion documents [15]. Gangemi *et al.* [12] built a model which uses cognitively inspired frames for the detection of user, topic and subtopic of opinion.

2.3. Online Forums

Thread structure has been used to identify the users' views using sentiment classification for identification of attitudinal sentences, interaction dynamics of discussions and groups formation in forums [14].

Other promising work identifies evaluative and non-evaluative sentences from opinions in online posts [28]. The dialog structure of discussions is analyzed from debate perspective [25] and disagreement among posts [1]. Another work explores discussion threads of Reddit Community site and evaluates the comment thread using hLDA cluster method and finds that depth of comments increases with time [26]. Duan and Zhai use thread structure and propose smoothing schemes for natural language model. The scheme is twofold, comprised of model expansion and count expansion [10]. A recent work related to our work studies the subjective analysis of online threads using limited non-lexical features for identification of thread subjectivity orientation using small datasets [6].

3. Problem Formulation and Problem Statement

In this section, the problem has been formulated and the problem statement has been presented.

3.1. Problem Formulation

An online forum provides opportunity to all users to initiate a new topic by creating a new thread. The thread initiator adds the content and the thread initiator post sets the topic for discussion. The thread topics can be objective or subjective. An objective topic consists of facts and figures, whereas we define a subjective topic as defined in [8] and the one that seeks the personal views and opinions. It is notable that topic can drift in the threads and our assumption may not hold right always but such exceptional cases are not out of the scope of the paper.

Formally, we define a forum post p is a sequence of words in a Vocabulary set V , a forum thread t is a sequence of posts i.e., $t = \{p_1, p_2, \dots, p_L\}$ where p_i is the i^{th} post in the thread and forum f to be a collection of threads $f = \{t_1, t_2, \dots, t_m\}$ where t_i is a thread. A thread is initiated by a user $u \in U$, and $U = \{u_1, u_2, \dots, u_n\}$ where n is the number of users in the forum. A thread is called subjective and denoted by s if its topic is subjective while the non-subjective thread, denoted by ns , provides factual information.

3.2. Problem Statement

Given an online forum f and the set of thread t , our aim is to classify each post p_i and thread t_i into one of the two given classes: Subjective (denoted by s or non-subjective (denoted by ns)).

In this research work, we consider that a thread has single topic which is defined by the thread initiator who posted the initial post. Analyzing subjectivity of threads within multiple topics is a separate research problem and is out of the scope. This assumption is similar consideration by recent work [6], using non-lexical features for subjectivity classification.

4. Proposed Features

The aim of the research is to explore the effect of using lexical as well as non-lexical features to classify the threads into subjective and objective threads with the help of standard machine learning techniques. In this section, we describe the various types of features that have been used for subjective analysis.

4.1. Post Level Features

Here, we discuss the features computed at the post level and further divide them into lexicon based and content based features as shown in Table 1.

Table 1. Description of post level features.

Feature	Description
Lexicon Based Features	
posScore	Positive sentiment score the post [Sentiment Features]
negScore	Negative sentiment score the post [Sentiment Features]
numPosWords	Number of Positive words normalized by total number of words in the post [Words Frequency Features]
numNegWords	Number of Negative words normalized by total number of words in the post [Words Frequency Features]
Content Based Features	
numURL	Number of URL in the post content
numCapital	Number of Capital Case words in the post content
boolUsername	Existence of Username mentioned in the post content
boolQuotedText	Existence of earlier thread posts quoted in the post content
numCharacters	Number of characters in the post

4.1.1. Lexicon based Sentiment Features

These features take into account sentiment of a post. An opinionated post is likely to have more content than objective post. The sentiment features of the post are computed using various resources such as sentiment lexicon (e.g., SentiWordNet¹ and WordNet-Affect²) and sentiment analysis tool (e.g., LIWC³ and SentiStrength⁴). We have used one of the most widely used SentiWordNet lexicon to compute the strength of the opinion expressed by the user in the post content. SentiWordNet computes the positive, negative and objectivity score the content. The features of posScore and negScore give the positive and negative scores of the post respectively. These two features are the sentiment features. The features of numPosWords and numNegWords are the number of positive and negative words normalized by the total of words in the post.

4.1.2. Content based Features

The features of post content can be helpful for subjectivity classification. It is anticipated that

objective thread does not need a lot of content as less conversation is required, but subjective threads can have a conversation and thus their content have certain characteristics. We posit that conversation related features help to identify subjective thread. The features of post content can be helpful for subjectivity classification. It is anticipated that objective thread does not need a lot of content as less conversation is required, but subjective threads can have a conversation and content have certain characteristics. We posit that conversation related features may help to identify subjective threads. The number of URLs (numURL) in post may be due users posting links to other posts or web pages to emphasize their point of view. The number of capital case words (numCapital) is considered as harsh or emotional content. To identify the dialog within the thread, user mentions the name of a user who has already commented on the topic. We take it as feature (boolUsername). Similarly, during conversation or replying existing comment, comment content may be copied as quoted content within new comment (boolQuotedText). It is also argued that to give more argument, lengthy content may be posted by the user in the subjective thread (numCharacters).

4.2. Thread based Features

Thread features are related to thread structure and are non-lexical features (see Table 2). These features are not concerned about language, lexicon, or even the topic of the thread so these features can be helpful for multi-lingual threads or even the language of the discussion is unfamiliar. We posit that subjective threads have more scope of conversation than objective threads and possess various thread-structure features which are based on assumption that the number of users participate in a conversation (numUser), more comments are posted (numPosts), and may be time conscious (numDays) and may consist of more lengthy content (numCharacters) to present more views. While in conversation, a user may post consecutive posts to present more views or opinions (numConsPosts). One user may comment and then any other user may reply and then first user again comments in response to second user's comment and thus a comment-reply cycle may be found in subjective threads (numCycleUsers). In addition to the numeric thread features, we present Boolean features as well. It is understandable that chances of consecutive posts and conversation cycle are less, thus we only propose the existence of these features while, for other proposed features, we only take only threads which have feature value more than average values of the respective features in all the threads of the dataset. We use these features to explore their role in classifying the threads into subjective and objective classes.

¹ <http://sentiwordnet.isti.cnr.it/>

² <http://wvdomains.fbk.eu/wvnaffect.html>

³ <http://www.liwc.net/>

⁴ <http://sentistrength.wlv.ac.uk>

Table 2. Description of Thread Level Features.

Feature	Description
Non-Lexical Discrete Features	
numConsPosts	Number of Consecutive Posts by the same user
NumCycleUsers	Number of Dialog Cycles of users exist in the thread
numUsers	Number of users having post in the thread
numDays	Number of days from first post till the last
numCharacters	Number of characters of all the posts in the thread
numPosts	Number of Posts in the thread
Non-Lexical Boolean Features	
boolConsPosts	Existence of Consecutive Posts by the same user
boolCycleUsers	Existence of Dialog Cycles of users in the thread
boolUsers	Number of users in the thread > Average number of user in all the threads
boolDuration	Number of days of the thread > Average number of days of all the threads
boolLengthyThread	Length of all the posts of the thread > Average Length of all the threads
boolMorePosts	Number of posts in the thread > Average number of posts in all the threads

5. Experimental Setup

In this section, machine learning techniques applied, dataset and performance evaluation measures used have been elaborated.

5.1. Machine Learning Techniques

All the features have been computed using Oracle and state of the art machine learning techniques have been used using Oracle Data Miner. Oracle data miner uses k-fold cross validation techniques and provides classification methods free for research. We used standard 10-fold cross validation technique. Oracle Maximum Description Length (MDL)⁵ algorithm is used for feature selection which ranks predictive attributes by eliminating redundant or irrelevant attributes to enhance accuracy. Four machine learning techniques of Naïve Bayes, Decision Tree, Support Vector Machine (SVM) and Logistic Regression have been applied. Machine learning techniques are elaborated as follows:

5.1.1. Naïve Bayes

The Naïve Bayes algorithm is one of the probabilistic classification algorithms that considers the stochastic model to classify the target class c^* for a new document d , it computes

$$c^* = \arg \max_c P(c/d) \quad (1)$$

It uses Bayes' rule:

$$P(c/d) = \frac{P(c)P(c/d)}{P(d)} \quad (2)$$

$P(d)$ has no role in computing the target class c^* . To

estimate the term $P(c/d)$, Naïve Bayes divides it by supposing the conditional independence of features f_i 's given d 's class:

$$P_{NB}(c/d) = \frac{P(c) \prod_{i=1}^m P(f_i|c)^{n_i(d)}}{P(d)} \quad (3)$$

The training part assesses the relative frequency of $P(c)$ and $P(f_i/c)$, using add-one smoothing technique. The classifier's conditional classifier independence assumption performs very well for sentiment classification [6, 20].

5.1.2. Support Vector Machine

SVM is a non-probabilistic kernel-based binary linear classifier that is highly effective in traditional text classification. The classifier seeks the hyper-plane represented by vector dividing the positive and negative training data vectors with maximum margin. The output of an SVM binary classification model is given by:

$$f_i = b + \sum_{j=1}^m a_j y_j K(X_j, X_i) \quad (4)$$

Where f_i is the distance of each point to the decision hyperplane defined by setting $f_i=0$; b is the intercept; a_i is the Lagrangian multiplier for the j^{th} training data record; y_i is the corresponding target value (s,ns) in our case. SVM has shown good performance in subjectivity and sentiment analysis studies [6, 7, 9, 20].

5.1.3. Decision Tree

Decision tree learning uses a decision tree as a predictive model for classification purposes. The decision trees are built by dividing partition the document feature vector space into sub-tasks. After each iteration, the improved part is utilized using a greedy strategy and thus the whole tree is built. Decision trees can be interpreted by graphically plotting the tree structure. To classify, a label is predicted by following the branches from root node till the leaf node according to term features of the new data.

5.1.4. Logistic Regression

Logistic regression, a probabilistic statistical classification algorithm, is used to predict the target class based on set of features.

Suppose that conditional probability $\Pr(Y=1/X=1) = p(x:\theta)$, for some function p parameterized by function and the observations are independent of each other. It is notable that a sequence of Bernoulli trials y_1, y_2, \dots, y_n where there is a constant probability of target classes, the likelihood is as follows:

$$\prod_{i=1}^n p_i^{y_i} (1-p_i)^{1-y_i} \quad (5)$$

⁵<http://docs.oracle.com>

Oracle data miner provides binary classifier of logistic regression. Logistic regression showed promising results in this paper.

5.2. Data

The choice of forum dataset is significant as it should have topics including both factual and subjective and content should be generated by diverse from worldwide. We use data of BBC Forum, a public discussion forum, which has been used in [21] and provides the target values of subjective and objective. The topics of various topics have been discussed from general news, social issues to political and religious views for the period from July 2005 to June 2009. The statistics of the dataset are given in the Table 3 as follows:

Table 3. BBC dataset statistics.

Characteristics	Value
Number of Thread	97,946
Number of Posts	2,474,781
Number of Users	18,045
Average number of Posts in Thread	10
Average number of Users in Thread	8
Average number of Days in Thread	112
Average Length of Thread content	331

5.3. Performance Evaluation Measures

For the evaluation purposes, the standard performance evaluation measures of Accuracy, Precision, Recall and F-Measure have calculated using the following:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (6)$$

$$Precision = \frac{TP}{TP + FP} \quad (7)$$

$$Recall = \frac{TP}{TP + FN} \quad (8)$$

$$F - Measure = 2.Precision \cdot \frac{Recall}{Precision + Recall} \quad (9)$$

Where TP , TN , FP , FN represents True Positive, True Negative, False Positive and False negatives respectively.

6. Results and Discussion

Here, we present the post level and thread level results using four machine learning techniques. We have applied the four performance evaluation measures of accuracy, precision, recall and F-measure to show the detailed analysis of various types of features.

6.1. Post Level Results

The classification results in Table 4 depict that the no single classification algorithm is better than the other classification algorithm. We find that for lexicon based features, logistic regression shows better results. SVM and decision tree algorithms are better for content

based and for both the lexicon and content based features. Comparing the performance evaluation measure with one another, higher recall and F-measure has been achieved as compared to accuracy and precision. Content based features show better result than those of lexicon based features. The proposed content based features are related to conversation among the users within the thread rather than lexicon based features which are based on the sentiment nature of the content. This verifies our hypothesis that dialog like structure within subjective posts can be very helpful in classifying the posts into subjective and objective ones.

Table 4. Results of subjectivity analysis at post level.

Feature Type	Machine Learning Technique	Accuracy	Precision	Recall	F-Measure
Lexicon	NB	0.537	0.524	0.635	0.574
	DT	0.53	0.523	0.707	0.602
	SVM	0.518	0.522	0.474	0.497
	LogReg	0.62	0.6	0.729	0.658
Content	NB	0.633	0.598	0.821	0.692
	DT	0.641	0.604	0.831	0.699
	SVM	0.631	0.585	0.914	0.713
	LogReg	0.632	0.59	0.88	0.706
All	NB	0.571	0.566	0.626	0.595
	DT	0.644	0.604	0.845	0.705
	SVM	0.639	0.596	0.869	0.707
	LogReg	0.64	0.598	0.86	0.706

6.2. Thread Level Results

Table 5 presents that different algorithms show different results.

Table 5. Results of subjectivity analysis at thread-level.

Feature Type	Machine Learning Technique	Accuracy	Precision	Recall	F-Measure
Discrete	NB	0.715	0.688	0.723	0.753
	DT	0.682	0.627	0.701	0.705
	SVM	0.656	0.615	0.702	0.712
	LogReg	0.762	0.698	0.801	0.799
Boolean	NB	0.705	0.633	0.811	0.735
	DT	0.714	0.615	0.800	0.714
	SVM	0.642	0.621	0.872	0.702
	LogReg	0.726	0.689	0.846	0.778
All	NB	0.724	0.717	0.822	0.741
	DT	0.692	0.699	0.803	0.701
	SVM	0.662	0.723	0.798	0.777
	LogReg	0.771	0.786	0.833	0.825

Decision tree provides better results for all thread based features while overall logistic regression outperforms other three algorithms. Naïve Bayes and SVM show better results in existing research work, but both these show close results and all the four algorithms shown similar results. The results have shown better precision and accuracy and not good recall and f-measure, distinction is in the case of logistic regression as optimal results have been achieved using logistic regression. Boolean features have been taken from numeric features, but they show relatively comparable results as compared to numeric thread even though the majority of the features are merely based on the assumption that thread specific features based values are higher than the average of the

respective values for the entire dataset or not. Thus converting the numeric values into mere Boolean type does not cost performance and thus our hypothesis is proved that dialog based thread specific features do exhibit the nature of subjective thread classification.

7. Conclusions

In this work, we propose supervised machine learning model for subjectivity classification of online forum posts and threads. Various thread based non-lexical features have been used in addition to lexicon and content based features to classify the subjective and non-subjective posts and threads. We use four machine learning techniques and their comparative analysis has also been carried out. One of our main contributions is the introduction of non-lexical features that are helpful for identification of subjective threads. These features are not limited to any language and can be computed without even knowing what is mentioned or discussed in the online threads. Content based post-level features have also been introduced that help to identify dialog within the thread. In the future, we aim to examine the role of lexical and non-lexical features for mixed-sentiments using various machine learning techniques.

References

- [1] Abbott R., Walker M., Anand P., Tree J., Bowmani R., and King J., "How Can You Say Such Things?: Recognizing Disagreement in Informal Political Argument," in *Proceeding of Workshop on Languages in Social Media*, Oregon, pp. 2-11, 2011.
- [2] Abdul-Mageed M., Diab M., and Kubler S., "SAMAR: Subjectivity And Sentiment Analysis For Arabic Social Media," *Computer Speech and Language*, vol. 28, no. 1, pp. 20-37, 2014.
- [3] Abdulla S., Ramadass S., Altaher A., and Al-Nassiri A., "Employing Machine Learning Algorithms to Detect Unknown Scanning and Email Worms," *The International Arab Journal of Information Technology*, vol. 11, no. 2, pp. 140-148, 2014.
- [4] Abu Hammad A. and El-Halees A., "An Approach for Detecting Spam in Arabic Opinion Reviews," *The International Arab Journal of Information Technology*, vol. 12, no. 1, pp. 9-16, 2015.
- [5] Banea C., Mihalcea R., and Wiebe J., "Sense-Level Subjectivity In A Multilingual Setting," *Computer Speech and Language*, vol. 28, no. 1, pp. 7-19, 2014.
- [6] Biyani P., Bhatia S., Caragea C., and Mitra P., "Using Non-Lexical Features for Identifying Factual and Opinionative Threads in Online Forums," *Knowledge-Based Systems*, vol. 69, pp. 170-178, 2014.
- [7] Biyani P., Caragea C., Singh A., and Mitra P., "I Want What I Need!: Analyzing Subjectivity of Online Forum Threads," in *Proceeding of 21st ACM International Conference on Information and Knowledge Management*, Hawaii, pp. 2495-2498, 2012.
- [8] Bruce R. and Wiebe J., "Recognizing Subjectivity: A Case Study in Manual Tagging," *Natural Language Engineering*, vol. 5, no. 2, pp. 187-205, 1999.
- [9] Cambria E., Schuller B., Xia Y., and Havasi, C., "New Avenues in Opinion Mining and Sentiment Analysis," *IEEE Intelligent Systems*, vol. 28, no. 2, pp. 15-21, 2013.
- [10] Duan H. and Zhai C., "Exploiting Thread Structures to Improve Smoothing of Language Models for Forum Post Retrieval," in *Proceeding of 33rd European Conference on Advances in Information Retrieval*, Dublin, pp. 350-361, 2011.
- [11] Fabbriozio G., Aker A., and Gaizauskas R., "Summarizing Online Reviews Using Aspect Rating Distributions and Language Modeling," *IEEE Intelligent Systems*, vol. 28, no. 3, pp. 28-37, 2013.
- [12] Gangemi A., Presutti V., and Recupero D., "Frame-Based Detection of Opinion Holders and Topics: A Model and a Tool," *IEEE Computational Intelligence Magazine*, vol. 9, no. 1, pp. 20-30, 2014.
- [13] Hai Z., Chang K., Kim J., and Yang C., "Identifying Features in Opinion Mining via Intrinsic and Extrinsic Domain Relevance," *IEEE Transactions on Knowledge and Data Engineering*, vol. 26, no. 3, pp. 623-634, 2013.
- [14] Hassan A., Qazvinian V., and Radev D., "What's with the Attitude?: Identifying Sentences with Attitude in Online Discussions," in *Proceeding of Conference on Empirical Methods in Natural Language Processing*, Massachusetts, pp. 1245-1255, 2010.
- [15] Lavanya S. and Varthini B., "Sentiment Classification of Web Opinion Documents," in *Proceeding of International Conference in Electronics and Communication Systems*, Coimbatore, pp. 1-5, 2014.
- [16] Liu B., "Sentiment Analysis and Subjectivity," *Handbook of Natural Language Processing*, vol. 2, pp. 627-666, 2010.
- [17] Maynard D., Bontcheva K., and Rout D., "Challenges in Developing Opinion Mining Tools For Social Media," in *Proceeding of @NLP Can U Tag User Generated Content?! Via Lrec-Conf.Org*, Istanbul, pp. 15-22, 2012.
- [18] Mihalcea R., Banea C., and Wiebe J., "Learning Multilingual Subjective Language via Cross-Lingual Projections," in *Proceeding of 45th Annual Meeting of the Association of*

- Computational Linguistics*, Prague, pp. 976-983, 2007.
- [19] Pang B. and Lee L., "Opinion Mining and Sentiment Analysis," *Foundations and Trends in Information Retrieval*, vol. 2, no. 1-2, pp. 1-135, 2008.
- [20] Pang B., Lee L., and Vaithyanathan S., "Thumbs up? Sentiment Classification using Machine Learning Techniques," in *Proceeding of Conference on Empirical Methods in Natural Language Processing*, Philadelphia, pp. 79-86, 2002.
- [21] Prabowo R. and Thelwall M., "Sentiment Analysis: A Combined Approach," *Journal of Informetrics*, vol. 3, no. 2, pp. 143-157, 2009.
- [22] Seerat B. and Azam F., "Opinion Mining: Issues and Challenges (A survey)," *International Journal of Computer Applications*, vol. 49, no. 9, pp. 42-51, 2012.
- [23] Su F. and Markert K., "From Words to Senses: A Case Study of Subjectivity Recognition," in *Proceeding of 22nd International Conference on Computational Linguistics*, Manchester, pp. 825-832, 2008.
- [24] Bhatia S., Biyani P., and Mitra P., "Classifying User Messages For Managing Web Forum Data," in *Proceeding of 15th International Workshop on the Web and Databases*, Scottsdale, pp. 13-18, 2012.
- [25] Walker M., Anand P., Abbott R., Tree J., Martell C., and King J., "That is Your Evidence?: Classifying Stance in Online Political Debate," *Decision Support Systems*, vol. 53, no. 4, pp. 719-729, 2012.
- [26] Weninger T., Zhu X., and Han J., "An Exploration of Discussion Threads in Social News Sites: A Case Study of the Reddit Community," in *Proceeding of IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining*, Ontario, pp. 579-583, 2013.
- [27] Wiebe J. and Riloff E., "Creating Subjective and Objective Sentence Classifiers from Unannotated Texts," in *Proceeding of 6th International Conference on Computational Linguistics and Intelligent Text Processing*, Mexico, pp. 486-497, 2005.
- [28] Zhai Z., Liu B., Zhang L., Xu H., and Jia P., "Identifying Evaluative Sentences in Online Discussions," in *Proceeding of the 25th AAAI Conference on Artificial Intelligence*, San Francisco, pp. 933-938, 2011.



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