Aspect based Sentiment Analysis in Social Media with Classifier Ensembles

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***Abstract*—The analysis of user generated content on social media and the accurate specification of user opinions towards products and events is quite valuable to many applications. With the proliferation of Web 2.0 and the rapid growth of user-generated content on the web, approaches on aspect level sentiment analysis that yield fine grained information are of great interest. In this work, a classifier ensemble approach for aspect based sentiment analysis is presented. The approach is generic and utilizes latent dirichlet allocation to model a topic and to specify the main aspects that users address. Then, each comment is further analyzed and word dependencies that indicate the interactions between words and aspects are extracted. An ensemble classifier formulated by naive bayes, maximum entropy and support vector machines is designed to recognize the polarity of the user's comment towards each aspect. The evaluation results show sound improvement compared to individual classifiers and indicate that the ensemble system is scalable and accurate in analyzing user generated content and in specifying users' opinions and attitudes.**

Keywords*—*Classifier ensembles; sentiment analysis; natural language processing; latent dirichlet allocation; dependency tree analysis, social media

I. Introduction

The growth of web 2.0 and the rise of social media offer users various ways to state their opinions and experiences and have transformed them from passive information seekers to active producers. With the advent of Web 2.0 technologies and the social media, people have become more eager to express their opinions on web regarding almost all aspects of everyday life and express their attitude on events, products, activities, persons and entities [19]. Every day, a vast amount of textual content is posted in news portals, social networks and web 2.0 applications that are rich in opinions and attitudes and automated methods are needed to analyze and extract knowledge from them [22].

The recognition of the polarity of users' opinions can considerably contribute to the understanding of public attitude towards various events, products and entities. From a user centric scope, analyzing the text messages of a specific person can provide very indicative factors of the person's opinions, his/her behaviour and also provide deeper clues for determining his/her personality. Furthermore, regarding events and entities, from a topic centric perspective the analysis of user comments on a specific topic can provide very meaningful information about public stance, feelings and attitude towards a specific event. In this line, sentiment and opinion models can be employed to specify how people feel about a given entity or an event [23]. Mining this volume of opinions can provide indicative information for understanding collective human behaviour and can be valuable to many domains like product review analysis, marketing campaigns, political stance detection and many others. However, the accurate recognition of opinions in text is a very challenging task on its own and when it comes to the analysis of user generated data in social media, things can get even more challenging [1].

When coming to user generated content and opinions on products opinion mining has been studied manly on three different types of granularity, which are on document level, on sentence level and on feature level. Document level is also known as sentiment classification or document-level sentiment classification, and aims to find the general sentiment of the author of the text. For example, given a user review on a product, it determines whether the user is positive or negative about the product. Sentence level focuses on individual sentences and aims to find whether a sentence expresses an opinion or not and then whether the opinion expressed is positive or negative [10]. Studies have shown that both document level and sentence level analyses in general do not discover what exactly users liked or not [7][10]. So, there is a great necessity for the accurate fine grained determination of user's opinion and attitude towards each entity he/she addresses.

In the literature, most of the models and approaches for aspect based sentiment analysis rely on a sole classifier which they train on annotated data with the aim to recognize polarity of an opinion in terms of neutral, positive or negative direction. There are very few works that study aspect based analysis of user generated text using ensemble classifiers. However, given the special characteristics of the task of aspect based opinion mining on user generated data, ensemble classifiers are a quite suitable approach to be utilized to increase the accuracy of individual base classifiers. Indeed, ensemble classifiers that combine diverse base learners can yield better generalization performance in unseen data, and report better performance compared to base learners. In this line, in our work a classifier ensemble approach on aspect based analysis is presented.

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Latent Dirichlet Allocation (LDA) is utilized for topic modelling and natural language processing techniques are used to specify the word dependencies and determine interactions between words and aspects. Then, an ensemble classifier schema based on Naive Bayes, maximum entropy and support vector machine base classifiers is formulated to recognize the existence of polarity and then the exact polarity of users' opinions towards each aspect they address. The main contributions of this work are the following; first a generic method for performing aspect level analysis which utilizes LDA for topic modelling and also word dependencies to extract info about the way that aspects are addressed in users comments; second an ensemble classification schema for the recognition of the user's polarity towards the aspects he/she addresses is introduced. The evaluation results are quite impressive, indicating that the incorporation of word dependencies assists in the accurate specification of users opinions and also that the ensemble classifier schema performs robustly better than the individual classifiers.

The remainder of the paper is structured as follows. Section II background topics on classifier ensembles and describes related work. Section III presents our approach and describes its functionality. Section IV presents the experimental study conducted and the results collected. Finally, Section V concludes the paper and provides main directions for future work.

II. BACKGROUND TOPICS RELATED WORK

A. *Classifier Ensembles*

In the literature most of the approaches train, use and rely on individual classifiers to perform the textual classification. In this work, we present an ensemble classifier approach that aims to improve the accuracy of individual learners and examine its performance on sentiment analysis. The combination of classifiers is an effective method for improving the performance of a classification system [9]. There are many reasons for designing, developing and using classifier ensembles [5]. From a statistical scope, by constructing an ensemble schema out of trained classifiers, the algorithm can average their votes and reduce the risk of choosing the wrong or underperforming classifier on new data. Even when different classifiers are trained and report good performance, when just one is chosen, it may not yield the best generalization performance in unseen data. From a computational perspective, many learning algorithms work by performing some form of local search and it is very possible to get stuck at a local optimum. So, an ensemble constructed by running the local search from many different starting points may provide a better approximation to the true unknown function than any of the individual classifiers. Finally, from a representational scope the decision boundaries that separate data from different classes may be too complex and an appropriate combination of classifiers can make it possible to cope with this issue [5] as presented in Figure 1.

In this line, given the characteristics of the user generated textual data in social media platforms, the utilization of ensemble classifier methods to perform aspect based sentiment analysis seems to be a quite suitable approach. What is more, the combination of ensemble schemas, which are trained on textual features extended with word dependencies, constitutes an interesting and efficient approach and the work presented in this paper is a contribution towards examining this direction.

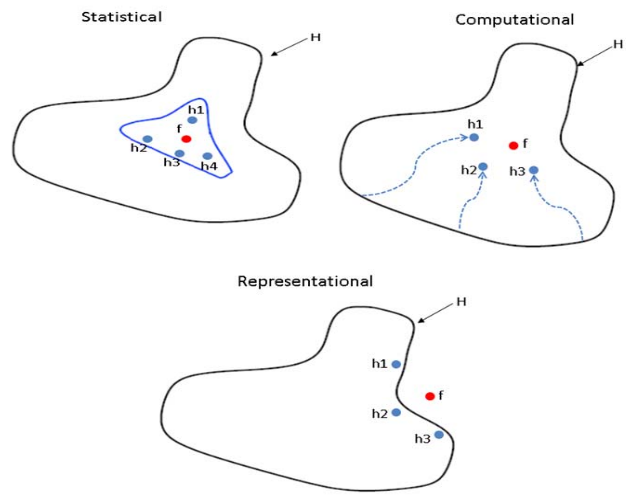

Fig. 1. Ensemble classifiers' benefits

B. *Related Work*

Sentiment analysis in social media is attracting the increasing attention of researchers in computer science and natural language processing. Throughout recent research in aspect based sentiment analysis in both academic and industrial community, a set of different techniques are proposed and developed in order to increase their efficiency. Several works study the way people express opinions and try to identify opinions in forums, social media and travel portals [3][8][11]. A detail description of approaches and techniques can be found in [13] [20][21].

Recently, the formulation of ensemble classification approaches has attracted the interest of research community and their performance has been studied on various types of textual data [6]. In the work presented in [4], authors explore tweet sentiment analysis using classifier ensembles. A classifier ensemble is formed using the base machine learning classifiers: random forest, support vector machines, multinomial naïve Bayes and logistic regression. In their study, authors experimented with a variety of tweet datasets and report that the classifier ensemble can improve classification accuracy. Also, they have compared strategies for the representation of tweets, like bag-of-words and feature hashing, and indicate that bag-of-words representation can achieve better accuracy. In the work presented in [25], authors study an ensemble classifier for sentiment classification and use an ensemble schema combining three algorithms: naïve Bayes, maximum entropy and a support vector machine, to recognize polarity (positive or negative) in text. The classifiers utilize part-of-speech based feature sets and authors indicate that the ensemble of classification algorithms on the same feature set perform robustly better than individual classifiers. In [24], authors experimented with the performance of an ensemble classifier which consisted of five base learners, that is naïve Bayes, maximum entropy, decision tree, k-nearest neighbor and support vector machine combined using random subspace method. Results indicate that the ensemble classifier substantially improve the performance of the individual base learners. In the work presented in [17], authors present an ensemble classifier that combines knowledge based and machine learning methods to detect emotions in text. The ensemble classifier schema reports better results than using solely the individual classifiers and authors suggest that ensemble learning methods can be used as a very viable approach for sentiment classification.

III. Ensemble Classifier System For Aspect Level Analysis

In this Section, we present the ensemble classifier approach to specify users' opinions towards aspects they address in their comments. In the following subsection, the architecture of the approach is described and its functionality is analyzed. The main stages of the workflow are illustrated in Figure 2.

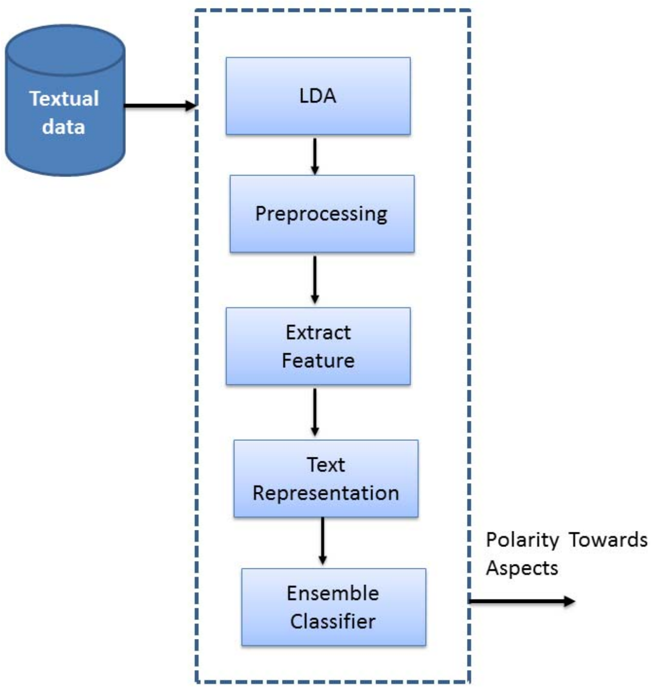

Fig. 2. Overview of the method

Initially, a given topic discussion, such a conversion topic on a social network, list of reviews on products, comments on articles on news portals, is analyzed and topic modelling is performed. The topic modeling is necessary in order to specify the main aspects that are addressed in users' comments. After that, each comment is separately analyzed and meaningful features are extracted. In addition, dependency analysis is performed and sentences that contain aspects are analyzed and word dependencies are specified. These word dependencies can provide indicative clues to the machine learning algorithms in order to specify attitude towards the specific aspect mentioned in the review/comment. After that, an ensemble classifier is designed to specify the polarity of each user's opinions towards aspects he/she addresses. The stages of the method are presented in detail below.

A. *Topic Modelling*

Initially, in the context of our approach, user-generated content on a thematic area (e.g. comments related to a product, a movie or users' tweets on an event on twitter as specified by the proper hashtag) are processed with the aim to model the conversation. The topic modelling is quite necessary in order to specify the main aspects that users address in their comments. For this purpose, Latent Dirichlet Allocation (LDA) [2] is used to analyse the topic conversation, model it and specify its main aspects. LDA is a powerful approach for the modelling of topic and it infers hidden topic structure form the reviews based on a probabilistic framework. The idea is that user generated content on a thematic area share the same topic set but each user generated content exhibits a different probabilistic mixture of those topics. The LDA model assumes that there is a hidden structure which consists of a set of topics in the whole textual dataset and relies on the co-occurrence of the words in the user generated content in order to infer the underlying hidden structure. LDA specifies two main outputs. The first output is a set of topics which are associated with the set of words, which contribute to the topic via their weights. The second output consists of a set of reviews with a vector of weight values displaying the probability of a review containing a specific topic. After the specification of the main aspects of the reviews corpus, the analysis of each user's specific comment/review/ opinion is conducted.

B. *Text Analysis Stages*

Data pre-processing stages aim to produce higher quality of text classification and to reduce the computational complexity. The aim of the pre-processing is to analyze textual data on sentence level and extract meaningful features that will assist the classifiers to perform their task. Initially, in the context of our method, user generated content is split into sentences and each sentence is handled separately. For the representation of natural language text, the bag-of-words (BOW) representation approach is adopted because of its simplicity and its appropriateness for the classification process. It is widely used in text mining applications in combination with removal of stop-words and stemming of useful words. In the system, sentences initially are tokenized and braked up into words and then each word is lemmatized and its base form is specified. Also, stop words are filtered out.

Part-of-speech tagging is performed on each sentence and automatically tags each word with the proper part of speech such as: noun, pronoun, adverb, adjective, verb, interjection, intensifier etc. The main aim is to specify and extract patterns in text, based on analysis of frequency distributions of the part-of-speech of words. Stanford natural language processing toolkit [12] is used for assigning Part Of Speech (POS) labels to every word in the sentence. After that, stemming and lemmatization is performed with the aim to replace words with their stems or their root base forms. The dimensionality of the BOW is reduced when root-related words, are mapped into one main word which is the lemma form of them. In our approach, Porter Stemmer [18] is utilized to perform the stemming task. Then, the stopwords removal stage aims to remove the stop words of the sentence. Stop words are used frequently in natural language and do not offer substantial information to the classification method. So, stop words removal process plays a pivotal role for reducing the dimensionality of the text and also for its further analysis as it assists in the identification of the remaining important key words.

In addition, features related with the word relations of each sentence are extracted and utilized in the classification process. The system analyses the structure of each sentence with the use of Stanford parser. Stanford parser is a very popular morphosyntactic analysis tool, and it is used to determine the grammatical structure of a sentence and specify for each word its base form (lemma) and its grammatical role in the sentence. Also, it specifies the relationships between the sentence's words and determines the corresponding dependencies, which provide remarkable assistance in sentence analysis. The dependency tree represents the complete grammatical relations between the sentence's words in a concise tree based approach. Those relationships among words are represented as triplets and they consist of the name of the relation type, the governor of the relationship and the dependent respectively. Dependencies in general indicate the way that sentence's words are connected and interact with each other. When the sentence morphosyntactic analysis is completed and the dependency tree is created, special parts of the dependency tree and specific words are further analyzed. The dependency tree is analyzed and the relationships and types of interactions/connections between the sentence words are examined. As an example case, let us consider the sentence: "The price of this camera is good". The dependencies of the sentence indicating the way that the sentence words are connected are the following:

det (price-2 , The-1)
nsubj (good-7 , price-2)
case (camera-5 , of-3)
det (camera-5 , this-4)
nmod (price-2 , camera-5)
cop (good-7 , is-6)

The dependency tree of the sentence is depicted in Figure 3.

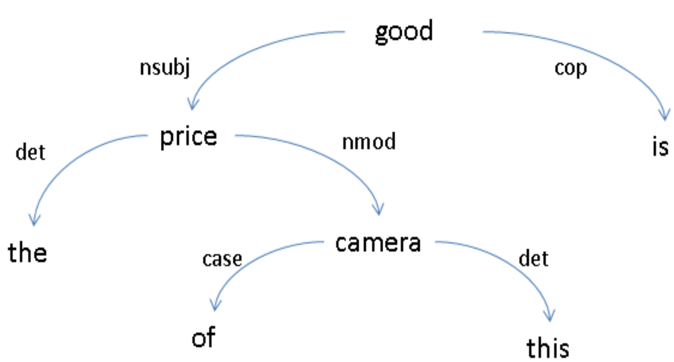

Fig. 3. The sentence's depedency tree

The word dependencies can provide indicative clues to the machine learning algorithm in order to specify user's attitude towards the specific aspect he/she mentioned and addressed in his/her review.

C. Ensemble Classifier Schema

The ensemble classifier is formulated based on three individual base classifiers which are a Naïve Bayes (NB), a maximum entropy (ME) and support vector machines (SVM). The feasibility of these classifiers in sentiment classification task is proven and in most cases outperforms other techniques and algorithms [16] [25]. The ensemble classifier combines the three individual classifiers on a majority voting approach and its overview is illustrated in Figure 4.

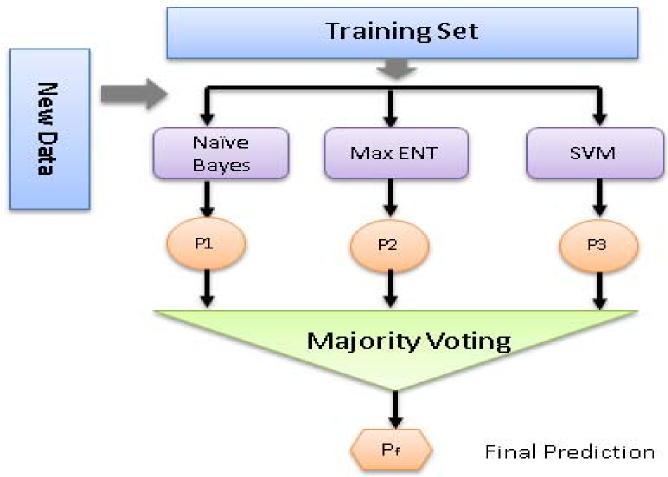

Fig. 4. The Ensemble classifer formulated

Naïve Bayes is based on Bayes theorem and assumes that documented words are generated through a probability mechanism. A universal feature of Naïve Bayes model is the conditional independence assumption that it makes. Specifically, Naïve Bayes algorithm in general assumes that words are mutually independent to each other and in this line; each individual word is treated to be an indication of the assigned polarity. The Bayesian formula calculates the probability of a defined polarity class as follows:

$$P(c|s) = \frac{P(c)P(s|c)}{P(s)}$$

In the formula, P(c) represents the probability that a sentence belongs to category 'c', P(s) represents the probability of the occurrence of sentence 's', P(s|c) represents the probability sentence 's' to belong to the category 'c' and finally, P(c|s) represents the probability that given the sentence 's', the sentence belongs to category c. The term P(s|c) can be calculated by taking into account that the conditional probabilities of occurrences of sentence words given category 'c', is as follows:

$$P(s|c) = \prod_{1 \le k \le n} P(s_k\,|c)$$

where $P(S_k|c)$ is the probability that the term (word) 'S_k' occurs given the category 'c' and 'n' represents the length of sentence 's'.

The Maximum entropy classifiers are feature based models that prefer the most uniform models that satisfy a given constraint. Labeled data in training phase are used to derive the constraints for the model that characterize the class. In contrast to Naïve Bayes, the Maximum Entropy classifier does not make independence assumption for its features. So, it is possible to add features to a Maximum Entropy classifier like words unigrams, bigrams and N-grams in general without worrying about the overlapping of the features. Maximum Entropy classifiers can achieve very difficult classification tasks and indicate good performance in various natural language processing tasks such as, sentence segmentation, language modelling and named entity recognition [14]. MaxEnt classifier can also be used when we can't assume the conditional independence of the features, something that is particularly true in text mining and sentiment analysis problems, where features such as words are not independent. The Max Entropy classifier requires more time to be trained compared to Naïve Bayes, mainly due to the optimization problem that needs to be solved in order to estimate the parameters of the model.

Support Vector Machines (SVMs) are supervised learning models with associated learning algorithms that are based on statistical learning theory. SVMs have been proven in many studies to be one of the most powerful learning algorithms for text categorization. SVM training algorithm mainly used to builds a model that assigns new textual data into a set of predefined categories. Given a set of N linearly separable points $S = \{xi \in Rn \mid i = 1, 2, \ldots, N\}$, each point xi belongs to one of the two classes, labeled as $yi \in \{-1, +1\}$. A separating hyperplane divides S into 2 sides, each side containing points with the same class label only. Thus the goal of the SVM learning is to find the optimal separating hyperplane that has the maximal margin to both sides. Besides that, SVMs can be used as linear and non -linear classifier. Since the feature space dimension is quite large in text classification, the classification problem is linear separable and so, linear kernels are suitable to be used [25].

The ensemble classifier combines the three individual learners on a majority voting approach in order to make the classification decision. Majority voting is the simplest and the most intuitive approach to combine the outputs of the base classifiers [9]. The notion to select a number of classifiers in order to formulate an ensemble schema has been studied in different ways and if the base classifiers make independent decision errors, it is proven that the majority voting method outperforms the performance of the best individual classifier [15] [26].

IV. Experimental Evaluation

An experimental study was performed in order to examine the performance of the method and the ensemble classifier model. Initially, a dataset of user comments on hotel reviews was formulated and used in the context of the study. The comments were collected from booking.com web portal and a total of 417 user reviews were indexed and analyzed. First the collected reviews were annotated by a human expert who specified for each comment, the aspects addressed and the polarity of the user towards each aspect. The annotated data stands as golden standard for the evaluation process and for assessing the performance of the classifiers. Initially, in the first part of the evaluation study, the performance of the method in determining if a user opinion towards an aspect is neutral or has polarity is assessed. Then, in the second part of the study, the performance in specifying the user's polarity towards the aspect in terms of positive or negative stance is examined.

A. Recognition of Neutral or Polarized Opinions

As far as the first part is examined, the method was evaluated in characterizing users' opinions towards aspects as polarized (in case users express positive or negative stance towards the aspect) or neutral. Roughly the two thirds of the dataset were used to train the classifiers and the remaining one third was used to estimate their performance. In Table I, the accuracy of the classifiers in specifying the polarity in terms of positive or negative content is presented.

TABLE I. Classifiers Accuracy in Neutral/Polarized Opinions

Features	***NB***	***MaxEnt***	***SVM***	***Ensemble***
BOW	0.77	0.76	0.79	0.82
BOW+ Pos	0.79	0.75	0.79	0.82
BOW+ Dep	0.79	0.76	0.81	0.84
BOW+Pos+Dep	0.81	0.79	0.83	0.86

The results indicate that the classifiers have very good performance in identifying if a user's opinion towards an aspect is neutral or has polarity. Among the base classifiers, the best performance is reported by the SVM classifier when both dependencies and word POS are utilized. Indeed, from a feature-scope, the performance of the classifiers is improved in cases where dependencies are utilized. What is more, the ensemble classifier performs robustly better than the base classifiers.

B. Recognition of Positive or Negative Opinions

The second part of the experiment aimed to assess the performance of the method in characterizing users' opinions as positive or negative. The data that have been classified correctly at the first level of the experiment to have polarity, constituted the dataset of this part of the experiment. Once again, the two thirds of the dataset were used to train the classifiers and the remaining one third was used to estimate their performance. The results are presented in Table II.

TABLE II. Classifiers Accuracy in Positive / Negative Polarity

	NB	***MaxEnt***	***SVM***	***Ensemble***
BOW	0.82	0.78	0.84	0.87
BOW+ Pos	0.84	0.79	0.84	0.88
BOW+ Dep	0.84	0.79	0.84	0.88
BOW+Pos+Dep	0.85	0.79	0.85	0.90

The evaluation results are quite impressive indicating that the incorporation of word dependencies assists in the accurate specification of user's opinions polarity. Among the individual classifiers, the best performance is reported by the SVM classifier when both the words post and dependencies are utilized. In addition, the results once again indicate that the ensemble classifier schema performs robustly better than the base classifiers. The performance of the ensemble classifier is up to 5.8% better compared to the performance of the best base classifier.

V. CONCLUSIONS AND FUTURE WORK

The vast amount of user generated info in the Web, necessitates accurate methods to analyze and specify users' opinions and attitudes towards events, products and entities. In this work, we present a method for aspect based sentiment analysis which relys on classifier ensembles. Latent Dirichlet Allocation is used to model topic and natural language processing techniques are used to specify dependencies on sentence level and determine interactions between words and aspects. An ensemble classifier based on Naive Bayes, maximum entropy and support vector machine base classifiers is formulated to recognize the existence of polarized stance and then specify the exact polarity of the user's comments towards each aspect. The evaluation results show that the method is efficient and that the ensemble classifier performs robustly better than individual learners and can be used as a very viable approach for sentiment classification.

There are various directions that future work could examine. A direction concerns the use of weights on the votes of the base classifiers and also the examination of bagging and boosting ensemble methods. Moreover, another direction concerns lexicons that could be exploited to specify words that convey positive or negative content and enhance the textual representation of the sentences with additional lexicon based features.

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