Approaches for Topic Modeling and Opinion Mining with Aspect Based Sentiment Classification using Machine Learning Approach

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Abstract: Aspect is nothing but the component or attribute of the product; it can be also the customers feeling about the different features of a product. The ABSA (Aspect Based Sentimental Analysis) is a SA method that separates content into perspectives (properties or segments of an item and service), and afterward designates everyone an estimation level (positive, negative or unbiased). The large distinction between SA and ABSA is that the previous just distinguishes the feeling of full text, while the last breaks down every content to recognize different aspects and decide the relating sentiment for each one of them. ABSA can extract aspects (attribute, expression or component) and sentiments (opinion about aspects). Sentiment analysis (SA) plays very important role in analyzing and summarizing all the opinions.

To identify the aspects of given target entities and the sentiment expressed towards each aspect this paper showcases a study on different approaches for topic modeling and opinion mining with system based on machine learning, which is strictly constrained and uses the training data as the only source of information.

Index Term: Aspect Based Sentimental Analysis (ABSA), Opinion Mining, Quality Assurance (QA), Aspect Mining, Sentimental Analysis, etc.

I. INTRODUCTION

Aspects can be implicit or explicit based on presence of aspect term. Implicit aspects are not containing any particular aspect term in statements of users' review. Instead, need to recognize by words or expressions users expressed in the reviews.

SA (Sentiment Analysis) is the investigation of analysing individuals and feelings, assessments, evaluations, and dispositions, toward substances, items, administrations, people and their viewpoints communicated in reviews. SA can be seen in three distinct degrees of granularity, they are aspect-level, sentence-level and document-level. Aspect-level SA, recognizes the assessment polarities on each extraordinary aspect of one objective substance. In sentence-level SA sentiment polarity communicated in each sentence of the survey is recognized. It deals with recognition of statements as objective or subjective. While document-level SA the sentiment polarity communicated in reviews is recognized. It extracts opinion baring words and detects its polarity. It also focuses on sentiment classification using supervised as well as unsupervised learning algorithms. Both approaches illustrate aspect base prediction according to different methodology.

Feature selection methods are classified into different aspect categories like wrapper, static and hybrid techniques. In filter based approaches, the selection of features can't reliant of any machine learning algorithm. In this, features are preferred on the base of their numerical weight. In the dynamic approach, first different subsets of features are identified then are evaluated using one of the classifiers. The hybrid approach is the combination different feature extraction as well feature selection methods, it also used various machine learning algorithms, in univariate filter approach features are evaluated with respect to relevance. Multivariate method considers correlation between features and avoids redundant features.

It is crucial for any e-trade business enterprise to analyze user's/customers feedback and to find out the sentiment of the customers for giving them better products and services. As large evaluations can also include remarks in a combined manner where a patron offers his opinion on distinctive product capabilities inside the equal overview, finding out the exact sentiment is tedious. The main features of these products are given in their introductions, and this provides an important resource for admin to improve the quality of the requirements of their own system. The extracted topic words from a system based on machine learning which uses training dataset of reviews as source of information are mapped with various aspects of an entity to perform the aspect-specific sentiment analysis on product reviews. Experiments with synthetic and real dataset show promising results compared to existing methods of sentiment analysis.

II. RELATED WORK

There are various approaches which are in development for detecting functional aspects and non-functional aspect in SRS. Some of them are implemented and some are in implementation stage. This chapter will focus on various technological approaches which help developers to improve the quality of the requirements of their own App.

- **Machine Learning (ML):**

  Machine learning is a subfield of artificial intelligence (AI). Because of this, machine learning facilitates computers in building models from sample data in order to automate decision-making processes based on data inputs. Any technology user today has benefitted from machine learning.

  In general, there are two types of machine learning algorithms, Supervised Machine Learning and Unsupervised Machine Learning. In addition, new categories evolve with development in the field which can be identified as reinforcement learning.

- **Sentimental Analysis:**

  Sentiment Analysis also known as *Opinion Mining* is a field within DM, ML that builds systems that try to identify and extract opinions within text. Usually, besides identifying the opinion, these systems extract attributes of the expression e.g.:

  - *Polarity*: if the speaker expresses a *positive* or *negative* opinion,

- *Subject*: the thing that is being talked about,
- *Opinion holder*: the person, or entity that expresses the opinion.

Currently, sentiment analysis is a topic of great interest and development since it has many practical applications. Since publicly and privately available information over Internet is constantly growing, a large number of texts expressing opinions are available in review sites, forums, blogs, and social media.

With the help of sentiment analysis systems, this unstructured information could be automatically transformed into structured data of public opinions about products, services, brands, politics, or any topic that people can express opinions about. This data can be very useful for commercial applications like marketing analysis, public relations, product reviews, net promoter scoring, product feedback, and customer service.

In this paper [1], authors propose an approach to gain and recommend requirements related information from App descriptions to help developers use the resource efficiently. Firstly, we construct a model by mining domain knowledge from App descriptions with the method proposed in our previous work, and use initial requirements to retrieve their related information from the model. Then, we analyze the information and recommend them from three aspects: static information of existing Apps for identifying the priorities of requirements; functional features and non-functional properties of features for giving detailed design of the Apps in requirements; and combinations of features for enriching the requirements.

In this paper [2], proposed an unsupervised model for detecting aspects in reviews. In this model, first a generalized method is proposed to learn multi-word aspects. Second, a set of heuristic rules is employed to take into account the influence of an opinion word on detecting the aspect. Third a new metric based on mutual information and aspect frequency is proposed to score aspects with a new bootstrapping iterative algorithm. The presented bootstrapping algorithm works with an unsupervised seed set. Finally, two pruning methods based on the relations between aspects in reviews are presented to remove incorrect aspects. The proposed model does not require labeled training data and can be applicable to other languages or domains. We demonstrate the effectiveness of our model on a collection of product reviews dataset, where it outperforms other techniques.

In this paper [3], proposed a multimodal aspect-opinion model (mmAOM) considering both user-generated photos and textual documents to simultaneously capture correlations between textual and visual modalities, as well as associations between aspects and opinions. By identifying the aspects and the corresponding opinions related to entities, we apply the mmAOM to entity association visualization and multimodal aspect-opinion retrieval. We have conducted extensive experiments on real-world datasets of entities including Flickr photos, Tripadvisor reviews, and news articles. Qualitative and quantitative evaluation results have validated the effectiveness of the multimodal aspect-opinion mining model, and demonstrated the utility of the derived aspects and opinions from mmAOM in applications of entity association visualization and aspect-opinion retrieval.

In this paper [5], a top-down method that extracts automatically an FM from functional requirements of product variants. Besides its automation, its novelty stems from the use of semantic information mined through natural language processing techniques to extract potential features from each product variant. To account for name variations, our method harmonizes the names of the features extracted from the product variants by using a classification technique to group similar features. In addition, to determine the feature type, it uses the formal concept analysis technique to distinguish mandatory from optional features. Furthermore, to structure the FM, it uses a set of semantic criteria to determine the constraints among the features. The paper reports on a quantitative and a comparative evaluation of the method on existing FMs, and it examines the conformity of the generated FMs to the input functional requirements, based on experts' feedbacks.

In this paper [7] presents a simple unsupervised learning algorithm for classifying reviews as recommended (thumbs up) or not recommended (thumbs down). The classification of a review is predicted by the average semantic orientation of the phrases in the review that contain adjectives or adverbs. A phrase has a positive semantic orientation when it has good associations (e.g., "subtle nuances") and a negative semantic orientation when it has bad associations (e.g., "very cavalier"). In this paper, the semantic orientation of a phrase is calculated as the mutual information between the given phrase and the word "excellent" minus the mutual information between the given phrase and the word "poor". A review is classified as recommended if the average semantic orientation of its phrases is positive. The algorithm achieves an average accuracy of 74% when evaluated on 410 reviews from Epinions, sampled from four different domains (reviews of automobiles, banks, movies, and travel destinations). The accuracy ranges from 84% for automobile reviews to 66% for movie reviews.

In this paper [8] classify movie reviews using features based upon these taxonomies combined with standard "bag-of-words" features, and report state-of-the-art accuracy of 90.2%. In addition, we find that some types of appraisal appear to be more significant for sentiment classification than others. Little work to date in sentiment analysis (classifying texts by 'positive' or 'negative' orientation) has attempted to use fine-grained semantic distinctions in features used for classification. We present a new method for sentiment classification based on extracting and analyzing appraisal groups such as "very good" or "not terribly funny". An appraisal group is represented as a set of attribute values in several task-independent semantic taxonomies, based on Appraisal Theory. Semi-automated methods were used to build a lexicon of appraising adjectives and their modifiers.

Most existing approaches methods utilize a preparation set and a test set for arrangement or classification. Training set is made of input feature courses and their corresponding class labels. Utilizing this preparation or training set, an arrangement(classification) model is created which tries to order the input courses into corresponding class names or labels. Then a test set is utilized to confirm the model by deriving the class labels of unknown feature courses. A variety of machine learning techniques like Simple Bayes (NB), NLP, and Support Course Machines (SVM) are utilized to classification of reviews. Some of the components that can be utilized for semantic classification are Term Absence or Presence, Term Repetition, invalidation, n-grams and Parts of Speech. These components can be utilized to discover the semantic identification of words, expressions, sentences and that of reports. Semantic orientated data is the polarity and it can be affirmative or negative.

III. CONCLUSION

Sentiment analysis, it is a huge term to classify user's opinion using Natural Language Processing (NLP) and Machine Learning (ML) Approach. Various researchers have done different methods for functional non-functional classification, aspect base classification, polarity based classification etc. Product review based sentiment analysis is similar to proposed sentiment analysis approaches.

The proposed approaches achieved very good results. The constrained versions were always above average, often by a large margin. The unconstrained versions were ranked among the best systems.

Above different approaches can be used to propose a system that uses the NLP and ML algorithm on user review and comments to detect user interested product to user on E-Commerce. The system will collect all reviews of products and perform sentiment analysis to detect functional and non-functional reviews in a report summary. This will be a feedback to the product owner and developers to increase the business and market value of their product by enhancing the features in their app.

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