A Versatile Sentiment Analysis of Multiple Online Reviews

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Abstract - In this Work, we present a novel strategy in producing summaries of multiple online reviews using a fine-grained sentiment extraction model for short texts, which is versatile to various areas and languages. Flexibility of a model is characterized as its capacity to be effectively altered and be usable on various areas and languages. This is significant because of the decent variety of spaces and languages accessible. The fine-grained sentiment extraction model is separated into two strategies: feeling order and perspective extraction. The estimation classifier is assembled using a three-level arrangement approach, while the aspect extractor is constructed using expanded biterm point model (eBTM), an augmentation of Latent Dirichlet Allocation subject model for short reviews. Results show that the conclusion classifier beats gauge models and industry-standard classifiers while the angle extractor beats other point models regarding viewpoint assorted variety and perspective extricating power. Likewise, using the Naver movies dataset, we show that online review summarization can be adequately built using the proposed strategies by looking at the consequences of our strategy and the results of a movie grants function.

Keywords - Sentiment Analysis, Online reviews, Aspect Extraction, Short reviews, Multiple reviews

I. INTRODUCTION

The amount of information available on the internet is constantly increasing. Usually both consumers and producers refer to online reviews for several reasons [1]. Buyers look at them to conclude whether to buy the displayed item/service or not based on their requests. Producers, on the other hand, look at them to improve their market methodology by amplifying the positive perspectives and improving the negative ones. Therefore, online movie review website has limited the user reviews to 150 characters. This raises to the problem in sentimental analysis because limiting the number of characters limits the number of words for a review. One essential concern with sentiment analysis of Online reviews is to computerize the comprehension of the immense measures of on the web surveys. One approach to solve this is to make a review summary that gives users a dense layout of rundown of perspectives and their comparing slant rating. There are extensive efforts on fine-grained sentiment extraction, a great deal of which utilizes topic modeling techniques [5–8] to automate the extraction of perspectives. Hence the primary concern with sentiment analysis of movie review is to automate the comprehension of the vast amount of online reviews.

The reason for this study is to propose a versatile way to deal with making a review summarization system for analyzing short web-based social media content with novel estimation and angle extraction algorithms. Past research works concentrated on the adaptability of a model. Adaptability is characterized as the model's capacity to be free regarding area, point, worldly, and language style [9]. On the other hand, in this paper, we targeted to developing the versatile methodology for summarization of short multiple reviews. We characterize flexibility as the ability of an approach to be easily modified for the making of models for different areas or languages. Notice that models are adaptable, and approaches are versatile. A methodology is utilized to make a model. There can be multiple products from various spaces just as reviews composed using various types of languages.

Making various methodologies for these unique areas and languages requires a lot of exertion and time. In this way, we endeavor to accomplish the versatility in our models with a corpus-driven methodology, where outer information other than the given corpus are not utilized. A few examinations are done utilizing numerous datasets from various languages and multiple domains, so as to confirm the flexibility of the model. The outcomes can be summarized as follows. The proposed sentiment classifier outperforms previous state-of-the-art classifiers and topic model-based classifiers. The proposed aspect extraction strategy beats LDA [10] and BTM [11] as far as angle assorted variety score and viewpoint extricating power. At long last, we show that the proposed engineering joining the feeling arrangement and angle extraction approach is successful in abridging audits, in view of a contextual analysis on online reviews.

II. RELATED WORK

In comparison with the amount of research done on flexibility, there are quite few studies that focus on adaptability on sentiment analysis. Sentimatrix [17] combines rule-based classification, statistical and machine learning methods in creating a sentiment analysis technique. They stated that grammar-based systems typically obtain better precision but are hard to adapt to new domains. Therefore, they designed the technique to be language independent, only using resources that are easily adaptable for any language such as tokenizers and annotations.

Tanev et al. [18] also mentioned the advantage in terms of adaptability of employing a bag of n-gram representations because it's easily adaptable to any languages. There are different ways to deal with the sentiment analysis that attention on short texts using machine learning [19–21] and tongue preparing [22–24]. one among the premier later and mainstream works is regulated by Yang et al. [21], where they consolidated a few syntactic highlights including POS labels and n-grams chose by a proportion of information gain into figuring estimation comparability for Chinese microblogs. Another ongoing work is proposed by Thelwall et al. [22], where they proposed SentiStrength for MySpace remarks, which utilizes human-explained estimation many registering the word assessment quality. This was embraced by Basiri et al. [23] where they included the remark history of the commentators to upgrade the supposition score. A multiple line of research is to consolidate AI and tongue handling for supposition examination.

Aldayel et al. [25] utilize both lexical-based and in this manner the bolster vector machines classifier to for crossover supposition examination for Arabic tweets.

Topic modeling techniques make use of latent Dirichlet allocation (LDA) or its variants to automatically extract aspects from text. Bagheri et al. [8] used an extension of LDA which will extract multiword aspects from text collections. However, unlike our approach presented during this paper, they didn't incorporate these aspects into a sentiment classifier to create a fine-grained sentiment extractionframework.

Titov et al. [5] constructed a joint model of text and aspect ratings for sentiment summarization. They provided their own predefined aspects and feed them to their model.

Jo et al. [6] also constructed a joint model called aspect and sentiment unification model (ASUM), but rather than creating their own predefined aspects, they used external sentiment seed words to assist with the classification of sentiment. They assume that each one words in one sentence only ask one aspect. this is often immediatelyextended by Kim et al. [7] which makes use of a tree-structured Bayesian nonparametric method called recursive Chinese Restaurant Process (rCRP) to also extract the aspect's hierarchy.

Since LDA was proposed in Blei et al. [10], it's gained an excellent attention within the research community of social media where texts to be processed is comparatively short. Karandikar et al. [31] used LDA to cluster short status messages.

Godin et al. [32] used LDA for recommending hashtags for tweets without hashtags. LDA may be a very effective thanks to extract topics from documents, but it's not as effective when handling short texts, as short texts are very sparse. due to this, various studies tackle the matter of constructing a subject model specifically for brief texts. One way to cope up with this shortcoming is to vary the input documents in how. Kim et al. used LDA with n-grams as its vocabulary to extend the quantity of input file. Zhu et al. improved the subject model by introducing an external knowledgebase to spot topics from text for better categorization. They also added weight to few features within the texts to urge other topics from the subject model.

Hong et al. [35] trained the subject model using Twitter messages aggregated by the one who created the message. This made the standard of learned topic even better than the Author-Topic model, which fails to model hierarchical relation between entities.

III. PROPOSED DESIGN

The principle of our methodology originates from the assumption that since the dataset comprises of short texts and paragraphs, one content may reveal just a single perspective or a multiple aspects in this way we have to choose assessments. This assumption is based from the exact hypothesis that one review contains one or more aspects [6]. Since the writings are short, we can expect that the majority of the writings have all things considered one sentence. From this assumption, we recommend that it is conceivable to isolate the models for notion characterization and the aspect extraction to cater a better performance and to think about the mode's versatility. The proposed review summarization structure is appeared in Fig. 1.

After preprocessing, a separate preparing information is utilized to prepare the estimation arrangement and the aspect extraction model. Utilizing separate survey datasets that are not yet grouped, the review summary is produced by experiencing the constructed sentiment classification model and aspect extraction model. In the approach segment, we present the two significant pieces of the rundown system of numerous short surveys: the first one is about the sentiment classification model and the subsequent one is about the aspect extraction model.

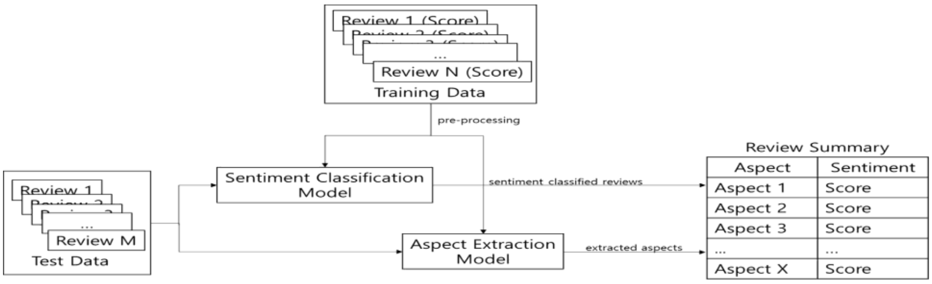


Fig. 1 Overview of sentiment analysis model framework

A. Multi-level Processing

The sentiment analysis model proposed in this paper may be a multi-level processing model where the primary two levels use two widely used approaches in sentiment classification: tongue processing techniques and supervised learning techniques. The third and final level combines the primary two levels employing a simple neural network algorithm. The tokens produced along side the dictionaries and lists inbuilt the preprocessing stage are wont to extract the features from texts.

B. Natural Language Processing

We compute Native sentiment scores dependent on natural language processing strategies. There are four lexical-based scores and two syntactic-based scores. The lexical-based scores are determined utilizing the great/awful adjective/adverb records. These lists are arranged by recurrence and accordingly can be deciphered as sentiment weights; the higher the recurrence of the word, the more it is slanted to the extremity list. Based on the lists, we at that point make a lexical score work that gives a score to a word, as demonstrated as follows. This function gives a score to a word based on its rank (position in the list).

$$LS(word,list) = \begin{cases} 2^{len(list)/100}, & \text{if } rank(word,list) < 5 \\ 2^{(len(list)-/100)-n}, & \text{if } rank(word,list) < n*100 \end{cases}$$

LS – lexical score

len – length of a list

word – the word whose LS is to be calculated

list – the list which contains the word

rank – position of the word in the list after sort

The function gives a bigger score to a word that has a higher ranking compared to a word that has a lower ranking in the list.

We also calculate two syntactic-based scores which are called naïve lazy syntactic scores. These scores are supported the assumption that there are two possible syntaxes of a sentence with a sentiment. the primary one is that the noun-adjective syntax where there is an adjective describing the noun. Another syntax is that the noun-adverb-verb syntax where there's an adverb describing the action of the noun given by the verb. for instance, the sentence "the actor was great" follows the noun-adjective syntax where actor is the noun and great is that the adjective

$$SS\ (n,\ adj) = \frac{LS\ (n,\ nouns) * LS\ (adj,\ [bad,\ good]adjectives)}{distance\ (n,\ adj)}$$

$$SS\ (n,\ adv,\ v) = \frac{LS\ (n,\ nouns) * LS\ (adv,\ [bad,\ good]adverbs) * LS\ (v,\ verbs)}{max\ (distance\ (n,\ adv),\ distance\ (n,\ v),\ distance\ (adv,\ v))}$$

SS – syntactic score

distance (n, adv) – distance between noun and adverb

The order of these words does not matter.
The lexical score function calculated above are used to add more weight on those words with high frequency.
These weights are normalized by dividing them to the distance between the words.
Machine Learning

In this Process, we use the character-based n-gram dictionary and therefore the word-based n-gram dictionary to create two sparse matrices. These matrices are then fed to 2 different support vector machine classifiers. We use an L2-loss L2-regularized support vector regression provided by LIBLINEAR, a library for giant linear classification specifically good for document classification. Each support vector machine classifier receives a sparse matrix as an input and therefore the sentiment score because the output and produces a true number between 0 and 1, inclusive.

The role of the second level classification is to seem at the patterns created by continuous characters and words. More specifically, the character-based support vector machine classifier takes care of continuous character patterns within the text. Short texts found within the web are presumably to be dirty. Character-based support vector machines classifier tackles that problem. Meanwhile, word-based support vector machines classifier accepts a cleaned and tokenized set of strings. Therefore, word-based support vector machines classifier classifies the text after it's cleaned.

C. Neural Network

The final level of the classification model is the combination of the first two levels. This is accomplished using the classical feedforward neural network and the backpropagation algorithm.

We combine all the outputs from the past levels, the lexical and syntactic scores from the primary level, and therefore the outputs of the support vector machine classifiers from the second level, for a complete of 8 features and feed all of them as an input of the neural network. The hidden layer consists of 15 nodes and therefore the output layer consists of a single node that contains the sentiment score. the ultimate sentiment score may be a real between 0 and 1, inclusive. The whole system is shown figuratively in Fig. 2.

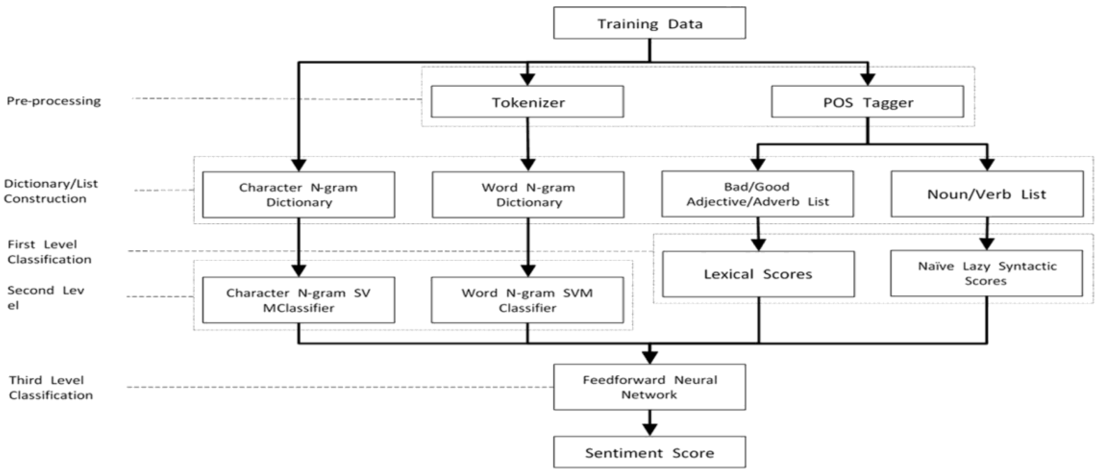


Fig. 2 Three-level processing sentiment model framework

D. Extended Biterm Topic Model

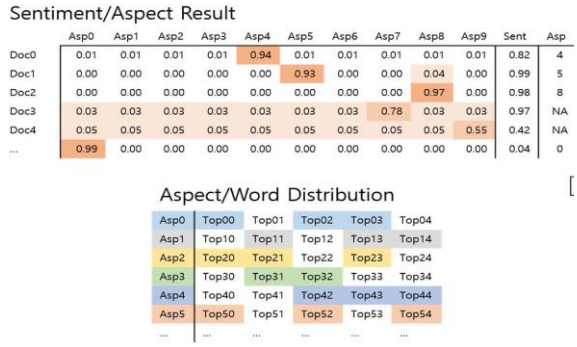
The aspect extraction proposed during this paper may be a modification of the prevailing biterm topic model, which we call extended biterm topic model (eBTM). the most difference between LDA and BTM is that LDA implicitly considers the word co-occurrence patterns inside a document by adding a document layer. However, due to the sparse word co-occurrence patterns on short text, the implicit patterns subsided effective. BTM suggests that if the co-occurrence patterns are explicitly generated, i.e. using biterms, they can become simpler for brief texts. Biterms are often simply described such within the short text “biterm topic model”, the extracted biterms are “biterm topic”, “topic model”, and “biterm model”. A biterm doesn't have a ordering, i.e. “biterm topic” and “topic biterm” are an equivalent.

But because BTM explicitly patterns out word co-occurrence, the entire collection of documents only has one shared topic distribution. We extend this approach by incorporating the document layer of LDA. eBTM turns back to LDA to find out the co-occurrence patterns of words implicitly using the document layer and uses the biterm approach of BTM to expand the dimensions of the short text. This way, eBTM still considers the word co-occurrence patterns while at an equivalent time creates a document level topic distribution.

IV. RESULT

A. Sentiment analysis

This area covers the consequences of sentiment classification on reviews from various areas and languages. We initially assess the need of the staggered characterization model. We change the anticipated and real scores into their extremity dependent on the fifty percent edge; the assumption score of 0.5 above is given a positive sentiment and negative sentiment assuming generally. We think about the conclusive outcomes to the correctnesses got by the first-and second-level classifiers. Each degree of classifiers delivers numerous characterizations.



Sentiment/Aspect Result

	Asp0	Asp1	Asp2	Asp3	Asp4	Asp5	Asp6	Asp7	Asp8	Asp9	Sent	Asp
Doc0	0.01	0.01	0.01	0.01	0.94	0.01	0.01	0.01	0.01	0.01	0.82	4
Doc1	0.00	0.00	0.00	0.00	0.00	0.93	0.00	0.00	0.04	0.00	0.99	5
Doc2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.97	0.00	0.98	8
Doc3	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.78	0.03	0.03	0.97	NA
Doc4	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.55	0.42	NA
...	0.99	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0

Aspect/Word Distribution

Asp0	Top00	Top01	Top02	Top03	Top04
Asp1	Top10	Top11	Top12	Top13	Top14
Asp2	Top20	Top21	Top22	Top23	Top24
Asp3	Top30	Top31	Top32	Top33	Top34
Asp4	Top40	Top41	Top42	Top43	Top44
Asp5	Top50	Top51	Top52	Top53	Top54
...	...	...	...	...	...

Fig .3 Sample Aspect extraction and summarization

A neural network technique significantly improves the accuracy of the classification model. We advance to the evaluation of the entire classification model as compared with other classifiers. We compare the performance of our classifier to both LingPipe (unigrams and bigrams), Stanford CoreNLP's sentiment classifier and ASUM [6]. LingPipe classifies texts by first separating subjective sentences from objective sentences then finds sentiments using word features. Stanford CoreNLP created a sentiment classifier supported deep learning technique called recursive neural network that builds on top of grammatical structures. ASUM may be a joint aspect-sentiment topic model that automatically finds sentiment of every found aspect with the utilization of sentiment seed words. Since ASUM needs seed words so as to run perfectly, we aren't ready to run ASUM on Korean and Chinese texts due to the unavailability of such golden standard list within the said language. this is often one among the inadaptability problems when combining the aspect extraction and sentiment classification. an equivalent goes for the CoreNLP classifier because the model only supports English texts. this is often another inadaptability problem when using extensive grammatical structures as features to find out a sentiment classification model.

B. Aspect Extraction

In this section, we present the results gathered from the extraction of aspects using eBTM. The assignment of aspects is completed manually by watching the aspect words discovered by the model. We compare our model to LDA, BTM, and ASUM in terms of aspect diversity and aspect extracting power. We use the Naver dataset to guage the aspect diversity and compare it to LDA and BTM, and that we use the Rotten Tomatoes dataset to guage the aspect extracting power and compare it to ASUM. the number of topics of all models are set to 10, apart from ASUM where 20 topics should be set because it extracts the positive and negative aspects differently. We use 0.1 because the alpha and 0.01 because the beta hyperparameters of LDA, BTM, and eBTM. We use 0.1 because the alpha and 1 as the gamma hyperparameters of ASUM. The beta hyperparameter of ASUM is about as follows: 0.001 if the word at hand isn't a seed word, 0.1 if the word may be a seed word of the subject at hand, and 0 if the word may be a seed word of another topic.

V. CONCLUSION

The present work proposed a versatile sentiment extraction algorithm for both short texts and paragraph. We exhibited that the mix of both natural language processing and machine learning techniques are more powerful than a solitary level classifier. We likewise displayed that neural system calculations are more qualified for slant characterization regarding accuracy, review, and Fmeasure. The subsequent sentiment classifier outflanks existing methodologies on a few datasets gathered from various spaces what's more, in various dialects, in this way demonstrating the model's flexibility. Online customers and viewers find it complex to going through all online reviews to decide about a product in online shopping. Summarization of multiple short online reviews has its social impact that viewers and customers can quickly grasp the aspects and its sentiment scores. Greater the sentiment score, greater the product is in its corresponding aspect

We also extend the biterm topic model for brief texts into eBTM. We report that eBTM outperforms LDA and BTM in terms of aspect diversity and outperforms LDA, BTM and ASUM in terms of aspect extracting power. The experimental results indicate that the proposed technique performs well on short texts where ASUM performs poorly on short texts. Our model isn't hooked in to external seed words and it's usable on different domains and languages. These results support our hypothesis that it's more appropriate to separate aspect extraction and sentiment analysis for adaptability. Finally, we show an efficient application of our fine-grained sentiment extraction model to summarization of multiple onlinereviews. Using the results of a movie award ceremony, we show the effectiveness of our online review summarization framework in two ways. We present that movies that received a gift have a better aspect sentiment score compared to those without a gift. We also demonstrate that our review summarization framework can differentiate movies with similar overall sentiment rating. One example of this application is to compare multiple reviews of a single product that is sold in multiple countries using review data. Since reviewer can distinguish reviews from different countries, this is a possible application of the review summarization framework.

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