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An Aspect-Level Sentiment Analysis Based on LDA Topic Modeling

Sina Dami[1*], Ramin Alimardani[1]

[1].Department of Computer Engineering, West Tehran Branch, Islamic Azad University, Tehran, Iran

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Abstract
Sentiment analysis is a process through which the beliefs, sentiments, allusions, behaviors, and tendencies in a written language are analyzed using Natural Language Processing (NLP) techniques. This process essentially comprises of discovering and understanding people's positive or negative sentiments regarding a product or entity in the text. The increased significance of sentiments analysis has coincided with the growth in social media such as surveys, blogs, Twitter, etc. The present study takes advantage of the topic modeling approach based on latent Dirichlet allocation (LDA) to extract and represent the thematic features as well as a support vector machine (SVM) to classify and analyze sentiments at the aspect level. LDA seeks to extract latent topics by observing all the texts, which is accomplished by assigning the probability of each word being attributed to each topic. The important features that represent the thematic aspect of the text are extracted and fed to a support vector machine for classification through this approach. SVM is an extremely powerful classification algorithm that provides the possibility to separate complex data from one another accurately by mapping the data to a space with much larger aspects and creating an optimal hyperplane. Empirical data on real datasets indicate that the proposed model is promising and performs better compared to the baseline methods in terms of precision (with 89.78% on average), recall (with 78.92% on average), and F-measure (with 83.50% on average).

Keywords: Natural Language Processing; Sentiment Analysis; Aspect-Level; Topic Modeling; LDA.

1- Introduction

Sentiment analysis or opinion mining is a research field aimed at expressing the behavior, sentiments, opinions, and analysis of various individuals regarding entities and their features. These entities can be goods, services, organizations, other individuals, events, and topics that have to do with information recovery and knowledge extraction from the test through data mining and natural language processing [1]. Text information in the world is divided into two groups of facts and sentiments [2]. Facts are real phrases about the entities, events, and their features, whereas sentiments are mental phrases that indicate the sentimental opinions of people and their thoughts and beliefs regarding an entity, event, or one of their features. So far, ample research has been conducted on factual information. For instance, information extraction [3], textual implication [4], text summarization [5], classification [6], clustering [7], and many other applications can be mentioned in natural language processing and text mining sciences [8]. In contrast, few studies have been conducted on sentimental information. One of the most important reasons for the shortage in studies on texts containing sentiments and beliefs compared to texts containing facts is the existence of much less sentimental information, particularly before the expansion of the worldwide web. Aside from the facts, beliefs and sentiments are quite significant too since we strive to know others' opinions whenever we want to decide on action [9].

We would ask the opinions of friends and families when deciding on the expansion of the worldwide web, and organizations and firms used to need public surveys, questionnaires, or interviews when they needed the opinions of the public regarding their goods or services [10]. The number of texts and pages containing sentiments started accelerating with the emergence of the worldwide web. In other words, the internet has changed how people's sentiments, opinions, and perspectives change so that people can reflect their opinions on commercial pages, internet groups, and blogs [11].

These online opinions of people make for a vast resource of assessable information that can be used for many applications. Basically, opinions and sentiments can be

✉ **Sina Dami**
Dami@wtiau.ac.ir

analyzed at three levels of granularity, including document, sentence and word. The sentiment expressed in an entire text, for example, review sentence or document, is called overall sentiment. The task of analyzing overall sentiments of texts is normally formulated as classification problem, e.g., classifying a review sentence or document into positive or negative sentiment. Then, different types of machine learning approaches trained using different levels of granularity (features) have been applied for overall sentiment analysis. The existing methods at each of these three levels can also be categorized into three groups including supervised learning, semi-supervised learning, and unsupervised learning.

The present study has adopted a hybrid approach combining supervised and unsupervised learning to perform topic modeling of texts and classify sentiments, respectively. Latent Dirichlet Allocation (LDA) was used for this purpose to model several latent variables (titles) in a set of texts encompassing words. A Support Vector Machine (SVM) was also used to classify and analyze sentiments in both positive and negative aspects. SVM learning precision and data classification in social media platforms can be enhanced using LDA for semantic extraction of the topics at the level or words' roots. On the basis of this hypothesis, following two research questions were identified: 1) What is the overall performance of aspect-level sentiment analysis based on LDA topic modeling? 2) How efficient is hybrid machine learning approach to extract aspects for sentiment analysis?

The main contributions of this research are as follows:

- Develop a topic modeling approach for aspect-based sentiment analysis applicable to any product or service.
- Specifically, identify the topics of books, electronics, video games, cell phones, luxury beauty and group their attributes into aspects.
- Adopt a hybrid approach combining supervised and unsupervised learning to perform aspect-based sentiment analysis.

2- 2- Literature Review

Researchers have mainly studied the process of sentiment analysis in three grained levels so far including the document (text) level, the sentence level, and the aspect level [12]. A commented text document (.g. a critic on a product) is classified as a text indicating a completely positive or a completely negative opinion. This type of classification considers the while text as one unit of information and assumes that the desired text is a commented text containing opinions regarding a specific entity (e.g. a certain phone). Sentiment classification at the sentence level [13] classifies the single sentences in a text; however, one cannot assume that a comment has been made in each sentence. The conventional method is to first divide the sentences into commenting and non-commenting sentences; a process called subjective classification. Then, the commenting sentences are classified into the sentences expressing positive comments and the ones expressing negative comments. Sentence-level sentiment classification can also be formulated as a three-class categorization so that each sentence can be classified as positive, negative, or neutral.

Compared to the document-level and sentence-level analysis, aspect-level analysis or sentiment analysis based on the aspect [14] is considerably more fine-grained. This analytical process extracts and summarizes users' opinions regarding the aspects/features of entities, which are called goals as well. For instance, the goal of aspect-based sentiment analysis in the case of a product's critics is to summarize the positive and negative opinions regarding the various aspects of the product, whether the overall opinion regarding the product is positive or negative. The main task of aspect-based analysis includes several sub-tasks including aspect extraction, entity extraction, and classification of aspect sentiments. For instance, in the case of the sentence "IPhone's audio quality is excellent but its battery is no good", the task of aspect extraction is to identify "iPhone" as the entity, and the aspect extraction must recognize that "audio quality" and "battery" are two distinct aspects. Aspect-level sentiment classification must also classify the sentiment expressed regarding Iphone's audio quality as a positive sentiment and the one regarding Iphone's battery as a negative sentiment. It must be noted that aspect and entity extraction are combined in many algorithms to make it work easier, and are called sentiment/opinion goal extraction or aspect extraction overall.

In user review mining, the approaches based on topic modeling and Latent Dirichlet Allocation (LDA) are important techniques used to extract the aspect of a product in aspect-based sentiment analysis [15]. The LDA approach has been proposed to address the problems and issues of LSA and PLSA algorithms [16]. LDA has been used in many sentiment analysis research works. In [17], LDA was used to understand the public response to COVID19 in Weibo. The authors collected 719,570 posts from the Weibo website using a web crawler and analyzed the data using text extraction techniques such as LDA topic modeling and sentiment analysis. Some of the results of this study indicated that in response to the COVID19, people learned about it, expressed their support for frontline workers and active individuals, give each other spiritual support, and expressed their concerns regarding life and economic revival when it some to preventive measures. Moreover, sentiment analysis indicated that the country's media and social media influencers help each other in posting positive sentiment information.

In [18], a new method is proposed to investigate the electronic reputation and negative sentiments regarding a tourism destination (Morocco in TripAdvisor) based on LDA. This study investigated around 39,216 TripAdvisor reviews from various attractions and places in Morocco to extract the latent aspects and dimensions in the reviews of tourists that have visited Morocco using LDA. Moreover, many studies using an adaptation of LDA for short texts have also been published, in which case the existing methods must be developed considering the problem of data scatter and the lack of synchronous patterns in short texts. In [15], an LDA-based method for aspect-level sentiment analysis of user reviews with short texts is proposed. The proposed method for aspect-level sentiment analysis was called the Sentence Segment LDA (SS-LDA). SS-LDA is a new adaptation of the LDA algorithm for product aspect extraction. Empirical results of examinations on some datasets revealed that SS-LDA is highly competitive in product aspect extraction. A similar work [19] was also performed social networks and micro-blogs, notably during the COVID-19 pandemic. In this work, an aspect-oriented sentiment classification was proposed using a combination of the prior knowledge topic model algorithm (SA-LDA), automatic labelling (SentiWordNet) and ensemble method (Stacking). Experimental results have shown that the proposed SA-LDA outperformed the standard LDA.

Venugopalan and Gupta [20] proposed an unsupervised approach for aspect term extraction, a guided Latent Dirichlet Allocation (LDA) model that uses minimal aspect seed words from each aspect category to guide the model in identifying the hidden topics of interest to the user. The guided LDA model is enhanced by guiding inputs using regular expressions based on linguistic rules. The model is further enhanced by multiple pruning strategies, including a BERT based semantic filter, which incorporates semantics to strengthen situations where co-occurrence statistics might fail to serve as a differentiator. The work has been evaluated on the restaurant domain of SemEval 2014, 2015 and 2016 datasets and has reported an acceptable evaluation.

Chen et al. [21] also combined user information and product information for classification but carried this out through sentence-level and word-level consideration that can account for both user priorities and product features at both sentence and word levels. Similarly, Dou [22] used a deep memory network to collect user and product information. The proposed model can be divided into two separate sections. Long Short-Term Memory (LSTM) is used in the first section to learn the display of a text. A deep memory network made up of several computational layers is used in the second section to predict the critical ranking for each text.

Mahadevaswamy and Swathi [23] investigated a technical review of sentiment analysis using a Bidirectional Long Short-Term Memory (LSTM) network. This network is deep and capable of leveraging long-term dependencies by bringing memory in the network for performing better analysis. Edara et al. [24] presented a deep learning model with LSTM network as an alternative to the classical sentiment analysis models.

Iparraguirre-Villanueva et al. [25] proposed an architecture to find out what people think about Monkeypox disease. They used a hybrid model based on CNN and LSTM architecture to determine the classification accuracy. Mohbey et al. [26] also proposed a hybrid architecture model based on CNN-LSTM models to find out people's feelings regarding Monkeypox epidemic. Their research goal was to investigate how the common sense about the Monkeypox disease to help politician in understanding of how the common views the epidemic, more deeply.

Although Recursive Neural Network with Long Short-Term Memory (LSTM) has been among the most successful techniques in many fields [27-30], but some research [13] and [14] indicate that the Support Vector Machine (SVM) approach performs better than RNN deep learning approach in terms of aspect-level sentiment analysis. Aurangzeb et al. [31] proposed an ensemble method based on the Support Vector Machine (SVM) for aspect-level sentiment analysis. Their method comprised of taking advantage of an evolutionary approach based on the Genetic Algorithm (GA) combined with the power of the SVM algorithm to examine multi-label text data. Empirical results on seven datasets (medical, hotel, movies, automobiles, proteins, birds, emotions, and news) demonstrated that using the SVM-GA algorithm outperformed many state-of-the-art algorithms such as Bayesian probability models [32] MLP and CNN neural networks [33], and multi-component learning methods [33, 35]. Therefore, this study also recommended an approach based on support vector machines combined with the advantages of LDA-based topic modeling techniques.

3- Proposed Method

Figure 1 demonstrates the process of the proposed method. The input data entering the system undergo preprocessing in the preprocessing stage, and the Eigenvalues are normalized. Then, topic modeling followed by reduction of the input data dimensions is carried out using the LDA algorithm to make the calculation more accurate and reduce calculation time. LDA observes all the words in the text, assigns the probability of each word belonging to each topic, and creates topics made out of words close to one another. Through this process, the redundant features that are not required in the analysis are eliminated, and only the features among the input data that affect the analysis remain. Then, training data extracted from the previous stage is used to build a support vector machine to train the system so that it can learn the textual sentiment analysis pattern. Thus, the build model will in fact be the base for this sentiment analysis. At the next stage, the learning model created in the previous stage is used to perform the sentiment analysis based on input data and determine what the result of textual sentiment analysis is. Eventually, we assess the extent to which textual sentiment analysis has been conducted accurately given the outputs of the sentiment analysis system, and obtain the respective assessment metrics. The details of the proposed process are discussed in the following.

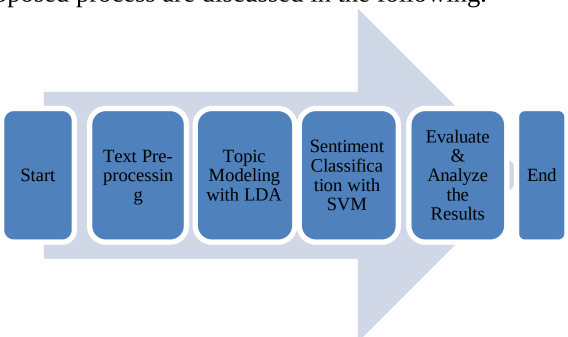


Fig. 1 The process of the proposed method

Algorithm 1 explains the details of how to use the proposed method.

Algorithm 1. Aspect-Level Sentiment Analysis Based on LDA Topic Modeling

```
   Input: Words w ∈ documents d
   Output: Sentiment
1. pre-processed text ← Pre-processing (w);
2. Topics ← LDA (pre-processed text);
3. Aspects ← Domain aspects;
4. for each Topic do
5.         Topic-Aspect mapping;
6. end
7. for each Aspect do
8.         for each Sentence words w in d do
9.                 if w contains Topic words then
10.                        Add Sentence words to Aspect sentences;
11.                else
12.                        Skip Sentence words w;
13.                end
14.        end
15. end
16.Sentiment Model ← SVMTrain (Aspect sentences);
17. Sentiment Classification Score ← SVMTest (Sentiment Model);
18. for each Aspect Sentences in d do
19.        if Sentiment Classification Score > 0 then
20.                Sentiment ← Positive;
21.        else
22.                if Sentiment Classification Score < 0 then
23.                        Sentiment ← Negative;
24.                else
25.                        Sentiment ← Neutral;
26.                end
27.        end
28. end
```

3-1- Text Preprocessing

Contrary to structured data, textual data are not easily accessible, so we have to use a process to extract the features out of textual data. One way to do so is to consider each word as a feature and find a criterion for the presence or absence of the word in a sentence or the document. This technique is called the Bag-of-Word (BoW). The first step to creating the BoW is to convert each document into a feature vector so that each vector demonstrates the words in each document. Term Frequency-Inverse Document Frequency (TF-IDF) is the conventional method to determine the importance of the words in this mode. Before any analysis, the TF-IDF data must be normalized. This section discusses how data are normalized. Suppose we have the set X with specific values as mentioned in the following equation:

$$X = \{X_1 . X_2 . \dots \ . X_n\}$$

Maximum and minimum members of the set are defined as Eqs. (1) and (2).

$$Min(X) = r \mid r \in X \ \wedge \ \forall \ s \in X : r \leq s \quad (1)$$

$$Max(X) = r \mid r \in X \ \wedge \ \forall \ s \in X : r \geq s \quad (2)$$

The set of the normalized values of each member of X normalized to fall between the values of a and b are calculated as Eq. (3) shows.

$$Norm(X) = \{ a + (b - a) * (X_i - \ Min(X) \ / \ (Max(X) - \ Min(X) \ ) \mid X_i \in X \wedge 1 \leq i \leq n \ \} \quad (3)$$

Thus, the data in the set will become more suitable for the respective analysis and comparisons.

3-2- Topic modeling of Text using LDA

Latent Dirichlet Allocation (LDA) is an unsupervised technique for the extraction of thematic information from a set of documents without labeled data. The main idea behind LDA is that documents are presented as a random combination of latent topics, each topic being the probability distribution of the words. Fig. 2 illustrates a graphic LDA model. In this figure, the nodes are random variables, the edges are the conditional relationships between the variables, and the rectangles are the iteration of the sampling steps throughout the production process by the number shown in the lower right corner of the rectangle. For instance, the inner rectangle which contains the random variables of z and w is repeated N_d times of D various documents. The variables hatched in the figure are observed variables and the non-hatched ones are the latent variables of the model.

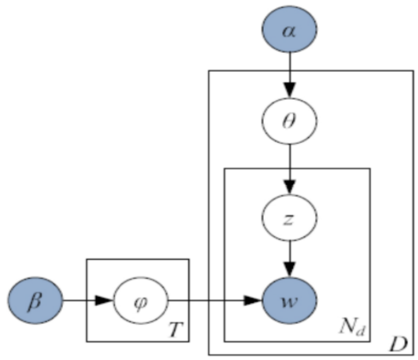


Fig. 2 The LDA structure in the form of a graphic probability model

LDA assumes that textual documents display various topics, i.e. they are made up of words that belong to various topics, and the ratio of the topics in the document varies. We can classify the document into a specific topic considering these ratios. For this purpose, a fixed set of words are considered as the glossary. The LDA method assumes that each topic is a distribution on this set of words; i.e. the words that are from one topic have a high probability in that topic. We assume that these topics are already specified. Now, we produce the words for each document among the available documents through the following two steps:

1. We randomly select the probability distribution on the topics;
2. For each word in the document:
   2.1. We specify a topic randomly using the probability distribution from the previous stage;
   2.2. We select a word from the glossary randomly given the specified probability distribution.

This probability model reflects how many topics each document is made up of. The first stage of this process demonstrates that various topics have different shares in one text. The second part of the second stage also indicates that each word in each document has been extracted from one of the topics while the first part of the second stage emphasizes that the topic has been selected from the probability distribution of topics on the documents. It must be mentioned that all documents include the same set of topics in this method, but each document incorporates different ratios of the topics.

Fig. 3 demonstrates the LDA model. M represents the number of texts and N represents the number of words in each text. The parameters of the model include:

α The Dirichlet prior distribution for the titles for each text

β Dirichlet prior distribution for the distribution of words for each title

θ_i The distribution of the titles for the ith text.

φ_k The distribution of words for the kth title

z_{ij} The latent variables of the jth word in the ith text

w_{ij} The jth word in the ith text

V the number of words

φ The $K \times V$ matrix of words' distribution for each title

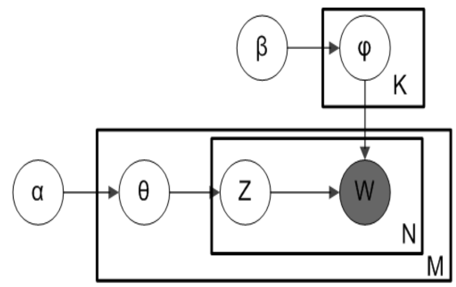


Fig. 3 The LDA model display

Only w_{ij} variables are observed and the rest are latent variables. Now, total data can be created based on the latent variables as follows:

Selecting the $\theta_i \sim Dir(\alpha)$ Dirichlet distribution for each $i \in \{1, \dots, M\}$

Selecting the $\varphi_k \sim Dir(\beta)$ Dirichlet distribution for each $k \in \{1, \dots, K\}$

For each w_{ij}:

Selecting the title of $z_{ij} \sim Multinominal(\theta_i)$

Selecting the words $w_{ij} \sim Multinominal(\varphi_{z_{ij}})$

More formally, Eq. (4) is used to calculate the word distribution according to the document.

$$p(w_i|d) = \sum_{j=1}^{K} p(w_i|z_j)p(z_j|d) \quad (4)$$

3-3- Sentiment Classification using SVM

Support vector machine is among the relatively new methods that have indicated good performance over the recent years compared to the older classification methods. The basis of the SVM classifier is linear data classification in which we try to select the line with a higher confidence margin. Solving the equation to find the optimal line for the data is performed through quadratic programming (QP) methods that are known methods used for solving constrained problems. The φ function is used to take the data to a space with a much higher dimension before the linear division so that the machine and classify highly complex data. To solve problems with extremely high dimensions using these methods, the Lagrangian duality theorem is used to minimize the problem into its dual form where a simpler function called the Kernel function which is the vector multiplication of the φ function instead of the complex *Phi* function that takes us to a space with high dimensionality.

Suppose x is the input vector in a space with m dimensions and has been transferred to the news feature space of M using the base function $\varphi_j(x), j = 1, \ldots, M$. Thus, each next m input vector of xi, $i = 1, \ldots, n$ (n is the number of samples) will be converted into a new feature vector $\varphi(x_i) = [\varphi_1(x_i), \varphi_2(x_i), \ldots, \varphi_M(x_i)]^T$. Then, the support vector separator is designed based on what was mentioned in the previous sections. The (nonlinear) function in the new feature space is created as $\hat{f}(x) = \varphi(x)^T \hat{w} + \hat{w}_0$ (the equation can be simplified assuming $\forall x: \varphi_0(x) = 1$ as the bias which is multiplied by $\hat{w}_0$). The separator is $\hat{G}(x) = sign\ \hat{f}(x)$ as it used to be. The dimensions of the new feature space can be considered extremely large or even infinite, and calculations and losing generalizability are what things that cause restrictions in this field if the base functions are not considered adequately. For instance, consider Fig. 4). This dataset cannot be simply classified with a line in the input space. Mapping to a space with greater dimensions is used in such cases.

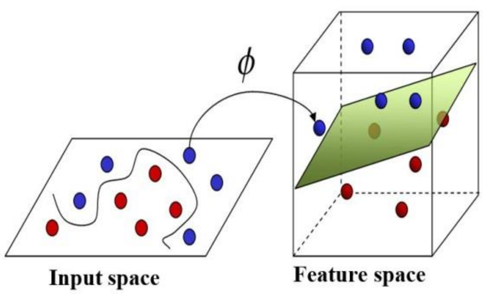


Fig. 4 Mapping a dataset to a space with greater dimensions

Thus, SVM tries to receive the input space with small dimensions and turn it into a space with greater dimensions using a method called the Kernel trick. This conversion turns an inseparable problem into a separable problem. These functions are called the Kernel functions. Kernel functions are pretty useful in nonlinear separation problems such as textual sentiment classification.

Although Kernel methods implicitly work in large spaces, it can be demonstrated that increasing the number of dimensions dies not to reduce their accuracy since the statistical learning theory has confirmed that the Kernel method's generalizability is ultimately dependent on the number of the samples classified incorrectly at the training stage. Thus, the selection of the Kernel function is the most significant issue in SVM. Many methods and principles such as Diffusion kernel, Fisher kernel, String kernel, etc. have been introduced for this purpose, and research is being carried out to obtain the Kernel matrix from the available data. In practice, a lower-degree polynomial Kernel or a Radial Base Function (RBF) kernel with an acceptable with is a good starting point. An SVM with RBF Kernel which has been used in the present study (Eq. (5)) which is quite close to RBF neural networks with Radial Base centers that are automatically selected for SVM.

$$K(X_i, X_j) = e^{-\|X_i - X_j\|^2 / 2\sigma^2} \tag{5}$$

4- Experimental Result

To evaluate the proposed method, the Amazon Review Dataset was used, which released in 2018 [36]. This Dataset includes reviews (ratings, summaries, text, time, helpfulness votes), product metadata (descriptions, category information, price, brand, and image features), and links. The data are available at https://cseweb.ucsd.edu/~jmcauley/datasets/amazon_v2/.

A real sample of customer review is shown in Fig. 5. As observable, the customer review consists of five important aspects:

- Rating: User rating of the product on a scale of 1 to 5.
- Summary: The title of the review
- Review text: The actual content of the review.
- Review time: The real time of the review (raw).
- Helpfulness: The number of people who found the review useful.

These aspects will help us comprehend and analyze the reviews to classify sentiments.

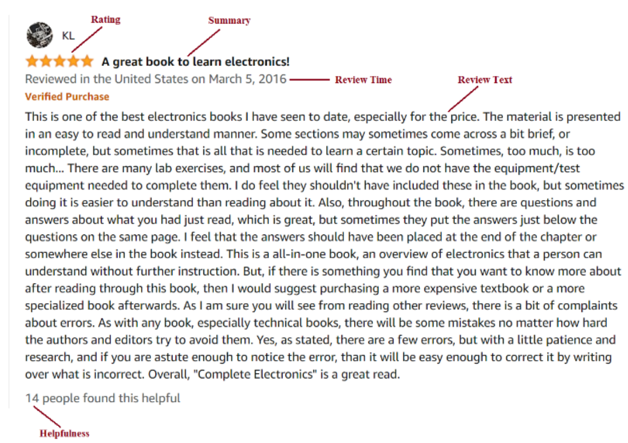


Fig. 5 Real Amazon customer review sample

The structure of the data is in JSON format as follows:

{
"reviewerID": "A2SUAM1J3GNN3B",
"asin": "0000013714",
"reviewerName": "J. McDonald",
"helpful": [2, 3],

"reviewText": "I bought this for my husband who plays the piano. He is having a wonderful time playing these old hymns. The music is at times hard to read because we think the book was published for singing from more than playing from. Great purchase though!",
"overall": 5.0,
"summary": "Heavenly Highway Hymns",
"unixReviewTime": 1252800000,
"reviewTime": "09 13, 2009"
}

We selected 5 per-category datasets, which includes 5-core reviews and product metadata for each category, mentioned in Table 1.

Table 1: Dataset description

Per-category	***Description***
Books	This category is about the reviews of books from Amazon[1].
Electronics	Electronics is a review dataset [37] collected from the Electronics category on Amazon with Clothing as an auxiliary category.
Cell Phones and Accessories	This category is about Amazon reviews predictions of Cell Phones and Accessories.
Luxury Beauty	This category performs sentiment analysis on Amazon reviews for Luxury Beauty products.
Video Games	This category is about classification and topic analysis of video game reviews, trained on Amazon user reviews.

[1] https://cseweb.ucsd.edu/~jmcauley/datasets.html#amazon_reviews

RapidMiner software was used to implement the proposed model. The parameters of SVM were set as Table 2.

Table 2: Parameter setting

Parameter	***Value***	***Description***
C	10	It is the regularization parameter, C, of the error term
kernel	rbf	It specifies the kernel type to be used in the algorithm
degree	3	It is the degree of the polynomial kernel function (‘poly’) and is ignored by all other kernels
gamma	auto	It is the kernel coefficient for ‘rbf’, ‘poly’, ‘sigmoid’. If gamma is ‘auto’, then 1/n_features will be used instead

10-fold cross-validation was used to evaluate the five groups in the dataset. This method splits each dataset into 10 random sections and considers nine sections as the training and the remaining one section as the testing set each time. Then, it implements the proposed algorithms 10 times, calculates the evaluation criteria, obtains their mean, and reports it as the final output.

The two common evaluation criteria in sentiment analysis include precision and recall, which are quite applicable and tangible in the evaluation of various data mining algorithms. Precision and recall are defined in Eqs. (6) and (7), respectively:

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

$$Recall = \frac{TP}{TP + FN} \tag{7}$$

Where TP (True Positive) represents the number of samples that have been correctly assigned to the positive class, FP (False Positive) indicates the number of samples that have been incorrectly assigned to the positive class, and FN (False Negative) represents the number of samples that have been incorrectly assigned to the negative class. It must be mentioned that positive and negative classes are the two positive and negative modes considered for the present data in the problem of sentiment classification. It can be demonstrated that every multiclass problem can easily be converted into a two-class problem by considering one class as positive and the others as negative each time. Thus, the calculations can be performed easily for the three classes of positive, negative, and neutral as well.

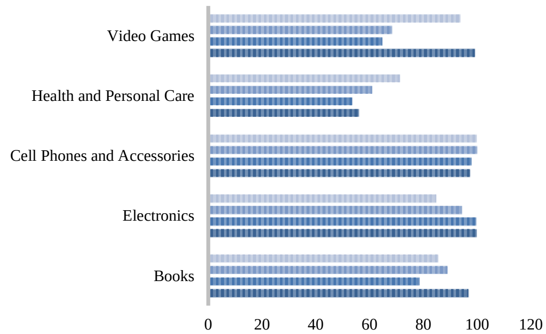
In addition to the two mentioned criteria, there are other criteria called the F-measure which is calculated based on the harmonic mean of precision and recall as indicated in Eq. (8).

$$F_{\beta} = \frac{(1+\beta^2) \times Precision \times Recall}{\beta^2 \times Precision + Recall} \tag{8}$$

One specific case of this parameter is the F-Score which equals F1 for β = 1 (Eq. (9)).

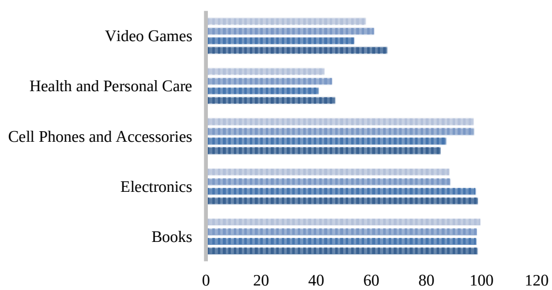
$$F_1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{9}$$

These criteria can be used to present the results of the evaluation. To conduct a comparative analysis on the proposed method, its performance was compared to the three algorithms of Bagging [38], RNN-GRU [39], and LSTM-CRF [40]. Figures 6-8 demonstrate the comparison of precision, recall, and F-measure divided by the groups using all mentioned methods. As can be observed, the percentage of the mentioned criteria generally indicated better performance for the proposed method in all datasets which reveals that the proposed method is promising.



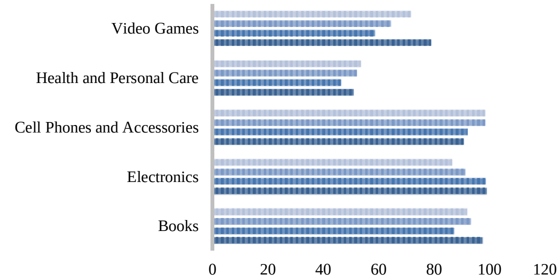
	Books	Electronics	Cell Phones and Accessories	Health and Personal Care	Video Games
Bagging	85.4	84.7	99.7	71.3	93.7
RNN-GRU	88.9	94.3	99.8	60.9	68.3
LSTM-CRF	78.6	99.6	97.9	53.6	64.7
LDA-SVM	96.8	99.7	97.3	56	99.1

Fig. 6 Comparison between the proposed method and other methods' precision (%)



	Books	Electronics	Cell Phones and Accessories	Health and Personal Care	Video Games
Bagging	99.4	88.2	97	42.9	57.9
RNN-GRU	98.2	88.5	97.1	45.7	60.9
LSTM-CRF	97.9	97.7	87	40.9	53.7
LDA-SVM	98.4	98.5	85.1	46.9	65.7

Fig. 7 Comparison between the proposed method and other methods' recall (%)



	Books	Electronics	Cell Phones and Accessories	Health and Personal Care	Video Games
Bagging	91.87	86.41	98.33	53.57	71.57
RNN-GRU	93.32	91.31	98.43	52.22	64.39
LSTM-CRF	87.19	98.64	92.13	46.4	58.69
LDA-SVM	97.59	99.1	90.79	51.05	79.01

Fig. 8 Comparison between the proposed method and other methods' F-measure (%)

Apart from the advantages of support vector machine's robustness, the use of topic modeling using the LDA algorithm improves precision, recall, and F-measure compared to the other methods. The proposed method had a favorable performance over the other methods for all cases of data with various observation probabilities, which clearly reveals its excellent performance. Although the proposed method has an insignificantly lower performance compared to the baseline method in a few cases, it leads to the best result and is the best method in most cases.

Looking at Fig. 6-8, we found that using LDA topic modeling improves the performance of aspect-level sentiment. Returning to the question raised at the beginning of this study, it is now possible to state that using the hybrid machine learning approach is efficient to extract aspects for sentiment analysis.

5- Conclusions and Recommendations

The present study proposed a new ethod for textual sentiment analysis using the approach of topic modeling based on Latent Dirichlet Allocation (LDA) combined with a support vector machine. In the process of topic modeling, each text comprises various topics and each topic includes various words. The LDA algorithm observes all these texts and tries to create topics made up of words that are semantically close to one another by assigning the probability of belonging to each topic to each word. Aside from developing the topics, it makes connections between them and the texts in the dataset. The important features that represent the thematic aspect of the text are extracted through this method and are fed to a support vector machine. The support vector machine is an extremely powerful classification algorithm that provides the possibility to accurately separate complex data from one another by mapping them to a space with extremely higher dimensions. As the results of the evaluation indicated, this approach was revealed to have higher precision, recall, and F-measure compared to the rival methods.

To extend the proposed method, deep learning techniques combined with the advantages of topic modeling can be used for deep extraction and display of the features and model long-term dependencies inherent in the text. Moreover, other semantic approaches such as semantic role labeling and the use of Ontology can also replace or be combined with topic modeling.

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