Pamukkale Univ Muh Bilim Derg, 28(5), 769-776 2022

Pamukkale Üniversitesi Mühendislik Bilimleri Dergisi

Pamukkale University Journal of Engineering Sciences

An ensemble approach for aspect term extraction in Turkish texts

Türkçe metinlerde hedef terimi çıkarımı için bir topluluk yaklaşımı

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Received/Geliş Tarihi: 09.06.2021 Revision/Düzeltme Tarihi: 09.08.2021 doi: 10.5505/pajes.2021.25902
Accepted/Kabul Tarihi: 19.08.2021 Research Article/Araştırma Makalesi

Abstract

Today, as a result of the inadequacies of the standard sentiment analysis, aspect-based sentiment analysis (ABSA) studies have great attracting interest. ABSA reveals detailed sentiment and opinion about every term/attribute in a text. The most important sub-stage of the ABSA method is the process of extracting the aspect terms from a text. This process becomes more difficult in texts with agglutinative language structures such as Turkish. In this study, we proposed an ensemble approach that uses statistical (TF-IDF), topic modeling (LDA and NMF), and rule-based methods together to extract aspect terms from Turkish user comments. The proposed method strategically combines the candidate aspect term obtained by different methods and determines the final aspect term lists. The proposed method has been tested on the SemEval-2016 ABSA benchmarking dataset, which consists of Turkish restaurant reviews. The experimental results of the proposed method were compared with previous studies on the same dataset.

Anahtar kelimeler: Aspect term extraction, Aspect based sentiment analysis, Turkish texts, Sentiment analysis.

Öz

Günümüzde standart duygu analizinin yetersiz kalması sonucunda, hedef tabanlı duygu analizi (HTDA) çalışmaları büyük ilgi görmüştür. HTDA, bir metindeki her terim/nitelik hakkında ayrıntılı duygu ve düşüncelerin ortaya çıkarılmasını sağlar. HTDA yönteminin en önemli alt aşaması, bir metinden hedef terimlerinin çıkarılması işlemidir. Türkçe gibi sondan eklemeli dil yapılarına sahip metinlerde bu süreç daha da zorlaşmaktadır. Bu çalışmada, Türkçe kullanıcı yorumlarından hedef terimlerini çıkarmak için istatistiksel (TF-IDF), konu modelleme (LDA ve NMF) ve kural-tabanlı yöntemleri bir arada kullanan bir topluluk yaklaşımı önerilmiştir. Önerilen yöntem, farklı yöntemlerle elde edilen aday hedef terim kümelerini stratejik olarak birleştirir ve nihai hedef terimleri listesini belirler. Önerilen yöntem, Türkçe restoran yorumlarından oluşan SemEval-2016 HTDA kıyaslama veri seti üzerinde test edilmiştir. Önerilen yöntemin deneysel sonuçları aynı veri kümesi üzerinde yapılan önceki çalışmalarla karşılaştırılmıştır.

Keywords: Hedef terim çıkarımı, Hedef tabanlı duygu analizi, Türkçe metinler, Duygu analizi.

1 Introduction

Today, many platforms provide users with the opportunity to share their experiences as comments as a result of purchasing a product or service. Social media applications are pioneer of those platforms. Social media applications encourage users to share their ideas and thoughts on any topic [1]. For TripAdvisor (450 million), Amazon (300 million), Uber (100 million), which have millions of users around the world, user experiences and satisfaction are of critical importance in determining product or service quality [2]. The fact that they have a strong dialogue with their users about their product or service feedback makes such institutions powerful. Service providers and consumers make informed decisions by feedback on services or products. Until recently, classical sentiment analysis approaches were preferred in the evaluation of user's feedback. Classical sentiment analysis classifies a text as positive, negative, or neutral on sentence or document level [3], [4]. However, the classical sentiment analysis approach considers the user's thoughts about the product or service in a general form. In other words, it cannot reveal the strengths and weaknesses of a product or service at an atomic level in terms of each term/attribute.

ABSA allows the revealing of sentiment and opinion about the sub-components of the product or service mentioned in a user comment [5]. ABSA is basically a current Natural Language Processing (NLP) problem that enables users to extract their sentiment and thoughts about each term/attribute of the product or service [6]. ABSA consists of two subtasks which are extraction of aspect terms and classification of aspect terms in terms of sentiment. In ABSA, an entity or feature in the text is called a term [7]. Aspect Term Extraction (ATE) is the task of uncovering attributes/terms within a user comment. The second task is the process of classifying each term in terms of sentiment. The aspect terms in an example of SemEval-2016 ABSA Turkish restaurant reviews are given in Figure 1.

Manzara güzel, ***yemekler*** güzel ama ***servis*** berbat.

Aspects	Sentiment
Manzara (view)	*positive*
Yemekler (food)	*positive*
Servis (service)	*negative*

Figure 1. An instance of SemEval-2016 ABSA Turkish restaurant reviews.

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In the review given in Figure 1, the user has a positive opinion of the view and the food, while the user has a negative opinion of the service. ABSA finds out opinions and attitudes from aspect terms in the text. In this respect, it is more difficult than standard sentiment analysis.

ATE is the most critical and difficult subtask of ABSA [8]. In a user comment on any product or service, aspect terms can be in explicit or implicit form [9],[10]. Explicit terms appear directly in the text, while implicit terms do not appear directly in the text. Implicit terms are often implied, not qualified by a name in the text. Therefore, extracting implicit terms is a more difficult than explicit terms. In addition, aspect terms can be in the form of a single word or multiple words. These difficulties in extracting aspect terms are ABSA's hot topic research areas.

The extraction of aspect terms can be divided into two subcategories as supervised and unsupervised learning-based methods [11]. The methods used in each category are given in Figure 2.

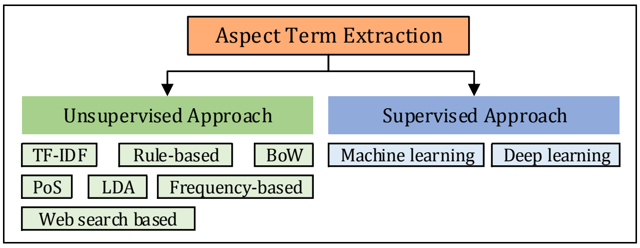

Figure 2. Aspect term extraction approaches.

In this study, an ensemble-based method, -the combination of LDA, rule-based, TF-IDF, and NMF-, is proposed to extract aspect terms from unstructured Turkish texts. In the proposed method, a series of data preprocessing is performed to reduce the unstructured data to normal form before extracting the aspect terms. Moreover, the effect of the form of the word in the text on the success of ATE was revealed in the extraction of the aspect terms. The proposed method has been run on the SemEval-2016 Turkish restaurant reviews dataset and its performance has been verified. The performance of the proposed model was found to be better than many of the previous studies on the same dataset.

This study consists of five main sections. Related words are presented in the second section. In the third section, basic information about the methods used is given. The general methodology of the study is given in the fourth section. The structure of the proposed method, dataset, and term extraction methods and results are given in this section. In the fifth section, the study is summarized from a general perspective.

2 Related work

Extraction of the aspect terms in the text differs according to the text features and language features. In [1], the Latent Dirichlet Allocation (LDA) algorithm is used to extract aspect terms from product reviews. Moreover, a dictionary-based approach used to classify aspect terms in terms of sentiment. In [8], Recurrent Neural Network (RNN) and Conditional Random Field (CRF) methods were combined to extract explicit terms. In [10], an ensemble method is proposed that uses a developed set of linguistic patterns together with Convolutional Neural Network (CNN) is proposed to extract aspect terms. While LDA used for the extraction of aspect terms in the [12], a machine learning-based ensemble learning approach used for the classification of extracting aspect terms. In [13], the aspect terms for the movie dataset reviews were obtained by a Gini Index-based feature selection method. Then, the aspect terms classified with the Support Vector Machine (SVM) classifier. In [14], aspect terms were extracted with the help of an ensemble-based model using the CRF method and the aspect term dictionary together. In [15], rule-based manual feature extraction was performed to extract aspect terms. Particle swarm optimization-based ensemble learning approach using CRF, SVM, and Maximum Entropy methods were used for feature selection. In [16], prominent terms were extracted using a contextual dictionary and Part of Speech (PoS) tags, and CRF was used for aspect term sentiment mapping. In [11], a bidirectional dependency tree network model based on Bidirectional Long Short-Term Memory (BiLSTM) and CRF is proposed to extract aspect terms. In [17], a knowledge-based stepwise method is proposed for the extraction of aspect terms. In [7], a combined K-Nearest Neighbor (KNN) and graph-based semi-supervised learning model are proposed for the extraction of aspect terms. In [18], a hybrid unsupervised learning model, which uses attention-based deep learning and language rules together, is proposed to extract aspect terms.

The task of processing Turkish texts for sentiment analysis is difficult due to the structure of the language [19]. Since Turkish is an agglutinative language, the process of extracting aspect terms is more complex than languages such as English. There are a limited number of aspect term extraction methods developed for the Turkish texts. In [19], aspect terms were manually extracted for movie reviews. In [20], aspect terms were extracted with the help of term frequencies and PoS tags. In another study aspect terms are extracted with the help of CRF algorithm [21]. In [22], a graph-based Laplace smoothing with Naive Bayes method is proposed to extract implicit aspect terms from hotel reviews. In [23], an approach that combines the frequency of words and web search frequencies is used to extract aspect terms from the texts. In [24], a rule-based method based on LDA, web search, and C-value is proposed for aspect terms extraction. In [25], LDA is used to extract aspect terms from hotel reviews. In [26], sentence segmentation-based LDA (SS-LDA) was proposed for aspect term extraction from Turkish reviews. In SS-LDA, instead of giving the sentences in the comments directly as an input to LDA, the sentences are divided into segments related to the aspect terms, and these segments are given as an input to LDA.

Considering the ATE studies on Turkish texts, it is seen that the forms of words in the text and the approaches based on the use of different methods for aspect extraction have not been investigated. In this study, an ensemble-based method, -the combination of LDA, rule-based, TF-IDF, and NMF-, is proposed to extract aspect terms from unstructured Turkish texts.

3 Background

In this section, we present briefly the background of the aspect extraction from unstructured Turkish texts. The mathematical models of these methods are not given in order to increase the readability of the study.

3.1 TF-IDF

Term Frequency-Inverse Document Frequency (TF-IDF) is a statistics-based method used to find words that represent text statistical from words in context [27]. This method is basically used to find important words in the text. It is frequently used in text mining and information extraction systems. This method makes calculations by using the frequency of a word in a document and the frequency of a word in another document together.

- **TF:** Represents the frequency of occurrence of a word in the document,
- **IDF:** Represents the frequency at which a word occurs among the documents.

Assume the context for TF and IDF calculations consists of D documents. Let's denote the set of documents as $D = \{d_1, d_2, d_3, \ldots d_n\}$ where N represents the total number of documents in the context. Here $d_n$represents a document in context. Document d consists of w_m words, m represents the number of words, let's denote document d as $d = \{w_1, w_2, w_3, \ldots w_m\}$. TF and IDF are calculated using Eq. 1 and Eq. 2.

$$TF(w,d) = \log(1 + frequency(w,d)) \tag{1}$$

$$IDF(w,D) = \log(\frac{N}{count(d \in D: w \in d)}) \tag{2}$$

3.2 LDA

Latent Dirichlet Allocation (LDA) is the most popular statistic-based topic modeling method. For LDA, it is basically assumed that a document contains more than one topic. In LDA, each topic in the document is based on the probability distribution of the words in the document [28]. This method uses the Bag of Words approach. It is an unsupervised learning method based on the principle of finding out which topic a word represents in a document with the help of Bayes theory [29]. Figure 3 shows the pipeline of the topic modeling with the help of LDA.

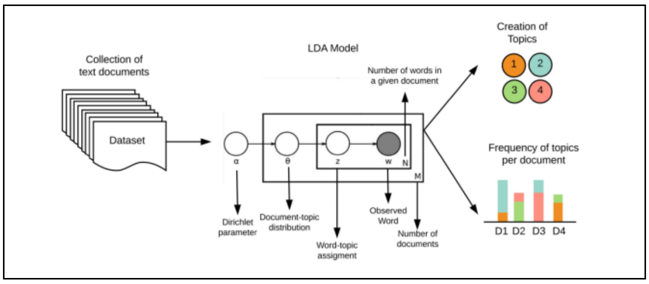

Figure 3. The pipeline of LDA for topic modeling [29].

3.3 NMF

Non-negative Matrix Factorization (NMF) is another method used for topic modeling in text contexts [30]. The NMF method was developed to reveal interpretable hidden components in datasets that of high-dimensional unlabeled data. NMF transforms the term-document matrix V into the product of W_+ and H_+ to uncover important hidden themes. The relationship between words and topics is represent by W_+ matrix. The relationship between topics and documents is represented by H_+ matrix in terms of the latent topic space. While the term-document matrix V is given as an input to NFM, it is aimed to obtain W_+ and H_+ matrices. The semantic scheme of NMF for topic modeling is given in Figure 4.

3.4 Performance metrics

The confusion matrix was used to evaluate the performance of the proposed method. The confusion matrix used to extract the aspect terms is given in Table 1. True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN) numbers were calculated according to the word sets related to the actual terms in the confusion matrix and the terms obtained from the proposed method. Accuracy, Precision, Recall, and F1 values calculated using the confusion matrix were calculated by Eq. 3, Eq. 4, Eq. 5, and Eq. 6, respectively. The performance of the model was evaluated in line with the F1 score.

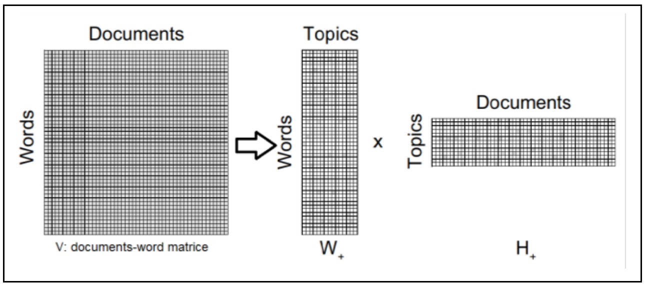

Figure 4. The semantic scheme of NMF for topic modeling [31].

Table 1. Confusion matrix for aspect term extraction.

		Predicted Values	
		Term	*Non-term*
Actual Values	*Term*	TP	FP
	Non-term	FN	TN

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

$$Recall = \frac{TP}{TP + FN} \tag{5}$$

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall} \tag{6}$$

4 Methodology

In this section, we present i- the dataset used in this study, ii- the architecture of the proposed model, iii- the results of the experimental studies.

4.1 Dataset

In this study, we used a Turkish restaurant dataset created in SemEval ABSA 2016 for evaluating the performance of the proposed method. The dataset consists of 1232 train and 183 test sentences. Moreover, 128 sentences from the training set and 20 sentences from the test set consist of non-sentiment sentences. In addition, there are a total of 881 unique aspect terms in the dataset. In the dataset, some aspect terms are "NULL", we excluded those terms from the evaluation. Since the proposed model is an unsupervised learning approach, the experiments of the proposed model within the scope of this study were carried out on the combination of train, and test set. The 10 aspect terms with the highest frequency in the dataset are given in Figure 5 with their frequency values.

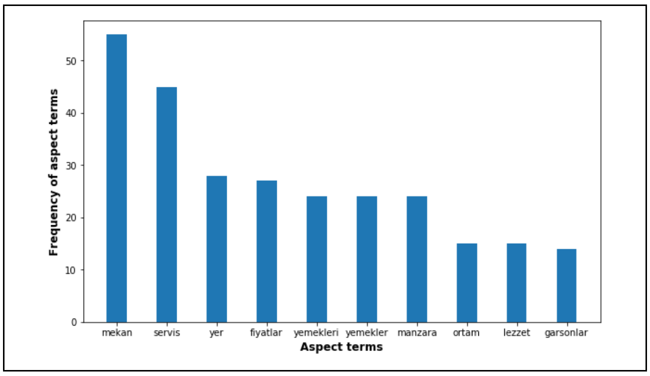

Figure 5. The 10 aspect terms with the highest frequency in the dataset.

4.2 Proposed model

In this study, the ensemble approach, which uses many statistical methods and rule-based approaches together, is proposed to extract aspect terms from unstructured Turkish texts.

Turkish is an agglutinating language; it is possible to produce new words in multiple formats by adding suffixes word roots. In this study, it is aimed to combine the power of more than one method in aspect term extraction task. The proposed method consists of four basic stages: data preprocessing, creating word forms using NLP, extracting aspect terms, and combining aspect terms strategically. The schematic view of the proposed method is given in Figure 6. A series application has been developed in the Python environment to implement the proposed method.

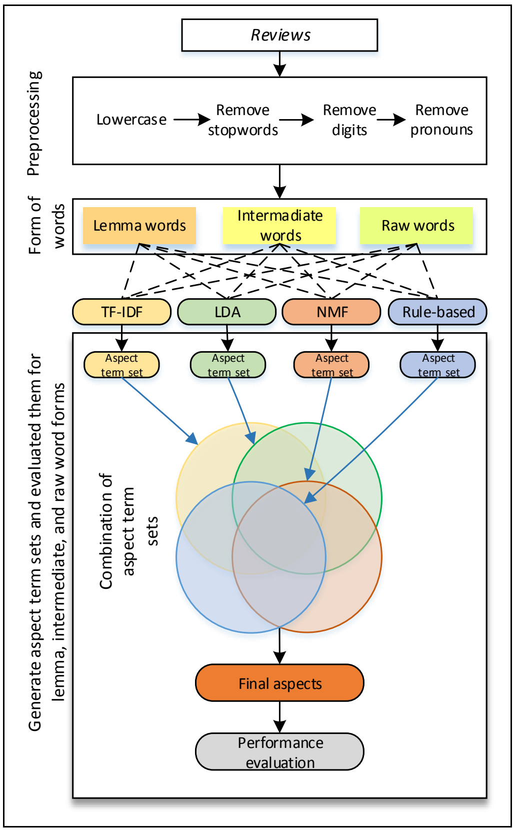

Figure 6. The proposed method: An ensemble approach for ATE.

As seen in Figure 6, user reviews are first pre-processed. After pre-processes, each token in the reviews is created in different forms such as lemma, intermediate, and raw. Candidate aspect terms are obtained with the help of unsupervised learning methods TF-IDF, LDA, and NFM on all three forms obtained. In addition to these methods, candidate aspect terms are also obtained with the rule-based approach. Finally, candidate aspect terms obtained from the aspect extraction method (TF-IDF, LDA, NFM, and rule-based) are combined with different strategies to generate final aspect terms.

4.2.1 Preprocessing of texts

Data preprocessing has positive contributions to the processing of texts with both statistical methods and machine learning methods [32]-[34]. In line with the purpose of working with data preprocessing, datasets are reduced to normal form by purifying them of noisy content. Zemberek [35], a Turkish natural language processing tool, was used for data preprocessing applied in this study. The data preprocessing applied to user comments in this study is as follows:

- **P1-Lowercase:** All characters in reviews have been converted to lowercase,
- **P2-Remove Stopwords:** Stopwords in reviews cannot be an aspect term/attribute for any product or service. Therefore, all stopwords in the reviews have been removed,
- **P3-Remove Digits:** The digits have been removed from the reviews,
- **P4-Remove Punctuations:** The punctuations have been removed from the reviews,
- **P5-Remove Pronouns:** The pronouns (ben (Eng; I), sen (Eng; you), biz (Eng; we), etc.) have been removed from the reviews,
- **P6-Remove Conjunctions:** The conjunctions (ama (Eng; but), ve (Eng; and), çünkü (Eng; because), etc.) have been removed from the reviews,
- **P7-Remove Determiners:** The determiners (bir (Eng; one), çok (Eng; much/more), az (Eng; little), etc.) have been removed from the reviews,
- **P8-remove adjective&adverb:** The adjective and adverb (yavaşça (Eng; slowly), lezzetli (Eng; delicious), az (Eng; little), etc.) have been removed from the reviews.

4.2.2 Form of words for ATE

In this study, three different forms of each word are discussed in the extraction of aspect terms. In this way, the effect of the affixes added to the word root on the derivation of terms was investigated. The data preprocessing steps applied for each word form are given in Table 2.

Table 2. The preprocessing steps applied to form of words.

Form of words	Preprocessing steps							
	P1	*P2*	*P3*	*P4*	*P5*	*P6*	*P7*	*P8*
Lemma word form	✓	✓	✓	✓	✓	✓	✓	✓
Intermadiate word form	✓	✓	✓	✓	✓	✓	✓	✓
Raw word form	✓	✓	✓	✓	☒	☒	☒	☒

The results of the proposed method were obtained for each form of the word. The forms used for words after data preprocessing are as follows:

- **Lemma Word Form:** Each new suffix added to Turkish words gives new meanings to the word. For this word form, the lemma of all the words in the user comment was taken using the Zemberek NLP tool,
- **Intermadiate Word Form:** In this form of words, no morphological process has been applied to the words,
- **Raw Word Form:** It has been used without any action on the words in the user comments. This word form is similar to the intermediate word form. However, the data preprocessing steps applied to both forms differ.

A sample comment exchange example for three word forms of a user comment in the dataset is shown in Figure 7. From the raw form to the lemma form, the text lengths shorten and the meanings of the words change. In the intermediate form, the meaning of the word in the sentence does not change, since no action is taken with the affixes of the word. In the example given in Figure 7, in the lemma form, the word "ferah (spacious)" is a noun, even though it seems like an adjective. The "ferah (spacious)" is analyzed by Zemberek as a noun. Therefore, "ferah (spacious)" was not removed as a result of P-8 which is a prepossessing step.

Raw form	"menü çeşitleri zengin fiyatları normalin biraz üstünde yinede caddedeki yorgunluğu atmanız ferah ferah oturabileceğiniz mekan"
Intermediate form	"menü çeşitleri fiyatları normalin üstünde yorgunluğu atmanız ferah ferah mekan"
Lemma form	"menü çeşit fiyat normal üst yorgun at ferah ferah mekan"

Figure 7. An example of review: Raw, intermediate, and lemma forms.

4.2.3 Generate candidate aspect terms sets

In this study, TF-IDF, LDA, NMF, and rule-based methods were used to extract aspect terms. Candidate term sets were extracted from each method for three forms of each review. Among these methods, TF-IDF generates frequency-based term sets of statistics-based words, while LDA and NMF generate candidate terms with the topic model approach. In this study, TF-IDF, LDA, and NMF were used to extract single-word aspect terms. In the dataset used in the study, there are aspect terms with two or more words. In order to extract such terms, a rule-based approach was used in line with the grammatical structure of the Turkish language. Explicit terms usually take the form of nouns within a review.

In this direction, the pseudocode of the algorithm of the rule-based approach used to extract aspect terms from two words is given in Figure 8. The PoS tag information of each word is used for rule-based aspect term extraction. In this approach, adjective/adverb + noun sequences are used to obtain terms from the review.

Candidate aspect term sets were created with the help of each method. The performance of each method was evaluated separately on those candidate aspect term sets. The candidate term sets obtained from these four methods were handled with different strategies to reveal the effectiveness of these methods. In this study, we used sklearn framework for the implementation of TF-IDF, LDA, and NMF. The hyperparameters used for TF-IDF, LDA, NMF are given in Table 3.

```
Input: Review
Output: Aspect term list
token ⟵ split review by whitespace
term_list=[]
single_term=""
for word in token
  PoS⟵ Get PoS tag of word by Zemberek
  if PoS== adjective or PoS== adverb then
    candidate_word_1 ⟵next word in token
    PoS⟵ Get PoS tag of candidate_word_1 by Zemberek
    if  PoS==Noun then
      single_term ⟵candidate_word_1
      candidate_word_2 ⟵next word in token
      PoS ⟵Get PoS tag of candidate_word_2 by Zemberek
      if  PoS==Noun then
        merged_term ⟵ merge candidate words
        Add term list to merged_term
      else
        Add term list to single_term
      end if
    end if
  end if
end for
return term_list
```

Figure 8. Pseudocode of rule-based multiple word aspect term extraction.

Table 3. Hyperparameter of LDA, NMF, and TF-IDF used in this study.

Methods	Hyperparameters
LDA	{n_components=10,max_iter=5, learning_method='online', learning_offset=50}
NFM	{n_components=10, max_iter=5, alpha=0.1, l1_ratio=0.5}
TF-IDF	{ max_df=0.80, min_df=2, max_features=1000, use_idf=False, analyzer = 'word'}

4.2.4 Combine candidate aspect terms sets

In this study, the ensemble approach was used to extract the explicit aspect terms. The aspect terms obtained by four different methods were combined in line with three different strategies to form the final aspect term list. These strategies are Union-I, Union-II and Union-III. They are as follows:

- **Union-I:** It is the final list of aspect terms consisting of aspect terms are in at least one of the aspect term sets obtained by the four methods which are TF-IDF, LDA, NMF, and Rule-based,
- **Union-II:** It is the final list of aspect terms consisting of aspect terms that are in at least two of the aspect term sets obtained by the four methods,
- **Union-III:** It is the final list of aspect terms consisting of aspect terms that are in at least three of the aspect term sets obtained by the four methods.

The TF-IDF, LDA, NMF, and rule-based aspect term sets obtained from the dataset were combined with the Union-I, Union-II, and Union-III strategies. The performances of the aspect term sets obtained as a result of each method were examined.

4.2.5 Results and discussion

The proposed ensemble method aspect terms extraction method was applied on Turkish restaurant reviews produced in the SemEval ABSA 2016. In experimental studies, first of all, explicit aspect terms in texts were extracted from lemma word, intermediate word, and raw word forms with TF-IDF, LDA, NMF, and Rule-based methods. The results of the four methods used to extract aspect terms and the results of Union-I, Union-II, and Union-III combining the results of these four methods with different strategies are given in Table 4.

Table 4. Aspect term extraction results of the proposed model in term of F1 score.

Method	Form of Words		
	Lemma Word	Intermediate Word	Raw Word
	F1 (%)	F1 (%)	F1 (%)
TF-IDF	40.78	60.07	59.64
LDA	39.66	60.23	57.88
NMF	39.93	59.64	57.34
Rule-based	25.72	40.29	38.42
Union-I	42.54	61.08	59.30
Union-II	41.13	60.97	58.88
Union-III	39.64	60.02	58.21

Regarding the results in Table 4, F1 scores of TF-IDF, LDA, NMF, and Rule-based methods in the extraction of aspect terms, it is seen that TF-IDF is better than other methods. Among the three different word forms, the intermediate form outperformed the lemma and the raw form. TF-IDF, LDA, NMF and Rule-based methods used in this study handle data with different approaches. With the proposed ensemble approach, it is seen that the combinations of the aspect terms obtained by these methods provide better performance. It is seen from the results in Table 4 that Union-I approach on the intermediate word form provides better term extraction performance from Union-I, Union-II, and Union-III methods, which are the ensemble approaches. From the experimental results, it has been seen that the use of more than one method together in agglutinative languages with complex grammatical orders such as Turkish gives good results. The confusion matrix of the Union-I method, which provides the highest F1 score in the experiments, is given in Figure 9.

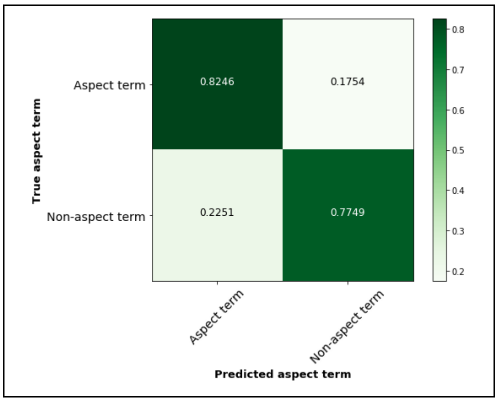

Figure 9. Confusion matrix of Union-I method.

The 10 aspect terms with the highest frequency extracted from the dataset via the proposed method are given in Figure 10. The highest frequency term extracted by the proposed method is "mekan (place)". This aspect term is also the highest frequency term in the dataset. That is, the proposed method correctly is extracted the highest frequency aspect term in the dataset.

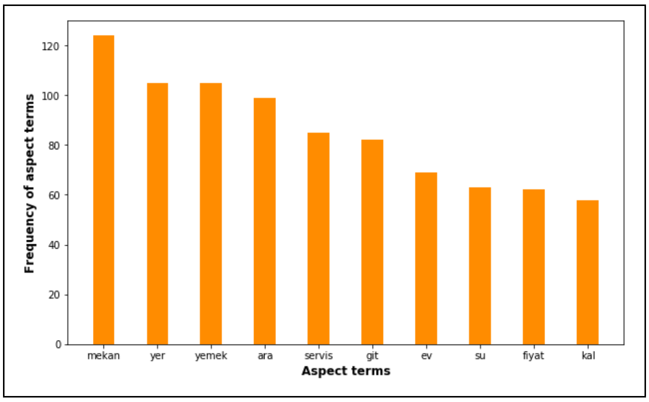

Figure 10. The 10 aspect terms with the highest frequency extracted by the proposed method.

In order to show the effectiveness of the proposed model, the results of the term extraction studies performed on the same dataset were compared with the results of the proposed method. The F1 scores of previous studies and the results of the proposed method are given in Table 5. It is seen that the proposed method is approximately 5% better than the [36], [21], and [24]. These methods treat the reviews in the dataset as a whole, as in our study. In other words, it does not ignore the parts of the reviews that are not related to the aspect terms. However, in [26], parts of sentences that are not related to the aspect terms are excluded. In other words, not all words in the reviews are used to determine aspect terms with LDA. On the other hand, although all the words in the reviews were considered as aspect terms in our study, the results of our proposed method were close to the SS-LDA results. In [26], SS-LDA requires a series of preliminary steps to extract aspect terms such as sentence segments, and grouping of sentence segments. The preliminary steps require manual operations which are the construction of Turkish sentiment dictionary, frequent nouns list, and confidence values of aspect and aspect-related words. Hence, the implementation of SS-LDA to large datasets requires more effort than our proposed method.

Table 5. Comparison of aspect term extraction results on SemEval ABSA 2016 Turkish dataset.

Reference	Method	F1 (%)
[36]	Dictionary-based	41.86
[21]	CRF	53.12
[24]	Rule-based	56.28
[26]	SS-LDA	62.25
Proposed method (Union-I)	An Ensemble Approach	61.08

The proposed method has strengths and weaknesses. One of the strengths of the proposed method is that it combines more than one method strategically. In addition, the proposed method is easy to adapt to other languages for ATE. Since the proposed method is an unsupervised learning approach, it does not require training data. Therefore, it provides an advantage in terms of the implementation of the method. On the other hand, one of the weaknesses of the proposed method is that it treats every word in the review as a possible aspect term. The important contribution of the proposed method is the determination of aspect terms with a high F1 score as a result of performing combined unsupervised learning methods on different forms of each word in the review.

5 Conclusions

Today, in addition to classical sentiment analysis studies, the interest in ABSA is increasing day by day. ABSA provides more detailed information about a product, service, or topic than classical sentiment analysis. The most critical stage of the ABSA method is ATE. In this study, a new ensemble method is proposed for unstructured Turkish user's comments.

The proposed method is based on the use of statistical, rule-based, and topic modeling methods together. The candidate aspect term sets obtained by these methods were combined with different strategies and the effective powers of these methods were combined. The proposed method was tested on the SemEval ABSA 2016 dataset, which is a Turkish aspect-based sentiment analysis benchmark dataset. As a result of the experimental studies, the effectiveness of the proposed method was confirmed. The proposed method provided a better F1 score than many of the previous studies on the same dataset. In future studies, it is planned to use deep learning methods and statistical methods together in order to extract Turkish aspect terms from Turkish texts.

6 Acknowledgment

This research has been funded by the Scientific and Technological Research Council of Turkey (TÜBİTAK) with Grant No: 119E655.

7 Author contribution statements

In the scope of this study, Mehmet Umut SALUR contributed to the formation of the idea, literature review, algorithm design, writing the manuscript. İlhan AYDIN contributed to the formation of the idea, algorithm design and reviewing the manuscript. Maen JAMOUS contributed to the obtaining results and implementation of application.

8 Ethics committee approval and conflict of interest statement

There is no need to obtain permission from the ethics committee for the article prepared.

There is no conflict of interest with any person / institution in the article prepared.

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