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LISA: Language-Independent Method for Aspect-Based Sentiment Analysis

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ABSTRACT Understanding ''what others think'' is one of the most eminent pieces of knowledge in the decision-making process required in a wide spectrum of applications. The procedure of obtaining knowledge from each aspect (property) of users' opinions is called aspect-based sentiment analysis which consists of three core sub-tasks: aspect extraction, aspect and opinion-words separation, and aspect-level polarity classification. Most successful approaches proposed in this area require a set of primary training or extensive linguistic resources, which makes them relatively costly and time consuming in different languages. To overcome the aforementioned challenges, we propose an unsupervised paradigm for aspect-based sentiment analysis, which is not only simple to use in different languages, but also holistically performs the subtasks for aspect-based sentiment analysis. Our methodology relies on three coarse-grained phases which are partitioned to manifold fine-grained operations. The first phase extracts the prior domain knowledge from dataset through selecting the preliminary polarity lexicon and aspect word sets, as representative of aspects. These two resources, as primitive knowledge, are assigned to an expectation-maximization algorithm to identify the probability of any word based on the aspect and sentiment. To determine the polarity of any aspect in the final phase, the document is firstly broken down to its constituting aspects and the probability of each aspect/polarity based on the document is calculated. To evaluate this method, two datasets in the English and Persian languages are used and the results are compared with various baselines. The experimental results show that the proposed method outperforms the baselines in terms of aspect, opinion-word extraction and aspect-level polarity classification.

INDEX TERMS Aspect-based sentiment analysis, aspect extraction, polarity classification, topic modeling.

I. INTRODUCTION

Sentiment analysis, also referred to as opinion mining, is the process of analyzing the characteristics of opinions, feelings and emotions expressed in textual data provided for a certain topic or object [1]. Sentiment analysis is widely used by companies to promote their services and products' sales [2]–[4]. In commercial business, sentiment analysis systematically models the users' requirements and views which in turn contributes to the organization's perception of the customer service. On the other hand, sentimental analysis can be leveraged for the political benefits through analyzing the voters' views toward each candidate. Through studying users' reviews in recommender systems, their interests can be extracted to offer suitable products regarding the users' tastes [5]. Generally, the role of sentiment analysis would be highlighted in any field dealing with users' views. One of the important subtasks in sentiment analysis is polarity classification. In this subtask, the semantic orientation of a text is distinguished through automatic analysis. This can be explicitly identified if the writer has a positive, negative, or neutral opinion. In particular, the polarity classification can be executed at three different levels: (a) *Document level* in which it is assumed that the whole document is about an entity and a unique polarity is determined for each document, (b) *Sentence-level* whereby only one aspect and polarity will be determined for each sentence of the document, and (c) *Aspect-level*, in which all the constituent

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aspects and their polarity are determined for each document (sentence).

Aspect-based sentiment analysis (ABSA) has recently gained significant popularity, as people may have varying opinions about different aspects of a product or entity. The three substasks that need to be performed in ABSA are as follows [1]: (1) First, aspects of each topic or entity are extracted, e.g. it should be determined that ''laptop'' has aspects such as battery, screen, price, etc. It is obvious that determining these aspects depends on the domain and may vary in each dataset. (2) The opinion words of each aspect are determined and separated from aspect words. For instance, in the aspect of price, ''reasonable'' and ''free'' are positive, whereas ''expensive'' and ''waste'' are negative words. (3) The aspect-based polarity and constituent aspects are determined. For example, a text about ''laptop'' may be positive in the aspect of ''price'', but negative in the aspect of ''battery''.

Main studies conducted in ABSA are categorized in two basic sets: supervised and unsupervised. The leading unsupervised studies are divided into two topic model-based and linguistic resources-based categories. However, there are two main challenges in the existing researches. Firstly, research on ABSA has mainly focused on English language, and it has received less attention in other languages because of their poor linguistic resources, and the lack of unsupervised effective methods for other languages. Second, in most of the available methods, only a part of the three introduced subtasks is covered, whereas for a successful ABSA system all the three should be fully executed. Thus, an unsupervised method for ABSA is proposed in this study, which not only covers all the three subtasks, but is also easy to execute on most languages, specifically those with limited linguistic resources. There are three main steps in the proposed method which is called *LISA* (Language-Independent method for aspect-based Sentiment Analysis) hereinafter:

- In the first step (Domain knowledge generation), a prior knowledge including a polarity lexicon and aspects of each topic is injected into the system. Polarity lexicon refers to terms with their associated semantic orientation (positive, negative or neutral). Due to the lack of a reliable polarity lexicon in many languages, an automatic translation approach is used to generate the polarity lexicon in the languages. Also, aspect means a collection of informative words belonging to each subtopic/property of a topic or product. To extract aspects ELDA, a method presented by the authors in [2], is employed.
- After extracting aspects and the polarity lexicon related to each language, in the second step, probability of any word associated to each aspect/sentiment is calculated in an expectation-maximization fashion. This step is inspired by the idea mentioned in [6], which is based on PLSA topic model.
- Finally, the aspect and polarity classification is rendered on the documents and the polarity of all aspects in each document is determined.

Advantages of *LISA* over conventional methods in ABSA are:

1) *Language independence*: considering that most methods of ABSA, which have led to good results, require high training dataset or various linguistics resources which are not available for many languages [7], creating an unsupervised method with high accuracy that does not depend on the writing language, would be helpful. To prove this claim, the proposed method has been evaluated in Persian as well, alongside English, and the results are presented in the evaluation section.
2) *Covering all important subtasks in ABSA, i.e. aspect extraction, opinion words identification, and aspect-based polarity classification*: Most developed methods for ABSA address some of these subtasks that only could be useful in specific conditions with no proper results in general cases. In contrast, the proposed method can be suitable for ABSA in different datasets and languages.
3) *Generating weighted polarity lexicon based on aspect*: The probability of any word is determined conditioned on each aspect/sentiment through applying LISA on each dataset. Such word sets can be seen as aspect-based weighted polarity lexicon.
4) *Proposing a customizable method*: The proposed methodology is highly customizable since it can function with varying types of aspect extraction and term weighing algorithms.

The rest of this paper is organized as follows. In the next section, previous studies and several relevant methods in the domain of aspect-based sentiment analysis are introduced. In section 3, the process of polarity lexicon generation and aspect extraction is described, followed by the description of term weighting method and its uses for aspect-based sentiment analysis. Some explanations on implementation and evaluation of the proposed system are mentioned in the fourth section. Finally, in the last section, conclusions are presented and explained.

II. PREVIOUS WORKS

Over past years, a considerable number of studies have paid attention to the domain of aspect-based sentiment analysis. At the center of almost all approaches, a polarity lexicon is used to detect and extract subjective terms in text. Polarity lexicons can be created manually [8]–[10], or semi-automatically by a small set of manually annotated terms to extract other polarity terms using different methods such as similarity measure, bootstrapping strategy or other NLP methods [11], [12]. Some other semi-automatically approaches use a linguistic resource (e.g., WordNet or a thesaurus) as the core, and employed semantic distance measures [13], [14], or analyzing the glosses and synsets (SentiWordNet) [15], for making the polarity lexicon. In addition to English, attempts have been made to build polarity lexicon in other languages including Chinese [4], [16], Spanish [17], German [18] and Arabic [5]. Along with the creation of polarity lexicon, many methods have been presented for aspect and polarity classification. Some focus on supervised machine learning methods. For example, in [19], the effect of using n-gram on different classifiers is discussed. In [20], a method for the simultaneous use of several classifiers through creating a voting system is provided and in [21] deep recurrent neural network (RNN) and support vector machine methods using lexical, word, syntactic, morphological, and semantic features are trained and compared. Another category of methods use polarity lexicon and other linguistic resources for aspect and polarity classification. For example, in [22], using the knowledge base FreeBase [23], aspect words are extracted, and then the combination of several polarity lexicons in English is used to determine the polarity at the aspect level. In [9], the performance of six acknowledged polarity lexicons in English is compared. There are also many examples of lexicon-based methods in other languages. Another group of methods is based on topic models, the most renowned of which are Probabilistic Latent Semantic Analysis [24] and latent Dirichlet allocation [25]. Methods like Topic Sentiment Mixture (TSM) [6] and QPLSA [3] are based on PLSA. TSM is a supervised method that is trained with the help of an online sentiment retrieval service. In TSM, each document is formed through sampling a mixture model including background, topic, and two (positive and negative) sentiments. In QPLSA, from each document, a number of quad-tuples (head, modifier, rating, entity) are extracted, and the aspect identification and rating are executed using the extracted knowledge and PLSA method. However, most of the mentioned methods have two problems which make them inappropriate for exploiting in different languages: (a) many methods that have achieved good results are supervised or require extensive linguistic resources. These methods need to be highly learnt and such data is not available for many languages. (b) Neglecting the covering of all subtasks in aspect-based polarity detection leads to lower performance quality of such works in different languages. The most similar studies to the proposed method are those conducted in the LDA-based methods [26]–[28]. The first activity in this category is Joint Sentiment Topic Model (JST Model) [29]. In the JST model, an additional sentiment layer is added to the basic LDA model, and the probability of the word is calculated on the condition of the topic and sentiment. In this model, the topic word is not separated from sentiment. After the JST model, the ASUM method [30] based on the fact that all words in a sentence are of a specific aspect, was proposed. To extract positive and negative aspects, two initial seeds are used, and these seeds are manually created and added to the model. The output of this model is pairs of (aspect, sentiment). In other words, in this model the aspect words are not separated from the sentiment words either. The comparisons made indicate the superiority of the ASUM model to JST [30]. Hence, in this study the ASUM method is used as one of the baselines to evaluate the proposed method. Recently, more LDA-based approaches have been proposed for ABSA, including, a model called JAST [31]

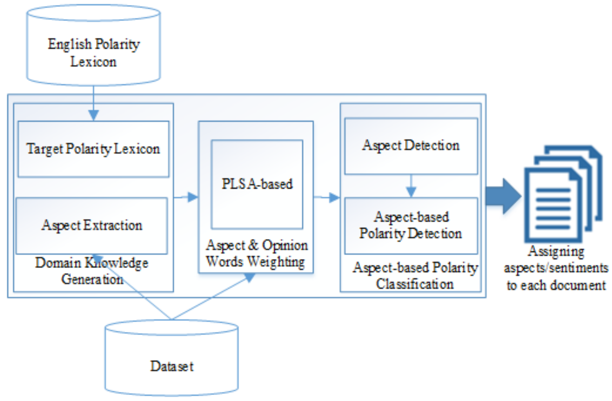

FIGURE 1. Overview of the LISA method.

(Joint Aspect Based Sentiment Topic). In JAST more focus is placed on separation of general and aspect-specific words, in addition to the common subtask in ABSA. To do so, for each specific polarity, three types of word distributions are extracted, including aspect, general and aspect-specific opinion distribution. In this method, a polarity lexicon is used for the opinion polarity of words, and also for the separation of general and aspect-specific words, and finally the method is evaluated in English. Also, in [32], a method is proposed using LDA and word embedding, in which the user must first define the desired aspects and enter an introducer word for each aspect and each sentiment, and then the system will determine polarity at the level of the aspect according to these inputs. This system is evaluated in English, Spanish, French and Dutch. But in brief, although there are different methods for ABSA, still a method that, in addition to covering all ABSA subtask, can be easily and accurately applied in different languages, is less considered. Hence, in the proposed method, these challenges are addressed.

III. LISA METHOD

In this section, an unsupervised approach for aspect-based sentiment analysis is proposed which is called LISA (Language-Independent method for aspect-based Sentiment Analysis). As shown in Figure 1 and algorithm 1, the method contains three main steps: (1) Domain knowledge generation; (2) Terms weighting; (3); Aspect-based polarity classification. The steps will be introduced in the following subsections (A to C).

A. DOMAIN KNOWLEDGE GENERATION

In the first step of LISA, called Domain knowledge generation, the prior knowledge including polarity lexicon and aspects words is injected into the system. In this section, generation and application of this prior knowledge is discussed.

1) POLARITY LEXICON

Polarity lexicon refers to terms with their associated semantic orientation (positive, negative or neutral) which is in fact the first required knowledge in many sentiment analysis systems [1]. There are several useful polarity lexicons

Algorithm 1 LISA Method

Comments:
In this algorithm, our LISA approach is outlined, which is composed of three main phases:
(I) Domain knowledge generation (lines 1-5);
(II) Term weighting (lines 6-10);
(III)Aspect-level polarity classification (lines 11-13);

Inputs:
D= $D_1, D_2, \ldots, D_n$, dataset from n domains in language lang;
EOL, Hu-Liu English Opinion Lexicon

Parameters and variables:
PL, Polarity Lexicon in target language(lang)
K, set of all aspects for each domain
d, document in domain D_i
t, term (word)
k, aspect ∈ K
l, sentiment label (positive, negative, or neutral)

Output:
List(d), set of all aspects/sentiments in document d

 # Generate the target polarity lexicon
1 **if** ∄ *reliable polarity lexicon in lang* **then**
2   *PL* ← *translation EOL to target language*
3 **else**
4   *PL* ← *lang Opinion Lexicon*
 # Extract the aspects related to each domain
5 *K* ← *ELDA(D)*
 # Initial probability of each term in any aspect/sentiment and the probability of any aspect/sentiment associated with document
6 $p^0(t|k, l)$ ← *initial based on* (6) *and* (8)
7 $p^0(k, l|d)$ ← *initial based on* (9)
8 **while** *LOG(Collection) is converged or for specific iterations* **do**
9   *Calculate hidden variable* $p^n(z_{d,t,k,l})$ *based on* (5)
10   *Calculate* $p^{n+1}(t|k, l)$ *and* $p^{n+1}(k, l|d)$ *based on* (5)
 # Predict aspects/sentiments in each document
11 **for** *each aspect/sentiment {k,l}* **do**
12   **if** *(p(k, l|d) > Threshold* **then**
13   *List(d)* ← {*k,l*}

published for English, including Hu-Liu Opinion Lexicon [13], MPQA [8], and SentiWordNet [15]. The lexicon used in this study is Hu-Liu, containing 2006 positive and 4783 negative words. But since the proposed method should be easily applicable for all languages, in case on lack of a reliable polarity lexicon in the target language, the translation of an existing polarity lexicon to the target language can be used. Even though simple translation will have deficiencies in the target language, as the major goal of using polarity lexicon is to basically train the system, the simple translation is adequate enough for generating the required prior knowledge. As mentioned, to prove independence of the language of writing, the proposed method will be evaluated in Persian as well, not only in English. To create Persian polarity lexicon, Hu-Liu lexicon is translated into Persian by means of an English-to-Persian dictionary. Regarding the polarity orientation, each Persian word has inherited the polarity (e.g. positive or negative) from the English lexicon. Once the redundant words are removed, the extracted Persian polarity lexicon contains 1014 positive and 1346 negative words.

2) ASPECT EXTRACTION

Aspect extraction is the process of extracting words related to each feature or subtopic from a specific topic or product. For instance, words like battery, charger, and charge can be an aspect in laptop. Aspects existing in each topic constitute primitive domain knowledge required for the proposed method. To extract the aspects, ELDA - a method previously proposed by authors in [2] - is used. This method is created based upon LDA topic model. In this method words' co-occurrence is used as prior knowledge in a repeating (iterative) algorithm. This knowledge is extracted form similar aspects and undergoes some filters to remove or minimize the effect of incorrect knowledge. Ultimately, adding this knowledge through basic LDA in each cycle, improves the accuracy of determined aspects. ELDA output is the aspects related to each topic, determining the number of aspects and also words of each aspect. More details of the method are presented in [2]. It should be noted that, in this step of the proposed method, any approach of aspect or topic extraction can be used, but the higher accuracy of aspects extraction leads to an overall ultimate accuracy of the method. In the evaluation section, different methods and their impact on the ultimate accuracy are compared.

B. TERM WEIGHTING

After extracting the required knowledge, the second step is terms weighting, inspired by the idea used in [6]. To introduce the proposed term weighting for ABSA, it is viewed as a generative model, i.e. when a user is going to write a special document about a product, he/she decides on the aspect firstly and then on polarity. Afterwards, the desired term is chosen from the aspect/sentiment cluster. To this end, PLSA model has been used, which is one of the most important and efficient methods of topic detection [2]. The overall schema of PLSA method is shown in Figure 2 for a document d with K aspects and T terms.

In the term weighting step, a sentiment layer is added to PLSA model, enabling it to calculate the probability of any term associated with the aspect and sentiment. Figure 3 shows the overall scheme of the step.

As can be seen in Figure 3, each document may include different K aspects and L sentiment labels and is created by repeating the following stages:

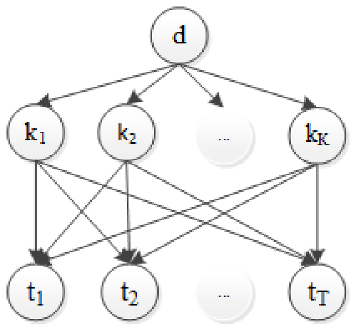

FIGURE 2. PLSA method.

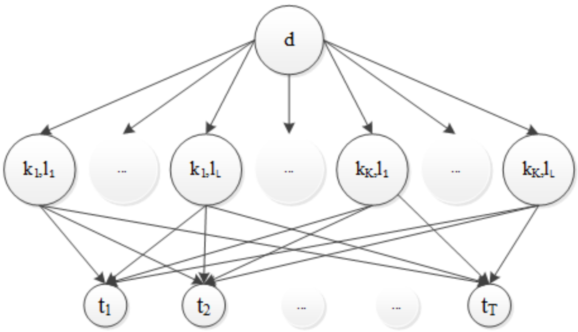

FIGURE 3. PLSA-based term weighting step.

- Choose an aspect k and a sentiment l according to conditional probability $p(aspect_k, sentiment_l|doc)$.
- Generate the term by drawing from $p(term_t|aspect_k, sentiment_l)$.

To calculate each term associated with its aspect/sentiment, the equation (1) is used where it is assumed that the number of topics and sentiment labels is fixed. In this paper, the number of aspects equals 15 for each domain and three (neutral, positive and negative) labels are assumed for sentiment labels that "neutral" shows words introducing each aspect. Also, "positive" and "negative" are the aspect's polar terms.

$$\begin{aligned} &p(term_t|doc) \\ &\quad = \sum_{k=1}^{K}\sum_{l=1}^{L} p(term_t|aspect_k, sentiment_l) \\ &\quad\quad \times p(aspect_k, sentiment_l|doc). \end{aligned} \tag{1}$$

As shown in (1), $P(term_t|doc)$ depends on the probability of the term in any aspect/sentiment as well as on the probability of any aspect/sentiment associated with the document. The formula is expressed with abbreviations for a better understanding and summarization in (2).

$$p(t|d) = \sum_{k=1}^{K}\sum_{l=1}^{L} p(t|k,l)p(k,l|d) \tag{2}$$

Considering that the term is independent, the *doc* likelihood is calculated in (3).

$$p(d) = \prod_{t=1}^{T}(\sum_{k=1}^{K}\sum_{l=1}^{L} p(t|k,l)p(k,l|d))^{TF(t,d)} \tag{3}$$

where $TF(t, d)$ is the number of term t in document d and T is the number of unique terms in corpus. Through taking logarithm of the two sides of the equation (3), the general of collection is obtained.

$$\begin{aligned} &\log(Collection) \\ &\quad = \sum_{d=1}^{N}\sum_{t=1}^{T} TF(t,d) \\ &\quad\quad \times \log\sum_{k=1}^{k}\sum_{l=1}^{L} p(t|k,l)p(k,l|d) \end{aligned} \tag{4}$$

When $LOG(Collection)$ is maximized, the final value of $P(t|k, l)$ and $P(k, l|d)$ are determined which are the probability of each word conditioned on each aspect/sentiment and the probability of each aspect/sentiment conditioned on each document. It is worthy of note that the two constraints $\sum_{t=1}^{T} p(t|k,l) = 1$ and $\sum_{k=1}^{K}\sum_{l=1}^{L} p(k,l|d) = 1$ are always true in the process, meaning that the sum of each word's probability in each aspect/sentiment equals one, and that each document is thoroughly covered by the aspect/sentiments. To maximize $LOG(Collection)$, an Expectation-Maximization (EM) approach is used and the values of the two probabilities $p(t|k, l)$ and $p(k, l|d)$ are computed in a loop until the LOG value is converged in a specific value; in this state, the local maximum for $p(t|k, l)$ and $p(k, l|d)$ are calculated. As shown in (5), as shown at the bottom of the next page, in each iteration, the hidden variable $p^n(z_{d,t,k,l})$ is determined. Then, $p(t|k, l)$ and $p(k, l|d)$ are computed based on this variable.

But for proper functioning of the proposed weighting method, a proper initial value is required, for which the extracted prior knowledge is used. In this case, $p^0(t|k, l = \text{"}neutral''\text{)}$ is given values based on (6), as shown at the bottom of the next page. In (6), $DF(t)$ is the document frequency of the term t in the dataset, N is the number of documents in each domain and k is the set of extracted words for aspect k. POS (NEG) and $|POS|$ ($|NEG|$) are the set and size of positive and negative words, respectively.

For aspect, positive and negative words weighting, the extracted prior knowledge are used. According to (6), if extracted words for each aspect are not in positive and negative sets, they gain high probability for being neutral in the aspect. Other terms except polar words are also given a mere probability, which increases in the repetition procedure of (5), in case they are related to the aspect. But, polar terms have no chance to get probability in neutral sentiment. To determine the probability of a term in each aspect being positive (negative), the equation (7) defined in [2] is used to calculate the relation between two words.

$$Rel(t, t') = \frac{\sum_{d\in D|(t,t')\in d} \frac{1}{|d|}}{\sum_{d\in D|t'\in d} \frac{1}{|d|}} \tag{7}$$

According to (7), the higher co-occurrence of the terms t and t' and also more specific term t' in the dataset can cause the higher relation of the two terms. Further, the size of the document is used to normalize and minimize the effect of document size. In (8), the probability of each word's positivity (negativity) in each aspect defined based on relation, is calculated.

$$p^0(t|k, l = \text{“positive”}) = \begin{cases} \dfrac{\sum_{t' \in k} Rel(t, t') + \frac{1}{|POS|}}{\sum_{t' \in POS} \sum_{t'' \in k} Rel(t', t'') + 1} & if (t \in POS) \\ 0 & else \end{cases}$$

$$p^0(t|k, l = \text{“negative”}) = \begin{cases} \dfrac{\sum_{t' \in k} Rel(t, t') + \frac{1}{|NEG|}}{\sum_{t' \in NEG} \sum_{t'' \in k} Rel(t', t'') + 1} & if (t \in NEG) \\ 0 & else \end{cases} \quad (8)$$

According to (8), as the relation of positive (negative) terms with the terms of an aspect increases, their probability of being positive (negative) is higher. In other words, the positivity of each term in each aspect is determined based on its relation with the aspect's terms. Please note that, in this paper, the separation of aspect and polar word is rendered based on polarity lexicon. Although assuming the terms that are not in the polarity lexicon as likely aspect terms and vice versa, may not always be correct, but as shown in [31], the separation can produce reasonable results. For assigning initial values to $p(k, l|d)$, equation (9) is used. According to (9), each document is covered equally with all aspects/ sentiments.

$$p^0(k, l|d) = \frac{1}{K \times L} \quad (9)$$

After the initialization step, EM algorithm is iteratively performed to calculate the probability of each term conditioned on aspect/sentiment and the probability of each aspect/sentiment conditioned on the document.

C. Aspect-level polarity classification

The third and last step in LISA is aspect and polarity classification. At this stage, aspects in each document are detected and the polarity in each aspect is also determined. Different approaches can be employed to detect aspect and polarity based on the calculated probabilities in the previous stage, for instance summing up the probabilities of all words in each aspect/sentiment, or using aspect/sentiments as a classifier's training set and then determining the class of each document. But in the proposed method, since in the previous step $p(k, l|d)$ is also calculated alongside $p(t|k, l)$, the $p(k, l|d)$ is used to determine the aspect and polarity. For each document, the aspects/sentiments with a probability greater than a certain threshold are chosen as document constituent aspect/sentiment. In the next section, we will evaluate the proposed method and the impact of each step on the results.

TABLE 1. List of product domains from Persian dataset.

#	Category	#Sentences
1	Laptop	20000
2	Phone Case	14000
3	Cell Phone	20000
4	Computer	20000
5	Networking	14000
6	Laptop Accessories	20000
7	Tablets	20000
8	Computer Accessories	10000
9	Camera	20000
10	Office Supplies	20000
11	Cell Phone Accessories	20000
12	Camera Accessories	20000
13	Drives and Storage	20000

IV. EXPERIMENTS AND RESULTS

This section evaluates the proposed method in three different subtasks. To do so, first, the efficiency of the method in aspect extraction is investigated. Then the accuracy of opinion words is evaluated and ultimately, polarity classification is carried out. Since the proposed method is claimed be easily useful for languages with limited linguistic resources, evaluations will be carried out in the Persian language in addition to English. To run the evaluation and comparison four baselines are used:

- LDA: A well-known method in topic modeling, which is unsupervised and is used only to identify the topic [25].

$$p^n(z_{d,t,k,l}) = \frac{p^n(t|k, l)p^n(k, l|d)}{\sum_{k'=1}^{K} \sum_{l'=1}^{L} p^n(t|k', l')p^n(k', l'|d)}$$

$$p^{n+1}(t|k, l) = \frac{\sum_{d=1}^{N} TF(t, d)p^n(z_{d,t,k,l})}{\sum_{d'=1}^{N} \sum_{t'=1}^{T} TF(t', d')p(z_{d',t',k,l})}$$

$$p^{n+1}(k, l|d) = \frac{\sum_{t=1}^{T} TF(t, d)p^n(z_{d,t,k,l})}{\sum_{k'=1}^{K} \sum_{l'=1}^{L} \sum_{t'=1}^{T} TF(t', d')p(z_{d,t',k',l'})} \quad (5)$$

$$p^0(t|k, l = \text{“neutral''}) = \begin{cases} \dfrac{\frac{1}{DF(t)} + \frac{1}{N-(|POS|+|NEG|)}}{\sum_{t'=1}^{T} \frac{1}{DF(t')} + 1} & if (t \in k \wedge t \notin POS \wedge t \notin NEG) \\ \dfrac{\frac{1}{N-(|POS|+|NEG|)}}{\sum_{t'=1}^{T} \frac{1}{DF(t')} + 1} & if (t \notin k \wedge t \notin POS \wedge t \notin NEG) \\ 0 & if (t \in POS \vee t \in NEG) \end{cases} \quad (6)$$

TABLE 2. An example of extracted aspects (Incorrect words are underlined in red and aspect categories are specified manually).

PRICE& SHIPPING				STORAGE DEVICES			
LISA	ELDA	LDA	ASUM	LISA	ELDA	LDA	ASUM
price	price	price	laptop	drive	hard	drive	drive
money	money	review	great	netbook	drive	windows	hard
buy	buy	machine	price	memory	memory	hard	memory
model	worth	worth	computer	card	sd	system	dvd
purchase	waste	star	money	dvd	external	dvd	windows
extra	purchase	shipping	product	external	disk	cd	netbook
deal	model	design	buy	cd	card	software	disk
apple	cost	cost	worth	disk	dvd	window	cd
shipping	expensive	money	love	file	flash	home	slow
cost	deal	case	apple	slot	thumb	xp	system

```
<sentence id="79:3">
    <text>super fast processor and really nice graphics card..</text>
    <Opinions>
        <Opinion category="CPU#OPERATION_PERFORMANCE" polarity="positive"/>
        <Opinion category="GRAPHICS#GENERAL" polarity="positive"/>
    </Opinions>
</sentence>
```

FIGURE 4. An example of SemEval 2016 task 5 English laptop dataset.

- ELDA: A method for determining the aspects of a topic that uses the knowledge in similar aspects to improve LDA [2].
- ASUM: Unsupervised and LDA-based approach for aspect and polarity detection that uses two initial positive and negative seeds.
- P-ASUM: It is the application of ASUM for Persian. In this method, the translated version of Hu-Liu lexicon is used instead of the original Lexicon.

A. DATASETS AND PRIMARY SETTINGS

To evaluate the proposed method, three different datasets are used. First, a Persian dataset that has been collected from online shopping websites in Persian, containing 13 different product domains related to electronic goods. This set is part of the dataset used in [2]. In Table 1, a list of product names along with the number of sentences in each document is presented.

Second, the English Dataset used in LTM (Dataset 1K) contains 50 different domains, each containing 1000 documents. Details of this dataset are found in [33]. Since both introduced datasets only contain documents in each domain, and the aspects of each document, as well as the polarity of each aspect are not specified, for the polarity classification, the dataset of the SemEval 2016 workshop is used. This dataset includes 2500 English sentences in the context of the laptop, and for each sentence, the constituent aspects as well as the polarity of each aspect are determined. In Figure 4, an overview of a document from this dataset is given.

According to Figure 4, the sentence expressed in the tag text includes two aspects, CPU and Graphics, where the polarity is positive in both. In order to evaluate the proposed method in ABSA, sentences of this dataset have been added to the laptop domain of the LTM dataset, and all evaluations are performed on this hybrid dataset, later called the

TABLE 3. Topic coherence of each model on the Persian and LTM+ corpora.

	LISA	ELDA	LDA	ASUM
LTM+ dataset (Sentence-based)	-9649.5	**-9334.5**	-9593.6	-9772.8
Persian dataset (Sentence-based)	-9139.3	**-8154.7**	-8481.6	-8218.1
Persian dataset (Document-based)	-3951.7	-3332.9	-3543.5	**-2946.9**

TABLE 4. Comparing Log(collection) for different iteration.

	LTM+ dataset (Sentence-based)	Persian dataset (Sentence-based)
Iter0	-74919	-511632
Iter1	-54845	-328124
Iter2	-50451	-316271
Iter3	-46946	-309473
Iter4	-44738	-305446
Iter5	-43376	-302878

LTM+ dataset. To perform evaluations, all documents are first broken into constituent sentences, and each statement is assumed in the form of a document (except in evaluations that both document-based and sentence-based are tested), then stop words and low-frequency words are removed. In all evaluations for each domain, 15 aspects are extracted, and in each aspect, 20 words are considered as aspect introducers. In addition, assigning values to all parameters of ELDA and the other baseline methods are performed according to their original articles.

B. ASPECT EXTRACTION

As stated, in the proposed method, extracted aspects by the ELDA method are used as the prior knowledge, and finally, after executing the EM algorithm, words with the highest probability $p(t|k, l = \text{``}neutral\text{''})$ are chosen as introducer words for each aspect. To assess the accuracy of aspect extraction in Table 2, the output of the words for the proposed method and baselines are compared.

According to Table 2, extracted words in the proposed method and ELDA are more related words and contain more knowledge about each aspect. In order to have a more precise evaluation, the aspects are compared in terms of the topic

TABLE 5. Examples of polar words of the laptop doamin.

PRICE & SHIPPING (POSITIVE)		PRICE & SHIPPING (NEGATIVE)		BATTERY (POSITIVE)		BATTERY (NEGATIVE)	
LISA	ASUM	LISA	ASUM	LISA	ASUM	LISA	ASUM
worth	easy	expensive	hard	impressed	works	useless	impressed
free	cheap	wrong	bad	excellent	fast	complaint	hot
reasonable	cheaper	junk	free	powerful	great	fault	warm
bargain	expensive	waste	problem	better	free	error	wrong
convenience	worse	fool	fault	awesome	odd	doubt	solid
accurate	free	hater	disappointed	worked	useless	difficult	cheap
fun	support	cheap	trouble	perfect	cheapest	hassle	fancy
winner	satisfied	fault	wrong	satisfied	perfect	joke	sturdy
fancy	reasonable	warning	waste	genuine	hard	issue	problem
saving	timely	flaw	lost	pretty	wow	needles	handy

coherence [34]. This criterion is given in (10).

$$C(A, V^{(a)}) = \sum_{m=2}^{M} \sum_{l=1}^{m-1} \ln\left(\frac{CODF(v_m^{(a)}, v_l^{(a)}) + 1}{DF(v_l^{(a)})}\right) \tag{10}$$

In (10), $V^{(a)} = (v_1^{(a)}, ldots, v_M^{(a)})$ is a list of M words with the highest probability in aspect A, which is assumed 20 in this paper, DF represents the document frequency and $CODF$ the co-occurrence rate of two terms in different documents. In Table 3, the mean of topic coherence in various topics related to the proposed method and baselines is presented in two Persian and LTM+ datasets. The results are reported based on the last execution cycle of each method. In the Persian dataset, the results are presented in two modes: document-based and considering each sentence as a sentence-based document.

According to Table 3, the best results obtained in the sentence-based mode are those related to ELDA. In ELDA, a prior knowledge based on co-occurrence of terms is used to improve aspects, and since co-occurrence plays an important role in the topic coherence criterion, the results are predictable. In the document-based examination, the results of ASUM are better than the rest of the modes. In ASUM, the words of each sentence are considered of an aspect, so finally the words of the frequent sentences are commonly identified as aspects. So the presence of excessive redundant sentences in the documents improves coherency. But it should be noted that co-occurrence alone cannot be a good criterion for measuring the accuracy of the aspects; for example, in the extracted aspects of the proposed method, there is stronger semantic relationship than LDA and ASUM, examples of which are presented in Table 2. Therefore, in the following sections, a more precise comparison of the proposed LISA method and the effect of the aspect extraction accuracy in ABSA is discussed.

C. POLAR WORD DETECTION AND WEIGHTING

After the prior knowledge generation step, EM algorithm is iteratively performed to probability of each term conditioned on aspect/sentiment is achieved. Various repetitions increase the amount of $LOG(Collection)$ and thus a relative optimum for probabilities is achieved. In Table 4, the mean of $LOG(Collection)$ is presented in five iterations of LISA in the Persian and LTM+ datasets.

TABLE 6. Precision@10 of the LISA and P-ASUM models on the Persian dataset.

	ASPECT	LISA	P-ASUM
Laptop	Battery	0.73	0.57
	Purchase	0.77	0.67
	Display	0.87	0.57
	Memory	0.80	0.43
	Average	**0.79**	**0.56**
Camera	Battery	0.67	0.47
	Purchase	0.70	0.60
	Display	0.90	0.67
	Memory	0.67	0.67
	Average	**0.74**	**0.60**
Tablet	Battery	0.77	0.57
	Purchase	0.73	0.67
	Display	0.93	0.80
	Memory	0.80	0.47
	Average	**0.81**	**0.63**
Mobile	Battery	0.87	0.60
	Purchase	0.73	0.63
	Display	0.90	0.63
	Memory	0.90	0.60
	Average	**0.86**	**0.62**
Average		**0.796**	**0.603**

According to Table 4, the execution of each iteration improves the $LOG(Collection)$ and, consequently, leads to a more appropriate weighting for the probabilities. In Table 5, examples of polar words of the laptop domain, related to the LISA and ASUM methods, are presented. After the qualitative examination of extracted words, since extracted words have ranks, pericision@10 criterion is used for the quantitative comparison. In this criterion, the top 10 words of each category are extracted and manually labeled to related and unrelated. The precision@10 is calculated based on the manually tags in Persian dataset. To this end, for the four products - laptop, camera, tablet, and mobile phones - positive, negative and neutral words are considered in the four aspects of battery, quality, display, and memory. According to Tables 5 and 6, the best results are from the proposed method. Accordingly, the addition of polar and aspect words and the implementation of the EM method to achieve a relative optimum, improve the extracted words.

D. ASPECT-LEVEL POLARITY CLASSIFICATION

In the last assessment, the accuracy of the LISA in aspect and polarity classification is discussed. For this purpose, as stated

TABLE 7. Categorization of datasets in 15 aspects.

1	BATTERY & POWER_SUPPLY
2	DISPLAY
3	MULTIMEDIA_DEVICES
4	HARDWARE & MOTHERBOARD & HARD_DISC& OPTICAL_DRIVES
5	FANS_COOLING
6	GRAPHICS
7	OS & SOFTWARE
8	LAPTOP (GENERAL & MISCELLANEOUS & USABILITY)
9	LAPTOP (PRICE) & SHIPPING
10	LAPTOP (CONNECTIVITY) & PORTS
11	LAPTOP (OPERATION_PERFORMANCE & QUALITY & DESIGN
12	SUPPORT & WARRANTY & COMPANY
13	CPU & MEMORY
14	LAPTOP (PORTABILITY)
15	KEYBOARD & MOUSE

TABLE 8. Precision, recall and F-measure of the LDA, ELDA, ASUM and LISA methods.

		Equality	+1	+2	+3
Precision	LDA	0.42	0.37	0.34	0.32
	ELDA	0.46	0.41	0.37	0.35
	ASUM	0.31	-	-	-
	LISA	**0.49**	**0.46**	**0.44**	**0.42**
		Equality	+1	+2	+3
Recall	LDA	0.42	0.57	0.65	0.71
	ELDA	0.46	0.62	0.70	0.76
	ASUM	0.31	-	-	-
	LISA	**0.49**	**0.69**	**0.81**	**0.89**
		Equality	+1	+2	+3
F-measure	LDA	0.42	0.45	0.45	0.44
	ELDA	0.46	0.49	0.48	0.48
	ASUM	0.31	-	-	-
	LISA	**0.49**	**0.55**	**0.57**	**0.57**

above, the SemEval 2016 dataset is used in the context of laptop. First, the categories in this dataset are divided into 15 groups (equal to the number of extractive aspects of the methods), as shown in Table 7. After segmentation, the accuracy of the aspect detection is first measured. This measurement takes place in four different modes. In first mode, the number of extracted aspects of methods is exactly equal to the number of aspects in the dataset, and in the next three modes there are respectively 1, 2 and 3 aspects more than the datasets. For example, consider Figure 4, the document has two aspects, thus, in the case of equality two aspects, and in +1, +2 and +3 modes, there are respectively 3, 4, and 5 aspects extracted through various methods, and on this basis precision, recall and F-measure are calculated. It should be noted that in the baselines, the probability of aspect on condition of the document is used to extract the aspects. Table 8 shows the results.

Examining the results of Table 8 reveals that one of the reasons for the weakness in results is the existence of the general aspect (aspect 8 in Table 7). Therefore, experiments were repeated with the removal of the general aspect, the results of which are given in Table 9.

Table 9 indicates that removing the general aspect has improved the results of all methods, which is due to the interference of the general aspect with other aspects. Among the methods compared, the proposed method has operated better than others, which shows that the extraction of a prior knowledge and proper weighting can result in improved aspect detection. ELDA is the second best method, which is used as the prior knowledge in the proposed method. In the ELDA method, similar aspects are used to increase the accuracy of the aspects in the basic LDA method. The ASUM has the lowest results and only one aspect is detected for each sentence, so this method cannot function properly in sentences with multiple aspects. After examining the aspects extaction, the accuracy of the polarity classification is tested. For this purpose, the polarity accuracy is calculated for aspects that are properly assigned to documents. In this comparison, aspects with neutral polarities is not considered and only the positive and negative polarities are measured. Also, to examine the influence of language dependent methods, the proposed method is tested by adding negation. For this purpose, the prefixes 'not', 'no', 'n't', and 'never' are used, and wherever these terms are seen, the first next word (after removing stop word and low frequency words) gets a "not_" prefix. Also, all positive words in the lexicon are added to negative words with the prefix "not_", and the process is also performed for negative words, vice versa. Finally, the proposed method is implemented once in the new state and the results are presented in Tables 10 and 11.

According to Tables 10 and 11, the role of negation in improving the accuracy of sentimental analysis is discussed by comparing LISA with negation and original LISA method. As shown, the accuracy of LISA has only decreased about 3% when the role of negation is eliminated. Therefore, the proposed LISA method can properly detect polarity even without

TABLE 9. Precision, recall and F-measure of the LDA, ELDA, ASUM and LISA methods after the removal of general aspect.

		Equality	+1	+2	+3
Precision	LDA	0.55	0.45	0.40	0.33
	ELDA	0.60	0.51	0.45	0.41
	ASUM	0.41	-	-	-
	LISA	**0.62**	**0.53**	**0.49**	**0.45**
		Equality	+1	+2	+3
Recall	LDA	0.55	0.65	0.71	0.75
	ELDA	0.60	0.71	0.76	0.80
	ASUM	0.41	-	-	-
	LISA	**0.62**	**0.76**	**0.85**	**0.89**
		Equality	+1	+2	+3
F-measure	LDA	0.55	0.53	0.51	0.46
	ELDA	0.60	0.59	0.57	0.54
	ASUM	0.41	-	-	-
	LISA	**0.62**	**0.62**	**0.62**	**0.60**

TABLE 10. Accuracy of polarity detection after the removal of general aspect.

	Equality	+1	+2	+3
LISA	0.73	0.71	0.70	0.70
LISA + Negation	0.75	0.73	0.73	0.73

TABLE 11. Accuracy of polarity detection with the general aspect.

	Equality	+1	+2	+3
LISA	0.75	0.75	0.74	0.73
LISA + Negation	0.77	0.78	0.77	0.77

adding negation, and can be used in different languages, without the linguistic resources.

V. CONCLUSION

This paper presents a novel unsupervised aspect-based sentiment analysis method called LISA. To propose this method at the first phase, a preliminary polarity lexicon and aspect sets are selected. Then, an EM algorithm which is based on PLSA is fed by these sets. Finally, the aspects and polarities of any document in aspect-level polarity classification step is determined. The comparison of proposed LISA method with the introduced baselines indicates that prior knowledge and suitable term weighting improve the accuracy of aspect and polarity detection. This improvement shows that the polarity of any term is tightly associated to its aspect. Moreover, the proposed method eliminates the disadvantage of language specification method and proposes a general approach for different languages. For future research, studying other weighting methods and aspect extraction algorithms, and their effect on the final result can be suggested. Also, adding a language dependent section to the proposed method can be an interesting idea. In this case, if a language has linguistic resources or semantic rules such as negation or intensifier determination, adding these to the basic method can improve the results.

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