Persian Sentence-level Sentiment Polarity Classification

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***Abstract*—Assigning positive and negative polarity into Persian sentences is difficult task, there are different approaches has been proposed in various languages such as English. However, there is not any approach available to identify the final polarity of the Persian sentences. In this paper, the novel approach has been proposed to detect polarity for Persian sentences using PerSent lexicon (Persian lexicon). For this, we have proposed two different algorithms to detect polarity in the sentence and finally SVM, MLP and Naïve Bayes classifier has been used to evaluate the performance of the proposed method. The SVM received better results in comparison with Naïve Bayes and MLP.**

***Index Terms*—Sentiment Analysis, Persian, Machine Learning**

I. Introduction

Analysing of web content is becoming very important due to augmented communication via Internet, and the number of online opinions has been increased. Therefore, the sentiment analysis has been introduced to classify the data based on their polarity. The sentiment analysis is automated application that can be used in different field to structure the data [1]–[7]. Analyse of sentiment has been spread into different fields such as marketing, sport, movies, news etc. There are lots of opinions available online about different product and service, and sentiment analysis can help users to make better decision by recommending pros and cons of a product. For example, if someone decide to buy a laptop, they can read these online opinions and decide which laptop is better [8]–[21]. It is noted that 90% of users' reads online reviews and opinions before they make buying decision [22]–[25]. The recent studies focused on issues in different types of opinions to determine the knowledge gaps and discover the future challenges [26]–[28].

There is huge amount of data available online in different languages and in unstructured form that need to be converted into useful form. To overcome this challenge most of approaches has been proposed in English language and other languages e.g. Persian. Where Persian language is less developed to overcome this challenge, therefore, this paper focused on identifying the polarity for Persian sentences [29]–[31]. In this paper, the novel framework has been proposed to detect Persian sentences polarity. For these two algorithms has been proposed to detect polarity in the Persian sentences. The first algorithm detects part-of-speech (POS) tag in Persian sentences, it detects tag such as adjective, adverb, noun and verb in the sentence, the second algorithm is used to detect negation in the sentence, PerSent lexicon has been used to assign polarity to the detected POS features. Section II provides the related work, section III is provides the methodology, section IV is experiment and result and finally section V concludes the paper.

II. Related Work

In this section, the related work for sentiment analysis will be discussed, there are various approaches to detect polarity in the sentence.

- Document level: In the document level, the task is to understand the overall polarity of the whole document. For example, the document contains various positive and negative comments about different product, the final polarity of the document will be identified.
- Sentence level: The task is determining whether the expressed sentence is positive, negative or neutral [10], [32].
- Aspect level: The task in aspect level is to identify the different aspect of the sentence, for example, من سرويس رستوَران دوست دَاشتم ولي غذَا دوست ندشتم ("I like the restaurant service but I did not like the food"), the tone of sentence is negative but some aspect is not negative, the aspect level extract these features from sentence, the "restaurant service" and "food" غذَا سرويس رستوَران will be extracted from sentence.

Ikeda et al, [33] proposed an approach for detect polarity in English for movie reviews. First the data is collected, after pre-processing, there are different features such as unigram, bigram and trigram are selected. The proposed approach achieved accuracy of 76%.

Choi and Cardie etl at, [34] proposed an approach to identify the polarity of the sentence using novel technique which is used lexicon to find the characteristic of data directly. This method is used to find the relation and characteristic between words and sentences. The proposed system received better performance to detect negative sentences in compare to positive sentence. Alamoudi et al, [35] proposed a novel model based on the rating-based feature and evaluate features using English document sentiment analysis. There are n-gram features has been extracted to evaluate the performance of the system. The overall performance of the system was 93.24%.

Basiri et al. [36] addressed the problem of lack of resources in Persian by developing a lexicon and an automatically labelled sentence-level corpus. A Naive Bayes classifier was trained on the collected corpus to determine the polarity in short sentences. However, the proposed approach is lack of comparison results with the state-of-the-art approaches. In addition, Ebrahimi et al. [37] proposed a method to detect polarity in Persian online reviews based on adjectives extracted from the sentence and translated SentiWordNet lexicon. However, the proposed method is limited to adjectives and it does not exploit nouns, adverbs and verbs that provide extra information on the underlying sentiment. Moreover, Razavi et al. [38] detect polarity based on extracted nouns and adjectives and a Persian lexicon. However, the proposed approach do not exploit the word order and hierarchical semantic dependency.

Recently, Zhao et al. [39] proposed a model to detect sentiment in product reviews using deep learning classifiers. The words are first converted into an embedding vector representation and then a deep learning classifier is used to classify sentiments. The experimental results showed the effectiveness of their proposed CNN (87%) as compared to LSTM (82%). Sohangir et al. [40] proposed a framework to detect sentiment in the financial market. The StockTwits dataset was used, and feature selection method such as chi-square was used to select features. Finally CNN classifiers were used to evaluate the performance of the approach. The proposed framework obtained an accuracy of 70.88%. Wagh et al. [41] proposed an approach to identify the sentiment in tweets and twitter API utilized to collect the tweets. Different classifiers such as Naive Bayes and Logistic Regression were used to evaluate the performance of the approach. Experimental results showed that logistic regression achieved better accuracy as compared to Naive Bayes. Pitsilis et al. [42], proposed a framework to discern hateful content in social media using LSTM classifier. The authors collected data from Twitter and fed extracted features into an LSTM classifier. The results demonstrated the effectiveness of LSTM as compared to SVM.

The table I summarise some of the existing approaches of sentiment classification polarity for various languages.

III. Methodology

In this section, we will discuss about proposed framework to detect polarity in Persian language sentences. The figure below display the proposed framework to identify the polarity of Persian language sentences.

The algorithm shows in Fig 2 has been proposed to identify the final polarity of Persian sentence. The JHAZM part-of-speech tag of tag has been used to identify the tag for Persian sentence.

The algorithm shows in Fig 3 has been proposed to identify the negation in the Persian sentence, if word نبود is appeared in the sentence with positive polarity, change the overall polarity into negative and if this word is appearing with negative polarity change polarity into positive.

Pre-processing: The pre-processing step is consisting of tokenisation, normalisation and stop words removal. The tokenisation is processing of breaking texts into single tokens, normalisation is processing of removing noised in the text. For example, فيلم عَاَاَالي بود (The movie was greatttt) will be changed into فيلم عَالي بود (The movie is great) and stop word is removing unnecessary words such as به از (from, to etc.).

PerSent lexicon: In order to identify the polarity of Persian sentences, the PerSent lexicon will be used, the lexicon contains 1500 Persian words along with their part-of-speech tag and their polarity [43]–[46].

Persian polarity: In order to calculate the overall polarity of the sentence, the noun, adjective, adverb and verb are extracted from the sentence. The tag such as determiners are discarded. The following equation has been used:

$$Sp = \frac{Np + Vp + AVp + ADJp}{n} \tag{1}$$

Sp denote the sentence polarity, N-p denote the noun polarity, Vp denote verb polarity, AV-P is adverb polarity and ADJ-P denotes adjective polarity. For example, فيلم خوبي بود (The movie was great), فيلم NOUN, خوبي ADJECTIVE, بود - VERB. The adjective and verb is extracted and the PerSent lexicon will used to identify the polarity of the sentence, the formula number one has been used to calculate the overall polarity of the sentence. Once the polarity of the sentence has been identified the following rules has been used to identify the whether sentence is positive, negative or neutral.

If sentence polarity is greater than 0 then the polarity of the sentence is positive, if it is less than 0 is negative and equal to 0 is neutral.

IV. Results and Discussions

Dataset: The Persian movie review dataset has been used to evaluate the performance of the proposed approach, the table below display the result of proposed approach. The JHAZM is Python tools for Persian NLTK contain part-of-speech tag, dependency parser, normalisation and stemming. The movie reviews contain 1000 positive and 1000 negative sentences. The movie has been collected from www.caffecinema.com and

TABLE I
COMPARISON OF THE CURRENT APPROACHES

Reference	Language	Accuracy	Comments
Li et al, 2013	English	66.60%	Detecting polarity based on the rules
Barbieri et al, 2016	Italian	71.84%	It used to detect irony in the Italian sentence
Jie et al, 2009	English	63.74%	It is used to detect word polarity.
Remus et al, 2010	German	74.40%	It is used lexicon to identify polarity of German words
Shoukry, and Rafea, 2012	Arabic	72.60%	It is used to identify polarity of Arabic Sentence
Martín-Valdivia et al, 2013	Spanish	75.30%	It is used to identify polarity of Spanish sentences
Ghorbel, and Jacot, 2011	French	93.50%	It is used to identify final polarity of French movies

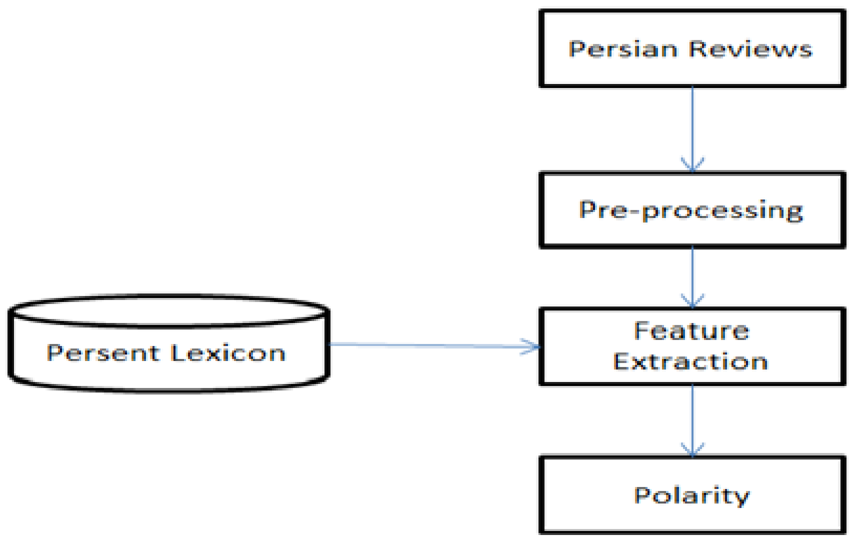

Fig. 1. Proposed Framework for Persian Sentiment Analysis

www.cinematicket.org, the collected movie reviews are from 2014-2017 movies.

The SVM (standard vector machine) classifier has been trained, the JHAZM (Persian NLTK Python tool) has been used to extract part-of-speech tag of the Persian sentence, the adjective, noun, adverb and verb has been extracted from sentence, then SVM classifier has been trained, 10-fold cross validation has been used. The combination of the feature received better result in compare with other extracted features. The SVM, MLP and Naïve Bayes classifier trained using Sklearn and 10-fold cross validation has been used.

The SVM is received better performance in comparison with Naïve Bayes classifier. The mixture of part-of-speech tag (adjective, adverb, noun and verb) received better performance in comparison with other features. The mixture of bigram features and part-of-speech feature received better performance in comparison with other unigram and part-of-speech tag features.

The adjective is performed better in comparison with other part-of-speech tag because the adjective is identified the polarity of the sentence. The weakness of proposed approach for Persian sentence polarity detection is not able to handle sarcasm in the sentence, it is required to develop system to detect sarcasm in the sentence, the further study is required to detect ironic and sarcasm in the sentence to improve the performance of the approach. The Table 4 display the example of Persian sentence polarity detection approach, the input sentences, English translation and final polarity of the sentence.

V. CONCLUSION

In this paper, a novel approach has been proposed to identify the polarity of the Persian sentences, the approach has been proposed to extract POS tag of the Persian sentence, then PerSent lexicon (Persian lexicon) has been used to assign polarity to extracted features and SVM, MLP and Naïve Bayes classifiers has been used to evaluate the performance of the approach. In the future work, we will develop an approach of multilingual polarity detection for Persian, Arabic and English.

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TABLE II
RESULT OF NAIVE BAYES

Feature	**Accuracy**	**Feature**	**Accuracy**
Unigram	68.78%	Bigram + Adjective	74.28%
Bigram	73.32%	Bigram + Adverb	73.56%
Adjective	73.07%	Bigram + Verb	73.31%
Adverb	65.56%	Noun + Verb + Unigram	72.57%
Noun	72.05%	Adverb + Noun + Unigram	74.68%
Verb	67.74%	Adjective + Verb + Unigram	75.19%%
Noun + Verb	72.23%	Adjective + Noun + Unigram	76.34%
Adverb + Noun	73.97%	Adjective + Adverb + Unigram	74.23%
Adjective + Verb	74.13%	Noun + Verb + Bigram	72.57%
Adjective + Noun	74.82%	Adverb + Noun + Bigram	74.68%
Adjective + Adverb	73.32%	Adjective + Verb + Bigram	75.19%%
All POS Tag	81.24%	Adjective + Noun + Bigram	76.34%
Unigram + Adjective	73.09%	Adjective + Adverb + Bigram	74.23%
Unigram + Adverb	69.21%	All POS + Unigram	78.97%
Unigram + Verb	68.97%	All POS + Bigram	79.36%
Unigram + Noun	72.58%	All POS + Unigram + Bigram	78.15%

TABLE III
RESULT OF MLP

Feature	**Accuracy**	**Feature**	**Accuracy**
Unigram	69.53%	Bigram + Adjective	74.89%
Bigram	74.98%	Bigram + Adverb	75.61%
Adjective	74.69%	Bigram + Verb	74.96%
Adverb	66.09%	Noun + Verb + Unigram	73.46%
Noun	73.42%	Adverb + Noun + Unigram	73.39%
Verb	69.45%	Adjective + Verb + Unigram	69.67%
Noun + Verb	73.25%	Adjective + Noun + Unigram	74.69%
Adverb + Noun	74.01%	Adjective + Adverb + Unigram	74.92%
Adjective + Verb	73.97%	Noun + Verb + Bigram	75.23%
Adjective + Noun	74.89%	Adverb + Noun + Bigram	76.01%
Adjective + Adverb	74.72%	Adjective + Verb + Bigram	75.98%
All POS Tag	82.23%	Adjective + Noun + Bigram	74.78%
Unigram + Adjective	74.21%	Adjective + Adverb + Bigram	76.53%
Unigram + Adverb	69.75%	All POS + Unigram	80.29%
Unigram + Verb	70.68%	All POS + Bigram	81.41%
Unigram + Noun	74.38%	All POS + Unigram + Bigram	80.02%

TABLE IV
RESULT OF SVM

Feature	**Accuracy**	**Feature**	**Accuracy**
Unigram	75.63	Bigram + Adjective	79.61
Bigram	75.92	Bigram + Adverb	80.01
Adjective	78.93	Bigram + Verb	76.57
Adverb	74.21	Noun + Verb + Unigram	77.36
Noun	75	Adverb + Noun + Unigram	81.89
Verb	70.61	Adjective + Verb + Unigram	82.96
Noun + Verb	75.03	Adjective + Noun + Unigram	82.3
Adverb + Noun	74.63	Adjective + Adverb + Unigram	82.64
Adjective + Verb	74.59	Noun + Verb + Bigram	79.73
Adjective + Noun	79.63	Adverb + Noun + Bigram	82.34
Adjective + Adverb	80	Adjective + Verb + Bigram	86.68
All POS Tag	81.29	Adjective + Noun + Bigram	87.4
Unigram + Adjective	76.39	Adjective + Adverb + Bigram	88.37
Unigram + Adverb	75.93	All POS + Unigram	88.53
Unigram + Verb	75.11	All POS + Bigram	88.62
Unigram + Noun	74.6	All POS + Unigram + Bigram	89.62

Input: Persian sentences

Output: Polarity

Split the sentence into POS tag

If tag **Adjective** available in the lexicon:

Calculate polarity

else

continue

If tag **Adverb** available in the lexicon:

Calculate polarity

else

continue

If tag **Verb** available in the lexicon:

Calculate polarity

else

continue

If tag **Noun** available in the lexicon:

Calculate polarity

else

continue

If tag contains polarity

Calculate average to find overall polarity

end

Fig. 2. Proposed Algorithm for Persian sentence-level Sentiment Analysis

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Input: Persian Negation

Output: Polarity

If Sentence contains “نبود” (Not) and overall polarity for tag is above 1

Change polarity to -1

Else

Change polarity to +1

Fig. 3. Proposed Algorithm for Persian sentence-level Negation Sentiment Analysis

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