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A review of studies conducted in opinion mining

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Abstract: *With the advent of Web 2, the required platform for commenting and sharing it in web space was provided for users, and it became a part of the daily activities of the users in cyberspace. Besides that, the emergence of social networks and boom of these networks intensified these activities, and today users' comments are frequently found in cyberspace. Unlike the past, users can easily express their views on political, sporting, or economic events, or they can even comment on a commodity they have bought and share their satisfaction or dissatisfaction of the purchased goods and make it available to other users. Today, prior to buying a product, every person looks for the comments of those who have purchased and used this product. All these reveal the importance of opinion mining field. Opinion mining (OM) area looks for a way to classify these comments. This is because due to the high volume of these opinions, one cannot manually review and sum up these comments, and the advantages of today's technologies must be used to analyze and classify these comments. Sciences such as data mining, text mining, and the methods used in natural language processing are used for OM.*
Key words: *opinion mining,genetic algorithm , evolutionary algorithm, sentiment analysis*

INTRODUCTION

The history of OM and sentiment analysis dates back to late 1990, but it was in early 2000 that it received more attention and became one of the important fields of information management. Until early 2000, sentiment detection approaches were mostly based on machine learning techniques, and then gradually natural language processing techniques were used in this field [1]. Real applications mentioned above are just some of the reasons of popularity of sentiment analysis among researchers. Sentiment analysis is known an NLP problem. Before the year 2000, little research had been done in this area. One reason is that there were a small number of texts in digital format. Since 2000 onwards, this area has increasingly grown and is now one of the most active research subjects in the field of NLP. This issue is examined in the areas of Data Mining, Web Mining, and Information Retrieval as well. In fact, sentiment analysis and OM are expanding from computer science to other fields such as management science. In the next sections, we will first have an overall review of the research conducted from the beginning to now, and then studies conducted in Persian language will be discussed in specific.

2. Overview

Carbonell did one of the first activities in the field of OM and sentiment analysis (SA) in 9791. He designed a computer model of mental understanding. This model modeled political opinion of an individual from the Liberal

Party or the Conservative Americans according to the policy of the United States and Russia as well as international politics [2]. Hearst (1992) used the method based on natural language processing to classify documents based on emotion and not based on subject. He classified the whole document sentiment based on linguistic models [3]. In 1997, the first dictionary of OM terms was created using the syntax. In 1997, McKeown and Hatzivassiloglou classified words based on their semantic trends and used semantic tendency of the words or phrases in the text to determine the total semantic orientation of text [4]. Then in 2000, Subasic and Huettner created a fuzzy dictionary manually for emotional classification of text in the field of identifying the emotional load of the words by combining natural language processing and fuzzy logic techniques. Table 1 shows the number of articles found in Google Scholar database based on Opinion Mining and Sentiment Analysis keywords until 2013.

Table 1: The number of articles found in the database Google Scholar [5]

Original Language	2013	2012	2011	2010	2009	2008	2007	2006	2005	2004	2003	Total
Chinese	19	23	9	10	5	4	3	2	1	-	-	76
Arabic	9	6	5	-	-	-	-	-	-	-	-	20
Spanish	6	7	-	1	1	-	-	-	-	-	-	15
German	1	3	-	2	-	1	-	-	-	-	-	7
Italian	1	3	-	2	-	1	-	-	-	-	-	7
Farsi	2	-	-	-	-	-	-	-	-	-	-	2
Independent of language	542	467	303	228	163	87	49	36	10	11	2	1900

3. English

English as an international language, in addition to being used to connect people in the world, but it is also the scientific language as well, and all articles are written in this language. Besides that, many studies have been done on this language. OM field is no exception. From the beginning, OM has been very popular in English and thousands of articles have been published in this area. According to Lu Bing's claim in his book [6], until 2015, about 1500 articles have been published in this area, most of which are about the English language. In this paper, we try to discuss the most prominent studies in OM in the English language. In English, three data sets are used as reference datasets and many papers take use of these data sets to prove the effectiveness of their methods. At the end of this section, we introduce the best algorithms presented for OM in English ever. You will see that today, the proposed methods for English OM have reached accuracy over 90%. Reaching that accuracy represents that OM capabilities can be easily used in other areas. Three approaches have been proposed for OM. In this section, we will provide all successful research in all three approaches briefly. Those studies have been selected for presentation that in addition to being successful have simpler structure, and by reading them, the reader realizes the method of use easily [7].

3.1. The approach of using machine-learning algorithms

Peng and Li [8] have done the first work in the field of OM using this approach in 2002. In this study, three machine-learning algorithms, Naïve Bayes, Maximum Entropy and SVM, have been used to classify the film opinions in positive and negative groups. In this study, the datasets used are in the film field collected from imdb.com website. This dataset contains 1000 positive and 1000 negative film opinions. At the stage of feature-selection, three features of single word, two words, and three words are used. Single word feature means every word examined alone. Two-word feature means two words used together as a unit to be investigated. Three-word feature means three words used together as a unit to be investigated. For example, in the sentence “I think it was an excellent film” is examined as “I” “think” “it” “was” “an” “excellent” “film” in single-word feature. Besides these features the words presence or non-presence has been taken into consideration. At the end of the study, two-word feature and SVM algorithm with accuracy of 28.9 percent are introduced as the best feature and algorithm. This research has been effective in two ways: first, because it is known as the first article in OM and after this study, the attention of researchers was drawn to this field. Second, this is because dataset of this article has been used in the future by many other data to test the proposed method. Moreover, researchers have regularly considered this dataset as valid dataset. This research is the most successful study in OM with five thousand citations. In another study, Zhang et al. [9], using two famous algorithms of machine learning, NaiveBayes and SVM, try to classify dataset consisting of the opinions on a restaurant. The main objective of this study is to evaluate the effect of feature selection and feature size on the accuracy of OM. In this study, a comprehensive set of features is discussed: single-word, two-word, and three-word features and presence or absence of words. Along with that, the size of feature from 50 to 6100 features was considered as variable to be able to obtain the best feature selection and feature size. The dataset studied included 5100 positive and 5100 negative opinions about the restaurant. Finally, the highest accuracy was when the number of features has been from 900 to 1100 and using these features, NaiveBayes algorithm has been obtained. According to the claim of the authors in this study, accuracy 59.6 has been obtained.

3.2. Dictionary using approach

Another approach of OM is the use of dictionary for classifying opinions. In this approach, helping resources are used for classification. These sources can be a dictionary, search engine, or a set of adjectives and adverbs. The advantage of these non-supervised methods is that, there is no need for data for labeling, and the data is labeled without the data, and this classification can thus be done that is a great advantage. In supervised methods, to create the model, data must be available based on labeling that is sometimes a time-consuming and difficult task. The first study of this approach has been conducted by Thorne [10] in 2002. This article aims to calculate PMI for each word and this is done by searching any word with two words “poor” and “excellent.” Each word is first searched by the explorer with two mentioned words and based on the number of words searched the positivity or negativity of each word is detected. If a word is positive, according to the authors' claim, when searched with the word “excellent,” more searches can be obtained because this word is used in positive texts more frequently than in negative texts. The dataset used in this study includes 410 opinions in various areas. The highest accuracy reported in this article is 84% that was obtained in the range of cars and the lowest was 66% for comments on the film, but the average accuracy for all domains have been reported about 74%. The success of this study was in that it could attract the researchers' attention from machine learning algorithm methods to unsupervised methods. This research, with more than four thousand citations, is the second successful work in the field of OM. Lou and Friends [11] try to use adverbs and adjectives on opinions in Chinese for OM. Positive and negative power of the sentence can be obtained by multiplying adverb into adjectives. Power of adjectives is done by adjectives rules and link analysis and power of adverbs has already been determined from -1 to +1. A total of 100 adverbs and 3497 adjectives have been used in the classification. The dataset contains 2000 positive and 2000 negative comments. The area where the opinions are collected is hotel area. At the end of their stay, hotel guests have published their opinions. According to the authors' claim, the best accuracy achieved is 71.65. In this study, the only features used are Chinese adjectives and adverbs.

3.3. The Combined approach for OM

In combined approaches, it is tried to use the advantages of both approaches supervised and unsupervised. In combined approaches, both external sources and machine learning algorithms have been used. Dong et al. [21] have tried to boost the efficiency of emotional classification by combining the two approaches, machine learning, and semantic-emotional approach. For this, three types of features have been used; the first two types have been created using machine learning and the third type by using emotional approach. In the third type features, by using Senti Word Net, the emotional charge of each feature is marked, and if the emotional charge is not neutral (positive or negative), it adds it to the feature set for training the model. In this study, two data sets are used. One famous Blitz [13] dataset and other dataset collected from criticism of online products. Finally, using Information Gain technique, feature selection is done and the features whose IG is higher than 0.0025 are deleted. The authors claim that with a low number of features, one can present more accurate and efficient OM methods. in terms of mining methods to than could be provided. In the end, according to the authors, 84 percent accuracy is obtained.

Bohol Maqed et al. [14] proposed a hybrid approach to review OM in Arabic. In this paper, it is tried to use Arabic adjectives and SVM algorithm to test OM on various Arabic sources. The adjectives used in this article are 3982 collected manually. The adjectives collected have later been used as a feature in SVM algorithm. The dataset of the article is very diverse. Dataset includes 2798 chats, 3015 tweets, 3008 sentences from Arabic Wikipedia, and 3097 sentences from forums. The existence of diverse and numerous dataset make the study exempted from dependencies of data because one of the charges against OM is over dependence of the method to its training data. Claimed accuracies for this combined approach are 73% for tweets, 84% for forums, and 70% for chat and

Wikipedia. This study describes the quality of combined methods in a simple way. Then, using adjectives, the necessary features are prepared and these features are sent to machine learning algorithms to classify. By combining machine learning techniques and dictionaries, Ortigoy et al. [15] have tried a new method for OM on Facebook Comments. They first created an emotional dictionary to use in this approach, and in the next stage, the created dictionary was used for classifying datasets using machine-learning algorithms such as SVM, decision trees, and Naive Bayes. The dataset used in this study consists of 3000 Facebook posts composed of 1000 positive, 1000 negative, and 1000 neutral messages. The highest accuracy reported in the study is 83.27 percent.

As noted, OM studies have a long history in the English language and methods with a precision of 90 percent are obtained. The most successful methods proposed for OM have been shown in Table 2. In this table, three shared datasets were used by researchers as a dataset whose methods were assessed. These three datasets are the most prestigious and the most basic datasets in the language English. In Table 2, the best results obtained with the use of these dataset have been introduced.

Table 2: Results obtained in the English language until 2015 [7]

Row	Articles	Dataset	Results
1	[16]	Pang and Lee [17]	92.70% accuracy
2	[18]		90.45% F1
3	[19]		90.2% accuracy
4	[20]		89.6% accuracy
5	[21]		87.70% accuracy
6	[22]		87.4% accuracy
7	[23]		86.5% accuracy
8	[24]		85.35% accuracy
9	[25]		81% F1
10	[26]		79% accuracy & 86% F1
11	[27]		76.6% accuracy
12	[28]		76.37% accuracy
13	[29]		75% precision
14	[30]		79% precision
15	[31]	Pang et al. [8]	Approx. 90% accuracy
16	[32]		88.5% accuracy
17	[33]		87% accuracy
18	[8]		82.9% accuracy
19	[16]		78.08% accuracy
20	[34]		75% accuracy
21	[29]		60% precision
22	[35]		86.04%
23	[12]	Blitzer et al. [13]	84.15% accuracy
24	[36]		80.9% (Avg.) accuracy
25	[21]		85.15% (Avg.) Max. 88.65%
26	[32]		88.7% accuracy
27	[27]		71.92% accuracy
28	[9]	Other(restaurant)	95/6% accuracy
29	[14]	Other(forum)	84% accuracy
30	[15]	Other(facebook)	83/27% accuracy
31	[10]	Other	74% (AVG.) Max. 84% accuracy
32	[11]		71/65% precision

To be able to properly compare the proposed methods in text mining and OM sciences, the approaches should be assessed based on a common set of data. In this paper, we briefly describe these three datasets that have been formed in the table above based on comparing different methods on this data.

Table 3: Standard datasets in English

Dataset	Negative	Positive	Neutral
Pang and Lee[8]	1000	1000	0
Pang and Lee[17]	1250	1250	2500
Blitzer[13]	1000	1000	0

As you can see in Table 3, the first dataset is related to Pang and Lee that is considered as the first theoretical work in OM. In this dataset, we have 2000 film opinions composed of 1000 positive and 1000 negative opinions. In the second dataset, Pang and Lee have released a more complete dataset. In this dataset, there are 5000 thousand film opinions, of which 2500 are neutral, 1250 negative, and 1250 positive. In the third data set that has been prepared by Blitz, 2000 opinions including positive and negative were presented, but the difference of this dataset is collecting product opinions. Blitz has collected these goods opinions using Amazon website.

4. Application

Due to the 15 years of efforts of the scientists about OM in English language, today, we witness methods in OM with high precision of 90%. The new approach is using this field for real-life applications. In this section, we will discuss briefly the areas that have benefited from OM in recent years. The use of OM has a wide range. In this part, we will only try to mention some to explain the importance of OM for the audience [7].

4. Prediction of box office

One of the areas where OM has found application is predicting box office. The first study in this area has been conducted in 2010. This study sought to anticipate events, using social networks. In this paper [37], by collecting 2.9 million tweets from the Twitter social network in a 42-seven-month period about 24 films, it is tried to predict the sales of box office of these films.

First, tweets are collected and then their being positive or negative is determined by OM. In this case, box office sales of the movie have been determined based on the rate of positive or negative tweets. The accuracy of prediction by this method is reported to be 98%. The authors claim that in addition to the box-office of movies, using social networking, we can predict everything based on the rate of attention positive and negative opinions. This high success rate of his study in predicting the box office of the films led to prevalent use of OM to predict a variety of topics. In addition to the article cited, several studies have been conducted to predict the sale of goods, videos, and other cases using three supervised, unsupervised and combined approaches

4. 2. Predicting the rate of stock

In this area, the purpose of using OM is to classify people's feelings about various companies and predicting the stock price of these companies based on people's opinions about them.

Ballen et al. [38] conducted a comprehensive investigation to find out the relationship between people's moods and daily rates of stock prices. In this study, using two tools, Opinion Finder to detect positivity, negativity, and GPOMS as a measure of the mood of the people, have been used on tweets. To find the relationship between mood and stock price by nearly 8.2 million tweets, 9850498 tweets produced during 8 months by about 2.8 million users, Dow Jones stock average rate has been studied. According to the authors' claim, there is a significant relationship between Exchange rate and mood of the people, and by OM of people's tweets, one can have an accurate prediction of stock price in the coming days. OM of tweets has been considered based on positive and negative groups of people, happy or sad moods, but in GPOMS, moods have been divided into 6 groups: cheerful, kind, reliable, comfortable, worried, and vital. In this research, with OM of tweets and mood analysis of Google, it has been tried to get people's moods, and then by checking the stock price, the relationship between these two was established. This study has highly been regarded research, and it has been a leading article in this area.

3.4. Business analysis

OM could also be considered in business analysis. Companies and firms can use OM of their customers to adopt strategies and ways to solve their problems. Kasment et al. [39] try to predict the status of newspapers in terms of number of subscribers by examining the contents of the emails exchanged between a newspaper and its subscribers. In this study, using OM, the relationship between newspapers and their subscribers is determined and thus the future status of the number of subscribers. In this study, dataset includes 18331 e-mails that have been purchased from a Belgian newspaper. Then, using LIWC software, OM is done on the contents of the email. Supervised and unsupervised methods are used together for OM. Finally, authors' claim is that based on the relationship between a company and its customers, one can accurately predict the future of this relationship. Data mining is used to check the quality of the relationship.

4.4 Predicting election results

Tumasobhan et al. [40] (2010) have tried to use Twitter social network and OM to predict the results of Federal Elections of Germany. The dataset contains about 104 thousand tweets that in the final weeks before the election have been collected by the authors. These tweets are collected using the names of the main six parties of the elections using Twitter applications. In this study, for OM, LIWC software has been used and to predict the combination of positive and negative tweets.

5. Persian Language

According to Lu Bing, in his book [6], about 1500 articles have been published in this area. A large part of this retrospective study has been conducted in English and Chinese. In recent years, attention to OM has increased in Persian language, and in this opportunity, it will be tried to assess articles published in Persian in the field of OM briefly. Persian OM is in the beginning and limited efforts have been made in this area. Of course, as mentioned above, except for English and Chinese, other languages are at the beginning to achieve maturity in OM methods. Besides, a wide variety of tools such as dictionaries are available for English that are not available in Farsi and researchers have to translate them into Farsi to use these tools and translations have many errors and reduce the power of the provided methods. Moreover, Farsi language has a lot of problems and challenges due to various reasons such as different spoken and written language and language structure that make Persian language researchers go through more difficult paths to achieve powerful ways.

In his article, Basiri et al. [41] seek to provide a framework for Persian OM. In this paper, which was presented in 2014 in English, writers look for Persian OM using unsupervised methods. The authors have presented two new features for their research.

1. Providing unsupervised approach based on dictionaries for Persian OM
2. Providing two datasets for Persian OM

In this study, the entered text is normalized then using Persian error finder approaches, the text lexical errors are corrected. The words written with mistakes in terms of spelling are corrected and the changes are applied. After this stage, word stemming is done. Then the sentences of each text are separated and analyzed. Thus, this is a study at sentence level and the sentences being positive or negative are reviewed at the end. Until this part of the work, preprocessing steps are introduced. In all the studies of data mining or text mining, first, dataset is refined using preprocessing steps. Then it comes to the stage of sentence classification. At this point, using words tank, positive and negative nature of the words is extracted. Senti Strength dictionary is used, which is a very popular and famous dictionary in the English language. To use this dictionary, they have translated it into Persian, something that is also done manually by the authors of this paper. Dictionaries present words as positive or negative and show their severity with a number between 1 and 5: for example: happy +5, good +2, or horrible -4.

In this method, after the separation of sentences, words that form sentences are numbered by dictionaries, and by adding up these numbers, a sentence being positive or negative is determined. The dataset offered contains two sets of product data: the first dataset consists of 1100 opinion and the second data set includes 263 comments about the product. To prove the success of their method, the authors have compared the results obtained by this method with the results obtained by algorithms of machine methods of learning. This method results are compared with the results obtained by Naïve Bayes, decision tree, and SVM algorithms, and according to the authors, the accuracy obtained by the proposed method is 10 percent higher than the methods listed in [24] on the same data sets.

Shams et al. [43] (2012) somehow offered the first work in OM in Persian in a paper presented in English. In this paper, a subjective dictionary containing 8027 words was used. The dictionary is in English and authors have translated it into Farsi. After translation of these words, they have been used for the classification of positive and negative comments.

The authors have considered the intended words as input, and using the subjective dictionary they have separated them as positive and negative words and sent them to LDASA algorithm. The output of the algorithm determines the positive or negative nature of the opinions. Dataset used has 400 opinions as positive and negative for three product groups: mobile phones, digital cameras, and hotels. One thousand two hundred opinions have been evaluated. To assess the performance of the proposed method, LDASA algorithm is used. According to the authors' 7 to 15 percent performance improvement has been reported. The best result was obtained for hotels claimed as 78%.

Ali Mardan and Aghayi [44] (2015) have provided a combined method for Persian OM. In this method, first words are separated by Senti Word Net Dictionary, and then these words are used as features for classification by SVM algorithm. In this study, first preprocessing stage is performed then the most repeated words in the text are separated, and these words are translated into English. At this stage, Senti Word Net dictionary is used to determine the polarity of each of the words. This word whose polarity is marked is sent to SVM algorithm as the feature, and this algorithm creates a model to classify by supervision.

Senti Word Net Dictionary is one of the most influential dictionaries in OM. It offers three numbers for every word. These figures reflect the degree of positive or negative or neutrality polarity of these words. For example, for the word "good" positive polarity is 0.57, negative polarity is 0.25, and neutral polarity is defined zero. For the word "bad" positive polarity is zero, negative polarity is 0.625, and neutral polarity is defined as 0.375. This dictionary is for free in Java class available to the public. Dataset is composed of 1566 opinions collected from hoteling sector. To evaluate the proposed method, the results are compared with the algorithm of the results of Naïve Bayes and SVM. According to the authors, when words highly repeated words are selected as features, the achieved improvement is in its highest state. To implement this research Weka software has been used. The best results reported for classification is the accuracy of 75.83 percent. In a study, Karimiyan and Dadgar [54] seek a solution for OM in Persian using a dictionary. In this study, the following steps have been taken. After collecting the goods opinions, the required preprocessing is performed on the comments. In preprocessing stage, it is tried to correct misspellings and unify text comments. After preprocessing, goods features are extracted based on products specifications. For example, for mobile phones, appearance, battery, camera, body, display, memory, data transfer, CPU, sound, and other features are extracted. After extracting features, the intended dictionary is created. To do this, dictionary associated with features of descriptive dictionary and denial dictionary are used. At this stage, dictionary is manually created. After that, supervision algorithm patterns are extracted. This step is done semi-automatically, and at the end, 1186 patterns are found. Finally, based on patterns found goods opinions classification is done. According to the authors' claim, the resulting accuracy of the proposed method is 89%. The strength of this work is attention to characteristics of the product, something neglected in offering OM methods in Persian before. Dataset consisted of three models of mobile phones that have been collected through the Digikala website, and 1250 comments consisting of 5853 sentences have been assessed.

Haj Mohammadi and Ibrahim [46] (2013) presented a method for OM in Persian based on SVM supervised algorithm. In this study, two prestigious machine learning algorithms, NaiveBayes and SVM, have been tested. In feature selection stage, three features, single-word, two-word, and three-word, are used. Single-word feature means every word is examined alone. Two-word feature means two words are examined next to each other. Three-word feature means three words used together as a unit to be investigated. For example, in the sentence "I think it was an excellent film" is examined as "I" "think" "it" "was" "an" "excellent" "film" in single-word feature. The dataset contains 200 positive and 200 negative comments. In this study, comments written for the films are discussed. To collect data, critic web site is used. The small size of the dataset is one of the weaknesses of the study. Finally, the best results achieved through single-word features and the presence of words using SVM algorithm have been obtained. The highest accuracy reported is 72.66 percent. This research aims to examine two classical classification algorithms, SVM and Naive Bayes, and at the end, the superiority of SVM classification in

Farsi OM is confirmed. In general, SVM algorithm is known as the best classification algorithm. With a focus on feature selection in Persian OM, Bagheri and Sareh [42] have tried to offer a new method for Persian OM. In this method, first preprocessing stage is done. Then the words exiting in the opinions are rooted. By rooting the redundancy of the words disappears. In these circumstances, we can do classification with better features. As words in Persian get both suffix and prefix, they have their subtleties for rooting. After this stage, we have the words in their root mode. In this study, after rooting, features like word frequency, word frequency variance, and features offered by MI are used and features are refined. Then using the known machine learning algorithms Naive Bayes, feature training and creating the model begin. The authors have applied changes to MI feature selection method and used it in modified way. Finally, according to their claims, the highest accuracy obtained by Naive Bayes algorithm and modified feature selection methods of MI has been reported as 85%. Dataset of the study consists of 1010 product opinions, of which 511 are positive comments and 509 are negative comments. These comments are about mobile phone that is more attractive to buyers. According to various models, users share their opinions about them more. The results obtained in Persian language are summarized in Table 4.

Comparing the methods provided for Persian OM is almost impossible because in any proposed method, different datasets have been used. In these circumstances, comparison of the accuracies obtained is non-scientific, and for scientific comparison, the proposed methods should be applied on a common dataset, so that based on accuracy obtained, scientific evaluation of the presented methods is performed. One of the weaknesses in Persian OM is lack of valid dataset available to everyone.

Table 4: Results obtained until 2015 in Persian

Row	Dataset	Approach	Year	Article	Result
1	Hotel [43]	Dictionary	2012	[43]	78% accuracy
2	Videos [46]	Machine learning	2013	[46]	72.66% criterion f
3	mobile phone [42]	Machine learning dictionary	2013 2014	[42] [41]	85% criterion f 95% criterion f
4	Mobile phone Digikala [45]	Dictionary	2014	[45]	89% criterion f
5	Hotels[44]	Combined Combined	2015 2015	[44] [47]	83.57% accuracy 87% accuracy

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