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A Comparative Classification of Approaches and Applications in Opinion Mining

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Abstract

With the growing availability of online resources on Web and popularity of fast and rich resources of opinion sharing such as online review sites and personal blogs, opinion mining has become an interesting area of research. Opinion mining is a process that is used for automatic extraction of knowledge from the opinion of others about some particular topic or problem. In addition, sentiment analysis, an application of natural language processing, has been witnessed a blooming interest over the past decades. Sentiment analysis is an extension of data mining that extracts and analyzes the unstructured data automatically. The aim of sentiment analysis and opinion mining is extraction of opinion from Web sites and classifying the polarity of text in terms of positive (good), negative or neutral (surprise). Mood mining causes make-decisions to be done automatically. The purpose of this study is to illustrate of the recent trend of research in the sentiment analysis and its related areas. In this paper, we survey various techniques of sentiment analysis and propose a new classification of these techniques. In the end, we present a comparative evaluation of such techniques in terms of accuracy, f-measure, and f-score.

Keywords: Sentiment Analysis, Opinion Mining, Text Classification, Natural Language Processing

Introduction:

Text mining is a new method used in different fields such as machine learning, information retrieval, and computational linguistics. Web mining is a sub-sequent of text mining used to mine the semi-structured Web data in form of Web content mining, Web structure mining and Web usage mining. Opinion mining (OM) also called sentiment analysis (SA) is a process, used for automatic extraction of knowledge from the opinion of others about some particular topic or a product or problem. The goal of OM is to make computer able to recognize and express emotions [1]. SA is a machine learning approach in the machine analyzes and classifies the human's sentiments, emotions, and opinions about some topic which are expressed in the form of either text or speech [2, 3][4] . Figure 1 depicts the hierarchy of data mining and how OM is located in this hierarchy [5, 6].

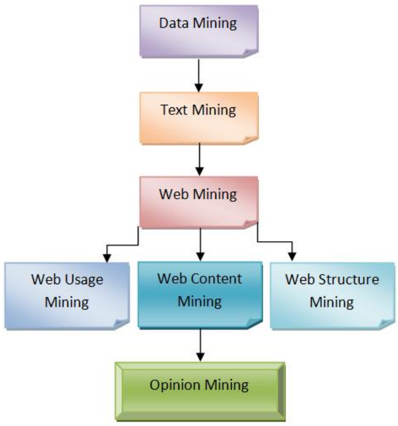

Figure (1) Hierarchy of Data mining [5]

Recently, OM has become a interesting area of research, because the growing availability of online resources on Web and popularity of fast and rich resources of opinion sharing such as online review sites and personal blogs, has been growing [3, 4] [5, 6]. OM or SA is an extension of data mining that extracts and analyzes the unstructured data, automatically [7]. It is a natural language processing (NLP) technique that automatically extracts the opinion, sentiments, attitude, emotions, views, etc in proper context and classify these into different categories such as positive, negative, or neutral. An opinion can be described as a quadruple consisting of a Topic, Holder, Claim and Sentiment [8]. Here, the Holder believes a Claim about the Topic and expresses it through an associated Sentiment [9].

Sentiments can be classified at various levels: Aspects or feature level, sentence level and document level. Aspects or feature level sentiment classification classifies the sentiments based on the sentiments polarity of each aspects or feature about some target object. On the other hand, sentence level sentiment classification classifies each sentence based on their sentiment polarity towards some topic. In document level sentiment classification the polarity of whole document is determined. It classifies the entire document into positive, negative or neutral class [6] [7].

The SA classification techniques can be divided into Machine Learning, Lexicon Based, and Hybrid approaches. The Machine Learning (ML) approach applies the famous ML algorithms and uses linguistic features. The text classification methods using ML approach can be divided into supervised and unsupervised learning methods. The Lexicon Based approach can be divided into Corpus Based and Dictionary Based approach.

The Hybrid approach combines the advantages of both the techniques.

Rest of the paper is organized as follows. Section II briefly presents the literature review. In section III, we describe architecture and processes of SA. We introduce existing approaches for SA and OM and classify them in section IV. In section V, we evaluate and compare these approaches. The paper is concluded in section VI.

2. Literature Review

In this section, we describe the CDS, and LA.

Basic Concepts

Formally stating SA is the computational study of opinions, sentiments and emotions expressed in text [10]. The goal of SA is to detect subjective information contained in various sources and determine the mind-set of an author towards an issue or the overall disposition of a document [11].

The words opinion, sentiment, view and belief are used interchangeably but they have subtle differences. Below, we explain these words.

Opinion: A conclusion thought out yet open to dispute (each expert seemed to have a different opinion). An opinion is a positive or negative view on Object/Feature from an opinion holder. Opinion can be either direct or comparative.

View: subjective opinion (very assertive in stating his views).

Belief: deliberate acceptance and intellectual assent (a firm belief in her party‘s platform).

Sentiment: a settled opinion reflective of one‘s feelings (her feminist sentiments are well-known).

SA is applied on user generated content on the Web which contains opinions, sentiments or views. SA, which is also called OM, is the field of study which analyzes people’s opinions, sentiments, evaluations, appraisals, attributes and emotions towards entities such as products, services, organizations, individuals, issues, events, and topics.

A key problem in this area is sentiment classification, where a document is labeled as a positive or negative evaluation of a target object (film, book, product, etc.) The evaluation of opinion can be done in two ways:

Direct opinion gives positive or negative opinion about the object directly [12]. For example, “The picture quality of this camera is poor” expresses a direct opinion.

Comparison means to compare the object with some other similar objects [12]. For example, “The picture quality of camera-y is better than that of camera-x.” expresses a comparison.

Lui [10] mathematically represented an opinion as a quintuple (o, f, so, h, t), where o is an object; f is a feature of the object o; so is the orientation or polarity of the opinion on feature f of object o; h is an opinion holder; t is the time when the opinion is expressed.

Object: An entity which can be a product, person, event, organization, or topic. The object can have attributes, features or components associated with it.

Feature: An attribute (or a part) of the object with respect to which evaluation is made.

Opinion holder: The holder of an opinion is the person or organization that expresses the opinion.

Opinion orientation or polarity: The orientation of an opinion on a feature f indicates whether the opinion is positive, negative or neutral.

Opinion strength: It is the scale or intensity of opinion indicating how strong it is [6] [11, 13].

Main fields of research in SA are Subjectivity Detection, Sentiment Prediction, Aspect based Sentiment Summarization, Text summarization for Opinions, Contractive viewpoint Summarization, Product Feature Extraction, and Detecting opinion spam [4].

Subjectivity Detection is the task of determining whether text is opinionated or not. Sentiment prediction is about predicting the polarity of text whether it is positive or negative. Aspect based Sentiment summarization provides sentiment summary in the form of star ratings or scores of features of product. Text summarization generates a few sentences that summarize the reviews of a product. Contrastive viewpoint summarization puts an emphasis on contradicting opinions. Product feature Extraction is a task that extracts the product features from its review. Detecting opinion spam is concerned with identifying fake or bogus opinion from reviews [4].

Data Resources

User opinion is a major criterion for the improvement of the quality of services. Blogs, review sites, data and micro blogs provide a good understanding for the deliverable level of the products and services provided to customers [5].

Blogs: People write about the topics they want to share with others on a blog. Blog pages have become the popular means to express one‘s personal opinions about any product or topic.

Review sites: For any user in making a purchasing decision, the opinions of others is being an important factor. A large number of user-generated reviews are available on the Internet. The reviewers data used in most of the sentiment classification studies are collected from the e- commerce websites such as www.amazon.com.

Data Set: The work in the field uses movie reviews data for classification. The dataset contains different types of product reviews extracted from Amazon.com including Books, DVDs, Electronics and etc.

Tools

There is a wide range of tools in market that performs automatic sentiment analysis on a given text. These tools utilize existing online textual content generated from sites such as Amazon, Twitter, Face book, etc. Several sentiment search engines exist where users run typical queries on any topic of interest, and generate text results. Usually the results are coded and categorized into two or three polar categories. Some examples currently available are: Sentiment140, Opinion Crawl, OpenAmplify, Amplified Analytics, SAS Sentiment Analysis Manager, Twittratr, IBM Social Sentiment Index, SAS Sentiment Analysis Studio, TweetSentiments, Red Opal, Review Seer tool, OpinionFinder, Weka, and OpenNLP [13-15].

3. Architecture and Processes in SA and OM

OM concludes whether user’s view is positive, negative, or neutral about product, topic, event, etc. OM and summarization process involve three main steps namely, Opinion Retrieval, Opinion Classification and Opinion Summarization [5].

Opinion Retrieval: It is the process of collecting review text from review websites. This step involves retrieval of reviews, micro blogs, and comments of user.

Opinion Classification: Primary step in sentiment analysis is classification of review text. Given a review document $D = \{d_1 \dots d_n\}$ and a predefined categories set C = {positive, negative}, sentiment classification is to classify each d_i in D, with a label expressed in C. The approach involves classifying review text into two forms, namely positive and negative.

Opinion Summarization: Summarization of opinion is a major part in opinion mining process. The opinion summarization process mainly involves the following two approaches. Feature based summarization is a type of summarization involves finding frequent terms (features) that are appearing in many reviews. The summary is presented by selecting sentences that contain particular feature information. Features present in review text can be identified using Latent Semantic Analysis (LSA) method. Term frequency is the number of term occurrences in a document. If a term has higher frequency it means that is more important for summary presentation. In many product reviews, certain product features appear frequently and are associated with user opinions about it. Figure 2 shows the architecture of OM which demonstrates how the input is being classified on various steps to summarize the reviews.

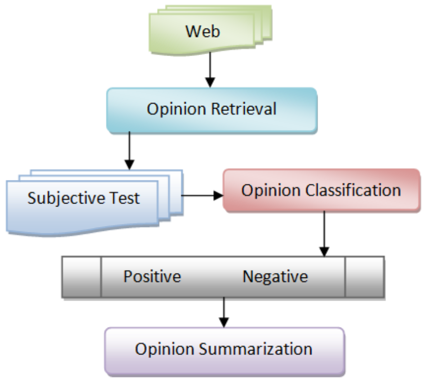

Figure 2- Architecture of OM [5]

Figure 3 depicts the workflow of OM showing how the opinions are being extracted from people review over their comment. Opinion feature extraction is a sub problem of OM [16].

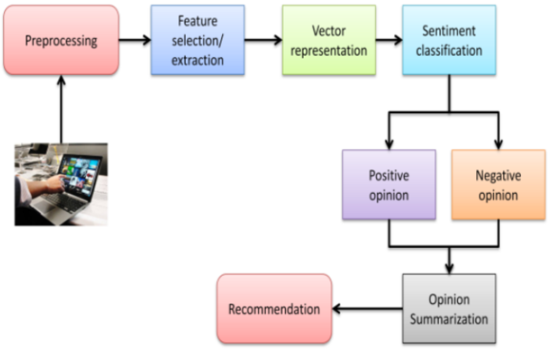

Figure (3) Workflow of OM [16]

The elements of OM process include pre-processing, Feature Extraction, Feature Selection, Features weighting mechanism, and Feature Reduction.

Pre-processing: In this process, raw data taken is pre-processed for feature extraction. The pre-processing phase is further divided into a number of sub phases as follows: Tokenization splits up the sentences of a text document into terms or tokens by removing white spaces, commas and other symbols. Stop word removal removes articles (like a, an, the). Stemming decreases relevant tokens into a single type. Case normalization is a process that has English texts to be published in both higher and lowercase characters and turns the entire document or sentences into lowercase/uppercase.

Feature Extraction: The feature extraction phase deals with feature types (which identifies the type of features used for OM), feature selection (used to select good features for opinion classification), feature weighting mechanism (weights each feature for good recommendation) and reduction mechanisms (features for optimizing the classification process).

Feature Types: The types of features used for OM could be: 1: Term frequency (The presence of the term in a document carries weight age). 2: Term co-occurrence (features which occurs together like unigram, bigram or n-gram), 3: Part of speech information (POS tagger is used to separate POS tokens). 4: Opinion words (Opinion words are words which express positive (good) or negative [17] emotions [16]. 5: Negations (Negation words (not, not only) shifts sentiment orientation in a sentence) and 6: Syntactic dependency (It is represented as a parse tree and it contains word dependency based features) [5] [6] [7] [8] [9].

Feature Selection: This task may include 1: Information gain (based on the presence and absence of a term in a document a threshold is set and the terms with less information gain is removed). 2: Odd Ratio (It is suitable for binary class domain where it has one positive and one negative class for classification. 3: Document Frequency calculates the number of appearances of a term in the available documents in the corpus and based on the computed threshold the terms are removed.

Features weighting mechanism: The mechanisms are of two types. They are 1: Term Presence and Term Frequency- word which occurs occasionally contains more information than frequently occurring words. 2: Term frequency and inverse document frequency (TFIDF) - Documents are rated where highest rating is given for words that appear regularly in a few documents and lowest rating for words that appear regularly in every document.

Feature Reduction: It reduces the feature vector size to optimize the performance of a classifier.

Adjectives only: Adjectives have been used most frequently as features amongst all parts of speech. A strong correlation between adjectives and subjectivity has been found. Although all parts of speech are important people most commonly use adjectives to depict most of the sentiments and a high accuracy has been reported by all the works concentrating only on adjectives for feature generation.

Adjective-Adverb Combination: Most of the adverbs have no prior polarity, but when they occur with sentiment bearing adjectives, they can play a major role in determining the sentiment of a sentence. Adverbs alter the sentiment value of their associated adjective. Adverbs of degree, on the basis of the extent to which they modify this sentiment value, are classified as:

Adverbs of affirmation: certainly

Adverbs of doubt: maybe

Strongly intensifying adverbs: exceedingly

Weakly intensifying adverbs: barely

Negation: never

Some of the positive Adjectives are as follows: dazzling, brilliant, phenomenal, excellent and fantastic. Negative Adjectives examples are: suck, terrible, awful, unwatchable, and hideous.

Subjectivity detection can be defined as the process of selecting opinion containing sentences. This should not play any role in deciding on the polarity of the review, and should be filtered out. Hence, the Polarity Classifier assumes that the incoming documents are opinionated. In Information extraction, both topic-based text filtering and subjectivity filtering are complementary. In order to mine opinion, the main concentration is on non-factual information in text. There are various affect types; in particular here the concentration is on the six "universal" emotions namely: anger, disgust, fear, happiness, sadness and surprise [9].

4. Classification of Existing Approaches

Sentiments can be classified at various levels: Aspects or feature level, sentence level and document level. Aspects or feature level sentiment classification classifies the sentiments based on the sentiments polarity of each aspect or feature about some target object. Sentence level sentiment classification classifies each sentence based on its sentiment polarity towards some topic. In document level sentiment classification the polarity of whole document is determined. It classifies the entire document in positive, negative or neutral classes [6] [7].

Document level OM: This level is a single review about a topic that is opinionated. The basic information unit is a single document of opinionated text [18]. In the case of forums or blogs, comparative sentences may appear and customers may compare two products with similar characteristics. Hence, document level analysis is not desirable in forums and blogs. Therefore, subjectivity/objectivity classification is very important in this type of classification [5][18] .

The document level sentiment classification has its own advantages and disadvantages. As an advantage we can get an overall polarity of opinion text about a particular entity from a document. A disadvantage is that the different emotions about different features of an entity could not be extracted separately [4]. For document level classification both supervised and unsupervised learning methods can be used. Any supervised learning algorithm such as naïve Bayesian, and Support Vector Machine (SVM), can be used to train the system [18].

Sentence level OM: In sentence level Opinion Mining, the polarity of each sentence is calculated. The same document level classification methods can be applied to the sentence level classification problem but objective and subjective sentences [12] must be found out. The subjective sentences contain opinion words which help in determining the sentiment about the entity. Then, the polarity is classified into positive and negative categories. The advantage of sentence level analysis lies in the subjectivity/ objectivity classification[4] [5] [18].

Phrase level OM: The phrase level sentiment classification is a much more pinpointed approach to OM. The phrases that contain opinion words are found out and a phrase level classification is done. In some other cases, where contextual polarity also matters, the result may not be fully accurate. Negation of words can occur locally. If there are sentences with negating words which are far apart from the opinion words, phrase level analysis is not desirable. The process is Identifying Opinion Words, the role of negation words and But-Clauses[18] [12] .

The SA classification techniques can be divided into Machine Learning Approaches, Lexicon Based Approaches, and Hybrid Approaches. Figure 4 depicts our classification.

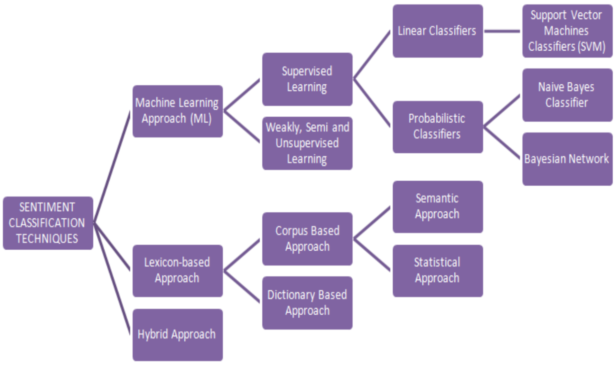

Figure (4) Classification of OM Approaches

4.1. Machine Learning Approach

The Machine Learning Approach (ML) applies the prominent ML algorithms and uses linguistic features. The text classification methods using ML approach can be divided into supervised and unsupervised learning methods. The supervised methods use a large number of labeled training documents. The unsupervised methods are used when it is difficult to find these labeled training documents features [4].

The aim of ML is to develop an algorithm to optimize the performance of the system using example data or past experience. The ML provides a solution to the classification problem and involves two steps: learning the model from a corpus of training data and classifying the unseen data based on the trained model [7] .

The ML approaches can be divided into supervised and unsupervised learning methods.

4.1.1. Supervised Machine Learning Techniques

In Supervised ML techniques, two types of data sets are required: training and test. An automatic classifier learns the classification factors of the document from the training set and the accuracy in classification can be evaluated using the test set. The ML algorithms such as SVM, Naive Bayes [17] and maximum entropy (ME) are used successfully in many research works and they performed well in the sentiment classification.

The first step in Supervised ML technique is to collect the training set. Then the appropriate classifier is selected. After that, the classifier is trained using the collected training set. The key step in the Supervised ML technique is feature selection. The classifier selection and feature selection determine the classification performance. The most common techniques used for feature selection are:

Opinion words and phrase: By considering adjectives and adverb, most of the opinion words can be extracted from the document, but sometimes nouns or verbs may also express opinion. Once opinions are collected, their polarity can be calculated using statistical-based or lexicon based techniques.

Terms and their frequency: uni-grams or n-grams with their frequency of occurrence are considered as features.

Part of speech [19] information: In this approach, POS tag of words is used in determining the feature. In POS tagging, each word is tagged by considering its position in the grammatical context.

Negations: Negation word reverses the meaning, so it is an important factor in polarity calculation.

The supervised ML approach can be divided into Linear classifier and Probabilistic classifier. The Linear classifier is such as SVM and the Probabilistic classifier is such as Naive Bayes, and Bayesian Network.

Probabilistic classifiers use mixture models for classification. The mixture model assumes that each class is a component of the mixture. These kinds of classifiers are also called generative classifiers, because each mixture component is a generative model that provides the probability of sampling a particular term for that component [4].

4.1.2. Unsupervised Machine Learning Techniques

In contrast with supervised learning, unsupervised learning has no explicit targeted output associated with input. Class label for any instance is unknown so unsupervised learning is about to learn by observation. Clustering is a technique used in unsupervised learning. The process of gathering objects of similar characteristics into a group is called clustering. Objects in one cluster are dissimilar to the objects in other clusters [4] [5].

4.2. Lexicon Based Approach

The Lexicon Based Approach is an Unsupervised Learning approach, because it does not require prior training data-sets. It is a semantic orientation approach to OM in which sentiment polarity of the existing features in the given document are determined by comparing these features with semantic lexicons. Semantic lexicon contains lists of words whose sentiment orientation is already determined. It classifies the document by aggregating the sentiment orientation of all opinion words available in the document. A document with more positive word lexicons is classified as positive, while the document with more negative word lexicons is classified as negative. The key steps of lexicon based SA are as follows [20]:

1. Preprocessing: This step cleans the document by removing HTML tags and noisy characters in the document, by correcting spelling mistakes, grammar mistakes, punctuation errors and incorrect capitalization and replacing non-dictionary words such as abbreviations or acronyms of common terms with their actual term.
2. Feature Selection: This step extracts the feature presented in the document by using techniques such as POS tagging.
3. Sentiment Score Calculation: The sentiment score s is initialized with 0. For each extracted sentiment word, checks whether it is presented in the sentiment dictionary. If it is present with negative polarity, w then s = s-w or in case of positive polarity, w then s = s + w.
4. Sentiment Classification: If s is less than a particular threshold value then the document is classified as negative otherwise positive [9].

The Lexicon Based Approach can be divided into Corpus Based Approach and Dictionary Based Approach.

4.2.1. Corpus Based Approach

The common corpus-driven approach determines the emotional affinity of words through learning their probabilistic affective scores from a large corpus. The approach to assign a happiness factor to words depending on the frequency of their occurrences in happy-labeled blog posts. It compared to their total frequency in a corpus containing blog posts labeled with "happy" and "sad" mood annotations. They also compare the happiness factor scores of words with the scores in the list. It is hard to prepare a huge corpus to cover all English words so it is not as effective as the dictionary based approach when it is used alone. The main advantage of this approach is that it can help to find domain and context specific opinion words using a domain corpus. The corpus based approach is realized using statistical or semantic approaches [4] [5].
The statistical approaches find the co-occurrence patterns or seed opinion words. It can be done by obtaining posterior polarities in corpus. By using the entire set of indexed document, it is possible to solve the problem of the unavailability of some words. The word has positive polarity if it occurs more frequently in positive texts, or its polarity is negative if it occurs often in negative texts. If it has same occurrence, then it is neutral word. So, the polarity of word can be identified by analyzing the occurrence frequency.
For computing the similarity between words, this approach assigns sentiment values directly based on different principles. For semantically close words, this principle gives similar semantic values. By using relative count of positive and negative synonyms of this word, it determines the sentiment polarity of an unknown word. To perform sentiment analysis task semantic approaches can be mixed with the statistical approaches.

4.2.2. Dictionary Based Approach

This approach uses lexical resources such as WordNet to automatically acquire emotion-related words for emotion classification experiments. Starting from a set of primary emotion adjectives, they retrieve similar words from WordNet utilizing all senses of all words in the synsets that contain the emotion adjectives. The process exploits the synonym and hyponym relations in WordNet to manually find words similar to nominal emotion words. The affective weights are automatically acquired from a very large text corpus in an unsupervised fashion [4] [5].
A small set of opinion words collected manually. Then, this set is grown by finding their synonyms and antonyms in the WordNet and thesaurus. After finding new words, these words are added to the seed list and the next process starts. This process stops when no new words are found. To remove or correct the errors manual inspection process will be done. As a disadvantage, this method cannot find the opinion words with domain and context specification orientations [20].

4.3. Hybrid Approach

Some researchers combined the supervised ML and lexicon based approaches together to improve sentiment classification performance. The hybrid approach combines the advantages of both the techniques. It is inheriting high accuracy from supervised machine learning algorithm and achieving stability for lexicon based approach[9].

5. Comparative Evaluation

In this section, we evaluate and compare several works in terms of accuracy, F-measure, and F-score [21]. The results can be seen in Table 1.

Table1- Comparative Evaluation Results

Result	***Domain***	***Lang.***	***Year***	***Alg.***	***Ref.***
Accuracy=75% F-Measure=0.68	Microblog Twitter	English	2011	SVM	[22]
65<Accuracy<84	Automobile Banks Movie Travel Destinations	English	2002	Lexicon	[23]
80<Accuracy<86 68<Accuracy<90	Movie, Product reviews	English	2013	NB, SVM, ANN	[24]
Accuracy= 86%	Movie reviews	English	2004	minimumcut SVMs Naive Bayes	[25]
Accuracy= 85%	Movie reviews	English	2006	SVM	[26]
Accuracy=88.5%	Movie reviews	English	2011	LDA,LSA	[27]
Accuracy=59.8%	Movie reviews	English	2012	SVM, k-nearest neighbor	[28]
F-Score =87%	Cell Phone	Persian	2014	Lexicon	[29]
Accuracy=66.8%	Reviews	Chinese	2012	Lexicon, SVM	[30]
Accuracy=82.3%	Software, Movie reviews	English	2012	Supervised lexicon	[31]
Accuracy=85.4%	Twitter reviews	English	2011	supervised lexicon	[32]

Basiri et al. [29] proposed a new framework for SA in Persian. They propose a new unsupervised, lexicon-based approach for SA in Persian. They introduce two resources for their approach: a Persian Lexicon that associates Persian sentiment words and their polarity, and a manually gathered dataset that is annotated by human coders for polarity detection. They first devise a Persian polarity lexicon which is a list of words associated with their sentiment polarity. Then, they review common challenges of Persian language processing such as misspelling, word spacing, stemming, and use of informal words and propose effective solutions for them. Finally, they assess the performance of the proposed method in classifying the polarity of online cell phone reviews.

Kouloumpis et al. [22] evaluate the usefulness of existing lexical resources as well as features that capture information about the informal and creative language used in microblogging. They use a supervised approach and data preprocessing consists of three steps: tokenization, normalization, and POS tagging. They use a variety of features for their classification experiments. They want to evaluate the effectiveness of the features for SA in Twitter data. This approach achieved an accuracy of 75%.

Turney presents a simple unsupervised learning algorithm for classifying reviews as recommended (thumbs up) or not recommended (thumbs down). According to him, the semantic orientation of a phrase is calculated as the mutual information between the given phrase and the word “excellent” minus the mutual information between the given phrase and the word “poor”. The algorithm achieves an average accuracy of 74% when evaluated on 410 reviews from Epinions, sampled from four different domains (reviews of automobiles, banks, movies, and travel destinations). The accuracy ranges from 84% for automobile reviews to 66% for movie reviews[23].

Moraes et al. [24] present an empirical comparison between SVM and ANN regarding document-level sentiment analysis. They discuss requirements, resulting models and contexts in which both approaches achieve better levels of classification accuracy. They adopt a standard evaluation context with popular supervised methods for feature selection. Based on the benchmark dataset of Movies reviews, ANN outperformed SVM by a statistically significant difference, even on the context of unbalanced data. Their results have also confirmed some potential limitations of both models, which have been rarely discussed in the sentiment classification literature, such as the computational cost of SVM at the running time and ANN at the training time.

Pang and Lee [25] propose a novel machine-learning method that applies text-categorization techniques to just the subjective portions of the document. They apply to classify a movie review as “thumbs up” or “thumbs down”. It can be implemented using efficient techniques for finding minimum cuts in graphs. They achieve an accuracy of 86.4%.

Kennedy and Inkpen [26] use a data set of classified movie reviews. They examine the effect of valence shifters on classifying the reviews. The first method classifies reviews based on the number of positive and negative terms they contain. The second method uses a ML algorithm, SVM. The accuracy of classification is 85%.

Maas et al. [27] evaluate a model with document-level and sentence-level categorization tasks in the domain of online movie reviews. They present a model to capture both semantic and sentiment similarities among words. Their model yielded around 88.5% accuracy.

Goldberg and Zhu [28] present a graph-based semi-supervised learning algorithm to address the sentiment analysis task. They performed experiments using the movie review documents. They created a graph on both labeled and unlabeled data to encode certain assumptions for this task. They identified positive sentences using SVM and k-nearest neighbors. Then, they solved an optimization problem to obtain a smooth rating function over the whole graph.

Fang et al. [30] considered both general purpose lexicon and domain specific lexicon for determining polarity orientation of sentiment words and feed these lexicons into supervised learning algorithm, SVM. They found that general purpose lexicon performed very poor while domain specific lexicon performed very well. The system classified the sentiment in two steps: first the classifier is trained to predict the aspects and next the classifier is trained to predict the sentiments related to the aspects collected in the first step. Their system yielded around 66.8% accuracy.

Mudinas et al. [31] combined lexicon based and learning-based approaches to develop a concept-level sentiment analysis system, pSenti. It utilized advantages of both the approaches and attained stability and readability from semantic lexicon and high accuracy from a powerful supervised learning algorithm. They extracted sentiment words and considered it as features in the machine learning algorithm. This hybrid approach achieved an accuracy of 82.30%.

Zhang et al. [32] carried out entity level sentiment analysis. They utilized both the supervised learning techniques and lexicon based techniques. By lexicon based method they extracted sentiment words. By using Chi-square test on the extracted seeds additional seeds are discovered. Sentiment polarities of newly discovered seed are determined through a classifier, which are already trained using initial seeds. There is no manual task in the proposed system and it achieved around 85.4% of accuracy.

6. Conclusion

The OM also called SA is a process, used for automatic extraction of knowledge from the opinion of others about some particular topic or a product or problem. The goal of OM is to enable computers recognize and express emotions. In this paper, we reviewed various techniques of sentiment analysis and proposed a new classification of these techniques. In addition, we presented a comparative evaluation of these techniques in terms of accuracy, f-measure, and f-score. Hybrid techniques are the same in term of accuracy approximately. Persian is a challenging language for sentiment analysis and this study also revealed that there are few resources and tools available for this language. As a result, future works may concentrate more on sentiment analysis in Persian and propose techniques to improve its text processing.

References:

A. B. Goldberg and X. Zhu, "Seeing stars when there aren't many stars: graph-based semi-supervised learning for sentiment categorization," in Proceedings of the First Workshop on Graph Based Methods for Natural Language Processing, 2006, pp. 45-52.

A. Balahur, R. Steinberger, M. Kabadjov, V. Zavarella, E. Van Der Goot, M. Halkia, et al., "Sentiment analysis in the news," arXiv preprint arXiv:1309.6202, 2013.

A. Buche, D. Chandak, and A. Zadgaonkar, "Opinion mining and analysis: a survey," arXiv preprint arXiv:1307.3336, 2013.

A. Kaur and V. Gupta, "A Survey on Sentiment Analysis and Opinion Mining Techniques," Journal of Emerging Technologies in Web Intelligence, vol. 5, pp. 367-371, 2013.

A. Kennedy and D. Inkpen, "Sentiment classification of movie reviews using contextual valence shifters," Computational intelligence, vol. 22, pp. 110-125, 2006.

A. Kumar and T. M. Sebastian, "Sentiment analysis: A perspective on its past, present and future," International Journal of Intelligent Systems and Applications (IJISA), vol. 4, p. 1, 2012.

A. L. Maas, R. E. Daly, P. T. Pham, D. Huang, A. Y. Ng, and C. Potts, "Learning word vectors for sentiment analysis," in Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies-Volume 1, 2011, pp. 142-150.

A. Mudinas, D. Zhang, and M. Levene, "Combining lexicon and learning based approaches for concept-level sentiment analysis," in Proceedings of the First International Workshop on Issues of Sentiment Discovery and Opinion Mining, 2012, p. 5.

B. Liu, "Sentiment analysis and subjectivity," Handbook of natural language processing, vol. 2, pp. 627-666, 2010.

B. Pang and L. Lee, "A sentimental education: Sentiment analysis using subjectivity summarization based on minimum cuts," in Proceedings of the 42nd annual meeting on Association for Computational Linguistics, 2004, p. 271.

D. Ankitkumar, P. R. R. Badre, and P. M. Kinikar, "A Survey on Sentiment Analysis and Opinion Mining," International Journal of Innovative Research in Computer and Communication Engineering, vol. 2, pp. 6633-6639, 2014.

D. Osimo and F. Mureddu, "Research challenge on opinion mining and sentiment analysis," Universite de Paris-Sud, Laboratoire LIMSI-CNRS, Bâtiment, vol. 508, 2012.

E. Kouloumpis, T. Wilson, and J. Moore, "Twitter sentiment analysis: The good the bad and the omg!," Icwsm, vol. 11, pp. 538-541, 2011.

F. Aisopos, G. Papadakis, and T. Varvarigou, "Sentiment analysis of social media content using N-Gram graphs," in Proceedings of the 3rd ACM SIGMM international workshop on Social media, 2011, pp. 9-14.

G. Angulakshmi and D. R. ManickaChezian, "An Analysis on Opinion Mining: Techniques and Tools," International Journal of Advanced Research in Computer and Communication Engineering, vol. 3, pp. 7483-7487, 2014.

G. Vinodhini and R. Chandrasekaran, "Sentiment analysis and opinion mining: a survey," International Journal, vol. 2, 2012.

H. Rahmath and T. Ahmad, "Sentiment Analysis Techniques - A Comparative Study," IJCEM International Journal of Computational Engineering & Management, vol. 17, pp. 25-29, 2014.

H. Tang, S. Tan, and X. Cheng, "A survey on sentiment detection of reviews," Expert Systems with Applications, vol. 36, pp. 10760-10773, 2009.

K. Khan, B. B. Baharudin, and A. Khan, "Mining opinion from text documents: A survey," in Digital Ecosystems and Technologies, 2009. DEST'09. 3rd IEEE International Conference on, 2009, pp. 217-222.

L. Zhang, R. Ghosh, M. Dekhil, M. Hsu, and B. Liu, "Combining lexiconbased and learning-based methods for twitter sentiment analysis," HP Laboratories, Technical Report HPL-2011, vol. 89, 2011.

M. Annett and G. Kondrak, "A comparison of sentiment analysis techniques: Polarizing movie blogs," in Advances in artificial intelligence, ed: Springer, 2008, pp. 25-35.

M. E. Basiri, A. R. Naghsh-Nilchi, and N. Ghassem-Aghaee, "A Framework for Sentiment Analysis in Persian," OPEN TRANSACTIONS ON INFORMATION PROCESSING, vol. 1, p. 14, 2014.

N. Mishra and C. Jha, "Classification of Opinion Mining Techniques," International Journal of Computer Applications, vol. 56, pp. 1-6, 2012.

P. D. Turney, "Thumbs up or thumbs down?: semantic orientation applied to unsupervised classification of reviews," in Proceedings of the 40th annual meeting on association for computational linguistics, 2002, pp. 417-424.

R. Moraes, J. F. Valiati, and W. P. G. Neto, "Document-level sentiment classification: An empirical comparison between SVM and ANN," Expert Systems with Applications, vol. 40, pp. 621-633, 2013.

R. Varghese and M. Jayasree, "A survey on sentiment analysis and opinion mining," IJRET: International Journal of Research in Engineering and Technology eISSN, vol. 23191163, 2013.

S. A. Kadam and M. S. T. Joglekar, "Sentiment Analysis, an Overview," International Journal of Research in Engineering & Advanced Technology, 1/4, p1, vol. 7, 2013.

S. A. Selvam and S. Abirami, "A Survey on Opinion Mining Framework," International Journal of Advanced Research in Computer and Communication Engineering, vol. 2, pp. 3544-3549, 2009.

S. Chandrakala and C. Sindhu, "Opinion Mining and sentiment classification a survey," ICTACT journal on soft computing, 2012.

S. Veeramani and S. Karuppusamy, "A Survey on Sentiment Analysis Technique in Web Opinion Mining," International Journal of Science and Research (IJSR) Volume, vol. 3, 2014.

S.-M. Kim and E. Hovy, "Determining the sentiment of opinions," in Proceedings of the 20th international conference on Computational Linguistics, 2004, p. 1367.

W. Zhang, H. Xu, and W. Wan, "Weakness Finder: Find product weakness from Chinese reviews by using aspects based sentiment analysis," Expert Systems with Applications, vol. 39, pp. 10283-10291, 2012.