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Sentiment Analysis of Arabic Tweets: With Special Reference Restaurant Tweets

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ABSTRACT

Sentiment analysis is an emerging area, its use in industry and business sector is increasing due to provision of sentiment of the core information applications are requiring. The product manufacturers always require some method to know the future acceptance of their product in production. This is among the key knowledge to enhance the quality of the product and improve the underlined process. The research undertakes sentiment analysis of Arabic tweets extracted through Twitter microalgae. The methodology was divided in two phases. Analysis of text models for many combinations of text is done; few examples are stop word reduction, stemming, and n-gram. The other phase applied and analyzed results of classifiers like Naive Bayes, SVM and K-nearest neighbour. Arabic Sentiment Analysis is a challenging task because, applications developed for Arabic natural language processing focused only modern Arabic, while less focusing the various dialects in operation by different regions like North Africa, Egypt and Gulf States. Rapidminer is a tool used to conduct the simulation. Semantic analysis classifiers are developed to learn manually annotated data.

This yielded eighty eight percent accuracy of cross validation. It is evident that picking preprocessing strategies for the reviews enhances the ability of the classifiers. In future the research aims to solve target identification of tweets and classify tweets with the help of patterns.

Keywords: **-** Sentiment Analysis, opinion mining, Arabic, Twitter.

I. INTRODUCTION

In the last decade text classification and summarization becomes an attractive and interesting area for researchers and developers of data mining. There is an acute requirement for auto extraction and summarization of massive and significant information in this area. This information can be used by users and applications. Lot of research has been done to address the issue. The most popular technique is categorization of topic. In this technique documents are categorized on the basis of strategies represented by them [1], [2].Currently a technique has evolved to categorize the documents on the basis of opinions made by users or according to their sentiments[3]–[6].This means to classify documents as positive or negative based on associated data[7].

The main generator of this research area is social networks and bloggers. These online networks are driven by people's choices and accepted or rejected by their say. The websites are now rich with different commercial aspects, knowledge stores, entertainment sources, books and articles and much more.

The study is coming up with initial processing and feature extraction techniques for Arabic tweets. Precision and accuracy for Sentiment Analysis (SA) will be measured too. Classifiers like Naive Bayes, *K*-Nearest neighbor (K-NN) and SVM are used for validation. Rapidminer is used for experimentation [30].

Arabic is the language of the Holy Quran used by almost one billion Muslims across the world, different dialects are spoken by nearly 200 million people. Arabic is the main language for twenty two Arab league members, and official language of 3 countries [8].

The Arabic language has major differences from most popular languages like English and Chinese. Arabic has many grammatical forms, varieties of word synonyms, and different word meanings that vary depending on many factors like word order [9].

Based on its morphology, syntax, and lexical combinations Arabic can be classified into language sub classes: i) Conventional Arabic (CA), ii) Dialectal Arabic (DA) and lastly iii) Modern yet standard Arabic (MSA) [10]. Social sites and micro-blogs, such as twitter [31] use DA [11].

People posting text on social networks and micro-blog, such as twitter tend to DA and informal writing style or different spell combinations. Furthermore Arabic Users (AU) sometimes uses a mixture of many languages. Here is one example *"الحمدالله لقينا مطعم فاضي????????? (at Johnny Rockets)"*. Additionally tweets do carry irony, mixed and/or bi-meaning or polar words. Natural Language Processing (NLP) for DA is not the easy road the diversity in dialects is huge and mostly written in nonstandard text [12].

A. *Sentiment Analysis (SA)*

SA is a growing area mainly employing NLP, linguistics processing and mining of text.SA can detect and pull out decision able information from source content [13]. The functionality of SA analyzes opinions reviews, and emotions for categorization purpose. SA is not a newer term. In history people have used advises of friends for decision formulation. Product and service surveys are newer examples. Now social sites offer blogs and suggestion boxes for the same purpose. This all proves that user opinions are precious in whatever form they are.

Sentiment expression is divided among four levels, each layered to others

1. Document sentiment classification *This is the most researched* sentiment expressing method [7]. The method treats the document as a single unit and refrain decision as positive, negative or indecisive. Sentiment analysis properties are also important, as negating terms for example ***not***; this can flip reverse the meaning of sentiment, from positive to negative or the other way.

2. Sentence subjectivity and sentiment classification In this level, technique try to extract subjective meanings of objective sentences and then refrain positive or negative decision. The technique works well for simple sentences, but there are still many issues for comparative sentences, as, 'I love the walk but it is quite far'.

3. Aspect-Based Sentiment Analysis Techniques at this level analysis document along with sentence levels. The technique has some side benefits cannot refrain positive or negative decisions directly, hence unable to form the decisive opinion. Targets word in opinion is termed as entity, and explanatory words are called features. For example 'Samsung Galaxy' is entity word and' form factor ' is a feature here.

4. Aspect-based opinion summarization
The techniques at this level employ all opinions based upon multiple aspects from various documents and refrain positive or negative decision. One example is, find subjective results in percentages like,'**70**%users uses Samsung Galaxy'.

SA still has many open challenges. One of them is writers having various writing styles. The writing style can confuse SA to take same word as negative for one case while negative for the other. One example is word' short' ,'قصير'can be taken negatively in this case 'The mobile battery performance is short','أداءالبطاريةالمحمولقصير" On contrary it can give positive decision in other cases like' The mobile lag time is short','قصير وقت لها يبدو النقال الهاتف".A U forms different opinions variable to time. One more drawback is the basic assumption used for SA is that social site users give comparative opinions which can relate directly to positive or negative decisions.

B. *Arabic Language Issues*

Arabic language is not orthographical by nature when compared with other languages. It has twenty eight letters; words are written right to left. The shape of letters connecting to other letters changes as per their occurrence. The letter can occur in the beginning of a word or in the middle or it can also come at end of word. The connection can happen with previous and successive letter or with previous only or with successive only. One example is letter B'ب'which can have different shapes like,'بـ' when coming in start, the example is this word 'باب',meaning door. Other form is 'ـبـ'this comes in the center, for example''مكتبة'meaning book achieve. The form at end is'ـب'which is connected to pre-words, see this example'كتـب', meaning plural of books. One more end form is'ب'which is not in pre-word connection; the example is'كتاب', meaning a book. Though machine learning techniques can work with basic language concepts, but for Arabic the assumption change and job is tougher. The tokenization process which is basic part of language processor and written easily by programmer, is quit complicated when written for Arabic. One reason is Arabic don't letter capitalization neither having enforced punctuation rules. The job was easy for English, as every sentence has to begin with a capital letter and finish with a dot. The morphological richness for Arabic is high, even a single word can possess up to four tokens.

Stemming is another significant step in NLP. Stemming also becomes tedious for Arabic. For standard languages a stem may have a pre-fix form or may have a post-fix form to associate with grammar. While for Arabic other than standard affixes there exist infixes, which can add stem to the root themselves. This becomes very complicated for NLP especially stemming Arabic documents. Stemming by simple means cannot distinguish between letters at root letters with affixes. Stemming is done in two ways. In first way, a word is reducedto3-letter root. In second way (light-stemming) common prefixes and suffixes are removed without reduction of word from the root. The process is not applicable to Arabic precisely, mainly stemming reduces thewordsto3-letterroot,on contrary words can exhibit four-letter or five-letter roots.

Arabic dialects bring variation from country to country. Colloquial Arabic is the dominant form on social websites. The research uses stemming and light stemming for intimal language processing. The strategy is explained in Section4.

The rest of this paper is organized as follows. Section 2 is a related work section that gives an idea about previous work in sentiment analysis. Details of the relation detection and evaluation methodology are presented in Section 3. Section 4 presents the results obtained, while Section 5 presents an outlook on the proposed method and results obtained. The conclusion and future work are set out in Section 6.

II. RELATED WORK

Existing work has been reviewed in perspective of Arabic SA. The literature was focused on SA preprocessing, extraction and meaning formulation (analysis) and classification of existing studies. Strategies are classified into supervised learning and semi supervised learning. Previous work on SSA has used manually annotated gold-standard data sets to analyze which feature sets and models perform best for this [29]. The focus of previous researchers is on English. Some existing work is related to Arabic-MSA as given in [14]. Arabic social media is researched by few of the researchers, examples are given in [15]; [16]; [17]; [18].A study [18] evaluates the attributes of MSA. Additionally some studies test models using a data set mainly populated through twitter. A study [17] uses cross-validation to evaluate their classifiers. A researcher [16] takes a held-out dataset mainly small portion of dataset constructed for the training. The dataset is no real representation of realistic example. In reality training models are applied to categorize stemmers for twitter with a good span of time-period.

Pang et al. [19] explained how it is insufficient for desired results by combining algorithms written for text categorization. SA is not similar to text categorization hence it was obvious. An example is text categorization, where negation words are taken as stoppers and stoppers are eliminated. In contrast SA employ negation as significant words. The initial processing methods used for the research varies. The research employed different models like n-gram and bag-of-word. The extension to these methods is discussed in coming sections.

El-Halees's [20] has done Arabic SA. Their technique integrates k-NN with lexicon-classification and maximum entropy. The combined method can predict document polarity. All 3 classifiers were used in sequence. Lexical classifier detects opinion-terms and the sentiment. This classifier was constructed combinations of positive and negatives. The dictionaries used for words are i) live dictionary (online) and ii) SentiStrength [21].The former has twenty six hundred sentiments of English. These sentiments are converted to Arabic language while keeping scoring strength intact. This can serve as an alternate Arabic sentiment lexicon. After that max entropy classifier was used to filter the documents possessing sentiment probability higher than a desired limit. Third step is K-NN training which employs sentiment-lexicons for supervised learning. This dataset is not public hence a result comparison cannot be performed.

A study [22] extracted sentiments using text-messages related to money matters. The purpose of the research was to define grammar norms for Arabic words and terms widely used to express financial information. The study employed newsfeed to track the news related to transactions, stock exchange terms, money flow and other related words. The study formed certain rules on the bases of found patterns, these rules helped in detecting change frequency in sentiments. The work was further used for common idiom development for Arabic, English and Chinese with localized grammar. [23]. The developed idioms employed comparison of distributions of words which were domain specific with general words which were corpus. The original work was though [22] lexicon-based learning. The aim of that work was to identify grammars patterns always positive or patterns which are related to negativity. Abbasi et al. [24] classified sentiments for multiple languages. The precision was improved using feature-selection technique. One more study tried to extract patterns related to financial information flow using web-crawlers into the newsfeeds [25]. The study employed around 600+ combination of words carrying positivity while around 900+ words for negativity. They came up with a similarity graph for Arabic. Their graph was employed to analyze the reviews associated to sentiments. The work concluded that same efficiency of classification for SA of Arabic can be achieved compared to other languages. Another research constructed corpus containing two hundred and fifty positive and equally negative reviews related to films[26] using web extraction technique. NLP was conducted on the reviews, liken-grams (for uni, bir or tri grams), removal of stop word and stemming. SVM and Naïve-Bayes were employed for classification. The approach is quite similar to the proposed one, though proposed approach has a wider scope in terms of initial processing of the sentiments.

On the basis of this literature discussion the conclusion can be drawn in the favor of initial processing (or pre-processing) text processing techniques. Preprocessing techniques can help multiple decisions at large. The techniques can help in correction of spell errors, depleting wrong punctuations and unwanted symbols from source. Another potential area is removal of stop words. The stop word removal requires a bit care that negative polarity must be handled first. Stemming was also helpful in total word reduction. Term-frequency was used to assign weight age to filtered terms. Feature selection and reduction was employed to further decrease the size of vocabulary. The study evaluate effect pre-processing methods for SA in terms of precision and accuracy.

III. PROPOSED APPROACH

3core methods are being used to extract sentiment from text, they are i) lexicon, ii) supervised-learning, or iii) combination of the both. In supervised learning classifiers are trained for prediction sentiments to assess tweets. This can be used to build a model of classification. The technique also requires labeled set of tweets/texts. Annotation is manual job and quite hectic. Another technique is based upon use of lexicon or archive of words with their related sentiment. Lexicon contain three types of words i) Positive, ii) Negative and iii) Neutral. Lexicons basically mean that every word poses a sentiment irrespective of the context in which they are use. One case is the word 'love''حب'carry positive while another case,' hate', 'كراهية'carries negativity in sentiment. Lexicons can work independent to labeled datasets. Combined method employs both classifiers and lexicons for enhanced efficiency. Literature indicates that supervised learning has superior results in comparison with lexicons.

The proposed approach used supervised learning to extract sentiment from tweets, which required an annotated dataset. Hence a synthetic dataset was generated. Text is represented by a set of words in this approach. Every tweet has to be parsed and tokenized (for words extraction). Every taken is then assigned a weighted value, which is term frequency–inverse document frequency TF-IDF[27]. We use different Representation of tweets: the base line vector minus pre-processing stemming vectors for normal stemmed words; light-stemming vectors; n-grams stem vectors. Supervised learning methods (k-NN, SVM, and Naïve Bayes) were employed to categorize Arabic tweets. Further this was used to form negative or positive classes. Data mining is using all mentioned classifiers with quite proficiency [28]. Impact and working of every classifier is analyzed under effect of dataset associated with the vector representation model. Main concept evaluates the data set suitability for the mentioned classifier and the most appropriate is picked for future steps in mind.

IV. IMPLEMENTATION

A. *Dataset*

Twitter Search API has been taken to extract corpus. The API has the functionality to access real-time tweets in bulk and to investigate into the content they hold. Data cleansing is the next step for collected tweets. Cleansing take care of spell errors, typos, redundant words and normalized the non-language words, other symbols and URL.

The tweets were collected by querying the Twitter API for a number of entities i.e. *Sudan 'السودان', lang:ar (Arabic), Restaurant 'مطعم', and Hotel 'فندق'.* The query terms were then replaced by place-holders to avoid bias.

The data set contains 909 multi- dialectal Arabic tweets, randomly retrieved over the period from September1st toNovember1st2015.

Total 959 tweets were collected, among them459were positive while450 were negative. Around800features were marked from this data. The extracted content contained dialects with spell errors. One classical example is “ وجبات المأكولات البحرية المقدمه من مطعم سيتي ووك هنقريستيشن #الذواقه #مطاعم_الرياض #سيتي_ووك #صحي #لذيذ #شهي”,”بالخمممس (@ مطعم دنيا البخاري)”the replace duplicate characters have been replaced, any other language characters were eliminated too and spelling were corrected.

B. Vector Generation

Baseline vectors were result of tokenization of collected data. Features remained same without any pre-processing process like stemming or stop words. Feature weights were calculated with the help of TF-IDF. Subsequently stemming was applied to features. Rapidminer is the tool for stemming which contain the normal mode and light-stem mood too. Stemming provided reduction to each feature and placed itinto3-letter root. Light-stemming eliminated prefixes and suffixes.

In step3,stop words were removed then measure the accuracy of the three classifiers.

In step 4 the tweets are converted to vectors having *n*-gram words. In start the process assigned *N* = 1 and computed accuracy of recent classifier. Next step assign *N* = 2 and re-compute accuracy of same classifier and this is repeated. The stopping condition is when accuracy of the classifier in use cannot be enhanced further.

In next step preprocessing methods are combined. Later on when the best *n* is identified, the acquired vectors are processed again to compute the most highly correlated *n*-grams values. TF-IDF is used for weighing the feature or words.

V. RESULTS ANDANALYSIS

C. *Evaluation Metrics*

To evaluate the performance of our suggested framework Accuracy, precision, recall and f_measure were used.

1. Performance of SVM Classifier

TABLE I

SVM Performance

SVM	accuracy	precision	recall	f_measure
BOW	87.33%	85.49%	90.03%	87.70%
stemming	84.67%	79.60%	93.36%	85.93%
stop words	**88.00%**	**87.79%**	88.37%	**88.08%**
bigram	82.00%	75.73%	94.35%	84.02%
trigram	74.17%	66.37%	**98.34%**	79.25%

Table I shows the performance evaluators (precision, recall, accuracy, and f_measure) as result of SVM for various representations. A scan seen from the table, SVM gives its best values for accuracy and precision when we remove stop words and it was 88.00% for accuracy and 87.79% for precision. The best for recall was 98.34 we gain it when we use trigram. This can be said that SVM (word *n*-grams) and feature-correlations have improved the polarity tracking. Light stem method built inside Rapidminer is used but it has not given any remarkable performance gain as shown in table I.

2. Performance of Naive Bayes Classifier

Table II

Naïve Performance

Naïve	accuracy	precision	recall	f_measure
BOW	83.67%	79.42%	91.03%	84.83%
stemming	83.17%	79.07%	90.37%	84.34%
stop words	85.00	80.67	92.45	86.00
bigram	84.67%	80.12%	92.36%	85.80%
trigram	84.83%	80.35%	92.36%	85.94%

Table II contains performance results for Naive Bayes. Naive Bayes benefited greatly from feature reduction and stop words removal. It is obvious as Naive Bayes works on assumption that less inter dependence among features and feature compression maintains those features, which are less correlated. Naïve Bayes exhibited good performance with combination of word *n*-grams with feature compression and with stop word removal (i.e. step 6). In Step 6, accuracy equals 85.00, recall equals 92.45,precision equals 80.67 and f_measure equals 86.00

3. Performance of KNN Classifier

Table III

KNN Performance

KNN	accuracy	precision	recall	f_measure
BOW	59.67%	96.83%	20.27%	33.52%
stemming	59.50%	96.77%	19.93%	33.06%
Stop words	69.17%	94.62%	40.86%	57.08%
bigram	51.83%	92.86%	4.32%	8.25%
trigram	52.33%	100.00%	4.98%	9.49%

Table 3 refer to KNN performance evaluators. KNN performs similar to others mentioned above. Precision is enhanced with elimination of stop words using feature compression. Recall and f_measure increase when word *n*-grams are integrated with feature compression and stop word elimination. Maximum achieved accuracy is 69.17% through stop word elimination and with feature compression.

VI. CONCLUSION

The paper focuses SA for Arabic tweets. The dataset consists of over 900tweets: with a good balance of negative and positive sentiments. The data was result of use of twitter API. Mostly as per structure each tweet was short reaching 140characters.The data was having informal structures, non-standard dialects and many spell errors as they were coming from variety of users.

Several aspects of data representations were investigated in this work. The feature vectors of the tweets were preprocessed in several ways and the effects of these on the classifiers' accuracy were investigated. The results show that light stemming combined with stop words removal improved the performance of the classification slightly.

The results also show that feature reduction, by keeping only features that are highly correlated with the classes and less correlated with each other, improved the classification accuracy for the three classifiers.

Finally, word *n*-grams improved the results as well. *n-grams* helped in capturing the negated phrases and common phrases that are used in expressing sentiment.

The performance of the classifiers was dependent on the preprocessing strategy. For example, SVM accuracy reached 88.00% when correlated features were used and stop words removed, as this enhances the independence between features of the tweets. *n*- grams as a preprocessing strategy worked well for both SVM and KNN; both reach the maximum precision when trigram is used.

This work deals with sentiment analysis at document level. We found that the best classifier to be used with Arabic tweets is SVM with combination of n-gram and stop word removal.

We will extend this work to find the sentiment at the sentence level. Furthermore, the work could be extended to deal with finding opinions about aspects and opinion target.

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