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Sentiment Analysis of Arabic Tweets in Sudanese Dialect

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Abstract— **Sentiment analysis is the field of science that deals with extracting opinions embedded in human oral or written speech. In this paper we focus on sentiment analysis of Arabic tweets written using either Modern Standard Arabic or Sudanese dialectical Arabic. We have created our own lexicon which contain 2500 words and we have applied three different classifiers on the dataset namely; Support Vector Machine (SVM), Naive Bayes (NB) and K-Nearest Neighbor (K-NN), to classify the tweets based on its polarity into positive or negative. We evaluate our work by four different measures which are Precision, Recall, Accuracy and F-measure. The results show that, SVM achieved the best Recall, Accuracy and F-measure and it equals 95.1%, 76.5% and 84.4% respectively. While NB achieved best Precision and it equals to 85.1%.**

Index Terms— **Sentiment Classification, Opinion Mining Sentiment Analysis, Social Media, Sudanese Dialect, Arabic natural Language.**

I. Introduction

Opinion mining or sentiment analysis is the field of science that is interested in extracting opinions that very frequently are embedded in customer's comments. It has been extensively studied in the literature for the English language. By comparison, relatively few works have targeted sentiment analysis in Arabic texts [2]. There are several granularities for sentiment analysis. A popular work is to determine whether a text is subjective or objective [4]. Another common work is to determine whether a text is written to express a positive or negative opinion [3]. Sentiment analysis deal with extracting the polarity of the text (positive, negative or neutral). A third category deals with finding the strength of an emotional state in text. Such as "happy", "sad" and "angry" [2]. There are two approaches for detecting sentiment in any text [18]. The first one relies on linguistic resources such as dictionaries and lexicons [5]. The second one is based on machine learning [5]. Some researchers have combined the previous two approaches. The lexicons are very hard to build manually and they are depending on the domain. Sentiment analysis is hard to detect for many reasons; one reason is that people use different writing styles to express their opinions. A second reason is that sentiment is context dependent [6]. One of the problems in Arabic is using a noun with positive polarities as a person names such as the word (Saleem); which means Right in English. Saleem as an adjective indicates positive sentiment but as a person name it is neutral (i.e. it has no sentiment). In general Arabic is divided into three types: Classical Arabic, Modern Arabic, and Colloquial Arabic. As the official language of 22 countries, there are 49 million Arab users of Facebook [7]. Arabic language is a high complex language, which embeds five critical challenges for Natural Language Processing (NLP) task,1) Arabic is not a case-sensitive language; it has no capital letters. 2) Arabic is a high inflectional language; often a single word has more than one affix, such that it may be expressed as a combination of prefix(s), lemma, and suffix(s) [8]. 3) Arabic has some variants in spelling and typographic forms. 4) Arabic texts have different meanings. For example, "Ragab" in Arabic may be used as a person name, or month. 5) Arabic resources, such as corpora, gazetteers, and NLP tools, are not free [9]. Existing Facebook sentiment analysis focus on the English language but very few focuses on Arabic slang comments [7]. It is classified into many regional forms in the Middle East [10], which are Arabian Peninsula Arabic (Khaliji Arabic), Syro-Palestinian Arabic, Egyptian Arabic and Maghrebi Arabic.

On the other hand, the analysis of social media has attracted a great deal of attention recently. Because the users of social media generate a huge volume of comments on a daily basis. These reviews and comments reflect the opinions of users about different issues and it is very interesting to be able to detect the positive and negative comments.

II. Related Works

A) Tagwa M. [31] presented some of previous works in sentiment analysis by using two techniques: a lexicon-based technique and a Corpus-based technique. They addressed some experiments and studies that deal with sentiment analysis in Arabic. Their study aims to use sentiment classification for Arabic tweets around Khartoum. They used different techniques for Arabic sentiment analysis applied in Arabic tweets around Khartoum and decide if the sentiment is happiness (positive), sadness (negative) or neutral. The methodology of their work is creating a corpus of Arabic tweets around Khartoum. Then build a lexicon for Arabic words. This lexicon contains a total of words divided in two groups; the words indicating happiness (positive) and sadness words (negative) with experts in language. They used two types of classification techniques, SVM and naive Bayes.

B) Afnan A. Al-Subaihin et al. [17] proposed a lexicon-based sentiment analysis tool for colloquial Arabic text used in chatting, daily conversation and within social media. They have an independent component in their work which is game-based lexicons, that are based on human expertise. SVM, Naïve Bayes and Maximum Entropy classifiers are used in this study. However, they have proven that, SVM achieved the higher accuracy. Their tool should rely partially

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texts based on human judgment to overcome the problem arise from using non-standardized colloquial Arabic text.

C) Taysir H. A. Soliman et al. [14] built a sentiment analysis approach for Slang Sentimental Words and Idioms Lexicon (SSWIL) of opinions. They proposed a Gaussian kernel SVM classifier for Arabic slang language to classify Arabic news's comments on Facebook. They collected 1846 comments from news websites like: Aljazera1, BBCarabic2, Alyoum Alsabe3 and Alarabia4 and Constitution Facebook Page. They applied three types of classification. The first classification type using Classical Lexicon (SVM) without SSWIL, the second type using Classic Lexicon and SSWIL, and the third type using SSWIL only. They show that the extraction techniques fail to extract the opinion words at the first classification type but it performs well at the second type after adding the SSWIL. The first classification type produces 5.35% accuracy rate, while the second classification type produce 86.86% and applying the system using SSWIL only, it gives 43.02% as a percent of comments classification and 56.98% not classified. The results are enhanced in the second type after applying SSWIL lists.

D) Al-Kabi et al. [13] built a novel sentiment analysis tool called colloquial Non-Standard Arabic - Modern Standard Arabic-Sentiment Analysis Tool (CNSAMSA- SAT), for both colloquial and modern standard Arabic MSA. They collected 1,080 Comments and reviews from 70 social media, and manually assigned each of them to one of the three polarity values (positive, negative, and neutral). The collected Arabic reviews and comments use Egyptian, Iraqi, Jordanian, Lebanese, Saudi, and Syrian dialects. A Naive Bayes classifier is used to determine the comment or review domain. The results show that, the accuracy of determining the polarity was 90% yields, with a 10% error rate. They identify some of the reasons that may show limitations in the tool such as the polarity of some of the phrases depends mainly on the domain they were used into. For example, the Arabic word (high) within the comment "This is a high cost product." leads to consider the polarity of the comment as negative, while using the same Arabic word (high) within the comment "High-quality service" leads to consider the polarity of the comment as positive. These two Arabic sample comments demonstrate why the effectiveness of the developed tool to determine the polarity of each Arabic comment within a domain is better than its effectiveness when it is applied on a general dataset.

E) Mohammed N. Al-Kabi et al. [10] developed an opinion mining and analysis tool for Arabic language (Standard or MSA and colloquial). The tool accepts comments and opinions as input. And it is capable to identify the polarity, subjectivity, and strength of each comment. They build 18 lexicons manually. Two general purpose lexicons were built to identify polarity, and 16 domain-specific lexicons were built to identify the polarity with eight different domains: Technology, Books, Education, Movies, Places, Politics, Products and Society. They used Naive Bayes to classify the domain of the comments. Their experiments showed that the proposed tool yields more accurate results when it is applied on domain-based Arabic comments relative to general- based Arabic comments. As they present the tool yield 93.9% accuracy to classify the comments into their proper domains, a 90% accuracy to identify the real polarity, and a 96.9% accuracy to identify the strength of the comments. This study used a small dataset, and the proposed tool is incapable to deal with emoticons and chat language.

F) Al-Kabi et al. [11] collected and analyzed Arabic comments from social network (Yahoo!). They detailed analysis of different information such as the reviews' length, numbers of likes/dislikes, polarity distribution and the languages used. The total number of the Arabic reviews and comments used in this study is 4625, contains the topic, comments, manual polarity, gender of the users. which leads to unbalanced classes 2812, 1230, and 583 for negative, positive and neutral classes, respectively. They applied two classifiers (SVM and Naïve Bayes) on these datasets and compared between them. The result illustrates that the best accuracy achieved is 68.2% using the SVM.

III. Tools and Techniques

In our work the tool we have used is RapidMiner and we have worked with three different classification techniques.

A) RapidMiner

RapidMiner is a java-based open source data mining and machine learning software. It has a graphical user interface (GUI) where the user can design his machine learning process without having to code [16]. Then all process is transformed into an XML (extensible Markup Language) file. RapidMiner includes many operators that support text mining such as Text Processing package. It includes more operators such as tokenization, stemming and filtering stop words. The tool can deal with the Arabic language that's why we have chosen it.

B)Classification Techniques

In our work we have used three different type of classification techniques which are Support Vector Machine (SVM), Naive Bayes (NB) and K-Nearest Neighbor (K-NN).

1. Support Vector Machines classification approach:

Support Vector Machines (SVM) is one of the discriminative classification approaches which is commonly recognized to be more accurate. SVM classification approach is based on Structural Risk Minimization (SRM) principle from statistical learning theory. SRM is an inductive principle for model selection used for learning from finite training data and it provides a method for controlling the generalization ability of learning machines that uses a small size training data. The idea of this principle is to find a hypothesis to guarantee the lowest true error. In addition to this, the derivation of SVM is mathematically rigorous and very open to theoretical understanding and analysis.

SVM needs both positive and negative training datasets which are uncommon for other classification methods. It is outstanding from the others with its better classification performance and its ability in handling documents with high-dimensional input space and culls out most of the irrelevant features. The good generalization characteristic of SVM is due to the implementation of SRM which entails finding an optimal hyper-plane, thus guaranteeing the lowest classification error. Besides, a capacity which is independent of the dimensionality of the feature space makes SVM a highly accurate classifier in most applications. However, the major drawback of SVM is its relatively complex training and categorizing algorithms and also the high time and memory consumptions during the training stage and classifying stage due to its convoluted training and categorizing algorithms. Besides, confusions occur during the classification tasks because the documents could be annotated to several categories because of similarities are typically calculated individually for each category [19].

2. Naïve Bayes classification approach:

It is a classification technique based on Bayes' Theorem with an assumption of independence among predictors. In simple terms, a Naive Bayes classifier assumes that the presence of a particular feature in a class is unrelated to the presence of any other feature. Even if these features depend on each other or upon the existence of the other features, all of these properties independently contribute to the probability. Naive Bayes model is easy to build and particularly useful for very large data sets. Along with simplicity, Naive Bayes is known to outperform even highly sophisticated classification methods [20].

3. K-Nearest Neighbor (K-NN) classification approach:

K-Nearest Neighbor (K-NN) is an instant-based learning algorithm that categorized objects based on closest feature space in the training set. The training data is mapped into multi-dimensional feature space. The feature space is partitioned into regions based on the category of the training set. A point in the feature space is assigned to a particular category if it is the most frequent category among the k nearest training data. During the classifying stage, KNN classification approach finds the k closest labeled training samples for an unlabeled input sample and assigns the input sample to the category that appears most frequently within the k subset. As KNN outperforms the other classification approaches by its simplicity, it only requires a small training set with small number of training samples, an integer which specifies the variable of k and a metric to measure closeness [16].

IV. EXPERIMENTATION

Our experiment consists of the following three phases:

1. *Data collection:*

One of difficulties for Arabic language is the lack of publicly available Arabic lexicons [27] in comparison with English. And in general, for sentiment analysis, it is better to collect a large amount of data to be used for training the classifier. Because increasing the amount of training data in the dataset, it is always improving the accuracy of the classification.

In our work, we started the first step by building our own lexicon which contains 2500 words from Sudanese dialect. It is manually collected from different social media and Arabic websites. We used Twitter's API to collect Arabic tweets. The collected data has different sizes and different categories used for training and testing.

In the second step, we classified the words manually into positive and negative. We have 608 positive and 1246 negative words as a training dataset. And we used 646 tweets collected from twitter as testing dataset.

2. *Data Preprocessing*:

This phase includes subphases as the following:

- Data cleaning: removing irrelevant information, such as URLs and special characters, for example @, &.
- Removing duplicated characters: this is a common practice in tweets and other social media in Arabic, where one of the letters is repeated many times, for example "رهيييييب" which mean nice in English. We reduced any repeated characters in to two character.
- Tokenization: we separated out words from tweets into tokens. These tokens could be words even words of only one characters. We extracted any alphanumeric string between two white spaces.
- Removing stopword: we removed any word carry no information. By other words we removed any word that doesn't have a meaning (articles preposition), such as "من" ،"على" ،"في"which mean "in", "on", "from "in English.
- Stemming: We removed any affixes (prefixes that added to the beginning of the word, infixes that added to the middle of the word, or/and suffixes that added to the ending of the word) from words to reduce these words to their stems or roots under the assumption that words with the same stem are semantically related. For example, we reduced "scientist" and "sciences" to "science".
- Normalization: we transformed tweets into a single canonical form that it might not have had before. We eliminated the diacritical markings, non-letters, letter Hamza (ء). Also, replaced أ and إ with ا, replaced final ى with ي, and replaced final ة with ه.

Table 1: Example of preprocessing a tweet

Preprocessing Step	Tweets After Preprocessing
The original tweet	أنا ارفض صفوف العيش شديييد دي شنو البهدلة دي!!
Data cleaning	أنا ارفض صفوف العيش **شديييد** دي شنو البهدلة دي
Removing Duplicated Characters	أنا ارفض صفوف العيش شدييد دي شنو البهدلة دي
Tokenization	أنا، ارفض، صفوف، العيش، شدييد ،**دي**، **شنو**، البهدلة، **دي**
Stopword Removal	أنا **ارفض صفوف العيش** شدييد **البهدلة**
Stemming	**أنا** رفض صف عيش شدييد بهدل
Normalization	انا رفض صف عيش شدييد بهدل

3. *Sentiment Classification*:

The data is divided into training and testing dataset. Training dataset used to build the classification models based on SVM, NB and K-NN classifiers. The data classified based on its polarity to positive and negative classes. Testing dataset is used to predict the polarity of the tweets.

Table 2: Sample of Classified Tweets.

Tweet	In English	Class
الفلم دا حلو حلاة	**This movie is nice.**	**Positive**
الزول دا قلبو مقطوووع	**This is afraid person**	**Negative**
البت دي فاكاها في روحها شديد	**This is a conceited girl**	**Negative**
الاكل دا ظاااابط	**This is delicious food**	**Positive**
اللوشن دا طلع ماسورة	**This lotion is not good**	**Negative**

V. Results

Four different measures were calculated which are Precision, Recall, Accuracy and F-Measure for every classifier, to evaluate the correctness of classifying testing tweets as positive or negative. Table 3 below shows a confusion matrix that introduces these measures.

Table 3: Confusion Matrix for Two Classes Pos and Neg

	Predicted Class	
Actual Class	Pos	Neg
Pos	TP	FN
Neg	FP	TN

In the table above we have four parameters (True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN)), which are needed to calculate the measures.
TP: is the number of tweets that were correctly classified as positive.
TN: is the number of tweets that were correctly classified as negative.
FP: is the number of tweets that were classified as positive but they are negative.
FN: is the number of tweets that were classified as negative but they are positive.
Therefore, the formula of the measures is the following:
Precision = TP/(TP+FP)
Recall = TP/(TP+FN)
Accuracy = (TP+TN)/(TP+FP+FN+TN)
F-measure = 2* (Precision*Recall)/ (Precision*Recall)
Table 4, 5, 6, 7, 8 and 9 below, shows the results of each classifier in our experiments with our dataset.

Table 4: True Positive and True Negative for the Support Vector Machine

	TP	TN
Predicted Positive	234	61
Predicted Negative	374	1185

Table 5: Class Precision, Recall, Accuracy and F-Measure for the Support Vector Machine

Classifier	Precision	Recall	Accuracy	F-Measure
SVM	76.01%	95.10%	76.5%	84.4%

From table 5 above we notice that, Support Vector Machine achieved good results for Recall which equal to 95.10%.

Table 6: True Positive and True Negative for the Naïve Bayes

	TP	TN
Predicted Positive	518	731
Predicted Negative	90	515

Table 7: Class Precision, Recall, Accuracy and F-Measure for the Naïve Bayes

Classifier	Precision	Recall	Accuracy	F-Measure
SVM	85.12%	41.33%	55.71%	55.5%

In table 7 above, Naïve Bayes achieved good result for Precision which equal to 85.12%.

Table 8: True Positive and True Negative for the K-Nearest Neighbor

	TP	TN
Predicted Positive	180	63
Predicted Negative	428	1183

Table 9: Class Precision, Recall, Accuracy and F-Measure for the K-Nearest Neighbor

Classifier	Precision	Recall	Accuracy	F-Measure
SVM	73.43%	94.94%	73.5%	82.8%

From table 9 above we notice that, K-Nearest Neighbor achieved good result for Recall which equal to 94.94%.

Figure 1 below shows a composition of the results of the three classifiers in detail.

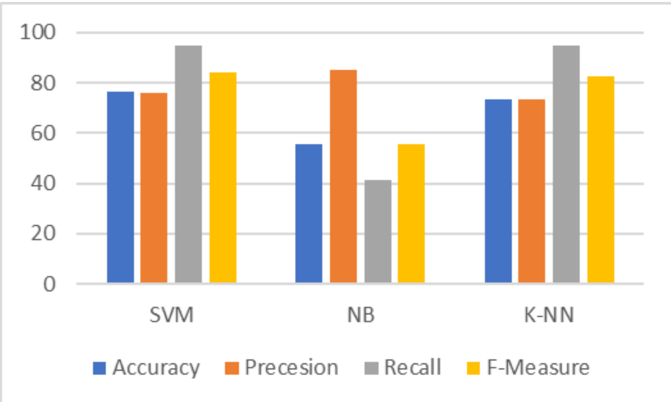

Figure 1: Accuracy, Precision, Recall and F-measure for the three classifiers.
From figure 1 above we found that the best Accuracy, Recall and F-measure was achieved by Support Vector Machine. While the best Precision was achieved by Naïve Bayes.

VI. Conclusion

This paper considered sentiment analysis in Arabic tweets which are written in Sudanese dialect. A new lexicon for Sudanese dialect was built, which consists of 2500 tweets. We split the data into training and testing sets. The SVM, Naïve Bayes and K-NN classifiers were applied to detect the polarity of the given tweets of the training set. The results of posterior experiments with the testing set show that, SVM achieved the best Accuracy, Recall and F-measure and it equals 95.1%, 76.5% and 84.4% respectively. While Naïve Bayes achieved best Precision and it equals to 85.1%. As we know this lexicon is the first lexicon of Sudanese dialect. And according to the results, our work could be very valuable to identify positive and negative opinions of customers for marketing purpose. And also, for detect negative comments related delicate issues (racism, etc..).

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