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Aspect Oriented Sentiment Analysis Model of Arabic Tweets

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ABSTRACT

New web standards are implicitly designed to cater the needs of growing social media, blogger networks, discussion forums, and micro-bloggers, etc. These reviews are facing continuous growth because the users of social networking websites create a massive volume of reviews (tweets, blogs, etc.) daily about products, services, and personals. These tweets and reviews carry user views about numerous ongoing topics and issues in an unstructured text written in natural language. The issue can be any service being offered, recent product reviews, the point of view of news, excitement for ongoing entertainments, or sports comments. Hence, there is an acute need to analyse such text. One application is to know user feedback about food being served or quality of serving by a restaurant. Most tasks related to feature based opinion mining, which requires detection of product entities referred inside the reviews, which are necessary to identify product features expressed in customers' reviews. Hundreds of studies are available, which will be difficult for the potential customer to read and take a decision upon purchasing any product. As a result, mining essential information from product reviews and then presenting it to potential customers is performed at various levels. Arabic Sentiment Analysis is a challenging task because most natural language processing (NLP) tools for Arabic are developed for Modern Standard Arabic (MSA) only and these tools fail to capture the broad range of dialects used in Arabic micro-blogs such as Twitter. This paper focuses on evaluating Arabic tweets, especially for restaurant services. In the process, many Arabic-language related challenges have been documented and treated. In this research, we construct a prototype for Arabic sentiment analysis of tweets with corresponding Arabic Opinion Lexicon (AOL) and Arabic Tweet Sentiment Analyzer (ATSA). The prototype has been designed and tested using customer's opinions obtained from tweeter; it accepts tweets as input, generates polarity, and determines the tweet target as outputs. Additionally, the prototype can ascertain the type of tweet as subjective, objective, positive, or negative and give a summarization of tweet polarity.

Keywords:- Arabic Sentiment Analysis; frequent pattern; feature based level; Arabic sentiment analyzer; Opinion Polarity

I. INTRODUCTION

In recent years the era has seen a boom in communication specially over social media. Social media is not only Facebook or similar network websites, but it also includes micro-blogs such as Twitter and photo sharing like Instagram, and profession linking as LinkedIn and much more. Text messaging has become the core feature among all, which can record user opinions, reviews, surveys and discussion on some ongoing event, some new product, quality of service, some personality and news. These expressions of review or opinions are called sentiments in the terminology of opinion mining. The biggest source of messaging is still Short Messaging Service (SMS), and a fast emerging source is Twitter, which generated tweets. This massive traffic of sentiments has brought many new workable opportunities. The user opinions and user trends can be precisely calculated using data mining and language processing approaches. However, dealing with SMS and tweets is not as simple as dealing with conventional text based systems such as a newswire.

The biggest problem with this new kind of messaging is that their length is limited, expressions are bold and informal, they don't follow grammar, and spelling rules and many abbreviations and customized short forms are used [1]. Furthermore, the text comprises of typo errors, misspells, slangs, words of other languages (than the one being shared), website links and many hashtags. These issues call for tools development which can build lexicons and syntactic hierarchy to cope with all these problems before opinions can be mined. But creating a data mining system which can work efficiently with these limitations is not an easy task. Though researchers have shown a great ambition for extracting user opinions through sentiments mining, available on social networks. Still, less research is focused on Twitter. The interest manly came in some particular areas like healthcare, disaster recovery, or online financial handlings. Twitter include a lot of unnecessary information in the messages e.g. followers details, hashtags, and re-tweets [43]. There is a definite need for an acute model that can extract the valuable opinions with an acceptable efficiency from tweets and other messages. Social media is a free world where the user expresses their views boldly and honestly which are very helpful in calculating their unbiased review of the subject [2]. Some organizations give weightage to the user reviews (even on Twitter) issued against their product or services. These companies use Twitter to look for their customer reviews about their services; because the success or failure of any business is measured by its ability to analyze customers' reviews of its products. Analysis of these reviews is necessary for ensuring continuous customer satisfaction and for further improvements of current and future products [3]. Consequently, understanding preferences of customers is crucial from a product manufacturer's perspectives as it helps in product development, marketing and consumer relationship management. On the other hand, customers use reviews by others to make a decision on whether or not to purchase a product or to use services.

Naturally, tweets can be up to 140 characters long written in an unstructured natural language text. As such, their processing requires appropriate knowledge from different domains that include database, information retrieval, information extraction, machine learning, and natural language processing. However, when the number of tweets is large, it becomes difficult for dealers to keep track of customers' opinions and sentiments. In the past few years, researchers looked at different ways of taking advantage of opinions in what is now known as opinion mining or sentiment analysis[4]-[6].

According to the scope of the input, researchers divided Sentiment analysis into three categories; document based classification, sentence based classification and phrasal based classification. If it is documented level classification the task is done in two additional steps, first is to extract sentiments and secondly is to compute polarity. For sentence based it is direct sentiment extraction and polarity computation. There are numerous tools available for English and Chinese. The problem with these tools is that they cannot be customized to work with the Arabic language. Few Arabic specific tools are available though they cannot distinguish between Standard Arabic or Colloquial version. The writing style of Arabic is Semitic languages with a flow from right to left. Arabic contains twenty eight consonants, without distinction of the upper or lower case letters. Formation of grammar based analyzers or Part of Speech (POS) is an essential component[7]. Opinion Mining on Arabic text is not popular among researches due to some limitations[8].

The Arabic language has different problems in this regard: the Arabic language is in itself very complex regarding structure and morphology when compared to other languages such as English. The Arabic language is a highly inflectional and derivational language which makes monophonically analysis a very complex and challenging task [9] with many word forms and diacritics, e.g. the word "سمك الطاولة" can be tagged as either noun phrase when the word "سمك" is taken as "fish" or as a verb phrase if taken as "thickness". Furthermore, Arabic opinions are highly subjective to context domains, where you may face words that have different polarity categories in various contexts. Arabic Internet users mostly used colloquial Arabic rather than using classical or Modem Standard Arabic (MSA) forms, where colloquial Arabic resources are scarce, this complicates the use of semantic approaches for mining opinions. The percentage of spelling mistakes within these Arabic opinions is high, and this represents an additional challenge. Additionally, there is in unlabeled-classical-Arabic-text, which is required for input into a Supervised Learning Algorithm and there is an absence of an opinion Lexicon for the Arabic language, which thwarts polarity measurement of extracted subjective text. For that, a list of a list of pre-processing strategy was applied, and opinion lexicon for Arabic was developed to handle these problems as shown in section II

The focus of this paper is on explicit feature-based sentiment analysis of tweets at the sentence level. Such task will be accomplished in two steps.

- Identification of Features: Identify the features that customers have expressed opinions on (called opinion features).

- Classification of Opinions: Classify the opinion of the user into positive and negative classes and find the opinion target in each tweet [10].

There are various methods for feature extraction and refinement have been applied on feature-based opinion mining:

- **frequency-based methods [10],[28]:** very simple and quite efficient way but it produce too many non-aspects, miss low-frequency aspects, require the manual tuning of various parameters (thresholds) and makes them hard to port to another database.

- **Relation-based Methods [45], [46]:**

Find low- frequency aspects but it produces many non-aspects matching with the relation patterns.

- **Supervised Learning Techniques[47], [48]:** **S**upervised learning approaches to overcome the limitations of frequency- and relation- based, methods by learning the model parameters from the data but it need manually labeled data for training.

- **Topic Modeling Techniques [49],[50]:** **N**o need for manually labeled data, perform both aspect extraction and grouping at the same time in an unsupervised manner, but it requires a large volume of (unlabeled) data to be trained accurately

Accordingly, these tasks are accomplished through an Arabic Tweet Sentiment Analyzer(ATSA), which is the proposed method for feature based sentiment analysis. ATSA is described in section III, related works in opinion mining is discussed in Section II, Section III discusses feature based extraction using frequent pattern mining, the results are discussed in section IV, and lastly a conclusion is revealed in section V.

II. RELATED WORK

Pang et al. [11] developed polarity categorizations for the opinions using documents. El-Halees [12] compared the polarity classification methods suited for materials. Few researchers like Elhawary and Elfeky [15], Yi et al. [13], Abdul-Mageed et al. [16], and Kim et al. [14], came up with sentence categorization methods by sentence polarity. They also tried to detect positive and negative sentence present in the target sentence. The contextual polarity was established for polar sentences (after polarity detection) at phase level [17].

Elhawary and Elfeky [15] found that Arabic dataset is missing which can sample the user reviewers and annotate the sentiments. For English dataset, many official websites are there but no such source available for Arabic. The researchers [15] themselves formed a dataset of product or service reviews, and later on, they trained classifiers utilizing eighty percent of the data. Then these reviews were used to refer to documents. Arabic lexicons were also constructed to ease the overall process. Lexicons were helpful in determining the polarity of the sentence. Polarities were divided in negative, neutral or positive.

Another research generated a corpus for modern Arabic and associated polarity lexicons [16]. Researchers came up with Subjectivity and Sentiment Analysis (SSA) technique which was automated while using manual annotation. Satisfactory performance was observed.

El-Halees [12] employed multiple techniques to calculate the polarity of the documents containing the source sentiments. In first step lexicon scanning was done on full text. Secondly, the resultant classified documents were fed to maximum entropy as training data which subsequently classifies some other material. A classification was generated with the help of KNN to classify the rest of the documents .

Sentiments were analyzed on the bases of outcome or the classification they fall in. Conventionally, sentiment analysis lead to the detection of positivity, negativity or neutrality. Elhawary and Elfeky [15], Wilson et al. [18], and Abbasi et al. [19], showed lexicon based sentiment scoring method to detect the type of opinions and its positivity, negativity or neutrality. They also determined the strength of classification as strong or weak. To improve the precision of classification, detection weighted feature schemes have been proposed as well. One such study [20], give weights to the elements of classification by the occurrence of the term inside the corpus. Their method showed remarkable results for sentiment classification.

Few studies remained domain oriented, and they collect the features for the domain they belong to as explained by Balahur et al. [21]. They use “term” to refer to a particular product category. After categorization, polarity detection is done for the attributes of every feature with the help of annotated corpus. Few studies construct clues using domain related features in conjunction with opinion subject. Choi et al. did Another study, [22] and proposed a framework for sentiment analysis. The framework analyzes the sentiments; take the clue related to the original opinion subject from the expressed sentence (could be an organization, a user or some happening). A domain oriented classifier comprising of the clues in issue and user opinions using partially supervised technique were used. Few more researchers like Choi et al. [22], Yi et al. [14], and Kim et al. [15], performed opinion extraction through the topic in focus using the sentiment clues. The result was classified as the primary issue of the sentimental expression being studied. Ortiz et al. [23] evaluated domain free sentiment analysis method in comparison with multi-domain opinion based corpus. The study exhibited significant precision through qualitative and non-automatic language information. Al-Subaihin et al. [24] developed a technique (as a tool) using MSA to segmented user comments (or reviews) into text-phrases which were then used for meaning extraction and lexicon formation. This technique was able to define a rule against a text-pattern (word or pair of words), which was later used to match and extract annotation from similar patterns. Lastly, polarities were measured from the patterns of the sentiment. These particular tools are utilized for this research to handle standard and non-standard Arabic.

Al-Kabi et al. [25] came up with a comparison of a pair of existing tools. These sentiment tools (1.SocialMention and 2.Twendz) are available on the internet under a free license and work well with MSA and English. The researchers proposed multi-polarity dictionaries for Arabic, English, and emotions. Results showed that 1. Performed better the 2. Similarly one more researcher Khasawneh et al. [26] compared 1.SocialMention and 2.SentiStrength for MSA only, by feeding a thousand user-reviews (extracted from social sites and micro bloggers). Their results declared 2. to be more efficient. Another work classified (4625 derived from Arabic search engine) user reviews regarding four subjects, i)Arts, ii)Science, iii)Technology, and iv)Politics. Certain features like sentence length, total associated likes, polarity weights and primary language were extracted as well.

Hu and Liu's[10], established feature-based opinion summarization, they used association rule mining algorithm, to obtain frequent item sets as accurate product features only in the form of noun phrases identified by a part-of-speech (POS) tagger. Apriori algorithm was used for finding everyday words; however, their method does not consider the position of the phrase in a sentence.

Popescu and Etzioni [28], removed noun phrases which do not contain any features rather than on determining sentence or review polarity, by computing a pointwise mutual information (PMI) score between the expression and some meronymy discriminators associated with the entity class.

Blair-Goldensohn et al. [29], considered mainly those noun phrases that are in sentiment-bearing sentences or in some syntactic patterns which indicate sentiments. Ku et al.[30], made use of the TF-IDF scheme considering terms at the document level and paragraph level. Moghaddam and Ester[31], augmented the frequency-based approach with an additional pattern-based filter to remove some non-aspect terms. Their work also predicted aspect ratings. Scaffidi et al.[32], compared the frequency of extracted frequent nouns and noun phrases in a review corpus with their occurrence rates in a generic English corpus to identify real aspects. Long et al[33], extracted feature(nouns) based on frequency and information distance. Jeong[34] proposed an enhanced feature extraction and refinement method that effectively extracts correct features from review data by exploiting both grammatical properties and semantic characteristics of feature words and refines the features by recognizing and merging similar ones[6]. Rahamatallah, Limia et al.[43] Construct Arabic Sentiment Analyzer(ASA) to extract an implicit feature from customer reviews.

From the above description of the selected literature review, it is clear that there are few studies in the area of opinion miming of Arab dialectic based upon social media and micro-blogs. But there is an urgent need for tools to deal with opinion mining due to the evolution and growth of WEB2. Also, there is an increasing number of users that use Arabic for posting their opinions which push this need too.

The proposed technique will follow these steps:

- Develop a tool for analysis of Arabic opinions (ATSA).
- Construct opinion lexicon for Arabic opinion word.
- Identify the features which appear among user comments.
    - o Generate n-gram model to resolve the problem of order the word in sentence
- Calculate the subject and associated polarity from the user reviews/opinions.
- Identify opinion holder or target in each tweet
- Summarizing the results

III. FEATURE BASED EXTRACTION USING FREQUENT PATTERN MINING

Feature-based opinion extraction system takes as input a set of user reviews for a particular product or service and produces a set of relevant feature. User opinions can relate to a person, company, happening, news or some sellable entity, now onward 'object' will be utilized for all such entities [5].

The object comprises of smaller units and some attributes. One such example is "restaurant" comprised of "location", "menu" and "service". These units further have attributes for example "menu" is having menu-design, and menu-day. Similarly "meal" is possessing different properties like meal-price, meal-flavor, and meal-serving. Although users are very careless while placing their review for an object, they don't explicitly mention the object name, its sub unit or even the attributed being discussed. A feature represents both (the unit and quality). Some particular feature (F), when found in text-phrase (T), is correlated to T explicitly. For example, if the T is " سعر الوجبة غالي"" the meal price is high", then the explicit feature F is "meal price". If F does not explicitly appear in T but lesser frequent than specific ones. Consequently, only specific features will be discussed beyond this point.

IV. ARABIC TWEET SENTIMENT ANALYZER (ATSA)

Most of the original works on feature-based opinion mining are frequency based approaches. They provide a set of candidate words since some words could represent features, and some are not, thus they still need filtering to get real features. Relation-based approaches use the feature-sentiment relationships to identify features and sentiments. One of these relationships is mainly used as a syntactic relation between features and sentiments. Arabic Tweet Sentiment Analyzer (ATSA) is proposed by taking the advantages of both approaches, for identifying feature and define semantic orientations using the Arabic Opinion Lexicon(AOL). A simple way to merge these approaches is to use a set of predefined syntactic for filtering. However, syntactic patterns can only be utilized for the language and the type of text (full sentences, sentence segments, phrases, etc.) in which they are defined. In other words, each language or text type has its grammatical structure and moreover its syntactic patterns.

Figure (1) describes Arabic Tweet sentiment analyzer (ATSA) can mine opinions of customer tweets and identify tweet target, it takes tweet texts as input, and outputs tweet subjectivity, polarity, and destination. It first segments the tweet into segments, then uses these sections as transactions to find frequent nouns or noun phrases. Filtering familiar noun phrases are done by syntactic relation to group synonyms features.

Using Twitter API 909 multi- dialectal Arabic tweets randomly retrieved. Each tweet has been saved into a separate file.

Data cleansing is the next step for the collected tweets. Cleansing removes Diacritics (tashkeel) and, spell errors, typos, redundant letters and words, normalized the non-language words, other symbols, and URL.

The tweets were collected by querying the Twitter API for *lang:ar (Arabic), and Restaurant 'مطعم'*. The query terms were then replaced by place-holders to avoid bias. The total number of tweets that used to construct the corpus are 909 tweets, among them 459 were positive while 450 were negative. We manually labeled the tweets to collect the baseline results used to evaluate our proposed method. The details of the manual labeling are described as follows: The tweets have been shown to two expert annotators. They read the tweets and identified all features and associated polarities. According to features polarities, they are classified into two categories: positive (1), negative (-1). An example of the manual tagging is shown in Table 1. Finally, the manual results and the output produced by our system are compared with each other.

Table 1: Example Of Manual Labeling

Tweet	Manual Labeling
مطعم سيزلر هاوس يوجد في الرياض شارع التحليه اقسم بالله من ارقى وافضل المطاعم وخدمه رائعه وتعامل ممتاز	ارقى المطاعم 1 افضل المطاعم1 خدمه رائعه1 تعامل ممتاز1
في مطعم عندنا اسمه فيروز قاردن وصلوه للسماء من المدح رحتله وكان سعره غالي اطلالته جميلة لكن اكله خياس الله يديم النعمة	سعره غالي1- اطلالته جميلة1 اكله خياس1-

A. *Preprocessing step*

Some preprocessing steps were performed for normalization and preparation of the extracted. Firstly, remove punctuations along with non-Arabic letters. Specified Arabic letters pass through standardization, for example (Yaa', "ئ ,ي") is converted into (Yaa', ي). Similarly (أ ,إ, and آ) are replaced by (bare Alif, ا) and on same pattern (taa', haa', "ه,ة") becomes (haa',ه). Secondly, the tweets were tokenized. Stop words removed. Obtained vector representations for the terms from their textual descriptions by performing (Term occurrences).

B. *Part-of-Speech Tagging (POS)*

The Stanford POS tagger is applied to produce tags for each word and identify simple noun and noun groups. For instance,

e.g.<(ROOT(S (NP (NN مطعم)(NP (NNP سيزلر)(NNP هاوس))) (VP (VBD طعم)(NP (NNP ونظافه) (NNP واكلهم))(NP (NN كثير) (JJ واسعارهم) (JJ معقولهم)))))

< NN'> indicates a noun and <NP> indicates a noun phrase. The POS tagged information of each word is then saved in the transaction file.

C. *Feature -based sentence segmentation*

Due to its nature, tweets might be in incorrect syntactic form, sentence fragments, short phrases, or missing punctuations. The presence of adjectives in a tweet usually means that the tweet is subjective and contains opinions[35].

For an opinionate tweet that includes multiple feature (aspects), one of the key issues for the feature- based opinion is to split such a multi-feature sentence into multiple single-feature units as the basis for the feature-based opinion. To tackle this problem, we propose a Chunker model that takes a tweet as input and produces single feature segments. For example, the tweet:" مطعم هادي و انيق"

can be segmented into two single feature units, as :

"مطعم هادي " و " مطعم انيق "

Our first intuition is to treat single-feature segmentation by taking dependency relations for nominal sentence ((adjective (صفة) and noun (موصوف)).

Table 2. Dependency Relations For Nominal Sentences

Relation	Arabic	Dependency	Dependent → Head
adj	صفة	Adjective	adjective → noun
poss	مضاف إليه	Possessive	second noun → first noun
pred	مبتدأ وخبر	Predicate of a	predicate → subject
app	بدل	Apposition	second noun → first
spec	تمييز	Specification	second noun → first

Table(2) [43] shows the relation between an adjective and the noun it describes, as well as the dependencies that relate pairs of nominal (predicate, apposition, and specification). The polarity of a tweet is obtained by determining the majority of polarized features which our model identified. If the major features are polarized as positive, then the tweet polarity is considered positive. Likewise, if the major features are polarized as negative, then it considered as negative. Otherwise, the tweet polarity is considered as neutral

D. N-gram model

The N-gram word model is a method that finds a series of the consecutive word of length n. The most commonly used ones are unigram, bigram and trigram models. An n-gram sized one is termed unigram. N-gram sized two is termed bigram. And n-gram sized three is referred as a trigram. Then exist n-grams with higher sizes like 4-gram or 5-gram. Example is " لوسين اجمل مطاعم المملكة " its bigram will be as follows:

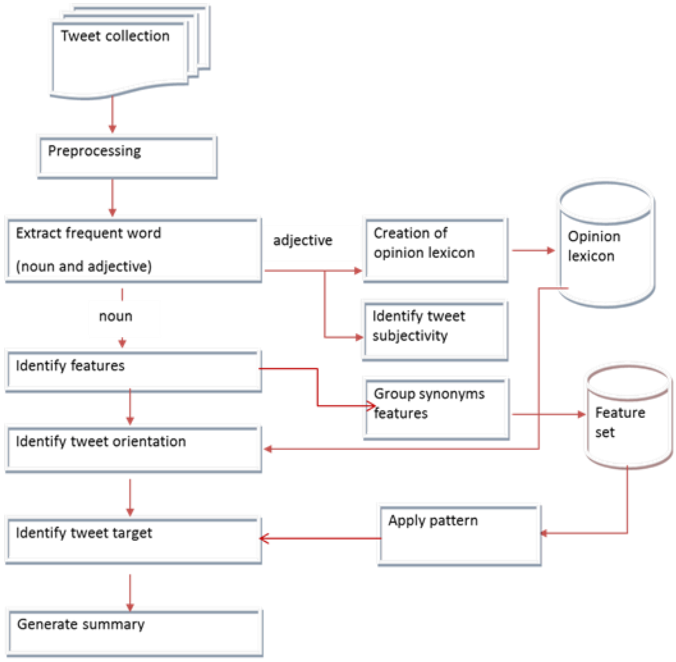
"لوسين اجمل", " اجمل مطاعم" ," مطاعم المملكة "

E. Frequent Features Generation

Up to this step, features of more interest to customers will be extracted. To that end, a tool that discovers frequent patterns is used. In our context, an itemset is a set of words or a phrase that occurs together. Association rules are used to determine correlations among a set of items in the database.

These relationships are based on co-occurrence of the data Items rather than the inherent properties of the data themselves (as with functional dependencies). Association rule and frequent item set mining is becoming an extensively researched area resulting in the development of faster algorithms. A fast and scalable algorithm, Frequent Pattern tree algorithm, FP-Growth[36], is used to extract frequent words that are most popular in the text (nouns and adjectives)

Figure (1) Arabic Tweet Sentiment Analyzer (ATSA) Model



to find all frequent itemsets. Association rule mining take this sentence as a transaction but it is inappropriate for the function as association rule mining cannot handle the proper sequence in this sentence, though this remains significant for natural language processing. Thus the pre-processing methods are used to find patterns which can further extract features (n-gram).The FP- Growth module was then applied to generate the frequent item-sets, the nouns or noun phrases that appear in more than 1% (minimum support). The common candidate features are stored to the feature set for further processing.

F. FP-Growth Algorithm

Let I ={a1, a2, . . . , am} be a set of items, and a transaction database DB=_T1, T2, . . . , Tn_, where Ti (i ∈ [1 . . . n]) is a transaction which contains a set of items in me . The support of a pattern A, where A is a set of items, is the number of transactions containing A in the database. A pattern A is frequent if A's support is no less than a predefined minimum support threshold, *minsup*. Given a transaction database DB and a minimum support threshold, the problem of finding the complete set of frequent patterns is called the frequent-pattern mining problem.

The FP-Growth algorithm allows frequent itemsets discovery without candidate generation and works in two steps. In the first step, it builds a compact data structure known as FP tree for itemsets from a set of transactions that satisfy a user- specified minimum support. In the second step, it extracts frequent itemsets directly from the FP tree. Also, only frequent itemsets with a maximum of four words will be considered since a product feature contains no more than three words.

G. Grouping Candidate Features

Synonym groups can yield feature reduction, and this will not harm the complete information as various users express phrases through a variety of words of similar meanings. Most of the previous methods do not consider feature grouping at all. More or less they use synonyms grouping. However, some synonyms might give many errors in the result of feature set generation. Using the syntactic role words are groupes. Using traditional Arabic grammar of iierab (إعراب) which assigns a syntactic role to each word in a sentence. Pairs of syntactic units are related through directed binary dependencies table (3) show the syntactic relation between noun and another word that define the first word e.g. " اسعار السمك" is Possessive Construction "مضاف ومضاف إليه".

TABLE(3) ASSOCIATION RULES WITH N-GRAM

size	support	Item
1	0.15	اسعار السمك

H. Creation of opinion lexicon

Opinion words are words that people use to express a positive or negative opinion. Previous work on subjectivity [37]-[38] developed a strong correlation with adjectives. Adjectives are used for prediction of subjectivity, or for expression of the opinion. The study paper employed adjectives for opinion mining. In this particular case, association mining is unsuitable specially for detection of frequent item-sets adjectives. Such item-sets are more likely the opinion words. Association mining is handy when a customer expresses their opinion through fix words every time. Generally, adjectives possess similar orientation like their synonyms. Adjectives also exhibit opposite orientations like their antonyms. The proposed work utilizes positive seeds with negative adjectives. The seeds set is then expanded using online dictionary.

I. Target Identification

The tweet target feature terms identify based on noun phrases according to the following patterns: Base Noun Phrase (BNP). This pattern restricts the tweet target feature terms to one of the following patterns: NN, NN NN, JJ NN, NN NN NN, JJ NN NN, JJ JJ NN, where NN and JJ are nouns and adjectives. Definite Base Noun Phrase (dBNP). This pattern restricts tweet target feature terms to exact base noun phrases, which are noun phrases (BNP) preceded by the definite article the:ال”. Beginning Definite Base Noun Phrase (bBNP). bBNPs are dBNPs at the beginning of a sentence followed by a verb phrase. Table(4) give n example of that

Table(4) Example of *Target Identification*

Tweet	*مطعم قنصلات جاكرتا من افضل و ارقى المطاعم في جاكرتا*
POT	*مطعم*/NN *قنصلات*/NNS *جاكرتا*/NNP *من*/IN *افضل*/JJR *و*/CC *ارقى*/VBD *المطاعم*/DTNN *في*/IN *جاكرتا*/NNP
Target	*مطعم قنصلات جاكرتا*

J. Summary Generation

After all the previous steps, generating the A novel information summarizing based on and NLP technique, which is simple enough and bases upon these steps:

- Fetch tweets from the directory.
- POS tagger are applied
- Fragment the tweets depend on adjective
- Fetch a feature from a feature list
- Assign weight to the each tweet based on the opinion lexicon. (lexicon contains positive words, negative words)
    - If found negation word it usually reverses the opinion expressed in a sentence.
    - Negation words include traditional words such as “no”, (eg.ليس, لم, غير ولا ،ليست)
- Sum up the weight(positive\negative) of the each feature to get weight and displayed
- Sum up the positive\negative tweet of the each feature to get overall tweets summary.

Table(5) Set Of Feature With Same Meaning

Feature
وجبة
أطباق
اصناف
اكلات
الطبخ

V. RESULTS AND DISCUSSIONS

Tests were executed to measure the efficiency of proposed tool to see how effective it is in identifying subjectivity, polarity and target features from collected tweets. The metrics, which measured the model's quality by user-opinions, is as follows:

1. Accuracy: How close is the measured value of the real.

Accuracy (A) is shown in equation (V.I).

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad \text{.... (V.I)}$$

Here TP denotes true-positive, while FP represents a false-positive. TN stands for true-negative, and FN refers to false-negative [39]. All terms in the equation are in the form of rates.

2.Recall (R) is represented by equation (V.II) adopted from [41].

$$Recall = \frac{TP}{_{i}TP + FN} \quad \text{.................... (V.II)}$$

3.Precision(P) is shown in equation (V.III).

$$Precision_i = \frac{TP}{TP + FP} \quad \text{.................. (V.III)}$$

Here TP count of correctly classified tweets with decision true-positive, while FP is measured a number of falsely classified tweets with decision false-positive. FN is the count of falsely classified tweets with decision false-negative, the terms are used from [42].

Table(6) Evaluation Of Subjectivity Results

Class	A	P	R
Dataset	93.9%	93.0%	93.0%

Table(7) Evaluation Of Polarity Results

Decision/Class	A	P	R
Dataset	89.85%	89.36%	91.30%

Table(8) Evaluation Of Target Identification

Decision/Class	A	P	R
Dataset	75.47%	70.0%	100%

Table (5) represents a set of feature with the same meaning to minimize the size of the set of candidate feature this group of the word will be "وجبة". The overall accuracy of SUBJECTIVITY is represented in the table (6), which remained almost ninety four (94) percent. Furthermore, table (6) presents recall and precision values. Table (7) shows the overall accuracy, precision, and recall of POLARITY. Table (8) shows the overall accuracy, precision, and recall of target identification. It can be observed that the efficiency is relatively low because the tweets were taken randomly and contained implicit features. However, there is a problem that some frequent nouns and noun phrases such as restaurant name may not be real tweet target features as seen in Figure (2).

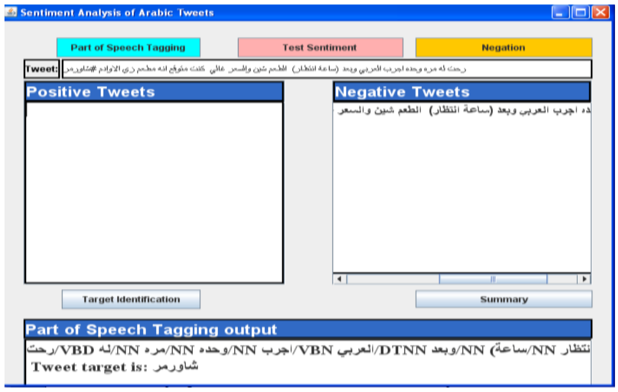
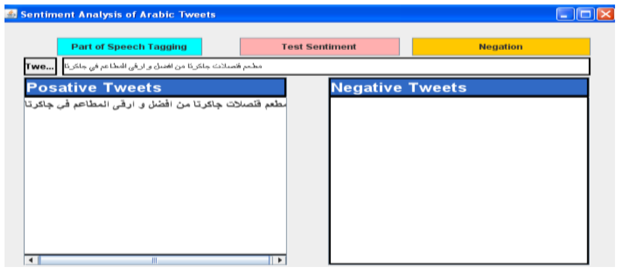


Figure (3) shows an example of polarity identification. Figure (4) shows a case of tweet target identification. Figure (5) shows an example summary for the feature



"السعر". Figure (6) shows that the proposed technique has handled the negation word.

Figure (2) A Case Of Restaurant Name as Tweet Target

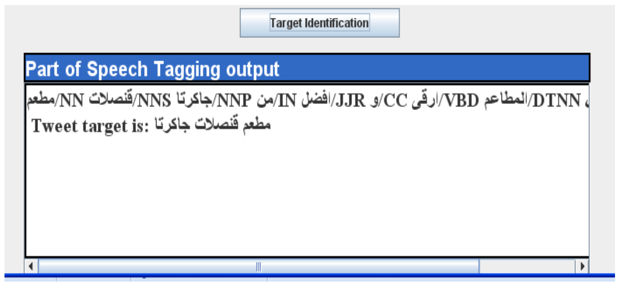
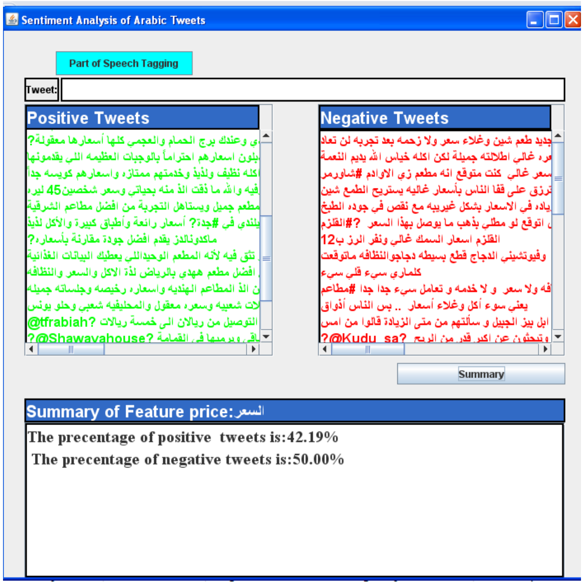


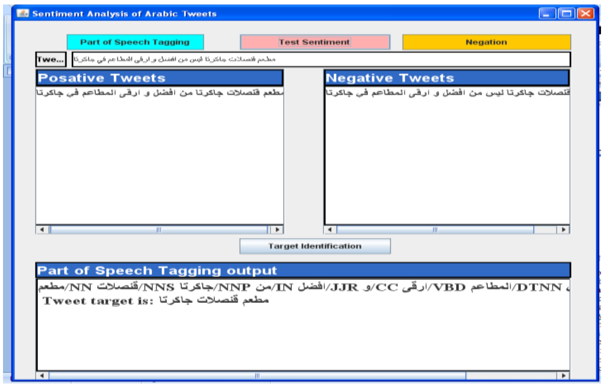
Figure (3) An Example Of Polarity Identification

Figure (4) A Case Of Tweet Target Identification

Figure (4) An Example of Summary for the Feature Price "السعر".



Figure(5) Handle Negation Word



VI. CONCLUSION

The study comes up with certain methods which can perform mining and summarization of Arabic tweets with the help of language processing. The aim of the survey remained to construct ATSA. ATSA provided a feature oriented summary and target identification of a massive set of Arabic tweets of a restaurant. Experiments indicated that the proposed work is very efficient. The propose techniques are necessary in a way that people are using the web for their expression of opinion. Review summarization can also give an extra edge to product manufacturing and sales divisions.

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