LABR: A Large Scale Arabic Book Reviews Dataset

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Abstract—We introduce LABR, the largest sentiment analysis dataset to-date for the Arabic language. It consists of over 63,000 book reviews, each rated on a scale of 1 to 5 stars. We investigate the properties of the dataset, and present its statistics. We explore using the dataset for two tasks: sentiment polarity classification and ratings classification. We provide standard splits of the dataset into training, validation and testing, for both polarity and ratings classification, in both balanced and unbalanced settings. We extend the work done in Aly and Atiya [2013] by performing a comprehensive analysis on the dataset. In particular, we perform an extended survey of the different classifiers typically used for the sentiment polarity classification problem. Also we construct a sentiment lexicon from the dataset that contains both single and compound sentiment words and we explore its effectiveness.

I. INTRODUCTION

The internet is full of platforms where users can express their opinions about different subjects, from movies and commercial products to books and restaurants. With the explosion of social media, this has become easier and more prevalent than ever. Mining these troves of unstructured text has become a very active area of research with lots of applications. Sentiment classification is among the most studied tasks for processing opinions Pang and Lee [2008]. In its basic form, it involves classifying a piece of opinion, e.g. a movie or book review, into either having a positive or negative sentiment. Another form involves predicting the actual rating of a review, e.g. predicting the number of stars on a scale from 1 to 5 stars. On the other hand, the goal of feature-based opinion mining is to identify the main entity in the review (e.g. a review of a movie or a product) or analyze the attitude towards a certain aspect of the review (e.g. the performance of one actor or the battery life of a camera).

A lot of work has been proposed that target most of the challenging aspects of the sentiment analysis task, [Maynard et al., 2012] discuss some of these challenges. These challenges have some similarities across different languages but there are many challenges and problems that are specific to each language.

Most of the work done in sentiment analysis and the data sets gathered target the English language with very little work on Arabic. One of the reasons is the prevalence of English websites where 55% of the visited websites on the Internet use English. Another reason is the complexities of the Arabic language and the different Arabic dialects existing in each Arab country and even within each Arab country. However, Arabic is the sixth most widely spoken language, and therefore it is important to develop sentiment analysis tools for it. In this work, we set out to address the lack of large-scale Arabic sentiment analysis datasets in this field, in the hope of sparking more interest in research in Arabic sentiment analysis and related tasks. Towards this end, we introduce LABR, the Large-scale Arabic Book Review dataset. It is a set of over 63,000 book reviews, each with a rating of 1 to 5 stars. This is a more comprehensive analysis with further contributions than the preliminary work of Aly and Atiya [2013].

The contributions in this paper can be summarized as follows:

1) We present the largest Arabic sentiment analysis dataset to-date (up to our knowledge).
2) We provide standard splits for the dataset into training, validation and testing sets. This will make comparing different results much easier. We will make the dataset and the splits publicly available.
3) We apply of a wide range of classifiers to the large set of book reviews that we collected.
4) We construct a sentiment lexicon from the dataset, and explore its properties and effectiveness.

II. RELATED WORK

A. Related Work

Sentiment analysis is handled by either lexicon-based approaches, machine learning approaches like text classification tasks, or hybrid approaches [Pang and Lee, 2008].

For lexicon-based approaches [Taboada et al., 2011] developed a Semantic Orientation CALculator and used some annotated dictionaries of words where the annotation covers the word

Languages used on the Internet
http://en.wikipedia.org/wiki/Languages_used_on_the_Internet
polarity and strength. They used Amazon’s Mechanical Turk service to collect validation data to their dictionaries and based their experiments on four different corpora with equal numbers of positive and negative reviews. [Gindl et al., 2010] and [Ding et al., 2008] used a sentiment lexicon that depends on the context of every polarity word (contextualized sentiment lexicon) and based their experiments on customer reviews from Amazon and TripAdvisor\(^2\).

In general lexicon-based sentiment classifiers show a positive bias [Kennedy and Inkpen, 2006], however [Voll and Taboada, 2007] implemented normalization techniques to overcome this bias.

For machine learning approaches [Pak and Paroubek, 2010] used part of speech and n-grams to build sentiment classifiers using the multinomial naive Bayes classifier, SVM and conditional random fields. They tested their classifiers on a set of hand annotated twitter posts. [Jiang et al., 2011] proposed an approach to target dependent features in the review by incorporating syntactic features that are related to the sentiment target of the review. They built a binary SVM classifier to perform the classification of two tasks: subjectivity classification and polarity classification.

For hybrid approaches, [Kouloumpis et al., 2011] used n-gram features, lexicon features, and part of speech to build an AdaBoost classifier. They used three different corpora of Twitter messages (HASH, EMOT and iSieve) to evaluate their system. [Gräbner et al., 2012] constructed a domain specific lexicon and used it to back the classification of the reviews. They used a data set for customer reviews from TripAdvisor.

Concerning the Arabic language, little work has considered the sentiment analysis problem. [Abbasi et al., 2008] performed a multilingual sentiment analysis of English and Arabic Web forums. [Abdul-Mageed et al., 2014] proposed the SAMAR system that perform subjectivity and sentiment analysis for Arabic social media using some Arabic morphological features. Abdul-Mageed and Diab [2012a] proposed a way to expand a modern standard Arabic polarity lexicon from an English polarity lexicon using a simple machine translation scheme. Elhawary and Elfeky [2010] built a system that mines Arabic business reviews obtained from the internet. Also, they built a sentiment lexicon using a seed list of sentiment words and an Arabic similarity graph. Shoukry and Rafea [2012] tested the effect of some Arabic preprocessing steps (normalization, stemming, and stop words removal) on the performance of an Arabic sentiment analysis system. Some Arabic sentiment data sets have been collected as follows (summarized in Table I).

**OCA** Opinion Corpus for Arabic Rushdi-Saleh et al. [2011] contains 500 movie reviews in Arabic, collected from forums and websites. It is divided into 250 positive and 250 negative reviews, although the division is not standard in that there is no rating for neutral reviews. It provides a 10-star rating system, where ratings above and including 5 are considered positive and those below 5 are considered negative.

**AWATIF** is a multi-genre corpus for Modern Standard Arabic sentiment analysis Abdul-Mageed and Diab [2012b]. It contains 2855 reviews collected from Wikipedia talk pages and forums.

**TAGREED** (TGRD), **TAHRIR** (THR) and **MONTADA** (MONT) Abdul-Mageed et al. [2014] used the three corpora to evaluate SAMAR system (A System for Subjectivity and Sentiment Analysis).
### III. Sentiment Analysis Challenges

Sentiment analysis is still a formidable natural language processing task Maynard et al. [2012] because unlike text categorization where the tokens depend largely on the domain or the category, in sentiment analysis we usually have three semantic orientations (positive, negative, and neutral) and most tokens can exist in the three categories at the same time. Another reason is the language ambiguity where one or more polarity token depends on the context of the sentence. Also many Internet users tend to give a positive rating even if their reviews contain some misgivings about the entity, or some sort of sarcastic remarks, where the intent of the user is the opposite of the written text.

Some challenges are specific to Arabic language such as few research work Abbasi et al. [2008]; Abdul-Mageed et al. [2011]; Abdul-Mageed and Diab [2011]; Abdul-Mageed and Diab [2012b], and very few available datasets for different natural language processing tasks. In addition, the complexities of the Arabic language, due to Arabic being a morphologically rich language, add a level of complication (see El-Beltagy and Rafea [2009] and El-Beltagy and Rafea [2011]). Another problem is the existence of Modern Standard Arabic side by side with different Arabic dialects, which are not yet standardized. El-Beltagy and Ali [2013] presented some other challenges specific to the Arabic language such as the unavailability of colloquial Arabic parsers. This is a problem that faces all solutions that depend on the parsed structure of the sentence. Also there is a need for person named entity recognition as some Arabic names are derived from adjectives. Another challenge is that the sentiment of compound phrases is often not related to that of its constituent words.

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### IV. Dataset Collection and Properties

#### A. Dataset Collection

We downloaded over 220,000 reviews from the book readers social network www.goodreads.com during the month of March 2013. These reviews were from the first 2143 books in the list of Best Arabic Books. After harvesting the reviews, we found out that over 70% of them were not in Arabic, either because some non-Arabic books or translations of Arabic books to other languages exist in the list. After filtering out the non-Arabic reviews, and performing several pre-processing steps to clean up HTML tags and other unwanted content, we ended up with 63,257 Arabic reviews.

#### B. Dataset Properties

The dataset contains 63,257 reviews that were submitted by 16,486 users for 2,131 different books. Table II contains some important facts about the dataset and Fig. II.1 shows the number of reviews for each rating. The number of positive reviews is much larger than that of negative reviews. We believe that this is because the books we got reviews for were the most popular books, and the top rated ones had many more reviews than the least popular books. Figure II.2 shows some examples from the data set.

The average user provided 3.84 reviews with the median being 2. The average book got 29.68 reviews with the median being 6. Fig. IV.1 shows the number of reviews per user and book. As shown in the Fig. IV.1c, most books and users have few reviews, and vice versa. Figures IV.1a-b show a box plot of the number of reviews per user and book. We notice that books (and users) tend to have (give) more positive reviews than negative reviews, where the median number of positive reviews per book is 5 while that for negative reviews is only 2 (and similarly for reviews per user).

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**Table I:** Arabic sentiment data sets, including the one we present here.

| Data Set Name | Size | Source | Type | Cite |
|---------------|------|--------|------|------|
| TAGREED (TGRD)| 3015 | Tweets | MSA/Dialectal | Abdul-Mageed et al. [2014] |
| TAHRIR (THR)  | 3008 | Wikipedia TalkPages | MSA | Abdul-Mageed et al. [2014] |
| MONTADA (MONT)| 3097 | Forums | MSA/Dialectal | Abdul-Mageed et al. [2014] |
| OCA (Opinion Corpus for Arabic) | 500 | Movie reviews | Dialectal | Rushdi-Saleh et al. [2011] |
| AWATIF | 2855 | Wikipedia TalkPages/Forums | MSA/Dialectal | Abdul-Mageed and Diab [2012b] |
| LARR (Large Scale Arabic Book Reviews) | 63,257 | GoodReads reviews | MSA/Dialectal | Aly and Atiya [2013] |

**Table II: Important Dataset Statistics.**

| Statistic | Value |
|-----------|-------|
| Number of reviews | 63,257 |
| Number of users | 16,486 |
| Avg. reviews per user | 3.84 |
| Median reviews per user | 2 |
| Number of books | 2,131 |
| Avg. reviews per book | 29.68 |
| Median reviews per book | 6 |
| Max tokens per review | 3,736 |
| Avg. tokens per review | 65 |
| Number of tokens | 4,348,553 |
| Number of sentences | 342,199 |
Figure IV.1: Users and Books Statistics. (a) Box plot of the number of reviews per user for all, positive, and negative reviews. The red line denotes the median, and the edges of the box the quartiles. (b) the number of reviews per book for all, positive, and negative reviews. (c) the number of books/users with a given number of reviews.

Figure IV.2: Tokens and Sentences Statistics. (a) the number of tokens per review for all, positive, and negative reviews. (b) the number of sentences per review. (c) the frequency distribution of the vocabulary tokens.

Fig. IV.2 shows the statistics of tokens and sentences. The reviews were tokenized and rough sentence counts were computed. The average number of tokens per review is 33, the average number of sentences per review is 3.5, and the average number of tokens per sentence is 9. Figures IV.2a-b show that the distribution is similar for positive and negative reviews. Fig. IV.2c shows a plot of the frequency of the tokens in the vocabulary in a log-log scale, which conforms to Zipf’s law Manning and Schütze [1999].

V. Experiments

In this paper we take the preliminary work Aly and Atiya [2013] as a starting point, and develop comprehensive simulations and analysis. In particular, we perform here an extended survey of the different classifiers typically used for the sentiment polarity classification problem. In addition we present a method for generating a sentiment lexicon from the dataset and explore its effectiveness.

A. Data Preparation

In order to test the proposed approaches thoroughly, we partition the data into training, validation and test sets. The validation set is used as a mini-test for evaluating and comparing models for possible inclusion into the final model. The ratio of the data among these three sets is 6:2:2 respectively.

We extend the work in [Aly and Atiya, 2013] by adding a class for neutral reviews. In particular, instead of partitioning into positive and negative reviews, the data is divided into three classes (positive, negative, and neutral) where ratings of 4 and 5 are mapped to positive, rating of 3 is mapped to neutral, and ratings 1 and 2 are mapped to negative. We constructed two sets of data. The first one is the balanced data set, where the number of reviews are equal in each class category, by setting the size of the class to the minimum size of the three classes. The second one is the unbalanced data set, where the number of reviews are not equal, and their proportions match those of the collected data set.
We explored using the dataset for two tasks: (a) Sentiment polarity classification: where the goal is to predict if the review is positive i.e. with rating 4 or 5, is negative i.e. with rating 1 or 2, or neutral with rating 3; and (b) Rating classification: where the goal is to predict the rating of the review on a scale of 1 to 5.

In the two tasks a wide range of standard classifiers are applied to both the balanced and unbalanced datasets using n-gram range of all unigrams, bigrams and trigrams where the n-gram range of N degree is a combination of all lower n-grams starting from unigrams, bigrams, ... etc. till the degree N. For example the trigram range is a combination of unigrams, bigrams and trigrams. Figure II.3 shows the number of reviews in every class for both balanced and unbalanced sets, while Figure II.4 and Table III show the statistics of the number of features for uni-grams range, bi-grams and trigrams range. Also the experiment is applied on the TF-Idf (token frequency inverse document frequency) of the n-grams. This a way to normalize the document’s word frequency in a way that emphasizes words that are frequent or existing in the current document, while not frequent in the remaining documents. The equation is shown in V.1.

\[
TfIdf_{word, document} = \log(1 + \text{Freq}(word, document)) * \log(\frac{\text{TotalDocuments}}{\text{TotalFreq}(word)})
\]

The classifiers used in this experiment are widely used in the area of sentiment analysis and can be considered as a baseline for any further experiments. The classifiers are:

1) **Multinomial Naive Bayes**: A well-known method that is used in many NLP tasks. In this method each review is represented as a bag of words \(X = \langle x_1, x_2, ..., x_n \rangle\) where the feature values are the term frequencies then the Bayes rule can be applied to form a linear classifier.

\[
\log(p(class|X)) = \log(p(class)) + \sum_{i=1}^{n} p(x_i|class)/p(X)
\]

2) **Bernoulli Naive Bayes**: In this model features are independent binary variables that describe the input \(X = \langle 1, 0, 1, 0 \rangle\), which means that the binary term occurrence is used instead of the frequency of the term in the bag of words model. Both of the naive Bayes generative models are described in details in McCallum et al. [1998].

3) **Support Vector Machine**: Linear SVM is a classifier that partitions the data using the linear formula \(y = W \cdot X + p\), selected in such a way that it maximizes the margin of separation between the decision boundary and the class patterns (hence the name large margin classifier). SVM can be generalized to multiclass case using one versus all classification trick.

4) **Passive Aggressive**: It is an online learning model that uses a hinge-loss function together with an aggressiveness parameter \(C\) in order to achieve a positive margin high confidence classifier. The algorithm is described in details in [Crammer et al., 2006] with two alternative modifications that improve the algorithm’s ability to cope with noise.

5) **Stochastic Gradient Descent**: It is an algorithm that is used to train other machine learning algorithms such as SVM where it samples a subset of the training examples at every learning step. Then it calculates the gradient from this subset only, and uses this gradient to update the weight vector \(w\) of SVM classifier. Be case of its simplicity and computational advantage, it is widely used for large-scale machine learning problems[Bottou and Bousquet, 2007].

6) **Logistic Regression**: The binary logistic regression uses a sigmoid function \(h_w(x) = f(x) = \frac{1}{1 + e^{-w \cdot x}}\) as a learning model, then it optimizes a cost function that measures the likelihood of the data given the classifier’s class probability estimates then for the multiclass problem one versus all solution is used. The cost function can be formulated as

\[
Cost(\bar{y}) = -\frac{1}{m} \sum_{i=1}^{n} [y^{(i)} \log(h_w(x^{(i)})) + (1 - y^{(i)}) \log(1 - h_w(x^{(i)}))]
\]

where \(m\) is the total number of patterns, \(x^{(i)}\) is the \(i^{th}\) pattern and \(y^{(i)}\) is the correct class of the pattern \(i\).

7) **Perceptron**: It is a simple feed-forward single layer linear neural network with a unit step function as an activation function. It uses an iterative algorithm for training the weights. However, this algorithm does not take into account the margin like for the case of SVM.

8) **K-Nearest Neighbor**: A simple well-known machine learning classifier that based on the distances between the patterns in the feature space. Specifically, a pattern is classified according to the majority class of its K-nearest neighbors.
Table IV-V shows the result for each classifier after training on both the training and the validation set and evaluating the result on the test set (i.e. the train:test ratio is 8:2). Note that in the sentiment polarity classification task the inclusion of a third class "neutral" makes the problem much harder, and we get a lower performance than the case of two-class case ("positive" and "negative"). The reason is that there is a large confusion between neutral and positive, and between neutral and negative. Sometimes the numbered ratings (1 to 5), from which we extract the target class contradict what is written in the review, in a way that even an experienced human analyzer will not get it right. Two accuracy measures are used to calculate the performance which are the weighted accuracy and weighted F1 measure.

From table IV we can make the following observations:

1) The balanced set is more challenging than the unbalanced set. We believe that this is due to the fact that it contains much fewer reviews compared to the unbalanced set. This makes a lot of the n-gram have fewer training examples, and therefore leading to less reliable classification.

2) We can get a good overall accuracy and F1 of over 70% using especially the SVM and the logistic regression classifiers. This is consistent with previous results in Aly and Atiya [2013] suggesting that the SVM and the logistic regression are a reliable choice.

3) Passive aggressive, and perceptron are also a good choice of classifiers, with the careful choice of parameters.

VI. SENTIMENT LEXICON

A. Lexicon Generation

Manually constructing a sentiment lexicon is a formidable task due to the coverage issues and the possible ambiguity and multible meanings of many words. Also compound phrases open up many permutations of word combinations which will be hard to group in the lexicon. So we propose a simple method for extracting a baseline sentiment lexicon from the LABR dataset. This lexicon can be extended easily to other datasets or domains. Our method utilizes a useful feature of the linear SVM and logistic regression as they inherently apply some sort of feature selection. This is because the weight values are an indication of the importance of the n-gram. For example, n-grams that have negligible weights are deemed unimportant and ineffective. This is especially true if we use the L1 error measure for training the SVM (defined as \( \|x\|_1 = \sum |x_i| \)). In this case, the weights for many insignificant ngrams will end up being zero. So, we utilize this fact to perform an automatic generation for the most informative ngrams by ordering the weights from the SVM and the logistic regression classifiers then selecting the highest 1000 weights, as indication for positive sentiment ngrams, and the lowest 1000 weights as indication for negative sentiment ngrams. We then manually review them to remove any erroneous n-grams. We end up with a list of 348 negative n-grams and 319 positive n-grams. We also constructed a list of 31 Arabic negation operators. Table VI gives some examples from the sentiment lexicon where it is clear that some difficult compound phrases were captured using our approach.

B. Lexicon Experiments

In order to test the effectiveness of the generated domain specific lexicon we reran the sentiment analysis experiments on the unbalanced training set. The goal is to test the effectiveness of the lexicon as a stand-alone input, and also in combination with the trigram features used in the previous experiments. The lexicon was used as a feature vector of length 667 features (348 negative ngrams and 319 positive ngrams). If using the lexicon as stand-alone is as successful, then we would have reduced the number of features from several millions to just 667, leading to a much simpler classifier. Moreover, this opens up the possibility of using some complex classifiers that were computationally infeasible with large feature vectors. These classifiers may perhaps outperform the simpler classifiers typically used in large NLP problems. As a comparison, we consider the Arabic sentiment lexicon developed by El-Beltagy and Ali [2013] (see also ElSahar and El-Beltagy [2014] for more details of its construction). This is a general purpose lexicon that is developed by growing a small seed of manually labeled words using an algorithm that considers co-occurrence of words in the text. It consists of 4392 entries of both compound and single sentiment words Table VII shows the sentiment lexicon experimental results on the validation set. Also, Table VIII shows the results on the test set, when we use a combined training and validation set for training the models. We can observe that the lexicon only model is just a little worse than the tri-gram model. However, the difference is not large. This is an interesting fact considering that the former uses only 0.02 % of the amount of features of the latter. Another observation is that our constructed lexicon outperforms the lexicon by El-Beltagy and Ali [2013]. But this has mainly to do with the fact that ours is domain-specific, while theirs is general purpose. There are many entries in our lexicon that are specific to the book review domain, and can therefore make a difference in performance. For example, see in Table VI the expressions "worth reading", "I imagine myself there", and "I felt the novel". This indicates that it is always a good practice to augment general purpose lexicons with domain-specific expressions.

VII. SUMMARY AND CONCLUSION

In this work we presented LABR dataset the largest Arabic sentiment analysis dataset to-date. We explored its properties and statistics, provided standard splits, and performed a comprehensive study, involving testing a wide range of classifiers and exploring their effects. Also we presented a
### Table IV: Experiment 1: Polarity Classification Experimental Results

| Features | MNB | SVM | Logistic Regression | Passive Aggressive | Perceptron | KNN |
|----------|-----|-----|---------------------|-------------------|------------|-----|
|          | Balanced | Unbalanced | Balanced | Unbalanced | Balanced | Unbalanced |
|          | 1g | 1g+2g | 1g+2g+3g | 1g | 1g+2g | 1g+2g+3g |
| Tf-Idf   | Yes | Yes | Yes | Yes | Yes | Yes |
| MNB      | 0.558/0.560 | 0.573/0.577 | 0.572/0.577 | 0.706/0.631 | 0.705/0.609 | 0.706/0.612 |
| SVM      | 0.576/0.570 | 0.581/0.584 | 0.582/0.586 | 0.680/0.551 | 0.680/0.550 | 0.680/0.550 |
| Logistic Regression | Yes | Yes | Yes | Yes | Yes | Yes |
| Passive Aggressive | Yes | Yes | Yes | Yes | Yes | Yes |
| Perceptron | Yes | Yes | Yes | Yes | Yes | Yes |
| KNN      | Yes | Yes | Yes | Yes | Yes | Yes |

The numbers represent weighted accuracy / F1 measure where the evaluation is on the test set.

### Table V: Rating Classification Experimental Results

| Features | Balanced | Unbalanced |
|----------|----------|------------|
|          | 1g | 1g+2g | 1g+2g+3g | 1g | 1g+2g | 1g+2g+3g |
| Tf-Idf   | Yes | Yes | Yes | Yes | Yes | Yes |
| MNB      | 0.590/0.560 | 0.590/0.588 | 0.589/0.588 | 0.724/0.709 | 0.720/0.723 | 0.717/0.725 |
| SVM      | 0.629/0.661 | 0.632/0.666 | 0.628/0.668 | 0.818/0.784 | 0.815/0.787 | 0.812/0.789 |

The numbers represent weighted accuracy / F1 measure where the evaluation is on the test set.

### Table VI: Examples from the sentiment lexicon.

| Positive | Compound Positive | Negative | Compound Negative |
|----------|------------------|----------|------------------|
| Wonderful | رائع | Not like it | لا يناسب التقييم |
| Interesting | مثير | Disgusting | تولع الامور |
| Great | عظيم | Disgusting | شقت الغرنا |
| Excellent | رائع | Disgusting | شقت الغرنا |
| Excellent | رائع | Disgusting | شقت الغرنا |
| Beautiful | جميلة | Ugly | لا يناسب التقييم |
| Beautiful | جميلة | Ugly | لا يناسب التقييم |
| Beautiful | جميلة | Ugly | لا يناسب التقييم |
| Beautiful | جميلة | Ugly | لا يناسب التقييم |

### Table VII: Sentiment lexicon experimental results on the validation set

| Features | MNB | SVM | Passive Aggressive | Logistic Regression | Perceptron | KNN |
|----------|-----|-----|-------------------|---------------------|------------|-----|
|          | Balanced | 1g | 1g+2g | 1g+2g+3g | Balanced | 1g | 1g+2g | 1g+2g+3g |
| Tf-Idf   | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| MNB      | 0.769/0.627 | 0.710/0.556 | 0.670/0.454 | 0.670/0.454 | 0.670/0.454 | 0.670/0.454 | 0.670/0.454 | 0.670/0.454 |
| SVM      | 0.692/0.625 | 0.670/0.556 | 0.670/0.454 | 0.670/0.454 | 0.670/0.454 | 0.670/0.454 | 0.670/0.454 | 0.670/0.454 |
| Logistic Regression | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Passive Aggressive | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Perceptron | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| KNN      | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

The numbers represent weighted accuracy / F1 measure where the experiment is on the validation set.
small sentiment lexicon that is extracted from the dataset and explored its utility. From the experiments we observe that SVM and logistic regression are the best two classifiers. Moreover, using the constructed lexicon we obtain competitive results. We hope this data set would be of good use, and these results would be a guide for future Arabic sentiment work.

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Table VIII: Sentiment lexicon experimental results on the test set The numbers represent weighted accuracy / F1 measure where the evaluation is on the test set. LEX1 indicates our generated lexicon, LEX2 indicates lexicon by El-Beltagy and Ali [2013] and Trigrams indicates the trigram range features from the training set.
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