Optimized Training and Evaluation of Arabic Word Embeddings

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TODO: Add years to online references, commit to style, fix tables in experiments, capitalize MADAMIRA, choose a correlation measure (see embedding paper), spellcheck, fix big citation urls

FOR PART 2: Freq/DomFreq/NeighborFreq/Buzz evaluation, translate analogy task for evaluation, add inter-rater reliability, examine subset of evaluation task with more fluent evals

Abstract

Word embeddings are an increasingly important tool for NLP tasks that require semantic understanding of words. Methodologies and properties of English word embeddings have been extensively researched. However, little attention has been given to the production and application of Arabic word embeddings. Arabic is far more morphologically complex than English due to the many conjugations, suffixes, articles, and other grammar constructs. This has a significant effect on the training and application of Arabic word embeddings. While there are a number of techniques to break down Arabic words through lemmatization and tokenization, the quality of resulting word embeddings must be investigated to understand the effects of these transformations. In this work, we investigate a number of preprocessing methods and training parameterizations to establish high quality methodologies for training Arabic word embeddings. Using a new semantic similarity task created by fluent Arabic speakers we are able to identify the training strategies that produce the best results for each task. We also offer a suite of accessible open source Arabic NLP tools. To summarize, the main contributions of this work include improved methodologies for training Arabic word vectors, an open semantic similarity task developed by native Arabic speakers, and a python package of Arabic text processing tools.

1 Introduction

Arabic word embeddings are numerical vector representations of a word's meaning - both semantic meaning and syntactic meaning. These embeddings are obtained using machine learning algorithms - word2vec - that utilize the context a word appears in to infer its meaning (Mikolov et al., 2013a; Mikolov et al., 2013b). This works very well as words with similar meanings tend to be used in similar contexts, which are defined by the preceeding and following n words. For example, the sentences *I eat bread every night* and *I eat rice every night* are examples of how food words may appear in similar contexts. With enough text to process, we can train numerical vectors to learn that bread and rice appear in these *common-for-food* contexts. Similarly, we can learn syntactic relationships because different parts of speech appear in certain context patterns as well.

High quality word embeddings provide a representation of the meaning of a word, without ever translating or referencing a dictionary. We can obtain the semantic and syntactic meaning directly from a corpus of natural written language. With accurate word embeddings, we can perform powerful vector operations to investigate the relationships between words in a corpus. A few of the possible operations are measuring the similarity of two words, identifying which word from a set is least similar, and solving basic analogies (Mikolov et al., 2013b). The classic demonstration of word embeddings is to take (the embeddings of) *king*, subtract *man*, and add *woman*. The resulting embedding should be near to the embedding for *queen* in the embedding vector space. Intuitively, this allows us to subtract the male gender meaning from king's embedding, add the female gender

meaning, and end up with an embedding equivalent to queen's embedding (Mikolov et al., 2013c). While word embeddings have been analyzed and evaluated for different tasks in English corpa (Mikolov et al., 2013a; dos Santos and Gatti, 2014), word embeddings in other languages have received less attention. Arabic word embeddings have been included in multi-lingual work on embeddings like generic part-of-speech tagging (Al-Rfou et al., 2013). However, the process of training word vectors for a language so morphologically different from English has not been explored. Every language has different levels of morphological complexity. This complexity may have a significant effect on how the word embeddings should be trained and the tasks that the word embeddings can be used for. According to one of the only papers attempting to quantify the Arabic vocabulary, Arabic itself has around 250 prefixes, 4500 regular derivative roots, 1000 derivative regular forms, and 550 suffixes to build words from, meaning there are around $6 * 10^10$ possible Arabic words (Ahmed, 2000). While the number of sensical words is estimated to be between 12 and 500 million words by unofficial sources (Souag, ; Da'na,), the vocabulary is much larger than the 1 million word vocabulary of English (NPR,). In this paper, we focus on different preprocessing and training parameters to bring the performance of Arabic word embeddings closer to that of English word embeddings.

Having word embeddings in different languages allows us to avoid translation when using these embeddings for different natural language processing and machine learning tasks. These embeddings can allow for the interpretation of topics in media, or provide an understanding of how similar words are to a subject. An example application would be to use the embeddings to learn what words are highly similar to words representing fear, and then compute the degree to which some media is using fearful language in the context of political or economic termoil.

Methodologies and properties of English word embeddings have been extensively researched, however little attention has been given to the production and application of Arabic word embeddings. Written Arabic words often carry more contextual information about objects, tense, gender, and definiteness than English, meaning that Arabic unigrams occur less frequently on average than English unigrams. This has a significant effect on the training and application of Arabic word embeddings, as the embeddings are trained on unigram tokens.

The contributions of this work are as follows: 1) We perform a comparative empirical evaluation of Arabic and English word vectors using both a semantic similarity task and a syntactic similarity task. We show that standard parameters for English word embeddings lead to poor Arabic word embeddings. 2) We developed an open-source software package that provides easy access to important Arabic natural language processing tools. 3) We evaluate this task using more high quality human labels than other similar evaluations. 4) We present an empirical analysis identifying the parameters that are most effective for our tasks, identifying a set of best practices for training Arabic word embeddings.

The remainder of this paper is organized as follows. In Section 2 we present work related to training, evaluating, and utilizing Arabic word vectors. In Section 3 we provide an overview of the process and parameters required to train word vectors in Arabic. Section 4 describes our methodology to measure the quality of word vectors against a semantic similarity task. In Section 5 we present the results of our parameter sweep and evaluations of Arabic word vectors. This leads to Section 6 in which we inspect our results to find the best methods for creating Arabic word vectors according to our evaluation tasks. Following this we describe the software created to perform our analyses in Section 7. Section 8 offers our thoughts on further work and conclusions.

2 Related Literature

Word embeddings have gained popularity over the past few years since Mikolov et al. published the word2vec algorithms in 2014 (Mikolov et al., 2013b; Mikolov et al., 2013a). While new algorithms and applications have received a great amount of research attention, word embeddings are often considered in the English-like language cases. Arabic differs greatly from English in many ways important to natural language processing. An excellent summary of the most important challenges that come with Arabic is provided by Farghaly et al. (Farghaly and Shaalan, 2009). Al-Rfou et al. computed word embeddings for 100 languages using Wikipedia articles (Al-Rfou et al.,

2013). This work is the closest to ours, as it inspired our system of semantic and syntactic evaluation. However, we believe our use of a semantic similarity task provides a better quantitative evaluation. Additionally, this work does not actually look at Arabic-specific training methods, which we would like to improve Arabic embedding quality. Zirikly et al. utilized Arabic word vectors to improve named-entity recognition performance, normalizing hamzas, elongated words, and number normalization (Zirikly and Diab, 2015). However, this work did not seek out any further improvements for training Arabic word vectors. Belinkov et al. utilize Arabic word vectors in a question answering task, reporting slight improvements when their training data was lemmatized using Madamira (Belinkov, 2015). Further normalization is not performed in their work. Some research has been done to utilize morphology to alter the training algorithms of English word embeddings to learn morphological similarities (Luong et al., 2013), but this work makes no attempt to extend the method beyond English. This work is also focused on utilizing morphological similarities within a language rather than overcome morphological complexity that exists in a language as morphologically complex as Arabic. In summary, Arabic word vectors are being used, but the process of training them has not been explored or optimized as we aim to do with this work.

In English, there are some accessible open source natural language processing tools, especially those made available through Stanford University. However in Arabic, the list of strong NLP tools is a bit shorter. Habash et al. developed Mada+Tokan to perform tokenization, part of speech tagging, and lemmatization (Habash et al., 2009). Diab published the Amira software as fast and robust option for phrase chunking and POS tagging (Diab, 2009). Recently, these tools have been brought together into the Madamira software package, comprised of a suite of Arabic NLP tools that includes tokenization, lemmatization, phrase chunking, and part of speech tagging (Pasha et al., 2014). While powerful and robust, Madamira's lack of open source code and inaccessible input and output make it difficult to use in short NLP experiment scripts. Our python package provides a wrapper to help with this difficulty, providing simple calls to process and access commonly desired output from Madamira.

Word similarity tasks are widely used for NLP experimentation and evaluation, and a long list of semantic similarity data was compiled by Faruqui et al. (Faruqui and Dyer, 2014). However, few of these are available in Arabic. Faruqui refers to two data sets that have been translated to Arabic by Hassan et al. (Hassan and Mihalcea, 2009), the 353 word WordSimilarity-353 and the 30 word Miller-Charles datasets (Finkelstein et al., 2001; Miller and Charles, 1991). However, this translation was done by a single Arabic speaker using the English semantic similarity scores (Hassan and Mihalcea, 2009). In their paper, they cite that with 5 translators on a Spanish task, they obtained unanimous translations 74% of the time, and further rescoring produced a correlation of .86. Our work attempts to alleviate these losses by beginning with Arabic words and evaluating them all with multiple fluent Arabic speakers.

3 Training Word Embeddings in Arabic

There are a number of decisions to be made when training word embeddings in Arabic. We have chosen to use the word2vec framework to train, although there are other proposed methods to obtain word embeddings that are highly similar (Pennington et al., 2014). We chose word2vec as there is more public research available to reference and excellent open software support. The main decisions to be made when training word2vec embeddings in Arabic are how to preprocess the text, how to normalize the text, and how to parameterize the word2vec algorithms. The remainder of this section describes different consideration for each of these steps, explains options and training parameters that can be adjusted, and presents the specific training parameters we used in our evaluation.

3.1 Preprocessing Options

Preprocessing is very important when analyzing Arabic text. Much of the linguistic information in the grammar is contained in various affixes to words. This is very different from English, where information is often contained in stand-alone pronouns and articles. Word2vec captures information at a word level, so separating these affixes into individual words greatly changes what is learned during training.

The three main preprocessing options that we consider for this task are 1) leave the text unedited,

2) tokenize the text to make affixes individual words, and 3) lemmatize the text to drop most affixes and preserve only the core idea of each Arabic word.Tokenization breaks each word into simple grammatical tokens and creates separate words from affixes such as the definite article and the various pronouns. Lemmatization completely removes such affixes from the corpus, mapping each word to a base word that represents the core meaning of the word. It reduces words to a single tense, gender, and definiteness, but preserves the basic grammatical form. An English equivalent would be to map both *he jumped* and *she jumps* to *he jumps*.

3.2 Normalization

Normalizing Arabic text can greatly reduce the sparsity of the word space in Arabic. We always normalize the corpus by removing English characters, reducing all forms of the letters alif, hamza, and yaa to single general forms (respectively ا,ء,and ي). The options we consider variable are removing diacritics and reducing both English and Arabic numerical characters to the number sign.

3.3 Parameterizations

The main parameters of word2vec that are considered are algorithm, embedding dimension, and window size. Both CBOW and Skipgram algorithms are considered (Mikolov et al., 2013a). The embedding dimensions considered are 100 and 200. We chose these dimensions as the typical range is between 100 and 300, where more dimensions require more time and data to train well. We lack the gratuitous amount of data that is available freely for English, so we chose to keep only smaller dimensionalities. The window sizes considered are 4 and 7, which is how far to either side of the word being trained we look for context. For the other parameter values, refer to Table 1. Hierarchical softmax and negative sampling are methods to sample training data efficiently. Downsampling is used to decrease the influence of high frequency words in the corpus. We use hierarchical sampling and some downsampling as together they have been shown to perform well on complex vocabularies with infrequently represented words and phrases (Mikolov et al., 2013b).

Parameter	Value	Explanation
sg	$[0, 1]$	Algorithm
$size$	$[100, 200]$	Dimensionality
$window$	$[4, 7]$	Context window
$mincount$	5	Filters rare words
$sample$	$1e-5$	Downsampling
$seed$	1	Random seed
hs	1	Hierarchical softmax
$negative$	0	Negative sampling
$iterations$	5	Training iterations

Table 1: Training Parameters

4 Evaluating Arabic Word Embeddings

It is a complex problem to evaluate the quality of word embeddings. The word2vec methods produce unsupervised vectors that maximize the probability of predicting a word given the context that it appears near in the training corpus.

We want a large semantic similarity task to accurately evaluate the Arabic word embeddings. The largest Arabic semantic similarity task that we could find is a manually translated version of the WordSimilarity-353 task (Finkelstein et al., 2001; Hassan and Mihalcea, 2009). We created a semantic similarity task consisting of 1000 word pairs with similarity scores. Between 2 and 5 fluent Arabic speakers labeled each word pair with a similarity score in the range 0-1, where pairs with a score of 1 indicates that the words are extremely related.

To begin creating this task, we selected 1250 of the most common words in the Arabic Wikipedia dump (Meta, 2016) at `https://dumps.wikimedia.org/arwiki/20150901/`, excluding words that occur in more than 5% of the sentences. The remaining words were then translated into English with Google translate, queried against the Big Huge Thesaurus API for either synonyms or antonyms, and translated back to Arabic (Google, ; Labs,). The original word and the resulting synonym or antonym were then paired up. Half of the pairs are at this point synonyms, one quarter are antonyms, and one quarter are shuffled with other pairs to be randomly matched. This distribution is synonym heavy because the Big Huge Thesaurus database has more data on synonyms than antonyms. The various APIs involved introduce a large amount of noise, to the point that some synonym pairs end up as unrelated Arabic words. We take advantage of this

noise to distribute the relatedness of words across the 0 to 1 scale.

This list of 1250 word pairs was then distributed to fluent Arabic speakers such that each pair is scored by multiple evaluators. We provided simple instructions to evaluate the relatedness of the words on a scale of 0 to 5 for ease of labeling. The values that they provided were then scaled from 0 to 1 and averaged.

When evaluating a model parameterization with the WordSimilarity-353 task or our similarity task, we perform the same preprocessing on the word pairs as we do on the training corpus for each model. Each word pair's embeddings are first obtained from the model, and then an absolute cosine similarity score is obtained between them. The cosine similarity is compared against the similarity task's score. The model is scored on both the mean absolute difference between the scores and the correlation between the task scores and model scores.

5 Experimental Results

We perform a parameter sweep over the various preprocessing techniques, normalization options, and word2vec parameterizations to determine the optimal word embedding methods. The text corpus for training the embeddings is an Arabic Wikipedia dump from `https://dumps.wikimedia.org/arwiki/20150901/` (Meta, 2016), cleaned by dropping Wikipedia markup, punctuation, and non-Arabic characters. All preprocessing options are precomputed first, generating multiple versions of the Arabic Wikipedia corpus. Then word vectors are trained for each parameterization. The vectors are then ran through evaluation tasks, recording various performance statistics.

The baseline results for English vectors are shown in Table 2. There are two models shown, each evaluated on the WS353 English word similarity task. The first is an English model trained under a default parameterization (skipgram, window of 7, 100 dimensions) on the same number of words as our Arabic models. The second is the publically available pre-trained vectors trained on the 300 billion word Google News Corpus. The metrics that we choose to display are mean error and correlation with the evaluation task. The mean error is the mean absolute distance between the vector estimate and the evaluation task estimate for word pair similarity. The default vectors exhibit an impressive .268 mean error, and both models show a high correlation with the evaluation task scores. The Google News vectors display an impressive .65 correlation score to the task, showing the power of well-trained word vectors.

Method	Mean Error	Correlation
5 Million	0.268	0.549
Google News	0.313	0.65

Table 2: Baseline English Results

Tables **??** and **??** show the results of models trained on differently preprocessed text. Table **??** contains results from the similarity task that we developed, and Table **??** contains the results from the WS353 Arabic task (Finkelstein et al., 2001; Hassan and Mihalcea, 2009). None of the Arabic models reach either the level of correlation or accuracy that the default English model does. These tabels are sorted by mean error, revealing traits that improved their performance on evaluation tasks. We analyze these results in Section **??**.

6 Recommendations for Arabic Word Embeddings

The least accurate results for both Arabic semantic similarity tasks were those models trained on unprocessed Arabic text. Additionally, the accuracies of unprocessed text were far below the English default baseline. This goes to show that Arabic word embeddings do benefit in semantic accuracy when preprocessed to tokens and lemmas. Additionally, tokenized Arabic tends to have a higher accuracy on the tasks than lemmatized Arabic.

Also to note is the effect of normalizing digits and tashkil (voweling). When lemmatizing the Arabic, there seems to be a consistent increase in performance if you then remove tashkil. Tokenization and unprocessed Arabic do not seem to have the same improvements with lemmatization.

7 Arapy

All preprocessing, normalization, and training processes utilize the python package we developed, which we will release as an open source utility. It utilizes various software resources, including gensim, Madamira, the Google Translate API,

the Big Huge Thesaurus API, (Google, ; Labs,).
We developed a package of Arabic text processing tools while working on this research. Arapy includes many useful tools for simple natural language processing tasks that can be difficult when working with Arabic. The first is a module providing a MADAMIRA wrapper that provides access to the part-of-speech tagging, base phrase chunking, tokenization, and lemmatization features of MADAMIRA. There is also a wrapper providing various tools for training and evaluating Arabic word embeddings, largely as a wrapper for gensim methods. Arapy also includes a modules for Arabic text normalization, translation with Google Translate, simulation of an Arabic thesaurus using translation and the Big Huge Thesaurus API, and cleaning the Arabic Wikipedia dump.
The dependancies for this package are Java for MADAMIRA, the MADAMIRA jar and a license for MADAMIRA, gensim for word2vec model operations, a Google API key for translation, a Big Huge Thesaurus API key for thesaurus simulation,

8 Conclusion and Future Directions

The contributions of this work are as follows: 1) We perform a comparative empirical evaluation of Arabic and English word vectors using a semantic similarity task. We show that standard parameters for English word embeddings lead to poor Arabic word embeddings. 2) We develop and open-source a simple software package that provides easy access to important Arabic natural language processing tools. 3) We present a semantic similarity task using a team of native Arabic speakers. This task is larger than other published tasks and uses multiple native speakers to manually provide high quality human labels. 4) We present an empirical analysis identifying the parameters that are most effective for our tasks, identifying a set of best practices for training Arabic word embeddings.

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