Optimized Training and Evaluation of Arabic Word Embeddings

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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 best practice strategies for training Arabic word embeddings. Using a new semantic similarity task created by fluent Arabic speakers and a part of speech tagging task, we were 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. Together, this work provides best practices 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., 2013; **?**). 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 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. The classic demonstration of word embeddings is to take (the embeddings of) *king*, subtract *man*, and add *woman*. The resulting embedding is closest to the embedding for *queen*. 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.

We would like accurate Arabic word embeddings so we can interpret the general topics of discussion in Arabic media without using translation or ignoring some words belonging to a topic. An example application would be to use the embeddings to learn what words are highly similar to words similar to fear (in Arabic), 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 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.

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., 2013; **?**). 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. 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. The main decisions to be made are how to preprocess the text, how to normalize the text, and how to parameterize word2vec.

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 ,,and Ł). 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. The embedding dimensions considered are 100 and 200. We chose these because... The window sizes considered are 5 and 8, which is how far to either side of the word being trained we look for context. For the other parameters, refer to table n for values and explanations.

4 Evaluating Arabic Word Embeddings

It is a complex problem to evaluate the quality of word embeddings. The word2vec methods produce vectors that maximize the probability of predicting a word given the context that it appears near in the training corpus. This context provides both semantic and syntactic information about each word. As our preprocessing methods may have significant effects on how much of this information is provided, we use two evaluation tasks to understand the semantic and syntactic quality of our embeddings.

4.1 Semantic Understanding Evaluation

As we perform a large parameter sweep in 5, we wanted 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). As we wanted a larger list generated specifically for Arabic and evaluated by multiple fluent Arabic speakers, we created a list of 1000 similarity scores for given Arabic word pairs using fluent Arabic speakers. The semantic similarity task consists of 1000 Arabic word pairs given a similarity score in the range 0-1. 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 cite this, excluding words that occur in more than 5% of sentences. These words were then translated into English with Google translate (Google,), queried against the big huge thesaurus API for either synonyms or antonyms, and translated back to Arabic (Labs,). The original word and the resulting synonym or antonym are then paired up. Half of the pairs are at this point synonyms, one quarter are antonyms, and one quar-

ter are shuffled with other pairs to be randomly matched. This distribution is synonym heavy because the synonym database is more extensive and accurate than the antonym database. The various APIs involved introduce a large amount of noise, to the point that some synonym pairs will be completely unrelated Arabic words. We take advantage of this noise to attempt to distribute the relatedness of words across the 0 to 1 scale.
This list of word pairs was then given in parts to fluent Arabic speakers such that each pair was seen by at least two evaluators. We provided simple instructions to evaluate the relatedness of the words on a scale of 0 to 5. The values that they provided were then scaled from 0 to 1 and averaged. textcolorredWhen evaluating a parameterization, we performed the same preprocessing on the word list as we did to the corpus prior to training. Each word pair's embeddings were compared for an absolute cosine similarity score and the parameterization is given a score for its mean absolute difference from the task's similarity score.

4.2 Syntactic Understanding Evaluation

The syntactic understanding of the word embeddings was evaluated via a part-of-speech tagging task. A selection of Arabic documents were first tagged with part-of-speech values using Madamira's NLP analysis, once for each preprocessing method (Pasha et al., 2014). For each parameterization, a simple recurrent neural network set up for sequence to sequence learning is trained to predict the part-of-speech of a word using its embedding. One document is held out as a test set for the network, and the accuracy of the network on this set was taken as the syntactic understanding score for the parameterization.

5 Experimental Results

We performed a broad 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 cleaned with our Arapy package.
All preprocessing, normalization, and training processes that we use utilize the Arapy package we developed, which is released as an open source utility. It utilizes various software resources, including gensim, Madamira, the Google Translate API, the Big Huge Thesaurus API, etc. CITE. All preprocessing options are precomputed first, generating multiple versions of the Arabic Wikipedia corpus. Then word vectors are trained for each parameterization. The vectors were then ran through both evaluation tasks, recording various performance statistics.
The final results are shown here.

MSE	**Correlation**	**MSE**	**Correlation**
0.24906550819050233	0.089042946229289488	0.30084243485480844	0.085354904495056158
0.26233746257062202	-0.031079243124832671	0.29839882495696568	0.11268495749045816
0.24906550819050233	0.089042946229289488	0.30084243485480844	0.085354904495056158
0.0	nan	0.0	nan
0.25593636419063409	0.068313010198957066	0.30309368690294614	0.083286937319710055
0.24906550819050233	0.089042946229289488	0.30084243485480844	0.085354904495056158
0.0	nan	0.0	nan
0.25593636419063409	0.068313010198957066	0.30309368690294614	0.083286937319710055
0.25593636419063409	0.068313010198957066	0.30309368690294614	0.083286937319710055
0.24906550819050233	0.089042946229289488	0.30084243485480844	0.085354904495056158
0.0	nan	0.0	nan
0.0	nan	0.0	nan
0.24906550819050233	0.089042946229289488	0.30084243485480844	0.085354904495056158
0.26233746257062202	-0.031079243124832671	0.29839882495696568	0.11268495749045816
0.24906550819050233	0.089042946229289488	0.30084243485480844	0.085354904495056158
0.0	nan	0.0	nan
0.25593636419063409	0.068313010198957066	0.30309368690294614	0.083286937319710055
0.25593636419063409	0.068313010198957066	0.30309368690294614	0.083286937319710055
0.24906550819050233	0.089042946229289488	0.30084243485480844	0.085354904495056158
0.26233746257062202	-0.031079243124832671	0.29839882495696568	0.11268495749045816
0.0	nan	0.0	nan
0.26233746257062202	-0.031079243124832671	0.29839882495696568	0.11268495749045816
0.24906550819050233	0.089042946229289488	0.30084243485480844	0.085354904495056158
0.0	nan	0.0	nan
0.24906550819050233	0.089042946229289488	0.30084243485480844	0.085354904495056158
0.0	nan	0.0	nan
0.26233746257062202	-0.031079243124832671	0.29839882495696568	0.11268495749045816
0.0	nan	0.0	nan
0.26233746257062202	-0.031079243124832671	0.29839882495696568	0.11268495749045816
0.0	nan	0.0	nan
0.0	nan	0.0	nan
0.0	nan	0.0	nan
0.26233746257062202	-0.031079243124832671	0.29839882495696568	0.11268495749045816
0.26233746257062202	-0.031079243124832671	0.29839882495696568	0.11268495749045816
0.0	nan	0.0	nan
0.25593636419063409	0.068313010198957066	0.30309368690294614	0.083286937319710055
0.26233746257062202	-0.031079243124832671	0.29839882495696568	0.11268495749045816
0.25593636419063409	0.068313010198957066	0.30309368690294614	0.083286937319710055
0.24906550819050233	0.089042946229289488	0.30084243485480844	0.085354904495056158
0.24906550819050233	0.089042946229289488	0.30084243485480844	0.085354904495056158
0.0	nan	0.0	nan
0.0	nan	0.0	nan
0.0	nan	0.0	nan
0.24906550819050233	0.089042946229289488	0.30084243485480844	0.085354904495056158
0.24906550819050233	0.089042946229289488	0.30084243485480844	0.085354904495056158
0.0	nan	0.0	nan
0.25593636419063409	0.068313010198957066	0.30309368690294614	0.083286937319710055
0.0	nan	0.0	nan
0.25593636419063409	0.068313010198957066	0.30309368690294614	0.083286937319710055
0.24906550819050233	0.089042946229289488	0.30084243485480844	0.085354904495056158
0.25593636419063409	0.068313010198957066	0.30309368690294614	0.083286937319710055
0.0	nan	0.0	nan
0.24906550819050233	0.089042946229289488	0.30084243485480844	0.085354904495056158
0.26233746257062202	-0.031079243124832671	0.29839882495696568	0.11268495749045816
0.25593636419063409	0.068313010198957066	0.30309368690294614	0.083286937319710055

MSE	Correlation
0.12278282592900455	0.65045858524545697

6 Recommendations for Arabic Word Embeddings

The best results for the semantic similarity task are xxx.
The best results for the semantic similarity task are xxx.
Other recommendation we have are xxx.

7 Arapy

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 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 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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