Deriving adjectival scales from continuous space word representations

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Abstract
Continuous space word representations extracted from neural network language models have been used effectively for natural language processing, but until recently it was not clear whether the spatial relationships of such representations were interpretable. Mikolov et al. (2013) show that these representations do capture syntactic and semantic regularities. Here, we push the interpretation of continuous space word representations further by demonstrating that vector offsets can be used to derive adjectival scales (e.g., okay < good < excellent). We evaluate the scales on the indirect answers to yes/no questions corpus (de Marneffe et al., 2010). We obtain 72.8% accuracy, which outperforms previous results (∼60%) on this corpus and highlights the quality of the scales extracted, providing further support that the continuous space word representations are meaningful.

1 Introduction
There has recently been a surge of interest for deep learning in natural language processing. In particular, neural network language models (NNLMs) have been used to learn distributional word vectors (Bengio et al., 2003; Schwenk, 2007; Mikolov et al., 2010): the models jointly learn an embedding of words into an $n$-dimensional feature space. One of the advantages put forth for such distributed representations compared to traditional $n$-gram models is that similar words are likely to have similar vector representations in a continuous space model, whereas the discrete units of an $n$-gram model do not exhibit any inherent relation with one another. It has been shown that the continuous space representations improve performance in a variety of NLP tasks, such as POS tagging, semantic role labeling, named entity resolution, parsing (Collobert and Weston, 2008; Turian et al., 2010; Huang et al., 2012).

Mikolov et al. (2013) show that there are some syntactic and semantic regularities in the word representations learned, such as the singular/plural relation (the difference of singular and plural word vectors are equivalent: apple − apples ≈ car − cars ≈ family − families) or the gender relation (a masculine noun can be transformed into the feminine form: king − man + woman ≈ queen).

We extend Mikolov et al. (2013)'s approach and explore further the interpretation of the vector space. We show that the word vectors learned by NNLMs are meaningful: we can extract scalar relationships between adjectives (e.g., bad < okay < good < excellent), which can not only serve to build a sentiment lexicon but also be used for inference. To evaluate the quality of the scalar relationships learned by NNLMs, we use the indirect yes/no question answer pairs (IQAP) from (de Marneffe et al., 2010), where scales between adjectives are needed to infer a yes/no answer from a reply without explicit yes or no such as Was the movie good? It was excellent. Our method reaches 72.8% accuracy, which is the best result reported so far when scales are used.

2 Previous work
We use the continuous word representations from (Mikolov et al., 2011), extracted from a recurrent neural network language model (RNNLM), whose
three-layer architecture is represented in Figure 1.

![Figure 1: The architecture of the RNNLM.](http://www.fit.vutbr.cz/~imikolov/rnnlm/word_projections-1600.txt.gz)

In the input layer, \( w(t) \) is the input word represented by 1-of-\( N \) coding at time \( t \) when the vocabulary size is \( N \). When there are \( M \) nodes in the hidden layer, the number of connections between the input layer and the hidden layer is \( NM \) and the connections can be represented by a matrix \( U \).

The hidden layer is also connected recurrently to the context \( s(t-1) \) at time \( t-1 \) (\( s(0) \) is initialized with small values like 0.1). The connections between the previous context and the hidden layer are represented by a matrix \( W \). The dimensionality of the word representations is controlled by the size of \( W \). The output of the hidden layer is \( s(t) = f(Uw(t) +Ws(t-1)) \), where \( f \) is a sigmoid function.

Because the inputs of the hidden layer consist of the word \( w(t) \) and the previous hidden layer output \( s(t-1) \), the current context of the RNN is influenced by the current word and the previous context. Therefore, we can regard that the continuous representations from the RNNLM exploit the context implicitly considering the word sequence information (Mikolov et al., 2010).

\( V \) is an \( N \) by \( M \) matrix representing the connections between the hidden layer and the output layer. The final output is \( y(t) = g(Vs(t)) \), where \( g \) is a softmax function to represent the probability distribution over all the words in the vocabulary.

When the RNN is trained by the back propagation algorithm, we can regard the \( \text{th} \) column vector of \( U \) as the continuous representation of the \( \text{th} \) word in the vocabulary since the column was adjusted correspondingly to the \( \text{th} \) element of \( w(t) \). Because the \( s(t) \) outputs of two input words will be similar when they have similar \( s(t-1) \) values, the corresponding column vectors of the words will also be similar.

Mikolov et al. (2013) showed that constant vector offsets of word pairs can represent linguistic regularities. Let \( w_a \) and \( w_b \) denote the vectors for the words \( a \) and \( b \), respectively. Then the vector offset of the word pair is \( w_a - w_b \). If \( a \) and \( b \) are syntactically or semantically related, the vector offset can be interpreted as a transformation of the syntactic form or the meaning. The offset can also be added to another word vector \( c \). The word vector nearest to \( w_a - w_b + w_c \) would be related to word \( c \) with the syntactic or semantic difference as the difference between \( a \) and \( b \), as it is the case for the \( \text{king, man, and woman} \) example, where \( \text{king} - \text{man} + \text{woman} \) would approximately represent \( \text{king} \) with feminine gender (i.e., \( \text{queen} \)). They also tried to use the continuous representations generated by Latent Semantic Analysis (LSA) (Landauer et al., 1998). However, the results using LSA were worse because LSA is a bag-of-words model, in which it is difficult to exploit word sequence information as the context.

For all the experiments in this paper, we use the precomputed word representations generated by the RNNLM from (Mikolov et al., 2013). Their RNN is trained with 320M words from the Broadcast News data (the vocabulary size is 82,390 words), and we used word vectors with a dimensionality of 1,600 (the highest dimensionality provided).\(^1\) We standardized the dataset so that the mean and the variance of the representations are 0 and 1, respectively.\(^2\)

### 3 Deriving adjectival scales

Here we explore further the interpretation of word vectors. Assuming that the transformation of form or meaning represented by the vector offset is linear, an intermediate vector between two word vectors would represent some “middle” form or meaning. For example, given the positive and superlative forms of an adjective (e.g., \text{good} and \text{best}), we expect that the word representation in the middle of

\(^1\)We also experimented with smaller dimensions, but consistent with the analyses in (Mikolov et al., 2013), the highest dimensionality gave better results.

\(^2\)http://www.fit.vutbr.cz/~imikolov/rnnlm/word_projections-1600.txt.gz
Table 1: Words with corresponding vectors closest to the mean of positive:superlative word vectors.

Table 2: Adjectival scales extracted from the RNN: each row represents a scale, and for each intermediate point the closest word in term of cosine similarity is given.

Figure 2: An example of vectors with the highest cosine similarity to intermediate points on the line between furious and happy.

Tables 1 and 2 demonstrate that the word vector space is interpretable: intermediate vectors between two word vectors represent a semantic continuum.

4 Evaluation: Indirect answers to yes/no questions

To evaluate the quality of the adjective scales learned by the neural network approach, we use the corpus of indirect answers to yes/no questions created by (de Marneffe et al., 2010), which consists of question-answer pairs involving gradable modifiers to test scalar implicatures. We focus on the 125 pairs in the corpus where both the question and answer contain an adjective: e.g., Is Obama qualified? I think he’s young. Each question-answer pair has

3These 125 pairs correspond to the ‘Other adjective’ category in (de Marneffe et al., 2010).
been annotated via Mechanical Turk for whether the answer conveys yes, no or uncertain.

4.1 Method
The previous section showed that we can draw a line passing through an adjective and its antonym and that the words extracted along the line are roughly semantically ordered. To infer a yes or no answer in the case of the IQAP corpus, we use the following approach illustrated with the Obama example above (Figure 3). Using WordNet 3.1 (Fellbaum, 1998), we look for an antonym of the adjective in the question qualified: unqualified is retrieved. Since the scales extracted are only roughly ordered, to infer yes when the question and answer words are very close, we set the decision boundary perpendicular to the line connecting the two words and passing through the midpoint of the line.

Since the answer word is young, we check whether young is in the area including qualified or in the other area. We infer a yes answer in the former case, and a no answer in the latter case. If young is on the boundary, we infer uncertain. If a sentence contains a negation (e.g., Are you stressed? I am not peaceful.), we compute the scale for stressed-peaceful and then reverse the answer obtained, similarly to what is done in (de Marneffe et al., 2010).

Since a word can have multiple senses and different antonyms for the senses, it is important to select the most appropriate antonym to build a more accurate decision boundary. We consider all antonyms across senses and select the antonym that is most collinear with the question and the answer. For the word vectors of the question w_q, the ith antonym w_{ant_i}, and the answer w_a, we select ant_i where argmax_{ant_i} |cos(w_q − w_a, w_q − w_{ant_i})|. Figure 4 schematically shows antonym selection when the question is good and the answer is excellent: bad and evil are the antonym candidates of good. Because the absolute cosine similarity of good-excellent to good-bad is higher than to good-evil, we choose bad as the antonym in this case.

4.2 Results and discussion
Table 3 compares our results with previous ones where adjectival scales are considered: de Marneffe et al. (2010) propose an unsupervised approach where scales are learned from distributional information in a Web corpus; Mohtarami et al. (2011)’s model is similar to ours but uses word representations obtained by LSA and a word sense disambiguation system (Zhong and Ng, 2010) to choose antonyms. To compare with Mohtarami et al. (2011), we use macro-averaged precision and recall for yes and no. For the given metrics, our model significantly outperforms the previous ones (p < 0.05, McNemar’s test).

Mohtarami et al. (2011) present higher numbers obtained by replacing the answer words with their synonyms in WordNet. However, that approach fails to capture orderings. Two words of different degree are often regarded as synonyms: even though furious means extremely angry, furious and angry are synonyms in WordNet. Therefore using synonyms, the system will output the same answer irrespective of the order in the pair. Mohtarami et al. (2012) also presented results on the interpretation of indirect questions on the IQAP corpus, but their method

|             | Acc | P   | R   | F1  |
|-------------|-----|-----|-----|-----|
| de Marneffe (2010) | 60.00 | 59.72 | 59.40 | 59.56 |
| Mohtarami (2011) | –   | 62.23 | 60.88 | 61.55 |
| RNN model    | 72.80 | 69.78 | 71.39 | 70.58 |

Table 3: Score (%) comparison on the 125 scalar adjectival pairs in the IQAP corpus.
Figure 5: Question words (bold), their antonyms (italic), and answer words (normal) of four pairs from the IQAP dataset. The words are visualized by MDS.

did not involve learning or using scalar implicatures.

Figure 5 gives a qualitative picture: the question words, antonyms and answer words for four of the IQAP pairs are visualized in 2D space by multidimensional scaling (MDS). Note that MDS introduces some distortion in the lower dimensions. Bullet markers correspond to words in the same pair. Question words, antonyms, and answer words are displayed by bold, italic, and normal fonts, respectively. In the Obama example previously mentioned (Is Obama qualified? I think he’s young.), the question word is qualified and the answer word is young. In Figure 5, qualified is around (2,-20) while its antonym unqualified is around (-6,-24). Since young is around (-7,-8), we infer that young is semantically closer to unqualified which corroborates with the Turkers’ intuitions in this case. (1), (2) and (3) give the other examples displayed in Figure 5.

(1) A: Do you think she’d be happy with this book?  
B: I think she’d be delighted by it.

(2) A: Do you think that’s a good idea?  
B: It’s a terrible idea.

(3) A: The president is promising support for Americans who have suffered from this hurricane. Are you confident you are going to be getting that?  
B: I’m not so sure about my insurance company.

In (1), delighted is stronger than happy, leading to a yes answer, whereas in (2), terrible is weaker than good leading to a no answer. In (3), the presence of a negation will reverse the answer inferred, leading to no.

5 Conclusion

In this paper we give further evidence that the relationships in the continuous vector space learned by recurrent neural network models are interpretable. We show that using vector offsets, we can successfully learn adjectival scales, which are useful for scalar implicatures, as demonstrated by the high results we obtain on the IQAP corpus.

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