MODELING COMPOSITIONALITY WITH MULTIPlicative RECurrent NEURAL NETWORKS

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ABSTRACT

We present the multiplicative recurrent neural network as a general model for compositional meaning in language, and evaluate it on the task of fine-grained sentiment analysis. We establish a connection to the previously investigated matrix-space models for compositionality, and show they are special cases of the multiplicative recurrent net. Our experiments show that these models perform comparably or better than Elman-type additive recurrent neural networks and outperform matrix-space models on a standard fine-grained sentiment analysis corpus. Furthermore, they yield comparable results to structural deep models on the recently published Stanford Sentiment Treebank without the need for generating parse trees.

1 INTRODUCTION

Recent advancements in neural networks and deep learning have provided fruitful applications for natural language processing (NLP) tasks. One important such advancement was the invention of word embeddings that represent a single word as a dense, low-dimensional vector in a meaning space (Bengio et al., 2001) from which numerous problems in NLP have benefited (Collobert & Weston, 2008; Collobert et al., 2011). The natural next question, then, was how to properly map larger phrases into such dense representations for NLP tasks that require properly capturing their meaning. Most existing methods take a compositional approach by defining a function that composes multiple word vector representations into a phrase representation (e.g. Mikolov et al. (2013b), Socher et al. (2013), Yessenalina & Cardie (2011)).

Compositional matrix-space models (Rudolph & Giesbrecht, 2010; Yessenalina & Cardie, 2011), for example, represent phrase-level meanings in a vector space and represent words as matrices that act on this vector space. Therefore, a matrix assigned to a word should capture how it transforms the meaning space (e.g. negation or intensification). Meaning representations for longer phrases are simply computed as a multiplication of word matrices in sequential order (left-to-right, for English). Their representational power, however, is accompanied by a large number of parameters — a matrix for every word in the vocabulary. Thus, learning can be difficult.

But sequential composition of words into phrases is not the only mechanism for tackling semantic composition. Recursive neural networks, for example, employ a structural approach to compositionality: the composition function for a phrase operates on its two children in a binary parse tree of the sentence. Single words are represented in a vector-space. Different ways of defining the composition function lead to different variants of the recursive neural network. In the original work on this topic (Socher et al., 2011), a simple additive affine function with an additional nonlinearity is used. The matrix-vector recursive neural network of Socher et al. (2012) extends this by assigning an additional matrix to each word, similar to the aforementioned matrix-space models; and the composition function involves a matrix-vector multiplication of sibling representations. More recently, Socher et al. (2013) defines a bilinear tensor multiplication as the composition function — to capture multiplicative interactions between siblings.

On the other hand, recurrent neural networks (RNNs), a neural network architecture with sequential prediction capabilities, implicitly model compositionality when applied to natural language...
sentences. Representation of a phrase can be conceptualized as a nonlinear function that acts on the network’s hidden layer (memory), which results from repeated function composition over the hidden layer and the next word in the phrase/sentence (see Section 3.2). Unfortunately, it is possible that conventional additive recurrent networks are not powerful enough to accommodate some of the more complex effects in language, as suggested in previous work on (multiplicative and additive variants of) recursive neural networks (e.g. Socher et al. (2013)). More specifically, even though additive models can theoretically model arbitrary functions when combined with a nonlinearity, they might require a very large number of hidden units, and learnability of large parameter sets from data might pose an issue.

To this end we investigate the multiplicative recurrent neural network as a model for compositional semantic effects in language. Previously, this type of multiplicative sequential approach has been applied to a character-level text generation task (Sutskever et al., 2011). In this work, we investigate its capacity for recognizing the sentiment of a sentence or a phrase represented as a sequence of dense word vectors. Like the matrix-space models, multiplicative RNNs are sequential models of language; and as a type of recurrent NN, they implicitly model compositionality. Like the very successful multiplicative recursive neural networks, multiplicative RNNs can capture the same types of sibling interactions, but are much simpler. In particular, no parse trees are required, so sequential computations replace the associated recursive computations and performance does not depend on the accuracy of the parser.

We also show a connection between the multiplicative RNN and compositional matrix-space models, which have also been applied to sentiment analysis (Rudolph & Giesbrecht, 2010; Yessenalina & Cardie, 2011). In particular, matrix-space models are effectively a special case of multiplicative RNNs in which a word is represented as a large “one-hot” vector instead of a dense small one. Thus, these networks carry over the idea of matrix-space models from a one-hot sparse representation to dense word vectors. They can directly employ word vector representations, which makes them better suited for semi-supervised learning given the plethora of word vector training schemes. Multiplicative recurrent networks can be considered to unify these two views of distributed language processing — the operator semantics view of matrix-space models in which a word is interpreted as an operator acting on the meaning representation, and the sequential memory processing view of recurrent neural networks.

Our experiments show that multiplicative RNNs provide comparable or better performance than conventional additive recurrent nets and matrix-space models in terms of fine-grained sentiment detection accuracy. Furthermore, although the absence of parse tree information puts an additional learning burden on multiplicative RNNs, we find that they can reach comparable performance to the recursive neural network variants that require parse tree annotations for each sentence.

2 RELATED WORK

Vector Space Models. In natural language processing, a common way of representing a single token as a vector is to use a “one-hot” vector per token, with a dimensionality of the vocabulary size. This results in a very high dimensional, sparse representation. Additionally, every word is put at an equal distance to one another, disregarding their syntactic or semantic similarities. Alternatively, a distributed representation maps a token to a real-valued dense vector of smaller size (usually on the order of 100 dimensions). Generally, these representations are learned in an unsupervised manner from a large corpus, e.g. Wikipedia. Various architectures have been explored to learn these embeddings (Bengio et al., 2001; Collobert & Weston, 2008; Mnih & Hinton, 2007; Mikolov et al., 2013a) which might have different generalization capabilities depending on the task (Turian et al., 2010). The geometry of the induced word vector space might have interesting semantic properties (king - man + woman ≈ queen) (Mikolov et al., 2013b). In this work, we employ such word vector representations as the initial input representation when training neural networks.

Matrix Space Models. An alternative approach is to embed words into a matrix space, by assigning matrices to words. Intuitively, a matrix embedding of a word is desired in order to capture operator semantics: the embedding should model how a word transforms meaning when it is applied to a context. Baroni & Zamparelli (2010) partially apply this idea to model adjectives as matrices that act on noun vectors. In their theoretical work, Rudolph & Giesbrecht (2010) define a proper matrix space model by assigning every word to a matrix; representations for longer phrases are computed
by matrix multiplication. They show that matrix space models generalize vector space models and argue that they are neurologically and psychologically plausible. Yessenalina & Cardie (2011) apply this model to fine-grained sentiment detection. Socher et al. (2012) use a structural approach in which every word is assigned a matrix-vector pair, where the vector captures the meaning of the word in isolation and the matrix captures how it transforms meaning when applied to a vector.

Compositionality in Vector and Matrix Spaces. Commutative vector operations such as addition (e.g. bag-of-words) or element-wise multiplication provide simple composition schemes (Mitchell & Lapata, 2010). Even though they ignore the order of the words, they might prove effective depending on the length of the phrases, and on the task (Mikolov et al., 2013b). More complex non-commutative composition functions can be modeled via sequential or structural models of the sentence. In particular, compositionality in recurrent neural networks can be considered as transformations on the memory (hidden layer) applied by successive word vectors in order. Recursive neural networks employ a structural setting where compositions of smaller phrases into larger ones are determined by their parent-children relationship in the associated binary parse tree (Socher et al., 2011, 2012, 2013). In matrix space models, compositionality is naturally modeled via function composition in sequence (Rudolph & Giesbrecht, 2010; Yessenalina & Cardie, 2011).

Sentiment Analysis. Sentiment analysis has been a very active area among NLP researchers, at various granularities such as the word-, phrase-, sentence- or document-level (Pang & Lee, 2008). Besides preexisting work that tried to formulate the problem as binary classification, recently fine-grained approaches were explored (Yessenalina & Cardie, 2011, Socher et al., 2013). Ultimately, the vast majority of approaches do not tackle the task compositionally, and in addition to bag-of-words features, they incorporate engineered features to account for negators, intensifiers and contextual valence shifters (Polanyi & Zaenen, 2006, Wilson et al., 2005, Kennedy & Inkpen, 2006, Shaikh et al., 2007).

3 Preliminaries

3.1 Matrix-space models

A matrix-space model models a single word as a square matrix that transforms a meaning (state) vector to another vector in the same meaning space. Intuitively, a word is viewed as a function, or an operator (in this particular case, linear) that acts on the meaning representation. Therefore, a phrase (or any sequence of words) is represented as successive application of the individual operators inside the phrase.

Let \( s = w_1, w_2, \ldots, w_T \) be a sequence of words of length \( T \) and let \( M_w \in \mathbb{R}^{m \times m} \) denote the matrix representation of a word \( w \in \mathcal{V} \) where \( \mathcal{V} \) is the vocabulary. Then, the representation of \( s \) is simply

\[
M(s) = M_{w_1}M_{w_2} \ldots M_{w_T}
\]

which yields another linear transformation in the same space. Observe that this representation respects word order (unlike, e.g. a bag of words). Note that even though \( M(s) \) is modeled as a linear operator on the meaning space, \( M(s) \) as a function of \( \{M_w \}_{i=1..T} \) is not linear, since it constitutes multiplications of those terms.

Applying this representation to a task is simply applying the function to an initial empty meaning vector \( h_0 \), which results in a transformed, final meaning vector \( h \) that then is used to make a decision on the phrase \( s \). In the case of sentiment detection, a sentiment score \( y(s) \) can be assigned to \( s \) as follows:

\[
y(s) = h^\top u = h_0^\top M(s)u = h_0^\top \prod_t M_{w_t}u
\]

In such a supervised task, matrix-space model parameters \( \{M_w \}_{w \in \mathcal{V}}, h_0, u \) are learned from data. \( h_0 \) and \( u \) can be fixed (without reducing the representative power of the model) to reduce the degrees of freedom during training.

3.2 Recurrent neural networks

A recurrent neural network (RNN) is a class of neural network that has recurrent connections, which allow a form of memory. This makes them applicable for sequential prediction tasks of arbitrary...
spatio-temporal dimension. They model the conditional distribution of a set (or a sequence) of output variables, given an input sequence. In this work, we focus our attention on only Elman-type networks (Elman [1990]).

In the Elman-type network, the hidden layer $h_t$ at time step $t$ is computed from a nonlinear transformation of the current input layer $x_t$ and the previous hidden layer $h_{t-1}$. Then, the final output $y_t$ is computed using the hidden layer $h_t$. One can interpret $h_t$ as an intermediate representation summarizing the past so far.

More formally, given a sequence of vectors $\{x_t\}_{t=1..T}$, an Elman-type RNN operates by computing the following memory and output sequences:

$$
\begin{align*}
    h_t &= f(W x_t + V h_{t-1} + b) \\
    y_t &= g(U h_t + c)
\end{align*}
$$

where $f$ is a nonlinearity, such as the element-wise sigmoid function, $g$ is the output nonlinearity, such as the softmax function, $W$ and $V$ are weight matrices between the input and hidden layer, and among the hidden units themselves (connecting the previous intermediate representation to the current one), respectively, while $U$ is the output weight matrix, and $b$ and $c$ are bias vectors connected to hidden and output units, respectively. When $y_t$ is a scalar (hence, $U$ is a row vector) and $g$ is the sigmoid function, $y_t$ is simply the probability of a positive label, conditioned on $\{x_\tau\}_{\tau=1..t}$.

For tasks requiring a single label per sequence (e.g. single sentiment score per sentence), we can discard intermediate outputs $\{y_t\}_{t=1..(T-1)}$ and use the output of the last time step $y_T$, where $T$ is the length of the sequence. This also means that during training, external error is only incurred at the final time step. In general, supervision can be applied at any intermediate time step whenever there are labels available in the dataset, even if intermediate time step labels are not to be used at the testing phase, since this makes training easier.

4 METHODOLOGY

4.1 Multiplicative Recurrent Neural Network

A property of recurrent neural networks is that input layer activations and the hidden layer activations of the previous time step interact additively to make up the activations for hidden layers at the current time step. This might be rather restrictive for some applications, or difficult to learn for modeling more complex input interactions. On the other hand, a multiplicative interaction of those layers might provide a better representation for some semantic analysis tasks. For sentiment detection, for example, “not” might be considered as a negation of the sentiment that comes after it, which
might be more effectively modeled with multiplicative interactions. To this end, we investigate the multiplicative recurrent neural network (or the recurrent neural tensor network) for the sentiment analysis task that is the main focus of this paper (Sutskever et al., 2011).

mRNNs retain the same interpretation of memory as RNNs, the only difference being the recursive definition of \( h_t \):

\[
\begin{align*}
  h_t &= f(x_t^TA^{[1..d_h]}h_{t-1} + Wx_t + Vh_{t-1} + b) \\
  y_t &= g(Uh_t + c)
\end{align*}
\]

where \( A \) is a \( d_h \times d_x \times d_h \) tensor, and the bilinear operation \( x^TAy \) defines another vector as \( (x^TAy)_i = x^TA[i]y \) where the right-hand side represents the standard vector matrix multiplications and \( A[i] \) is a single slice (matrix) of the tensor \( A \). This means that a single entry of \( h_{t,i} \) is not only a linear combination of entries \( x_{t,j} \) and \( h_{t-1,k} \), but also includes multiplicative terms in the form of \( a_{jk}x_{t,j}h_{t-1,k} \).

We can simplify Equation 5 and 6 by adding bias units to \( x \) and \( h \):

\[
\begin{align*}
  h_t &= f(x_t^TA^{[1..d_h]}h_{t-1}') \\
  y_t &= g(U'h_t')
\end{align*}
\]

where \( x' = [x; 1] \) and \( h' = [h; 1] \). With this notation, \( W, V \) and \( b \) become part of the tensor \( A' \) and \( c \) becomes part of the matrix \( U' \).

### 4.2 Ordinal Regression with Neural Networks

Since fine-grained sentiment labels denote intensity in addition to polarity, our class labels are ordinal in nature. Therefore, we use an ordinal regression scheme for neural networks, as described in Cheng et al. (2008). Intuitively, each sentiment class denotes a threshold for which the instances belonging to the class have sentiment values less than or equal to. If an instance \( s \) belongs to class \( k \), it automatically belongs to the lower order classes \( 1, \ldots, k-1 \), as well. Therefore, the target vector for instance \( s \) is \( r = \begin{bmatrix} 1, \ldots, 1, 0, \ldots, 0 \end{bmatrix}^T \) where \( r_i = 1 \) if \( i < k \) and \( r_i = 0 \) otherwise. This way, we can consider the output vector as a cumulative probability distribution on classes.

Because of the way class labels are defined, output response is not subject to normalization. Therefore, output layer nonlinearity in this case is the elementwise sigmoid function \( \frac{1}{1+\exp(-x)} \) instead of the softmax function \( \frac{\exp(x_i)}{\sum_j \exp(x_j)} \) which is traditionally used for multiclass classification.

Note that with this scheme, output of the network is not necessarily consistent. To decode an output vector, we first binarize each entry, by assigning 0 if the entry is less than 0.5 and 1 otherwise, as in conventional binary classification. Then we simply start from the entry with the lowest index, and whenever we observe a 0, we assume all of the entries with higher indices are also 0, which ensures that the resulting target vector has the proper ordinal form. As an example, \( [1, 0, 1, 0]^T \) is mapped to \( [1, 0, 0, 0]^T \). Then finally, we assign the corresponding integer label.

### 4.3 Relationship to Matrix-Space Model

In this section we will show the connection between mRNNs and matrix space model.

Let us assume a purely multiplicative mRNN, without the bias units in the input and hidden layers (equivalently, \( W = V = b = 0 \)). In such an mRNN, we compute the hidden layer (memory) as follows:

\[
  h_t = f(x_t^TAh_{t-1})
\]

Furthermore, assume \( f = I \) is the identity mapping, rather than a nonlinearity function. We can view the tensor multiplication in two parts: A vector \( x_t \) multiplied by a tensor \( A \), resulting in a matrix which we will denote as \( M(w_t) \), to make the dependence of the resulting matrix on the word \( w_t \) explicit. Then the matrix-vector multiplication \( M(w_t)h_{t-1} \) resulting in the vector \( h_t \). Therefore, we can write the same equation as:

\[
  h_t = (x_t^TA)h_{t-1} = M(w_t)h_{t-1}
\]
and unfolding the recursion, we have
\[ h_t = M(w_t)M(w_{t-1}) \ldots M(w_1)h_0 \] (11)

If we are interested in a scalar response for the whole sequence, we apply the output layer to the hidden layer at the final time step:
\[ y_T = u^\top h_T = u^\top M(w_T) \ldots M(w_1)h_0 \] (12)

which is the matrix space model if individual \( M(w_t) \) were to be associated with the matrices of their corresponding words (Equation 2). Therefore, we can view mRNNs as a simplification to matrix-space models in which we have a tensor \( A \) to extract a matrix for a word \( w \) from its associated word vector, rather than associating a matrix with every word. This can be viewed as learning a matrix-space model with parameter sharing. This reduces the number of parameters greatly: instead of having a matrix for every word in the vocabulary, we have a vector per word, and a tensor to extract matrices.

Another interpretation of this is the following: instead of learning an individual linear operator \( M_w \) per word as in matrix-space models, mRNN learns \( d_x \) number of base linear operators. mRNN, then, represents each word as a weighted sum of these base operators (weights given by the word vector \( x \)). Note that if \( x \) is a one-hot vector representation of a word instead of a dense word embedding (which means \( d_x = |V| \)), then we have \( |V| \) matrices as the base set of operators, and \( x \) simply selects one of these matrices, essentially falling back to an exact matrix-space model (see Figure 1). Therefore mRNNs provide a natural transition of the matrix-space model from a one-hot sparse word representation to a low dimensional dense word embedding.

Besides a reduction in the number of parameters, another potential advantage of mRNNs over matrix-space models is that the matrix-space model is task-dependent: for each task, one has to learn one matrix per word in the whole vocabulary. On the other hand, mRNNs can make use of task-independent word vectors (which can be learned in an unsupervised manner) and only the parameters for the network would have to be task-dependent. This allows easier extension to multitask learning or transfer learning settings.

5 Experiments

5.1 Setting

Data. For experimental evaluation of the models, we use the manually annotated MPQA corpus (Wiebe et al., 2005) that contains 535 newswire documents annotated with phrase-level subjectivity and intensity. We use the same scheme as Yessenalina & Cardie (2011) to preprocess and extract individual phrases from the annotated documents, and convert the annotations to an integer ordinal label \{0, 1, 2, 3, 4\} denoting a sentiment score from negative to positive. After preprocessing, we
have 8022 phrases in total with an average length of 2.83. We use the training-validation-test set partitions provided by the authors to apply 10-fold CV and report average performance over ten folds.

Additionally, we use the recently published Stanford Sentiment Treebank (SST) (Socher et al., 2013), which includes labels for 215,154 phrases in the parse trees of 11,855 sentences, with an average sentence length of 19.1. Similarly, real-valued sentiment labels are converted to an integer ordinal label in \(\{0, \ldots, 4\}\) by simple thresholding. We use the single training-validation-test set partition provided by the authors. We do not make use of the parse trees in the treebank since our approach is not structural; however, we include the phrase-level supervised labels (at the internal nodes of the parse trees) as labels for partial sentences.

### Problem formulation

For experiments on the MPQA corpus, we employ an ordinal regression setting. For experiments on SST, we employ a simple multiclass classification setting, to make the models directly comparable to previous work.

In the classification setting, output nonlinearity \(g\) is the softmax function, and the output \(y\) is a vector valued response with the class probabilities. Ordinal regression setting is as described in Section 4.2.

### Evaluation metrics

For experiments using the MPQA corpus, we use the ranking loss as in Yessenalina & Cardie (2011), defined as \(\frac{1}{n} \sum_i |y_i - r_i|\) where \(y\) and \(r\) are predicted and true scores respectively. For experiments using SST, we use accuracy, \(\frac{1}{n} \sum_i 1(y_i = r_i)\) as in Socher et al. (2013).

### Word vectors

We experiment with both randomly initialized word vectors (RAND) and pretrained word vector representations (VEC). For pretrained word vectors, we use publicly available 300 dimensional word vectors by Mikolov et al. (2013b), trained on part of Google News dataset (~100B words). When using pretrained word vectors, we do not finetune them to reduce the degree of freedom of our models.

Additionally, matrix-space models are initialized with random matrices (RAND) or a bag-of-words regression model weights (BOW) as described in Yessenalina & Cardie (2011).

### 5.2 Results

Quantitative results on the MPQA corpus are reported in Table 1. The top group shows previous results from Yessenalina & Cardie (2011) and the bottom group shows our results.

We observe that mRNN does slightly better that RNN with approximately the same number of parameters (0.5232 vs. 0.5265). This suggests that multiplicative interactions improve the model over additive interactions. Even though the difference is not significant in the test set, it is significant in the development set. We partially attribute this effect to the test set variance. This also suggests that multiplicative models are indeed more powerful, but require more careful regularization, because early stopping with a high model variance might tend to overfit to the development set.

The randomly initialized mRNN outperforms its equivalent randomly initialized matrix-space model (0.6799 vs. 0.7417), which suggests that more compact representations with shared parameters learned by mRNN indeed generalize better.

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**Table 1: Average ranking losses (MPQA)**

| Method | Loss  |
|--------|-------|
| PRank  | 0.7808 |
| Bag-of-words LogReg | 0.6665 |
| Matrix-space\_Rand \((d_h = 3)\) | 0.7417 |
| Matrix-space\_BOW \((d_h = 3)\) | 0.6375 |
| RNN\_vec \((d_h = 315)\) | 0.5265 |
| mRNN\_vec\_Rand \((d_h = 2)\) | 0.6799 |
| mRNN\_vec \((d_h = 25)\) | 0.5278 |
| mRNN\_vec\_tanh \((d_h = 25)\) | 0.5232 |
| mRNN\_tanh \((d_h = 25)\) | 0.5147 |

**Table 2: Average accuracies (SST)**

| Method | Acc (%)  |
|--------|----------|
| Bag-of-words NB | 41.0 |
| Bag-of-words SVM | 40.7 |
| Bigram NB | 41.9 |
| VecAvg | 32.7 |
| Recursive\_tanh | 43.2 |
| MV-Recursive\_tanh | 44.4 |
| mRecursive\_tanh | 45.7 |
| Recurrent\_vec \((d_h = 315)\) | 43.1 |
| mRecurrent\_vec \((d_h = 20)\) | 43.5 |
The mRNN and RNN that use pretrained word vectors get the best results, which suggests the importance of good pretraining schemes, especially when supervised data is limited. This is also confirmed by our preliminary experiments (which are not shown here) using other word vector training methods such as CW embeddings (Collobert & Weston, 2008) or HLBL (Mnih & Hinton, 2007), which yielded a significant difference (about 0.1 – 0.2) in ranking loss.

To test the effect of different nonlinearities, we experiment with the identity, rectifier and tanh functions with mRNNs. Experiments show that there is small but consistent improvement as we use rectifier or tanh over not using extra nonlinearity. The differences between rectifier and identity, and tanh and rectifier are not significant; however, the difference between tanh and identity is significant, suggesting a performance boost from using a nonlinear squashing function. Nonetheless, not using any nonlinearity is only marginally worse. A possible explanation is that since the squashing function is not the only source of nonlinearity in mRNNs (multiplicativeness is another source of nonlinearity), it is not as crucial.

Results on the Stanford Sentiment Treebank are shown in Table 2. Again, the top group shows baselines from Socher et al. (2013) and the bottom group shows our results.

Both RNN and mRNN outperform the conventional SVM and Naive Bayes baselines. We observe that RNN can get very close to the performance of Recursive Neural Network, which can be considered its structural counterpart. mRNN further improves over RNN and performs better than the recursive net and worse than the matrix-vector recursive net. Note that none of the RNN-based methods employ parse trees of sentences, unlike their recursive neural network variants.

6 CONCLUSION AND DISCUSSION

In this work, we explore multiplicative recurrent neural networks as a model for the compositional interpretation of language. We evaluate on the task of fine-grained sentiment analysis, in an ordinal regression setting and show that mRNNs outperform previous work on MPQA, and get comparable results to previous work on Stanford Sentiment Treebank without using parse trees. We also describe how mRNNs effectively generalize matrix-space models from a sparse 1-hot word vector representation to a distributed, dense representation.

One benefit of mRNNs over matrix-space models is their separation of task-independent word representations (vectors) from task-dependent classifiers (tensor), making them very easy to extend for semi-supervised learning or transfer learning settings. Slices of the tensor can be interpreted as base matrices of a simplified matrix-space model. Intuitively, every meaning factor (a dimension of the dense word vector) of a word has a separate operator acting on the meaning representation which we combine to get the operator of the word itself.

From a parameter sharing perspective, mRNNs provide better models. For matrix-space models, an update over a sentence affects only the word matrices that occur in that particular sentence. On the other hand, in an mRNN, an update over a sentence affects the global tensor as well. With such an update, the network alters its operation for similar words towards a similar direction.

One drawback of mRNNs over conventional additive RNNs is their increased model variance, resulting from multiplicative interactions. This can be tackled by a stricter regularization. Another future direction is to explore sparsity constraints on word vectors, which would mean that every word would select only a few base operators to act on the meaning representation.

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