Abstract

Recursive Neural Network (RecNN), a type of models which compose words or phrases recursively over syntactic tree structures, has been proven to have superior ability to obtain sentence representation for a variety of NLP tasks. However, RecNN is born with a thorny problem that a shared compositional function for each node of trees can’t capture the complex semantic compositionality so that the expressive power of model is limited. In this paper, in order to address this problem, we propose Tag-Guided HyperRecNN/TreeLSTM (TG-HRecNN/TreeLSTM), which introduces hypernetwork into RecNNs to take as inputs Part-of-Speech (POS) tags of word/phrase and generate the semantic composition parameters dynamically. Experimental results on five datasets for two typical NLP tasks show proposed models both obtain significant improvement compared with RecNN and TreeLSTM consistently. Our TG-HTreeLSTM outperforms all existing RecNN-based models and achieves or is competitive with state-of-the-art on four sentence classification benchmarks. The effectiveness of our models is also demonstrated by qualitative analysis.

Introduction

Recently, as deep neural models are popular in NLP research community, learning distributed sentence representation becomes a basic but crucial problem for a variety of NLP tasks, including but not limited to sentence classification (Kim 2014; Tai, Socher, and Manning 2015), question answering (Tan et al. 2016; Shen, Yang, and Deng 2017), and natural language inference (Yu and Munkhdalai 2017; Lin et al. 2017). In a common perspective, sentences are considered as sequences of words and recurrent neural networks (RNN) with long short-term memory (LSTM) (Hochreiter and Schmidhuber 1997) and convolutional neural networks (CNN) (Kim 2014) are adapted to model sentences sequentially. However, this type of models can’t always achieve the best performance because they ignore the syntactic structure.

In contrast, RecNN (Socher et al. 2011) assigns a vector representation to each word at the leaf nodes of the pre-obtained syntactic parse tree structures and composes word/phrase pairs to get phrase representation at each non-leaf nodes recursively over trees. The final representation of root node is regarded as sentence representation. It is from a completely different perspective that natural language allows speakers to determine the meaning of a longer expression based on the meanings of its words and the rules used to combine them (Socher et al. 2012).

Shortly after the standard RecNN is presented, researchers are aware that different from RNN, a group of shared parameters of semantic composition function limits the capacity of RecNN because different types of word/phrase pairs require pretty different composition rules. For example, the compositionality function of a verb-noun pair should distinguish from the function of an adverb-adjective pair intuitively. Therefore, some RecNN-based models are proposed for modeling the diversity and complexity of semantic composition. Overall speaking, these RecNN variants can be divided into two classes which partition composition function according to implicit and explicit rules respectively. The first class of models (Socher et al. 2012; Socher et al. 2013a; Socher et al. 2013b; Dong et al. 2014; Qian et al. 2015; Huang, Qian, and Zhu 2017) modeling the diversity and complexity of semantic composition. Overall speaking, these RecNN variants can be divided into two classes which partition composition function according to implicit and explicit rules respectively. The first class of models (Socher et al. 2012; Socher et al. 2013a; Socher et al. 2013b; Dong et al. 2014) do not take syntactic information into consideration. Therefore, models have to determine a suitable composition function without any guidance, which makes the learning of models more difficult. The other class of models (Qian et al. 2015; Huang, Qian, and Zhu 2017) define an untied composition function for different Part-Of-Speech (POS) tags which represents syntactic roles of words and phrases. These models can select corresponding function ac-
cording to tag information at each node. However the num-
ber of parameters are one or two orders of magnitude much
larger than standard RecNN so that models easily suffer
from overfitting.

In this paper, we propose Tag-Guided Hyper
RecNN/TreeLSTM (TG-HRecNN/TreeLSTM) to learn
a dynamic semantic composition function over tree
structures with the help of POS tags. We introduce
hypernetwork framework (Ha, Dai, and Le 2017) into
RecNN/TreeLSTM. In the proposed models, a main
RecNN/TreeLSTM whose parameters are tag-specific, is
used to compose word/phrase pairs and learn sentence
representation as ordinary RecNNs do. The purpose of
hyper RecNN/TreeLSTM is to predict parameters of the
main RecNN/TreeLSTM dynamically under the guidance
of POS tags. Our work is inspired by recent progress
in dynamic parameter prediction (Bertinetto et al. 2016)
and the motivation is two-fold. First, to obtain tag-specific composition
functions, without increasing the number of parameters
significantly, a hypernetwork which takes the factors that
determine the semantic composition rules as inputs and
has a similar architecture with main RecNN, is a good
choice. The factors include POS tags of nodes and hidden
vectors which have been proved to be useful in previous
works. Liu, Qiu, and Huang (2017b) conduct a pioneer
work which firstly combines dynamic parameter prediction
with RecNN. But their prediction network namely meta
network, takes only hidden vector as inputs so that it is
unable to capture syntactic information as discussed above.
The empirical results show this work does not perform
strongly enough so that it is meaningful to discovery a way
to combine dynamic parameter prediction with RecNN as
well as achieve excellent performance.

Second, we have observed the tag distribution is very
imbalanced over datasets. For example, in Stanford Sentimen-
tment Treebank (Socher et al. 2013b) corpus, the frequen-
cies of different POS tags differ from less than ten to tens
of thousands. There are over 70 different types of tags in
amount and if considering the combination of parent and
child nodes, the tag configurations of nodes are much more.
It is unrealistic to establish a composition function for each
configuration explicitly. In case of overfitting due to dis-
crete representation of POS tags, we use low-dimension dis-
tributed vectors to represent tags which we term tag embed-
ding.

We focus on learning sentence representation over con-
stituency parser tree in which each non-leaf node just has
two children. We give an example for constituency tree in
Figure 1. It should be noted when parsing sentences into
constituency trees, POS tags of word/phrase are obtained si-
multaneously so no extra preprocessing is need for our mod-
ecls except parsing. In summary, our contributions are as fol-

1. To improve the semantic composition process over tree
structures, we introduce hypernetwork framework into
RecNN and propose two novel models: TG-HRecNN and
TG-TreeLSTM. Semantic composition parameters of our
models are predicted dynamically under the guidance of
POS tag information.

2. We design the information fusion layer to incorporate
POS tag and semantic information at each node to guide
the composition process. The obvious gap between our
models and DC-RecNN/TreeLSTM (Liu, Qiu, and Huang
2017b) manifests the effectiveness of tag information in
dynamic parameter prediction.

3. Experiments on five datasets for two typical NLP tasks
show proposed models both obtain significant improve-
ment compared with RecNN and TreeLSTM consist-
tently. Specially, TG-HTreeLSTM outperforms all exist-
ing RecNN-based models and achieves or is competitive
with state-of-the-art performance on four sentence clas-
sification benchmarks. The qualitative analysis illustrates
how our model works.

Related Work

Recursive Neural Networks

Since RecNN (Socher et al. 2011) was proposed, several
works focus on improving composition function over tree
structures. Socher et al. (2013) replace vectors with matrix-
vector pairs to represent nodes and matrix-vector multipli-
cations are expected to model semantic composition flexibly
and adaptively. Socher et al. (2013b) utilize more complex
bilinear neural tensor layer as composition function. Dong
et al. (2014) improve RecNN by learning multiple com-
position functions whose outputs are summed up weight-
edly with self-adaptive weights. However, too much param-
eters make the learning of these models difficult. Besides
these implicit ways to make composition function more flex-
ible, Socher et al. (2013a) and Qian et al. (2015) estab-
lish different composition function for each type of syn-
tactic constituents. Qian et al. (2015) also propose a Tag
Embedded RNN (TE-RNN) which firstly uses embedding
vectors to represent POS tags of words/phrases and then
takes tag vectors as inputs of composition function. A sim-
ilar idea about exploiting POS tags has also been intro-
duced into TreeLSTM (Huang, Qian, and Zhu 2017). Liu,
Qiu, and Huang (2017) and Liu et al. (2017) aim to ad-
dress the non-compositional phenomenon and compose non-
compositional phrases with a special function.

In addition, there are other explorations on enhancing
the RecNN. LSTM cell could also help to learn long-term
dependencies over trees (Tai, Socher, and Manning 2015).
Teng and Zhang (2017) propose a bi-directional version of
TreeLSTM.

Dynamic Parameter Prediction

The idea of dynamic parameter prediction that modifies the
weights of one network by another is closely related to the
concept of fast weights (Schmidhuber 1992) in which one
network can produce context-dependent weight changes for
a second network. Recently, this idea draws researchers’s
attention again because of the renaissance of deep neural
networks. Bertinetto et al. (2016) attempt to learn example-
dependent network weights for one-shot learning. Jia et
al. (2016) introduce a framework which can dynamically generates CNN filters depended on network inputs. Ha, Dai, and Le (2017) propose a hypernetwork framework to generate weights for recurrent networks. They can be seen as a form of relaxed weight-sharing in the time dimension. Due to the similarity between RNN and RecNN, we construct our model based on this framework. Liu, Qiu, and Huang (2017b) firstly employ the idea of dynamic parameter prediction to improve RecNN while the parameters are generated by exploiting limited information so state-of-the-art performance is not achieved.

Background: Hypernetwork

Hypernetwork (Ha, Dai, and Le 2017) framework is proposed to break the parameter sharing characteristic of recurrent networks. In this framework, there are two RNNs which are called hyper RNN and main RNN respectively. The former network is a standard RNN and is utilized to predict parameters of main RNN dynamically. Input sequences, such as sentences, are modeled by the latter as an ordinary RNN. Parameters of main RNN are called hyper parameters. The formulation of hyper RNN is given by:

\[
h_t = \phi(W(z_w)x_t + U(z_u)h_{t-1} + b)
\]

All \(z_w, z_u\) vectors are outputs of hyper RNN and parameter matrices \(W, U\) and bias \(b\) are functions of corresponding \(z_w, z_u\) where \(z_w, z_u \in \mathbb{R}^d\). The input \(x_t \in \mathbb{R}^d\), hidden state \(h_t \in \mathbb{R}^h\) and nonlinearity \(\phi\) are same as that in the standard RNN. The equation of hyper RNN update is similar with that of standard RNN:

\[
h_t = \phi(W\hat{x}_t + U\hat{h}_{t-1} + b)
\]

All \(\hat{x}_t, \hat{h}_{t-1}\) are linear functions of \(\hat{h}_t\):

\[
z_t = W\hat{h}_t + b
\]

where \(z_t \in \mathbb{R}^d\) is the parameter matrix and \(W, U\) are hyper RNN parameters. If directly projecting \(x_t\) into the matrix \(W\), it may be not practical because we have to maintain a \(h \times d \times 3\) learnable tensor so that the memory usage becomes too large for real problems. An approximate mechanism is to revise equation 1 in the following way:

\[
h_t = \phi(Wz_w + Wz_u + Uh_{t-1} + b)
\]

We can see that now \(z_w, z_u\) modify the corresponding parameters by scaling each row of weight matrix linearly by an element in vector. Although in this way the degrees of freedom of parameter prediction process is reduced, the memory usage becomes available. It should be noted that in practice the dimension of hypernetwork is much lower than that of main network which means the total number of model parameters will not increase significantly.

Proposed Models

RecNNs can model sentences over tree structures. They use a group of shared parameters to compose word/phrase pairs recursively which limits the expressive power of models. Inspired by the fact that word/phrase pairs with different POS tags require different semantic composition functions, we introduce the hypernetwork framework into vanilla RecNN and TreeLSTM and propose Tag-Guided Hyper RecNN and Tag-Guided Hyper TreeLSTM respectively. Both of them consist of a hyper network and a main network as hyper RNN. Figure 2 shows the illustration of proposed model. At each nodes of the tree, adaptive composition parameters are predicted dynamically according to POS tag information.

Tag-Guided HyperRecNN (TG-HRecNN)

For a non-leaf node \(j\) in constituency parse trees, the RecNN obtains its hidden state \(h_j \in \mathbb{R}^h\) by composing the hidden states of its left child and right child, namely \(h^l_j\) and \(h^r_j\) respectively. The composition function is a simple affine transformation as follows:

\[
h_j = f(U[h^l_j, h^r_j] + b)
\]

where \(U \in \mathbb{R}^{h \times 2h}\) is the parameter matrix and \(b \in \mathbb{R}^h\) is the bias. \(f = \tanh\) is a standard element-wise nonlinearity.

TG-HRecNN consists of a main RecNN and a hyper RecNN. The hyper RecNN is similar to a standard RecNN whose composition function is given by:

\[
\tilde{h}_j = \phi(W\tilde{x}_j + U[\tilde{h}^l_j, \tilde{h}^r_j] + b)
\]

Compared to vanilla RecNN, there is an additional input \(\tilde{x}_j \in \mathbb{R}^d\) which contains POS tag information to determine the semantic composition at current node. We design an information fusion layer to compute \(\tilde{x}_j\) and we delay introducing this layer until Sec 4.3. \(\tilde{h}_j \in \mathbb{R}^h\) denotes the hidden state and \(W \in \mathbb{R}^{h \times d}, \tilde{U} \in \mathbb{R}^{h \times 2h}\) and \(b \in \mathbb{R}^h\) are learnable parameters.

Similar to the main RNN in equation 5, the composition function of main RecNN has dynamic parameters:

\[
h_t = \phi(Wz_w + Wz_u + Uh_{t-1} + b)
\]
\[ h_j = f \left( z_u \odot U \begin{bmatrix} h'_j \\ h'_{j'} \end{bmatrix} + z_b \right) \tag{8} \]

All \( z(.) \in \mathbb{R}^2 \) are computed through linear transformation as equation 4 where \((.) \in \{w, b\} \):

\[ z(.) = W_{h_i(.)} h_j + b_{h_i(.)} \tag{9} \]

**Tag-Guided HyperTreeLSTM (TG-HTreeLSTM)**

Tai, Socher, and Manning (2015) adopts a standard LSTM cell to TreeLSTM cell which can be used as composition function over constituency parse trees. The hidden state \( h_j \) now is calculated as follows:

\[
\begin{bmatrix}
\hat{g}_j \\
\hat{f}_j \\
\hat{l}_j \\
\hat{c}_j
\end{bmatrix} = \begin{bmatrix} \tanh \\ \sigma \end{bmatrix} \begin{bmatrix} W_x j + U \begin{bmatrix} h'_j \\ h'_{j'} \end{bmatrix} + b \end{bmatrix} \tag{10} \]

\[ c_j = i_j \odot \hat{g}_j + f'_j \odot c'_j + f_j \odot c_j \]

\[ h_j = o_j \odot \tanh(c_j) \tag{12} \]

where \( c_j \in \mathbb{R}^h \) denotes the memory cell. \( x_j \in \mathbb{R}^d \) is the input of node \( j \) which is word embedding at leaf nodes or zero at non-leaf nodes. \( \sigma \) denotes sigmoid function and \( \odot \) denotes elementwise multiplication. \( i_j, f_j, o_j \) are termed input gate, forget gate and output gate respectively. The superscript \( l \) and \( r \) represent the left child and right child respectively. For binarized trees this model computes two untied forget gates for each children. All matrices \( W \in \mathbb{R}^{5h \times d}, U \in \mathbb{R}^{5h \times h} \) and bias \( b \in \mathbb{R}^{5h} \) are learnable parameters.

TG-HTreeLSTM also consists of a main TreeLSTM and a hyper TreeLSTM. The composition formulation of hyper TreeLSTM is almost identical to TreeLSTM except the definition of \( \tilde{x} \in \mathbb{R}^d \) which will be described in Sec 4.3:

\[
\begin{bmatrix}
\tilde{g}_j \\
\tilde{f}_j \\
\tilde{i}_j \\
\tilde{c}_j
\end{bmatrix} = \begin{bmatrix} \tanh \\ \sigma \end{bmatrix} \begin{bmatrix} \tilde{W} x_j + \tilde{U} \begin{bmatrix} h'_j \\ h'_{j'} \end{bmatrix} + \tilde{b} \end{bmatrix} \tag{13} \]

\[ \tilde{c}_j = \tilde{i}_j \odot \tilde{g}_j + \tilde{f}'_j \odot \tilde{c}'_j + \tilde{f}_j \odot \tilde{c}_j \]

\[ \tilde{h}_j = \tilde{o}_j \odot \tanh(\tilde{c}_j) \tag{15} \]

where \( \tilde{W} \in \mathbb{R}^{5h \times d}, \tilde{U} \in \mathbb{R}^{5h \times 2h} \) and \( \tilde{b} \in \mathbb{R}^{5h} \) are learnable parameters. Then we use \( \tilde{h}_j \in \mathbb{R}^h \) to dynamically predict parameters of main LSTM:

\[
\begin{bmatrix}
g_j \\
i_j \\
f'_j \\
\hat{f}_j \\
o_j
\end{bmatrix} = \begin{bmatrix} \tanh \\ \sigma \end{bmatrix} \begin{bmatrix} z_w \odot W x_j + z_u \odot U \begin{bmatrix} h'_j \\ h'_{j'} \end{bmatrix} + z_b \end{bmatrix} \tag{16} \]

All \( z(.) \in \mathbb{R}^2 \) are computed through linear transformation by equation 9 where \((.) \in \{w, u, b\} \) and hidden state \( h_j \) can be obtained by equation 11-12.

**Information Fusion Layer**

To enable the hyper network to guide the semantic composition of the main network, we incorporate the syntactic information and semantic representation into \( \tilde{x} \), the input of hyper network at each node in equation 6 and 12. For a non-leaf node \( j \), we refer to \( t_j \in \mathbb{R}^d \) as its tag embedding and the tag embeddings of its children are denoted by \( t'_j, t'_{j'} \) respectively. We consider \( t_j, t'_j, t'_{j'} \) as syntactic information which determine the composition function at each node. We make use of the semantic information about the node as well. In equation 3, the hyper RNN (Ha, Dai, and Le 2017) utilizes the hidden state of last time step \( x_t \) and current input \( h_{t-1} \) of main RNN. However, the input \( x_t \) in non-leaf node \( j \) is zero. To fill this gap, we resort to the head-lexicalized (\( ? \)) in PCFG parser. A non-leaf node is associated with a head word which is the head word of one of its children according to pre-defined rules. Teng and Zhang (2017) firstly exploit it in neural network in a soft gated way. We calculate the head word \( x_j \) for a non-leaf node \( j \) in a similar way while utilizing tag embeddings as additional inputs:

\[ a_j = \sigma(W_{head}[t_j; t'_j; t'_{j'}; x_j; x'_{j'}] + b_{head}) \tag{17} \]

\[ x_j = a_j \odot x'_j + (1 - a_j) \odot x''_j \tag{18} \]

where \( x'_j, x''_j \in \mathbb{R}^d \) are the head word of two children nodes. \( a_j \) controls the composition of head words adaptively. \( W_{head} \in \mathbb{R}^{d \times (3l + 2d)} \) and \( b_{head} \in \mathbb{R}^d \) are learnable parameters. Then we can calculate the \( \tilde{x}_j \) with two heuristic strategies. The first is to directly concatenate all tag embeddings and semantic representations as follows:

\[ \tilde{x}_j = ReLU(W_{\tilde{x}}[t_j; t'_j; t'_{j'}; x_j; x'_j; x''_{j'}] + b_{\tilde{x}}) \tag{19} \]

where \( ReLU \) is Rectified Linear Units as nonlinearity. \( W_{\tilde{x}} \in \mathbb{R}^{d \times (3l + 2h + d)} \) and \( b_{\tilde{x}} \in \mathbb{R}^d \) are learnable parameters. The other strategy is to project tag embeddings and semantic representations separately and then operate an element-wise multiplication between them:

\[ \tilde{x}_j = ReLU(W_{\tilde{x}1} t_j \odot W_{\tilde{x}2} x_j + b_{\tilde{x}2}) \tag{20} \]

Output Layer

Given a sentence with its parser tree, proposed models can compute hidden state of each node over the tree recursively. The hidden state \( h_j \) computed by proposed models can be regarded as the representation of the phrase spanned by node \( j \). Specially, we use the hidden state of root node \( h_{root} \) as the sentence representation and apply it to two realistic NLP tasks. We utilize different output layers for two tasks.

For **sentence classification**, we should predict a label \( \hat{y} \) from a pre-defined class set \( \mathcal{Y} \) for a sentence \( x \). We directly feed the sentence representation \( h_x \) into a softmax classifier.

\[ p(y|x) = \text{softmax}(W_{s} h_x + b_{s}) \]
the prediction is given in this way:
\[ \hat{y} = \arg \max_y p(y|x) \]

For text semantic matching, we deal with a classification problem about sentence pairs. Given two sentences \( s \) and \( t \), we need to predict a label \( \hat{y} \) which represents the relation between them. We firstly obtain their representations \( h_s, h_t \) with a parameter shared TG-HRecNN/TreeLSTM and then combine the features in this way:
\[ h_x = [h_s \odot h_t; |h_s - h_t|] \]

We feed it into a network of one hidden layer with ReLU activation before into softmax classifier:
\[ \hat{p}_\theta(y|x) = \text{softmax}(W_s h_{mlp} + b_s) \]

The training objective for two tasks is to minimize the cross-entropy of the predicted and true label distributions:
\[ \text{loss} = -\frac{1}{|D|} \sum_{k=1}^{|D|} \log \hat{p}_\theta(y^{(k)}|x^{(k)}) \]

where \( |D| \) is the number of training samples, \( x^{(k)} \) and \( y^{(k)} \) are the \( k \)-th sample and label in dataset respectively. Then the prediction is given in this way:
\[ \hat{y} = \arg \max_y \hat{p}_\theta(y|x) \]

**Experiments**

**Datasets**

To evaluate the effectiveness of proposed models, we conduct experiments on four benchmarks for sentence classification and SICK dataset for text semantic matching:

- **SST**: Stanford Sentiment Treebank [Socher et al. 2013b] for sentiment classification. SST-1 denotes the evaluation with fine-grained labels (very positive, positive, neutral, negative, very negative) and SST-2 denotes the evaluation with binary labels by neglecting the neutral samples during test. During training, we also utilize the phrase-level labels as previous works do.

- **MR**: Movie reviews with two polarity classes. (positive/negative) [Pang and Lee 2005] \(^2\)

- **SUBJ**: Subjectivity datasets with two classes. (subjective/objective) [Pang and Lee 2004] \(^3\)

- **TREC**: TREC question dataset with six question classes (e.g. location). [Li and Roth 2002] \(^4\)

- **SICK**: Sentences Involving Compositional Knowledge for text entailment with three classes (entailment, contradiction, neutral). [Marelli et al. 2014] \(^5\)

The detailed dataset statistics are listed in Table 1.

**Implementation Details**

In all experiments, we initialize word embeddings with 300-dimensional Glove 840B vectors [Pennington, Socher, and Manning 2014]. We only fine-tune word embeddings on SST during training. We use AdaGrad [Duchi, Hazan, and Singer 2011] optimizer with an initial learning rate of 0.05. The hidden size of main networks \( h \) is 150. The hidden size of hyper networks \( \tilde{h} \) is 50 and the input size of hyper networks \( d \) is 100. The dimension of tag embedding is 50. We apply dropout on both embedding and output layer with a dropout rate of 0.5. Recurrent dropout [Semeniuta, Severny, and Barth 2016] with a dropout rate of 0.25 for main networks is applied for sentence classification and 3e-5 L2-regularization is applied for text semantic matching. The minibatch size is always 50. We obtain the constituency parser trees and POS tags of word/phrases using Stanford Parser [Klein and Manning 2003]. The code is implemented with Theano [Theano Development Team 2016].

**Sentence Classification**

We first compare proposed models with RecNN-based models as well as baseline models. Then we make comparison between TG-HTreeLSTM and non RecNN-based state-of-the-art models.

**Comparison with RecNN-Based Models**

The experimental results about this comparison are displayed in columns 2 to 6 in Table 2. Firstly, we find that TG-HRecNN and TG-HTreeLSTM both outperform RecNN and TreeLSTM on all datasets. Specially, compared with RecNN and TreeLSTM, TG-HRecNN and TG-HTreeLSTM obtain about 5.4%/4.8% and 2.7%/2.4% improvements on SST-1/SST-2 respectively which are much greater than those on other datasets. We think it is because there are phrase-level labels in SST so that the dynamic parameter prediction process can get more supervision during training. The vanilla RecNN are more easily boosted by dynamic parameter prediction and TG-HRecNN is competitive with strong baseline CNN and BiLSTM surprisingly. Secondly, compared with TG/TE-RNN and TE-LSTM which also exploit POS tags to enhance the expressive power of semantic composition function, our models are still superior to them. This means that to guide the semantic composition function dynamically with POS tags the hypernetwork framework is

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\(^1\)https://nlp.stanford.edu/sentiment/

\(^2\)http://nlp.stanford.edu/projects/glove/

\(^3\)https://www.cs.cornell.edu/people/pabo/movie-review-data/

\(^4\)http://cogcomp.org/Data/QA/QC/

\(^5\)http://clic.cimec.unitn.it/composes/sick.html
Table 2: Accuracies of baseline models (in the first group), proposed models (in the last group) and previous RecNN-based models (in the second and third group) on five datasets. The concat and multi denotes two different strategies in information fusion layer described in Sec 4.3.

| Model                        | SST-1 | SST-2 | MR   | SUBJ | TREC | SICK |
|------------------------------|-------|-------|------|------|------|------|
| CNN (Kim 2014)               | 48.0  | 88.1  | 81.5 | 93.4 | 93.6 | -    |
| Bidirectional LSTM (Tai, Socher, and Manning 2015) | 49.1  | 87.5  | -    | -    | -    | -    |
| RecNN (Socher et al. 2011)  | 43.2  | 82.4  | 76.4 | 91.8 | 90.2 | 74.9 |
| MV-RNN (Socher et al. 2012) | 44.4  | 82.9  | -    | -    | 75.5 |      |
| RNTN (Socher et al. 2013b)  | 45.7  | 86.4  | -    | -    | 76.9 |      |
| AdaMC-RNN (Dong et al. 2014) | 45.8 | 87.1  | -    | -    | -    | -    |
| TG-RNN (Qian et al. 2015)   | 46.1  | 86.2  | 76.4 | -    | -    | -    |
| TE-RNN (Qian et al. 2015)   | 47.8  | 86.5  | 77.9 | -    | -    | -    |
| TreeLSTM (Tai, Socher, and Manning 2015) | 51.0 | 88.0  | 81.2 | 93.4 | 93.6 | 77.5 |
| AdaHT-LSTM (Liu, Qiu, and Huang 2017a) | 50.2 | 87.8  | 81.9 | 94.1 | -    | -    |
| iTLSTM (Liu et al. 2017)    | 51.2  | 88.2  | 82.5 | 94.5 | -    | -    |
| TE-LSTM (Huang, Qian, and Zhu 2017) | 52.6 | 89.6  | 82.2 | -    | -    | -    |
| BiTreeLSTM (Teng and Zhang 2017) | 53.5 | 90.3  | -    | -    | 94.8 | -    |
| TG-RecNN (Liu, Qiu, and Huang 2017b) | -    | 86.1  | 80.2 | 93.5 | 91.2 | 77.9 |
| DC-TreeLSTM (Liu, Qiu, and Huang 2017b) | -    | 87.8  | 81.7 | 93.8 | 93.8 | 80.2 |
| TG-RecNN+concat (Proposed)  | 49.6  | 87.1  | 81.1 | 93.8 | 93.4 | 78.3 |
| TG-RecNN+multi (Proposed)   | 49.3  | 87.2  | 80.9 | 93.7 | 93.6 | 77.5 |
| TG-HTreeLSTM+concat (Proposed) | 53.7 | 90.2  | 82.9 | 94.7 | 95.0 | 83.6 |
| TG-HTreeLSTM+multi (Proposed) | 53.2  | 90.4  | 82.6 | 94.9 | 95.8 | 83.3 |

Table 3: Comparison between the proposed model and non RecNN-Based state-of-the-art models for sentence classification. The symbol * indicates besides GloVe this model also uses CoVe word embeddings which are trained with external resources.

| Model                        | SST-1 | SST-2 | MR   | SUBJ | TREC |
|------------------------------|-------|-------|------|------|------|
| AdaSent (Zhao, Lu, and Poupart 2015) | -    | -    | 83.1 | 95.5 | 72.4 |
| d-TBCNN (Mou et al. 2015)    | 51.4  | 87.9  | -    | -    | 96.0 |
| DSCNN-Pretrain (Zhang, Lee, and Radev 2016) | 50.6  | 88.7  | 82.2 | 93.9 | 95.6 |
| BLSTM-2DCNN (Zhou et al. 2016) | 52.4  | 89.5  | 82.3 | 94.0 | 96.1 |
| NTI (Yu and Munkhdalai 2017) | 53.1  | 89.3  | -    | -    | -    |
| BCN+Char+CoVe * (McCann et al. 2017) | 53.7  | 90.3  | -    | -    | 95.8 |
| TG-HTreeLSTM (Proposed)      | 53.7  | 90.4  | 82.9 | 94.9 | 95.8 |

Comparison with non RecNN-Based State-of-the-art Models Table 3, we list the accuracies of our TG-HTreeLSTM model and state-of-the-art models for sentence classification. Overall, TG-HTreeLSTM has consistently strong performances on four datasets and achieve the best scores on SST. We can find AdaSent (Zhao, Lu, and Poupart 2015) performs very well on MR and SUBJ and keeps the state-of-the-art on the two datasets since 2015. Nevertheless, the gap between TG-HTreeLSTM and AdaSent is 0.2% on MR and 0.6% on SUBJ which are relatively small. On TREC, TG-HTreeLSTM is also competitive with the best BLSTM-2DCNN (Zhou et al. 2016) model with a 0.3% gap. This comparison shows that TG-HTreeLSTM has excellent generalization ability.

It should be emphasized that although BCN+Char+CoVe * (McCann et al. 2017) has almost the same results as TG-HTreeLSTM on SST, it uses extra CoVe word embeddings which are obtained by training a machine translation model. If combing with CoVe
model probably performs better.

**Text Semantic Matching**

The last column in Table 2 summarizes the performance of different models on SICK. It should be noted that the aim of this experiment is to prove that proposed models can improve RecNN/TreeLSTM for different NLP tasks instead of pursuing state-of-the-art performance. So we only compare sentence encoding-based models which encode two sentences into vectors and then classify as described in Sec 4.4. TG-HRecNN and TG-HTreeLSTM achieve 3.4%/6.1% improvements than RecNN and TreeLSTM respectively. Although TG-HRecNN is only competitive with DC-RecNN, TG-HTreeLSTM shows effective performance in this task and outperforms DC-TreeLSTM with 3.4% accuracy.

**Qualitative Analysis**

To explain the effectiveness of proposed models, we conduct experiments to examine how the hyper RecNN predicts the composition parameter of main RecNN dynamically. As we describe in Sec 4, hyper RecNN modifies the parameters by scaling each row of the parameter matrix. So we examine the value of each dimension of $z_u$ in equation 8 which is output by hyper RecNN and determines the final composition parameter of main RecNN on the test set of SST. We find the occurrence of large value of some dimensions of $z_u$ is dominated by nodes with specific tag types. Table 4 illustrates some examples of these interpretable dimensions which supports that proposed models can predict reasonable composition parameter for different types of word/phrase pairs by enlarging different rows of the parameter matrix.

We also find the occurrence of large value in some dimensions is dominated by nodes with specific sentiment polarity. In figure 3, we give a sample to visualize the behaviours of 13-rd dimension which is sensitive to negative sentiment. The label of the whole sentence is very negative while labels of phrases are neutral except “did it ever get made”. The values of this dimension get much larger at two nodes with negative label than those at other nodes. Although during test no label can be seen, this dimension of $z_u$ entails sentiment information so that our model can give a correct prediction with adaptive composition parameters.

**Conclusion**

In this paper, we introduce hypernetwork framework into RecNNs to address the problem caused by shared composition parameter. We propose two novel RecNN variants in which a hyper RecNN taking as inputs POS tag information predicts the composition parameter of main RecNN dynamically. An information fusion layer is designed to incorporate POS tag and semantic information for parameter prediction. Our models beat all RecNN-based models on five datasets for sentence classification and text semantic matching. Proposed TG-HTreeLSTM achieves or is competitive with state-of-the-art on four sentence classification benchmarks. We also give qualitative analysis to explain why our models work well.

Experimental results show that proposed models are able to encode a sentence into powerful distributed representation, which will benefit many NLP tasks. In future work, we will employ our models as sentence encoders and apply encoded sentence embedding to high level tasks, such as document classification and reading comprehension. We will also explore the effectiveness of other syntax information for guiding dynamic parameter prediction.

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**Table 4**: Some interpretable dimensions of $z_u$ with the types of word/phrase pairs of the nodes where dynamic composition parameters have large scale in corresponding rows. The last column gives several examples for each type of pairs. "+" splits the tags or phrases of pairs.

| Dimensions | Tag Types | Examples for Phrases to Compose |
|------------|-----------|---------------------------------|
| 16-th      | JJ+NN     | aching+beauty, perfect+film, recent+favoured, implausible+situation |
| 30-th      | DT+NN     | a+movie, this+examination, the+film, no+picture |
| 62-nd      | NP+PP     | the classic films+of Jean Renoir, the most powerful thing+in life, every opportunity+for a breakthrough |
| 79-th      | ADJP+NN   | most impossibly dry+account, far more thoughtful+film, weak or careless+performance |
| 132-nd     | IN+NP     | of+mystery and quietness, in+his bratty character, in+a mess of purposeless violence |

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