An enhanced Tree-LSTM architecture for sentence semantic modeling using typed dependencies

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Abstract

Background: Tree-based Long short term memory (LSTM) network has become state-of-the-art for modeling the meaning of language texts as they can effectively exploit the grammatical syntax and thereby non-linear dependencies among words of the sentence. However, most of these models cannot recognize the difference in meaning caused by a change in semantic roles of words or phrases because they do not acknowledge the type of grammatical relations, also known as typed dependencies, in sentence structure.

Methods: This paper proposes an enhanced LSTM architecture, called relation gated LSTM, which can model the relationship between two inputs of a sequence using a control input. We also introduce a Tree-LSTM model called Typed Dependency Tree-LSTM that uses the sentence dependency parse structure as well as the dependency type to embed sentence meaning into a dense vector.

Results: The proposed model outperformed its type-unaware counterpart in two typical NLP tasks – Semantic Relatedness Scoring and Sentiment Analysis, in a lesser number of training epochs. The results were comparable or competitive with other state-of-the-art models. Qualitative analysis showed that changes in the voice of sentences had little effect on the model’s predicted scores, while changes in nominal (noun) words had a more significant impact. The model recognized subtle semantic relationships in sentence pairs. The magnitudes of learned typed dependencies embeddings were also in agreement with human intuitions.

Conclusion: The research findings imply the significance of grammatical relations in sentence modeling. The proposed models would serve as a base for future researches in this direction.

Keywords: Sentence Representation Learning, Universal Dependencies, Semantic Relatedness Scoring, Sentiment Analysis
1. Introduction

Sentence modeling is a crucial step in NLP tasks, including but not limited to Sentence Classification (Liu & Guo, 2019; Xia et al., 2018), Paraphrase Identification (Agarwal et al., 2018; Jang et al., 2019), Question Answering (Liu et al., 2019; Zhu et al., 2020), Sentiment Analysis (Kim, 2014; Tai et al., 2015), and Semantic Similarity Scoring (Shen et al., 2020; Tien et al., 2019). Word meanings are represented using neural embedding (Bengio et al., 2003; Mikolov et al., 2013; Pennington et al., 2014; Turian et al., 2010), and sentence semantics are derived from these word vectors using compositional models. Many of the earlier models adopted for composition were either Bag-of-Words (BOW) (Mitchell & Lapata, 2008) or sequential (Mueller & Thyagarajan, 2016; Tai et al., 2015), as shown in Figure 1. The BOW model treats sentences as a mere collection of words, and compositional functions are simple vector operations (Mitchell & Lapata, 2008). Sequential models, on the other hand, consider text as a sequence of words. However, sequential models fail to capture non-linear dependencies between words that are common in natural languages.

![Sequential model for semantic composition](image1)

(a) Sequential model for semantic composition

![Tree-structured composition model based on dependency tree](image2)

(b) Tree-structured composition model based on dependency tree

Figure 1: Compositional model for sentence modeling. The $w_i$ are word-embedding and $s$ is the semantic representation for the sentence

Tree-structured models overcome this drawback by using model architectures that either reflects the parse tree of the sentences (Socher et al., 2010, 2011, 2012, 2013; Tai et al., 2015) or latent trees learned for specific tasks (Choi et al., 2018; Yogatama et al., 2017). Though these Tree-based models effectively exploit the syntax and thus the relationships among words in a sentence, they ignore a valuable piece of information - the type of word relationship. A word-pair can have different types of grammatical relations in different sentences. These relationships are represented in the sentence’s dependency

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A dependency tree is a graphical notion of a sentence with each node corresponding to a word in the sentence. Each edge of a dependency tree, labeled by the dependency type, marks a dependency relation between the two words. Hereafter, we refer to these relations as Typed Dependencies (De Marneffe & Manning, 2008; Schuster & Manning, 2016). These typed dependencies also contribute to the semantics of the text.

We illustrate this with an example. Consider the two sentences:

1. Dogs chased cats in the garden
2. Cats chased dogs in the garden.

In the sentences (1) and (2), the word-pair (Dogs, chased) shares a parent-child relationship in their dependency trees, as shown in Figure 2.

Figure 2: Two identical dependency trees that differ only in their edge labels.

The typed dependency of (Dogs, chased) in the first sentence is “dobj” for Direct object whereas, in the second sentence, it is “nsubj” for Nominal subject. Nominal subject dependency indicates “Dogs” is the subject for the action “chased” while in the first case, direct object relation indicates “Dogs” is the object of “chased”. A model that fails to acknowledge this difference treats both the relation as same.

Though some recent researches (Kim et al., 2019; Liu et al., 2017; Qian et al., 2015; Wang et al., 2017) try to address the inability of classic deep learning models to handle syntactic categories differently by using POS and constituency tags, the role of typed dependencies hasn’t been much explored yet. The first notable work using typed dependencies was by Socher et al. (2014) in the Semantic Dependency Tree-RNN model (SDT-RNN). SDT-RNN is a recursive neural network modeled based on the dependency tree. The model trains a separate feed-forward neural network for each dependency type, making it highly data-intensive and complex to train.

In Dependency-based Long Short-Term Memory (D-LSTM) network, Zhu et al. (2018) add an α–weighted supporting component derived from the subject, object, and predicate of the sentence to the basic sentence representation generated by standard LSTM. The Part-of-Speech based LSTM (pos-LSTM) model by Zhu et al. (2019) derives the supporting component from the hidden representation of constituent words and its tag specific weights. The pos-LSTM model gave the best results when it used only the hidden representation of nouns in the sentence to compute the supporting component, which indicates noun words played a more significant role compared to others. The D-LSTM

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1As in Stanford typed dependencies, which later evolved to Universal Dependencies. Both are used interchangeably in this paper.
and pos-LSTM models are not syntax-aware as they are sequential, and the grammar is used only to identify semantic roles or POS tags. Nevertheless, these models showed improvement over their base model Manhattan LSTM (MaLSTM) (Mueller & Thyagarajan, 2016).

Shen et al. (2020) proposed a Tag-Guided Hyper Tree-LSTM (TG-HTreeLSTM) model, which consists of a main Tree-LSTM and a hyper Tree-LSTM network. The hyper Tree-LSTM network uses a hypernetwork to dynamically predict parameters of main Tree-LSTM using the POS tag information at each node of the constituency parse tree. Structure-Aware Tag Augmented Tree-LSTM (SATA TreeLSTM) (Kim et al., 2019) uses an additional tag-level Tree-LSTM to provide supplementary syntactic information to its word-level Tree-LSTM. These models have shown remarkable improvement over the tag-unaware counterpart in sentiment analysis of sentences. These facts motivated us to investigate further the role of grammar, precisely that of grammatical relationships in semantic composition.

1.1. Research Objectives and Contributions

This research has two primary objectives:

(1) To propose a generic LSTM architecture that can capture the type of relationship between elements of the input sequence and,

(2) To develop a deep neural network model that can learn a better semantic representation of sentences using its dependency parse structure as well as the typed dependencies between words.

This work also aims to perform a qualitative analysis of the results to study the role of typed dependencies in measuring semantic relatedness.

To capture relationship type, we introduce an additional neural network called Relation gate to the LSTM architecture that can regulate the information propagating from one LSTM unit to another based on an additional control parameter \( r \). We use this Relation gated LSTMs to propose the Typed Dependency Tree-LSTM for computing sentence representation. Our model is based on Tai et al. (2015)'s Dependency Tree-LSTM and outperforms it in two sub-tasks - Semantic relatedness scoring and Sentiment Analysis.

The contributions of this paper are:

(1) Relation gated LSTM (R-LSTM) architecture that uses an additional control input to regulate the LSTM hidden state

(2) Typed Dependency Tree-LSTM model using R-LSTMs for learning sentence semantic representation over the dependency parse tree.

(3) A qualitative analysis of the role of typed dependencies in language understanding

The rest of the paper is organized as follows. Section 2 gives a brief overview of LSTMs and Dependency Tree-LSTM architecture. The architecture of the proposed Relation gated LSTM (R-LSTM) and a formal description of the Typed DT-LSTM model are given in sections 3 and 4 respectively. The experiments are detailed in section 5. We report the results of these experiments and their qualitative analysis in section 6. Section 7 concludes the work with a remark on future prospects of the proposed model.
2. Background

2.1. Long Short Term Memory (LSTM)

Recurrent neural networks (RNN) can process input sequences of arbitrary length by repeatedly applying a transition function on each element of the sequence. The input to an RNN unit at time step \( t \) is the current input \( x_t \) and the hidden state \( h_{t-1} \) from its previous time step. The final output of RNN could be either the output generated from the hidden state at the last time step or a sequence of outputs, one each from every hidden state, depending on the task addressed. LSTMs (Hochreiter & Schmidhuber, 1997) are a form of RNN that can retain its state for longer sequences using its cell memory. Gates of an LSTM allows it to update the cell memory selectively. An LSTM unit consists of three gates – forget gate, input gate and output gate, and two memory states – cell state and hidden state. All these are vectors in \( \mathbb{R}^d \), where \( d \) is a hyperparameter – the memory state dimension. Figure 3 shows the architecture of standard LSTM unit. Equation 1 denotes the set of transitions of an LSTM unit at time step \( t \).

\[
\begin{align*}
  i_t &= \sigma(W^{(i)}x_t + U^{(i)}h_{t-1} + b^{(i)}), \\
  f_t &= \sigma(W^{(f)}x_t + U^{(f)}h_{t-1} + b^{(f)}) , \\
  o_t &= \sigma(W^{(o)}x_t + U^{(o)}h_{t-1} + b^{(o)}) , \\
  u_t &= \tanh(W^{(u)}x_t + U^{(u)}h_{t-1} + b^{(u)}) , \\
  c_t &= i_t \odot u_t + f_t \odot c_{t-1} , \\
  h_t &= o_t \odot \tanh(c_t)
\end{align*}
\]

where \( \sigma \) denotes the logistic sigmoid function and \( \odot \) is pointwise multiplication. The gating vector \( f_t, i_t, \) and \( o_t \) are outputs of feedforward neural networks that take \( x_t \) and previous hidden state \( h_{t-1} \) as inputs. The forget gate \( f_t \) restraints the extent of
Figure 4: Composition of a Dependency Tree-LSTM node with two children (Tai et al., 2015)

information propagated from the previous hidden state. The input gate $i_t$ controls what
information from the current input supplements the cell state. The output gate $o_t$ is
responsible for selecting how much of the cell state flows to the next time step as its
hidden state. By using these three gates, LSTM units are capable of selecting only vital
information from the inputs, retaining and propagating them along the LSTM chain.
Standard LSTMs are strictly sequential and hence unable to acknowledge any non-linear
dependencies in the input sequence.

2.2. Dependency Tree-LSTMs

Tree-structured models are a natural choice for text processing as the sentences have
an inherent hierarchical structure conveyed by its parse tree. A pioneering work in this
category is the Tree-LSTM, proposed by Tai et al. (2015), in which each LSTM unit
can take input from multiple LSTM units forming a tree topology. Tai et al. (2015) also
proposed two variants of Tree-LSTM, namely - Child-Sum Tree-LSTMs and N-ary Tree-
LSTMs for sentence representation. The former is suited for trees having nodes with an
arbitrary number of unordered children, while the latter is for trees having nodes with
at most N children in a fixed order. A child-sum tree-LSTM over dependency parse tree
is known as Dependency Tree-LSTM (DT-LSTM). Each node of a DT-LSTM takes as
input a vector $x_t$ and an arbitrary number of hidden states, one from each of its child
nodes. Equation 2 denotes the set of transitions of a DT- LSTM unit at time step $t$.

$$h_{C(t)} = \sum_{k \in C(t)} h_k,$$

where $C(t)$ is the set of all child nodes of the node $t$.

Unlike the standard LSTMs, the gating vectors and cell states of the DT-LSTM unit
depend on the hidden state of not just one but multiple child units. The DT-LSTM unit has multiple forget gates, one for each of its child units, allowing it to emphasize information from selected child nodes based on the task addressed. At each node $t$ of the DT-LSTM, the input vector $x_t$ is the word-embedding corresponding to the headword at that node. The hidden state $h_t$ is an abstract representation of the sub-tree rooted at $t$. The cell state of the parent node depends on the sum of the cell states of its child nodes, hence the name child-sum LSTMs (Refer Figure 4).

Though Tree-based LSTMs respect non-linear dependencies between words in the sentence, neither Tree-LSTMs nor any of its variants explicitly make use of the type of these dependencies. The intuition behind our proposed Typed Dependency Tree-LSTM is that an LSTM unit can learn to make informed decisions on what information it passes to the next LSTM unit if it knows the kind of dependency they share. To equip LSTM with this knowledge, we propose the relation gated LSTM (R-LSTM) with an additional control input $z_t$. R-LSTM has an additional gate, hereafter referred to as relation gate $r_t$, that can regulate its hidden state $h_t$ based on this control input $z_t$. The proposed architecture is discussed in section 3.

3. Relation gated LSTM Architecture

Relation gated LSTM (R-LSTM) is an enhancement of standard LSTM. R-LSTM consists of 4 gates – forget gate, input gate, output gate and a relation gate, and two memory states – the hidden state and the cell state. The architecture of R-LSTM is shown in figure 5. The relation gate and hidden state of R-LSTM at time step $t$ with successor $t'$ is given by the equation 3. For sequential model $t' = t + 1$ whereas for tree-based model $t'$ depends on the tree topology used.

$$r_{t'} = g(W^{(r)} z_{t'} + b^{(r)})$$

$$h_{t'} = o_t \odot \tanh(c_t \odot r_{t'})$$

where $g$ is a non-linear activation function.
The three gates $i_t, f_t, o_t$ and other vectors are computed using equation 1 of standard LSTM (Refer Section 2.1). The relation gating vector $r_{tt'}$ controls how much information from the cell state $c_t$ should be transferred to the hidden state $h_t$ of unit $t$ and thereby propagate to the next unit $t'$. The control input $z_{tt'}$ represents the relation between the inputs $x_t$ and $x_t'$. The relation gate of R-LSTM depends only on this control input $z_{tt'}$. Unlike standard LSTMs, the hidden state of R-LSTM depends not just on the cell state and the output gate but also on the relation gate.

Relation gate is useful in the NLP scenario where words can share different types of relations, and these relation types affect their semantic composition. In our proposed Typed DT-LSTM, the control input $z_t$ represents the type of dependency the word at node $t$ has with its headword at node $t'$. Note that, in a dependency parse tree, any node $t$ can have only one parent $t'$. In the Dependency Acyclic Graphs (DAGs) representation, a word can have different types of dependencies with different words in the sentence, i.e., a node can have more than one parent. Accommodating such multiple relationships is trivial in R-LSTMs. In such cases, R-LSTM would have multiple control inputs and therefore, multiple hidden states, one for each of its dependencies. Having multiple hidden states allows an R-LSTM unit to transmit different information to each of its parent units based on the kind of relation it shares. Figure 6 shows an R-LSTM unit with two parent units. The relation gates are drawn separately for clarity, though R-LSTM unit has only one relation gate and thus only one relation weight matrix $W^{(r)}$. The relation gating vector $r_{tt'}$ can be computed by equation 3 for each $t' \in P(t)$, parents of node $t$.

![Figure 6: R-LSTM with two control inputs and two hidden states.](image)

4. Typed Dependency Tree-LSTMs

As mentioned in section 2.2, Dependency Tree-LSTM uses the same set of weights for every LSTM units and hence is not aware of the relation type between them. In this section, we propose Typed DT-LSTM model that can learn embeddings of the type of grammatical relation between the word pairs using R-LSTMs. We hypothesize that this knowledge helps our model to build better semantic representation of sentences. Like
the DT-LSTM (Tai et al., 2015), our Typed DT-LSTM architecture also follows the dependency tree topology. In addition, we make use of the typed dependencies obtained by the dependency parse, which is detailed below.

Let $D$ be an ordered universal set of typed dependencies in the language.

$$D = [d_1, d_2, \ldots, d_l], l = |D|$$  (4)

Given a sentence $S = (w_1, w_2, \ldots, w_n)$ with $n$ words. The dependency parse of $S$ is defined by a set of typed dependencies,

$$TD(S) = \{d_j(w_{t'}, w_t), d_j \in D, w_t \in S, w_{t'} \in S \cup \{\text{ROOT}\}\}$$  (5)

$TD(S)$ directly maps onto a dependency tree with nodes as words (except the root node) and edges labeled $d_j$ from node $w_t$ to $w_{t'}$ for every $d_j(w_{t'}, w_t)$ in $TD(S)$. The root of the tree is a special node $\text{ROOT}$. An edge labeled root connects the root word of the sentence to the $\text{ROOT}$. Each R-LSTM($t$) unit in the model corresponds to a node $t$ of the tree. The R-LSTM($t$) takes as input – (1) $x_t$, the vector representation of the word $w_t$, (2) the relation vector $z_t = e_{d_j}$ (a binary vector with 1 at dimension $j$ and 0 elsewhere), if $d_j(w_{t'}, w_t) \in TD(S)$ and (3) the output from its child R-LSTM units. The output of R-LSTM($t$) – i.e. the cell state $c_t$ and hidden state $h_t$, propagates to its parent R-LSTM($t'$). We can now combine the equations 2 and 3 to formally define the Typed DT-LSTM as given in equation 6.
\[ h_{c(t)} = \sum_{k \in C(t)} h_k, \] (6)

\[ i_t = \sigma(W^{(i)} x_t + U^{(i)} h_{c(t)} + b^{(i)}), \]

\[ f_{tk} = \sigma(W^{(f)} x_t + U^{(f)} h_k + b^{(f)}), \]

\[ o_t = \sigma(W^{(o)} x_t + U^{(o)} h_{c(t)} + b^{(o)}), \]

\[ u_t = \tanh(W^{(u)} x_t + U^{(u)} h_{c(t)} + b^{(u)}), \]

\[ c_t = i_t \odot u_t + \sum_{k \in C(t)} f_{tk} \odot c_k, \]

\[ r_t = g(W^{(r)} z_t + b^{(r)}), \]

\[ h_t = o_t \odot \tanh(c_t \odot r_t) \]

The relation gating vector of the node \( t \) given by \( r_t \in \mathbb{R}^d \) is learned using \( z_t \in \mathbb{R}^t \) the one-hot encoding of the typed dependency between \( t \) and its parent node in the dependency tree.

Intuitively, the weight matrix \( W^{(r)} \in \mathbb{R}^{l \times d} \) can be interpreted as a task-specific embedding of typed dependencies, where each column \( w_j \) corresponds to the dependency type \( d_j \) in the set \( D \). This typed dependency embedding is analyzed in detail in section 6.2.

5. Experiments

We evaluate our model, Typed DT-LSTM using relation gated LSTM, on two tasks: (1) Semantic relatedness scoring of sentence pairs and (2) Sentiment classification of movie reviews.

For both the tasks, we follow the training and evaluation method proposed by [Tai et al., 2015]. The sentences in the training set are parsed using Stanford dependency parser [Chen & Manning, 2014; Manning et al., 2014]. We initialize word representations with pre-trained Glove [Pennington et al., 2014] word embedding. All parameters are randomly initialized. The 47 universal typed dependencies are encoded as one-hot vectors. The proposed Typed DT-LSTM generates sentence embeddings for each sentence. We use a softmax classifier to generate the semantic score/sentiment label from this sentence semantic vector(s). Supervised training algorithm trains the model end-to-end to generate sentence representation as well as semantic score/sentiment labels. For semantic relatedness scoring, the word embeddings are kept fixed; they are not learnable parameters of the model.

5.1. Semantic Relatedness Scoring

Semantic relatedness scoring aims to predict a real-valued relatedness score for a given sentence pair based on the semantic similarity between its sentences. For each pair of a

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2 subscript \( t' \) is dropped because a node can have only a single parent in a tree

3 Glove: [http://nlp.stanford.edu/data/glove.42B.300d.zip](http://nlp.stanford.edu/data/glove.42B.300d.zip)
sentence \((S_l, S_r)\) in the training set, the Typed DT-LSTM model generates a sentence vector pair \((h_l, h_r)\). We follow the Siamese architecture (Bromley et al., 1993) where the model weights for sentences in the pair are tied. The element-wise product \(|h_l \odot h_r|\) and absolute difference \(|h_l - h_r|\) is then input to a neural network classifier. The classifier uses the softmax function to predict the semantic similarity of sentences as a probability distribution \(\hat{p}\) over the \(K\) classes. The equation 7 calculates the predicted semantic score,

\[
h_s = \sigma(U(h_l \odot h_r) + V(|h_l - h_r|) + b_h),
\]

\[
\hat{p}_\theta = \text{softmax}(Wh_s + b_p),
\]

\[
\hat{y} = r^T \hat{p}_\theta, \quad r = [1, 2, 3, \ldots, K]
\]

To train the model, we construct a target probability distribution \(p\) from the actual similarity score \(y\), such that \(y = r^T p\). Each \(i\)th element \(p_i\) in \(p\) is assigned as,

\[
p_i = \begin{cases} 
1 - |y - i|, & i \in \llbracket y \rrbracket, \llbracket y \rrbracket \\
0, & \text{otherwise} 
\end{cases}
\]

The model trained by back-propagation minimize the regularized KL-divergence between \(p^{(j)}\) and \(\hat{p}^{(j)}_\theta\) for each sentence pair \((S_l, S_r)^{(j)}\) in the training set of size \(m\).

\[
J(\theta) = \frac{1}{m} \sum_{j=1}^{m} KL(p^{(j)}\|\hat{p}^{(j)}_\theta) + \frac{\lambda}{2} \|\theta\|^2_2,
\]

5.2. Sentiment Classification

The task intends to predict the sentiment of phrases in sentences. The sentiment classification is modeled as a binary classification (positive/negative) task. For each sentence \(S\) in the training set, Typed DT-LSTM generates a set of hidden representations corresponding to the nodes in the dependency parse tree of \(S\). The hidden representation \(h_t\) is an abstract representation of the sentiment of the phrase spanned by the node \(t\). At each node \(t\), a softmax classifier maps the hidden representation \(h_t\) to a probability distribution \(p^{(t)}_\theta(y|\{x\}_t)\) over \(K\) classes. The value of \(p^{(t)}_\theta(y|\{x\}_t)\) is the probability of class label \(y\) given \(\{x\}_t\) – the subtree rooted at the node \(t\). The predicted class label \(\hat{y}^{(t)}\) of node \(t\) is the class label \(y\) with the maximum \(p^{(t)}_\theta(y|\{x\}_t)\) value.

\[
p^{(t)}_\theta(y|\{x\}_t) = \text{softmax}(Wh_t + b),
\]

\[
\hat{y}^{(t)} = \arg \max_y p^{(t)}_\theta(y|\{x\}_t).
\]

The supervised learning algorithm tries to minimize the negative log-likelihood of the true class labels \(y^{(t)}\) at each labeled node:

\[
J(\theta) = -\frac{1}{m} \sum_{j=1}^{m} \log \hat{p}^{(j)}_\theta \left( y^{(j)} \| \{x\}^{(j)} \right) + \frac{\lambda}{2} \|\theta\|^2_2,
\]

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Parameter | SICK-R | SST  
|---------|-------|------| 
| Learning rate | 0.1/0.2/0.25/0.3 | 0.1/0.2/0.25/0.3 | 
| Batch size | 25/50/100 | 25/50/100 | 
| Memory dimension | 120/150/100 | 165/168/170 | 
| Weight decay | 0.0001 | 0.0001 | 
| Optimizer | adagrad | adagrad | 

Table 1: Range of hyperparameters used for tuning the model. The best is shown in **bold**

where \( m \) is the total number of labelled nodes in the training set, and \( \lambda \) is the L2 regularization parameter for the model.

5.3. Datasets and Training details

For semantic relatedness scoring, we use Sentence Involving Compositional Knowledge (SICK) [Marelli et al., 2014] dataset consisting of 9927 sentence pair each annotated with a real-valued score, in the range 1 – 5 (1 being the least similar). The sentence pairs in the SICK dataset are sentences extracted from image and video description annotated by the average of ten human assigned scores. The standard train/dev/test split of 4500/500/4927 is used for the experiments.

For Sentiment classification, we used the Stanford Sentiment Treebank (SST) [Socher et al., 2013] dataset. The SST dataset consists of 11,855 sentences parsed using Stanford consistency parser to obtain 215,154 unique phrases. The phrases have manually assigned sentiment labels. We generated dependency parse trees for these sentences and labeled each node by the sentiment of the phrase in the training set that matches the node’s span. Dependency parse tree has a lesser number of nodes than its constituency counterpart, and not all nodes of the dependency tree have a matching phrase in the constituency parse tree. Thus we could label and use only a subset of the actual dataset for this experiment. The range of hyperparameters used is listed in table 1.

6. Results and Discussion

6.1. Modeling semantic relatedness

For semantic relatedness scoring, we evaluated the model’s performance using Pearson Correlation Coefficient and Mean-Squared Error between the actual relatedness score \( y \) and the predicted score \( \hat{y} \). We compare our results with deep learning models that use LSTMs or dependency tree or both for semantic composition. The models belong to four categories. The mean vector is the baseline, where the word vectors are averaged to get the sentence vector. In the first category we discuss sequential models that use LSTMs and GRUs (Gated Recurrent Units). In the second category are the tree-NN models that use the dependency tree structure but not the dependency type for composition. The third category consists of sequential models that use grammatical information to improve sentence representation. Our model falls in the fourth category, where the models use dependency structure along with the dependency type.

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4SICK : [http://alt.qcri.org/semeval2014/task1/index.php?id=data-and-tools](http://alt.qcri.org/semeval2014/task1/index.php?id=data-and-tools)

5SST dataset [http://nlp.stanford.edu/~socherr/stanfordSentimentTreebank.zip](http://nlp.stanford.edu/~socherr/stanfordSentimentTreebank.zip)
Table 2: Comparison of Typed Dependency Tree-LSTM with other LSTM models for semantic relatedness scoring. The values are taken from previously published results.

| Model            | Pearson’s r | MSE  |
|------------------|-------------|------|
| Mean vectors     | 0.7577      | 0.4557 |
| Seq. LSTM        | 0.8528      | 0.2831 |
| Seq. Bi–LSTM     | 0.8567      | 0.2736 |
| Seq. GRU         | 0.8595      | 0.2689 |
| MaLSTM           | 0.8177      | –     |
| DT-RNN           | 0.7923      | 0.3848 |
| DT-LSTM          | 0.8676      | 0.2532 |
| DT-GRU           | 0.8672      | 0.2573 |
| D-LSTM           | 0.8270      | 0.3527 |
| pos-LSTM-n       | 0.8263      | –     |
| pos-LSTM-v       | 0.8149      | –     |
| pos-LSTM-nv      | 0.8221      | –     |
| pos-LSTM-all     | 0.8173      | –     |
| SDT-RNN          | 0.7900      | 0.3848 |
| **Typed DT-LSTM** | **0.8731** | **0.2427** |

Table 2 shows that LSTM models are more efficient than standard RNN models, due to LSTM’s ability to retain information over longer sequences. The DT-LSTMs and DT-GRUs perform better than their sequential counterparts, validating that hierarchical structures are better in representing sentence semantics than sequences.

The D-LSTM model and pos-LSTM models that use word’s syntactic roles as additional information shows improvement over MaLSTM. For a fair comparison, we used MaLSTM and D-LSTM models without regression calibration, synonym augmentation, and pretraining (Zhu et al., 2018). The pos-LSTM-n that uses only noun words performs better than the pos-LSTM model that uses nouns and verbs, or all words. The D-LSTM that uses only the subject, predicate, and object fares better than all pos-LSTM models. These results indicate that words in certain syntactic roles are more useful in semantic representation.

In the fourth category, the only other model we are aware of that uses the dependency type is Semantic Dependency Tree-RNN model by Socher et al. (2014). The SDT-RNN, which was initially proposed for image captioning, does not show improvement over DT-RNN in relatedness scoring tasks. The major concern of the model is its complexity and network size. In SDT-RNN, each dependency type is represented by a separate neural network with a weight matrix of size $2d \times d$ where $d$ is the dimension of the word embedding. With 300 dimension GloVe embedding and 47 types of Universal dependencies, the number of parameters for the network is $600 \times 300 \times 47$. The SICK dataset is insufficient to train such a huge network efficiently. Typed DT-LSTM model represents each dependency type by a vector of 150 (size of the memory state) dimension and thus has a lesser number of parameters to be trained. We also compared the learning curves of Typed DT-LSTM with that of the base model DT-LSTM, as shown in Figure 8. The experiments show that Typed DT-LSTM can learn faster than DT-LSTM, i.e., with a fewer number of training epochs. As the only upper hand Typed DT-LSTM has over
DT-LSTM is the knowledge of dependency types, these results validate our hypothesis: typed dependencies can assist Tree-LSTM to learn semantic representations.

Table 3 shows the three most similar sentences retrieved from the SICK test dataset for three sample queries. The DT-LSTM assigns the same score for the sentences, “The turtle is following the fish” and “The fish is following the turtle” because their dependency trees differ only in the edge labels of which the model is unaware. Typed DT-LSTM’s scores show that the model has learned this difference.

For the second query “a boy is running towards the ocean”, the sentence with the most number of word overlap and a matching syntactic structure in the dataset was “a couple is running towards the ocean”. Our model ranked this fifth with a similarity score of 4.0. The sentence “a boy is running through the sand”, which is semantically closer, was ranked first with a score of 4.51, which indicates that the model considers a change in the subject word as more differentiating. The model can recognize the semantic similarity between the phrases “towards the ocean” and “through the sand”. For the third query, all the three retrieved sentences are semantically equivalent, and so are their predicted scores.

Table 4 lists some sample sentences from the SICK dataset along with the actual score (G) and the predicted score (S). The sentence pairs that were assigned the maximum score by the Typed DT-LSTM model, i.e., 4.9, were active-passive sentence pairs with the same meaning (Example 1 in Table 4). These results show that the model is insusceptible to change in the voice of sentences. We also examined sentence pairs, which differed only by a single word. The changes in subject or object word affected the predicted similarity scores more than the changes in other grammatical roles like determiner or adjectives.

In third example, changing man to woman in the sentence “A man is riding a horse” decreased the similarity score to 3.57, while changing a to some in the sentence “A man is preparing a dish” had little effect on scores. The above examples suggest that the effect of each grammatical relation in the overall meaning composition can be determined only by a detailed investigation of the magnitude of typed dependency embeddings.
Table 3: Three most similar sentences retrieved by Typed DT-LSTM from the SICK test set for each query sentence. $S_{DT}$ is the score assigned by Dependency Tree-LSTM and $S_{Typed-DT}$ is the score by the proposed Typed DT-LSTM.

Table 4: Sample sentences of different similarity scores from SICK test set data. $S$ is the predicted score and $G$ is the ground truth.
6.2. Typed Dependency Embeddings

As explained in section 4, the relation gate of Typed DT-LSTM learns a task-specific embedding of the Typed dependencies.

We compared the magnitudes of typed dependency embedding to understand how much each one contributes to the overall meaning composition. Table 5 lists the typed dependencies in the decreasing order of their magnitudes. We find that this order of precedence is in agreement with our human intuition. The relations like direct object (dobj), nominal modifier (nmod), adjectival modifier (amod), and nominal subject (nsubj) make more significant contributions in meaning understanding while relations like goes-with (goeswith) and adjectival clause (acl) contribute the least. Surprisingly, the pseudo dependency “root” didn’t top the list.

A detailed analysis of these embedding reveals some interesting observations. Consider two sample sentences expressing the same meaning, one in active voice and the other in passive:

(1) A woman is cracking the eggs.
(2) The eggs are being cracked by a woman.

Some typed dependencies of the two sentences are shown in Figure 9.

![Figure 9: Dependency trees of two semantically equivalent sentences; one in active and other in passive voice](image)

In the first sentence, typed dependency between the word pair (cracking, woman) is nsubj and that between (cracking, eggs) is dobj. In the second sentence, the dependency types for the two pairs are nmod and nsubjpass, respectively. We found that the vector difference (both in magnitude and direction) between nsubj and nmod is approximately the same as that between dobj and nsubjpass which implies,

\[ nsubj : nmod :: dobj : nsubjpass \]
Model Accuracy(%)  
LSTM 84.9  
Bi-LSTM 87.5  
2-layer LSTM 86.3  
2-layer Bi-LSTM 87.2  
CT-LSTM 88.0  
DT-LSTM 85.7  
Typed DT-LSTM 86.4  

Table 6: Comparison of Typed Dependency Tree-LSTM with LSTM models for binary sentiment classification on SST dataset. The values are taken from previously published results.

This similarity suggests that our model has learned not just the relationship types in word pairs but also how these relationship types change as they transfer from active to passive voice.

6.3. Modeling sentiment analysis

We compared the accuracy of the Typed DT-LSTM model with that of other state-of-the-art LSTM models (Table 6) on the task of predicting the sentiment of phrases in movie reviews. We found that the proposed model outperformed standard LSTM as well as DT-LSTM in the accuracy of prediction. The accuracy is comparable with that of bidirectional LSTM but lesser than that of the constituency tree-LSTM (CT-LSTM). The results clearly indicate that Typed LSTM is superior to DT-LSTM in recognizing sentiments of text.

6.4. Theoretical and Practical Implications of Research

From a theoretical point of view, our research findings imply the significance of grammatical relations in modeling sentence semantics. Most existing deep learning researches in NLP have focused only on the word meaning and syntactic structure of sentences. Hence, these sentence representations are insufficient to recognize semantic differences due to changes in the grammatical role of their words. The proposed models would serve as a base for future studies on role of typed dependencies in meaning understanding.

This research has practical implications in NLP tasks like Question Answering, Natural Language Inference, Recognizing Textual Entailment, Paraphrase Identification, and Duplicate Question merge, as semantic modeling is a fundamental and crucial step in all of these. Tree-LSTMs has also recently gained much attention in biomedical literature mining for extracting relations like protein-protein interaction, chemical-gene association. So the proposed enhancement in the Tree-LSTM model would advance recent research efforts in these directions as well.

7. Conclusion and Future work

The contributions of this research are three-fold. First, a Relation gated LSTM (R-LSTM) generic architecture has been proposed. The relation gate of R-LSTM network learns separate gating vectors for each type of relationship in the input sequence. As a second contribution, a Typed Dependency Tree-LSTM model has been proposed that
make use of dependency parse structure and grammatical relations between words for sentence semantic modeling. Third, a qualitative analysis of the role of typed dependencies in language understanding is performed. Experiments show that the proposed model outperforms DT-LSTM in terms of performance and learning speed in semantic relatedness scoring tasks and sentiment analysis.

We compared the proposed model with other state-of-the-art methods for semantic composition. The Typed DT-LSTM can identify subtle relation between phrases in the sentence pair, and thereby score better correlation with the human rating.

The role of dependency types in semantic composition has not yet been explored in the deep learning context. The proposed computational models would encourage future research efforts in this direction. We intend to experiment with Typed DT-LSTM for modeling sentence semantics in other NLP tasks like paraphrase detection, natural language inference, question answering, and image captioning where DT-LSTMs has already shown promising results.

A detailed analysis of the typed dependency embedding learned by the model reveals some interesting insights into language understanding. From a linguistic point of view, these embeddings are worth exploring further.

Finally, the relation gated LSTM architecture proposed in this work is an idea that can be adapted to other domains as well. LSTMs has become de-facto for many sequence modeling problems. For those tasks that need to model not just the nodes but also the different kinds of links between them, R-LSTM would be an alternative to LSTMs. Our results show that R-LSTMs are capable of learning the relation between LSTM units.

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