A Sequential Neural Encoder with Latent Structured Description for Modeling Sentences

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Abstract—In this paper, we propose a sequential neural encoder with latent structured description (SNELSD) for modeling sentences. This model introduces latent chunk-level representations into conventional sequential neural encoders, i.e., recurrent neural networks (RNNs) with long short-term memory (LSTM) units, to consider the compositionality of languages in semantic modeling. An SNELSD model has a hierarchical structure that includes a detection layer and a description layer. The detection layer predicts the boundaries of latent word chunks in an input sentence and derives a chunk-level vector for each word. The description layer utilizes modified LSTM units to process these chunk-level vectors in a recurrent manner and produces sequential encoding outputs. These output vectors are further concatenated with word vectors or the outputs of a chain LSTM encoder to obtain the final sentence representation.

Index Terms—recurrent neural network, long short-term memory, sentence modeling, syntax structure.

I. INTRODUCTION

SINCE sentence modeling serves as the basis for a wide range of natural language processing (NLP) tasks, many sentence encoders have been developed to produce vector representations for describing sentence meanings. Traditionally, the representation of a sentence can be derived based on simple statistics and linguistic rules (e.g., bag-of-words or bag-of-n-grams [1]). However, these models suffer from the lack of context and word order information. With the development of word embedding and deep learning techniques, the focus on sentence modeling has shifted to deriving the compositional sentence representation from a sequence of word vectors using neural networks [2], such as convolutional neural networks (CNNs) [3], [4] and recurrent neural networks (RNNs).

RNNs are currently the most popular sentence encoding models, and they process sentences word by word using a chain structure. Ideally, RNNs own the capability to retain the history information from an arbitrarily long context window [5]. However, the problem of vanishing and exploding gradients during model training make it difficult for RNNs to learn long-range dependencies [6], [7]. To overcome the deficiency of RNNs, the ones that use long short-term memory (LSTM) units [8] was proposed and have been successfully applied to many NLP tasks, including dependency parsing [9], named entity recognition [10], [11], question answering [12], [13], machine translation [14]–[16], and so forth. However, due to their flat chain structure, LSTM-RNNs are incapable of utilizing syntactic information, which is intrinsically embedded in natural languages, to composite words into sentences for semantic representation [17].

Some efforts have been made to extend chain-structured LSTMs to tree-structured topologies, i.e., Tree-LSTMs [18], [19], to address this issue. Tree-LSTMs process sentences in a hierarchical and recursive manner by propagating information up a given parsing tree to consider long-distance interactions over syntax structures. Tree-LSTMs have outperformed chain-structured LSTM-RNNs in some NLP tasks, such as sentiment classification and semantic relatedness analysis [18]. However, there are still some deficiencies with Tree-LSTMs. First, the construction of Tree-LSTMs depends on external syntax parsers. A high-performance parser is difficult to construct and may not be available for all languages. Second, Tree-LSTMs derive a state vector for each non-leaf node in the parsing tree. Therefore, combining Tree-LSTMs with other sequential encoders that produce a state vector for each word is not straightforward. Third, the recursive tree structure makes the training of Tree-LSTMs time consuming because the batch-mode computation commonly adopted for training conventional LSTM-RNNs cannot be applied to directly train Tree-LSTMs.

Therefore, this paper proposes a novel neural encoder, named sequential neural encoder with latent structured description (SNELSD), for modeling sentences. This model introduces latent chunk-level representations into conventional sequential neural encoders, i.e., LSTM-RNNs, to implicitly consider the compositionality of languages in semantic modeling. Here, word chunks are adopted as intermediate units between words and sentences for sentence modeling. The boundaries of word chunks are hidden and determined in a task-dependent way, which is different from the conventional text chunking [20] task in NLP. An SNELSD is a hierarchical chain-structured model that is composed of a detection layer...
and a description layer. The detection layer estimates the boundaries of latent word chunks and obtains a chunk-level representation for each word. The description layer processes these representations using modified LSTM units. The model parameters are estimated in an end-to-end manner without using parsing trees. Therefore, the outputs of SNELSDs are sequential, and they can be conveniently augmented with other semantic representations, such as word vectors and the states of LSTM-RNNs, to produce a more comprehensive description of sentence meanings.

The proposed SNELSD model has two main characteristics. First, latent word chunks are adopted as the intermediate units between words and sentences in SNELSD to consider syntax-related structure information during sentence modeling. The conventional text chunking task aims to identify constituent parts of sentences (nouns, verbs, adjectives, and so forth) and then link them to higher order units (noun groups, verb groups, phrases, and so on), which is also called shallow parsing. Chunking sentences into several essential parts is also considered to be a basic cognitive mechanism of human reading. For example, previous research indicated that chunking reading material or separating sentences into meaningful related parts improved the reading comprehension of readers with low reading ability. The mental process of chunking words into phrases was considered to be necessary since our mind can not hold more than approximately four to seven separate items in short-term memory.

Second, word chunks are treated as hidden units, and the latent chunk-level representations are embedded in a sequential model structure. The SNELSD model is designed in an end-to-end manner, which learns to split sentences into hidden word chunks without relying on additional text chunking algorithms. In other words, the SNELSD model is capable of exploring the latent structure information of sentences in a task-dependent manner. In contrast to Tree-LSTMs, which adopt tree-structured topologies, the proposed SNELSD model still follows the chain structure, which guarantees efficient model training by using batch-mode computation and makes it convenient to combine other sequential sentence encoders.

In this paper, we first introduce the architecture and related computational formulas of our SNELSD model after a brief review of related works. Then, we evaluate the proposed SNELSD model on a natural language inference (NLI) task and a sentiment analysis (SA) task by comparing it with other sentence encoders, including LSTM-RNNs and Tree-LSTMs. The main contributions of this paper are twofold. On the one hand, this paper proposes a novel sequential neural encoder that implicitly considers the influence of syntax structure on semantic modeling. The SNELSD model has a two-layer hierarchical chain structure, which makes a good balance between the flat chain structure (i.e., LSTM-RNN) and the hierarchical tree structure (i.e., Tree-LSTM). In other words, the SNELSD is an absolutely sequence-based model similar to the LSTM-RNNs, and it also utilizes the strategy of processing sentences hierarchically as does Tree-LSTMs. However, our SNELSD model does not rely on additional syntax parsing or text chunking modules but rather explores the latent structured information within sentences through end-to-end training.

Fig. 1. Structure of a long short-term memory (LSTM) unit.

II. RELATED WORK

A. Text Chunking

Text chunking, also called shallow parsing, is an NLP task that aims to identify the constituent parts of sentences (nouns, verbs, adjectives, and so on) and then link them to higher order units (noun groups, verb groups, phrases, and so forth). As an alternative to full parsing, which is more complicated and less robust, text chunking has been applied to many NLP tasks, such as information extraction (IE) and question answering (QA), to extract and represent syntax-related information.

The SNELSD model proposed in this paper adopts word chunks as intermediate units between words and sentences for sentence modeling. The use of word chunks here is different from the conventional text chunking task in two aspects. First, the conventional text chunking task is generally performed over sequences of part-of-speech tags based on syntactic regular expressions, and its outputs typically have syntactic labels. However, the determination of word chunks in SNELSD models is not syntax dependent but rather task dependent by employing end-to-end model training. Therefore, the construction of SNELSD models does not rely on additional syntax parsing or text chunking algorithms. Second, in contrast to text chunking, which provides explicit boundaries of syntactic units, the word chunks in SNELSD models are latent descriptions, which are represented by the probabilities of a chunk boundary existing after each word.

B. Long Short-Term Memory

The long short-term memory (LSTM) model was proposed to address the gradient vanishing and exploding problem when training recurrent neural networks (RNNs). RNNs with LSTM cells (LSTM-RNN) have been widely used in NLP applications for the sequential modeling of sentences. An LSTM cell is a complex hidden unit. As shown in Fig. 1.
RNNs with bidirectional LSTM units (BLSTM-RNNs) are states of internal vectors, including an input gate $i_t$, a forget gate $f_t$, and a memory cell $c_t$, respectively. Therefore, an RNN that uses all non-leaf nodes can be used to compose the sentence representation.

![Fig. 2. The structures of 1-layer LSTM and Tree-LSTM networks. (a) The flat chain structure of a 1-layer LSTM-RNN. (b) The hierarchical recursive structure of a Tree-LSTM. The gray leaf nodes are input word vectors, and the hidden states of all non-leaf nodes can be used to compose the sentence representation.](image)

it contains three gates, namely, input gate $i_t$, output gate $o_t$, and forget gate $f_t$, which determine whether to utilize the input, whether to create an output, and whether to update the cell memory state, respectively. Therefore, an RNN that uses LSTM cells is capable of remembering the information from a long span of time steps. The following equations define a regular LSTM unit.

\[
\begin{align*}
    i_t &= \sigma(W_i x_t + U_i h_{t-1} + b_i), \\
    f_t &= \sigma(W_f x_t + U_f h_{t-1} + b_f), \\
    o_t &= \sigma(W_o x_t + U_o h_{t-1} + b_o), \\
    c_t &= f_t \odot c_{t-1} + i_t \odot \tanh(W_c x_t + U_c h_{t-1} + b_c), \\
    h_t &= o_t \odot \tanh(c_t),
\end{align*}
\]

where $\sigma$ is the sigmoid function and $\odot$ is the element-wise multiplication between two vectors. At the $t$-th step, the LSTM unit accepts word vector $x_t$ as input, and it employs a set of internal vectors, including an input gate $i_t$, a forget gate $f_t$, an output gate $o_t$, and a memory cell $c_t$, to generate a hidden state $h_t$. Fig. 2(a) shows the flat chain structure of a 1-layer LSTM-RNN. For a sentence $X = [x_1, x_2, \ldots, x_L]$ with $l_x$ words, we can use either the sequence of output hidden states $[h_1, h_2, \ldots, h_L]$ or the last hidden state $h_L$ as the final sentence representation.

To access both the preceding and succeeding contexts, RNNs with bidirectional LSTM units (BLSTM-RNNs) are commonly adopted. A BLSTM-RNN can be viewed as two independent LSTM-RNNs that process a sentence along the forward and backward directions. For example, to encode a sentence $X = [x_1, x_2, \ldots, x_L]$ with a length of $l_x$, the two independent LSTM-RNNs compute the sequences of hidden states $\{\tilde{h}_1, \tilde{h}_2, \ldots, \tilde{h}_L\}$ and $\{\tilde{h}_1, \tilde{h}_2, \ldots, \tilde{h}_L\}$. Then, these two sequences are merged by concatenating the two hidden states $\tilde{h}_t$ and $\tilde{h}_t$ at the same time position to obtain the final representation for sentence $X$.

A deep LSTM-RNN can be constructed by stacking multiple recurrent hidden layers one on the top of another. The LSTM units in the first layer accept a word sequence as input, and the upper layers accept the hidden states of the lower layers as input. The final sentence representation is composed of the hidden states of the top layer. A deep BLSTM-RNN can be constructed in a similar way.

Similar to LSTM-RNN, the SNELSD model proposed in this paper is also a sequential encoder for sentence modeling. However, the SNELSD adopts a two-layer hierarchical chain structure, in which the hidden units in the two layers are not LSTMs, and they have different architectures to fulfill different functions. The details of SNELSDs will be introduced in Section III.

C. Tree-LSTMs

Tree-LSTMs have recently been investigated to incorporate syntactic parsing information for deriving the representation of sentences [18], [19], [29], [50]. Tree-LSTMs are developed from chain-structured LSTMs and have tree-structured network topologies, as shown in Fig. 2(b). At the $t$-th node of a binary parsing tree, an input vector $x_t$, which is a word vector at leaf nodes and a zero vector at non-leaf nodes, and the hidden vectors of its two child nodes (the left child $h^L_{t-1}$ and the right child $h^R_{t-1}$) are taken as the inputs to calculate the hidden state vector $h_t$ of the current node. These input vectors are used to configure the memory cell $c_t$ and the four gates, i.e., the input gate $i_t$, output gate $o_t$, and two forget gates $f^L_t$ and $f^R_t$. Moreover, the memory cell $c_t$ considers the memory vectors $c^L_{t-1}$ and $c^R_{t-1}$ from the two child nodes. Specifically, the forward propagation of a Tree-LSTM unit can be calculated as follows [29].

\[
\begin{align*}
    i_t &= \sigma(W_i x_t + U^L_i h^L_{t-1} + U^R_i h^R_{t-1} + b_i), \\
    f^L_t &= \sigma(W_f x_t + U^L_f h^L_{t-1} + U^L_f h^R_{t-1} + b^L_f), \\
    f^R_t &= \sigma(W_f x_t + U^R_f h^L_{t-1} + U^R_f h^R_{t-1} + b^R_f), \\
    o_t &= \sigma(W_o x_t + U^L_o h^L_{t-1} + U^R_o h^R_{t-1} + b_o), \\
    u_t &= \sigma(W_u x_t + U^L_u h^L_{t-1} + U^R_u h^R_{t-1} + b_u), \\
    c^L_t &= f^L_t \odot c^L_{t-1} + i_t \odot \tanh(W_c x_t + U_c h^L_{t-1} + b_c), \\
    c^R_t &= f^R_t \odot c^R_{t-1} + i_t \odot \tanh(W_c x_t + U_c h^R_{t-1} + b_c), \\
    h_t &= o_t \odot \tanh(c^L_t + c^R_t),
\end{align*}
\]

Similar to Tree-LSTMs, the SNELSD model proposed in this paper also aims to introduce the compositionality of languages into the semantic modeling of sentences. However, the SNELSD model utilizes hidden word chunks and an end-to-end training strategy, thus avoiding the reliance on additional syntax parsing. Furthermore, SNELSD is a sequential model, not a recursive one with tree structures, which guarantees the efficiency of model training and the convenience of combining other sequential encoders.

III. SEQUENTIAL NEURAL ENCODER WITH LATENT STRUCTURED DESCRIPTION (SNELSD)

The LSTM-RNN and Tree-LSTM models exploit a flat chain structure and a hierarchical tree structure, respectively.
Our SNELSD model utilizes a hierarchical chain structure, which can be considered as a trade-off between LSTM-RNNs and Tree-LSTMs. Specifically, an SNELSD model has a two-layer structure as shown in Fig. 3. The first layer, named the detection layer, predicts the boundaries of latent word chunks in an input sentence and derives a chunk-level vector for each word. The second layer, named the description layer, utilizes modified LSTM units to process these chunk-level vectors in a recurrent manner and produces sequential encoding outputs. The details of these two layers will be introduced in this section.

A. Detection Layer

The detection layer is designed to segment a sentence into word chunks. For a sentence with \( n \) words, the detection layer accepts the sequence of word vectors \( \{x_1, x_2, ..., x_n\} \) as input and produces a sequence of chunk-level vector representations \( \{p_1, p_2, ..., p_n\} \) together with a sequence of boundary indicators \( \{r_1, r_2, ..., r_n\} \). The value \( r_t \) represents the possibility of a chunk boundary existing after word \( x_t \), which is a continuous measurement between 0.0 and 1.0. In other words, the word chunks are considered to be hidden units in the proposed SNELSD model.

The structure of a detection unit is shown in Fig. 4. At the \( t \)-th step, the detection unit receives the current word vector \( x_t \), the next word vector \( x_{t+1} \), the chunk boundary indicator of the previous step \( r_{t-1} \) and the chunk-level representation of the previous step \( p_{t-1} \) as input, and it returns a chunk boundary indicator \( r_t \) together with the updated chunk-level representation at the current step \( p_t \). Mathematically, a detection unit is defined by the following equations.

\[
i_{t}^{0} = \sigma(W_{i}^{0}x_{t} + U_{i}^{0}p_{t-1} + b_{i}^{0}),
\]
\[
f_{t}^{0} = \sigma(W_{f}^{0}x_{t} + U_{f}^{0}p_{t-1} + b_{f}^{0}),
\]
\[
p_{t}^{0} = f_{t}^{0} \odot p_{t-1} + i_{t}^{0} \odot \tanh(W_{p}^{0}x_{t} + U_{p}^{0}p_{t-1} + b_{p}^{0}),
\]
\[
p_{t}^{1} = \tanh(W_{p}^{1}x_{t} + b_{p}^{1}),
\]
\[
p_{t} = (1 - r_{t-1}) \odot p_{t}^{0} + r_{t-1} \odot p_{t}^{1},
\]
\[
r_{t} = \sigma(p_{t}; x_{t+1})^T u_r.
\]

These equations can be divided into three operations. The first is when the words \( x_{t-1} \) and \( x_t \) belong to the same word chunk, which means that the word \( x_t \) is not at the beginning of a new word chunk. The updated chunk-level representation, denoted as \( p_{t}^{0} \) here, depends on both the input word \( x_t \) and the previous chunk-level representation \( p_{t-1} \), as shown in (13)-(15). Two internal gate vectors, i.e., an input gate \( i_{t}^{0} \) and a forget gate \( f_{t}^{0} \), are adopted to control the continuous encoding process within a certain word chunk. This is similar to the conventional LSTM unit since a word chunk can be considered as a very short sentence. Second, when the word \( x_{t-1} \) is at the end of the last word chunk and the word \( x_t \) is at the beginning of a new word chunk, the updated chunk-level representation, denoted as \( p_{t}^{1} \) here, only depends on the input word \( x_t \), as shown in (16). Finally, these two different chunk-level representations \( p_{t}^{0} \) and \( p_{t}^{1} \) are linearly fused using the boundary indicator \( r_{t-1} \), as shown in (17). The boundary indicator \( r_t \), which describes the possibility of a chunk boundary existing after word \( x_t \), is also calculated using \( p_t \) and the following word \( x_{t+1} \), as shown in (18).

B. Description Layer

The function of the description layer is to derive the representation of a sentence from the sequence of chunk-level representations \( \{p_1, p_2, ..., p_n\} \) given by the detection layer. The structure of a description unit is shown in Fig. 5 and is formulated as follows.

\[
h_{t} = \sigma(W_{h}x_{t} + U_{h}p_{t} + b_{h}),
\]
\[
h_{t+1} = \tanh(W_{h}x_{t} + U_{h}p_{t} + b_{h}),
\]
\[
p_{t} = \sigma(p_{t}; x_{t+1})^T u_r.
\]
\( m_t = (1 - r_t) \cdot p^* + r_t \cdot p_t, \)
\( i_t = \sigma(U_i h_{t-1} + W_i m_t + b_i), \)
\( f_t = \sigma(U_f h_{t-1} + W_f m_t + b_f), \)
\( o_t = \sigma(U_o h_{t-1} + W_o m_t + b_o), \)
\( c_t = f_t \odot c_{t-1} + i_t \odot \tanh(U_c h_{t-1} + W_c m_t + b_c), \)
\( h_t = o_t \odot \tanh(c_t). \)

At the \( t \)-th step, the description unit accepts the chunk-level representation \( p_t \), the boundary indicator \( r_t \) and the hidden state of the previous step \( h_{t-1} \) as inputs and generates an updated hidden state \( h_t \). A description unit is a modified LSTM unit. The difference is that a blended input vector \( m_t \) is calculated to replace \( p_t \) for sequential encoding, as shown in (19). In this equation, \( p^* \) is a constant vector to be estimated. The motivation for introducing \( m_t \) is to emphasize the chunk-level representation \( p_t \) of the words, which is the last word of a chunk (i.e., \( r_t = 1 \)), and to ignore the chunk-level representation of intermediary words within a chunk (i.e., \( r_t = 0 \)).

From (16)-(24), we find that the detector layer degrades to a simple \( \tanh \) project layer to process word vectors and the description unit is simply identical to a conventional LSTM unit when \( r_t \) is constantly equal to 1.

An SNELSD model can work in either stand-alone mode or joint mode. In stand-alone mode, the sequence of hidden state vectors \([h_1, h_2, \ldots, h_n]\) produced by the description layer are used directly for sentence representation. In joint mode, these hidden state vectors are further concatenated with word vectors \([x_1, x_2, \ldots, x_n]\) or the output of an auxiliary chain-structured sentence encoder (e.g., BLSTM-RNN) at each step to produce a more comprehensive description of sentence meanings. In either mode, all the model parameters including word embeddings and all transformation matrices are learned in an end-to-end manner.

IV. EVALUATION TASKS

Two NLP tasks, namely, natural language inference (NLI) and sentiment analysis (SA), are adopted to evaluate the performance of our proposed SNELSD model. In this section, we briefly introduce these two tasks and explain how to apply SNELSD models to accomplish these two tasks.

A. Natural Language Inference (NLI)

Understanding entailment and contradiction is fundamental to understanding the meaning of natural language [23], [31]. Thus, the inference about entailment and contradiction is a valuable task for evaluating sentence encoding models. Specifically, the natural language inference (NLI) task aims to determine whether a natural language hypothesis \( h \) can be inferred from a natural language premise \( p \), as described in the following example [31].

\( p: \) Several airlines polled saw costs grow more than expected, even after adjusting for inflation.

In this example, the hypothesis \( h \) can be regarded as being entailed from the premise \( p \).

In recent years, there have been advances in NLI. One main advancement is the availability of a large annotated dataset, the Stanford Natural Language Inference (SNLI) dataset [23], which contains 570K human-written English sentence pairs manually labeled by multiple human subjects. For each sentence pair, the annotation indicates whether the premise sentence entails the hypothesis sentence, whether they are contradicting each other or whether they have no inference relation. With its large-scale and human-grounded annotation, the SNLI dataset is competent for training rather complicated sentence encoding models.

We evaluate our SNELSD model based on the infrastructure of the enhanced BLSTM inference model (EBIM) [29], which has achieved nearly state-of-the-art performance on the SNLI task. Let two sentences of word vectors \( A = [a_1, a_2, \ldots, a_n] \) and \( B = [b_1, b_2, \ldots, b_n] \) denote the premise sentence and the hypothesis sentence. Each \( a_i \) or \( b_j \in \mathbb{R}^2 \) is an embedding of an \( l \)-dimensional vector, which can be initialized with pre-trained word embeddings. The goal is to predict a label \( y \) that indicates the inference relationship between \( A \) and \( B \). The architecture of EBIM can be divided into four parts, as follows.

1) Sentence encoding: First, the premise and hypothesis sentences \( A \) and \( B \) are input into a sentence encoder to obtain their context representation vectors \([\bar{a}_1, \ldots, \bar{a}_n]\) and \([\bar{b}_1, \ldots, \bar{b}_n]\) as
\[
\bar{a}_i = \text{Sentence Encoder}(A), \forall i \in [1, \ldots, n_a],
\]
\[
\bar{b}_j = \text{Sentence Encoder}(B), \forall j \in [1, \ldots, n_b].
\]

In the original EBIM, the sentence encoder is a single-layer BLSTM-RNN model. Here, we replace it with the other models introduced above for comparison, including multi-layer LSTM-RNN and BLSTM-RNN, Tree-LSTM, and the SNELSD model proposed in this paper. Note that when a Tree-LSTM is utilized to encode sentences, the number of derived representation vectors \( n_a = l_a \) and \( n_b = l_b \) because all the other models have sequential structures.

2) Soft alignment: The attention weights \( e_{ij} \) between each pair of \( \bar{a}_i \) and \( \bar{b}_j \) are calculated as
\[
e_{ij} = \bar{a}_i^\top \bar{b}_j, \forall i \in [1, \ldots, n_a], \forall j \in [1, \ldots, n_b].
\]
Subsequently, the attention weights \( e_{ij} \) are normalized and are utilized to obtain soft alignment vectors \( \bar{a}_i \) and \( \bar{b}_j \) for both sentences as
\[
\bar{a}_i = \sum_{j=1}^{n_b} \frac{\exp(e_{ij})}{\sum_{k=1}^{n_b} \exp(e_{ik})} \bar{b}_j, \forall i \in [1, \ldots, n_a],
\]
\[
\bar{b}_j = \sum_{i=1}^{n_a} \frac{\exp(e_{ij})}{\sum_{k=1}^{n_a} \exp(e_{ik})} \bar{a}_i, \forall j \in [1, \ldots, n_b].
\]
3) Inference collection and composition: We collect the inference-related information using the context representation vectors \( \bar{a}_i, \bar{b}_j \) and soft alignment vectors \( \tilde{a}_i, \tilde{b}_j \) calculated above. Specifically, the EBIM model uses vector concatenation, vector difference, and element-wise product to collect the inference sequences \( m_a \) and \( m_b \) as follows:

\[
m_a = [\tilde{a}_i; a_i - \tilde{a}_i; \tilde{a}_i \odot \tilde{a}_i],
\]

(30)

\[
m_b = [b_j; b_j - \tilde{b}_j; \tilde{b}_j \odot \tilde{b}_j],
\]

(31)

where \( a, b, \tilde{a}, \) and \( \tilde{b} \) are the sequences composed of \( a_i, b_j, \tilde{a}_i, \) and \( \tilde{b}_j, \) respectively. Then, the sequences \( m_a \) and \( m_b \) are composed using a BLSTM-RNN model together with average and max pooling to obtain a fixed-dimensional discriminative vector \( v \), which describes the inference relationship between the entire premise sentence and its hypothesis. The calculation is as follows:

\[
v_{1,i} = \text{BLSTM}(m_a), \forall i \in [1, ..., n_a],
\]

(32)

\[
v_{2,j} = \text{BLSTM}(m_b), \forall j \in [1, ..., n_b],
\]

(33)

\[
v_{1,\text{ave}} = \frac{1}{n_a} \sum_{i=1}^{n_a} v_{1,i}/n_a, \quad v_{1,\text{max}} = \max_{i=1}^{n_a} v_{1,i},
\]

(34)

\[
v_{2,\text{ave}} = \frac{1}{n_b} \sum_{j=1}^{n_b} v_{2,j}/n_b, \quad v_{2,\text{max}} = \max_{j=1}^{n_b} v_{2,j},
\]

(35)

\[
v = [v_{1,\text{ave}}; v_{2,\text{ave}}; v_{1,\text{max}}; v_{2,\text{max}}].
\]

(36)

4) Inference determination: Finally, the vector \( v \) is fed into a multi-layer perceptron (MLP) classifier that has a hidden layer with \( tanh \) activation and a \( softmax \) output layer. The output vector \( y \) is a 3-dimensional vector that indicates the probability of three different inference relationships between the premise sentence and its hypothesis.

B. Sentiment Analysis (SA)

Sentiment analysis (SA) [32] aims to determine the attitude of someone with respect to some topics or the overall contextual polarity or emotional reaction. There are many commercial and social applications related to sentiment analysis. Actually, sentiment analysis can utilize multimodal data including text, speech and video [33]–[35]. In natural language processing, a basic sentiment analysis task is to classify the polarity of a given text at the document, sentence, or feature and aspect level. Therefore, sentence modeling is essential for this task. In this paper, we evaluate our SNELSD model on the sentiment polarity task using the Stanford Sentiment Treebank dataset (SST) [36]. This dataset includes fine-grained sentiment labels for 215,154 phrases in the parse trees of 11,855 sentences. Each label can be one of the 5 sentiment classes from very negative to very positive (–--, –, −, 0, +, ++). The following examples are taken from this dataset, in which only the sentence-level labels are shown.

+: taking care of my cat offers a refreshingly different slice of Asian cinema

−: no movement, no yuks, not much of anything

Since the focus of this paper is sentence modeling, we exclude the phrase-level samples in the SST dataset and only use sentence-level samples for evaluating different sentence encoders.

The overall architecture of the SA model used in this paper is much simpler than that for NLI. In an input sentence \( X = [x_1, x_2, ..., x_{n_x}] \), each \( x_i \in \mathbb{R}^l \) is an \( l \)-dimensional embedding vector, which can be initialized with pre-trained word embeddings. First, the sequence of words \( X \) is sent into a sentence encoder to obtain the context representations \( [x_1, ..., x_{n_x}] \) as

\[
x_i = \text{Sentence Encoder}(X), \forall i \in [1, ..., n_x].
\]

(37)

Here, the sentence encoder can be LSTM-RNN or the proposed SNELSD model. Similar to (25) and (26), \( n_x = l_x \) since both LSTM-RNN and SNELSD model has sequential structures. Then, a discriminative vector \( v \) is obtained by performing average and max pooling on \([x_1, ..., x_{n_x}] \) as

\[
v_{\text{ave}} = \frac{1}{n_x} \sum_{i=1}^{n_x} x_i/n_x, \quad v_{\text{max}} = \max_{i=1}^{n_x} x_i,
\]

(38)

\[
v = [v_{\text{ave}}; v_{\text{max}}].
\]

(39)

Finally, the vector \( v \) is fed into an MLP classifier to determine the sentiment polarity of the input sentence.

For the evaluation of Tree-LSTM, we directly use the constituency Tree-LSTM model in [18] which has the same structure with that described in Section IV-C. Particularly, the Tree-LSTM models in [18] only use the state of root node as the final sentence representation.

V. EXPERIMENTS ON NLI

A. Experimental Setup

In our experiments, the Stanford Natural Language Inference (SNLI) dataset [23] was adopted. Following previous work [23], the sentence pairs lacking consensus among multiple human annotators were removed, and this dataset was split into a training set, a development set, and a test set with 549,367, 9,842, and 9,824 sentence pairs, respectively.

The entire NLI model was constructed following the introduction in Section IV-A. Various sentence encoders, including LSTM-RNN, BLSTM-RNN, Tree-LSTM, and the proposed SNELSD model, were integrated to achieve the sentence encoding in (25) and (26). The constituency parse trees for constructing Tree-LSTM models were produced using the Stanford PCFG Parser 3.5.3 [37]. All word embeddings and the hidden state vectors of sentence encoders had 300 dimensions. Specifically, the hidden states of the BLSTM-RNN model had 600 dimensions since it was composed of two unidirectional LSTM-RNNs along different directions. The model parameters of the sentence encoders were estimated in an end-to-end manner together with the parameters of other parts of the NLI model. The word embeddings were initialized by pre-trained 300-D Glove 840B vectors [38]. Out-of-vocabulary (OOV) words were randomly initialized with Gaussian-distributed samples. Cross-entropy was adopted as
the loss function for model training, and the Adam [39] method was adopted for optimization. The first momentum was set to be 0.9 and the second to be 0.999 in Adam optimization. The initial learning rate was 0.0004, and the batch size was 128. Dropout with a rate of 0.5 was applied to the MLP layer and the word embedding layer.

B. Performance of SNELSD in Stand-Alone Mode

We compared the performance of using SNELSD in stand-alone mode for sentence modeling with that of using the LSTM-RNN and Tree-LSTM models. Considering that an SNELSD has a two-layer sequential structure, four different LSTM-RNNs, including 1-layer and 2-layer unidirectional LSTM-RNNs and 1-layer and 2-layer BLSTM-RNNs, were used for comparison. The NLI accuracies of using these sentence encoders are shown in Part A of Table I.

First, we observe that the SNELSD model achieved similar performance with the Tree-LSTM model, which exploited syntactic information explicitly. The SNELSD model performed better than the 2-layer LSTM-RNN, which also had a 2-layer unidirectional LSTM-RNN structure. However, the accuracy of the SNELSD model was still lower than that of the 2-layer BLSTM-RNN. One possible reason for this result is the lack of backward processing in SNELSD.

Furthermore, it can be found that both 1-layer LSTM-RNN and BLSTM-RNN outperformed their 2-layer counterparts and the two models with structured descriptions (i.e., Tree-LSTM and SNELSD). Although it has been observed empirically that multi-layer RNNs achieved better performance than 1-layer RNNs on some tasks, such as machine translation in an encoder-decoder framework [2], the gains of using stacked RNNs for sentence modeling are still not theoretically clear [40]. One possible reason for the superiority of 1-layer RNNs in our experiment is that stacking RNN layers or introducing a structured description leads to abstract and compositional representations of sentences, which may be inappropriate for the NLI task. Some less compositional descriptions, such as the meanings of individual key words in sentences, are also important for deciding the inference relationship between two sentences.

In terms of the training efficiency of different models, we observed that the training speed of SNELSD was similar with 2-layer LSTM, but significantly faster than Tree-LSTM in our experiments. As discussed in Section 1, the sequential architecture of SNELSD guarantees the efficiency of model training.

C. Performance of SNELSD in Joint Mode

The performance of using SNELSD in joint mode was further investigated through experiments. Here, the hidden state vectors produced by the SNELSD model were concatenated with unprocessed word embeddings or with the output of a 1-layer BLSTM-RNN to achieve the sentence encoding in (25) and (26). Some models that combined the output of LSTM-RNNs, BLSTM-RNNs, and word embeddings for sentence modeling were also constructed for comparison. The results of these models are shown in Parts B and C of Table I.

Comparing the results in Part B of Table I with those in Part A, we find that the concatenation with word embeddings failed to improve the performance of 1-layer RNNs, whereas it increased the accuracy of 2-layer RNNs and the SNELSD model. Comparing the results in Part C with those in Part A, we can observe the positive effects of concatenating the output of 1-layer BLSTM-RNN with 2-layer LSTM-RNN and the SNELSD model. These results demonstrate the importance of utilizing a comprehensive sentence representation for the NLI task.

As shown in Parts B and C of Table I, the proposed joint-mode SNELSD model achieved the highest accuracy of 88.0% among all evaluated sentence encoders. This result demonstrates that by introducing a latent structured description, the SNELSD model is able to provide some useful structured semantic information for NLI that conventional sequential sentence encoders may ignore.

D. Comparison with State-of-the-Art Results

Here, the proposed method using SNELSD models was compared with other published state-of-the-art methods on the benchmark SNLI task. The results are shown in Table II. All the models compared here utilized the framework of word-by-word attention between the semantic representation of two sentences. The methods marked with (1)-(7) adopted a

| Models | Train | Test |
|--------|-------|------|
| (1) decomposable attention model [41] | 89.5 | 86.3 |
| (2) NTI-SLSTM-LSTM [42] | 88.5 | 87.3 |
| (3) EBIM [29] | 92.9 | 87.7 |
| (4) ESIM [43] | 92.6 | 88.0 |
| (5) BiMPM [44] | – | 86.9 |
| (6) [SNELSD; 1-layer BLSTM] | 92.2 | 88.0 |
| (7) [SNELSD; 1-layer BLSTM]* | 94.1 | 88.3 |
| (8) ESIM + Syntactic tree-LSTM (Ensemble) [43] | 93.5 | 88.6 |
| (9) BiMPM (Ensemble) [44] | – | 88.8 |
| (10) [SNELSD; 1-layer BLSTM]* (Ensemble) | 93.3 | 88.7 |

The performance of using SNELSD in joint mode was further investigated through experiments. Here, the hidden state vectors produced by the SNELSD model were concatenated with unprocessed word embeddings or with the output of a 1-layer BLSTM-RNN to achieve the sentence encoding in (25) and (26). Some models that combined the output of LSTM-RNNs, BLSTM-RNNs, and word embeddings for sentence modeling were also constructed for comparison. The results of these models are shown in Parts B and C of Table I.

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| (9) BiMPM (Ensemble) [44] | – | 88.8 |
| (10) [SNELSD; 1-layer BLSTM]* (Ensemble) | 93.3 | 88.7 |
single model for NLI, and the methods marked with (8)-(10) ensembled multi-models for decision making.

The decomposable attention model [41] marked with (1) can be treated as a simplified edition of EBIM. The most obvious difference between them is that the decomposable attention model employs feedforward neural networks, whereas the EBIM model uses BLSTM-RNNs to encode the sentences and to compose the inference information. We can find that this model behaved considerably worse than the other models shown in Table I1.

The NTI-SLSTM-LSTM model [42] marked with (2) utilized a full binary tree structure, which incorporates the sequential LSTM-based encoding, recursive networks and complicated combination of attention. However, this model still performed worse than EBIM and joint-mode SNELSD. The tree structure also made training of the model time consuming.

The EBIM model [29] marked with (3) is the same as the model using 1-layer BLSTM-RNN as the sentence encoder in Table I. The ESIM model [43] marked with (4) is an improved version of the EBIM model [29]. The only difference is that the ESIM model introduces a 1-layer feed-forward neural network with the ReLU activation function to reduce the dimensions of $m_{a}$ and $m_{b}$ calculated at the inference collection step described in Section IV-A.

The BiMPM model [44] marked with (5) is almost the same as EBIM. There are two main differences between these models. The first difference is that the original word representation used in BiMPM is the concatenation of pre-trained GloVe word embeddings and character-composed embeddings derived from an LSTM-RNN [44]. The second difference is that BiMPM adopts a more complicated matching operation than EBIM. We find that both EBIM and joint-mode SNELSD were superior to BiMPM.

The models marked with (6) and (7) utilized joint-mode SNELSD in an EBIM and ESIM fashion, respectively. When combining joint-mode SNELSD with ESIM, the outputs of SNELSD and 1-layer BLSTM-RNN were concatenated after inference collection and dimension reduction. It can be observed that models (6) and (7) achieved higher NLI accuracies than their counterparts using 1-layer BLSTM-RNN for sentence modeling. Furthermore, combining joint-mode SNELSD in an ESIM fashion achieved an accuracy of 88.3%, which is the best result among all single-model methods listed in Table II. A close examination on the test set errors made by models (4) and (7) shows that about 3.5% test set samples were misclassified by model (4) while classified correctly by model (7). On the contrary, about 3.2% test set samples were misclassified by model (7) while classified correctly by model (4). More than 70% of the errors made by these two models were the same. This implies that there still exist common deficiencies with these two models. We also observed that some of the common errors made by these two models were due to the lack of background and commonsense knowledge.

![Fig. 6. Visualization of latent word chunks in SNELSD for NLI. Each line corresponds to a hypothesis sentence in the SNLI test set. The value of the chunk boundary indicator $r_{t}$ is written below the $t$-th word in the sentence together within a red-green scale color block. When the color block is more red, the value of $r_{t}$ is smaller, which means that it is more unlikely to have a word chunk boundary after the word $x_{t}$. In contrast, when the color block is more green, the value of $r_{t}$ is larger, and the probability of a chunk boundary existing after the word $x_{t}$ is higher. For better illustration, red arrows are added to indicate the positions where $r_{t}$ is higher than 0.9.](image-url)
during the inference. How to integrate external knowledge represented by lexical databases, such as WordNet [45], into the sentence modeling and matching of NLI is a topic worth further investigation.

The model marked with (8) assembled an original ESIM and a modified ESIM using a syntactic Tree-LSTM for sentence encoding and information composition [43]. It achieved a significant improvement over the single ESIM model. The model marked with (9) assembled two BiMPMs with identical architectures [44]. Similarly, we constructed an ensemble model using two instances of model (7) trained independently. Thus, two posterior probability vectors corresponding to the three options of NLI were returned for each sentence. Similar to the model ensemble strategy used in [43], [44], these two posterior probability vectors were averaged to obtain the final one for decision. It can be observed that our SNELSD model didn’t achieve as much gain as the BiMPM model from the ensemble. One possible reason is that the performance of our single SNELSD model was quite stable among its instances trained independently.

E. Visualization of Latent Word Chunks in SNELSD for NLI

As described in Section I, an SNELSD model segments sentences into word chunks in a task-dependent manner for sentence modeling. The word chunks are latent and described by a sequence of stochastic chunk boundary indicators. Here, the calculated boundary indicators \( r_t \) for several sentence examples are displayed to visualize the latent word chunks considered in SNELSD modeling. The single SNELSD model in Part A of Table I was adopted here, and the results are shown in Fig. 6. In this figure, each line corresponds to a hypothesis sentence in the SNLI test set. The value of \( r_t \) is written below the \( t \)-th word in the sentence together within a red-green scale color block. When the color block is more red, the value of \( r_t \) is smaller, which means that it is more unlikely to have a word chunk boundary after the word \( x_t \). Conversely, when the color block is more green, the value of \( r_t \) is larger, and the probability of a chunk boundary existing after the word \( x_t \) is higher. For better illustration, red arrows are added in Fig. 6 to indicate the positions where \( r_t \) is higher than 0.9.

As shown in Fig. 6, the chunking patterns provided by the SNELSD model can partially capture the main grammar structure of a sentence. Most of the phrase boundaries have a high value of \( r_t \), which means that they are also judged to have high possibilities of being word chunk boundaries in the SNELSD model. This result is reasonable since the SNELSD model learns how to segment sentences into word chunks by task-dependent and end-to-end model training, and the syntax-related information should be useful for the NLI task.

VI. EXPERIMENTS ON SA

In contrast to NLI, which concerns the relationship between two sentences, sentiment analysis (SA) is to classify a single sentence. In this section, we performed experiments to compare the SNELSD, LSTM-RNN and Tree-LSTM models on SA similar to Section [V].

A. Experimental Setup

We used the Stanford Sentiment Treebank (SST) dataset and the same data split as in Socher et al. (2013) [36], in which the number of training, development and test sentences were 8,544, 1, 101, and 2, 210, respectively. Since the focus of this paper is on sentence modeling, we excluded the phrase-level samples in the SST dataset and only used sentence-level samples for evaluating different sentence encoders.

The framework introduced in Section IV-B was followed to construct the SA model. Different sentence encoders were used to fulfill the sentence encoding in (37) for comparison. During model training, cross entropy was chosen as the loss function for optimization, and the Adadelta method was used for the optimization process. The \( \epsilon \) was set to 1e−6 and \( \rho \) was set to 0.95 for Adadelta optimization. The batch size was 16. All word embeddings and the hidden state vectors of sentence encoders had 300 dimensions. Specifically, the hidden states of the BLSTM-RNN model had 600 dimensions since it was composed of two unidirectional LSTM-RNNs along different directions. The drop-out strategy was not applied to avoid the instability among different training trials. The word embeddings were initialized by pre-trained 300D GloVe 840B vectors [38]. The results are shown in Table III where the evaluated sentence encoders were the same as those shown in Table I. All the results in Table III are the averages and standard deviations of 40 training trials on the test set.

| Sentence Encoder | Test(std) |
|------------------|-----------|
| 1-layer LSTM     | 46.7(0.89)|
| 1-layer BLSTM    | 46.9(1.30)|
| 2-layer LSTM     | 46.2(1.32)|
| 2-layer BLSTM    | 46.6(1.80)|
| Tree-LSTM [18]   | 47.7(0.67)|
| SNELSD           | 46.8(1.28)|
| [1-layer LSTM; word embedding] | 46.2(1.27)|
| [1-layer BLSTM; word embedding] | 46.8(1.46)|
| [2-layer LSTM; word embedding] | 46.0(1.00)|
| [2-layer BLSTM; word embedding] | 46.1(1.35)|
| [SNELSD; word embedding] | 46.7(0.90)|
| [2-layer LSTM; 1-layer BLSTM] | 47.0(1.14)|
| [SNELSD; 1-layer BLSTM] | 47.9(1.24)|

TABLE III

AVERAGE ACCURACIES (%) WITH STANDARD DEVIATIONS OF USING DIFFERENT SENTENCE ENCODERS ON SA.
It can be observed that the Tree-LSTM model achieved the best performance among all evaluated sentence encoders. Similar to the NLI results shown in Table I, the 2-layer LSTM and BLSTM models also performed worse than their 1-layer counterparts on the SA task, which is consistent with the experimental results in [18]. However, our SNELS model, which had a similar 2-layer unidirectional chain structure as the 2-layer LSTM-RNN, outperformed both 2-layer LSTM and 2-layer BLSTM and obtained almost the same test accuracy as 1-layer LSTM and BiLSTM. This result implies that the detection layer and description layer in our SNELS model may be capable of utilizing latent structure information in sentences that conventional LSTM units cannot capture.

1This result was derived using the codes for training the constituency Tree-LSTM model in [18].

C. Performance of SNELSD in Joint Mode

Similar to Section V-C, we further evaluated the performance of the SNELSD model working in joint mode, and the results are summarized in Parts B and C of Table III.

Comparing the results in Part B of Table I with those in Part A, it can be found that the concatenation with word embeddings degraded the performance of all sentence encoders, particularly for the 1-layer LSTM and 2-layer BLSTM models, which had a significant accuracy reduction of approximately 0.5%. This result is inconsistent with the results on the NLI task and implies that to simply consider the representation of all individual words in the sentence modeling may be inappropriate for the SA task.

Examining the results in Part C of Table III, it can be observed that both 2-layer LSTM and our proposed SNELSD model benefited from the concatenation with another 1-layer BLSTM encoder. The joint-mode SNELSD model achieved an accuracy of 47.9%, which was the highest accuracy among all the evaluated sentence encoders. This result further confirms that the SNELSD model can truly capture some information that ordinary LSTMs models cannot capture.

D. Comparison with Published Results

Most existing works on the Stanford Sentiment Treebank (SST) dataset trained their models using both phrase-level and sentence-level labels. The best published results we can found that only adopted sentence-level samples of this dataset for model training and testing are compared in Table IV.
The S-LSTM [19] marked with (1) is also a tree-structured LSTM model, which is similar to our Tree-LSTM model but initialized their word embeddings randomly. The models marked with (2) and (3) are CNN-based models [47] using Word2Vec [48] and GloVe [38] to initialize word embeddings, respectively. We can find that the joint-mode SNELSD model achieved the best performance among all these models.

E. Visualization of Latent Word Chunks in SNELSD for SA

We also visualized the chunking pattern of applying the SNELSD model on the SA task. The values of $r_t$ of the SNELSD model in Part A of Table III were used for illustration, and the results are shown in Fig. 7. The first 5 sentences had negative sentiment labels, whereas the last 3 sentences were positive. From this figure, it can be found that the word chunk boundaries tend to exist following the words with strong emotion polarities. This result is reasonable since more attention should be given to these words for sentiment analysis.

Comparing Fig. [7] with Fig. [6], we can see that the chunking pattern provided by our SNELSD model is truly task dependent, which illustrates the flexibility of our SNELSD model to be compatible with different tasks.

VII. CONCLUSION

This paper has proposed a novel sentence encoding model named sequential neural encoder with latent structure description (SNELSD). This model has a 2-layer hierarchical chain structure and splits sentences into latent word chunks by end-to-end learning. A natural language inference (NLI) task and a sentiment analysis (SA) task are introduced to evaluate the proposed SNELSD model. The experimental results show that the proposed SNELSD model can fit these tasks very well and that joint-mode SNELSDs outperform ordinary LSTM models by capturing and utilizing the latent structured information of sentences in a task-dependent manner. Applying the proposed SNELSD model to more tasks, such as paragraph comprehension and question answering, will be the tasks of our future work.

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