Learning Natural Language Inference using Bidirectional LSTM model and Inner-Attention

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Abstract
In this paper, we proposed a sentence encoding-based model for recognizing text entailment. In our approach, the encoding of sentence is a two-stage process. Firstly, average pooling was used over word-level bidirectional LSTM (biLSTM) to generate a first-stage sentence representation. Secondly, attention mechanism was employed to replace average pooling on the same sentence for better representations. Instead of using target sentence to attend words in source sentence, we utilized the sentence's first-stage representation to attend words appeared in itself, which is called "Inner-Attention" in our paper. Experiments conducted on Stanford Natural Language Inference (SNLI) Corpus has proved the effectiveness of "Inner-Attention" mechanism. With less number of parameters, our model outperformed the existing best sentence encoding-based approach by a large margin.

1 Introduction
Given a pair of sentences, the goal of recognizing text entailment (RTE) is to determine whether the hypothesis can reasonably be inferred from the premises. There were three types of relation in RTE, Entailment (inferred to be true), Contradiction (inferred to be false) and Neutral (truth unknown). A few examples were given in Table 1.

| P                      | The boy is running through a grassy area. |
|------------------------|------------------------------------------|
| The boy is in his room. |                                          |
| C                      |                                          |
| A boy is running outside.|                                        |
| E                      |                                          |
| The boy is in a park.   |                                          |
| N                      |                                          |

Table 1: Examples of three types of label in RTE, where P stands for Premises and H stands for Hypothesis also explored by many researchers, but not been widely used because of its complexity and domain limitations.

Recently published Stanford Natural Language Inference (SNLI) corpus makes it possible to use deep learning methods to solve RTE problems. So far proposed deep learning approaches can be roughly categorized into two groups: sentence encoding-based models and matching encoding-based models. As the name implies, the encoding of sentence is the core of former methods, while the latter methods directly model the relation between two sentences and didn’t generate sentence representations at all.

In view of universality, we focused our efforts on sentence encoding-based model. Existing methods of this kind including: LSTMs-based model, GRUs-based model, TBCNN-based model and SPINN-based model. Single directional LSTMs and GRUs suffer a weakness of not utilizing the contextual information from the future tokens and Convolutional Neural Networks didn’t make full use of information contained in word order. Bidirectional LSTM utilizes both the previous and future context by processing the sequence on two directions which helps to address the drawbacks mentioned above.

1http://nlp.stanford.edu/projects/snli/
A recent work by [Rocktäschel et al., 2015] improved the performance by applying a neural attention model that didn’t yield sentence embeddings. In this paper, we proposed a unified deep learning framework for recognizing textual entailment which dose not require any feature engineering, or external resources. The basic model is based on building biLSTM models on both premises and hypothesis. The basic mean pooling encoder can roughly form an intuition about what this sentence is talking about. Obtained this representation, we extended this model by utilize an Inner-Attention mechanism on both sides. This mechanism helps generate more accurate and focused sentence representations for classification. In addition, we introduced a simple effective input strategy that get ride of same words in hypothesis and premise, which further boosts our performance. Without parameter tuning, we improved the art-of-the-state performance of sentence encoding-based model by nearly 2%.

2.1 Sentence Encoding Module

Sentence encoding module is the fundamental part of this model. To generate better sentence representations, we employed a two-step strategy to encode sentences. Firstly, average pooling layer was built on top of word-level biLSTMs to produce sentence vector. This simple encoder combined with the sentence matching module formed the basic architecture of our model. With much less parameters, this basic model alone can outperformed art-of-state method by a small margin. (refer to Table 3).

2 Our approach

In our work, we treated RTE task as a supervised three-way classification problem. The overall architecture of our model is shown in Figure 1. The design of this model we follow the idea of Siamese Network, that the two identical sentence encoders share the same set of weights during training, and the two sentence representations then combined together to generated a "relation vector" for classification. As we can see from the figure, the model mainly consists of three parts. From top to bottom were: (A). The sentence input module; (B). The sentence encoding module; (C). The sentence matching module. We will explain the last two parts in detail in the following subsection. And the sentence input module will be introduced in Section 3.3.
attention mechanism weights. More attention was
given to important words.

The idea of “Inner-attention” was inspired by the
observation that when human read one sentence,
people usually can roughly form an intuition about
which part of the sentence is more important accord-
ing past experience. And we implemented this idea
using attention mechanism in our model. The atten-
tion mechanism is formalized as follows:

\[ M = \tanh(W^y Y + W^h R_{ave} \otimes e_L) \]
\[ \alpha = \text{softmax}(w^T M) \]
\[ R_{att} = Y\alpha^T \]

where \( Y \) is a matrix consisting of output vectors
of biLSTM, \( R_{ave} \) is the output of mean pooling
layer, \( \alpha \) denoted the attention vector and \( R_{att} \) is the
attention-weighted sentence representation.

2.2 Sentence Matching Module

Once the sentence vectors are generated. Three
matching methods were applied to extract relations
between premise and hypothesis.

- Concatenation of the two representations
- Element-wise product
- Element-wise difference

This matching architecture was first used by
(Mou et al., 2015). Finally, we used a SoftMax layer
over the output of a non-linear projection of the gen-
erated matching vector for classification.

3 Experiments

3.1 DataSet

To evaluate the performance of our model,
we conducted our experiments on Stanford
Natural Language Inference (SNLI) corpus
(Bos and Markert, 2005). At 570K pairs, SNLI
is two orders of magnitude larger than all other
resources of its type. The dataset is constructed
by crowdsourced efforts, each sentence written
by humans. The target labels comprise three
classes: Entailment, Contradiction, and Neutral

Recently, (Yang et al., 2016) proposed a Hierarchical At-
tention model on the task of document classification also used
for but the target representation in attention their mechanism is
randomly initialized.

(two irrelevant sentences). We applied the standard
train/validation/test split, containing 550k, 10k, and
10k samples, respectively.

3.2 Parameter Setting

The training objective of our model is cross-entropy
loss, and we use minibatch SGD with the Rmsprop
(Tieleman and Hinton, 2012) for optimization. The
batch size is 128. A dropout layer was applied in the
output of the network with the dropout rate set to
0.25. In our model, we used pretrained 300D Glove
840B vectors (Pennington et al., 2014) to initialize
the word embedding. Out-of-vocabulary words in
the training set are randomly initialized by sampling
values uniformly from (0.05, 0.05). All of these em-
bedding are not updated during training . We didn’t
tune representations of words for two reasons: 1. To
reduced the number of parameters needed to train.
2. Keep their representation stays close to unseen
similar words in inference time, which improved
the model’s generation ability. The model is imple-
mented using open-source framework Keras.

3.3 The Input Strategy

In this part, we investigated four strategies to modify
the input on our basic model which helps us increase
performance, the four strategies are:

- Inverting Premises (Sutskever et al., 2014)
- Doubling Premises (Zaremba and Sutskever, 2014)
- Doubling Hypothesis
- Differentiating Inputs (Removing same words
appeared in premises and hypothesis)

Experimental results were illustrated in Table 2.
As we can see from it, doubling hypothesis and
differentiating inputs both improved our model’s
performance. While the hypotheses usually much
shorter than premises, doubling hypothesis may ab-
sorb this difference and emphasize the meaning
twice via this strategy. Differentiating input strat-
ety forces the model to focus on different part of
the two sentences which may help the classification
for Neutral and Contradiction examples as we ob-
served that our model tended to assign unconfident
instances to Entailment. And the original input sen-
tences appeared in Figure 1 are:

Premise: Two man in polo shirts and tan pants im-
mersed in a pleasant conversation about photograph.
| Input Strategy          | Test Acc. |
|------------------------|-----------|
| Original Sequences     | 83.24%    |
| Inverting Premises     | 82.60%    |
| Doubling Premises      | 83.66%    |
| Doubling Hypothesis    | 82.83%    |
| Differentiating Inputs | 83.72%    |

Table 2: Comparison of different input strategies

**Hypothesis:** Two man in polo shirts and tan pants involved in a heated discussion about Canon.

**Label:** Contradiction

While most of the words in this pair of sentences are same or close in semantic, it is hard for model to distinguish the difference between them, which resulted in labeling it with Neutral or Entailment. Through differentiating inputs strategy, this kind of problems can be solved.

### 3.4 Comparison Methods

In this part, we compared our model against the following art-of-the-state baseline approaches:

- **LSTM enc:** 100D LSTM encoders + MLP. (Bowman et al., 2015)
- **GRU enc:** 1024D GRU encoders + skip-thoughts + cat, -. (Vendrov et al., 2015)
- **TBCNN enc:** 300D Tree-based CNN encoders + cat, , -. (Mou et al., 2015)
- **SPINN enc:** 300D SPINN-NP encoders + cat, , -. (Bowman et al., 2016)
- **Static-Attention:** 100D LSTM + static attention. (Rocktäschel et al., 2015)
- **WbW-Attention:** 100D LSTM + word-by-word attention. (Rocktäschel et al., 2015)

The cat refers to concatenation, - and denote element-wise difference and product, respectively. Much simpler and easy to understand.

### 3.5 Results and Qualitative Analysis

Although the classification of RTE example is not solely relying on representations obtained from attention, it is still instructive to analysis Inner-Attention mechanism as we witnessed a large performance increase after employing it. We hand-picked several examples from the dataset to visualize. In order to make the weights more discriminated, we didn’t use a uniform colour atla cross sentences. That is, each sentence have its own color atla, the lightest color and the darkest color denoted the smallest attention weight the biggest value within the sentence, respectively. Visualizations of Inner-Attention on these examples are depicted in Figure 2.

![Figure 2: Inner-Attention Visualizations.](image)

We observed that more attention was given to Nones, Verbs and Adjectives. This conform to our experience that these words are more semantic richer than function words. While mean pooling regarded each word of equal importance, the attention mechanism helps re-weight words according to their importance. And more focused and accurate sentence representations were generated based on produced attention vectors.

### 4 Conclusion and Future work

In this paper, we proposed a bidirectional LSTM-based model with Inner-Attention to solve the RTE problem. We come up with an idea to utilize attention mechanism within sentence which can teach itself to attend words without the information from another one. The Inner-Attention mechanism helps produce more accurate sentence representa-
tions through attention vectors. In addition, the simple effective diversing input strategy introduced by us further boosts our results. And this model can be easily adapted to other sentence-matching models. Our future work including:

1. Employ this architecture on other sentence-matching tasks such as Question Answer, Paraphrase and Sentence Text Similarity etc.
2. Try more heuristics matching methods to make full use of the sentence vectors.

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