Syntax-aware Natural Language Inference with Graph Matching Network

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***Abstract*—The task of entailment judgment aims to determine whether a hypothesis is true (entailment), false (contradiction), or undetermined (neutral) given a premise. While previous methods strike successful in several benchmarks and even exceed the human baseline, recent researches show that it remains arguable if the methods learn statistical bias in the datasets. In this paper, we propose the syntax-aware NLI (SynNLI) model, which utilizes graph matching networks to obtain syntax-guided contextualized representation while aligning the premise and hypothesis accordingly. We show that the proposed method outperforms multiple baseline models on MNLI develop set, and visualize the model internal behavior.**

***Index Terms*—graph neural networks, recognize textual entailment, natural language inference, dependency tree**

I. Introduction

Entailment judgment is arguably one of the most fundamental language understanding tasks. It aims to determine inferential relationship (i.e., entailment, contradiction, or neutral) between a premise and a hypothesis. The task is considered an important mission in natural language understanding (NLU) because of the wide range of downstream applications such as question answering, and the ability for testing the understanding of natural language. With the release of large datasets like SNLI [1] and MultiNLI [2], many neural network approaches have been proposed in recent years. Many works [3]–[12] adopt complex neural architectures that decompose the task into subtasks (e.g., encoding, matching, etc.), and most of them adopt attention-based matching as a part of their modules. However, previous approaches fail to generate a precise token alignment among premises and hypotheses. The strategies they adopt to improve alignment accuracy are primarily generating better token representations; however, humans conduct alignment not only base on word sense similarity but also base on structure analogy [13]. For example, consider the premise and hypothesis pair "Allen travels from America to China" and "Allen travels from China to America", a human can easily tell that this is a contradiction, but according to our probing experiments, both Decomp-Att [3] and RoBERTa [14] give entailment predictions. A similar probing shows that current models struggle to handle negation when there is high lexical overlap as well, for example: "Alice does not like to eat pizza. Chris likes to eat pizza. Bob likes to eat pizza" and "Alice likes to eat pizza. Chris likes to eat pizza. Bob likes to eat pizza". To address the above-mentioned limitation, we explore the possibilities to utilize heterogeneous graph matching networks, which consider both structure analogy and word sense similarity, to encode and align premise and hypothesis. To the best of our knowledge, this is the first work of introducing graph matching methods to the task of entailment.

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Our contributions are 4-fold:

- We propose a novel model utilizing graph matching networks for the task of entailment judgment.
- Experimental results show that our model outperforms several baseline models.
- We visualize the model internals and provide interpretations.
- Through the experiments, we point out the remaining problems for future study.

II. Related Work

Natural language inference has been studied for many years. Early approaches focused on rule-based or statistical methods using hand-craft features [15].

With the release of large annotated corpora [1], [2], a lot of deep learning methods are proposed. We divide previous works into classes: sentence encoding based, sentence matching based, knowledge incorporation, representation improvement, etc. based on their architectures or how they improve.

Sentence encoding based methods [9]–[12], [16] adopt Siamese architecture [17] that maps each sentence into a vector space and do comparison afterwards.

Sentence matching based methods [3]–[8] consider cross sentence information and often outperform sentence encoding based models. This shows that lower-level interaction between sentence pairs is indispensable, and motivates us to adopt graph matching network [18] on the task of NLI.

External knowledge plays an important role in NLI. In recent years, works that try to incorporate organized knowledge bases (e.g., knowledge graphs (KG)) [19]–[23] are proposed. They insert external knowledge at different levels. KGA-Net

[22] concatenates word embedding with knowledge embedding. KIM [19] improves ESIM by modifying the attention mechanism to take KG into account. KCI-TEN [20], ConseqNet [21], and KES [23] tries to improve the performance of NLI models by providing knowledge background to the classifier.

In 2018, the pretrained transformer masked language model known as BERT [24] stroke successful in various fields of NLP, including NLI. Under the hood it utilizes intense self and cross multi-head attention along with the transformer block structure to achieve the amazing results.

There are many attempts to improve BERT [14], [25]–[29], some of them focus on the pretraining or training step of the transformer encoder. For example, RoBERTa [14] enlarges the corpora and batch size and achieved state-of-the-art on the GLUE benchmark [30] for natural language understanding, MT-DNN [28] presents that multi-task learning with shared parameters can boost the performance of the model on the end tasks, and T5 [29] converts all text-based language problems into a text-to-text format and uses them to train a universal encoder-decoder model.

Despite the high accuracy the models achieved, analyses [31]–[37] show that current NLI models tend to learn surface features, adopt false heuristics [38], and are vulnerable to adversarial attacks [39]. Also, the computational resource required to pretrain masked language models with a huge parameter size is inaccessible to the general public.

Recent researches show that graph neural networks [40]–[42] are successful in modeling graph-structured data. And there are works [43]–[46] taking graph neural networks to various domains of NLP.

In this work, inspired by the success of sentence matching models and graph neural networks, we explore the possibilities to apply graph matching networks to NLI.

III. Method

The proposed model is composed of 4 layers: (1) input layer, (2) contextualized embedding layer, (3) syntax enhance matching layer, and (4) output layer. In the following sections, we will describe the architecture layer by layer. Fig. 1 illustrates a high-level view of SynNLI.

A. Input Layer

Our model accepts two sentences and their dependency graphs as input, i.e., P (premise), G_p and H (hypothesis), G_h, in which the G_p and G_h are generated by an open-source dependency parser provided by Stanza [47]. The Stanza parser tokenizes the input text and decomposes the document into sentences, where each sentence is a dependency tree with tokens in the sentence. To introduce a constituent prior that nearby words tend to relate to each other, we connect the adjacent word pairs by adding special "const:next" and "const:prev" edges between them. An example is shown in Fig. 2.

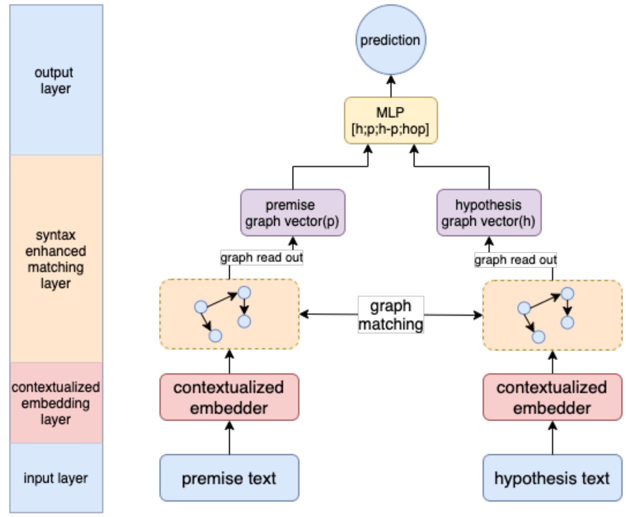


Fig. 1. Overall model architecture. Input hypothesis and premise first get their contextualized word embeddings by a contextualized embedder and is applied with a heterogeneous graph matching network to get graph embeddings of the premise graph and hypothesis graph. Then an MLP makes the final judgment by the two graph embedding vectors.

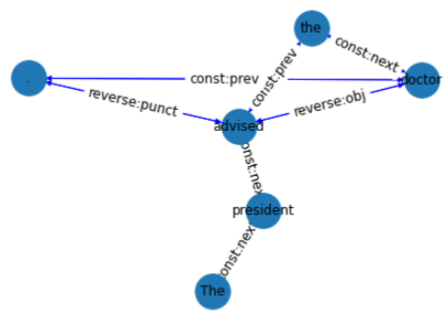


Fig. 2. An example of the input dependency graph.

B. Contextualized Embedding Layer

This layer aims to learn a d-dimensional contextualized word representation for each token (tokenized by the dependency parser) in P and H. We use ELMO [48] as the contextualized embedder. The outputs of the layer are two sequences of d-dimensional vectors $w_h, w_p \in \mathbb{R}^{d\times n}, \mathbb{R}^{d\times m}$, where n, m are the sequence length of hypothesis and premise respectively.

C. Syntax Enhance Matching Layer

In the syntax enhance matching layer, we view each token in premise and hypothesis as a node in the dependency graphs. Then we strengthen the syntactic knowledge of representation by updating each node's representation with its neighbors. At the same time, we do cross attention at each layer to obtain cross-sentence information in various granularity [18]. Finally, a graph readout is performed to aggregate the information from P and G to two fix-sized vectors.

More formally, the output of previous layer are tensors $w_h, w_p \in \mathbb{R}^{d\times n}, \mathbb{R}^{d\times m}$. They pass through L layers of graph matching network similar to [18], which is explained in the following sections.

1) Graph Matching Net: Let $h_i^{(l)} \in \mathbb{R}^{d\times 1}$ be the representation of node i in the l-th layer of the graph network. We have the input in this layer $h^0 = w_p, w_h$, and the last layer is h^L, which is then aggregated to fix-sized vectors g_p, g_h as the output of this layer.

For all $l \in \{0, 1, ..., L-1\}$, h^{l+1} is obtained by the following equations, (4) from h^l, where each node i in the graphs is updated with messages from its neighbors ($m_{j\to i}$) and matched to all the nodes in the other graph ($\mu_{j\to i}$).

$$m_{j\to i} = f_{message}(h_i^l, h_j^l, \phi(i), \phi(j), \tau(e_{i,j})) \tag{1}$$

$$\mu_{j\to i} = f_{match}(h_i^l, h_j^l)\ \forall i \in G_p, j \in G_h \tag{2}$$

$$h_i^{l+1} = f_{node}(h_i^l, \sum_{j\in N(i)} m_{j\to i}, \sum_{j'\in G'} \mu_{j'\to i}) \tag{3}$$

$$g = f_G(\{h_i^L | \forall i \in G\}) \tag{4}$$

Here ϕ, τ are mapping from id to type for nodes and edges respectively, note that we model the dependencies as directed graphs, i.e. $\tau(e_{u,v}) \neq \tau(e_{v,u})$.

We now discuss the choice of functions in the proposed model.

2) Message Passing: To model different dependency relations, we adopt relational graph convolution network [49].

$$m_{j\to i} = \mathbf{\Theta}_{\tau(e_{i,j})} \cdot h_j \tag{5}$$

where $\mathbf{\Theta}_{\tau(e_{i,j})}$ is trainable parameter.

3) Graph Matching: An attention-based matching is applied to get cross sentence information from the other graph. Intuitively, $\sum \mu_{j\to i}$ measures the difference between h_i and its closest neighbor in the other graph.

$$\mu_{j\to i} = a_{j\to i}(h_i - h_j) \tag{6}$$

$$a_{j\to i} = \text{softmax}_j(s(h_i, h_j)) \tag{7}$$

In (7), s is a similarity function. We choose cosine similarity for the proposed model.

4) Node update: To update the representation from the aggregated message from graph message passing and graph matching, we have:

$$f_{node} = \text{GRU} \tag{8}$$

5) Graph Readout: Then we readout the graph embeddings for G_P and G_H using the aggregation module proposed in [50],

$$g_p = \text{MLP}_G\left(\sum_{v\in G_p} \sigma(\text{MLP}_{gate}(h_v^L)) \odot \text{MLP}_{value}(h_v^L)\right) \tag{9}$$

$$g_h = \text{MLP}_G\left(\sum_{v\in G_h} \sigma(\text{MLP}_{gate}(h_v^L)) \odot \text{MLP}_{value}(h_v^L)\right) \tag{10}$$

where MLP denotes multilayer perceptron.

D. Output Layer

With the graph embeddings g_p and g_h we can get the final prediction by the vector comparisons and a feed forward network.

$$y = \text{MLP}(w_{[CLS]}; g_p; g_h; g_p - g_h; g_p \odot g_h) \tag{11}$$

IV. Experiments

A. Data

To show the effectiveness of the proposed model, we evaluate on the MultiNLI dataset [2] and HANS dataset [38].

1) MultiNLI: The Multi-Genre Natural Language Inference (MultiNLI) corpus is a crowd-sourced collection of 433k sentence pairs annotated with textual entailment information. The corpus is similar to the SNLI [1] corpus, but it covers a wider range of genres of spoken and written text, and supports cross-genre generalization evaluation. MultiNLI has become a popular choice for evaluating the performance of NLI models since its release.

2) HANS: While MultiNLI being one of the default choices for evaluating the performance of NLI models, recent researches ([32], [33], [38]) show that models trained on MultiNLI are lack of compositional knowledge of the language. In [38], the authors developed the Heuristic Analysis for NLI Systems (HANS) dataset to determine whether statistical NLI models adopt fallible syntactic heuristics: the lexical overlap heuristic, the subsequence heuristic, and the constituent heuristic. The dataset is adopted to test whether the proposed model adopts the same untrue heuristics.

B. Implementation Details

We use Pytorch [51], AllenNLP [52], and Pytorch Geometric [53] in our model implementation. The source code is available at https://github.com/EazyReal/2020-IIS-internship.

Since the dimension of the graph matching network is set to 300 in the experiment, to make compatible the output of the contextualized embedder and the input of the graph matching network, we use a simple linear projection layer. The number of layers L is set to 3.

We explored some different choices of modules, including BiMPM with 10 perspectives [8] for graph matching and

CGConv [54] for message passing, but no substantial improvement is observed.

We train our model on MultiNLI [2] dataset for 8 epochs with an AdamW optimizer provided in [55]. The learning rate is set to 0.0005 and the weight decay is set to 0.01.

C. Results

1) MultiNLI: The performance comparison (accuracy) on MultiNLI dataset [2] is shown in Tab. I. Since pretrained transformer models [14], [24]–[27] have an enormous amount of parameters and are thus computational expensive in terms of both memory and training/evaluation time, we do not adopt them as baseline models in this paper. We show that our proposed method outperforms multiple baseline models.

TABLE I
PERFORMANCE COMPARISON (ACCURACY) ON MULTINLI.

Model/Accuracy Model	**MultiNLI**	
	Matched	***Mismatched***
Majority	36.5	35.6
CBOW*	64.8	64.5
BiLSTM*	66.9	66.9
Di-SAN [10]	71.0	71.4
Gated Att BiLSTM# [9]	73.2	73.6
HBMP [12]	73.7	73.0
ESIM† [4]	76.8	75.8
KIM(ESIM+WordNet) [19]	77.2	76.4
SynNLI(proposed)	77.4	77.5
BERT base [24]	84.6	83.4

[a] If not specified, the accuracy is reported by the original paper. Models with *, †, # are reported from [2], [7], [19] respectively.

2) HANS: The performance comparison on HANS [38] dataset (models trained on MultiNLI) is shown in Tab. II. While adopting strong inductive bias by propagating information alone dependencies in the proposed model, the experiment result shows that our model still performs poorly on the HANS development set. However, when we trained the proposed model on the HANS training set, the validation accuracy is close to 100%, emphasizing the weakness of MultiNLI [2] training data revealed in related studies [32], [33], [38].

TABLE II
PERFORMANCE COMPARISON (ACCURACY) ON HANS DATASET.THE NEUTRAL AND CONTRADICTION LABELS ARE MERGED INTO A SINGLE LABEL, NON-ENTAILMENT. THE ACCURACY EXCEPT FOR THE PROPOSED MODEL IS REPORTED BY THE ORIGINAL PAPER [38].

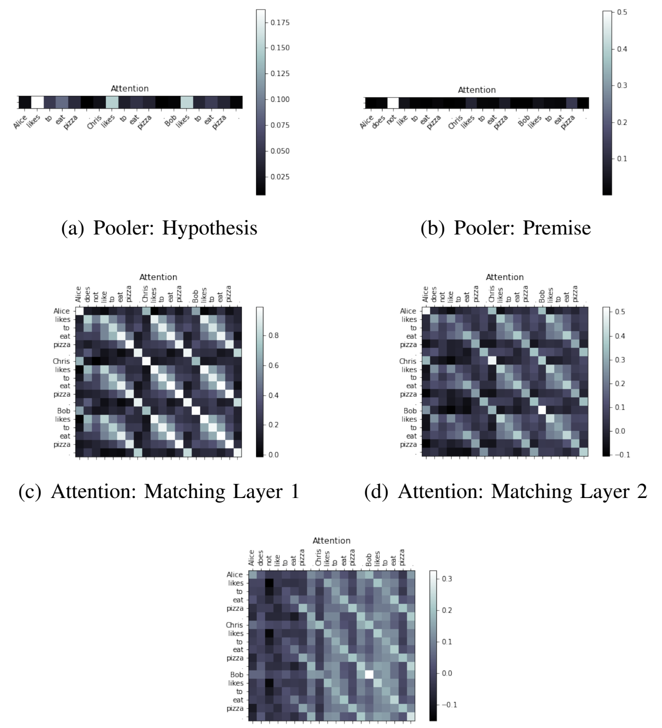
Model	**Correct: Entailment**			**Correct: Non-entailment**		
	Lexical	***Subseq.***	***Const.***	***Lexical***	***Subseq.***	***Const.***
Decomp-Att [3]	1.00	1.00	0.98	0.00	0.00	0.03
ESIM [4]	0.99	1.00	1.00	0.00	0.01	0.00
SPINN [11]	0.94	0.96	0.93	0.06	0.14	0.11
BERT [24]	0.98	1.00	0.99	0.04	0.02	0.20
Proposed	0.97	0.99	0.98	0.02	0.06	0.03

D. Model Interpretation by Attention Visualization

To provide an interpretation of the proposed model, we visualize the attention in the graph readout layers and the graph matching components. The result is shown in Fig. 3 and Fig. 4.

In Fig. 3, we can see by the attention score in the last matching layer that the representation of ”like” in the subsequence ”Alice does not like...” is different from the one in the subsequence ”Alice likes...”. We can also see that poolers (i.e. graph readout module) view ”not” and ”like” as important words.

For Fig. 4, in the first layer, our model match ”China” to ”China”, ”America” to ”America”; however, after message passing, the similarity between the ”China”s and the ”America”s in the sentence pair is lower since they have different roles in their dependency trees.



(a) Pooler: Hypothesis (b) Pooler: Premise

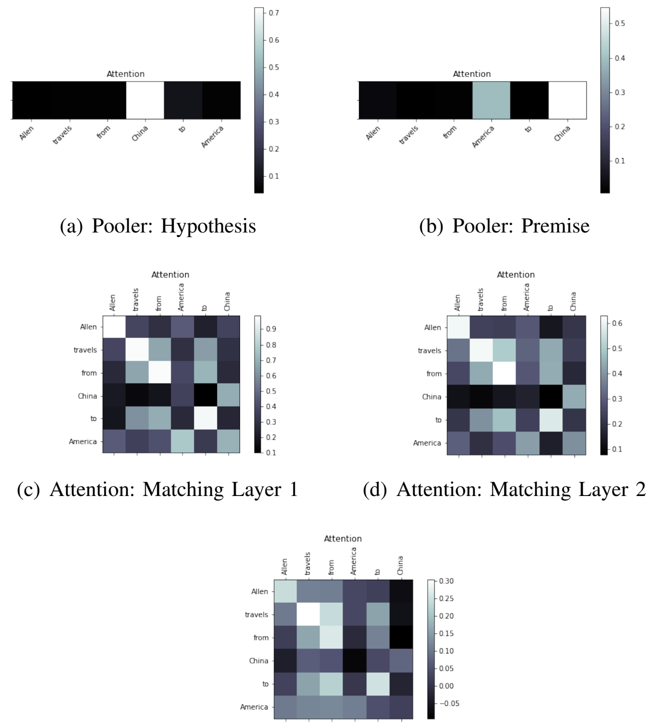
(c) Attention: Matching Layer 1 (d) Attention: Matching Layer 2

(e) Attention: Matching Layer 3

Fig. 3. An example of the proposed model solving a long sequence with partial negation instance that RoBERTa [14] fails. The premise is ”Alice does not like to eat pizza. Chris likes to eat pizza. Bob likes to eat pizza”, the hypothesis is ”Alice likes to eat pizza. Chris likes to eat pizza. Bob likes to eat pizza”, and the gold label is ”contradiction”.

V. CONCLUSION

In this work, we propose the syntax-aware NLI (SynNLI) model. Different from previous NLI models, we utilize graph matching network and view tokens as nodes and do encoding and matching according to dependency relations. We evaluated our model on the MultiNLI and the HANS datasets. Experimental results show that our model achieves competitive results and outperforms several baselines on MultiNLI. We



(a) Pooler: Hypothesis

(b) Pooler: Premise

(c) Attention: Matching Layer 1

(d) Attention: Matching Layer 2

(e) Attention: Matching Layer 3

Fig. 4. An example of the proposed model solving a lexical swap instance. The premise is ”Allen travels from America to China”, the hypothesis is ”Allen travels from China to America”, and the gold label is ”contradiction”.

also provide visualizations of the model internals for interpretation. However, though adopting strong inductive bias by propagating messages alone dependencies, the proposed model still fails to generalize to the HANS dataset when trained on MultiNLI corpora, calling for the need for quality datasets for NLP research.

VI. Future directions

- Due to the limited time, we did not do a thorough parameter search for the proposed method. Different hyperparameters and model settings (e.g., message passing module, graph matching module, dimensions, number of layers) can be explored for better performance.
- The experiment result on HANS emphasizes the need for quality datasets for NLP research.
- We would like to discuss the feasibility of a variant of graph matching network for NLP, which generates embeddings that are purely dependent on the structural information of nodes, without considering word sense. This can be achieved by using POS or SRL embeddings for nodes, dependency relation embeddings, and crystal graph convolution [54]. And we can use the similarity between the embeddings to gate the cross attention between tokens in different sentences.

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