CSE 517: Project Proposal

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Abstract

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1 Introduction

Natural language inference (NLI) is the task of characterizing entailment and contradiction relationships between texts. We seek to improve NLI models by adding syntactic features into existing models. The well-known decomposable attention (DA) neural network (Parikh et al., 2016) obtained state of the art results on the SNLI (Bowman et al., 2015) dataset at its time of publication while using drastically fewer parameters than previous NLI models.

We intend to extend this model and evaluate it on SNLI, MultiNLI (Williams et al., 2017), the SNLI and MultiNLI hard splits (Gururangan et al., 2018), and smaller domain specific datasets like Scitail (Khot et al., 2018).

2 Previous Work

Our project will build on previous work done by Pang et al. (2018).

In previous work, we created the syntail-v1 model whose architecture is shown in figure 1. We have obtained mixed results as shown in table 1 when naively incorporating syntactic information into the DA model.

Wihthout ELMo, syntail-v1 improves an impressive 8.4% in test accuracy over the baseline decomposable attention model on the SciTail dataset. However, once ELMo is added to the model, almost the exact happens. Adding syntactic information decreases test accuracy by 6.7%.

3 Proposed Methods

We plan to use state-of-the-art constituency (Stern et al., 2017) and dependency (Dozat and Manning, 2016) parsers to investigate if incorporating syntactic features improves the performance of the decomposable attention network. Additionally, we hope to understand how syntactic features interact with contextual word embeddings like ELMo (Peters et al., 2018) and BERT (Devlin et al., 2018) in a task like NLI.

We will first investigate different ways of incorporating syntactic information. Pang et al. (2018) use a constituency parser to obtain an encoding of the premise and hypothesis that is used when characterizing their relationship. We believe that incorporating syntactic features earlier in the pipeline, especially before the premise and hypothesis are attended over one another, should improve performance.

We will then investigate different model architectures under a multi-task training objective where the jointly learns to both parse and predict entailment relationships.

Model	Embedding	Train Acc.	Test Acc.
DA	GLoVe 6b 300d	89.4%	70.1%
Syntail-v1	**GLoVe 6b 300d**	**92.1%**	**78.5%**
DA	**ELMo**	**98.4%**	**78.0%**
Syntail-v1	ELMo	88.8%	71.3%

Table 1: Syntail-v1 and DA model accuracies on the SciTail dataset.

4 Expected Outcomes

We will compare our models to the DA model as well as syntail-v1. We hope to evaluate our models on many diverse datasets as stated in section 3.

We expect that one of our modeling ideas will produce results that improve on the DA and syntail-v1 models. In the best case, we will show that syntax is crucial to building an accurate NLI system.

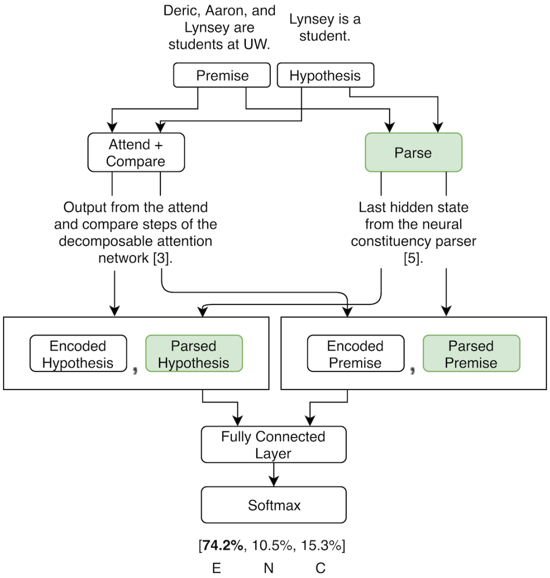

Figure 1: A simple method of incorporating syntax into the decomposable attention model.

5 Challenges

The first challenge involved in our project will be to modify syntail-v1 so that syntactic information is incorporated much earlier. It will also take significant time to investigate the best parsers to use for our model. After, we will write a new model under a multi-task training setup, which we anticipate will be a significant implementation challenge.

We expect to require significant compute power and time to adequately fine-tune and evaluate our models. Contextual word embeddings are especially costly to train, and the mixing ratio in a multi-task setup is well-known to be difficult to tune.

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