NLP Final Report

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1 Introduction

1.1 Problem Statement

A fundamental phenomenon of natural language is the variability of semantic expression, where the same meaning can be expressed by or inferred from different texts. Textual entailment recognition is the task of deciding, given two text fragments, whether the meaning of one text is entailed (can be inferred) from another text. Given two text fragments, one named text (t) and the other named hypothesis (h), respectively. The task consists in recognizing whether the hypothesis can be inferred from the text. Textual entailment has a three-class balanced classification problem over sentence pairs:

- Entailment
- Neutral
- Contradiction

1.2 Datasets

- SNLI: https://nlp.stanford.edu/projects/snli/
  - 530k sentence pairs
  - Stanford had custom sentence pairs manually written out by labelled by humans, that being SNLI.
- MultiNLI: https://cims.nyu.edu/~sbowman/multinli/
  - 433k sentence pairs
  - MultiNLI is a crowd-sourced dataset, which differs from SNLI where it has more cross-genre generalization, and a more varied dataset.

- SciTail: https://allenai.org/data/scitail
    - 27k sentence pairs
    - SciTail was created from science multiple choice quizzes, where each question and correct answer pair is labelled as entailment.
- SICK: https://paperswithcode.com/dataset/sick
    - 10k sentence pairs
    - SICK was created by taking datasets which have sentences that describe particular images, and labelling these descriptions.

1.3 Relevant Readings

https://aclanthology.org/W17-5301/

https://arxiv.org/pdf/1509.06664v1.pdf

https://nlp.stanford.edu/pubs/snli_paper.pdf

In order to begin the project, we had to read up on NLI, understand the basis of textual entailment, and the methods and standard practices that go into this classification task. We looked into papers that did specific implementations using Bowman models and LSTMs. We looked into how the construction of these attention models is usually done in both TensorFlow and PyTorch.

We looked into preprocessing of the data in various ways, such as BERT, RoBERTa, GloVe, and word2vec. We used BERT in our attention model for the mid-semester evaluations but had switched over to Glove for our next two versions of the implementation, and word2vec for our final implementation.

We upgraded from our mid-semester attention model to a Bowman model that uses a simple summation layer. We then replaced the summation layer with LSTMs and got better performance across all models. These LSTMs run in parallel for both premise and hypothesis vectors. However, in our final implementation, we used two sequential LSTMs, the first one inputting the premise vector and outputting its internal states as the initialisation to the next LSTM, which also inputs the hypothesis vectors.

For our larger datasets, the train accuracies have gone up from the mid 70% range to the lower 80% range while our test accuracies are also the same. For our smaller datasets, our train accuracies are in the 90% range while our test accuracies are in the

low 70% range, a sign that the smaller datasets make the model overfit on the training data slightly.

2 Implementation

Model 1: Using a Summation Layer

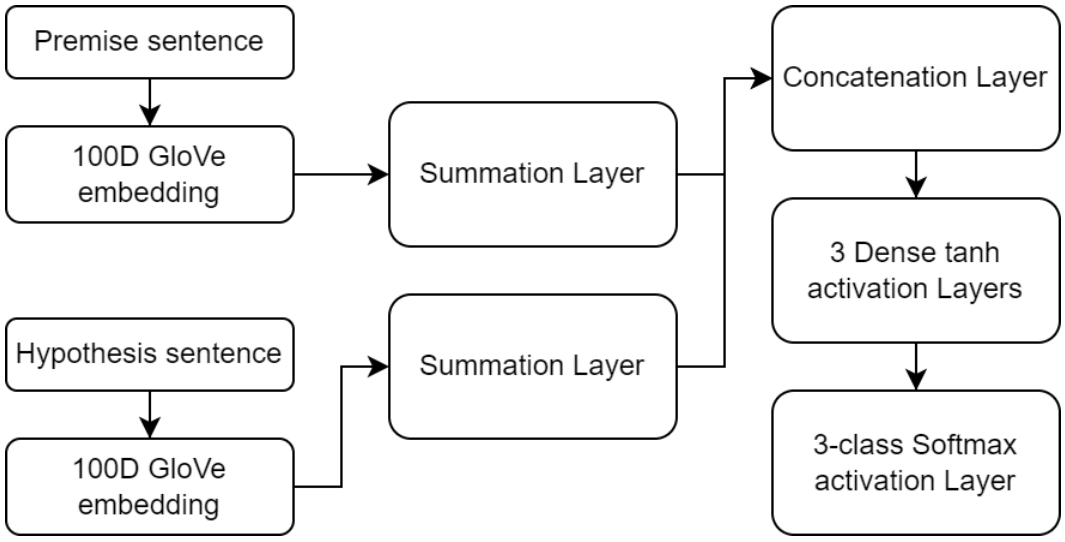
Our first model is a Bowman model using a simple summation layer.

The first component of the model is a word embedding layer that is set to be non trainable. The embedding matrix for this layer is initialized with the 300 dimensional glove embeddings trained on 840 billion tokens. It converts the vocabulary sized input dimension (around 30K) into 300 dimensions.

The update to the model from the previous submission is that previously, 100D glove vectors were directly used. Now, the embedded premise and hypothesis are sent into another layer that projects 300D vectors into a 100 dimensional space, followed by the application of tanh activation.

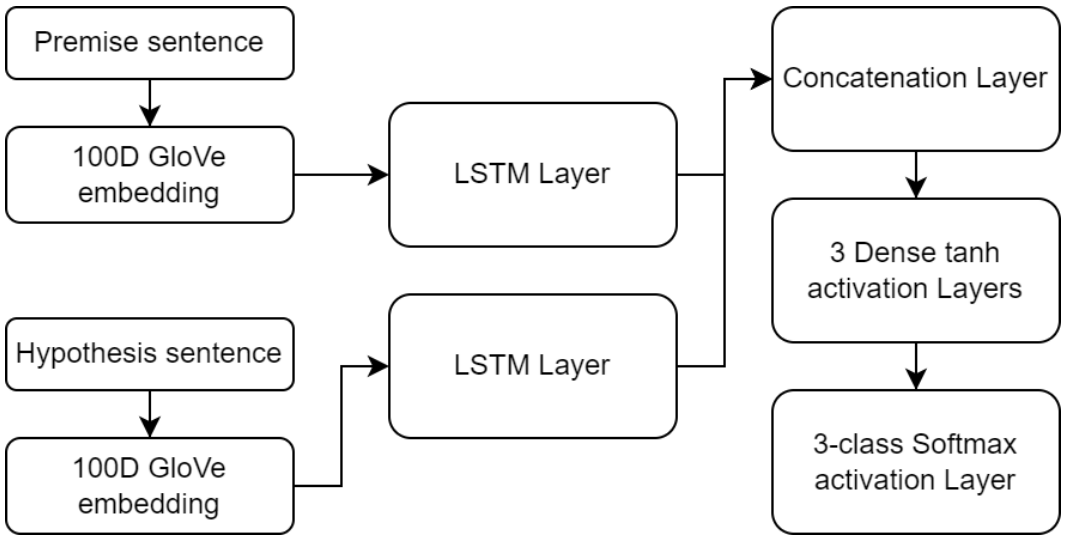
In the case of the simple summation layer, for both the premise and hypothesis the vectors along the sentence axis are summed. That is, maxLen number of tokens are summed to give a single 100 dimensional representation of the premise/hypothesis.

Followed by this is a concatenation layer that simple appends the hypothesis to the premise. A combination of fully connected layers with tanh activation and dropout layers are applied successively, before finally feeding the resultant 200 dimensional vector into a fully connected layer with softmax activation over 3 labels.



Model 2: Using an LSTM

We replace the summation layer from the previous model with an LSTM to make our second model. In this case, both the premise and hypothesis are sent into the LSTM with dropout and recurrent dropout both set to 0.2. Everything else regarding the model remains the same.



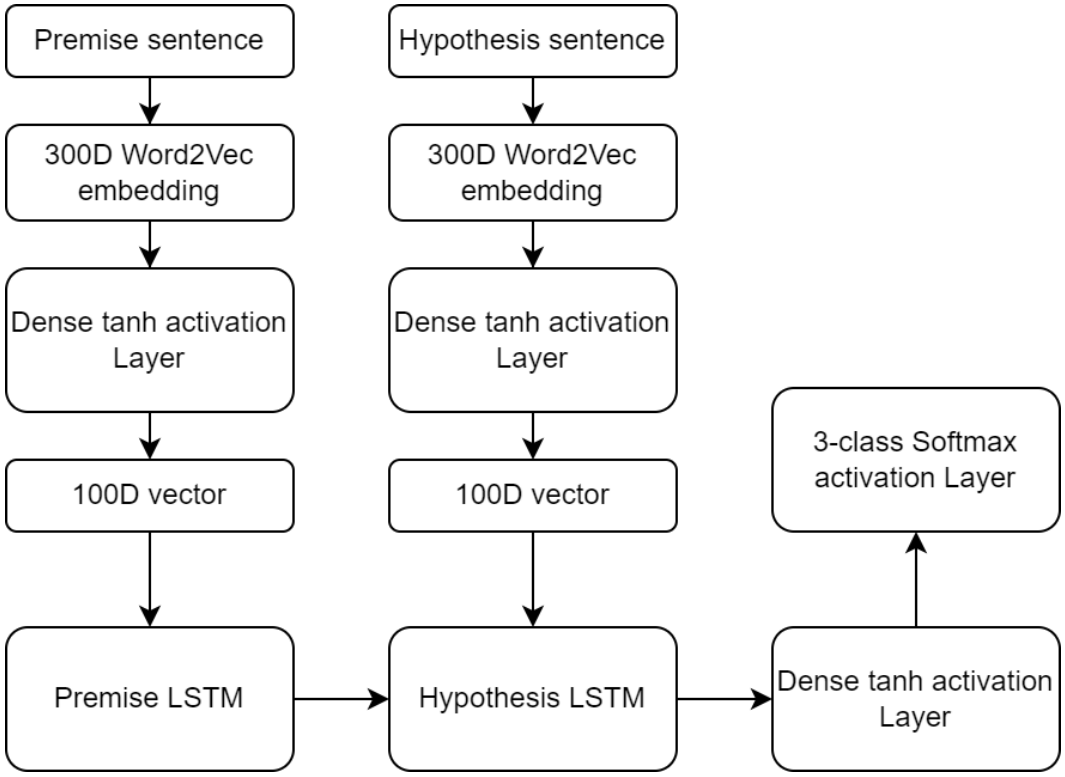
Model 3: Using two LSTMS

In our final model, we utilise two LSTMs as well as word2vec instead of glove.

The first component of the model is a word embedding layer that is set to be non trainable. The embedding matrix for this layer is initialized with the 300D word2vec vectors trained on Google News. It converts the vocabulary sized input dimension (around 30K) into 300 dimensions.

The embedded versions of the premise and hypothesis are then sent into a fully connected layer activated by the tanh function, to convert the 300-dimensional representations into 100 dimensions.

The first LSTM in this model is for premise and the second is for hypothesis. The one for the premise is set to return its final internal states. These states are then used to initialize the second LSTM - this is an attempt to make the hypothesis' LSTM be aware of the context given by the premise. Unlike the previous models, there is no concatenation here; the final 100 dimensional representation of the hypothesis is fed into a fully connected layer of tanh activation, followed by another fully connected layer with softmax activation over three output labels.



3 Conclusion

3.1 Results

- Summation Model:

Accuracy	Training	Validation	Test
SNLI	74%	77%	76%
MultiNLI	65.39%	67.23%	65.74%
SciTail	87.88%	70.68%	71.62%
SICK	88.21%	70.84%	70.49%

- LSTM Model:

Accuracy	Training	Validation	Test
SNLI	75.8%	78.21%	77.3%
MultiNLI	67.41%	65.98%	65.76%
SciTail	83.77%	72.83%	74.58%
SICK	95.66%	73.14%	72.65%

- Two LSTMs Model:

Accuracy	Training	Validation	Test
SNLI	81%	80%	80.13%
MultiNLI	70.29%	68.65%	67.47%
SciTail	97.97%	70.53%	74.58%
SICK	98.60%	58.79%	60.57%

- Test accuracies across models:

Model	Summation	LSTM	2LSTM
SNLI	76%	77.3%	80.13%
MultiNLI	65.74%	65.76%	67.47%

Model	Summation	LSTM	2LSTM
SciTail	71.62%	74.58%	74.58%
SICK	70.49%	72.65%	60.57%

3.2 Limitations

- Currently, it is obvious to us that models are more likely to overfit in smaller datasets. This can be seen in the case of SciTail and especially SICK, where models such as 2LSTM require more data to be feasible for classification.
- MultiNLI is a dataset
- Due to the extensive training time, and the large number of models, better hyperparameter optimization of the models can be done.