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Sprint 6 Results

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# Sprint Goal

## Optimize Neural Nets and the Train Function:

* Implement stratified k-fold cross validation to choose train and validation datasets for neural network model
* Add more layers into the neural nets **on track**
* Try to fine tune RoBERTa **on track**

## Feature Engineering and Label Model Optimization:

* This week, we will try to utilize roBERTa or other python packages to perform Entity Recognition **on track**
* Complete an error analysis of the BabbleLabble implementation for future use

# Results

1. Babblelabble example:

This week we have successfully run our BabbleLabble and create a set of labeling functions using natural language format. We first constructed the required data format for BabbleLabble, which is the RelationMention object. We have been struggling in this part for previous weeks, and we solved it by using functions to automatically analyze the pos\_tags of the sentences and generate matching ner\_tags and entities by ourselves. Now we are able to write basic labeling functions like “if there are any specific words in the sentence or between two entities”.

1. RoBERTa Encoding Transformation

We have looked into Attention Vector to reduce the dimension of the results of RoBERTA, but we’ve been struggling to find the right way to do it. Normally it is used in an encoder-decoder structure for machine translation.

We also found that RoBERTA can be directly used for classification, and started to try it.

Besides, we tried Matthews Correlation Coefficient to measure the performance of the model. (Matthews Correlation Coefficient is a good measure for evaluating unbalanced datasets.)

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| Metrics/Models | Baseline Model | Noisy Model | New features + 1 LSTM layer | New features + 2 LSTM layers | New features + 2 GRU layers |
| F1 Score | 0.509 | 0.4 | 0.377 | 0.383 | 0.385 |
| Accuracy | 0.58 | 0.63 | 0.606 | 0.62 | 0.602 |
| ROC AUC Score | 0.525 | 0.51 | 0.484 | 0.495 | 0.483 |
| Matthews Correlation Coefficient |  | 0.0165 |  |  |  |