Explainable Neual Approaches to Question Classification

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1 PROPOSAL

In this project we will focus on the task of question classification. With the provided dataset[1], the goal is to predict the label for any given question from 6 coarse classes (disregarding more fine-grained attributes). Since the dataset is unbalanced for some classes, prior preprocessing efforts such as down-sampling are required. The features we use will be at word-level, namely pre-trained word-embeddings (e.g. word2vec [6]). For model selections, we will adopt the FastText [4] model as the baseline for comparison, then further utilize deep learning techiques with the LSTM [2, 3] and TextCNN [5] models. Once implemented, some hyperparameter tunning will be performed and the three models will be evaluated with respect to their precision, recall and F1-score values, which are common metrics for the task [1, 7].

In sake of better interpretability of the models, an unsupervised component is planned to be added to one or both of our neural models, which for the text classification task, is a layer of binary latent variables that select what parts of the input expose features for final prediction. Detailed realization of this step is still under discussion, and will be decided later.

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