COMP-551 Final Project

T1-10: Distributed Representations of Sentences and Documents

Team: Linear Kernel Mustard

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I. Objective

For this project, we were tasked with recreating the baselines reported in the paper "Distributed Representations of Sentences and Documents" (Le & Mikolov, 2016). Our objective was two-fold: first we aimed to achieve the same basline performances as the paper, then if possible, to tune those baselines further, achieving more competitive performance. Though we anticipated that we would be able to beat the reported baselines, we did not have much expectation that we would outperform the main model of the paper, the Paragraph Vector model.

II. Methodology

Our methodology for this project was divided into several distinct phases. First, we applied some pre-requisite processing to the data set. Then, we implemented the simpler linear models that were reported in the paper. After this, we applied further tuning to these models, to optimize the performance wherever possible. We then explored alternative linear models, to see if any could outperform those chosen by the paper's authors. Finally, we explored the performance of the other, more complex models like word vector averaging and neural networks, though these were not intended to be the focus of our efforts.

A. Data Pre-processing

The pre-processing and feature selection composed a non-negligible part of our methodology, so we will cover the steps taken to process the raw data sets.

1) Manual Data Cleaning: In the first place, the sentence files provided in the Stanford sentiment analysis data set were encoded in Latin-1. Since our code would benefit from having a consistent encoding standard throughout the development process, we needed to handle these files with the UTF-8 encoding standard. This resulted in parts of the file being inconsistently encoded, with mojibake appearing occasionally throughout our dataset, which proved troublesome for Python's default IO implementation. Consequently, the first step of our data pre-processing involved cleaning the sentence file by replacing all Latin-1 encoded characters with their corresponding unicode equivalent.

Furthermore, the Stanford sentiment analysis data set is formatted with the intention of being used for syntax parsing models, as the sentences are structured in a tree-like format, and their corresponding sentiments are stored across several files. For our application, we wanted to handle the full text of each sentence, so we wrote the code necessary to convert the tree-like structure into simple "sentence-sentiment" pairs.

2) Vectorization: Once we had our data loaded in the proper format, we needed to extract the features from each sentence to create vectors for our models. The simplest representation would be bag-of-words, so we started with that, using sklearn's built in CountVectorizer.

However, we felt that just using bag-of-words wouldn't accurately capture the semantic similarity between inflected words (e.g. "film" and "films"), so we replaced CountVectorizer's built-in tokenizer with a tokenizer that tagged the parts of speech for each word and retrieved that word's lemma from the WordNet database. To do so, we took advantage of several features built into the nltk package. We also used a CountVectorizer that included both unigrams and bigrams (for our Bigram Naive Bayes implementation), which used the same tokenization scheme. For the Stanford dataset, word embedding vectors for the Word Vector Averaging model were obtained using the gensim module's word2vec library. The word embedding vectors were averaged into a single vector for each review, and the word2vec model hyperparameters were cross validated. The methods used to cross validate the hyperparameters are expanded on in the Word Vector Averaging section.

Similar to the paper under consideration, we labelled each sentence in the Stanford sentiment analysis dataset based on its sentiment score (using the labels Very Negative, Negative, Neutral, Positive, and Very Positive). We likewise created a set with coarser label classifications (with labels Negative and Positive), ignoring all neutral data points for our coarse-grain performance evaluations by using filtered datasets only containing reviews with score labels less than 0.4 and greater than 0.6. The sentences in the Stanford treebank were split into train (8544), dev (1101) and test splits (2210). The neutral-filtered datasets contain around 20% less data, with the three sets having 6920/872/1821 sentences.

The IMDB data set was vectorized in a similar way, but

since it used a binary label approach, we didn't need to make any modifications to the labels.

B. Simple Linear Models

For the simple linear model methodology, there is little to discuss that hasn't already been covered by the paper under consideration, but we will summarize the main points of each.

1) Naive Bayes:

2) Linear SVM:

3) Bigram Naive Bayes:

C. Improving Linear Models

1) Naive Bayes:

2) Linear SVM:

D. Alternative Simple Models

For each of the alternative simple models we tested, we used the default sklearn implementations. We will briefly touch upon our rationale for choosing these models, as well as the hyperparameters we tested, and what effect we anticipated they would have on the model's performance.

1) Random Forests: Sentiment analysis with bag-of-words can be ultimately thought of as an entropy based task. Since certain words are significantly more positive or negative than others, the use of these words is liable to heavily influence the overall sentiment of that review. Other words are only somewhat charged, so they will have only a mild influence on the overall sentiment.

Because of these facts, decision trees seem to be an excellent candidate for sentiment analysis. However, decision trees come with non-negligible downsides, not least of which are the long training times and the risk of overfitting.

The Random Forest classifier serves as an excellent compromise to these problems. The classifier creates multiple small trees based on random subsets of the features, so the training time is kept low overall, since no single tree is too deep and not as much consideration needs to be given to features that have low overall impact on the impurity.

For hyperparameters, we experimented with the maximum depth of each tree, the criterion used for deciding the split at each level of the tree, and the number of trees in the forest.

The impact of the maximum depth is easily understandable: if there are many words in our vocabulary with high entropy, then allowing our trees to use more of those words will create a more accurate ensemble of trees.

The number of trees in the forest has a similar rationale. Since results are averaged from the results of the trees, having more trees can reduce misclassifications that are caused by the random feature selection.

We didn't expect to see much variance in performance by changing the split criterion, since entropy and gini impurity are known to perform similarly well. We had expected entropy to perform slightly better, since entropy is more commonly used for classification into discrete classes. Nevertheless, there are only two criteria to choose between, so we felt as though it was worth considering in the event that our hypothesis was incorrect.

2) Logistic Regression: Logistic Regression, similar to Random Forests, attempts to identify "explanatory variables" that have an impact on determining the classification of a given vector, and it then fits a logarithmic distribution to that data.

In effect, since we anticipated that certain words would have a high impact on determining class, the Logistic Regression would be able to prioritize certain features in determining overall sentiment. We thought as well that it might perform even better than the Random Forests, since the Random Forests only indirectly prioritize important features through chance repitition. Since we have so few categories, and since our lemmatization approach to vectorization would likely increase the number of events per explanatory variable, we anticipated Logistic Regression to be one of our best performing models.

The hyperparameters we experimented with were the norm function used in the penalization, the tolerance for the stopping criteria, and the regularization strength.

The tolerance for stopping only has a real impact when we struggle to further improve our model, so we would expect a low tolerance to perform better, since it would keep training until it finds the optimal value.

The regularization strength determines how much cost we would attribute to increasing the magnitudes of our parameters, which means that lower regularization strength would allow us to better classify data sets without clear delineations between classes, and high regularization strength would reduce overfitting if there are fairly clear delineations between classes. As a result, we anticipated that a higher regularization strength (low C in sklearn) would give better performance for our coarse-grain evaluation models, whereas a lower regularization strength (high C in sklearn) would give better performance for our fine-grain evaluation models.

The norm function for penalization wouldn't have much impact on its own, but when coupled with high regularization strength, we would expect L2 to provide more accurate solutions.

3) K-Nearest Neighbors: K-Nearest Neighbors is notoriously ineffective for problems such as these, since the distance-based metrics used for calculating "nearness" fall apart at high dimensionalities. Nevertheless, the training time is effectively non-existent, and if it performed well, it would have the potential to prove the null hypothesis for the task at hand, so we thought it worthwhile to at least entertain this model.

The hyperparameters we considered were the number of neighbors queried for each testing point and the weight of each neighbor.

Varying the number of neighbors to a certain value k would expect to improve the model's performance if we anticipated data points of any given class to be found in clusters of size k. Changing the weight of the neighbors to scale based on the distance from the testing point would improve the performance of the model if we anticipated points to be found in tight, compact clusters.

Since we couldn't intuit the layout of the vectors in any meaningful way, our approach to tuning these parameters was more or less arbitrary.

E. Complex Models

1) Word Vector Averaging: For sentiment analysis tasks, contextual understanding and tone play a large role in the success of a classifier. The semantics and syntatic information present in the language must be successfully captured in order to more effectively analyze the sentiment expressed by a certain text. Word2vec is a group of shallow two-layer neural network models used to create word embeddings and are used to construct the contextual linguistic information of words. With word2vec, the similarities between words are efficiently captured in the form of word embedding vectors. The word vectors are positioned in the vector space based on the context each word shares with other words in the corpus. In the paper, a baseline model that averages neural word vectors (word2vec) and ignores word order was implemented. As a baseline, we will average the word embedding vectors of each review and then apply a simple Logistic Regression classifier on the averaged vectors. The vectors are averaged to account for variable review lengths. We hypothesized that the Word Vector Averaging method would not be able to perform better than the Neural Network and Paragraph vector methods because the word order information will be lost, similar to the bag of words approaches, and sophisticated language phenomena such as irony, and sarcasm will not be able to be recognized. However, we still believed that the contextual information captured by the word2vec model would still result in a effective classifier and could be further improved by hyperparameter tuning.

For the Stanford dataset, word embedding vectors for the Word Vector Averaging model were obtained using the gensim module's word2vec library. The word embedding vectors were averaged into a single vector for each review, and the word2vec model hyperparameters were cross validated using the default Logistic Regression sklearn classifier on the validation/development dataset vectors in order to obtain the optimal review embeddings. The word2vec model hyperparameters considered were the word vector dimensionality, context window size, number of training epochs, and the minimum word frequency threshold. Varying the values of the vector dimension size, context window size, and number of training epochs will allow for different amounts of contextual information to be captured but can result in higher computational complexity if increased. Generally the values of the hyperparameters should correlate with the general sentence size, as each sentence is treated as an individual document by word2vec. We hypothesized that larger values for these hyperparameters will result in a higher accuracy but with a greater computational cost. Changing the minimum word frequency threshold can help to reduce the noise created by infrequent words, which often do not play a role in helping to classify a sentiment. We hypothesized that the fine-grain model will require a higher minimum frequency threshold, as the noise caused by infrequent words will more negatively affect the classifier due to the increased number of possible label scores.The skip gram and CBOW models were both considered as well. We hypothesized that the skip gram model would generally always result in a higher classification accuracy, but would require a higher computation time, since the model must also weigh nearby context words more heavily than distant context words.

A default Logistic regression classifier was used to evaluate performance of the word2vec models using the development dataset word2vec vectors because of its speed and effective accuracy on binary and multinomial classification problems . After the word2vec model was optimally tuned, the vectors generated from the model are then used as input to a Logistic Regression classifier again. The Logistic Regression hyperparameters are then also hypertuned using the vectors generated from the development dataset and the final model is trained on both the training and development datasets for both the word2vec model and the Linear Regression Classifier before evaluating on the test dataset. Our hypothesized hypertuning results for the Logistic Regression classifier follows the same logic described by the Logistic Regression subsection above.

2) Neural Networks:

III. Results

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IV. Discussion

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V. Conclusion

VI. Statement of Contributions

VII. References