Investigating the Working of Text Classifiers

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Abstract

Text classification is one of the most widely studied task in natural language processing. Recently, larger and larger multilayer neural network models are employed for the task motivated by the principle of compositionality. Almost all of the methods reported use discriminative approaches for the task. Discriminative approaches come with a caveat that if there is no proper capacity control, it might latch on to any signal even though it might not generalize. With use of various state-of-the-art approaches for text classifiers, we want to explore if the models actually learn to compose meaning of the sentences or still just use some key lexicons. To test our hypothesis, we construct datasets where the train and test split have no direct overlap of such lexicons. We study various text classifiers and observe that there is a big performance drop on these datasets. Finally, we show that even simple regularization techniques can improve performance on these datasets.

1 Introduction

Document classification is one of the fundamental tasks in natural language processing (NLP) in which the objective is to categorize documents into one of the predefined classes. This has several applications such as topic classification and sentiment analysis. Document level classification remains a significant challenge: how to encode the intrinsic (semantic or syntactic) relations between sentences in the semantic meaning of document. This is crucial for sentiment classification because relations like "contrast" and "cause" have great influences on determining the meaning and the overall polarity of a document.

Traditionally, for document classification, bag-of-words approach [3] has been used for feature extraction followed by a supervised classification algorithm such as Naive Bayes [13] or Support Vector Machine (SVM) [6]. This simple approach ignores the word order and suffers from data sparsity problem when the size of training set is small.

The next generation of approaches involve neural networks which makes use of the word order information have been shown to outperform bag-of-words approach in document classification tasks [9] [8]. In order to extract sentence level features, Kim [9] applies single-layer Convolutional Neural Network (CNN) [11] on top of word vectors followed by max pooling over time. Johnson and Zhang [8] effectively train a bidirectional Long Short Term Memory (BiLSTM) [5] network with dynamic max pooling to represent a document. The motivation of using these multilayer neural networks taking order of words into account approaches to learn a continuous representation for document classification comes from the principle of compositionality (Frege [2]), which states that the meaning of a longer expression (e.g. a sentence or a document) depends on the meanings of its constituents,

However, we are of the opinion that state-of-the-art document classification techniques (like those listed above) do not actually use this mechanism, despite the motivations. Like any discriminative

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approach which can pick up any signal which might not generalize, it appears these technique still learn and rely heavily on key lexicons and just use these lexicons to classify the document, which might not generalize to new documents.

To test our hypothesis, we first construct datasets where the train and test splits have no direct overlap of such lexicons while taking care of class imbalance, although remaining language structure remains the same. We study the performance of various text classifiers on this new train-test split and compare the results with the commonly used random split of such a dataset. We observe that there is a big performance gap of current approaches on both such splits of a dataset. Finally, we show that even simple regularization techniques of replacing such key lexicons with random embeddings can significantly improve performance on the train-test split where there is no overlap of such keywords. We also provide two large-scale text classification corpus which contains both the random splits and lexicons based split.

2 Dataset Construction

We perform our experiments on three datasets whose details are described below. For each dataset, we construct its random split version (selection of training and test examples is done by random sampling) and lexicons based version. The ratio of test to train examples is kept approximately the same for the random split and lexicons based version of each dataset.

- **ACL IMDB**: This is a popular benchmark dataset [12] of IMDB movie reviews for sentiment analysis in which the task is to determine if a review either belongs to the positive or negative class. The random split version of this dataset contains an equal number of highly positive and negative reviews. To construct its lexicon based version, we apply our approach on the combined train and test sets of this dataset.
- **arXiv abstracts**: In this, the task is to do multiclass topic classification. We construct this dataset by collecting more than 1 million abstracts of scientific papers from "*arXiv*". Each paper has one primary category such as cs.AI, stat.ML, etc. which we use as its class label. We selected those primary categories which have at least 500 papers. In order to extract text data, we use the title and abstract of each paper.
- **IMDB reviews**: This is a much bigger version of the IMDB movie reviews dataset in which the task is to do fine-grained sentiment analysis. We collect more than 2.5 million reviews from IMDB and partition them into five classes[2] based on their ratings out of 10. In both the arXiv abstracts and IMDB reviews dataset, we keep the ratio of test set to train set as 0.6.

An overall summary of train/test splits of lexicon and randomized version for every dataset is provided in Table 1. Below, we provide details of the approach used for the construction of lexicons version of the datasets.

Identification of important label specific lexicons: We extract *tf-idf* weighted, unigram to five-gram word level features and train a multinomial Naive Bayes classifier[3] on the entire dataset. In order to rescale the weights of the features, we divide all feature values by the corresponding minimum value for that feature across all the classes. To identify lexicons, we select the top-k[4] features with maximum weight for every class.
Creation of lexicons-documents graph: For each class, we create an undirected graph in which the nodes are label specific lexicons and documents respectively. We create an edge in the graph if a lexicon occurs in a document. In such a graph, the edges only exist between lexicons and documents and not among each other.
Graph partitioning to generate train/test splits: We compute the number of connected components in the lexicons-documents graph. We identify the connected component with the maximum number of nodes and select all the documents it contains for the training set. The documents contained in all the other connected components are considered for the test set. If the ratio of the number of test to train documents is below a cutoff threshold, we repeat this process with a smaller set of lexicons.[5]

[2] Class labels are: *most-negative*, *negative*, *neutral*, *positive* and *most-positive*.

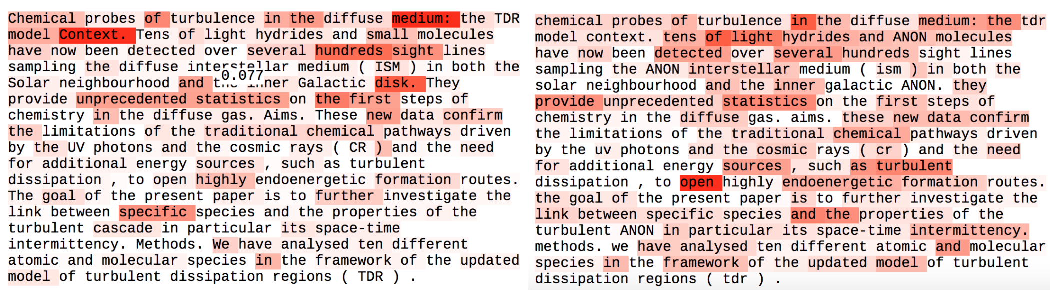
[3] We also experiment with Logistic Regression and SVM classifiers and observe that multinomial Naive Bayes selects the most diverse set of features.

[4] The value of k is 1500 for IMDB reviews dataset and 150 for arXiv abstracts dataset.

[5] We also tried spectral partitioning of this graph but it didn't generate balanced graph partitions in our case.

Table 1: This table shows the dataset summary statistics. c: Number of classes, l: Average length of a sentence, N: Dataset size, $|V|$: Vocabulary size

	arXiv abstracts				**IMDB reviews**				**ACL IMDB**			
	lexicons		random		lexicons		random		lexicons		random	
	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
c	127	127	127	127	5	5	5	5	2	2	2	2
l	162	140	153	153	299	252	278	281	290	254	234	228
N	668K	438K	664K	443K	1.48M	1.07M	1.49M	1.07M	23K	26K	25K	25K
$\|V\|$	297K	238K	301K	244K	590K	509K	601K	505K	75K	78K	75K	74K



(a) without Word Anonymisation **(b)** with Word Anonymisation

Figure 1: This heatmap shows the change in hidden state activations of max pooling BiLSTM encoder when some label specific keywords are anonymised for an example instance from arXiv abstracts dataset whose label is `astro-ph.GA`. In 1a, the trained classifier makes an incorrect prediction as it can be seen that the model is performing a keyword based classification. In 1b with word anonymisation, the attention span also involves other context words and the prediction is correct.

3 Method: Keyword Anonymization and Random Embedding Substitution

While working with various neural network models on both random and lexicons based version of each dataset, we observed that on the lexicons version, the network is easily able to learn the training data distribution and thus the model always overfits on the lexicons dataset. This is evident as the gap between training and test accuracy widens up (Table 2). We see that on the test accuracy difference on ACL IMDB, IMDB reviews and arXiv abstracts dataset is approximately 7%, 15% and 20% respectively. We hypothesize that this happens because the model is able to memorize the commonly occurring label specific keywords. During evaluation, when the model trained on lexicons dataset is not able to spot such keywords in the test data as they are non-overlapping partitions, the performance degrades quite rapidly as compared to the random split version.

In order to prevent the learning of degenerate representations by memorization of keyword specific rules by the model, we introduce more randomness in our training data split [4]. In the first step, we identify some keywords with high scores using a supervised classifier trained on top of bag of words as features. In the second step, we anonymise the corpus by replacing a single word selected at random from the occurrence of such keyword phrases by a placeholder word '`ANON`'. The third step is to assign random word embedding in the embedding layer during model training for every occurrence of the placeholder word '`ANON`' in the dataset.

In this way, we corrupt the information present in keywords by introducing some form of random noise in the data. This is one of the ways to regularize model training. We later show that this regularization forces the network to learn important context specific representations which are useful for text classification during test time.

These modified word embeddings are given as input to either LSTM or BiLSTM network whose hidden states are used to represent a document. In the case of LSTM, we use the final hidden state which is given as input to the classifier layer and for BiLSTM, we concatenate the hidden states of the forward and backward LSTMs followed by max pooling [1]. Training is done by minimizing the average cross entropy loss.

Table 2: This table shows the accuracy of our approach vs other models on randomly sampled dataset and lexicons based dataset. **Naive Bayes**: n-gram feature extraction using tf-idf weighting followed by Naive Bayes Classifier. **Logistic Regression**: n-gram feature extraction using tf-idf weighting followed by Logistic Regression Classifier. **Deep Sets**: Two-layers deep multilayer perceptron on top of word embeddings followed by max pooling over time (Zaheer et al. [18]). **LSTM (final hidden)**: Use of word level LSTM as a document encoder (Sutskever et al. [17]) in which final hidden state is used for classification. **BiLSTM (max pooling)**: Use of word level BiLSTM as a document encoder in which forward LSTM and backward LSTM hidden states are concatenated after max pooling (Conneau et al. [1]). **CNN (max pooling)**: Use of CNN with filters of different strides followed by max pooling over time (Kim [9]). **CNN (dynamic max pooling)**: Use of CNN with filters of different strides followed by dynamic max pooling over time (Johnson and Zhang [7]). **Anon LSTM**: LSTM encoder applied to the anonymised training data. **Anon BiLSTM**: BiLSTM encoder applied to the anonymised training data.

Model	**arXiv abstracts**		**IMDB reviews**		**ACL IMDB**	
	lexicons	random	lexicons	random	lexicons	random
Naive Bayes	40.39	57.61	41.55	54.86	79.34	89.81
Logistic Regression	40.64	65.06	41.84	60.03	80.57	**90.53**
Deep Sets	33.98	42.70	46.82	51.96	79.58	88.23
LSTM (final hidden)	45.25	65.04	48.61	64.60	81.89	90.60
BiLSTM (max pooling)	46.48	**67.83**	48.92	**64.80**	83.12	91.36
CNN (max pooling)	45.99	65.78	44.14	50.47	–	–
CNN (dynamic max pooling)	45.51	66.59	41.49	52.09	–	–
Anon LSTM (final hidden)	48.24	67.23	50.30	62.64	83.14	88.98
Anon BiLSTM (max pooling)	**48.69**	67.52	**51.37**	62.77	**84.12**	89.71

4 Experimental Setup

Our experimental setup is common for all the datasets. We initialize the parameters of the classifier embedding layer using pre-trained word embeddings which are learned using skip-gram approach ([14]) on the combined train and test splits. We select the most common 80K words for training and the other words are treated as unseen words (`UNK`). We use mini-batch stochastic gradient descent with a batch size of 150. To train LSTM, we perform truncated backpropagation up to 250 time steps for IMDB reviews and 150 time steps for arXiv abstracts. For optimization, we use Adam Optimizer [10] with default parameter settings. We perform gradient clipping by constraining the norm of the gradient to be less than 1 [15]. The hidden state of LSTM and BiLSTM has 1024 and 512 dimensions respectively. For model regularization, we apply dropout [16] on top of the word embedding layer.

5 Results and Discussion

In order to estimate the difficulty level on both the lexicon and random splits of a dataset, we do experiments with a wide range of popular approaches and show their results in Table 2. Firstly, it can be observed from the table that there is a big performance gap between the random split and lexicons based split for each dataset. For example, on the arXiv abstracts dataset, there is an accuracy drop of almost 20% between the results of the best performing Anon BiLSTM approach on the two corresponding dataset splits. Therefore, in order to narrow down the performance gap on this task, there is a need for approaches which can also learn more robust context based representations so that the performance on documents containing new unseen terms can be improved.

We also find that LSTM and BiLSTM based approaches perform the best in large scale text classification tasks for both the splits. Specifically, Anon BiLSTM with max pooling model performs around 2% better on arXiv abstracts dataset, 2.5% better on IMDB reviews dataset and gives around 1% improvement on ACL IMDB lexicons dataset. This shows that keyword anonymisation with random embedding substitution is a good strategy for model regularization in case of lexicons based split. We also find that apart from the adversely affecting the performance in case of IMDB reviews dataset, anonymisation does not much affect the performance of the random split in the other two datasets. From a qualitative perspective, we show in Figure 1 the change of hidden state activations for the BiLSTM encoder after the data is anonymised.

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