DocBERT: BERT for Document Classification

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Abstract

Pre-trained language representation models achieve remarkable state of the art across a wide range of tasks in natural language processing. One of the latest advancements is BERT, a deep pre-trained transformer that yields much better results than its predecessors do. Despite its burgeoning popularity, however, BERT has not yet been applied to document classification. This task deserves attention, since it contains a few nuances: first, modeling syntactic structure matters less for document classification than for other problems, such as natural language inference and sentiment classification. Second, documents often have multiple labels across dozens of classes, which is uncharacteristic of the tasks that BERT explores. In this paper, we describe fine-tuning BERT for document classification. We are the first to demonstrate the success of BERT on this task, achieving state of the art across four popular datasets.

1 Introduction

Until recently, the dominant paradigm in approaching natural language processing (NLP) tasks has been to concentrate on neural architecture design, using only task-specific data and shallow pre-trained word embeddings, such as GloVe (Pennington et al., 2014) and word2vec (Mikolov et al., 2013). Numerous literature surveys detail this historical neural progress: Young et al. (2018) describe a series of increasingly intricate neural NLP approaches, all of which follow the classical recipe of training on word embeddings of task-specific data. In their targeted review of sentence-pair modeling, Lan and Xu (2018) likewise examine neural networks that abide by this paradigm.

The NLP community is, however, witnessing a dramatic paradigm shift toward the pre-trained deep language representation model, which achieves state of the art in question answering, sentiment classification, and similarity modeling, to name a few. Bidirectional Encoder Representations from Transformers (BERT; Devlin et al., 2018) represents one of the latest developments in this line of work. It outperforms its predecessors, ELMo (Peters et al., 2018) and GPT (Radford et al.), staggeringly exceeding state of the art by a wide margin on multiple natural language understanding tasks.

The approach consists of two stages: first, BERT is pre-trained on vast amounts of text, with an unsupervised objective of masked language modeling and next-sentence prediction. Next, this pre-trained network is then fine-tuned on task-specific, labeled data. Crucially, the pre-trained weights for BERT are already provided—all that is required is to fine-tune the weights on a specific task and dataset, a relatively quick process.

BERT, however, has not yet been fine-tuned for document classification. Why is this worth exploring? For one, modeling syntactic structure is arguably less important for document classification than for BERT's tasks, such as natural language inference and paraphrasing. This claim is supported by our observation that logistic regression and support vector machines are exceptionally strong document classification baselines. For another, documents often have several labels across many classes, which is again uncharacteristic of the tasks that BERT examines.

Thus, in this paper, we explore fine-tuning BERT for document classification. Our key contribution is that we are the first to demonstrate the success of BERT on document classification tasks and datasets. We establish state-of-the-art results on four popular datasets for this task.

2 Background and Related Work

Over the last few years, neural network-based architectures have achieved state of the art for document classification. Liu et al. (2017) develop XMLCNN for addressing this problem's multi-label nature, which they call extreme classification. XMLCNN is based on the popular KimCNN (Kim, 2014), except with wider convolutional filters, adaptive dynamic max-pooling (Chen et al., 2015; Johnson and Zhang, 2015), and an additional bottleneck layer to better capture the features of large documents. Another popular model, Hierarchical Attention Network (HAN; Yang et al., 2016) explicitly models hierarchical information from documents to extract meaningful features, incorporating word- and sentence-level encoders (with attention) to classify documents. Yang et al. (2018) propose a generative approach for multi-label document classification, using encoder–decoder sequence generation models (SGMs) for generating labels for each document. Contrary to the previous papers, Adhikari et al. (2019) propose LSTM$_{reg}$, a *simple*, properly regularized single-layer BiLSTM, which represents current state of the art.

These task-specific neural architectures have dominated the NLP literature—until recently. Enabled by more computational resources and data, the deep language representation model has greatly improved state of the art on a variety of tasks. Under this paradigm, a neural network is first pre-trained on vast amounts of text under an unsupervised objective (e.g., masked language modeling and next-sentence prediction), and then fine-tuned on task-specific data. The resulting models achieve state of the art in question answering, named-entity recognition, and natural language inference, to name a few. Bidirectional Encoder Representations from Transformers (BERT; Devlin et al., 2018) currently represents state of the art, vastly outperforming previous models, such as the Generative Pretrained Transformer (GPT; Radford et al.) and Embeddings from Language Models (ELMo; Peters et al., 2018).

3 Model

We begin with the pre-trained BERT$_{base}$ and BERT$_{large}$ models, which respectively represent the normal and large model variants (Devlin et al., 2018). To adapt BERT for document classifica-
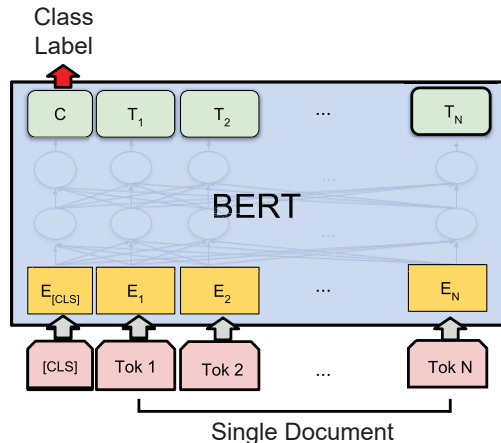

Figure 1: Document classification model formed by incorporating BERT with one additional output layer. Figure adapted from Devlin et al. (2018).

Dataset	C	N	W	S
Reuters	90	10,789	144.3	6.6
AAPD	54	55,840	167.3	1.0
IMDB	10	135,669	393.8	14.4
Yelp 2014	5	1,125,386	148.8	9.1

Table 1: Summary of the datasets. C denotes the number of classes in the dataset, N the number of samples, and W and S the average number of words and sentences per document, respectively.

tion, we follow Devlin et al. (2018) and introduce a fully-connected layer over the final hidden state corresponding to the `[CLS]` input token, as shown in Figure 1. During fine-tuning, we optimize the entire model end-to-end, with the additional softmax classifier parameters $W \in \mathbb{R}^{K \times H}$, where H is the dimension of the hidden state vectors and K is the number of classes. We minimize the cross-entropy and binary cross-entropy loss for single-label and multi-label tasks, respectively.

4 Experimental Setup

Using Hedwig,[1] a deep learning toolkit with pre-implemented document classification models, we compare the fine-tuned BERT models against HAN, KimCNN, XMLCNN, SGM, and regularized BiLSTMs. For simple yet competitive baselines, we run the default logistic regression (LR) and support vector machine (SVM) implementations from Scikit-Learn (Pedregosa et al., 2011), trained on the tf–idf vectors of the documents. We use Nvidia Tesla V100 and P100 GPUs for fine-

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[1] http://hedwig.ca

#	Model	Reuters		AAPD		IMDB		Yelp '14	
		Val. F_1	Test F_1	Val. F_1	Test F_1	Val. Acc.	Test Acc.	Val. Acc.	Test Acc.
1	LR	77.0	74.8	67.1	64.9	43.1	43.4	61.1	60.9
2	SVM	89.1	86.1	71.1	69.1	42.5	42.4	59.7	59.6
3	KimCNN Repl.	83.5	80.8	54.5	51.4	42.9	42.7	66.5	66.1
4	KimCNN Orig.	–	–	–	–	–	37.6[††]	–	61.0[††]
5	XML-CNN Repl.	88.8	86.2	70.2	68.7	–	–	–	–
6	HAN Repl.	87.6	85.2	70.2	68.0	51.8	51.2	68.2	67.9
7	HAN Orig.	–	–	–	–	–	49.4[‡]	–	70.5[‡]
8	SGM Orig.	82.5	78.8	–	71.0[†]	–	–	–	–
9	LSTM$_{base}$	87.6	84.9	72.1	69.6	52.5	52.1	68.6	68.4
10	LSTM$_{reg}$	89.1	87.0	73.1	70.5	53.4	52.8	69.0	68.7
11	BERT$_{base}$	90.5	89.0	75.3	73.4	54.4	54.2	72.1	72.0
12	BERT$_{large}$	**92.3**	**90.7**	**76.6**	**75.2**	**56.0**	**55.6**	**72.6**	**72.5**

Table 2: Results for each model on the validation and test sets; best values are bolded in blue. *Repl.* reports the mean of five runs from our reimplementations; *Orig.* refers to point estimates from [†]Yang et al. (2018), [‡]Yang et al. (2016), and [††]Tang et al. (2015).

tuning BERT, while we run the rest of the experiments on RTX 2080 Ti and GTX 1080 GPUs.

4.1 Datasets

We use the following four datasets to evaluate BERT: Reuters-21578 (Reuters; Apté et al., 1994), IMDB reviews, arXiv Academic Paper dataset (AAPD; Yang et al., 2018) and Yelp 2014 reviews. Reuters and AAPD are multi-label datasets, while IMDB and Yelp are single label. Table 1 summarizes the statistics of the datasets.

For AAPD, we use the splits provided by Yang et al. (2018); for Reuters, we use the standard ModApté splits (Apté et al., 1994). For IMDB and Yelp, following Yang et al. (2016), we randomly sample 80% of the data for training and 10% each for validation and test.

4.2 Training and Hyperparameters

We tune the number of epochs, batch size, learning rate, and maximum sequence length (MSL), the number of tokens that documents are truncated to. We observe that model quality is quite sensitive to the number of epochs, and thus the number must be tailored for each dataset. We fine-tune on Reuters, AAPD, and IMDB for 30, 20 and 4 epochs, respectively. Due to resource constraints, we fine-tune on Yelp for only one epoch. As is the case with Devlin et al. (2018), we find that choosing a batch size of 16, learning rate of 2×10^{-5}, and MSL of 512 tokens yields optimal performance on the validation sets of all datasets.

Hyperparameter study. To gauge the improvement over the default hyperparameters, as well as to highlight the differences in fine-tuning BERT for document classification, we explore varying several key hyperparameters: namely, the number of epochs and the MSL. Originally, Devlin et al. (2018) find that fine-tuning for three or four epochs works well for both small and large datasets alike. They also apply a generous MSL of 512, which may be unnecessary for document classification, where fewer tokens may suffice in determining the topic.

Furthermore, while conducting our experiments, we find that even fine-tuning BERT is a computationally intensive task. We argue that it is important to study these two hyperparameters, as they are major determinants of the computational resources required to fine-tune BERT. BERT$_{large}$, for example, requires eight V100s to fine-tune on our datasets, which is of course prohibitive. The number of epochs determines the duration of fine-tuning, while maximum sequence length dictates the models' memory and computational footprint during both fine-tuning and inference.

Thus, we vary the number of epochs and MSL on a few selected datasets. We choose Reuters and AAPD for analyzing the choice of epochs, since they use a non-standard 20 and 30 epochs, respectively. We select Reuters and IMDB for varying the MSL, since these two datasets differ greatly in average document length: Reuters documents average 144 words, while IMDB averages 394.
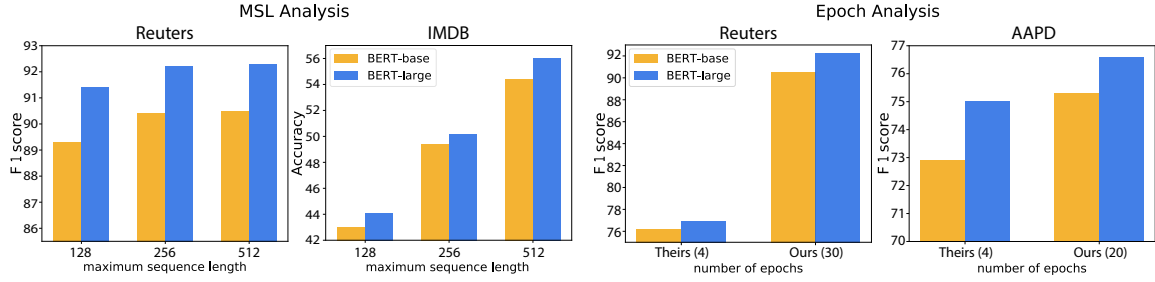
Figure 2: From left to right, results on the validation set from varying the MSL and the number of epochs.

5 Results and Discussion

We report the mean F_1 scores and accuracy across five runs for the reimplementations of KimCNN, XMLCNN, HAN and $LSTM_{reg}$ in Table 2. Due to resource limitations, we report the scores from only a single run for $BERT_{base}$ and $BERT_{large}$. We also copy the value from Yang et al. (2018) for SGM on AAPD in Table 2, row 8, as we have failed to replicate the authors' results using their codebase, environment, and data splits.

5.1 Model Quality

Trending with Devlin et al. (2018), $BERT_{large}$ achieves state-of-the-art results on all four datasets, followed by $BERT_{base}$ (see Table 2, rows 11 and 12). The considerably simpler $LSTM_{reg}$ model (row 10) achieves a high F_1 and accuracy of 87.0 and 52.8, respectively, coming close to the quality of $BERT_{base}$.

Surprisingly, the LR and SVM baselines yield competitive results for the multi-label datasets. For instance, the SVM approaches $BERT_{base}$ results on Reuters, with an F_1 score of 86.1, astonishingly exceeding most of our neural baselines (rows 2–11). This can also be observed on AAPD, where the SVM surpasses most of the neural models, except SGM, $LSTM_{reg}$, and BERT. However, on the single-label datasets, both LR and SVM perform worse than even our simple neural baselines, such as KimCNN. It is worth noting that LR and SVM take only a fraction of the time and resources for training our neural models.

5.2 Hyperparameter Analysis

MSL analysis. A decrease in the MSL corresponds to only a minor loss in F_1 on Reuters (see leftmost chart in Figure 2), possibly due to Reuters having shorter sentences. On IMDB (second subplot from left), lowering the MSL corresponds to

a drastic fall in accuracy, suggesting that the entire document is necessary for this dataset.

On the one hand, these results appear obvious. Alternatively, one can argue that, since IMDB contains longer documents, truncating tokens may hurt less. Figure 2 shows that this is *not* the case, since truncating to even 256 tokens causes accuracy to fall lower than that of the much smaller $LSTM_{reg}$ (see Table 2). From these results, we conclude that any amount of truncation is detrimental in document classification, but the level of degradation may differ.

Epoch analysis. The rightmost two subplots in Figure 2 illustrate the F_1 score of BERT fine-tuned using a various number of epochs for AAPD and Reuters. Contrary to Devlin et al. (2018), who achieve state of the art on small datasets with only a few epochs of fine-tuning, we find that smaller datasets require many more epochs to converge. On both the datasets (see Figure 2), we see a significant drop in model quality when the BERT models are fine-tuned on only four epochs, as suggested in the original paper. On Reuters, using four epochs results in an F_1 worse than even logistic regression (Table 2, row 1).

6 Conclusion and Future Work

We demonstrate that BERT can be fine-tuned successfully to achieve state of the art across four popular datasets in document classification. We describe and explore a few differences in this task, conducting an analysis for the maximum sequence length and number of epochs.

One direction of future work involves compressing BERT to both fine-tune and run tractably under resource-constrained scenarios. Currently, fine-tuning the large variant is prohibitively expensive, while inference is still too heavyweight for practical deployment.

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