PoWER-BERT: Accelerating BERT inference for Classification Tasks

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Abstract

BERT has emerged as a popular model for natural language understanding. Given its compute-intensive nature, even for inference, many recent studies have considered optimization of two important performance characteristics: model size and inference time. We consider classification tasks and propose a novel method, called PoWER-BERT, for improving the inference time for the BERT model without significant loss in the accuracy. The method works by eliminating word-vectors (intermediate vector outputs) from the encoder pipeline. We design a strategy for measuring the significance of the word-vectors based on the self-attention mechanism of the encoders which helps us identify the word-vectors to be eliminated. Experimental evaluation on the standard GLUE benchmark shows that PoWER-BERT achieves up to 4.5x reduction in inference time over BERT with < 1% loss in accuracy. We show that compared to the prior inference time reduction methods, PoWER-BERT offers better trade-off between accuracy and inference time. Lastly, we demonstrate that our scheme can also be used in conjunction with ALBERT (a highly compressed version of BERT) and can attain up to 6.8x factor reduction in inference time with < 1% loss in accuracy.

1 Introduction

The BERT model [3] has gained popularity as an effective approach for Natural Language Processing (NLP) tasks. It has achieved significant success on the standard benchmarks such as GLUE [26] and SQuAD [21], dealing with sentiment classification, question-answering, natural language inference and grammar checking. The model has been used in various applications ranging from text summarization [13] to biomedical text mining [11].

The model is known to be compute intensive, resulting in high infrastructure demands and latency, whereas low latency is vital for a good customer experience with NLP tasks. Therefore, it is crucial to design methods that reduce the computational demands of BERT in order to successfully meet the latency and resource requirements of a production environment.

Consequently, many recent studies have focused on optimizing the two performance metrics: the model size and inference time. The recently proposed ALBERT [10] is a highly compressed variant that achieves up to 9x reduction in model size over $\text{BERT}_{\text{BASE}}$ (with 108M parameters) by sharing parameters across the encoder layers and decomposing the embedding layer. Although ALBERT
Figure 1: Illustration of PoWER-BERT scheme over BERT\textsubscript{BASE} that has $L = 12$ encoder layers, each having $A = 12$ self-attention heads and a hidden size of $H = 768$. The words are first embedded as vectors of length $H = 768$. The numbers on top are output sizes for each encoder layer of BERT\textsubscript{BASE} for input sequence length $\ell = 128$. The numbers at the bottom are output sizes for each encode layer of PoWER-BERT. In this example, the first encoder eliminates 48 and retains 80 word-vectors, whereas the second encoder eliminates 7 more and retains 73 word-vectors. The hidden size remains at 768.

reduces the training time significantly, it has almost no impact on the inference time. Knowledge distillation based techniques such as DistilBERT [22] and BERT–PKD [25] try to optimize the above performance metrics by employing teacher-student models. In order to achieve meaningful reduction in model size and inference time, the student retains only a small number of encoders, albeit at noticeable loss in accuracy over BERT. Methods that prune the attention heads (Head–Prune) via measuring their significance [17] yield limited inference time reduction even when the model size is significantly reduced.

**Proposed Strategy.** We focus on classification tasks and propose a novel scheme, denoted by PoWER-BERT (Progressive Word-vector Elimination for inference time Reduction of BERT), for improving inference time. We show that, due to the self-attention mechanism in the BERT model, there is diffusion of information: as the word-vectors pass through the encoder layers, they start carrying similar information, leading to redundancy. Consequently, these word-vectors can be eliminated in a progressive manner as we move from the first to the last encoder. The elimination of word-vectors leads to reduction of computation, resulting in improved inference time. Here, we use the term word-vector to refer to an intermediate vector output generated by the encoders. An illustration of PoWER-BERT is presented in Figure 1; we shall use the term PoWER-BERT to refer to our scheme as well as the model output by it. We emphasize that our scheme does not eliminate model parameters but rather eliminates the intermediate word-vector representations.

**Main Contributions.** Our main contributions are as follows:

- We focus on classification tasks and propose PoWER-BERT for improving BERT inference time without significant loss in accuracy. We design a strategy for measuring the significance scores of the word-vectors based on the self-attention mechanism of the encoders. The model and training loss function are augmented to learn the importance of the word-vectors using these significance scores. This helps us identify the word-vectors to eliminate.

- We present an experimental evaluation on the standard GLUE benchmark, IMDB [14] and RACE [9] datasets which shows that PoWER–BERT achieves up to 4.5x reduction in inference time over BERT\textsubscript{BASE} with < 1% loss in accuracy.

- We show that our scheme can also be used in conjunction with ALBERT, one of the best known compressed variants of BERT. We attain up to 6.8x factor reduction in inference time.
over ALBERT on the GLUE benchmark.

- We perform a comprehensive comparison with the prior inference time reduction methods (DistilBERT, BERT-PKD and Head-Prune), and demonstrate that PoWER-BERT offers better trade-off between inference time and accuracy.

**Related Work.** In general, different methods for deep neural network compression have been developed such as sparsification via pruning network connections [5, 18], filter/channel pruning [6, 19], quantization to reduce the number of bits needed to store the learned weights [4], knowledge distillation from large model to small model [7, 23] and singular value decomposition of weight matrices [2, 8].

Some of these general techniques have also been explored for BERT like weight quantization [24, 28], structured pruning of weight matrices [27] and dimensionality reduction [10, 27]. Although these techniques offer significant model size reductions, they do not result in proportional inference time gains and some of them require specific hardware to execute. As discussed earlier, the BERT model allows for compression via other methods: sharing of encoder parameters [10], removing encoders via distillation [22, 25, 12], and reducing the number of attention heads [17, 16].

PoWER-BERT is an orthogonal technique that works by eliminating the word-vectors from the network, and can be used in conjunction with the other inference time reduction methods. Since we do not prune weights or layers, our model parameters remain the same and therefore parameter redundancy can be exploited using any of above mentioned prior work. As stated before, we demonstrate this by applying our method on ALBERT.

Prior works have also focused on sparsification of transformer attention to improve the translation accuracy [29, 1, 20, 15]. However, these methods do not focus on reducing either model size or inference time.

## 2 The PoWER-BERT model

Throughout the paper, we consider BERT\textsubscript{BASE}, but the techniques can be readily applied to other versions such as BERT\textsubscript{LARGE}.

Given an input sequence, the BERT model first embeds the words as vectors of length 768. These word-vectors are then passed through a pipeline of encoders. The encoders transform the word-vectors by capturing information from the other word-vectors via a self-attention mechanism. This leads to diffusion of information, as explained below.

**Diffusion of Information.** As the word-vectors pass through the encoders, they start progressively carrying similar information. We demonstrate the phenomenon through cosine similarity measurements. Let $\ell$ denote the input sequence length of the given dataset. Let $j \in [1, 12]$ be an encoder. For each input, compute the cosine similarity between each of the $\binom{\ell}{2}$ pairs of word-vectors output by the encoder. Then, derive the average over all inputs and pairs. We consider the SST-2 dataset from our experimental study and present the average cosine similarity over all the encoders; see Figure 2. We can observe that the similarity increases progressively over the encoders, implying diffusion of information.
PoWER-BERT. The core intuition behind the PoWER-BERT scheme is that due to the diffusion of information, it should be possible to eliminate word-vectors in a progressive manner across all the encoders. The scheme involves two critical, inter-related tasks. First, we identify a retention configuration: a monotonically decreasing sequence \((\ell_1, \ell_2, \ldots, \ell_{12})\) that specifies the number of word-vectors \(\ell_j\) to retain at encoder \(j\). For example, in Figure 1, the configuration is \((80, 73, 70, 50, 50, 40, 33, 27, 20, 15, 13, 3)\). Secondly, we do word-vector selection, i.e., for a given input, determine the \(\ell_j\) word-vectors to retain at each encoder \(j\). We first address the task of word-vector selection.

2.1 Word-vector Selection

Let \(\ell\) denote the input sequence length. Furthermore, assume that we are given a retention configuration \((\ell_1, \ell_2, \ldots, \ell_{12})\). Consider an encoder \(j \in [1, 12]\). The input to the encoder is a collection of \(\ell_{j-1}\) word-vectors arranged in the form of a matrix of size \(\ell_{j-1} \times 768\), (taking \(\ell_0 = \ell\)). Our aim is to select \(\ell_j\) word-vectors to retain and we propose two kinds of strategies, static and dynamic.

Static Strategies. The inputs are typically of varying length and get padded to achieve a uniform length of \(\ell\). A natural idea is to retain the first (or head) \(\ell_j\) word-vectors. Inputs longer than \(\ell_j\) would get trimmed and in that process many actual word-vectors may get eliminated. Nevertheless, the strategy aims at removing many PAD tokens on the average, since they carry little information. A related method is to fix \(\ell_j\) positions at random and retain word-vectors only at those positions across the dataset. We denote the strategies as Head-WS and Rand-WS, respectively (head/random word-vector selection). Both select \(\ell_j\) positions and use the same positions for all the inputs in a static manner.

Dynamic Strategies. While the word-vectors tend to carry similar information at the final encoders, in the earlier encoders, they have different levels of influence over the final prediction. Since the positions of these significant word-vectors vary across the dataset, a better idea is to select the positions in a dynamic manner on a per-input basis (as confirmed by our experimental evaluation).

In rest of the section, we develop a dynamic strategy based on measuring the significance of the word-vectors. Our aim is to devise a scoring mechanism satisfying the following criterion: the score of a word-vector must be positively correlated with its influence on final classification output.
(namely, word-vectors of higher influence get higher score). We accomplish the task by utilizing the self-attention mechanism in-built in the encoders and develop a dynamic strategy, denoted as Attn-WS. Towards that goal, we first recollect the self-attention mechanism.

**Attention Mechanism.** The encoder consists of a self-attention module and a feed-forward network (FFN). For BERT\textsubscript{BASE}, each self-attention module consists of 12 attention heads, capturing different features of the dataset. Each head $h \in [1, 12]$ is associated with three weight matrices $W^h_q$, $W^h_k$ and $W^h_v$ of size $768 \times 64$, called the query, the key and the value matrices.

Let $M$ be the matrix of size $\ell \times 768$ input to the encoder $j$. Each head $h$ computes an attention matrix:

$$A_h = \text{softmax} \left( (M \times W^h_q) \times (M \times W^h_k)^T \right)$$

with softmax applied row-wise. The attention matrix $A_h$ is of size $\ell \times \ell$, wherein each row sums to 1. The head computes matrices $V_h = M \times W^h_v$ and $Z_h = A_h \times V_h$ of sizes $\ell \times 64$. The output of the encoder is derived by combining and further processing the matrices $Z_h$ produced by the attention heads.

For a word $w'$, the row $Z_h[w',:]$ output by the head is given by $\sum_w A_h[w', w] \cdot V_h[w, :]$. In other words, the row $Z_h[w', :]$ is the weighted average of the rows of $V_h$, taking the attention values as weights. Intuitively, we can interpret the entry $A_h[w', w]$ as the attention received by word $w'$ from $w$ on head $h$.

**Significance Scores & Word-vector Selection.** In PoWER-BERT, we use the attention values to define significance scores of the word-vectors. For a word-vector $w$ and a head $h$, define the significance score of $w$ for $h$ as $\text{Sig}_h(w) = \sum_{w'} A_h[w', w]$. The overall significance score of $w$ is then defined as the aggregate over the heads: $\text{Sig}(w) = \sum_h \text{Sig}_h(w)$. Thus, the significance score is the total amount of attention imposed by $w$ on the other words. See Figure 3 (a) for an illustration.

We note that in the PoWER-BERT setting, the input matrix $M$ is of size $\ell_{j-1} \times 768$ and attention matrices are of size $\ell_j \times \ell_{j-1}$.
Given the scoring mechanism, we retain the topmost $\ell_j$ word-vectors. This is accomplished by inserting an extract layer between the self-attention module and the feed forward network. See Figure 4 for an illustration.

**Ablation Study.** We perform an ablation study to validate that our scoring mechanism satisfies the criterion we had aimed for: the score of a word-vector is positively correlated with its influence on the classification output. The study utilizes mutual information to analyze the effect of eliminating a single word-vector.

Fix an encoder $j \in [1, 12]$ and a position $k < \ell_j - 1$. We consider two models. The first is the fine-tuned BERT model, without any word-vector elimination. The second is a modified model that eliminates the $k^{th}$ most significant word-vector at encoder $j$ and does not perform any other eliminations at the other encoders. Let $X$ and $Y_k$ be the random variables that denote the classification output by the two models on a randomly chosen input. The mutual information $MI(X, Y_k)$ measures how much the two random variables $X$ and $Y_k$ agree with each other.

We perform the above analysis on the SST-2 dataset from our experimental study. The dataset has input sequence length $\ell = 64$ and two categories (binary classification). The number of positive and negative training inputs is approximately the same for this dataset and so the baseline entropy $H(X) \sim \ln(2) = 0.69$. Figure 3(b) shows $MI(X, Y_k)$ for all $k \in [1, 64]$ on encoders $j = 1, 3, 6, 9$ (the other encoders are omitted for the ease of readability). We can observe that as sorted-index $k$ increases (i.e., score decreases), the mutual information increases. This implies that lower the score of the deleted word (i.e., higher $k$), better is the agreement between the two models. Therefore, word-vectors of lower scores should be preferred for elimination. Furthermore, as the encoder index $j$ increases, the mutual information approaches the baseline entropy faster, implying that word-vectors of higher significance scores (or more word-vectors) can be eliminated from the later encoders.
2.2 Retention Configuration

We next address the task of determining the retention configuration. Analyzing all the possible configurations is untenable due to the exponential search space. Instead, we design a strategy that learns the retention configuration via two main ideas. First, we modify the extract layers to soft-extract that introduce parameters to learn the importance of the word positions. These learnt values are used to derive the number of ordered positions to retain. Secondly, the loss function is modified to control the trade-off between the number of positions to retain and the accuracy.

The Soft-extract Layer. For each encoder, we substitute the extract layer by a soft-extract layer. The extract layer either selects or eliminates a word-vector (based on scores). In contrast, the soft-extract layer would retain all the word-vectors, but to varying degrees controlled by learnable parameters.

Consider an encoder \( j \) and an input \( a_1, a_2, \ldots, a_\ell \). Sort the word-vectors in the decreasing order of their significance score. For a word-vector \( a_i \), let \( \text{Sig}_{idx}(a_i) \) denote the position of \( a_i \) in the sorted order; we refer to it as the ordered position of \( a_i \).

The soft-extract layer involves \( \ell \) learnable parameters, denoted \( r_j[1], \ldots, r_j[\ell] \), called retention parameters. The parameters are constrained to be in the range \([0, 1]\). Intuitively, the parameter \( r_j[k] \) represents the extent to which the \( k^{th} \) ordered position is retained. The soft-extract layer modifies the matrix output of the self-attention layer, as described below.

Let \( E^{in} \) denote the matrix of size \( \ell \times 768 \) output by the self-attention layer. For \( i \in [1, \ell] \), the row \( E^{in}[i,:] \) yields the word-vector \( a_i \). The soft-extract layer multiplies the vector by the scalar retention parameter corresponding to its ordered position:

\[
E^{out}[i,:] = r_j[\text{Sig}_{idx}(a_i)] \cdot E^{in}[i,:].
\]

The modified matrix \( E^{out}[i,:] \) is input to the feed-forward network. Figure 5 presents an illustration for the first encoder.

Loss Function. We define the mass at encoder \( j \) to be the extent to which the ordered positions are retained, i.e., \( \text{mass}(j ; r) = \sum_{k=1}^{\ell} r_j[k] \). Our aim is to minimize the aggregate mass over all the encoders with minimal loss in accuracy. Intuitively, the aggregate mass may be viewed as a budget on the total number of positions retained; \( \text{mass}(j ; r) \) is the breakup across the encoders.

We modify the loss function by incorporating an \( L_1 \) regularizer over the aggregate mass. As demonstrated earlier, the encoders have varying influence on the classification output. We scale the mass of each encoder by its index, as described below.

Let \( \Theta \) denote the parameters of the baseline BERT model and \( \mathcal{L}(\cdot) \) be the loss function (such as cross entropy or mean-squared error) as defined in the original task. We define the new objective function as:

\[
\min_{\Theta, r} \left[ \mathcal{L}(\Theta, r) + \lambda \cdot \sum_{j=1}^{L} j \cdot \text{mass}(j ; r) \right] \quad \text{s.t.} \quad r_j[k] \in [0, 1],
\]

where \( L \) is the number of encoders, \( j \in [1, L] \), and \( k \in [1, \ell] \). While \( \mathcal{L}(\Theta, r) \) controls the accuracy, the regularizer term controls the aggregate mass. The hyper-parameter \( \lambda \) tunes the trade-off.
Figure 5: Illustration of the soft-extract layer. First encoder is shown, taking \( \ell = 4 \). Here, the sorted sequence of the word-vectors are \( a_3, a_4, a_1, a_2 \); hence their ordered positions are 3, 4, 1, 2. For each word-vector, the parameter by which it is multiplied is shown.

The retention parameters are initialized as \( r_j[k] = 1 \), meaning all the ordered positions are fully retained to start with. We train the model to derive the retention configuration by setting \( \ell_j = \text{ceil}(\text{mass}(j)) \). To make it monotonic, we assign \( \ell_j = \min\{\ell_j, \ell_{j-1}\} \).

### 2.3 PoWER-BERT: Overall Scheme

Given a dataset, the scheme involves three training steps:

1. **Fine-tuning**: Start with the pre-trained BERT model and fine-tune it on the given dataset.
2. **Configuration-search**: Construct an auxiliary model by inserting the soft-extract layers in the fine-tuned BERT model and modifying its objective function. Train the model and derive the retention configuration.
3. **Re-training**: Derive the PoWER-BERT model by incorporating the extract layers to the fine-tuned BERT model. These layers perform progressive word-vector elimination as per the retention configuration determined in the previous step. Re-train the PoWER-BERT model.

While the auxiliary model involves additional parameters, the PoWER-BERT model does not. Inference is performed using the retrained PoWER-BERT model.

### 3 Experimental Evaluation

#### 3.1 Setup

**Datasets.** We evaluate our approach on the popular GLUE benchmark, IMDB and Reading Comprehension Dataset From Examinations (RACE). The datasets represent five natural language tasks:
Table 1: Performance comparison between PoWER-BERT and BERT. Inference done on a K80 GPU with batch of 128 for all datasets except RACE (batch of 64 is used). Matthew’s Correlation reported for CoLA, F1-score for QQP and MRPC, Spearman Correlation for STS-B, and Accuracy for the rest. Input sequence length used are 64 for CoLA, SST-2 and STS-B, 512 for IMDB and RACE, 256 for RTE and 128 for the rest.

Table 2: Performance comparison between PoWER-BERT and ALBERT. Here PoWER-BERT represents application of our scheme on ALBERT. The experimental setup is same as in Table 1.

Sentiment classification (SST-2, IMDB), Natural Language Inference (QNLI, MNLI-m, MNLI-mm, RTE), similarity matching (MRPC, QQP, STS-B), grammar acceptability checking (CoLA) and question-answering (RACE). We refer to [26] for details on these datasets.

Hyper-parameters. The PoWER-BERT approach consists of three steps (see Section 2.3). We specify the hyper-parameters for each step:

- **Fine-tuning**: For the fine-tuning step, learning rate and batch size were searched respectively from \(\{2 \times 10^{-5}, 3 \times 10^{-5}, 5 \times 10^{-5}\}\) and \(\{32, 64\}\), as suggested by BERT paper [3].

- **Configuration-search**: The configuration-search step involves the regularizer hyper-parameter \(\lambda\) that controls the trade-off between accuracy and inference time. \(\lambda\) is searched from the range \([0.0001, 0.01]\). For the soft-extract layer parameters, we perform a grid search with a learning rate in the range \([0.0001, 0.01]\) to get optimal results. For the rest of the parameters, the learning rate is the same as in the Fine-tuning step.

- **Re-training**: For retraining the PoWER-BERT model we again use the BERT learning rate mentioned in the Fine-tuning step.

The hyper-parameters for PoWER-BERT and other baseline methods were tuned on Dev dataset provided for GLUE and RACE tasks. For IMDB, the training data was subdivided into 80% for training and 20% for hyper-parameter tuning. The accuracy/correlation for GLUE were reported on the Test dataset by submitting the predictions to the GLUE website (https://gluebenchmark.com). The accuracies for IMDB and RACE were reported on the publicly available Test data.
Figure 6: Comparison with prior methods. Accuracy vs. inference time trade-off curves for different models reported on the test set as per the setup in Table 1. The cross represents the performance of BERT<sub>BASE</sub> and the dotted line represents its accuracy (for ease of comparison with other models).

**Maximum Input Sequence Length.** The inputs in the datasets are of varying length and are padded to get a uniform maximum length of $\ell$. Different values of $\ell$ have been used in prior work, for instance ALBERT uses $\ell = 512$ for all our datasets. However, only a small fraction of the inputs are of length close to the maximum length. Using large values of $\ell$ would lead to easy pruning opportunities and larger gains for Power-BERT. In order to make the baseline competitive, we set stringent values of $\ell$: we determined the length $\ell'$ such that at most 1% of the data is longer than $\ell'$ and fixed $\ell$ to be the value from $\{64, 128, 256, 512\}$ closest to $\ell'$.

### 3.2 Evaluations

**Comparison with BERT<sub>BASE</sub>.** Our first experiment evaluates the inference time speedup achieved by Power-BERT. For each dataset, we first reproduced the baseline accuracy by fine-tuning the BERT<sub>BASE</sub> model. For Power-BERT, we tuned the regularizer parameter $\lambda$ over Dev data so as to achieve a performance within 1% of the baseline. Table 1 presents a comparison of the inference
time achieved by the two models for a batch of 128 on single K80 GPU (averaged over 100 runs). We observe that PoWER-BERT offers 2x to 4.5x improvement in the inference time with < 1% loss in the accuracy across the datasets.

The PoWER-BERT model improves the inference time by eliminating the word-vectors. We illustrate the process by considering the CoLA and the RTE datasets and present the retention configurations selected by the model (corresponding to the accuracy and inference time in Table 1). On the CoLA dataset, the input sequence length is $\ell = 64$ and configuration is $(17, 15, 14, 13, 12, 11, 11, 9, 6, 5, 5, 5)$, whereas for the RTE dataset, $\ell = 256$ and the configuration is $(153, 125, 111, 105, 85, 80, 72, 48, 35, 27, 22, 5)$. Across the twelve encoders, the total number of word-vectors used by BERT$_{BASE}$ on the two datasets is $12 \times 64 = 768$ and $12 \times 256 = 3072$ word-vectors, respectively. In contrast, PoWER-BERT retains only a total of 123 and 868 word-vectors, respectively, leading to improved inference time.

### Combining our scheme with ALBERT

As discussed before, various techniques have been developed in prior work to compress BERT. Amongst these methods, ALBERT$_{BASE}$ [10] (with 12M model parameters) achieves the best known compression of 9x over BERT$_{BASE}$ by sharing parameters across encoders and decomposing the embedding matrix. PoWER-BERT does not remove any parameters; instead, it improves the inference time by eliminating word-vectors. Thus, PoWER-BERT is orthogonal to such compression techniques and can be applied over compressed models. To validate the hypothesis, we apply word-vector elimination over ALBERT$_{BASE}$. Similar to the previous experiment, we tune $\lambda$ to achieve an accuracy within 1% of ALBERT$_{BASE}$. Table 2 compares inference time over a batch of 128 inputs. It is interesting to note that even with substantial compression of the model, we are able to achieve 1.6x to 6.8x reduction in the inference time with negligible loss in accuracy.

### Comparison to Prior Methods

In this experiment, we compare PoWER-BERT with other inference time reduction methods presented in literature, namely DistilBERT [22], BERT-PKD [25] and Head-Prune [17]. The first two are distillation based methods that operate by reducing the number of encoders, whereas Head-Prune is based on pruning the number of attention heads. We present an empirical comparison of these techniques by studying the trade-off between accuracy and inference time.

For PoWER-BERT, we tune the regularizer parameter $\lambda$ and derive pareto-curves representing the trade-off. Similarly, pareto-curves are obtained for DistilBERT and BERT-PKD by selecting the number of encoders from $\{3, 4, 6\}$, and for Head-Prune, by tuning the hyper-parameters that control the number of heads being pruned.

The results are shown in Figure 6. We observe that for most of the datasets, the curve of PoWER-BERT exhibits marked dominance over the other curves. In other words, PoWER-BERT achieves the best accuracy for any fixed inference time and it also achieves the best inference time for any fixed accuracy.

### Word-vector Selection

In Section 2.1, we described three methods for word-vector selection: two static techniques, Head-WS and Rand-WS, that eliminate word-vectors at fixed positions and a dynamic strategy, denoted Attn-WS, based on the significance scores derived from the attention mechanism. In this experiment, we demonstrate the advantage of Attn-WS by taking the SST-2 dataset as an illustrative example. For all the three methods, we used the same sample retention
|                        | Head-WS | Rand-WS | Attn-WS |
|------------------------|---------|---------|---------|
| Entire dataset         | 85.4%   | 85.7%   | 88.3%   |
| Input sequence length > 16 | 83.7%   | 83.4%   | 87.4%   |

Table 3: Comparison of the accuracy of the word-vector selection methods on the SST-2 Dev set for a fixed retention configuration.

configuration of (64, 32, 16, 16, 16, 16, 16, 16, 16). The accuracy results are shown in Table 3. We observe that Attn-WS offers improved accuracy, as shown in the first row of the Table. We perform a deeper analysis by filtering inputs based on length. In the given sample configuration, most encoders retain only 16 word-vectors. Consequently, we selected a threshold of 16 and considered a restricted dataset with inputs longer than the threshold and the accuracy results are shown in the second row of the table.

Recall that Head-WS relies on eliminating as many pad tokens as possible on the average. We can see that the strategy fails on longer inputs, since many important word-vectors may get eliminated. Similarly, Rand-WS also performs poorly, since the method is oblivious to the importance of the word-vectors. In contrast, Attn-WS achieves higher accuracy by carefully selecting word-vectors based on their significance. The inference time is the same for all the methods, as the same number of word-vectors get eliminated.

4 Conclusions

We presented PoWR-BERT, a novel method for improving the inference time of the BERT model. Experiments on the standard GLUE benchmark show that PoWR-BERT achieves up to 4.5x gain in inference time with < 1% loss in accuracy. Compared to prior techniques, it offers better trade-off between accuracy and inference time. We showed that the method can be used in conjunction with ALBERT, a highly compressed variant of BERT. For future work, we plan to extend PoWR-BERT to wider range of tasks such as language translation and text summarization.
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