TiltedBERT: Resource Adjustable Version of BERT

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Abstract—In this paper, we proposed a novel adjustable fine-tuning method that improves the training and inference time of the BERT model on downstream tasks. In the proposed method, we first detect more important word vectors in each layer by our proposed context contribution metric and then eliminate the less important word vectors with our proposed strategy. In our method, the word vector elimination rate in each layer is controlled by the Tilt-Rate hyper-parameter, and the model learns to work with a considerably lower number of Floating Point Operations (FLOPs) than the original BERT_base model. Our proposed method does not need any extra training steps, and also it can be generalized to other transformer-based models. We perform extensive experiments that show the word vectors in higher layers have an impressive amount of contribution that can be eliminated and decrease the training and inference time. Experimental results on extensive sentiment analysis, classification and regression datasets, and benchmarks like IMDB and GLUE showed that our proposed method is effective in various datasets. By applying our method on the BERT_base model, we decrease the inference time up to 5.3 times with less than 0.85% accuracy degradation on average. After the fine-tuning phase, the inference time of our model can be adjusted with our method offline-tuning property for a wide range of the Tilt-Rate value selections. Also, we propose a mathematical speedup analysis that can estimate the speedup of our method accurately. With the help of this analysis, the proper Tilt-Rate value can be selected before fine-tuning or while offline-tuning phases.

Index Terms—NLP, Transformer Structure, BERT Model, TiltedBERT Model, Tilt-Rate (TR), GLUE Benchmark, Attention Context Emphasis (ACE) metric

I. INTRODUCTION

Recently, Transformer [3] based architectures achieved remarkable success in various Natural Language Processing (NLP) tasks, but the number of parameters of these models is around hundreds of millions. The training difficulty, inference latency, and small size of available datasets are the main concerns of using these models in real applications. [7] Fine-tuning of a pre-trained language model on downstream tasks is a useful way to mitigate some of these concerns including training effort and size of the dataset. GPT [4], BERT [5] and XLNet [6] are the examples of recently state-of-the-art pre-trained language models. The number of parameters is significant in these models hence the computational complexity bears billions of Floating Point Operations (FLOPs) for processing a single sample for inference.

The amount of inference phase computational effort made using these models on resource-limited system such as edge devices is impossible or causes unacceptable latency and energy usage management problems. In the literature, some methods are proposed to reduce the number of model computational efforts by decreasing the number of model parameters and removing or sharing some layers. In addition, distillation-based methods produce a student network with a much smaller number of parameters. These techniques try to mitigate computational costs by decreasing the number of model parameters and decreasing the number of FLOPs at the inference phase [8] [9] and heads [10] [11]. The main problems of these methods are pre-training from scratch, extra training steps, excessive computational efforts, the need for supplement datasets and significant accuracy degradation.

In this paper, we proposed the TiltedBERT model, a novel method that speeds up the pre-training and inference phase by a novel proposed word vector sort and elimination (SaE) approach that gradually decreases the effective word vectors in each layer and significantly reduces the number of encountered FLOPs. The main contributions in this work are:

- We propose a novel structure and training policy that speeds up the fine-tuning and inference times with negligible accuracy degradation for a wide range of NLP applications.
- The method significantly decreases the number of FLOPs that can be easily deployed on resource-limited devices like smartphones.
- After the fine-tuning phase, the model speedup can be tuned with the proposed offline-tuning property for a wide range of Tilt-Rate hyper-parameter values selections.
- An accurate analytical speedup estimation is presented for the proposed method that helps a system designer to determine the hyper-parameter selection before fine-tuning and while offline-tuning.
- We developed a new context contribution metric that experimentally shows the context contribution in each encoder self-attention layer is increased significantly at later encoder layers.
- The proposed method can be easily applied to other transformer-based models alongside various inference and training phases compression and acceleration methods.
II. RELATED WORK

One of the most effective pre-trained language models is Bidirectional Encoder Representations from Transformers (BERT) \([5]\). It has multi-layer transformer-based architecture. BERT\textsubscript{base} consists of an embedding layer and 12 stacked encoder layers. Each encoder layer contains an attention layer with 12 heads, an intermediate layer, and an output layer that is fully connected. The number of BERT\textsubscript{base} parameters is around 110M, the pre-training of which has taken 79 hours on V100x64 GPUs \([7]\).

Several methods have been proposed in the literature to mitigate the model size and latency, respectively, controlling the number of parameters and inference phase computational effort. It is shown that memory usage is linearly increased by increasing the number of model parameters. On the other hand, the inference time increases at a higher rate than the model size because of the model architecture.

ALBERT is a lighter version of the BERT model \([9]\). It used the cross-layer weight sharing and modified embedding layer structure, making the embedding size independent of the encoder stage hidden size. Moreover, the new Sentence Order Prediction (SOP) task is utilized in the pre-training phase instead of the Next Sentence Prediction task. ALBERT reports state-of-the-art results with its parameters reduction and modified pre-training policy. ALBERT is nine times smaller and 1.2 times faster than BERT\textsubscript{base} with less than 2.5% on average accuracy drop. A progressive layer dropping at the pre-training phase of BERT architecture offers up to 2.5 times speedup at the inference phase with more knowledge transferability, and better generalization on downstream tasks \([8]\). DistilBERT \([12]\), TinyBERT \([17]\), and MobileBERT \([15]\) are used the knowledge distillation techniques during the pre-training and offers up to 5.5 times faster inference on downstream task respect to BERT\textsubscript{base}. The main concern with these methods is the pre-training effort of the model from scratch, extra training steps, excessive computational efforts, and significant accuracy degradation.

FastBERT is proposed with adaptive inference time in which the model uses a sufficient number of encoder layers based on the sample difficulty \([13]\). It adjusts the number of executed layers dynamically to reduce the computational steps. In \([14]\) the model weights are encouraged to be exactly zero with the L0 regularization term. In \([16]\) experimentally shows that it is not necessary to use all layers of a pre-trained model in all downstream tasks. Studying various layer dropping strategies show that a significant amount of model weights is not necessary.

A parameter reduction method was proposed by identifying the most critical heads in each encoder layer using layer-wise relevance propagation and pruning the redundant heads \([10]\). It showed that the earlier layer’s heads are much more critical than the last encoder layers. Moreover, in \([11]\), it is shown that around 17% of attention heads can be removed at test time without significantly impacting performance.

PoWER-BERT proposes a word vector elimination method that eliminates redundant word vectors \([18]\). A supplement learn-able layer is added between each encoder self-attention and feed-forward layer, while an additional loss function term is used to train these supplement parameters. PoWER-BERT training consists of 3 steps of fine-tuning, elimination configuration search, and re-training that impose extra training effort.

III. PROPOSED METHOD

This section presents the philosophy behind the proposed TiltedBERT method and its architecture. Analyzing the number of FLOPs in the BERT\textsubscript{base} model shows that most of the FLOPs and latency takes place in the encoder stage. The word vector elimination strategy at the encoder stage is proposed based on our novel Attention Context Emphasis (ACE) metric. Which is the TiltedBERT architecture presented as follows:

A. Backgrounds

Fig. 1 shows the BERT\textsubscript{base} architecture with output classifier layers.
used for training stability and efficiency. The multi-head self-attention and feed-forward layers are composed of several fully-connected layers with many computational FLOPs.

B. BERT FLOPs Analysis

The inference time and its needed computational effort are directly related to the number of Floating Point Operations (FLOPs) at the inference phase. If the number of FLOPs in a network decreases, the inference time and computational effort are reduced accordingly.

Table. I shows the estimated FLOPs of BERT\textsubscript{base} at different layers and sub-layers along with the relative computational load of each layer. The amount of FLOPs is estimated based on the number of input tokens (T), the number of encoder layers (L), hidden state size (H), and the number of output labels (N). The experimental results show that for a typical case of T = 512, L = 12, H = 768 and N = 2, 99.8% of the computational complexity is at the encoder layers. Therefore, reducing the number of FLOPs at the encoder layers can reduce the total number of FLOPs and inference latency.

C. Attention Context Emphasis (ACE) metric

As mentioned in III-B, the main portion of latency and FLOPs occurs in the BERT encoder layers. The proposed idea is to reduce the FLOPs by eliminating the less important word vectors at each encoder layer and passing the remaining ones to the next layer. Therefore, the context contribution of word vectors at the output of each encoder layer is studied in this section.

The attention probability matrix already computed in the BERT encoder is used to define the proposed novel Attention Context Emphasis (ACE) metric. Fig. 2\textsuperscript{[5]}(left) shows the attention probability matrix of the BERT\textsubscript{base} model. The rows of this matrix are normalized to one. By calculating the average of the attention probability matrix of the heads, a 2-D matrix is created. The Score Vector (SV) results from the sum of this matrix along the unnormalized dimension. The SV indicates the contribution of each input word vector to the output. The average of the SV elements is one, and the median of this vector is bounded. We interpret the median of the score vector as our context contribution metric.

If the calculated Score Vector (SV) median is lower than the average, more than half of the elements are lower than the average value, and a few elements are larger than the average. In this case, the elements with the higher score values contribute more to the layer output and are valuable. Decreasing the median of the SV means that the number of less valuable word vectors is increased, and the contribution is decreased.

The Score Vector plays a key role in the TiltedBERT method. Attention Context Emphasis (ACE) algorithm uses this vector to find the contribution of word vectors in each layer. The algorithm of the ACE metric calculation is explained in Algorithm.\textsuperscript{[1]} The algorithm inputs are the BERT encoder layer word vectors and the model parameters, and the output is a vector that suggests the contribution of word vectors in each encoder self-attention layer output. The first step is to get a pre-computed attention matrix from the model, $M_{att}$. Then the average of this matrix is computed over all of its heads which provides $M_h$. In the next step, the summation of a resulted matrix over the unnormalized dimension is computed to result in $M_s$. $M_s$ matrix can be interpreted as the Score Vector. In the last step, the value of Attention Context Emphasis (ACE) is computed from the median of the score vector.

Fig. 3\textsuperscript{[5]} shows the results of the calculated value of ACE metric for BERT\textsubscript{base} encoder stage on IMDB\textsuperscript{[19]} dataset and several General Language Understanding Evaluation (GLUE)\textsuperscript{[20]} benchmark tasks. The ACE value is gradually decreases at subsequent encoder layers. The fitted curve to the ACE metric results shows that the ACE metric value decreased significantly as encoder layer number increases. This means that the context contribution decreases remarkably at last few layers.

### Algorithm 1 Attention Context Emphasis (ACE) metric

**Input:** Embedding layer output $\in R^{LTHT}$ & fine-tuned BERT model $\{T =$ number of input tokens, $L =$ number of encoder layers, $H =$ hidden state size $\}$

**Output:** Encoder Layers ACE metric value: $E_{att} \in R^L$

**Initialization**:

1. $E_{att} = [0]$

**LOOP Process**

2. for encoder in $BERT - encoders$ do

3. $M_{att} \leftarrow$ Encoder attention matrix: $\in R^{HTT}$

4. $M_h \leftarrow$ Mean of $M_{att}$ over heads: $\in R^{TT}$

5. $M_h \leftarrow$ Sum of $M_h$ over unnormalized dimension: $\in R^T$

6. $S_l \leftarrow$ Median of $M_s$: $\in R$

7. Append $S_l$ to $E_{att}$

8. end for

9. return $E_{att}$

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**Table. I**

| Layer Type          | FLOPs | Relative Complexity |
|---------------------|-------|---------------------|
| Input Hidden States |       |                     |
| Add & Normalization |       |                     |
| Feed Forward        |       |                     |
| Add & Normalization |       |                     |
| Multi-Head Self-Attention | | |
| Output Hidden States|       |                     |

**Fig. 2.** BERT\textsubscript{base}\textsuperscript{[5]} encoder architecture

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**Fig. 3.** (left) shows the attention probability matrix of the heads, a 2-D matrix along the unnormalized dimension. The SV indicates the contribution of each input word vector to the output. The average of this matrix is computed over all of its elements with the higher score values contribute more to the layer output and are valuable. Decreasing the median of the SV means that the number of less valuable word vectors is increased, and the contribution is decreased. The Score Vector plays a key role in the TiltedBERT method. Attention Context Emphasis (ACE) algorithm uses this vector to find the contribution of word vectors in each layer. The algorithm of the ACE metric calculation is explained in Algorithm.\textsuperscript{[1]} The algorithm inputs are the BERT encoder layer word vectors and the model parameters, and the output is a vector that suggests the contribution of word vectors in each encoder self-attention layer output. The first step is to get a pre-computed attention matrix from the model, $M_{att}$. Then the average of this matrix is computed over all of its heads which provides $M_h$. In the next step, the summation of a resulted matrix over the unnormalized dimension is computed to result in $M_s$. $M_s$ matrix can be interpreted as the Score Vector. In the last step, the value of Attention Context Emphasis (ACE) is computed from the median of the score vector.
TABLE I
BERT\textsubscript{BASE} FLOPs Study

| Stage          | Sub-stage                  | Sub-stage FLOPs Estimation\(^a\) | FLOPs Estimation | FLOPs Share\(^b\) | Latency Share\(^c\) |
|----------------|----------------------------|-----------------------------------|------------------|-------------------|---------------------|
| Embedding      | Word-embeddings            | 0                                 | 0                | 7TH               | 0.003%              |
|                | Position-embeddings        | 0                                 |                  |                   | 0.2%                |
|                | Layer-normalization        | 0                                 |                  |                   |                     |
| Encoder (x12)  | Attention-self             | 6LTH\(^2\) + 2HTL\(^2\)          | 6LTH\(^2\) + 2HTL\(^2\) | 25.1%             | 99.8%               |
|                | Attention-output           | 2LTH\(^2\)                        | 2LTH\(^2\)       |                   |                     |
|                | Intermediate               | 8LTH\(^2\)                        | 8LTH\(^2\)       |                   |                     |
|                | Output                     | 18LTH\(^2\)                       | 18LTH\(^2\)      |                   |                     |
| Classifier     | Pooler                     | 2H\(^2\)                          | 2H\(^2\)         | 0.0013%           | 0.036%              |
|                | Output                     | 4H                                |                  |                   |                     |

\(^a\) T = number of input tokens, L = number of encoder layers, H = hidden state size and N = number of output labels

\(^b\) With T = 512, L = 12, H = 768 and N = 2

\(^c\) IMDB \cite{19} dataset average relative inference time latency.

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D. TiltedBERT Architecture

According to section \[\text{III-B}\] almost all of the latency and FLOPs accrue in the encoder stage, and in section \[\text{III-C}\] shows that the encoder layers ACE metric value is decreased at later encoder layers. This section proposes details of our novel TiltedBERT model architecture based on the BERT\textsubscript{base} and past presented analyses and intuitions.

As mentioned, our proposed TiltedBERT model is based on BERT\textsubscript{base} model. The TiltedBERT encoder is similar to the original BERT encoder, but only the self-attention layer is revised. The TiltedBERT self-attention layer is presented in Fig. 3.

In Fig. 3, the score vector is obtained from the probability matrix. The probability matrix and values matrix on each head are sorted concerning the score vector. Then, the number of preserved word vectors is calculated with the Tilt-Rate hyper-parameter, and word vectors with less contribution are eliminated.

The number of remaining word vectors in each TiltedBERT encoder layer is calculated from "(1)". \(T_l\) is the number of current encoders output word vectors, \(l\) is the layer number, and \(T_{l-1}\) is the number of last layer output word vectors. \(\alpha_{TR}\) is the TR hyper-parameter that controls the preserved word vectors in each encoder layer.

\[ T_l = \max 1, [T_{l-1} \times \alpha_{TR}] \]  

(1)

Equation \[\text{(2)}\] presents the approximated number of processed word-vector in each encoder layer. From “Table. I” in each encoder layer, around 75\% of FLOPs occur after our added word-vector elimination layer and the remaining FLOPs accrued before this layer. Concerning this estimation, the effective number of processed word-vector combinations of the remaining word vectors before and after the word vector elimination layer.

\[ PW_l = \frac{T_{l-1} + 3T_l}{4} \]  

(2)

As mentioned in \[\text{IV}\] section, our method significantly decreases inference time without any extra training steps and additional training effort. For more intuition from our method speedup, in "(3)" and "(4)" the number of processed word vectors in the BERT\textsubscript{base} and TiltedBERT is presented. In these equations, \(L\) is the number of BERT encoder layers, \(T\) is the...
number of encoder input word vectors, and $\alpha_{TR}$ is the TR hyper-parameter.

$$PW_{BERT_{base}} = T \times L$$

$$PW_{TiltedBERT} = \sum_{l=0}^{L-1} \alpha_{TR} \times T \times \frac{1 + 3\alpha_{TR}}{4}$$ \hspace{1cm} (4)

Since almost all inference latency occurs in the encoder stage, the overall inference time speedup is near the encoder stage speedup. Equation (5) presents the estimated speedup of our method. In this formulation, we assume that the maximization of (1) is always returning the second term because the sentence length of understudy datasets is not very short, and our assumption remains valid in a wide range of Tilt-Rate selections.

$$K_{speedup} = \frac{4L \times (1 - \alpha_{TR})}{(1 + 3\alpha_{TR}) \times (1 - \frac{\alpha_{TR}}{L - 1})}$$ \hspace{1cm} (5)

For example, if $T$ and $L$ were 512 and 12 and $\alpha_{TR}$ were 0.8, the TiltedBERT inference time speed is around 3.09 times faster than $BERT_{base}$.
IV. EXPERIMENTS

This section will first overview the GLUE and IMDB benchmark and task and then present the TiltedBERT model and implementation settings. We evaluate the effectiveness of TiltedBERT in the extensive types of tasks. At the end of this section, the ablation studies are mentioned.

A. Datasets

We evaluate our TiltedBERT model on the IMDB dataset, which is single sentence classification task and General Language Understanding Evaluation (GLUE) benchmark which consist of 2 single-sentence classification tasks: SST-2 and CoLA, 2 multi-sentence similarity classification tasks: MRPC and QQP, 1 binary question answering task: QNLI, 3 natural language inference tasks: RTE, MNLI-M and MNLI-MM, and 1 multi-sentence similarity regression task: STS-B.

B. TiltedBERT Settings

We implement the TiltedBERT model based on the pre-trained BERT$_{base}$ model that consists of a tokenizer layer, 12 encoder layers with 768 hidden dimension sizes, and with a pooler output layer. Also, we add a proper classifier or regression layer at the end of the model. The total number of parameters of this model is around 110 million parameters.

As mentioned in section III-D, we put two supplementary parameter-less layers in the middle of each encoder stage that detect, sort, and eliminate less important word vectors based on our proposed policy. The number of model parameters has not changed with these modifications, but the number of word vectors in each layer decreases significantly with the encoder’s layer number.

The hyper-parameters of TiltedBERT are the same as the BERT$_{base}$. Only one supplement Tilt-Rate (TR) hyper-parameter is added to control elimination rate on fine-tuning and inference phases. The TiltedBERT model have 5 main hyper-parameters: learning rate - $[1 \times 10^{-10}, 5 \times 10^{-10}]$, batch size - $\{4, 8, 16, 32, 64, 128\}$, number of epochs - $\{3, 5\}$, Dropout - $[0.05, 0.15]$, and Tilt-Rate - $[0.65, 0.90]$.

The cross-entropy loss function is used for classification tasks fine-tuning and Mean Square Error (MSE) loss function for regression tasks. The linear learning rate scheduler is used for all tasks and warm-up for some. In all of the tasks, AdamW optimizer with $\epsilon = 1 \times 10^{-8}$, $\beta 1 = 0.9$ and $\beta 2 = 0.999$ is used.

We fixed the number of output tokens of the tokenizer layer based on each dataset: somehow, lower 1% of samples are truncated. The selected sentence length for each dataset is mentioned in “Table. IV”.

C. Implementation Details

The TiltedBERT implementation is in the PyTorch library, and an Nvidia Tesla P100 GPU is used. We used pre-trained BERT$_{base}$-uncased Hugging Face implementation and customized its layers. Our datasets are from the Hugging Face Datasets library, and the GLUE results are verified on the official GLUE server for consistency.

D. Experimental Results on GLUE and IMDB

We submit the predictions of TiltedBERT to the official GLUE server to obtain results on the test sets, and for the IMDB task, use available test labels to obtain results. The results of our TiltedBERT model summarized in “Table. III”.

The test results of TiltedBERT model respect to BERT$_{base}$ is presented in table “Table. III”. The inference time speedup and FLOPs of TiltedBERT for various tasks are mentioned. As observed in the table, our model inference time is up to 5.3 times faster than BERT$_{base}$ with trivial accuracy degradation. The TiltedBERT speedup to BERT$_{base}$ is 2.81 times on average with around 0.85% test result drop on average. These results indicate that the proposed method can effectively improve transformer-based models’ performances and resource usage.

The reported measured FLOPs reduction gain is consistent with inference speedup in our experiences, and slight differences are from other computational overheads.

The expected speedup results are calculated from $\epsilon$, and as observed, these calculated values are very much in line with inference time speedup and FLOPs reduction gain. Also, in our estimation, we assumed that all of the computational efforts are in the encoder stage and did not consider the tokenizer and classifier layers latencies. This consistency between our estimation with experimental results shows the correctness of our analysis.

The test results of the TiltedBERT model on several GLUE benchmark tasks to recently proposed methods are summarized in “Table. III”. We use BERT$_{base}$ model (L=12, h=12, d=768) as the basis for our comparisons. The test results, number of FLOPs reduction gain, and inference time speedup are mentioned on average for each model.

The table shows that the TiltedBERT results are very competitive to other baseline previous methods on the GLUE benchmark. TiltedBERT achieves 2.81 times speedup while less than 1% on average accuracy drops to the BERT$_{base}$ model. We use BERT$_{base}$ language model weights as the starting point for our TiltedBERT model, and we fine-tune the TiltedBERT on downstream tasks.

As shown in the “Table. III”, the DistilBERT model achieves 1.67 times average speedup with around 1.5% accuracy degradation. In DistilBERT, a pre-trained general-purpose language presentation model must be pre-training from the scratch model, and this pre-training step needs significant effort. The TinyBERT model speedup is 2.0 times with 0.5% accuracy drops on average. TinyBERT uses a two-stage learning framework that performs transformer distillation at pre-training and fine-tuning phases with considerable excessive computational effort. The MobileBERT model speedup is 5.5 times with around 1% accuracy drop, but this model starts from BERT$_{large}$ architecture for teacher and distill it to a slighter student with excessive training effort. The PoWER-BERT model speedup is 2.71 times with less than 0.7% accuracy drop. However, the training of this model consists of 3 phases: fine-tuning, elimination configuration search, and re-training that impose extra training effort.
Our proposed method does not need extra training steps, excessive computational effort, and supplement datasets compared to other compared methods. Also, after the fine-tuning phase, we can control the accuracy and speed metrics in a wide range of Tilt-Rate selection with the TiltedBERT offline-tuning property.

E. Ablation Studies

This section will conduct ablation studies to investigate the offline adjustable inference speedup and propose a design guide for efficient TiltedBERT implementation.

In Fig. 6(a) is presented the FLOPs numbers to the Tilt-Rate hyper-parameter value. As observed, the number of FLOPs exponentially decreased with the Tilt-Rate value, and by decreasing the Tilt-Rate a bit, the number of FLOPs and inference time is decreased significantly. In Fig. 6(b) the accuracy of fine-tuned TiltedBERT model on multiple tasks is presented and shown that the accuracy value is stable for a wide range of Tilt-Rate value selections. In Fig. 6(c) the accuracy results to the number of encountered FLOPs are plotted. The accuracy value is almost unchanged by decreasing about 60% of the FLOPs by our method.

In these experiments, we first fine-tune the TiltedBERT model on the downstream task and then sweep Tilt-Rate (TR) hyper-parameter around its preset value. We report the accuracy of models on validation sets because of the number of test set verification limits.

For fine-tuning TiltedBERT on a specific downstream task, the first step is to find the sentence length of the target dataset, and in the second step is to set the proper number of FLOPs or speedup with concerning use case considerations and choose the Tilt-Rate value with the above intuitions or our proposed speedup estimation formula. The last step is the selection of the other hyper-parameters which mentioned in IV-B and start fine-tuning. After the fine-tuning phase, the speedup error can be adjusted with TiltedBERT offline-tuning property.

CONCLUSIONS

In this paper, we proposed TiltedBERT that speedup the BERT_{base} inference time significantly with trivial accuracy drop. Also, the TiltedBERT speedup can be tuned after fine-tuning phase (offline-tuning property) by adjusting the Tilt-Rate hyper-parameter value. We develop an accurate analytical speedup estimation for the TiltedBERT and report the consistency between our analysis with experimental results. We propose a novel contribution metric that expresses each BERT encoder layer’s contribution values between 0 and 1. We apply this metric on extensive datasets, and in all of our experiments, the encoder layer context contribution is decreased with layer number. We investigate our method and analysis on GLUE benchmark and IMDB dataset and report our competitive results. For future works, we plan to improve our word vector elimination policy and boost our speedup by applying parameter reduction methods on the TiltedBERT.

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### TABLE III

Results Comparison Between BERT\textsubscript{BASE} [5], DISTILBERT [12], TINYBERT [17], MOBILEBERT [15], POWER-BERT [18] and TiltedBERT Models

| Model\textsuperscript{a} | CoLA | SST-2 | MRPC | QNLI | RTE | MNLI-M | MNLI-MM | STS-B | Avg | FLOPs | Speedup |
|------------------------|------|-------|------|------|-----|--------|---------|-------|-----|-------|---------|
| BERT\textsubscript{BASE} | 52.7 | 93.5  | 88.7 | 91   | 68.9| 84.7   | 83.8    | 84.3  | 80.95| 1    | 1       |
| DistilBERT             | 51.3 | 91.3  | 87.5 | 89.2 | 59.9| 82.2   | -       | 86.9  | 78.33| 2.00 | 1.67    |
| TinyBERT               | 51.1 | 93.1  | 87.3 | 90.4 | 70  | 84.6   | 83.2    | 83.7  | 80.42| 2.00 | 2.00    |
| MobileBERT\textsuperscript{b} | 50.5 | 92.8  | 88.8 | 90.6 | 66.2| 83.3   | 82.6    | 84.4  | 79.9 | 3.95 | 5.52    |
| Power-BERT             | 52.3 | 92.1  | 88.1 | 90.1 | 67.4| 83.8   | 83.1    | 85.1  | 80.25| -    | 2.71    |
| TiltedBERT             | 52.8 | 92.5  | 87.5 | 90.1 | 67.8| 83.7   | 82.8    | 83.7  | 80.1 | 2.89 | 2.81    |

\textsuperscript{a} Matthew’s Correlation reported for CoLA; F1-score for MRPC; Pearson Correlation for STS-B; Accuracy for the rest.

\textsuperscript{b} MobileBERT starting point is from BERT\textsubscript{large} architecture that is around three times more parameters with respect to BERT\textsubscript{BASE}.

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Fig. 6. (a) TiltedBERT FLOPs reduction gain versus Tilt-Rate (TR) in the various numbers of input sequence word vectors, (b) TiltedBERT offline validation set accuracy curves versus Tilt-Rate (TR) for SST-2 [21], MRPC [23], MNLI-M/MM [27] and QNLI [25] tasks, (c) TiltedBERT offline validation set accuracy curves versus FLOPs number for SST-2 [21], MRPC [23], MNLI-M/MM [27] and QNLI [25] tasks.

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