UNDIVIDED ATTENTION: ARE INTERMEDIATE LAYERS NECESSARY FOR BERT?

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ABSTRACT

In recent times, BERT-based models have been extremely successful in solving a variety of natural language processing (NLP) tasks such as reading comprehension, natural language inference, sentiment analysis, etc. All BERT-based architectures have a self-attention block followed by a block of intermediate layers as the basic building component. However, a strong justification for the inclusion of these intermediate layers remains missing in the literature. In this work we investigate the importance of intermediate layers on the overall network performance of downstream tasks. We show that reducing the number of intermediate layers and modifying the architecture for BERT_{BASE} results in minimal loss in fine-tuning accuracy for downstream tasks while decreasing the number of parameters and training time of the model. Additionally, we use the central kernel alignment (CKA) similarity metric and probing classifiers to demonstrate that removing intermediate layers has little impact on the learned self-attention representations.

Index Terms— BERT, reduced complexity, layer removal, language modeling, similarity analysis

1. INTRODUCTION

Language model pre-training has led to a number of break-throughs in NLP [1], [2], [3], [4] and have achieved state-of-the-art results on many non-trivial NLP tasks such as question-answering or natural language inference. In this problem domain, the BERT model, based on the [5] architecture has risen to prominence.

The BERT model architecture has multiple bidirectional Transformer [5] encoder blocks stacked together. Training BERT consists of first pre-training on large corpus of unlabeled data followed by fine-tuning on a much smaller, task-specific data set. Pre-training is computationally expensive and often requires several days to complete while fine-tuning can be completed in a much shorter time.

BERT models have significant parameter count and memory footprint, from 110M (BERT_{BASE}) to 340M (BERT_{LARGE}) to 8.3B (Megatron [6]) parameters. In this work, we demonstrate decreased model size and decreased training time with a negligible change in fine-tuning accuracy.

While demonstrating decreased model size and decreased training time is relevant to the field in and of itself, we feel it is also important to a provide deeper understanding of why our architectural modifications are effective. Similar to the work done in [7], we use the centered kernel alignment (CKA)

similarity metric [8] and probing linear classifiers [7] to gain insight into the improvements made by our architectural modifications.

2. RELATED WORK

Recent work, such as ALBERT [9], employ a number of approaches, such as decomposing the vocabulary matrix and cross-layer parameter sharing, to achieve similar accuracy to BERT but with 18x fewer parameters and 1.7x faster training. Other related work such as [10] changed the ordering of self-attention and intermediate blocks to create the *sandwich transformer*. Like us, the authors recognize that the ordering of self-attention and intermediate blocks in BERT networks is not well justified nor necessarily optimal. However, unlike ALBERT, their goal is to improve language modeling performance and not to decrease the network size or complexity. In this work, we share similar goals to ALBERT but employ a different approach that removes blocks of intermediate layers from the network. In fact, the ALBERT approach is complementary to the architectural changes we propose here.

3. ARCHITECTURAL MODIFICATIONS

BERT [1] is a stack of multiple Transformer encoder blocks with each encoder block further consisting of a separate multi-head self-attention block followed by an intermediate block (Figure 2). The importance of the self-attention block has been extensively analyzed in [7], [11], [12] and others.

An intermediate block is a four-layer feed-forward network containing a Gaussian error linear unit (GELU) [13] in between two linear layers followed by a dropout layer (see *Intermediate Block* of Figure 1). The intermediate block was added mainly to enrich the representations obtained from the self-attention block. However, the relevance of this block has not been well studied and no strong justification for their inclusion in Transformer-type architectures has been made in the literature.

3.1. Removal of Intermediate Blocks

Our main motivation is to decrease model size and complexity while quantifying and understanding any negative impact of reducing the number of intermediate blocks on model accuracy. To this end, we modify the BERT architecture by removing some of the intermediate blocks within the network. More specifically, an intermediate block will be added only after every n self-attention blocks. If the total number of self-attention blocks in the network is m then the modified

network will contain $\lfloor \frac{m}{n} \rfloor$ intermediate blocks. For example, when n=1 the network is unmodified and contains m intermediate blocks. However, when $n=\infty$ the modified network contains no intermediate blocks.

Note that n is an architectural hyper-parameter that can be changed to make trade-offs in network size, complexity and accuracy. We experiment with different values of n and analyze its effects with multiple fine-tuning tasks.

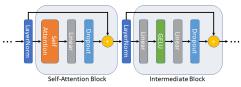


Fig. 1: Reference unit in the unmodified BERT network. The unmodified BERT_{BASE} network contains 12 of these units arranged sequentially.



Fig. 2: First six blocks of the unmodified network architecture. This BERT_{BASE} network will have a total of 12 self-attention blocks and 12 intermediate blocks.

The proposed modification removes the intermediate block every n self-attention blocks. An example of the modified BERT_{BASE} network with n=2 is shown in Figure 3. The modified network will still have the same number of self-attention heads and blocks as the unmodified network. However, the number of parameters in the network will decrease due to fewer intermediate blocks.



Fig. 3: First six blocks of the modified network architecture with n=2. Note the removal of intermediate blocks between every n=2 self-attention blocks (compare to Figure 2). Using this architecture, the modified BERT_{BASE} network will have only six intermediate blocks instead of the 12 which are found in the unmodified network.

4. CONVERGENCE RESULTS

In this section we present the convergence and accuracy results for $n \in \{1, 2, 3, 4, 6, \infty\}$ where n = 1 represents the unmodified network and $n = \infty$ represents the modified network with no intermediate blocks. We chose BERT_{BASE} as our reference model which has 12 self-attention blocks each of which is followed by an intermediate block with a hidden size of 768. We perform all our experiments on BERT_{BASE}, mainly due to limited computational resources and the extremely long times required to train larger models. Table 1 shows the total number of parameters along with the relative decrease in size and increase in throughput of the unmodified and modified BERT_{BASE} networks.

Table 1: Number of parameters, decrease in size and increase in throughput for unmodified and modified BERT_{BASE} networks with different values of n.

Network	Parameters	Size Decrease	Throughput Increase
Unmodified $(n = 1)$	110.10M	1.00x	1.00x
Modified $(n = 2)$	81.76M	1.35x	1.39x
Modified $(n = 3)$	72.31M	1.52x	1.59x
Modified $(n = 4)$	67.59M	1.63x	1.72x
Modified $(n = 6)$	62.86M	1.75x	1.87x
Modified $(n = \infty)$	53.41M	2.06x	2.28x

4.1. Pre-Training

All variants were pre-trained on the English Wikipedia and BookCorpus [14] data sets. Similar to [1], we follow a two-phase pre-training approach. For the first 90% of iterations, the model is trained with a sequence length of 128 and the remaining 10% is trained with a sequence length of 512. An initial learning rate of 10^{-4} was used for all variants including a linear warm-up schedule for the first 1% of training.

4.2. Fine-Tuning

Table 2 shows the results of fine-tuning with different downstream tasks. We evaluate our models on two popular benchmarks: The General Language Understanding Evaluation (GLUE) benchmark [15] and the Stanford Question Answering Dataset (SQuAD) [16]. From the GLUE benchmark, we chose MNLI, SST-2, and QQP as our primary tasks. The same set of hyper-parameters were used across all variants for each fine-tuning task.

Table 2: Fine-tuning results for unmodified and modified BERT_{BASE} networks with different values of n. The F1 and EM scores are shown for SQuAD v1.1, m/mm for MNLI, accuracy for SST-2 and F1 score for QQP.

Network	SQuAD	MNLI	SST-2	QQP
Unmodified $(n = 1)$	88.43/80.97	82.83/83.38	91.97	87.50
Modified $(n = 2)$	87.09/79.66	81.64/82.32	89.44	87.38
Modified $(n = 3)$	86.91/79.28	81.41/82.20	90.13	87.13
Modified $(n = 4)$	86.63/78.86	81.47/82.45	90.71	86.76
Modified $(n = 6)$	85.73/77.59	80.65/80.85	88.64	86.42
Modified $(n = \infty)$	83.27/74.59	79.07/79.85	89.33	85.44

From Table 2 we see that the modified BERT_{BASE} networks perform quite well compared to the unmodified network. Specifically, with $n \in \{2, 3, 4\}$ there is approximately 1-2% loss in accuracy across fine-tuning tasks while simultaneously providing a significant improvement in size and throughput (see Table 1). These results indicate that the nhyper-parameter can be used to make trade-offs in network size, speed and accuracy. For example, if an F1 score on SQuAD of approximately 87% is acceptable then a modified (n = 3) network could be used which would be approximately 1.5x smaller and 1.6x faster. Other trade-offs can be made for situations where the network is to be deployed onto a system with very limited memory and computational resources. In that case, minimizing network size and computational complexity would be critical and choosing a modified $(n = \infty)$ network would decrease memory usage by more than 2x and be approximately 2.3x faster than the unmodified (n = 1) network.

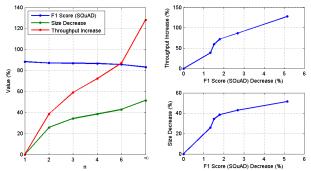


Fig. 4: F1 scores on SQuAD of modified BERT_{BASE} networks with different values of n along with the corresponding decrease in size and increase in throughput as a relative percentage to the unmodified (n=1) network. F1 score, throughput increase and size as a function of n (left). On the right, the trade-off between accuracy (absolute decrease in F1 score) and efficiency in either throughput (top right) or memory footprint (bottom right). Modified networks with $n \in \{2,3,4\}$ result in a significant size decrease and throughput increase while retaining a similar F1 score on SQuAD.

Using the values in Tables 1 and 2, Figure 4 shows the SQuAD F1 scores of the modified BERT_{BASE} networks along with their corresponding size decrease and throughput increase relative to the unmodified (n=1) network. The contribution of intermediate blocks to the final fine-tuning accuracy is not significant but their removal can significantly decrease size and increase speed, allowing trade-offs between accuracy and efficiency. For example, the F1 score of the modified (n=3) network decreases by approximately 1.5% but it is more than 34% smaller and 52% faster.

4.3. Intermediate Layer Removal Prior to Fine-Tuning

Results in 4.2 show that removing intermediate layers have little impact on network accuracy. However, can these intermediate layers be removed *before* the modified network is fine-tuned?

The unmodified BERT_{BASE} network is first pre-trained as described in Section 4 and then the intermediate layers are removed. After removal of the intermediate layers, the now modified BERT_{BASE} network is fine-tuned with SQuAD v1.1.

Table 3: Results with intermediate blocks removed prior to finetuning on SQuAD for modified BERT_{BASE} networks and different values of n. The F1 and EM scores are shown for SQuAD v1.1.

Network	SQuAD F1	SQuAD EM
Modified $(n = 2)$	84.20%	75.63%
Modified $(n = 3)$	76.99%	67.23%
Modified $(n = 4)$	72.03%	60.80%
Modified $(n = 6)$	65.45%	53.10%
Modified $(n = \infty)$	56.82%	43.66%

Table 3 clearly shows a significant degradation in F1 and EM scores for the modified BERT_{BASE} networks. For example, the decrease in F1 score for n=3 when the intermediate layers are removed before fine-tuning is 11.44% compared with Table 2 where the decrease is 1.52% for n=3. During pre-training it appears that the intermediate layers are performing important transformations to the representations

learned in the self-attention blocks. By removing these layers prior to fine-tuning, the self-attention blocks are unable to compensate during fine-tuning.

5. ANALYSIS OF INTERMEDIATE LAYERS

In this section, we demonstrate that removing intermediate layers makes only small changes to the learned representations of the modified BERT_{BASE} networks after fine-tuning. Our understanding begins with analyzing the similarities of self-attention blocks of unmodified and modified BERT_{BASE} networks using centered kernel alignment [8]. We then use attention-based probing classifiers [7] to analyze the contributions of the intermediate blocks.

5.1. Similarity of Self-Attention Layers

To better understand the importance of intermediate layers in BERT-type architectures, we analyze the self-attention blocks of both unmodified and modified BERT_{BASE} networks using the centered kernel alignment (CKA) similarity metric. The CKA similarity metric has useful properties such as invariance to both orthogonal transformations and isotropic scaling which is important when comparing architecturally similar but not identical networks.

We follow the procedure in [8] and perform the similarity analysis over multiple pre-training and fine-tuning trials of the unmodified and modified BERT_{BASE} networks. However, due to limited computational resources, performing an averaged CKA similarity analysis with multiple trials of fully pre-trained networks is not feasible. Instead, unmodified and modified BERT_{BASE} networks are partially pre-trained for 100,000 steps with a batch size of 256 and then fully fine-tuned

All BERT_{BASE} networks denoted as Unmodified or Modified are first partially pre-trained. All networks denoted Untrained are not pre-trained and have their weights initialized randomly. However, *all* networks are fully finetuned using SQuAD v1.1. This training procedure is used so that the similarity analysis is applied to only fine-tuned networks. The fine-tuning results for each network are shown in Table 4.

Table 4: Fine-tuning results after multiple trials of partial pretraining for unmodified and modified BERT_{BASE} networks using SQuAD. F1 and EM scores are for SQuAD v1.1, averaged over 5 trials of pre-training and fine-tuning for each network and shown along with the corresponding standard deviation.

Network	SQuAD F1	SQuAD EM
Untrained	$17.05\% \pm 0.21\%$	$8.62\% \pm 0.16\%$
Unmodified $(n = 1)$	$77.02\% \pm 0.38\%$	$66.92\% \pm 0.47\%$
Modified $(n = 2)$	$76.68\% \pm 1.04\%$	$66.20\% \pm 1.14\%$
Modified $(n = 3)$	$74.83\% \pm 0.79\%$	$64.13\% \pm 1.01\%$

After fine-tuning, each BERT_{BASE} network is used to encode the same 500 sentences from the WebText [17] data set to produce output activations from each of the self-attention blocks. These output activations are then used as the input to linear-kernel CKA.

Figure 5 shows the similarities between the same 12 self-attention blocks for different pairs of untrained (i.e. not

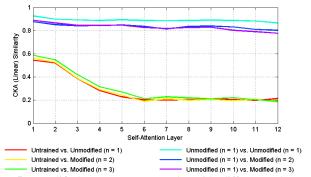


Fig. 5: Modified BERT_{BASE} networks with different values of n develop similar self-attention representations as the unmodified BERT_{BASE} network after pre-training and fine-tuning. However, these representations differ significantly from unmodified networks which have not been pre-trained (i.e. Untrained). CKA similarities are averaged over 5 trials of each network (15 pairs for Unmodified vs. Unmodified and 25 pairs for others).

pre-trained), unmodified and modified BERT_{BASE} networks. Similarities between unmodified and modified BERT_{BASE} networks are much higher than similarities with untrained networks. The similarities between unmodified and modified networks after training is quite high.

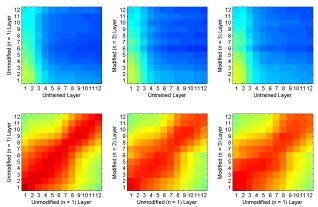


Fig. 6: Comparisons to BERT_{BASE} networks which have not been pre-trained (i.e. Untrained) show no structure and little CKA similarity with the unmodified and modified networks (top row). However, comparisons of unmodified BERT_{BASE} networks to modified networks with different values of n (lower center and lower right) have CKA similarity patterns which strongly resemble the self-similarity pattern of the unmodified network (lower left). CKA similarities are averaged over 5 trials of each network (15 pairs for Unmodified vs. Unmodified and 25 pairs for others).

Figure 6 shows the similarities between all 12 self-attention blocks for different pairs of untrained (i.e. not pre-trained), unmodified and modified BERT_{BASE} networks. Note that Figure 5 shows the diagonal (lower left to upper right) values seen in Figure 6. The comparisons between the untrained BERT_{BASE} network and the unmodified and modified networks are unstructured and show little similarity. On the other hand, the similarity *pattern* between unmodified and modified BERT_{BASE} networks shows the same diagonal structure as seen in the self-similarity pattern of the unmodified network. The comparatively high similarity between

unmodified and modified networks seen in Figure 5 and the similar patterns shown in Figure 6 both seem to indicate that removing intermediate blocks has little impact on the learned self-attention representations.

5.2. Contributions of Intermediate Layers

We use the analysis methods presented in [7] to further justify the removal of intermediate layers. In BERT, each individual attention head is known to specialize to particular aspects of syntax and the model's overall knowledge about syntax is distributed across multiple attention heads. Attention-based probing classifiers proposed in [7] measure the overall ability of the model to learn syntactic information. In [7], the probing classifiers are evaluated on the dependency parsing task for the Penn Tree Bank (PTB) data set [18]. These classifiers treat the BERT attention outputs as fixed and train only a small number of parameters. Basically, the classifier produces a probability distribution over each word that indicates how likely each other word in the sentence is its syntactic head. The Attn + GloVe probing classifier substantially outperforms other reference baselines in [7]. This suggests BERT's attention maps have a fairly thorough representation of English syntax.

We use the same Attn + GloVe probing classifier introduced in [7] and evaluate on the Universal Dependency gold standard for English, the English Web Treebank (EWT) data set [19] instead of PTB. Table 5 shows the UAS scores on EWT for different values of n. For this particular task it appears that fewer intermediate blocks result in an increase of the UAS score. Therefore, as seen earlier, this indicates that removing intermediate blocks has little impact on the model's ability to learn syntactic information.

Table 5: Attention-based probing classifier results for unmodified and modified BERT_{BASE} networks with different values of n.

Network	UAS Score
Untrained	24.20%
Unmodified $(n = 1)$	70.60%
Modified $(n = 2)$	69.80%
Modified $(n = 3)$	71.50%
Modified $(n = 4)$	70.80%
Modified $(n = 6)$	71.50%
Modified $(n = \infty)$	73.00%

6. CONCLUSION

In this work we proposed a modification to the BERT architecture focusing on reducing the number of intermediate layers in the network. With the modified BERT_{BASE} network we show that the network complexity can be significantly decreased while preserving accuracy on fine-tuning tasks. In addition, our analysis shows that reducing intermediate layers results in minimal changes to the learned representations of the modified BERT_{BASE} networks after fine-tuning.

For future work, we plan to apply our modifications to larger models like BERT_{LARGE} and GPT to show that the architectural changes can be used more widely. We also intend to integrate other network pruning techniques (e.g. ALBERT) with our modified architecture to further decrease size and increase throughput.

7. REFERENCES

- [1] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova, "Bert: Pre-training of deep bidirectional transformers for language understanding," *arXiv* preprint arXiv:1810.04805, 2018.
- [2] Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei, "Language models are few-shot learners," 2020.
- [3] Matthew E. Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer, "Deep contextualized word representations," 2018.
- [4] Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov, "Roberta: A robustly optimized bert pretraining approach," 2019.
- [5] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin, "Attention is all you need," 2017.
- [6] Mohammad Shoeybi, Mostofa Patwary, Raul Puri, Patrick LeGresley, Jared Casper, and Bryan Catanzaro, "Megatron-lm: Training multi-billion parameter language models using gpu model parallelism," arXiv preprint arXiv:1909.08053, 2019.
- [7] Kevin Clark, Urvashi Khandelwal, Omer Levy, and Christopher D. Manning, "What does bert look at? an analysis of bert's attention," 2019.
- [8] Simon Kornblith, Mohammad Norouzi, Honglak Lee, and Geoffrey Hinton, "Similarity of neural network representations revisited," 2019.
- [9] Zhenzhong Lan, Mingda Chen, Sebastian Goodman, Kevin Gimpel, Piyush Sharma, and Radu Soricut, "Albert: A lite bert for self-supervised learning of language representations," 2020.
- [10] Ofir Press, Noah A. Smith, and Omer Levy, "Improving transformer models by reordering their sublayers," 2020.
- [11] Paul Michel, Omer Levy, and Graham Neubig, "Are sixteen heads really better than one?," 2019.
- [12] Ian Tenney, Dipanjan Das, and Ellie Pavlick, "Bert rediscovers the classical nlp pipeline," 2019.

- [13] Dan Hendrycks and Kevin Gimpel, "Gaussian error linear units (gelus)," 2020.
- [14] Yukun Zhu, Ryan Kiros, Richard Zemel, Ruslan Salakhutdinov, Raquel Urtasun, Antonio Torralba, and Sanja Fidler, "Aligning books and movies: Towards story-like visual explanations by watching movies and reading books," 2015.
- [15] Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R. Bowman, "Glue: A multi-task benchmark and analysis platform for natural language understanding," 2019.
- [16] Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang, "Squad: 100,000+ questions for machine comprehension of text," *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, 2016.
- [17] Aaron Gokaslan, Vanya Cohen, Ellie Pavlick, and Stefanie Tellex, "Openwebtext corpus," urlhttp://Skylion007.github.io/OpenWebTextCorpus, 2019.
- [18] Mitchell P. Marcus, Mary Ann Marcinkiewicz, and Beatrice Santorini, "Building a large annotated corpus of english: The penn treebank," *Comput. Linguist.*, vol. 19, no. 2, pp. 313–330, June 1993.
- [19] Natalia Silveira, Timothy Dozat, Marie-Catherine De Marneffe, Samuel R Bowman, Miriam Connor, John Bauer, and Christopher D Manning, "A gold standard dependency corpus for english.," in *LREC*. Citeseer, 2014, pp. 2897–2904.