Further Boosting BERT-based Models by Duplicating Existing Layers: Some Intriguing Phenomena inside BERT

Wei-Tsung Kao∗, Tsung-Han Wu∗, Po-Han Chi, Chun-Cheng Hsieh, Hung-Yi Lee
National Taiwan University
{b05901009, r07942145, r08942074, r07942150, hungyilee}@ntu.edu.tw

Abstract
Although Bidirectional Encoder Representations from Transformers (BERT) have achieved tremendous success in many natural language processing (NLP) tasks, it remains a black box, so much previous work has tried to lift the veil of BERT and understand the functionality of each layer. In this paper, we find that removing or duplicating most layers in BERT would not change their outputs. This fact remains true across a wide variety of BERT-based models. Based on this observation, we propose a quite simple method to boost the performance of BERT. By duplicating some layers in the BERT-based models to make it deeper (no extra training required in this step), they obtain better performance in the down-stream tasks after fine-tuning.

1 Introduction
The progress of NLP based on deep learning advanced rapidly in recent years. In the past few years, people use pre-trained static word embedding [Mikolov et al., 2013] as features of words to solve lots of tasks, including word analogy, text classification, common name entity recognition (NER), etc. Several fine-grained analyses have been done on what static word embeddings capture [Levy and Goldberg, 2014]; the effect of hyperparameters, such as the dimension of static word embeddings, is also studied thoroughly [Yin and Shen, 2018].

Recently, the idea of contextualized word embeddings, [Peters et al., 2018] arises because it can achieve better performance than static word embeddings. BERT [Devlin et al., 2018] pre-trains a masked language model based on the transformer [Vaswani et al., 2017] to learn bidirectional contextualized representations of words. It can be quickly fine-tuned on many downstream tasks merely by appending a simple linear classifier, obtaining state-of-the-art results on a great number of NLP tasks such as text classification, natural language inference (NLI) [Wang et al., 2018], and question answering [Rajpurkar et al., 2018]. Although those BERT-based models can reach extraordinary performance on almost every NLP datasets, the black-box nature of deep learning models makes a fine-grained analysis on the contextualized word embedding and hidden representations much more difficult. It remains unclear that what those BERT-based models have learned and what features they extract.

People usually assume that the hidden states from the lower layers of BERT preserve more word identity, while the higher hidden states contain less word identity and more abstract information like syntactic or semantic information [Hewitt and Liang, 2019]. In this paper, we use a novel method to analyze the hidden states of every layer of BERT. During the pre-training stage, BERT takes a sequence of tokens as input, and the output layer, which is a linear classifier, takes the final hidden state to reconstruct the input token sequence. We found that when taking the hidden states other than the final ones as input, the linear classifier can also reconstruct the input token sequence with high accuracy. The results are counterintuitive because, during the pre-training stage, the linear classifier has never seen the input other than the final hidden states. This phenomenon is observed in most layers across variants of BERT-based models, including ALBERT [Lan et al., 2019]. The observation indicates that the hidden states of most layers in BERT preserve the word identity and have very close distribution, so they can be decoded into the input tokens by the same linear classifier.

The observation that most layers have close distribution indicates that each layer does not change the input a lot, and thus behaves like identity transform. Therefore, we assume that duplicating layers in the model would not largely change the behavior of the model a lot. The experimental results indeed show that when duplicating a few layers in the pre-trained BERT-based models, they still maintain pretty high input sentence word identity in almost every layer.

After observing the above counterintuitive properties of BERT, we shift the focus on how to utilize the properties. Because duplicating layers does not change the behaviors of BERT, we can simply use this approach to make the BERT-based models deeper without any extra effort. Then we fine-tune the deeper models on several famous NLP datasets of down-stream tasks, including SQuAD [Rajpurkar et al., 2018], SST-2 on GLUE [Wang et al., 2018], and SNLI [Bowman et al., 2015]. We find that this simple duplicating layer trick can boost the model performance on many datasets. Even for those state-of-the-art models such as ALBERT-

∗The two authors contribute equally to this paper.
Figure 1: (A) Probing hidden representations of BERT by output layer. (B) and (C) are the proposed approach, in which the layers of pre-trained models are duplicated, and then the deeper models are fine-tuned in the downstream tasks. (B) is for the BERT-based model other than ALBERT, and (C) is for ALBERT.

2 Related works

Probing task
Probing is one line of the analyzing researches in this domain. Tenney et al. [2019b] designs the edge probing problem that uses the contextualized word embeddings to train a simple model on some NLP tasks to probe what contextualized embeddings models have actually learned. Hewitt [2019] proposes structural probe, which can check whether syntax trees are embedded in a linear transform of a neural networks’ word representation space; then, it successfully shows that entire syntax trees are indeed embedded in the vector geometry of BERT.

Tenney et al. [2019a] uses a probing model to compare the syntactic and semantic information encoded in different layers of BERT, claiming that features from lower layers encode more syntactic information, whereas those from higher layers encode more semantic information. Brunner et al., 2019 trains a simple model to predict the hidden representations from one layer of BERT with input hidden representations from another layer.

Although the probing task can change the explanation problem to the supervised learning problem, the result heavily depends on the choice of the model family of probing model and the quality of optimization in the model family. It is not easy to separate the effect from the probing model itself. Hewitt and Liang [2019] proposes the concept of control task and selectivity to discuss the effect of different probing models.

Attention Visualization
Another popular way to explain the BERT model is by visualizing and analyzing the attention weights of the transformers. Vig [2019] proposes an open-source tool to visualize the attention weights. Clark et al. [2019] analyze and visualize the attention maps of BERT. Michel et al. [2019] discuss the role of multi-head attention in the BERT-based models, finding that the multi-head structure does not have a significant impact on the performance. However, the interpretability of the attention maps is still under discussion [Jain and Wallace, 2019].

Duplicating Layers
In the past, Dropout [Srivastava et al., 2014] is widely used when training deep neural networks, which can both keep models from overfitting and achieve better performance. Huang et al. [2016] utilize the similar concept on layers rather than units in one layer, also achieving great success in training very deep models. Then, Fan et al. [2019] apply the layer dropout technique on transformer-based language models. It can both boost the performance and help to prune the model.

Nonetheless, based on this layer drop method, we are still searching for yet another trick to improve performance. Also, the layer drop method cannot be applied to ALBERT. Then, instead of dropping the layers, here we try to add extra layers to BERT-based models. Note that when applying this duplicating-layer method, we can use layer drop trick [Fan et al., 2019] simultaneously, and we indeed apply this technique in our work.

3 Approach

3.1 Probing by Output Layer
The approach we used to probe the BERT-based models is shown in Figure 1 (A). BERT-based models are pre-trained by Masked Language Model (MLM), in which the model takes a token sequence with masking as input and learns to reconstruct the original token sequence. The output layer of the pre-trained BERT is a linear classifier, which takes the hidden states of the last layer as input, and output tokens. Here we used the output layer as the decoder to probe the hidden
states of BERT. Given an input token sequence, each layer of BERT outputs a sequence of vectors (hidden states). The output layer transforms each vector back into its original input token. In this way, with the output layer, we can transform the hidden states of a specific layer into a token sequence. Then we analyze the token sequence.

The approach used here is very different from the typical probing approaches, in which the classifier is learned for some specific layers with extra training data. For our method, the output layer has never seen the hidden states other than the last hidden layer before; nevertheless, when we use this output layer to decode every hidden layer, it does work.

In the experiments, we only analyze the case that input sentences do not have masking. When we use BERT in the following downstream tasks, the input sentences do not have masking, so the behavior of the model under the situation without masking is critical.

### 3.2 Duplicating Layers

In this subsection, we propose a new method to boost the performance of BERT-base models slightly. The approach is shown in Figure 1 (B) and (C). The basic idea is that we duplicate some layers in the BERT before fine-tuning, and fine-tune the model with more layers on the downstream tasks. At first glance, the proposed seems to come out of nowhere, but it would be clear why we think this approach may work after seeing the experimental results of probing by the output layer.

The approach for the BERT-based models other than ALBERT is shown in Figure 1 (B). Before fine-tuning on downstream tasks, we duplicate some of the pre-trained BERT layers to make the model deeper. Duplicating which layers would be more effective is still an open question. In the experiment section, we will further discuss this issue. We do not tie weights of the duplicated layer and the original one. That is, if we extend a 12-layer BERT into 24-layer BERT, after fine-tuning, there should be exactly 24 different layers of weights in the model.

When applying the same idea on ALBERT, there is a little difference, which is shown in Figure 1 (C). In ALBERT, all the layers share the same set of parameters. Therefore, for ALBERT, we do not need to consider where to insert new duplicated layers because all the layers have the same parameters. Here the ALBERT is pre-trained with $N$ layers, but here we fine-tune it with more than $N$ layers to see whether its performance can be improved.

### 4 Experiment

The experiments of probing by output layer are in Section 4.1, and in Section 4.2, duplicated layers are added on the pre-trained baseline models before fine-tuning them on each downstream task. All the models we analyzed in this paper are shown in Table 1, all of which use MLM as a pre-training task. Note that for both BERT-base and BERT-large, we use the uncased version. More specifically, we use whole-word-masking on BERT-large. As for Albert, we use the version-2 transformer proposed by Wolf et al. [2019]. For the downstream tasks, we used the Stanford Sentiment Treebank dataset (SST-2) [Socher et al., 2013], Stanford natural

| Model             | Layers | Hidden Dim | Heads |
|-------------------|--------|------------|-------|
| BERT-base         | 12     | 768        | 12    |
| BERT-large        | 24     | 1024       | 16    |
| ALBERT-base-v2    | 12     | 768        | 16    |
| ALBERT-large-v2   | 24     | 1024       | 16    |
| ALBERT-xlarge-v2  | 24     | 2048       | 16    |
| ALBERT-xxlarge-v2 | 12     | 4096       | 64    |

Table 1: Model used in experiments

![Figure 2: Average token accuracy of BERT on SST-2 dataset. Layer 0 means the static word embedding layer. Results on SQuAD 2.0 and SNLI are similar.](image)

Language Inference (SNLI) dataset [Bowman et al., 2015], and the Stanford Question Answering Dataset (SQuAD) [Rajpurkar et al., 2018].

### 4.1 Probing by Output Layer

Given a token sequence as input, we used the output layer to probe the hidden states of all the layers and obtained a token sequence from each layer. Then by considering the input token sequence as the ground truth, we compute token level accuracy for each layer. Figure 2 and Figure 3 shows average token level accuracy of BERT and ALBERT models, where the ground truths, or the input token sequences, are from SST-2 dataset. Results on SNLI and SQuAD are similar. Due to space limitations, we cannot show all the experimental results. Surprisingly, the accuracy of the intermediate layers of most of the models is higher than 80% except layer 0 (static embeddings) and BERT-large. That is, the input sentence can be reconstructed pretty well from all the layers by the output layer even though it only sees the last hidden layer during training. For BERT models, We can also see that fine-tuning only affects the last few layers, while other layers remain intact.

One concern is that the reason for this phenomenon is nothing but the skip-connection or LayerNorm structure. However, with these two structures, there’s still a large gap between the accuracy of BERT-large and BERT-base, especially in former layers. It is almost impossible to claim that merely with these structures can guarantee successful reconstruction.

Table 2 provides an example of probing. Notice that the token right behind the [CLS] token is not able to be reconstructed well in the last layer. This example is not a special
Figure 3: Average token accuracy of ALBERT on SST-2 dataset. Layer 0 means the static word embedding layer. Results on SQuAD 2.0 and SNLI are similar.

| Layer | Example of Decoded Sentence |
|-------|-----------------------------|
| Input | it's a bittersweet and lyrical mix of elements. |
| 0     | ##ningtome s a bittersweettrix lyrical mixfine elements, |
| 1     | itme s a bittersweetckle lyrical mix of elements, |
| 2     | itist s a bittersweet and lyrical mix of elements, |
| 3     | it was s a bittersweet and lyrical mix of elements. |
| 4     | it was s aconsweet and lyrical mix of elements. |
| 5     | it was s a bittersweet and lyrical mix of elements. |
| 6     | it was was a bittersweet and lyrical mix of elements. |
| 7     | it was was a bittersweet and lyrical mix of elements. |
| 8     | it’s a bittersweet and lyrical mix of elements. |
| 9     | it’s a bittersweet and lyrical mix of elements. |
| 10    | it’s a bitter souleet and lyrical mix of elements. |
| 11    | album’s a bitter souleet and lyrical mix of elements. |
| 12    | s a sadseet and lyrical mix of elements. |

Table 2: Here is one of the examples of probing using the output layer. The Acc here stands for the accuracy of tokens behind the special token [CLS].

The above experiments show that most layers have similar distributions, indicating that each layer, in fact, does not change the input much. Consequently, we assume that duplicating layers would not have a great influence on models. To verify this, we examine whether the input sentence can be reconstructed by the output layer if we duplicate some layers to make it deeper than the original pre-trained one. For BERT-base and BERT-large, the layers are duplicated by following the rules below. If we want to make the 12-layer BERT-base model become 15-layer, we duplicate the first three layers to achieve that; each layer can only be duplicated once. As a result, the 12-layer BERT-base can only be extended to 24-layer at most. For ALBERT, because all layers of ALBERT share the same set of parameters, we only have to determine how many layers we want it to be, and we can make it have any layer we want. The results are shown in Figure 4 and Figure 5. Here we only report the token accuracy of the output layer taking the last hidden states of the deeper model as input. As a result, the accuracy remains high after duplicating several layers for BERT-base and ALBERT-base. The accuracy of ALBERT-base maintains high after adding 6 extra layers or so. For ALBERT-large, the accuracy still remains high even when we duplicate ALBERT-large to 50 layers. As for ALBERT-xlarge and ALBERT-xxlarge, the accuracy drops more quickly. Based on these results, we have an insight that duplicating some layers without training may not change the behavior of the pre-trained model, especially, ALBERT-large, so we have the experiments in the next subsection.

Figure 4: Average token accuracy on SST-2 dataset with duplicated layers of BERT-base and 12-layer ALBERT models. Results on SNLI, SQuAD 2.0 are similar.

Figure 5: Average token accuracy on SST-2 dataset with duplicated layers of BERT-large and ALBERT models. Results on SNLI, SQuAD 2.0 are similar.
| BERT | Squad 2.0 | SNLI | SST-2 |
|------|-----------|------|-------|
|      | EM       | F1   | Acc (%) | Acc (%) |
| base (12)
| 72.91 | 76.06   | 89.56 | 91.32 |
| - (13) | 73.52 | 76.80 | 89.61 | 90.66 |
| large (24)
| 81.85 | 84.68   | 91.84 | 93.62 |
| - (25) | 81.20 | 84.44 | 91.94 | 93.35 |

Table 3: Performance of two kinds of BERT single models. The gray rows represent the baseline model, while others are the models with duplicated layers. As for the numbers in parentheses, they represent the number of layers in a model. For instance, (13) in the second row stands for extending three 12-layer BERT-based models to 13 layers by adding one duplicated layer separately. Then, these 13-layer models are picked based on their performance according to three development sets here. Lastly, We use pink cells to represent those models without improvement. On the contrary, we use the cyan cells to denote the best single model performance.

| ALBERT | Squad 2.0 | SNLI | SST-2 |
|--------|-----------|------|-------|
|        | EM       | F1   | Acc (%) | Acc (%) |
| base (12)
| 77.14 | 80.47   | 90.71 | 93.14 |
| - (13) | 77.95 | 81.27 | 90.90 | 92.48 |
| - (17) | 77.88 | 81.14 | 90.84 | 93.19 |
| - (20) | 78.60 | 81.56 | 90.50 | 92.81 |
| large (24)
| 81.66 | 84.75   | 91.45 | 94.56 |
| - (25) | 81.80 | 85.01 | 94.36 | 94.36 |
| - (27) | 81.97 | 85.29 | 91.69 | 94.44 |
| - (31) | 82.18 | 85.37 | 91.44 | 93.85 |
| xlarge (24)
| 84.42 | 87.60   | 92.33 | 95.00 |
| - (25) | 84.46 | 87.71 | 91.70 | 95.44 |
| - (26) | 84.67 | 87.89 | 92.36 | 95.00 |
| xxlarge (12)
| 86.14 | 89.36   | 93.34 | 96.89 |
| - (13) | 86.37 | 89.49 | 93.39 | 96.49 |
| - (18) | 86.04 | 89.25 | 93.49 | 96.81 |
| - (20) | -      | -     | 93.47 | 97.03 |

Table 4: Performance of four kinds of ALBERT single models. The definitions of colors are the same as those in Table 3.

4.2 Duplicating Layers

In this subsection, we show the results of duplicating layers in BERT-based models before fine-tuning. We conducted experiments on three downstream tasks: SQuAD 2.0, SNLI, and SST-2. When fine-tuning by the downstream tasks, we carefully chose hyperparameters to make sure the fine-tuned baseline models reach the performance close to the state-of-the-art. When fine-tuning those models with duplicated layers, we merely used the same hyperparameters as their baseline models. Therefore, it is worthwhile to mention that for all models with duplicated layers in this paper, we do not choose any hyperparameters for them. It is very likely that the proposed approach can show even better performance if we carefully choose the hyperparameters. Also, for every model with duplicated layers, we only trained them exactly once, whereas we trained each baseline model three times and reported their average scores to show more robust results.

The results of single model are shown in Tables 3 and 4. We found that even though not all models with duplicated layers can boost the performance, most models do benefit from those extra layers. Moreover, it is obvious that different tasks need different numbers of duplicated layers. Adding one duplicated layer for BERT is enough, whereas ALBERT usually needs more.

Additionally, we try to ensemble models with duplicated layers, hoping they can further boost the performance. We do the ensemble experiments on SQuAD, which is the most difficult one among all tasks in this work. We expect this method to be applied to those tough tasks, helping those state-of-the-art models achieve higher performance. Our ensemble method is merely summing up all the output probabilities of every model. From Table 5 and Table 6 we can see that the ensemble of those models with duplicated layers certainly boosts the performance.

Table 5: Performance of BERT ensemble models. The definitions of colors are the same as those in Table 3. Also, we do not report the ensemble BERT-large results here because we are not able to fine-tune any single model with duplicated layers that have higher performance than the baseline model. Note that sometimes we only show the top-3 ensemble score here and in Table 6 because the number of models that are better than the baseline is less or equal to 3. When this happens, we just pick all of them.

| ALBERT | Squad 2.0 |
|--------|-----------|
|        | EM | F1 |
| base-ensemble² | 78.85 | 82.04 |
| - top-3 ensemble (19,20,21)³ | 79.01 | 82.02 |
| - ensemble (14,15,19,20,22-24)⁴ | 79.33 | 82.30 |
| large-ensemble² | 82.49 | 85.63 |
| - top-3 ensemble (27,31,32)⁵ | 82.73 | 85.87 |
| - ensemble (25-32,35)⁶ | 82.96 | 86.07 |
| xlarge-ensemble² | 84.97 | 88.06 |
| - top-3 ensemble (26,30,32)⁷ | 85.50 | 88.59 |
| - ensemble (25,26,30,32)⁸ | 85.48 | 88.62 |
| xxlarge-ensemble² | 86.85 | 89.99 |
| - top-3 ensemble (13,15)³ | 86.87 | 89.91 |

Table 6: Performance of four kinds of ALBERT ensemble models. The definitions of colors are the same as those in Table 3.
baseline models. That is, directly duplicating layers on pre-trained BERT-based models before fine-tuning does not ruin the whole model; instead, it helps to improve the model performance.

The proposed approach does not improve performance in some cases. We found that models with duplicated layers can hardly obtain improvement on SST-2. The possible reason is that SST-2 is a relatively simple task comparing to the other two tasks; thus, the vanilla models can already reach quite high performance, leaving little room for improvement, so deeper models are not helpful. In addition, duplicating layer technique seems to be useless for BERT-large (this is the reason why we do not show the BERT-large result in Table 5). For all BERT-large models with duplicated layers, none of them is better than the baseline model. In fact, this result is not too surprising since from Figure 2, we can see that BERT-large has totally different layer properties compared with BERT-base. More generally, by observing Figure 2, Figure 3 and Figure 5, it seems that BERT-large is an exception among all BERT models and ALBERT models.

Even ALBERT-xxlarge’s pattern of token accuracy is much similar to BERT-base’s than BERT-large’s is.

For the models other than ALBERT, the rules to duplicate the layers influence the results. Due to space limitations, we can only briefly report the rule of thumb below:

1. Duplicating one specific layer multiple times hurts the model performance. Therefore, for all experiments regarding duplicating layers in this paper, each layer is copied at most once.

2. To extend a network from $N$ layers to $K$ layers, empirically, the best strategy is to insert each duplicated layer alternately from the front. That is, duplicate the first $K - N$ layers among the $N$ layers. We also try to insert new layers from behind, that is, duplicating the last $K - N$ layers, yet it does not benefit the performance.

5 Conclusion and Future Work

In this paper, we propose a brand new way to analyze the representations from different layers of the BERT-based models. Then we observe that the representations from almost every layer can be reconstructed to the input sentences by the output layer, even though it has never seen these representations during training. The counterintuitive results are intriguing, which provides another viewpoint when trying to analyzing BERT-based models, and will make the researchers rethink what do the BERT-based models learn in each layer. Last but not least, we propose a pretty simple method, duplicating layers, to improve models. On several NLP tasks, including SQuAD, SNLI, and SST-2, our method can indeed boost those models with state-of-the-art performance almost effortlessly. This trick can be further utilized with the ensemble methods as well.
References

[Bowman et al., 2015] Samuel R. Bowman, Gabor Angeli, Christopher Potts, and Christopher D. Manning. A large annotated corpus for learning natural language inference. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing (EMNLP). Association for Computational Linguistics, 2015.

[Brunner et al., 2019] Gino Brunner, Yang Liu, Damián Pascual, Oliver Richter, Massimiliano Ciaramita, and Roger Wattenhofer. On identifiability in transformers, 2019.

[Clark et al., 2019] Kevin Clark, Urvashi Khandelwal, Omer Levy, and Christopher D. Manning. What does bert look at? an analysis of bert’s attention, 2019.

[Devlin et al., 2018] 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.

[Fan et al., 2019] Angela Fan, Edouard Grave, and Armand Joulin. Reducing transformer depth on demand with structured dropout. arXiv preprint arXiv:1909.11556, 2019.

[Hewitt and Liang, 2019] John Hewitt and Percy Liang. Designing and interpreting probes with control tasks. arXiv preprint arXiv:1909.03368, 2019.

[Hewitt and Manning, 2019] John Hewitt and Christopher D. Manning. A structural probe for finding syntax in word representations. In North American Chapter of the Association for Computational Linguistics: Human Language Technologies. Association for Computational Linguistics, 2019.

[Huang et al., 2016] Gao Huang, Yu Sun, Zhuang Liu, Daniel Sedra, and Kilian Q Weinberger. Deep networks with stochastic depth. In European conference on computer vision, pages 646–661. Springer, 2016.

[Jain and Wallace, 2019] Sarthak Jain and Byron C. Wallace. Attention is not explanation, 2019.

[Lan et al., 2019] Zhenzhong Lan, Mingda Chen, Sebastian Goodman, Kevin Gimpel, Piyush Sharma, and Radu Soricut. Albert: A lite bert for self-supervised learning of language representations. arXiv preprint arXiv:1909.11942, 2019.

[Levy and Goldberg, 2014] Omer Levy and Yoav Goldberg. Neural word embedding as implicit matrix factorization. In Advances in neural information processing systems, pages 2177–2185, 2014.

[Michel et al., 2019] Paul Michel, Omer Levy, and Graham Neubig. Are sixteen heads really better than one? arXiv preprint arXiv:1905.10650, 2019.

[Mikolov et al., 2013] Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. Efficient estimation of word representations in vector space, 2013.

[Peters et al., 2018] Matthew E. Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. Deep contextualized word representations. CoRR, abs/1802.05365, 2018.

[Rajpurkar et al., 2018] Pranav Rajpurkar, Robin Jia, and Percy Liang. Know what you don’t know: Unanswerable questions for squad. arXiv preprint arXiv:1806.03822, 2018.

[Socher et al., 2013] Richard Socher, Alex Perelygin, Jean Wu, Jason Chuang, Christopher D. Manning, Andrew Ng, and Christopher Potts. Recursive deep models for semantic compositionality over a sentiment treebank. In Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing, pages 1631–1642, Seattle, Washington, USA, October 2013. Association for Computational Linguistics.

[Srivastava et al., 2014] Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. Dropout: a simple way to prevent neural networks from overfitting. The journal of machine learning research, 15(1):1929–1958, 2014.

[Tenney et al., 2019a] Ian Tenney, Dipanjan Das, and Ellie Pavlick. Bert rediscovers the classical nlp pipeline. arXiv preprint arXiv:1905.05950, 2019.

[Tenney et al., 2019b] Ian Tenney, Patrick Xia, Berlin Chen, Alex Wang, Adam Poliak, R Thomas McCoy, Najoung Kim, Benjamin Van Durme, Samuel R Bowman, Dipanjan Das, et al. What do you learn from context? probing for sentence structure in contextualized word representations. arXiv preprint arXiv:1905.06316, 2019.

[Vaswani et al., 2017] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. In Advances in neural information processing systems, pages 5998–6008, 2017.

[Vig, 2019] Jesse Vig. A multiscale visualization of attention in the transformer model. arXiv preprint arXiv:1906.05714, 2019.

[Wang et al., 2018] Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel Bowman. Glue: A multi-task benchmark and analysis platform for natural language understanding. Proceedings of the 2018 EMNLP Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP, 2018.

[Wolf et al., 2019] Thomas Wolf, Lyndsay Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, R’emi Louf, Morgan Funtowicz, and Jamie Brew. Huggingface’s transformers: State-of-the-art natural language processing. ArXiv, abs/1910.03771, 2019.

[Yin and Shen, 2018] Zi Yin and Yuanyuan Shen. On the dimensionality of word embedding, 2018.