

Investigating Transferability in Pretrained Language Models

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Abstract

While probing is a common technique for identifying knowledge in the representations of pretrained models, it is unclear whether this technique can explain the downstream success of models like BERT which are trained end-to-end during finetuning. To address this question, we compare probing with a different measure of transferability: the decrease in finetuning performance of a *partially-reinitialized* model. This technique reveals that in BERT, layers with high probing accuracy on downstream GLUE tasks are *neither necessary nor sufficient* for high accuracy on those tasks. In addition, dataset size impacts layer transferability: the less finetuning data one has, the more important the middle and later layers of BERT become. Furthermore, BERT does not simply find a better initializer for individual layers; instead, interactions between layers matter and reordering BERT’s layers prior to finetuning significantly harms evaluation metrics. These results provide a way of understanding the transferability of parameters in pretrained language models, revealing the fluidity and complexity of transfer learning in these models.

1 Introduction

Despite the striking success of transfer learning in NLP, remarkably little is understood about how these pretrained models improve downstream task performance. Recent work on understanding deep NLP models has centered on *probing*, a methodology for identifying how much knowledge exists about a linguistic task at different layers of a neural network, typically by training a simple classifier to perform the task given only the layer representations as input (Alain and Bengio, 2016; Conneau et al., 2018; Hupkes et al., 2018; Liu et al., 2019; Tenney et al., 2019a,b; Goldberg, 2019; Hewitt

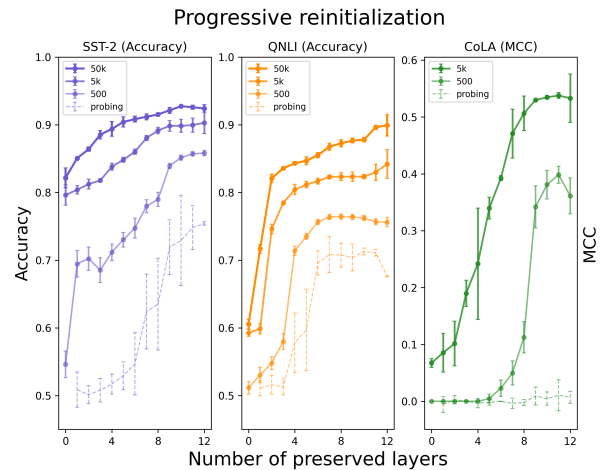


Figure 1: **First three BERT layers provide the majority of improvement on downstream metrics when finetuning data is plentiful, while more layers are helpful when data is scarce. In addition, probing performance does not indicate which BERT layers are necessary for finetuning.** Solid lines show finetuning results after reinitializing all layers past layer k in BERT-Base. 12 shows the full BERT model, while 0 shows a model with all layers reinitialized. Line darkness indicates subsampled dataset size. Dashed line shows probing performance at that layer.

and Manning, 2019). While probing aims to uncover what a network has already learned, a major goal of machine learning is *transfer*: systems that build upon what they have learned to expand what they *can* learn. Given that most recent models are updated end-to-end during finetuning (e.g. Devlin et al., 2018; Howard and Ruder, 2018; Radford et al., 2018), it is unclear how, or even whether, the knowledge uncovered by probing contributes to the transfer learning success of these models.

In a sense, probing can be seen as quantifying the *transferability of representations* in a layer, as it measures the downstream task performance of a simple model (e.g. logistic regression) when trained on features extracted from that layer. How-

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ever, when pretrained models are finetuned end-to-end on a downstream task, what is transferred is not the representations of the pretrained model, but its *parameters*, which define a sequence of functions for processing representations. Critically, as the weights of the entire network update during finetuning, these functions and the connections between them may shift, assisting optimization despite not (initially) extracting features correlated with this task. We refer to this broader phenomenon as *transferability of parameters*.

In this work, we investigate a methodology for measuring the transferability of layer parameters in a pretrained language model, using BERT (Devlin et al., 2018) as our subject of analysis. Our methods, described more fully in Section 2, involve partially reinitializing BERT with random weights and then observing the impact on downstream metrics after finetuning. By running multiple trials across different layers, tasks, and data sizes, this approach enables us to ask very granular questions about the transfer learning process: Are the early layers of the network more important than later ones for transfer learning? Do certain layers become less important depending on the task or amount of finetuning data? Does the position of a particular layer within the network actually matter, or would its presence anywhere suffice to aid optimization?

In brief, we find that:

1. The first few layers of BERT are sufficient to provide the majority of improvement on downstream metrics when finetuning data is plentiful, while more layers are helpful when data is scarce. (Figure 1, solid lines)
2. These benefits are not explained by probing performance on finetuning tasks. (Figure 1, dashed lines)
3. The layers most beneficial to finetuning differ by task: for some tasks, only the early layers are important, while for others the benefits are more distributed across layers. (Figure 2)
4. Reordering the pretrained BERT layers prior to finetuning significantly decreases downstream accuracy, confirming that BERT does not simply learn a better initialization for individual layers, but that learned interactions *across layers* are crucial to the success of finetuning. (Figure 3)

2 How many pretrained layers are necessary for finetuning?

Our first set of experiments aims to uncover how many pretrained layers are sufficient for accurate learning of a downstream task. To do this, we perform a series of **progressive reinitialization** experiments, where we reinitialize all layers after the k th layer of BERT-Base, for values $k \in \{0, 1, \dots, 12\}$. Note that $k = 0$ corresponds to a BERT model with all layers reinitialized, while $k = 12$ is the original BERT model. We do not reinitialize the BERT embeddings. As BERT uses residual connections (He et al., 2016) around layers, the model can simply learn to ignore any of the reinitialized layers if they are not helpful during finetuning.

We use the BERT-Base uncased model, implemented in PyTorch (Paszke et al., 2019) via the Transformers library (Wolf et al., 2019). We finetune the network using Adam (Kingma and Ba, 2014), with a batch size of 8, learning rate of $\alpha = 2e^{-5}$, and default parameters otherwise. More details about training, statistical significance, and methodological choices can be found in the Appendix. We conduct our experiments on three English language tasks from the GLUE benchmark, spanning the domains of sentiment, reasoning, and syntax (Wang et al., 2018):

SST-2 Stanford Sentiment Treebank involves binary classification of a single sentence from a movie review as positive or negative (Socher et al., 2013).

QNLI Question Natural Language Inference is a binary classification task derived from the SQuAD question answering dataset (Rajpurkar et al., 2016; Wang et al., 2018). The task requires determining whether for a given (question, answer) pair the question is answered by the answer.

CoLA The Corpus of Linguistic Acceptability is a binary classification task that requires determining whether a single sentence is linguistically acceptable (Warstadt et al., 2019).

Because pretraining appears to be especially helpful in the small-data regime (Peters et al., 2018), we isolate task-specific effects from dataset quantity by controlling for finetuning dataset size. To do this, we perform our progressive reinitializations on randomly-sampled subsets of the data: 500, 5k, and 50k examples (excluding 50k for CoLA, which contains only 8.5k examples). The 5k sub-

set size is then used as the default for our other experiments.

While similar reinitialization schemes have been explored by Yosinski et al. (2014); Raghu et al. (2019) in computer vision and briefly by Radford et al. (2018) in an NLP context, none investigate these data quantity- and task-specific effects.

Figure 1 shows the results of our progressive reinitialization experiments. These results show that when given a large amount of finetuning data, one only needs a small number of pretrained layers to see large gains on the evaluation objective. In the small-data regime, by contrast, more pretrained layers are needed to see similar accuracy gains. This suggests that larger finetuning datasets enable the network to learn a substitute for the parameters in the middle and later layers, whereas smaller datasets leave the network reliant on existing feature processing in those layers.

3 Does probing predict finetuning performance?

To compare against our reinitialization experiments, we conduct probing experiments for our finetuning tasks on each layer of the pretrained BERT model. Our probing model averages the hidden states of each layer, then passes the pooled representation through a linear layer and softmax to produce probabilities for each class. These task-specific components are identical to those in our reinitialization experiments; however, when training our probes we keep the parameters of the BERT model frozen.

Our results, presented in Figure 1 (dotted lines) show a significant difference between the layers with highest probing performance and reinitialization curves (solid lines). For example, the probing accuracy of SST-2 is highest in the later layers of the network and near chance at the earliest three layers. Despite this, these early layer parameters exhibit significant transferability: preserving them while reinitializing all other layers enables large gains in finetuning accuracy. Similarly, while no layers of BERT contain explicit knowledge of the CoLA task as measured by probing, the parameters in these layers still enable the optimizer to find a high-performing model during finetuning.

Qualitatively, we also observe that the curves for the smallest-data regime bear a greater similarity to the probing curves, especially for SST-2 and QNLI. Smaller finetuning datasets enable fewer updates to the network before overfitting occurs; thus, it

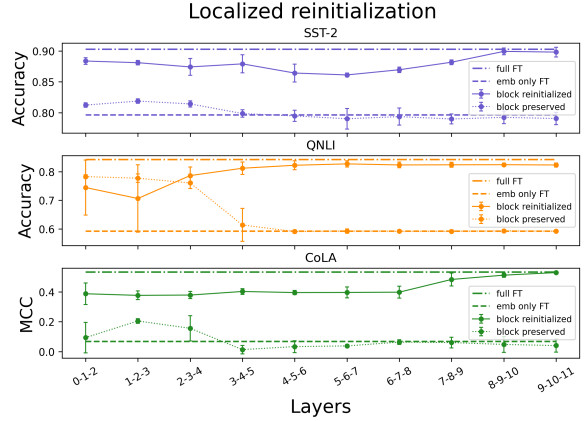


Figure 2: **Early layers provide the most QNLI gains, but middle ones yield an added boost for CoLA and SST-2.** Finetuning results for 1) reinitializing a consecutive three-layer block (“block reinitialized”) and 2) reinitializing all other layers (“block preserved”). Dashed horizontal lines show the finetuning performance of the full BERT model and the performance of a model with only embedding parameters preserved.

may be that finetuning interpolates between the extremes of probing (no data) and fully-supervised learning (enough data to completely overwrite the pretrained parameters). We leave a deeper exploration of this connection to future work.

4 Which layers are most useful for finetuning?

While the progressive reinitializations demonstrate the incremental effect of each BERT layer on transfer learning, it is of additional interest to assess the contribution of each layer relative to either the full BERT model or a completely reinitialized model, eliminating the *number* of pretrained layers as a possible confounder. To do so, we conduct a series of **localized reinitialization** experiments, where we take all blocks of three consecutive layers and either 1) *reinitialize* those layers or 2) *preserve* those layers while reinitializing the others in the network.¹ These localized reinitializations help determine the extent to which different layers BERT are either necessary (performance decreases when they are removed) or sufficient (performance is higher than scratch when they are kept) for finetuning. Again, BERT’s residual connections permit the model to ignore the outputs of reinitialized layers if they harm finetuning performance.

These results, shown in Figure 2, demonstrate

¹ See the Appendix for more discussion and experiments where only one layer is reinitialized.

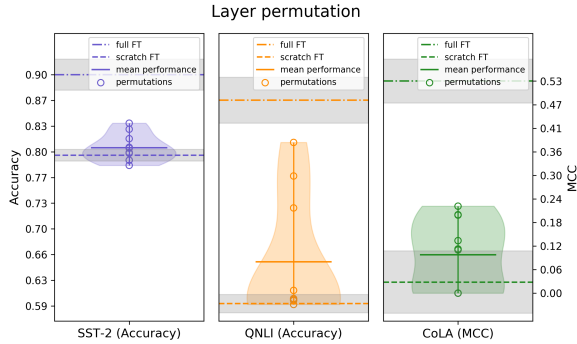


Figure 3: **Changing the order of pretrained layers harms finetuning performance significantly.** Dashed lines mark the performance of the original BERT model and the trained-from-scratch model (surrounded by $\pm 2\sigma$ error bars). Circles denote finetuning performance for different layer permutations, while the solid line denotes the mean across runs. The curved shaded region is a kernel density plot, which illustrates the distribution of outcomes.

that the earlier layers appear to be generally more helpful for finetuning relative to the later layers, even when controlling for the amount of finetuning data. However, there are strong task-specific effects: SST-2 appears to be particularly damaged by the removal of middle layers, while QNLI appears to be less able to reconstruct processing in the early layers relative to the other two tasks. These results support the hypothesis that different kinds of feature processing learned during BERT pretraining are helpful for different finetuning tasks, and provide a new way to quantify similarity between different tasks.

5 How important is the ordering of pretrained layers?

We also investigate whether the success of BERT depends mostly on learned *inter-layer phenomena*, such as learned feature processing pipelines (Tenney et al., 2019a), or *intra-layer phenomena*, such as a learned feature-agnostic initialization scheme which aid optimization (e.g. Glorot and Bengio, 2010). To approach this question, we perform several **layer permutation** experiments, where we randomly shuffle the order of BERT’s layers prior to finetuning. The degree that finetuning performance is degraded in these runs indicates the extent to which BERT’s finetuning success is dependent on a learned composition of feature processors, as opposed to providing better-initialized individual layers which would help optimization anywhere in

the network.

This methodology is distinct from the *shuffled init* methodology of Raghu et al. (2019) which involves permuting every parameter in their computer vision model, as opposed to permuting just the layers as we do.

These results, plotted in Figure 3, show that scrambling BERT’s layers reduces their finetuning ability to not much above a randomly-initialized network. This suggests that BERT’s transfer abilities are highly dependent on the intra-layer interactions learned during pretraining.

As we use the same permutation for the n th run of each task, we can compute paired correlation coefficients between tasks to evaluate whether a given permutation has similar effects across different task metrics. The relatively high correlations shown in Table 1 suggest that BERT finetuning relies on similar inter-layer structures across tasks.

Tasks compared	Spearman	Pearson
SST-2, QNLI	0.72 (0.02)	0.46 (0.18)
SST-2, CoLA	0.74 (0.02)	0.77 (0.01)
QNLI, CoLA	0.83 (0.00)	0.68 (0.03)

Table 1: **Specific permutations of layers have similar impacts on finetuning across tasks.** Paired correlation coefficients between task performances for the same permutations. Two-sided p -value in parentheses ($N=10$).

6 Conclusion

We present a set of experiments to better understand how different pretrained layers in BERT influence its transfer learning ability. Our results reveal the unique importance of transferability of parameters to the success of probing, distinct from the transferability of representations assessed by probing. We also reveal important tradeoffs that occur during transfer learning: task vs quantity of finetuning data, number vs location of pretrained layers, and presence vs order of layers.

While probing continues to advance our understanding of linguistic structures in pretrained models, these results indicate that new techniques are needed to connect these findings to their potential impacts on finetuning. These insights and methods presented here are one contribution toward this goal, and we hope they enable more work on understanding why and how these models work.

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A Reinitialization

We reinitialize all parameters in each layer by sampling from a truncated normal distribution with $\mu = 0, \sigma = 0.02$ and truncation range $(-0.04, 0.04)$. This matches how BERT was initialized (see the original BERT [code on GitHub](#) and the corresponding Tensorflow [documentation](#)).

B Subsampling, number of runs, and error bars

The particular datapoints subsampled can have a large impact on downstream performance, especially when data is scarce. In order to capture the full range of outcomes due to subsampling, we randomly sample a different dataset for each trial index. Due to this larger variation when data is scarce, we perform 50 runs for the experiments with 500 examples, while we perform 3 runs for the other settings. A scatterplot of the 500-example runs is shown in Figure 4.

Error bars shown on all graphs are 95% confidence intervals calculated with a t-distribution.

C Localized reinitializations of single layers

We also experiment with performing our localized reinitialization experiments at the level of a single layer. To do so, we perform three trials of reinitializing each layer $k \in \{1 \dots 12\}$ and then finetuning on each of the three GLUE tasks. Our results are plotted in Figure 5. Interestingly, we observe little effect on finetuning metrics from reinitializing each layer (with the exception of reinitializing the first layer on CoLA performance). This suggests either the presence of redundant information between layers, or that the “interface” exposed by the two neighboring layers somehow constrains optimization in a beneficial way.

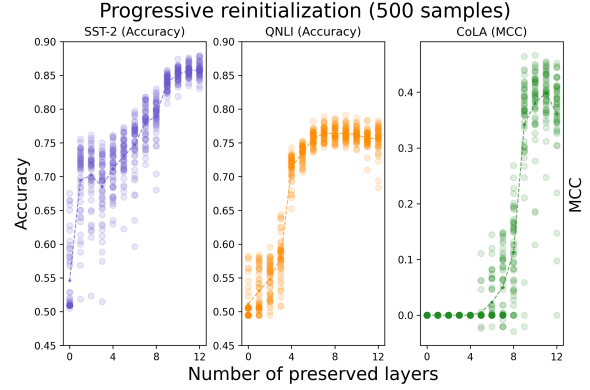


Figure 4: Finetuning results after reinitializing all layers past layer k in BERT-Base. 12 shows the full BERT model, while 0 shows a model with all layers reinitialized. Scatterplot of 50 runs per layer shown for subsampled dataset size 500. Dotted line shows the mean.

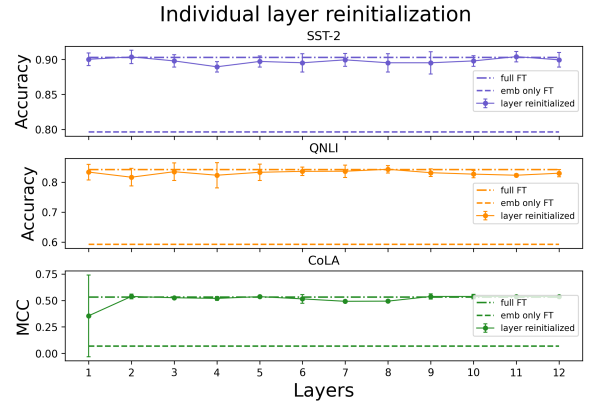


Figure 5: Performance on finetuning tasks after reinitializing an individual layer of BERT.

D Number of finetuning epochs

He et al. (2019) found that much or all of the performance gap between an ImageNet-pretrained model and a model trained from scratch could be closed when the latter model was trained for longer. To evaluate this, we track validation losses up to 10 epochs in our progressive experiments, for $k \in \{0, 6, 12\}$ across all tasks and for 500 and 5k examples. We find minimal effects of training longer than three epochs for the subsamples of 5k, but find improvements of several percentage points for training for five epochs for the runs with 500 examples. Thus, for the runs of 500 in Figure 1, we train for five epochs, while training for three epochs for all other trials. We train our probing experiments for 10 epochs on the full dataset.

E Higher learning rate for reinitialized layers

In their reinitialization experiments on a convolutional neural network for medical images, [Raghu et al. \(2019\)](#) found that a 5x larger rate on the reinitialized layers enabled their model to achieve higher finetuning accuracy. To evaluate this possibility in our setting, we increase the learning rate by a factor of five for the reinitialized layers. The results for our progressive reinitializations are plotted in Figure 6. A higher learning rate appears to increase the variance of the evaluation metrics while not improving performance. Thus, we keep the learning rate the same across layers.

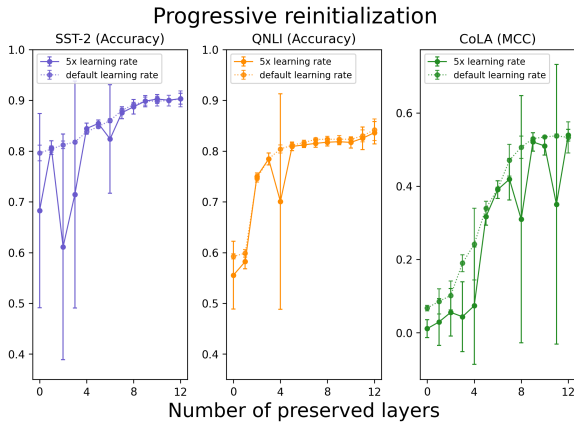


Figure 6: Finetuning the reinitialized layers with a larger learning rate does not improve finetuning performance.

F Layer norm

We also assessed whether preserving the mean and variance of activations across reinitialized layers might aid optimization. To do so, we preserved the layer norm parameters in our progressive runs with 5k examples. These trials are plotted in Figure 7, and demonstrate that preserving layer norm does not aid (and may even harm) finetuning of reinitialized layers.

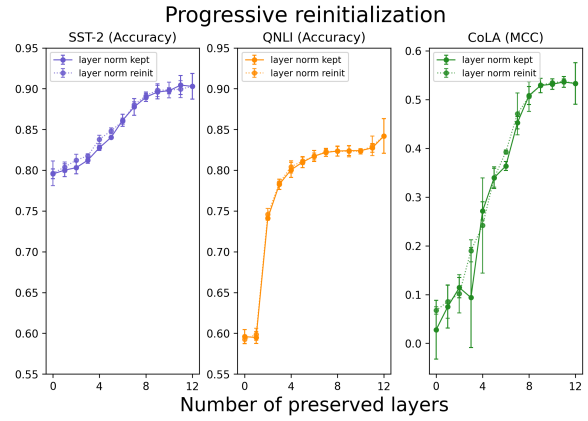


Figure 7: Preserving the layer norm parameters when reinitializing each layer does not improve finetuning performance.