AutoFreeze: Automatically Freezing Model Blocks to Accelerate Fine-tuning

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Abstract

With the rapid adoption of machine learning (ML), a number of domains now use the approach of fine-tuning models pre-trained on a large corpus of data. However, our experiments show that even fine-tuning on models like BERT can take many hours when using GPUs. While prior work proposes limiting the number of layers that are fine-tuned, e.g., freezing all layers but the last layer, we find that such static approaches lead to reduced accuracy. We propose, AutoFreeze, a system that uses an adaptive approach to choose which layers are trained and show how this can accelerate model fine-tuning while preserving accuracy. We also develop mechanisms to enable efficient caching of intermediate activations which can reduce the forward computation time when performing fine-tuning. Our evaluation on four NLP tasks shows that AutoFreeze, with caching enabled, can improve fine-tuning performance by up to $2.55 \times$.

1 Introduction

Developing ML models for new tasks is challenging and thus a number of tasks are bootstrapped with features or weights from existing models. This includes transfer learning [40], where features from a large pre-trained model are used on a new task and only the last few layers are trained to develop a specialized model. Closely related is the practice of fine tuning where weights from a pre-trained model are used to initialize training for a new task. Following initialization all layers of the model are trained until convergence. Model fine-tuning has been shown to achieve high accuracy: for example, fine-tuning Bidirectional Encoder Representations from Transformers (BERT) [9], a pre-trained language representation model, has been shown to achieve state-of-the-art results on several natural language processing (NLP) tasks such as sentiment analysis [26], topic classification [55] etc. In addition to the accuracy benefits, fine-tuning also reduces training resources required. For example, training BERT from scratch can take up to 4 days even when using 4 Cloud TPUs [9].

With a number of ML tasks using the above approach, we investigate the time and resources required for fine-tuning. We find that even fine-tuning for a few epochs can takes several hours even with the use of GPUs. This is primarily because the pre-trained models are often very computation-heavy, e.g., running one epoch of fine tuning on BERT BASE model, for Yelp dataset (Table 1) takes around 13 hours on a NVIDIA P100 GPU.

A natural approach to improve fine-tuning performance is to limit the number of layers of the model that are updated, thus making it similar to transfer learning. For example, if we consider BERT BASE which has 12 encoding blocks, prior approach in [22] trains a fixed number of blocks (e.g., the last 4 blocks) and freezes the weights for the remaining blocks. However, this approach can affect the final model accuracy. For example with the IMDb dataset [26] this approach can reduce the time for an epoch by 65%, but we find that the accuracy of the fine-tuned model suffers, dropping from 93.94% to 92.2%. Another approach used in prior work [5] is to apply the Lottery Ticket Hypothesis to identify matching subnetworks in pre-trained BERT models to enforce sparsity in models trained for different downstream tasks. While this approach retains accuracy and can lead to sparser models, it does not lead to improvements in training speed.
During fine-tuning, AutoFreeze adaptively determines layers which can be frozen. Once layers are frozen, the backward computation for those layers can be avoided. At later epochs, intermediate outputs are also cached leading to further gains.

In this paper we propose an improved approach where the number of model blocks that are updated during fine-tuning are adaptively chosen during the fine-tuning process. Our work is inspired by recent work of [16] who developed SVCCA, a new metric that captures how different layers of model change over the course of training. The SVCCA score for a layer, as proposed in [36], is computed by comparing the intermediate model weights with the final weights and can thus be used for post-hoc analysis. Applying that approach to model fine-tuning we observe that the initial layers of the model converge rapidly and thus we can freeze such layers. Freezing the initial layers means that the backward pass for those layers can be skipped, thereby reducing the computation required. While SVCCA scores show the promise of freezing layers early, we still need an online algorithm that can decide which layers should be frozen and when. We develop a gradient-norm based test that ranks layers by their rate of change and based on the select the slowest changing layers for freezing. We show that our test is effective at detecting when layers should can be frozen without affecting accuracy across multiple datasets.

Freezing early layers of a model can reduce the time taken by the backward pass, but we still need to do the forward pass corresponding to the frozen layers as shown in Figure 1. For a model like BERT\textsubscript{BASE} we find that even running just the forward pass can take 550 seconds per epoch with the IMDb dataset (Figure 2). We can further reduce the training time by using the observation that once model layers are frozen, then for a given data point, the output of the forward pass will remain the same across different epochs of training. Thus, along with freezing we can also cache the output of the forward pass up to the layer that has been frozen. Once the same data point is selected to be used again for training, we can load the pre-computed intermediate values from our cache and continue training.

We design AutoFreeze, a system for automatically freezing model blocks to accelerate fine-tuning. Our system consists of two main modules: a freezing module that has a pluggable decision engine that can make decisions on which layers should be frozen as training progresses. We also design a storage manager to implement the caching functions described above. The storage manager handles a number of common concerns in caching, including selecting the appropriate backend (CPU memory / SSD etc.) and deciding when to evict data from the cache. In addition, we observe that typically, the order in which data points are accessed varies across epochs. The storage manager takes into account the ordering of data access in future epochs to layout data in appropriate order when storing.

We evaluate AutoFreeze using a wide range of fine-tuning tasks including topic classification on the AG’s News dataset [55] and Sogou News dataset[43], sentiment analysis on Yelp Full dataset[55] and IMDb dataset [26], question answering on SQuAD2.0 dataset[37], multiple choice task on SWAG dataset[53], and text summarization on CNN/DailyMail dataset[15]. We find that AutoFreeze can improve training time by up to 55x while affecting accuracy by less than 0.1%. We also show that AutoFreeze is especially effective for large datasets like Yelp where freezing layers reduces fine-tuning time from 52.5 hours to 27 hours and caching further reduces this to 24.6 hours.
2 Motivation and Background

In this section we first provide background on model fine-tuning and transfer learning and detail why fine-tuning is expensive. Following that we motivate how freezing or limiting the number of layers of a model trained can lead to significant savings. Finally we show how static schemes that freeze a constant number of layers are ineffective.

2.1 Model Fine-tuning

Transfer learning and fine tuning of large pre-trained models has enabled use of deep models for specialized tasks. In transfer learning we use the features from a large pre-trained model and train only the last few layers to specialize on a new task, while in case of fine tuning the whole pre-trained model is trained on new task. Both transfer learning and fine tuning have several advantages over training models from initialization including i) enabling use of deep models when training data is scarce, ii) transferring common features among related tasks iii) significantly faster convergence that also reduces the computation time.

Although feature based transfer learning is very popular in computer vision tasks [40, 18, 2, 50, 4], recent works [17, 34] show that language models enjoy significantly better performance when using fine tuning. However, even when performing fine tuning, large models like BERT[9] require significant amount of time. For example, fine tuning BERT on the relatively small IMDB dataset [26], containing 25K points, takes around 3 hours on a single P100 GPU. On larger datasets like Yelp (Table 1) we see that fine-tuning can take more than two days. Even on the latest A100 GPUs, fine-tuning BERT\textit{LARGE} on the Yelp dataset can take around two hours. Thus the exorbitant cost of fine tuning can become a limiting factor for data scientists in developing new models.

2.2 BERT Model Architecture and Timing

To get a deeper understanding of the performance of fine-tuning on BERT, we first discuss the model architecture and then present a breakdown of fine-tuning time. We primarily focus on BERT\textit{BASE} which is depicted in Figure 3. BERT\textit{BASE} has 12 encoder layers, which are also called as Transformer blocks. Each
Transformer block is identical and comprises of a self-attention layer with 12 attention heads and a fully connected layer of size 768. In this work we refer to layer and transformer block interchangeably, therefore by freezing a layer we mean freezing the entire transformer block.

As discussed in prior work [13], fine-tuning for text classification tasks typically only requires around 4 epochs to achieve state-of-the-art accuracy. But the time taken per epoch is high because of two reasons:

**Memory constraints:** With the BERT model being large (model weights around 420 MB) and the intermediate activations of each layer also being large, the batch size that can be used for fine tuning is limited by GPU memory. With an NVIDIA P100 GPU, having 12GB of memory, we observe that we are limited to a batch size of 6. Even on latest, hardware like A100 GPU having 40GB of memory, the maximum batch size that can be supported is limited to 32.

**Computation needs:** The transformer blocks discussed above are also compute intensive and we observe that the gradient calculation time, especially in the backward pass can be significant. For example, when fine-tuning with the IMDb dataset, we see that doing a complete iteration takes around 435ms of which more than 50% is taken by the backward pass.

### 2.3 Statically Freezing Model Layers

One direct approach to reduce the computational cost is to only fine-tune a subset of the layers [22]. For example, as shown in Figure 2, only updating the last \( k \) layers of the BERT can lead to an almost linear decrease in time taken per iteration. This hints that avoiding gradient computation for certain layers (freezing) can significantly reduce training time.

We note that in order to realize the gain from freezing, the layers should be frozen in order, e.g. freezing layers 3 and 4 before freezing earlier layers 1 and 2 is not going to provide any speedup. This is due to usage of automatic differentiation [27] in popular deep learning libraries for backpropagation. Automatic differentiation uses the gradient of later layers to calculate the gradients of earlier layers, i.e., To calculate gradients of Layer 1 automatic differentiation requires gradient of Layer 2 to be calculated. However, this leads to the question of which layers should be frozen and how does freezing of layers effect the model accuracy.

First we consider simple static freezing schemes where a fixed number of layers are chosen to be updated during training as presented in [22]. In Figure 4, we compare static freezing schemes when fine-tuning BERTBASE with IMDb and Sogou dataset. We compare training the last 25%, 50%, 75% of the layers, or only the last layer, to full fine-tuning. We see that such static freezing schemes lead to 0.5% to 1.7% accuracy drop for IMDb. On the other hand for Sogou, we observe that while some static freezing schemes only suffer 0.2% accuracy loss, training only the last layer still leads to significant accuracy loss.

We also see similar results for an image classification workload where we fine-tune ResNet-18 model [14] pre-trained on CINIC-10 [8] with CIFAR-10 dataset. In Figure 4, we again see that training only the last layer leads to around 10% reduction in accuracy, while training 50% of the layers leads to 1.12% reduction in accuracy.

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1 Measured using PyTorch 1.0.1
These results show that static schemes for freezing can severely affect the accuracy of fine-tuning methods and cannot be generalized across different downstream tasks. Based on this, we propose an adaptive method that can select appropriate layers for freezing, thereby improving performance without affecting accuracy.

3 AutoFreeze Design

We next describe the design of AutoFreeze, a system for automatically freezing model layers during fine-tuning. We first discuss the scheme used by AutoFreeze to decide which layers to freeze and following that discuss how AutoFreeze can automatically cache intermediate outputs to further improve performance.

3.1 Adaptive Freezing for Fine-tuning

As described in Section 2.3, statically determining which layers to freeze can lead to reduced accuracy. Our insight is that layers which are closer to convergence are good candidates for freezing and by periodically inspecting the progress of each layer we can determine when a layer can be safely frozen.

We validate our intuition by using SVCCA, a recently proposed metric for understanding convergence of neural networks. SVCCA outputs SVCCA score a metric which can be used to evaluate the similarity between two layers of a neural network. To understand convergence of each layer individually perform a post-hoc analysis. They calculate SVCCA score by comparing the layers of the model during training with the layers of the already converged model. We use the same IMDB dataset as before and compute the SVCCA scores by comparing each layer’s weights periodically (5 times every epoch in this case) with the final weights of the model. SVCCA scores range from 0 to 1 with 1 indicating an exact match (i.e., that the intermediate weights match the final model weights). We observe two main takeaways from this experiment in Figure 5. First, we see that layers of the model converge in order with earlier layers (e.g., layers 0-4) reaching high SVCCA scores within one epoch. Second, while some layers converge fast other take significantly long time.

This indicates that an adaptive freezing scheme can provide performance benefits by freezing layers as they converge.

The above data validates our intuition about the benefits of adaptively freezing model layers. It also shows that SVCCA score will be an ideal metric for freezing since it can track convergence of a layer and freeze it once the layer reaches convergence. However calculating the SVCCA scores shown in Figure 5 requires knowledge of the final model weights, making it inapplicable in practice. Thus we need an online method that can estimate if a layer can be frozen without knowing the final model weights. We next describe how we can use the gradient values at each layer to estimate this.
Algorithm 1 Freezing Module

**Input:** List of layers that are not frozen activeLayers, Percentile for freezing N

**Input:** accumulated gradients for current interval $\Delta T_l$ and previous interval $\Delta T_{l-1}$

for layer $l$ in activeLayers do
    $\eta_l = \left| \frac{\|\Delta T_{l-1}\| - \|\Delta T_l\|}{\|\Delta T_{l-1}\|} \right|$  
end for

for layer $l$ in activeLayers do
    if $\eta_l < N^{th}$ percentile($\eta$) then
        freeze layer $l$
    else
        break
    end if
end for

Figure 6: Comparing Gradient Norm Test with Ideal: We compare our gradient norm test for $\eta_l = 25, 50$ and $75$ percentile, with an ideal SVCCA score based scheme on two datasets (a) IMDb (b) Sogou. We define the ideal scheme as freezing layers with SVCCA scores over 0.9 at each evaluation interval. We observe that gradient norm test with $\eta_l = 50$ percentile (median) closely matches the ideal scheme.

### 3.1.1 Gradient Norm Test

We next present an online test to determine if a layer should be frozen. Our intuition in designing this test is that the rate of change of the gradient values for a layer can be used to determine how fast the model weights are being updated for a particular layer. Consider that we accumulate gradients for each layer in the model ($\Delta$) and perform our test at fixed intervals ($T$). Then we define the gradient norm change for layer $l$, $\eta_l$, as

$$\eta_l = \left| \frac{\|\Delta T_{l-1}\| - \|\Delta T_l\|}{\|\Delta T_{l-1}\|} \right|$$  \hspace{1cm} (1)

We next rank the layers in the order of $\eta_l$ to determine the layer that is changing slowest. Given our earlier observation about how layers converge in order, we can designate a layer to be frozen if all the layers preceding it are frozen and it is the slowest changing layer. However, this assumes as strict order in the rate of change of gradient norms and we can thus further relax this by designating a layer to be frozen if all the layers preceding it are frozen and if its rate of change is in the bottom $N^{th}$ percentile, where $N$ is a tunable parameter. Algorithm 1 describes the above procedure.

Comparison of Gradient Norm Test to SVCCA score In Figure 6, we evaluate the performance of our proposed gradient norm test by comparing it with the ideal SVCCA score based freezing scheme that has access to the final model weights. In the ideal scheme, we denote a layer as frozen if its SVCCA score compared to the final model weights is above a fixed threshold of 0.9. In Figures 6a and 6b, we vary the percentile value used in Algorithm 1 and see that using too low a percentile value (e.g., 25th percentile) can make the test too conservative resulting in fewer frozen layers compared to the ideal. We also see that using too high a percentile value can lead to the test being too aggressive resulting. Finally we see that the median closely tracks the ideal freezing scheme. We perform further evaluation of the effect of varying $N$ in Section 4.4
3.2 Caching Frozen Layers

Freezing a prefix of the model layers can help us avoid running the backward pass on those layers while fine-tuning. However, given that the layer weights are fixed once they are frozen, we can also avoid the forward pass if we are able to materialize and cache the intermediate output in CPU memory/disk. For example, consider a case where 50% of the model layers are frozen after the first epoch. In this case if we can materialize the output of applying the first 50% of the layers and save it to disk, then for the following epochs we can directly load this intermediate data and thus also avoid the corresponding 50% of the forward pass.

However, there are two main considerations in implementing the above functionality. First, as model intermediate outputs can be large, we need to consider if accessing data from cache will be faster than performing the forward pass. Second, with the adaptive freezing algorithm described above, the number of layers frozen could be updated within an epoch making it challenging to determine which outputs should be saved and when.

For the first challenge, we measure the size and time taken for reading intermediate outputs when fine-tuning the Yelp dataset. For every example, the intermediate output is around 1.57MB and this remains the same across all layers as all the transformer blocks in BERT have the same output size. For a large dataset like Yelp, this is around 1TB of data and thus does not fit in memory of the Azure instances we were using (Section 4.2). However, given that we are limited to small batch sizes (around 6 examples on a P100), we only need to read around 10MB of data for one iteration and this takes around 25ms when using an SSD. On the other hand, doing a forward pass of one layer of BERT\textsubscript{BASE} takes around 11ms. Thus, in this case, we can see that loading data from SSD should provide a speed-up when more than 2 layers are frozen.

In general, the trade-off between caching and repeating the forward pass depends on the disk bandwidth, batch size and computation speed of the GPU. Evaluating this trade-off is not expensive in practice as few iterations of training can indicate how many layers of a model need to be frozen before caching becomes advantageous. We next describe our storage manager that can handle this trade-off.

3.2.1 Storage Manager

The storage manager (Figure 7a) is responsible for managing where data is cached and up to what layer should the forward pass be executed before saving to cache.

At the beginning of every epoch, the storage manager notes down the layer $L$ up to which the model was frozen. In that epoch for all data points that are processed, the output of the forward pass up to layer $L$ is written to cache.
We store the intermediate output to disk when it no longer fits in CPU memory. When the dataset (D points) is larger than the disk space available, we save I points to disk (I < D and I is the maximum number of points that fit on disk). During the next epoch, if the number of layers currently frozen is greater than the number of layers of forward pass that were completed before data was saved to cache, then the storage manager also evicts the data points once they are read. Based on the fact that the number of data points to be written will never surpass the number of data points read from disk, we will never exceed the disk space.

Finally as model training typically shuffles data across epochs, the storage manager also ensures that cached data points can be transparently accessed even if only part of the dataset has been cached. We do this by maintaining MappingShuffled, a mapping from the shuffled indices to the original indices for each epoch i. When writing the intermediate outputs to disk at epoch i, we write at the original indices retrieved from MappingShuffled. To read the data at index k at epoch i + 1 required for training, we read MappingShuffled_{i+1}[k]. While this approach incurs random reads/writes to the cache, since each data item is relatively large (∼1.5 MB) we have not found this to be an issue in practice. Finally, as shown in Figure 7a, we perform read, write and gradient computation in separate processes thereby pipelining I/O with compute.

3.3 Overall Design, Implementation

Putting the above two subsections together, our system AutoFreeze consists of two modules as shown in Figure 2 (1) Freezing Module that makes decision on the set of layers to freeze at different intervals of the fine-tuning procedure. (2) Storage Manager that caches intermediate outputs of the BERT encoder to disk in parallel to training when necessary. We implement AutoFreeze in Python and design it to work with Pytorch models. Our freezing module has a pluggable function that makes the decision on when to freeze a model layer. Currently we use the gradient norm test described in Algorithm 1 other approaches can be plugged in without affecting the caching or storage manager modules. When the storage manager is initialized we also create a directory hierarchy on the provided disks. This is to avoid overheads with ext4 when we have too many files stored in the same directory. Finally, we do not use any compression when storing data to disk as we found that the overhead from performing compression slows down our read and write speeds leading to slowdown.

4 Evaluation

4.1 Datasets

We evaluate AutoFreeze on four text classification datasets, one question answering dataset, one multiple choice dataset, three datasets in the GLUE benchmark and one text summarization dataset.

GLUE benchmark We use three datasets in the GLUE benchmark, including Microsoft Research Paraphrase Corpus (MRPC) [10], Stanford Sentiment Treebank (SST-2) [41], and Corpus of Linguistic Acceptability (CoLA) [46], to compare AutoFreeze with baselines (e.g. Lottery Ticket Hypothesis). MRPC is a corpus of sentence pairs with human annotations for whether the sentences in the pair are semantically
equivalent. The SST-2 task is to predict the sentiments of movie reviews. CoLA is composed of English acceptability judgments extracted from books and journal articles on linguistic theory, annotated with whether the sentences are grammatical English sentences.

**Sentiment analysis** We use a binary classification IMDb dataset [26] and a five-class version of the Yelp review dataset [55], where the goal is to classify the sentiment of the reviews on films and restaurants respectively.

**Topic classification** We use AG’s News [55] and Sogou news [43] datasets to evaluate AutoFreeze. The AG’s news dataset was created by choosing 4 largest classes from the original corpus, containing the categories of the news articles. We also use Sogou news created by prior work [43] to show the performance on Chinese text containing the category of the news based on the URL of the news articles.

**Question Answering** We use SQuAD 2.0 dataset [37] which extends the SQuAD 1.1 problem definition by enabling the possibility for “no short answer exists in the provided paragraph”, which makes the problem more practical.

**Multiple Choice** We use the Situations With Adversarial Generations (SWAG) [53] dataset contains sentence-pair completion examples that evaluate grounded commonsense inference. Given a sentence, the task is to choose the most likely continuation among four choices.

**Text Summarization** We follow the experiments in [24], and use the CNN/DailyMail news highlights dataset [15], which contains news articles and highlights.

### 4.2 Setup

We fine-tune BERT BASE with 12 transformer layers, hidden size of 768, and 12 self-attention heads. Unless specified, we use a Microsoft Azure Standard_NC6 VM with 1 NVIDIA P100 GPU.

**Classification tasks** We set max sequence length as 512 and the max number of epochs as 4 for fine-tuning on all the classification datasets we use. We keep the first 510 tokens as in [43] when the text’s length is greater than 512. We set the fine-tuning batch size to 6.

**Question Answering** Following [47], we set the fine-tuning batch size to 8 and max number of fine-tuning epochs to 3 to fine-tune SQuAD2.0 dataset. Similar to [4.2], we set the initial learning rate to 2e-5 and decay to slanted triangular learning rate at 0.3 and 0.6 proportions of total iterations.

**Multiple Choice** As in [47], we set the fine-tuning batch size to 32 and max number of fine-tuning epochs to 3 to fine-tune the SWAG dataset. We set the initial learning rate to 1e-5 and decay to slanted triangular learning rate at 0.3 and 0.6 proportions of total iterations.

Across all the above tasks, we set the per epoch evaluation intervals during fine-tuning to 5, and we perform the gradient norm test every \( \frac{k}{2} \) iterations (where \( k = \text{total number of iterations per epoch} \)). As in prior work [17], we used stepped learning rate schedule that decays to slanted triangular learning rate at 0.3 and 0.6 proportions of total iterations from initial learning rate of 1e-5. We set the percentile value for our adaptive freezing algorithm to be the 50th percentile by default unless specified. We run AutoFreeze for three runs with different random seeds for each dataset. In general, when transformer blocks of the BERT Encoder are frozen, we also freeze the embedding layer as Autograd will otherwise not allow gradients to flow backward [32]. In other words, when earlier blocks of the BERT encoder are frozen, the gradients for them are not available, so calculating the gradients for the Embedding layer before the Encoder cannot be achieved.

### 4.3 Comparison with baselines

We first compare AutoFreeze with the lottery ticket hypothesis [5] and static freezing in Table 2. We use the same datasets used in prior work [4] and for lottery ticket hypothesis, we report the fine-tuning time after finding the winning subnetworks by running Iterative Magnitude Pruning. As shown in the table, static freezing provides significant training speedup but does not generalize to different downstream tasks. For

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2 Also accounting for [SEP] and [CLS] tokens.
example, we observe that freezing up to the 9th layer of the BERT encoder results in around 11% accuracy loss for MRPC, while it only results in around 1% accuracy loss for the SST-2 dataset. As for the Lottery Ticket Hypothesis approach [5], although it provides comparable accuracy with full fine-tuning, it does not provide training speedup because it utilizes unstructured magnitude pruning where weights are pruned individually instead of in a group. Thus, while the winning subnetwork found by the Lottery Ticket Hypothesis is sparse (i.e. has some fraction of weights as 0), it does not provide actual speedup because there are not any computation savings consider the forward-backward structure used in DNN training. Overall we find that AutoFreeze can improve performance by up to 1.75x with minimal degradation in accuracy when compared to existing baselines.
4.4 Freezing, Caching Benefits

To further understand the benefits of freezing and caching in AutoFreeze on larger datasets, we compare AutoFreeze with fine-tuning all the parameters of BERT\textsubscript{BASE}.

**Accuracy/F1:** In left side of Figures 8, 9, 10, 11, 12, and 13, we plot the mean and the range (max, min) of accuracy values obtained by AutoFreeze as compared to the baseline. We see that the ranges for AutoFreeze overlap with the full fine-tuning line indicating that AutoFreeze is able to achieve comparable accuracy/F1. Similar to prior work [35], we also list the best accuracy/F1 reached across trials for the baseline and AutoFreeze on the right side of Figures 9, 8, 10, 11, 13, and 12. We include complete numbers in the Appendix in Table 4.

From the figures we see that for the Sogou and IMDb datasets, we observe 0.07% and 0.1% reduction in
mean of the best accuracy, while for AG News and Yelp F. datasets, we do not see any accuracy loss. From Figure 13, we see an loss of 0.11 in average F1 score for SQuAD2.0 across three runs. As for SWAG, we observe an accuracy loss of 0.01% in average accuracy.

**Training Speedup:** As shown in the right side of Figures 8, 9, 10, 11, 12, we are able to achieve an average training speedup by a factor of $1.55 \times 2.05 \times$ with respect to fine-tuning all the parameters for BERT\textsubscript{BASE}. AutoFreeze is particularly helpful on larger datasets. For the large-scale AG News dataset, AutoFreeze is able to save around 5 hours fine-tuning time. For Yelp F. dataset with 650K data points, we are able to significantly reduce the fine-tuning time by around 25 hours.

**Caching Benefits** Next, we evaluate the speedup gains achieved by turning on both the freezing module and the storage manager.

We see an average speedup of 2.08× on the classification, multiple choice, and question answering tasks compared to the full fine-tuning by enabling on both Freezing Module and Caching Module, which is a 1.14× improvement with respect to average speedup when only using the Freezing module. By enabling caching, we are able to achieve at most 1.25× more speedup compared to freezing. Generally, we obtain more speedup compared to freezing starting from the third epoch as we start to save the forward pass computation for the layers before layer $L$. For fine-tuning workloads that run for more epochs, the benefits of caching will be more pronounced as we show in Appendix A.3.

**Caching vs Computation trade-off** As described in Section 3.2, when $L$ layers are frozen, the training process consumes data at a rate that corresponds to performing forward and backward computation after layer $L$ while a reading process operates in parallel to fetch data for the next batch from the cache. Additionally, training process also needs to move data that needs to be written out from GPU to CPU and our measurements show that this adds at most 7% runtime overhead. Thus the balance between caching vs.
We set the exact same hyper-parameters as in [24] which results in a more aggressive policy, we get with four V layers. Varying number of evaluation intervals each epoch: We also vary how frequently the freezing module is invoked and Figure 16 shows the results with the IMDB dataset. We see that if the frequency is too low (e.g., 1 interval/epoch) then the speedup obtained is limited. On the other hand, using 10 intervals/epoch results in gradient vectors that are not fully representative, thus leading to a drop in accuracy. However, we find this trade-off is balanced for a range of values (2 to 5 intervals/epoch).

4.5 AutoFreeze on more advanced tasks, hardware

Text summarization: We ran AutoFreeze on text summarization following the experiments setup in [24]. We set the exact same hyper-parameters as in [24], we trained the BERTSUMAbs model for 200000 steps with four V100 GPUs in Google Cloud Platform. We set the total number of evaluation intervals to 20 and evaluate every 10000 steps during fine-tuning. Table 3 shows the Recall-Oriented Understudy for Gisting Evaluation (ROUGE) F score, which is a measurement for the similarity between a candidate document and reference documents, for AutoFreeze and full fine-tuning. We observe the loss of ROUGE F1 score is less than 0.15. Further, as shown in Table 3 AutoFreeze is able to achieve a speedup of 1.54 × comparing to full fine-tuning when fine-tuning for 200000 steps.

CINIC-10 transfer learning: Although BERT fine tuning is our primary focus, we also evaluate AutoFreeze on the vision task described in Section 2. We take a ResNet-18 model which is pre-trained with CINIC-10 and fine-tune this model for the CIFAR-10 dataset. In Figure 15 we observe that our freezing scheme is able to reduce the fine-tuning time by more than 2 × and still reaches a very similar accuracy as of full fine tuning. This demonstrates that our freezing scheme is can be applied on tasks other than BERT and we plan to explore other domains in detail in the future.

Using A100 GPUs: To prove the effectiveness of AutoFreeze on a more advanced hardware, we tested AutoFreeze on the latest NVIDIA A100 GPU. We set up the experiments on a p4d.24xlarge instance with eight A100s on AWS, and ran AutoFreeze on the AG’s News dataset. To match the total batch size of 24 for classification tasks, we set the per GPU batch size to 3. While full fine-tuning took 3030 seconds for four epochs, AutoFreeze only took 1670 seconds and reached comparable accuracy. Thus, we see a speed-up of 1.81 × on A100s which is comparable with the speedup achieved on P100s and shows that the benefits of AutoFreeze remain across hardware generations.

Finally, we also ran the experiment to fully utilize the memory of the A100 GPUs by setting the per GPU batch size to 16, and fine-tune BERT\textsubscript{LARGE} on AG News. AutoFreeze is able to finish fine-tuning for four epochs within 1304 seconds compared to 2020 seconds for full fine-tuning (1.54 × speed-up).

4.6 Varying learning rate, parameters

Applying to other learning rate schedules: To show the effectiveness of applying AutoFreeze on other learning rate schedules, we apply AutoFreeze on constant learning rate schedule with learning rate 1e-5. AutoFreeze achieves comparable accuracy with full fine-tuning with constant learning rate schedule of 1e-5, gaining a average training speedup by a factor of 1.65× on AG News. Results from other datasets are in Appendix A.2.

Using different percentiles: As shown in Figure 16a, we observe a trade-off between training speedup gains and model accuracy as we vary the percentile threshold used in Algorithm 1. The more aggressive our freezing policy is, the greater the accuracy loss will be. For example, if we set N to be 75th percentile which results in a more aggressive policy, we get 0.39% accuracy loss for the IMDb dataset. However, we do not see accuracy loss when we set N to be 25th or 50th percentile. On the other hand, increasing N gives us more training speedup. A policy with N = 75 achieves 20% more speedup compared with the N = 25 policy with 0.49% difference in max accuracies achieved.

Varying number of evaluation intervals each epoch: We also vary how frequently the freezing module is invoked and Figure 16b shows the results with the IMDB dataset. We see that if the frequency is too low (e.g., 1 interval/epoch) then the speedup obtained is limited. On the other hand, using 10 intervals/epoch results in gradient vectors that are not fully representative, thus leading to a drop in accuracy. However, we find this trade-off is balanced for a range of values (2 to 5 intervals/epoch).
4.7 AutoFreeze Overheads, Savings

Gradient Norm Test Overheads: As stated in Section 3.1.1, the gradient norm test has minimal overhead. The overhead mainly comes from accumulating the gradient vectors within an evaluation interval $T$. For example, for IMDb, the overhead for gradient accumulation in terms of time is 13 seconds for every interval, which is less than 1% of the execution time of an interval. The memory overhead for storing the gradients is 453MB for an epoch.

Memory Savings: As we freeze more transformer blocks of the BERT Encoder, we also get runtime memory savings. For example, we are able to reduce the runtime memory requirements for fine-tuning from 11327MB to 1945MB when we freeze all but the last layer of the BERT Encoder. Ideally, this allows us to use a larger batch size on a single GPU. However, applying adaptive greater batch size in the course of fine-tuning requires further investigation.

5 Related Work

Previous works have largely focused on reducing the size of BERT or improving the accuracy/stability for fine-tuning.

Improving Fine-Tuning Several methods [29, 31, 13] have been developed in NLP literature to achieve good performance when fine-tuning. [17] introduce ULFiT, a technique which has enabled state of the art performance when doing fine-tuning. Similarly [43] investigates fine-tuning methods of BERT on text classification tasks including layer selection, layerwise learning rate, and multi-task Learning. [43] shows lower layers contain more general information, and using features from the last layer of BERT gives the best fine-tuning performance. [19] proposes a smoothness inducing regularizer for improving robustness during training. Similarly other works have proposed different techniques [34, 16, 42] to improve performance of fine-tuning. In this work, our aim is to speed up time for fine-tuning without losing the accuracy gains provided by techniques proposed in [17]. We show that AutoFreeze achieves same performance as these methods but reduces time for fine-tuning by adaptively freezing layers at run time.

Model Compression Primary goal of several previous works is to reduce the size of the fine tuned model to enable fast inference. [23, 25] perform low rank approximations to reduce the size and compute requirements of the model. [38, 20, 44] use knowledge distillation to train a smaller model. [49] uses multiple teacher models to train a student for multi-task learning. Similarly [35, 3, 52] perform quantization to enable fast compression. On the other hand [7, 28, 70] reduce the model size using pruning. Similarly [11] use structured dropout to introduce sparsity. The goal of these methods is to reduce the time for inference which sometimes lead to more time spent in training. On the other hand in this work we aim to to reduce time for fine-tuning of the BERT model for new tasks.
Adaptive ML: Another line of work shows that certain layers of network can be skipped dynamically during inference to reduce inference time. [48], [23], [39] propose techniques for adaptively skipping layers at inference. Another recent work [41] uses gradient norms to adaptively tune communication in distributed learning. On other hand our work is primarily focused on speeding up fine-tuning for BERT.

Speeding up BERT Pre-training [12] present a method to speed up BERT pre-training by progressively increasing the size of the model by stacking layers. [54] propose speeding up of BERT pre-training by progressively dropping the layers during pre-training. [6] introduces EarlyBERT which extends the work done on finding lottery-tickets in CNNs [51] to speedup both pre-training and fine-tuning for BERT models. The experimental evaluation of EarlyBERT shows some degradation in accuracy for fine-tuning unlike our work where we have almost no accuracy loss, further EarlyBERT provides almost similar speedups as AutoFreeze.

6 Conclusion and Future Work

Fine-tuning pre-trained models has shown to be an efficient and accurate methodology for developing ML models for new tasks. However there are a number of performance challenges in fine-tuning. In this paper, we proposed AutoFreeze, a scheme to adaptatively freeze parts of the model that are closest to convergence during fine-tuning. We show that using AutoFreeze on NLP tasks can give up to 2.55x speed up without affecting accuracy. While this paper mainly focused on BERT due to its popularity, we plan to study if similar approaches also help in other domains like image classification or speech recognition. Our implementation is available at [https://github.com/uw-mad-dash/AutoFreeze](https://github.com/uw-mad-dash/AutoFreeze).
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A Appendix

A.1 Complete Results

Table 4 shows the max accuracy, iterations at which the max accuracy is achieved, and the end-to-end fine-tuning time for AutoFreeze and full fine-tuning across three random trials for the classification tasks. Table 5 shows the max F1, iterations at which the max F1 score is reached, and the end-to-end fine-tuning time for AutoFreeze and full fine-tuning for SQuAD 2.0 dataset. Table 6 shows similar measurements for the SWAG dataset. We observe that we gain similar speedup and max accuracy for all the runs for each dataset.

We also include the test accuracy convergence curve with respect to time for each of the three repeated runs using stepped learning rate schedule for each dataset in Figures 19, 20, 21, 22, 23, and 24. We see that AutoFreeze and full fine-tuning achieve comparable max accuracy with an average end-to-end training speedup of 2.05×, 1.55×, 2.05×, 1.94×, 1.81×, and 1.56× for AG News, Sogou News, IMDb, Yelp F., SQuAD2.0 and SWAG respectively. We can also see that the freezing speedup is on the same scale across different runs. We gain 2.55×, 1.96×, 2.55×, 2.15×, 1.95×, and 1.64× more speedup on average when turning on the storage manager for AG News, Sogou News, IMDb, and Yelp F., SQuAD2.0 and SWAG respectively compared to full fine-tuning. As shown in Figure 20b, we do not have significant improvements when turning on the storage manager as AutoFreeze decides to start freezing layers from the third epoch for this set of experiments. Accordingly, we are only able to achieve speedup gains from the last epoch through caching.

A.2 Constant learning rate schedule

To show that AutoFreeze is effective for other learning rate schedules, we run AutoFreeze using constant learning rate schedule with learning rate of 1e-5. As shown in Figure 17, AutoFreeze is able to achieve 1.65×, 1.96×, and 1.98× speedup for AG News, IMDb, and Sogou News with respect to end-to-end fine-tuning time without harming the model accuracy.

A.3 Caching benefits for longer runs

We next present the benefits brought by caching when we fine-tune BERT\textsubscript{BASE} for more than four epochs. We fine-tune BERT\textsubscript{BASE} on Sogou dataset for 6 epochs using stepped learning rate schedule with initial learning rate of 1e-5. As shown in Figure 18, AutoFreeze is able to achieve 2.16× speedup compared to the full fine-tuning. When the storage manager is turned on, we get 3.01× speedup compared with the baseline. The storage manager is able to get more significant speedup in this setup as AutoFreeze decides to freeze up to layer g at the end of the second epoch, thus saving most of the forward computation for future epochs. In general, we can save more forward computation time when we run the fine-tuning procedure for longer epochs. However, for the datasets we consider in this paper we use a maximum of four epochs. This is because, as reported in prior work [43], using more epochs doesn’t lead to significant improvements in accuracy for these datasets.
Figure 18: Benefits from AutoFreeze when the Sogou dataset is fine-tuned for more epochs (6 epochs). We see that caching can provide more benefits in this case.

| Dataset        | AutoFreeze | Full fine-tuning | Training Speedup |
|----------------|------------|------------------|------------------|
|                | Best Iteration | Accuracy | Training Time(s) | Best Iteration | Accuracy | Training Time(s) |         |
| AG News        | 80000      | 94.66          | 18993            | 40000         | 94.59     | 34559            | 1.82x   |
|                | 28000      | 94.68          | 15936            | 52000         | 94.66     | 33114            | 2.20x   |
|                | 80000      | 94.66          | 16242            | 36000         | 94.70     | 35058            | 2.16x   |
| Sogou News     | 21600      | 97.45          | 10795            | 28800         | 97.38     | 15552            | 1.44x   |
|                | 30600      | 97.12          | 9462             | 28800         | 97.32     | 15527            | 1.64x   |
|                | 28800      | 97.4           | 9866             | 28800         | 97.48     | 15478            | 1.57x   |
| Yelp F.        | 389988     | 68.96          | 97368            | 324990        | 68.83     | 188892           | 1.94x   |
|                | 389988     | 68.63          | 102859           | 194994        | 68.44     | 189207           | 1.84x   |
|                | 303324     | 68.94          | 92226            | 281658        | 68.91     | 188957           | 2.05x   |
| IMDb           | 9163       | 93.94          | 3543             | 4165          | 93.944    | 7304             | 2.06x   |
|                | 10829      | 94.024         | 3584             | 4165          | 93.944    | 7267             | 2.03x   |
|                | 15827      | 93.604         | 3512             | 8330          | 93.98     | 7253             | 2.07x   |

Table 4: AutoFreeze Performance Evaluation (Classification tasks): We report performance of AutoFreeze on 4 different datasets. Each experiment is repeated 3 times with different random seeds. We observe AutoFreeze leads to up to 2x reduction in fine tuning time while reaching same accuracy as full fine tuning.

Figure 19: [AG News] Test accuracy curve for each trial with respect to end-to-end training time for AutoFreeze, AutoFreeze with Caching turned on, and full fine-tuning.

| Dataset        | AutoFreeze | Full fine-tuning | Training Speedup |
|----------------|------------|------------------|------------------|
|                | Best Iteration | Dev F1 | Training Time (s) | Best Iteration | Dev F1 | Training Time (s) |         |
| SQUAD2.0       | 42881      | 74.83          | 11002            | 29687         | 74.90     | 21419            | 1.94x   |
|                | 29687      | 75.02          | 12163            | 29687         | 74.95     | 21532            | 1.77x   |
|                | 42881      | 74.78          | 12414            | 23090         | 75.05     | 21512            | 1.73x   |

Table 5: AutoFreeze Performance Evaluation (Question Answering): We report performance of AutoFreeze on SQuAD2.0. The experiment is repeated 3 times with different random seeds.
Table 6: **AutoFreeze Performance Evaluation (Multiple Choice):** We report performance of AutoFreeze on the SWAG dataset. Each experiment is repeated 3 times with different random seeds.

| Dataset | Best Iteration | Dev F1 | Training Time (s) | Best Iteration | Dev F1 | Training Time (s) | Speedup |
|---------|----------------|--------|-------------------|----------------|--------|-------------------|---------|
| SWAG    | 4138           | 80.85  | 4436              | 6437           | 80.72  | 6868              | 1.55x   |
|         | 6437           | 81.02  | 4663              | 6437           | 80.89  | 6848              | 1.47x   |
|         | 4138           | 80.88  | 4107              | 5057           | 80.92  | 6857              | 1.66x   |

Figure 20: **[Sogou News]** Test accuracy curve for each trial with respect to end-to-end training time for AutoFreeze, AutoFreeze with Caching turned on, and full fine-tuning.

Figure 21: **[IMDb]** Test accuracy curve for each trial with respect to end-to-end training time for AutoFreeze, AutoFreeze with Caching turned on, and full fine-tuning.

Figure 22: **[Yelp F.]** Test accuracy curve for each trial with respect to end-to-end training time for AutoFreeze, AutoFreeze with Caching turned on, and full fine-tuning.
Figure 23: [SQUAD2.0] Dev F1 curve for each trial with respect to end-to-end training time for AutoFreeze, AutoFreeze with Caching turned on, and full fine-tuning.

Figure 24: [SWAG] Dev accuracy curve for each trial with respect to end-to-end training time for AutoFreeze, AutoFreeze with Caching turned on, and full fine-tuning.