**Bigger&Faster: Two-stage Neural Architecture Search for Quantized Transformer Models**

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**Abstract**

Neural architecture search (NAS) for transformers has been used to create state-of-the-art models that target certain latency constraints. In this work we present Bigger&Faster, a novel quantization-aware parameter sharing NAS that finds architectures for 8-bit integer (int8) quantized transformers. Our results show that our method is able to produce BERT models that outperform the current state-of-the-art technique, AutoTinyBERT [1], at all latency targets we tested, achieving up to a 2.68% accuracy gain. Additionally, although the models found by our technique have a larger number of parameters than their float32 counterparts, due to their parameters being int8, they have significantly smaller memory footprints.

1 Introduction

Transformer models (such as BERT, RoBERTa, GPT-3 etc.) are incredibly capable across diverse domains, most notably natural language processing [1–4] and computer vision [5–7]. In recent years, transformer capability has been driven in large parts by expanding model sizes [8]. With state-of-the-art (SOTA) models now exceeding hundreds of gigabytes in size [9, 10], it has become incredibly costly to deploy and maintain services that rely on them. Additionally, the models are so large that achieving low latency solutions has become impossible without paying for the most advanced hardware. In many application areas, upper bound latency restrictions are required, for example chat bot services or real time object recognition. These applications occur across many diverse settings, from large cloud computing clusters to small edge devices. In these scenarios, the latency requirements are fixed and machine learning engineers must find the most performant (by some metric such as accuracy or F1 score) model that meets said requirement. To solve this problem we propose Bigger&Faster, a neural architecture (NAS) technique that focuses on finding optimal transformer models with fixed upper bound latency constraints.

Given a latency requirement and transformer model, Bigger&Faster employs a two-stage NAS solution to efficiently find an optimal architecture [11]. Our two-stage NAS process is composed of the following two steps: 1) a Supermodel is generated from a teacher model using knowledge distillation and one-shot learning and 2) an evolutionary search process is used to find optimal sub networks of the Supermodel - these sub networks are known as candidates. As the candidate models copy the weights from the Supermodel, two-stage NAS removes the need for lengthy training when evaluating candidates and thus reduces the total search time compared to previous NAS solutions. This reduction in training is absolutely essential when dealing with models as large as SOTA transformers.

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Preprint.
The candidates are evaluated for their latency and accuracy and the best performing candidate is selected as the final model.

In this paper we focus on BERT as our motivating transformer architecture. The current SOTA NAS process to find BERT models that satisfy a latency requirement [12] focuses solely on models with float32 parameters. Seen as the goal of the algorithm is to find the most accurate models at a certain latency target, it seems naive to not incorporate 8-bit integer quantization into this process in light of the inference speedup associated with such models on increasingly common commodity hardware (for example the Intel(R) Xeon(R) Platinum 8358, the hardware target we use in this paper). Additionally, as we will show, naively quantizing the float32 model that other NAS techniques create does not guarantee the best int8 model (this is discussed in section 4 and shown in figure 2). We thus aim to fix this problem by incorporating quantization into the NAS process itself. This means we will search directly for the best int8 model at a given latency constraint.

The final model is evaluated on the Multi-Genre Natural Language Inference (MNLI) dataset [13], a widely used dataset designed for evaluation of machine learning models’ sentence understanding. We aim to produce a model that hits a user inputted latency constraint whilst achieving a higher accuracy than the model with the same latency constraint generated from the existing SOTA technique [12] and baseline BERT models.

2 Background

NAS as a means to automatically design deep neural networks has been of particular interest in recent years. The technique involves defining some search space of model architectures and exploring that search space to find an optimal architecture. Many methods exist to conduct this search such as reinforcement learning, hill-climbing, and Bayesian optimization [14]. In each case, as the search happens candidate architectures must be evaluated. We can separate NAS techniques into two categories according to how this evaluation process is done:

1. **One-stage NAS:** When an architecture needs to be evaluated, a model is instantiated using that architecture and trained from scratch. After being trained it is evaluated using some metric.

2. **Two-stage NAS:** A Supermodel that has architectures larger than any candidate in the search space is trained. When an architecture needs to be evaluated, a model is instantiated using that architecture and shared weights with the supermodel. It is then either not trained or trained for a small number of epochs before being evaluated using some metric [11]. This sharing of weights and subsequent fewer rounds of training results in a huge evaluation time speedup.

Many NAS techniques have been able to surpass both baseline architectures, and tediously hand-crafted designs, indicating a real benefit to the search even beyond the gains from automating would-be human labor. Two-stage NAS was designed to accelerate the search process, especially for large models that required a large amount of compute power to repeatedly train. In particular, AutoTinyBERT applied two-stage NAS to BERT and was able to produce a resulting model that achieved higher or comparable accuracies / F1 scores on the GLUE benchmark whilst reducing inference latency by roughly 3-4 times [12] compared to the state-of-the-art (SOTA) search-based method (NAS-BERT) and the SOTA distillation-based methods (DistilBERT, TinyBERT, MiniLM and MobileBERT) [15–19]. AutoTinyBERT specifically uses NAS to create models that satisfy certain latency constraints, whilst maximising model accuracy, as opposed to targeting accuracy directly.

Model compression, meanwhile, has long been an area of interest and research as a means to achieve the results of large deep models without incurring the computational costs, whether for reasons of speed, energy efficiency, or resource constraints. Quantization is a well established technique for model compression which reduces parameter size by converting the relatively high-precision floating point values traditionally used throughout the model as weights and activations to lower-precision data types, at a potential cost of accuracy following from the loss of precision [20]. Due to the ever-increasing size of deep learning models, quantization has been used to allow large models to fit onto hardware with limited memory such as edge devices. These devices often use low power CPUs with limited processing power (such as Arduino). As well as memory reduction, quantization
can also be used to accelerate model inference through specific hardware support for low precision operation. Server-grade CPUs and GPUs have gained support for accelerating quantized models, in particular int8 models.

The corresponding latency reduction from this hardware acceleration means that under the same latency constraints, int8 quantized models can include more parameters compared to float32 models. This opens up a new direction for optimization by trading parameters’ precision for larger parameter counts, which inspires this work. Our work combine the success of both NAS for large language models and model quantization with the intent of reducing latency of large models whilst maximizing model accuracy.

3 Methodology

We propose a method to automatically search for an optimal quantized Transformer architecture, given a latency constraint. By optimal we mean maximising the accuracy achieved on a downstream fine-tuning task whilst still hitting an inference latency constraint. We use BERT as an example Transformer however our techniques can easily be applied to other Transformer based models. This section begins by presenting an overview of the Bigger&Faster method and then explores each step of technique in more detail.

3.1 Overview.

Figure 1 shows the full Bigger&Faster pipeline. Firstly, given some latency constraint, we use a latency predictor to narrow the search space of all possible architectures to just that of architectures that will meet the inputted latency constraint - we call the resulting search space, the narrowed search space. Note that this latency predictor is trained to predict the latency of int8 quantized models. The use of the latency predictor greatly accelerates the search space narrowing process as it removes the need to tediously profile the performance of all the model architectures present in the original search space.

We then apply two-stage NAS to the narrowed search space to find the optimal BERT configuration. As discussed in section 2, two-stage NAS requires a Supermodel that is used for weight sharing when we evaluate candidate models. The Supermodel’s training process is different from the regular BERT training process because its goal is to provide shared weights between sub-networks that reflect final sub-network performance. During super model training, a sub-model is randomly sampled and only its parameters are updated. This helps the Supermodel’s learned weights perform well as shared weights for various different sub-networks that will be sampled in the search process. To further improve the accuracy of the Supermodel and its sub-networks, we incorporated knowledge distillation into the training process by using a hard loss and distillation loss. Our evolutionary search algorithm is the same as that used in AutoTinyBERT [12] except for the fundamental difference in candidate models - we solely use int8 quantized as opposed to float32 candidate models.

3.2 Search space

We begin by defining the search space of BERT architectures we will search and the method by which this search space is reduced to only include models that hit the input latency constraint. As with any large deep neural network, BERT contains many architecture hyper-parameters that can be changed. In this work we restrict our architecture search space to only contain architectures that have homogeneous encoder blocks, that is the architecture of each encoder block is identical. Let \( e \) be the number of encoder blocks present in the model and \( d \) be the number of different individual encoder block architectures. Using homogeneous encoder blocks reduces our search space from polynomial order \( e \cdot O(d^e) \), to simply linear \( O(d) \). This reduction in search space size is essential because even two-stage NAS is very computationally intensive especially when applied to transformer models (that are frequently very large). Additionally, there exists little literature that shows non-homogeneous encoder block architectures perform better than homogeneous ones although this could be an interesting question to investigate in the future.

We consider varying the following key hyperparameters of encoder architectures:

1. \( h \) - The hidden layer size. This is the dimensionality of encoder and pooler layers.
2. \( f \) - The size of the dense feed forward layers.

We also vary \( e \), the number of encoder blocks. With these hyperparameters each model architecture we consider can be encoded in a three element tuple \((e, h, f)\). Let \( \mathcal{A} \) be the set of all architectures we consider. Naturally we must bound the values of \( e, h \) and \( f \) that we consider to ensure that \(|\mathcal{A}|\) is small enough to allow searches in reasonable times. In particular we define \( \mathcal{A} \) as follows:

\[
\mathcal{A} = \{(e, h, f) \in \mathbb{N}^3 : bound \land step\}
\]  

Where \( bound \) and \( step \) are defined as:

\[
\text{bound} = 1 \leq e \leq 5 \land 120 \leq h \leq 564 \land 128 \leq f \leq 1016
\]

\[
\text{step} = 12|h \land 12|f
\]

This results in the following architectures being present in \( \mathcal{A} \):

| Hyperparameter | Value present in \( \mathcal{A} \) |
|----------------|---------------------------------|
| \( e \)        | \([1, 2, 3, 4, 5]\)              |
| \( h \)        | \([120, 132, \ldots, 12k, \ldots, 516, 528]\) |
| \( f \)        | \([128, 140, \ldots, 12k, \ldots, 1004, 1016]\) |

Given this definition of \( \mathcal{A} \) we have \(|\mathcal{A}| = 14250\). Let \( l \) be the user inputted latency constraint they want their resulting model to achieve. We only wish to conduct a search over architectures that correspond to int8 quantized models that meet \( l \). \( \mathcal{A} \) contains many architectures that do not meet this constraint. For this reason, before conducting any search on \( \mathcal{A} \) to find an optimal model, we must find the narrowed search space of architectures that correspond to int8 quantized models that do meet \( l \). Let \( \mathcal{A}^* \) be this narrowed search space (note \( \mathcal{A}^* \subseteq \mathcal{A} \)). We find \( \mathcal{A}^* \) using a latency predictor \( \mathcal{L} \). \( \mathcal{L} \) is trained to take in some \( x \in \mathcal{A} \) and output the latency, \( x_l \), of the int8 quantized model with that architecture (for implementation details about \( \mathcal{L} \) see section 4). We denote this prediction by \( \mathcal{L}(x) = x_l \). We can thus construct \( \mathcal{A}^* \) as follows:

\[
\mathcal{A}^* = \{a \in \mathcal{A} : \mathcal{L}(a) < l\}
\]  

\( \mathcal{A}^* \) is then used during the evolutionary search step to output an optimal model.
3.3 Supermodel

During evolutionary search, candidate models are selected and instantiated using the weights from the Supermodel. For this reason, we need the Supermodel to have an architecture that is larger than any of those contained within $A$. Let $A_s$ be the architecture of the Supermodel and $\mathcal{E}$, $\mathcal{H}$, $\mathcal{F}$ be the sets of $e$, $h$ and $f$ values present in $A$. From the previously described size requirement, we have:

$$A_s = (\max(\mathcal{E}), \max(\mathcal{H}), \max(\mathcal{F}))$$

We instantiate a BERT model with architecture $A_s$ and use a modified training algorithm to train it. Its training process follows the method described in AutoTinyBERT. The method works as follows. For each input training batch, divide it into $n$ sub-batches and distribute them onto $n$ threads. Then for $m$ steps, sample $n$ sub models from the Supermodel and distribute them onto the $n$ threads and calculate the gradient update step to be taken. After these $m$ steps have completed, average all the gradient updates across the $n$ threads and use this average gradient to update the model weights. Knowledge distillation is also used during the training process, meaning the loss function is a mixture of a hard loss (that encodes the difference between the correct label and the prediction) and a soft loss (that encodes the difference between the models output and a separate larger pre-trained teacher model output).

3.4 Conducting evolutionary search.

We adapt the evolutionary search process from AutoTinyBERT. The algorithm is outlined in algorithm 1. The evolutionary search algorithm takes as input the narrowed search space $A^*$ and searches for the architecture in the space that corresponds to the int8 quantized model with the highest accuracy on some pre-chosen downstream task. During the search, whenever we evaluate some candidate architecture, we instantiate the architecture and quantize the resulting models linear layers to 8-bit integer values using PyTorch’s dynamic quantization library [21]. Note, unlike many other works concerning quantization, we do not simulate the quantization by simply injecting quantization error but rather conduct the quantization fully. This means the resulting architecture we find can easily be instantiated, trained, quantized and put into production using commonly available libraries (e.g. PyTorch and HuggingFace’s transformers library [22]).

4 Results and Discussions

4.1 Latency Results for BERT Models

To motivate why searching for int8 quantized models can outperform searching for full precision models, we benchmarked various quantized and non-quantized BERT models whose architectures were drawn from $A$. We used a compute cluster containing an Intel Ice Lake Xeon Platinum 8358 CPU @ 2.60GHz. This CPU was chosen intentionally as it comes enabled with the AVX-VNNI extension that allows for accelerated int8 operations. To benchmark the models we simply drew a set of architectures and instantiated full floating point models of each using PyTorch. We recorded the averaged latency of each model over 5 single sentence inputs (each containing 128 tokens). We then used PyTorch’s dynamic quantization library to quantize the models to int8 and re-ran the average latency test. Figure 2 shows the collected data. As described above, every single point in the plot represents a certain architecture for a BERT model. Its x-axis shows the corresponding model’s float32 inference result, while its y-axis shows the model’s int8 inference result. We also fitted a linear regression to the data to quantify the relationship between int8 and float32 inference times. The fitted line had the following equation:

$$\text{latency}_{\text{float32}} = 1.75 \times \text{latency}_{\text{int8}} - 2.65$$

As we can see from this fitted line, the int8 latency is significantly smaller than the float32 latency. This speed up shows the potential to fit a quantized model with more parameters while still meeting the same latency requirement.

At the same time, the two points at the top and bottom of the red line in figure 2 shows an interesting behaviour. The two points correspond to two different models that have exactly the same float32 latency result but vastly different int8 latency results. The difference is around 50%. Although we have chosen one specific example here, it is clear that this general trend holds true throughout the
Algorithm 1 Evolutionary Search

Inputs $T$, the number of generations of evolutionary search, $S$ the number of candidates to consider at generation, $p_m$ the mutation probability, $A^*$ the narrowed search space.

1: procedure QUANT EVOLVE SEARCH
2: $G_1 \leftarrow A^*$
3: for $t = 1, 2, \ldots, T$ do
4: $G_t \leftarrow \{\}$
5: while $|G_t| < S$ do
6: $\alpha_{\text{old}} \leftarrow$ a sample (without replacement) from $G_{t-1}$.
7: $\alpha_{\text{quant}} \leftarrow$ an 8bit quantized version of $\alpha_{\text{old}}$.
8: $p \leftarrow$ a uniform random number from 0 to 1.
9: if $p < p_m$ then
10: $\alpha_{\text{new}} \leftarrow$ a mutation of $\alpha_{\text{quant}}$.
11: else
12: $\alpha_{\text{new}} \leftarrow$ a random sample from $A$.
13: end if
14: Append $\alpha_{\text{new}}$ to $G_t$
15: end while
16: end for
17: $M \leftarrow$ the set of models with architectures from $G_T$ and weights from the Supermodel.
18: $M_{\text{quant}} \leftarrow \{\}$
19: for $m \in M$ do
20: Append quantized version of $m$ to $M_{\text{quant}}$
21: end for
22: $\alpha_{\text{opt}} \leftarrow$ the architecture of model with the best accuracy on the target task from $M_{\text{quant}}$.
23: return $\alpha_{\text{opt}}$
24: end procedure

data. The large variance in models’ int8 latency that have the same float32 latency makes it clear that we need to search independently for float32 and int8 models and that we cannot simply search for a float32 model and then quantize - rather our search must be quantization-aware if we wish to find the optimal int8 model.

4.2 Optimal Configurations for int8 BERT Models

Using the method described in section 3 we conducted searches for four different latency targets. We used $A$ as the full search space. For the latency predictor $L$ we used a simple multi layer perceptron that has 3 hidden layers and 2000 perceptrons in each layer and trained it on the architechtures and quantized latency results shown in 2. This implementation of $L$ was able to achieve a 3.28% mean average percentage error on a held out testing set.

We also searched for both a float32 model and an int8 model. The float32 model is used as a baseline comparison for our quantized method. For each latency target experiment, we conducted four rounds of evolutionary search. The final search result is shown in Table 2.

Based on the results, we can easily see our method outperforming the baseline. With quantization, we allow the model to have more parameters while remaining within the latency range restriction. Although the reduced precision for all the parameters changing from float32 to int8 will reduce the model’s performance to some extent, this loss is overpowered by the accuracy gain of additional parameters. For all four different latency constrains, int8 models beat their corresponding float32 counterparts. We also note that the accuracy improvement plateaus as latency increases. The most cost-effective accuracy improvements come from the model with 10 ms latency. Also, the lower section of Table 2 shows the number of parameters and size of the model in memory. As we can see, our method allows the model to include a larger number of parameters, but still yield a reduction in the model size.

To put our results in a wider prospective, we compared them with AutoTinyBERT and baseline BERT as shown in figure 3. In the figure, the x axis indicates model latency, while y axis indicates test accuracy on the MNLI dataset. Each method has several architectures with different model latency
Figure 2: Comparison of various models’ int8 version and float32 version latencies. The same float32 and int8 model configuration can result in very different corresponding latency values.

Table 2: Optimal model MNLI accuracy, #Parameter and model size for float32 and int8 BERT model from various search spaces with different latency constraints.

| Latency | w.o. Post-Training | w. Post-Training |
|---------|--------------------|------------------|
|         | float32 | int8 | float32 | int8 |
| 5ms     | 0.6026  | **0.6145** | 0.6452  | **0.6475** |
| 10ms    | 0.6342  | **0.6803** | 0.6917  | **0.7185** |
| 15ms    | 0.6650  | **0.6899** | 0.7169  | **0.7374** |
| 20ms    | 0.6737  | **0.6943** | 0.7237  | **0.7402** |

| Latency | #Parameter | Model Size |
|---------|------------|------------|
|         | float32 | int8 | float32 | int8 |
| 5ms     | 17M       | **18M** | 67MB    | **18MB** |
| 10ms    | 14M       | **20M** | 55MB    | **20MB** |
| 15ms    | 16M       | **24M** | 64MB    | **24MB** |
| 20ms    | 19M       | **27M** | 78MB    | **27MB** |

constraints, all of which we plot and connect with a line on the figure. For better performance, a model should have lower latency whilst achieving comparable or better accuracy. Thus, a better search strategy should give a curve closer to the upper left corner. The BERT baseline is a series of models that are generated by Google with different hyper-parameters. Although they are able to cover a wider range of models, the performance of their models under specific latency constraint is worse than AutoTinyBERT and Bigger&Faster. AutoTinyBERT outperforms BERT baseline, while Bigger&Faster provides by far the best performance. From a broader perspective, this demonstrates that performance increase (in terms of accuracy improvement, latency reduction and model compression) can be achieved by trading parameter precision for more parameters.

5 Related Works

Our method exists at the intersection of neural architecture search, and quantization. We will examine these areas separately and illustrate how our work builds novelty on prior work.
Figure 3: Comparison of models generated from baseline BERT, AutoTinyBERT and Bigger&Faster. Each model is represented by a point in the figure with its x coordinate showing its latency, while y coordinate showing its Accuracy for MNLI dataset. All models trained using the same dataset and for the same number of epochs.

NAS: In 2021, AutoTinyBERT introduced an evolutionary-search based NAS technique to automate the design of BERT architectures [12]. Their method allows for the selection of an optimal model design meeting a given latency constraint, and serves as the basis for our technique. We build upon their contributions by introducing the additional compression technique of quantization to int8 and integrating it deeply with the search process. This allows larger models (in terms of parameter number) to meet the same latency constraints due to aforementioned hardware acceleration.

NAS-BERT [15] also applied NAS to BERT to find smaller more efficient architectures. They however consider heterogeneous encoder block architectures, a route we specifically avoid due to large search spaces making search times more and more infeasible for larger and larger transformer models. Additionally, their technique does not incorporate any other compression schemes unlike our quantization aware method.

There is precedent for combining quantization and NAS to the end of a quantize-aware search. The 2018 JASQ method [23] provides ample evidence regarding the usefulness of quantization in combination with NAS, and helped to motivate our contributions, but is ultimately a very different endeavor. Where we applied exclusively int8 quantization to a search over model architectures for BERT, JASQ searches both architectures and quantization policies to produce an optimal CIFAR-10 CNN with quantization precision potentially mixed across layers. Because we were targeting latency improvements, including quantization policies in our search space was not viable as only int8 quantization has the most widespread support for hardware acceleration.

Quantization: There was prior evidence that our application of quantization to BERT would not excessively harm model accuracy so as to negate the gains achieved by it permitting larger models in the search process. In 2021, I-BERT found integer-only quantization of BERT can achieve an inference speed-up of up to 4 times with minimal impact to test accuracies [20]. Similarly Q8BERT used quantize-aware training to compress BERT models by a factor of four with comparable test accuracy [24]. Neither project approached the issue of NAS for optimal latency-constrained architectures, however, and thus remain distinct from our work. Additionally, we note that our method is far more flexible, allowing for the production of efficient BERT models across a wide range of sizes.

Many others have applied more extreme quantization to BERT. For example, GOBO [25] quantizes up to 99.9% of BERT parameters to 3bit values. Going even further, BinaryBERT [26] quantizes
BERT weights to binary values. These techniques were not suitable for our work because there does not exist common hardware acceleration for operations on such low precision values.

6 Conclusion

In conclusion, we presented a novel method that combines two-stage NAS and quantization to find latency constrained BERT models that outperforms the current state-of-the-art method. We motivate our work through the exploration of a dataset of full precision and quantized BERT model latencies. It shows dramatic latency reduction can be achieved when applying int8 quantization to a float32 model, which means under the same latency constraint, a model with more parameters can be used. At the same time, two full precision models that achieve the same latency may correspond to int8 quantized models whose latencies vary by 50%, illustrating the importance of searching directly for int8 quantized models. Our quantization-aware NAS achieves higher accuracy models at the same latency constraint, or at the extreme case half model latency whilst sacrificing less than a percent of model accuracy. Our contribution is novel in both its focus on int8 quantization in NAS to target latency requirements and its application of quantization-aware NAS to the domain of transformer models.

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