# **Big Little Transformer Decoder**

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### **ABSTRACT**

The recent emergence of Large Language Models based on the Transformer architecture has enabled dramatic advancements in the field of Natural Language Processing. However, these models have long inference latency, which limits their deployment, and which makes them prohibitively expensive for various real-time applications. The inference latency is further exacerbated by autoregressive generative tasks, as models need to run iteratively to generate tokens sequentially without leveraging token-level parallelization. To address this, we propose Big Little Decoder (BiLD), a framework that can improve inference efficiency and latency for a wide range of text generation applications. The BiLD framework contains two models with different sizes that collaboratively generate text. The small model runs autoregressively to generate text with a low inference cost, and the large model is only invoked occasionally to refine the small model's inaccurate predictions in a non-autoregressive manner. To coordinate the small and large models, BiLD introduces two simple yet effective policies: (1) the fallback policy that determines when to hand control over to the large model; and (2) the rollback policy that determines when the large model needs to review and correct the small model's inaccurate predictions. To evaluate our framework across different tasks and models, we apply BiLD to various text generation scenarios encompassing machine translation on IWSLT 2017 De-En and WMT 2014 De-En, summarization on CNN/DailyMail, and language modeling on WikiText-2. On an NVIDIA Titan Xp GPU, our framework achieves a speedup of up to 2.13× without any performance drop, and it achieves an up to 2.38× speedup with only a ~1 point degradation. Furthermore, our framework is fully plug-and-play as it does not require any training or modifications to model architectures. Our code will be open-sourced<sup>1</sup>.

### 1 INTRODUCTION

In recent years, the Transformer [59] has become the *de-facto* model architecture for a wide range of Natural Language Processing tasks. The potential of the Transformer architecture has been further enhanced by the emergence of Large Language Models (LLMs) with up to hundreds of billions of parameters trained on massive text corpora [3, 7, 10, 22, 44, 47, 51, 58, 79]. Despite their performance, efficiently running these models for inference is a challenge due to their large model size and runtime complexity. This limits their use generally, and it prohibits their use in many applications that require real-time responses.

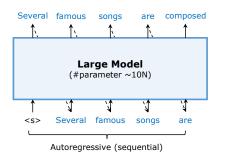
These computational inefficiencies are particularly pronounced in autoregressive generative tasks such as machine translation [2, 4], summarization [20], and language modeling [37]. For these tasks, models need to run iteratively to generate tokens sequentially, as each token is dependent on the previously generated tokens. This requires the models to load weight matrices, as well as the cached keys and values of previously generated tokens [42], for each token generation, thus preventing parallelization of the loaded values across multiple tokens. This makes autoregressive text generation memory bandwidth constrained during inference [8]. As a consequence, autoregressive generative tasks suffer from low hardware utilization as well as high inference latency. In contrast, non-autoregressive tasks, such as text classification [61], can process the entire input sequence with a single weight load, which is then shared across all input tokens in parallel. Given the increasing popularity of text generation tasks, in light of advancements in LLMs, it is critical to improve the inference latency and runtime efficiency of autoregressive decoding processes.

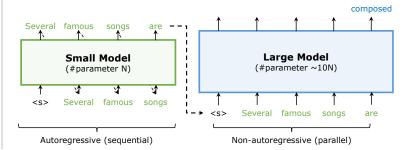
To overcome this, non-autoregressive decoding [14, 15, 18, 34, 35, 49, 55, 65, 66] has been explored to maximize token-level parallelization and reduce the inference latency of generative tasks by generating multiple tokens simultaneously. This approach can be more computationally efficient than the regular autoregressive process. However, non-autoregressive decoding tends to suffer in terms of text generation quality due to its assumption of conditional independence between output tokens [27]. In order to achieve comparable performance to that of autoregressive processes, non-autoregressive decoding generally requires complex and often task-dependent training strategies, supplementary hinting information that serves as a guide for the decoding process [35, 49, 55, 65, 66], and knowledge distillation [80].

In this paper, we introduce a novel framework named Big Little Decoder (BiLD)<sup>2</sup> that can be applied to various text generation scenarios to reduce inference latency without additional training iterations or modifications to the existing training pipeline or model architecture. As illustrated in Figure 1, the BiLD framework consists of two decoder models, a large model and small model, that work collaboratively to generate text sequences. In particular, only the small model is executed autoregressively to generate the majority of the text, taking advantage of its small runtime overhead. The large model only engages occasionally to refine the small model's inaccurate predictions, thus allowing for efficient non-autoregressive execution. This autoregressive small, non-autoregressive large scheme

 $<sup>^{1}</sup> https://github.com/kssteven 418/Big Little Decoder$ 

 $<sup>^2\</sup>mathrm{We}$  name this after ARM's big.LITTLE architecture [1] that switches between "LITTLE" processors that maximize power efficiency and "big" processors that maximize compute performance, based on the dynamic usage pattern.





**Figure 1:** Illustration of (Left) the normal autoregressive decoding procedure of a large model and (Right) BiLD that consists of a small model and a large model. In BiLD, the small model generates tokens autoregressively (i.e., sequentially) until it hands over control to the large model. The large model then takes as input the tokens generated by the small model in parallel, allowing for non-autoregressive (i.e., parallel) execution to generate the next token. This is expected to improve latency by allowing for more efficient utilization of underlying hardware.

results in a substantial improvement (2.13× without any performance drop) in end-to-end inference latency, compared to regular autoregressive execution, while maintaining similar or better generation quality. The effectiveness of our framework is also supported by our observation that the predictions made by small and large models only slightly disagree, and thus the small model can match the performance of the large model with a minimal refinement of its own predictions (Figure 2, Section 3.1).

In summary, our main contributions are as follows:

- We introduce BiLD, a general framework that allows faster inference of various text generation applications. Our framework is designed to coordinate a large model and a small model such that the large model is only executed infrequently and efficiently in a non-autoregressive manner to refine the small model's inaccurate predictions.
- We propose two simple yet effective policies for BiLD: the fall-back policy that allows the small model to hand control over to the large model if it is not confident enough (Section 3.3), and the rollback policy that allows the large model to review and correct the small model's inaccurate predictions (Section 3.4).
- We apply BiLD for 6 different text generation scenarios including IWSLT 2017 De-En [4] and WMT 2014 De-En [2] for machine translation, CNN/DailyMail [20] for summarization, and WikiText [37] for language modeling. Compared to the full autoregressive execution, BiLD achieved a speedup of up to 2.13× without a performance drop and 2.38× allowing ~1 point degradation on an NVIDIA Titan Xp GPU (Section 4.2).

### 2 RELATED WORK

# 2.1 Efficient Transformer Inference for Decoding

A variety of approaches have been proposed to increase the speed and reduce the overall inference costs of Transformers. Well-known approaches include efficient architecture design [25, 30, 33, 56, 63, 71], quantization [9, 29, 50, 70, 75, 77, 78], pruning [11, 13, 31, 32, 38, 46, 60], and neural architecture search [6, 52, 53, 62, 72, 76]. While these methods are generally suitable for Transformer-based tasks, some of the works have been focused on efficient decoding mechanisms to reduce the cost of regressive tasks.

One popular line of research that shares similarity to our work is non-autoregressive decoding. Non-autoregressive decoding, also known as parallel decoding, was first introduced in [15] as a method to reduce inference latency by producing multiple output tokens in parallel, thus avoiding sequential text generation. In this pioneering work, an encoder is trained to also predict the number of tokens that each source language token maps to in target language ahead of time, allowing for single-iteration decoding. Subsequent work has further improved the performance of non-autoregressive models by incorporating auxiliary or hinting information [35, 49, 55, 65, 66] to ensure more consistent and accurate parallel decoding, or by allowing multiple additional iterations to refine any inaccurate predictions [14, 18, 34]. Such a multi-iteration decoding scheme has been proposed in [16, 54, 67], which generates texts with fewer steps than the autoregressive scheme by inserting or deleting multiple tokens per iteration. However, these works require complex and often task-dependent training strategies and/or auxiliary information in order to achieve comparable performance to that of autoregressive models. In contrast, our methodology aims for a plug-and-play solution that does not require any training or additional information, making it applicable to a wide range of text generation scenarios.

Our work is also related to the approaches that reduce the decoding cost by making decoders shallow. The paper "Deep Encoders, Shallow Decoders" [27] demonstrates that increasing the depth of encoders and decreasing the depth of decoders can reduce decoding latency while still preserving performance. CALM [48] recently introduces early exiting, which dynamically adjusts the depth of the decoder for each token generation by terminating the inference at a middle layer and making a prediction using the intermediate hidden states, rather than executing until the end layer. To achieve good performance, CALM relies on the assumption that the predictions made in the earlier layers are consistent with those made in the final layer. In contrast, we find that this assumption does not always hold. As an example, for the mT5-Large, T5-Large, and GPT2-Large models that were used for evaluation (details in Section 4.1), we observed that the earliest layer that agrees with the final layer's prediction as an upper-bound performance estimate, following the oracle metric in [48]. On the validation sets of WMT 2014 De-En,

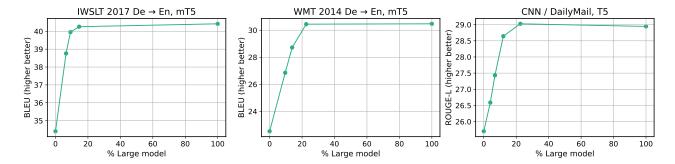


Figure 2: Quality of text generation for different proportions of the large model's engagement on the small model's prediction, evaluated on the validation datasets of three different generative tasks: (1) IWSLT 2017 De-En translation [4]; (2) WMT 2014 De-En translation [2]; and (3) CNN/DailyMail summarization [20]. The proportions of the large model's engagement are controlled by substituting the tokens predicted by the small model with the large model's prediction if the likelihood of the large model yielding the small model's prediction was below a certain threshold. We see that the small models can achieve a comparable generation quality to the large models if ~20% of their incorrect predictions were substituted.

CNN/DailyMail, and Wikitext-2, however, the metrics are  $\sim$ 16, 15, and 24 out of 24, 24, and 36 layers, respectively. This indicates that early exiting would not provide a significant performance gain in these cases. Our proposed framework is not dependent on this assumption, and thus it can be applied to a wider range of models and tasks.

## 2.2 Use of Multiple Models

Coordinating the use of multiple models has also been explored in knowledge distillation and ensemble learning. *Knowledge distillation* is a widely adopted methodology for enhancing the performance of smaller models by training them to replicate the behavior of larger, more complex models [21]. When applied to the Transformer architecture, this approach involves distilling the final logits [45, 57] and/or hidden states of a larger model, such as the attention map [26, 56, 64]. However, knowledge distillation is a static solution, meaning that the coordination between the small and large models occurs solely during the training phase. Thus, distillation requires additional training which can be more complex than stand-alone training. In comparison, our method is a training-free, dynamic solution that can be adaptive to the run-time behaviors of the models during the decoding process.

Ensemble learning is another approach for coordinating multiple models, wherein multiple models are trained independently and their predictions are combined to improve overall performance. Ensemble learning has been found to yield promising results for Transformer inference [23, 24, 36, 40, 73], particularly when the models aggregated are pre-trained on different datasets and use different techniques. However, ensemble learning generally requires running multiple models and combining their predictions at runtime, which can be computationally expensive and not optimized for latency. Our research aims to optimize both model performance and run-time latency.

Concurrently and independently of our work, [5] also proposes an interesting algoroithm to accelerate generative inference using a more powerful model to score and speculatively sample predictions from a less powerful model. While the idea of using two different models is similar, our approach differs in incorporating a dynamic window size that minimizes the large model's engagement by letting small models to predict more tokens if they are confident enough. Our approach also allows for explicit control of the latency and performance trade-off, thus allowing one to obtain multiple models with different latency constraints. Although [5] suggests an unbiased estimator to recover the exact probability distributions of the large model, it can still have a large variance that might affect current and future predictions. We empirically show that this can lead to performance degradation in various tasks (Section 4.2).

### 3 METHODOLOGY

# 3.1 Motivating Examples

It is known that large models achieve better text generation quality than small models in a wide range of generative tasks. However, the use of large models is accompanied by a longer end-to-end latency, which is further exacerbated by the regressive process of predicting one token at a time. Nevertheless, in many text generation scenarios, we observe that a small model with an order of magnitude smaller size than a large model can achieve comparable generation quality to the large model-provided that a small number of erroneous predictions are corrected. This implies that only a small fraction of the small model's predictions deviate from those of the larger model. To validate this claim, we evaluate three different generative benchmarks: IWSLT 2017 De-En translation [4]; WMT 2014 De-En translation [2]; and CNN/DailyMail summarization [20]. For the translation tasks, we prepare the large and small variants of mT5 [74], and for the summarization task, we use T5 [44]. See Section 4.1 for more details on these models. For every decoding iteration of the small model, we also let the large model make its own prediction. Then, we measure the likelihood of the large model predicting the token that the small model has generated. If the likelihood is below a certain threshold, we assume that the small model's prediction is unlikely and not accurate enough, and we replace it with the large model's prediction. By controlling the threshold, we can adjust the proportion that the large model engages in text generation.

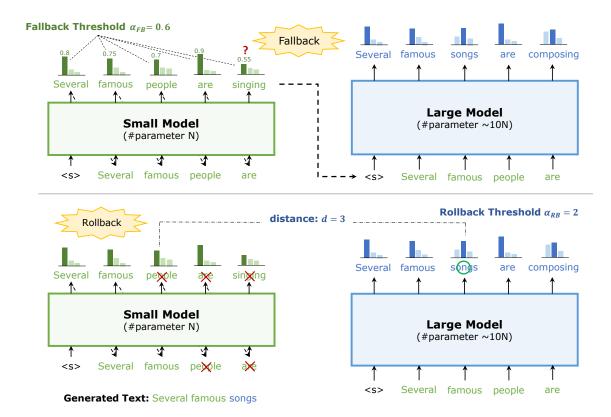


Figure 3: (Top) The fallback policy. When the small model generates tokens autoregressively, if the prediction probability of a specific token is below the predefined fallback threshold value  $\alpha_{FB}$ , the prediction is deemed to be not confident enough, and control is then shifted to the larger model to produce the corresponding token. (Bottom) The rollback policy. If the large model takes over the control, it produces its own predictions for all previous tokens, as well as the current token. If the prediction probability from the large model for a previously generated token deviates from the small model's prediction by a distance metric d exceeding the predetermined rollback threshold  $\alpha_{RB}$ , the small model's prediction is regarded as incorrect. In such a case, we roll back all predictions made by the small model that follow the corresponding token.

Figure 2 plots the text generation quality on the validation dataset of each benchmark for different proportions of the large model's engagement. Note that the left-most point (i.e., 0% large model) and the right-most point (i.e., 100% large model) in each plot represent the predictions made solely by the small and the large model, respectively. The results exhibit a clear trend across the tasks where the small models with  $\sim 10\times$  smaller sizes are able to retain the large model's generation quality only if approximately 20% of their incorrect predictions were substituted with the large model's predictions. While this experiment assumes an ideal case where the predictions that the large model would have made were available in each iteration as ground truth, it nonetheless demonstrates the feasibility of achieving the performance of the large model while maintaining the low latency of the small model for inference.

### 3.2 Problem Formulation

At nth decoding iteration, the small model and the large model each take as input a partially generated output text  $y_{1:n-1} = (y_1, \dots, y_{n-1})$ , and then generate a probability distribution over entire vocabulary  $p_S(y|y_{1:n-1})$  and  $p_L(y|y_{1:n-1})$ , respectively. Then, the next token

 $y_{n,S}$  and  $y_{n,L}$  are sampled from the probability distributions,

$$y_{n,S} \sim p_S(y|y_{1:n-1}),$$
 (1)

and

$$y_{n,L} \sim p_L(y|y_{1:n-1}).$$
 (2)

Depending on whether to use the small model or the large model for the nth decoding step, the nth token  $y_n$  can be either  $y_{n,S}$  or  $y_{n,L}$ . When deciding which model to use, it is not feasible to run the large model along with the small model for every decoding step to verify the predictions of the small model, as in the experiments in Section 3.1. Thus, it is necessary to hand over the control to the large model only when the small model is likely to make an inaccurate prediction. In other words, we need a simple policy  $\pi(y_{1:n-1})$  that takes as input the predicted tokens so far and returns a boolean value  $\{0, 1\}$  that indicates whether to use the large model:

$$y_n = \begin{cases} y_{n,S} & \text{if } \pi(y_{1:n-1}) = 0\\ y_{n,L} & \text{if } \pi(y_{1:n-1}) = 1. \end{cases}$$
(3)

The objective is to find a lightweight policy  $\pi$  that attains a good text generation quality on the validation examples with the minimum end-to-end latency. The text generation quality can be improved if

### Algorithm 1: Big Little Decoder

```
1: y \leftarrow [<s>]
2: while y[-1] \neq <eos>
       p_S \leftarrow \text{SmallModel}(y)
3:
       if \max(p_S[-1]) > \alpha_{FB}
4:
          # Use the small model's predicton
5:
          y \leftarrow y + [\text{sample}(p_S[-1])]
6:
7:
       else
          # Fallback to the large model
8:
9:
          p_L \leftarrow \text{LargeModel}(y)
          m \leftarrow \text{minimum index such that } d(p_L[m], p_S[m]) > \alpha_{RB}
10:
11:
12:
             # Rollback and use the large model's prediction
13:
             y \leftarrow y[:m] + [sample(p_L[m])]
          else
14:
             # Do not rollback and use the large model's prediction
15:
16:
             y \leftarrow y + [\text{sample}(p_L[-1])]
17: return y
```

the policy relies more on the large model. However, this will also lead to increased latency. As such, the policy must only invoke the large model when it is necessary.

In order to illustrate the mechanism by which latency is reduced, consider a simple case where the small model has generated tokens  $y_1$  through  $y_n$  autoregressively. If the large model were to take over the control and predict the next token,  $y_{n+1}$ , it can now take multiple inputs  $(y_1 \text{ through } y_n)$  in parallel, thus allowing for non-autoregressive inference. It is worth noting that this nonautoregressive approach would require the same amount of FLOPs as a regressive approach that predicts  $y_1$  through  $y_{n+1}$  sequentially; however, it is much faster on hardware due to its token-level parallelism and increased arithmetic intensity. If the latency saving from running the large model non-autoregressively, compared to running in autoregressively, is greater than the additional cost of running the small model, there is a net latency reduction. Note that the aim of this approach is *not* to reduce the runtime cost by reducing the number of FLOPs. In fact, due to the additional FLOPs incurred by running the small model on side, the total number of FLOPs will be greater than autoregressively running the large model. However, we demonstrate that by improving the hardware utilization and arithmetic intensity [68] of the entire decoding process, one can significantly reduce the latency despite the increased number of FLOPs. Figure 1 provides a high-level overview of how the small and the large models in BiLD coordinates for text generation.

We now turn to the main question of constructing an appropriate policy  $\pi$ . Here, we introduce two simple policies, the fallback policy and the rollback policy, which (despite their simplicity) result in high performance with significant latency reduction. We discuss the details of these policies in the following subsections.

# 3.3 Fallback Policy: Small Model Knows When to Stop Predictions

The first principle of the policy is that the small model should know how to decide when to hand over control to the large model, based on its confidence in its own prediction. That is, in cases where the small model is not confident about its prediction, it should allow the large model to take over. While confidence (or uncertainty, in reverse) quantification has been an active research area [12, 28], we find that a simple policy based on the maximum prediction probability, i.e.,  $\max_y p_S(y|y_{1:n-1})$ , is sufficient to measure the confidence, similar to the observations made in [19]. Specifically, if the maximum prediction probability is lower than a certain threshold  $\alpha_{FB}$ , then the small model's prediction is regarded to be not confident enough, and thus it is avoided. Instead, we *fallback* to the large model and generate the next token.

**Fallback Policy:** If  $\max_y p_S(y|y_{1:n-1}) < \alpha_{FB}$ , then fallback to the large model and set  $y_n = y_{n,L}$ .

# 3.4 Rollback Policy: Large Model Knows When to Revert Predictions

While the fallback policy allows the large model to take over when the small model is not confident enough, it is still possible that the small model is over-confident in its incorrect predictions [17]. Moreover, a single incorrect prediction at an early decoding iteration can lead to a catastrophic effect [48], as it will affect all subsequent token predictions. To avoid such cases, it is desirable to have the large model review the small model's predictions and ensure the validity of each prediction. In our framework, this comes without any extra cost. When the large model is provided with the tokens generated by the small model for its non-autoregressive prediction of the next token, it also produces its own predictions for all the previous decoding steps. In other words, given the partially generated text  $y_{1:n}$ , it generates  $p_L(y|y_{1:m})$  for all previous decoding steps  $m = 1, \dots, n-1$  as well as for the current decoding step m = n, which can be used to validate the small model's previous predictions.

Therefore, for some distance metric  $d(\cdot, \cdot)$  for comparing two probability distributions, we find the smallest decoding step m such that

$$d(p_S(y|y_{1:m}), p_L(y|y_{1:m})) > \alpha_{RB}$$
 (4)

for a predetermined threshold  $\alpha_{RB}$ . If such m exists, we regard the small model's previous prediction  $y_m$  to be inaccurate, and we rollback all predictions that follow, i.e.,  $y_m$  through  $y_n$ , since they are all dependent on the wrong prediction. We then replace  $y_m$  with  $y_{m,L}$ , the more accurate prediction from the large model. We discuss in Section 4.2 that the cross-entropy loss between the hard label from the small model and the soft label from the large model (which measures the likelihood of obtaining the small model's prediction from the large model's output) is a good choice for the metric d. Rollback may incur additional latency due to the need for duplicated computation for the reverted tokens. However, we demonstrate in Section 4.3 the net advantage of rollback as the improved text generation quality outweighs the additional latency.

**Rollback Policy:** If there exists a minimum  $m \in [1, n-1]$  such that  $d(p_S(y|y_{1:m}), p_L(y|y_{1:m})) > \alpha_{RB}$ , then rollback the predictions  $(y_m, \dots, y_n)$  and set  $y_m = y_{m,L}$ .

### 3.5 Big Little Decoder

Taken together, the Big Little Decoder (BiLD) framework consists of one small model, one large model, and a policy that determines

**Table 1:** Model configurations of the large and small models for each evaluation task. For comparison, the number of layers, hidden dimension, FFN dimension, and the number of decoder parameters (without embeddings) for each model are provided. For FSMT, the decoder of the small model (†) was trained by the authors.

Model	Task	# Layers	dim	FFN dim	# Params
mT5-large [74]	Machine	24	1024	2816	409M
mT5-small [74]	Translation	8	512	1024	25M
FSMT [39]	Machine	6	1024	4096	145M
FSMT <sup>†</sup> [39]	Translation	1	1024	4096	29M
T5-large [44]	Summarization	24	1024	4096	402M
T5-small [44]		6	512	2048	25M
GPT2-large [43]	Language	36	1280	5120	708M
GPT2-base [43]	Modeling	12	768	3072	85M

which model to use for each decoding iteration. The policy comprises two components: the fallback policy to fall back to the large model when the small model's prediction is not confident enough; and a rollback policy to roll back the small model's predictions if they deviate from the predictions of the large model. Algorithm 1 provides a summary of the end-to-end algorithm.

### 4 EVALUATIONS

### 4.1 Experiment Setup

To test the generalizability and validity of BiLD across different text generation scenarios, we select the benchmarks and models as described below. For all cases, we select two models from the same model group, one small and one large, that differ in size by approximately a factor of 10. Our framework is built on top of PyTorch [41] and the HuggingFace Transformers library [69] as well as their pre-trained model checkpoints.

Machine Translation. For machine translation, we use IWSLT 2017 German-English [4] and WMT 2014 German-English [2] as target benchmarks, and mT5 [74] and Facebook's machine translation model (FSMT) [39] as target models. For mT5, we use the 8-layer mT5-small and the 24-layer mT5-large as the small and large models, respecitvely. Both of the models are fine-tuned for 20 epochs on IWSLT and 1 epoch on WMT using batch size 16, warmup steps 10k, and peak learning rates of {0.5, 1, 2, 5}e-4 with linear decay, starting from the pre-trained checkpoints. For FSMT, we use the default 6-layer model as the large model. Since there are no model variants of different sizes, we freeze the encoder of the pre-trained large model and use it directly as the encoder of the small model. The training is conducted for 5 epochs using a batch size of 64, warmup steps 10k, and peak learning rates of {0.2, 0.5, 1, 2\e-4 with linear decay. For all cases, we perform greedy sampling and use the BLEU score on the validation datasets for evaluating the text generation quality.

**Summarization.** For summarization, we use pre-trained T5 [44] model on CNN/DailyMail [20] benchmark without additional finetuning. We use T5-small and large with 6 and 24 layers, respectively, for the small and large models. We perform greedy sampling and use ROUGE scores on the validation dataset for evaluation.

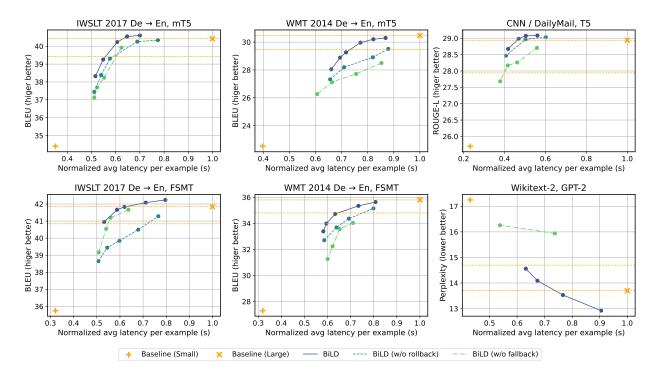
Language Modeling. For language modeling, we utilize a pretrained GPT2 [43] model on the Wikitext-2 benchmark [37]. Specifically, we use GPT2-base and large with 12 and 36 layers, respectively, for the small and large models. Both the small and large models are fine-tuned from the pre-trained checkpoints for 5 epochs using batch size 16 and peak learning rate of {0.5, 1, 2, 5}e-4 with linear decay. For evaluation, we measure the perplexity on the validation dataset by concatenating all the texts and chunking them into sequence lengths of 512.

Table 1 summarizes the large and small models used for each evaluation task along with the number of layers and widths of each model. Note that our proposed framework is independent of the underlying training strategies and can be used in any scenario where a set of small and large models for a specific task is available. All inference evaluations are conducted on a single NVIDIA Titan Xp GPU using a batch size 1, which is a common use case for online serving [48]. For cases in which the small and large models have individual encoders, we run both in order to provide the encoded states to the respective decoder of each model. For the distance metric *d* in Equation 4 for the rollback policy, we use the crossentropy loss between the hard label from the small model and the soft label from the large model as default. This corresponds to the likelihood of obtaining the small model's prediction from the large model's output distribution.

### 4.2 Main Results

4.2.1 **Latency Speedup.** Figure 4 illustrates the trade-off between the text generation quality and the average end-to-end latency (including encoder) of processing a single example, normalized by the latency of the large model. The Pareto-frontier curves for BiLD are obtained by controlling the fallback and rollback thresholds, which result in different latency versus text generation quality tradeoffs. For machine translation and summarization tasks that exhibit sharper distributions, we set the fallback thresholds to {0.4, 0.5, 0.6, 0.7, 0.8 and rollback thresholds to {1, 2, 3, 4}. For language modeling with flatter distributions, the fallback thresholds are selected among {0.01, 0.02, 0.05, 0.1, 0.2}. We also highlight that rollback is not applied to language modeling, as it measures perplexity by evaluating the likelihood of correctly predicting the ground-truth label, rather than generating a new token based on its own output distributions. Thus, there is no need for a rollback. For comparison, we also plot the large and small models as the baseline in the figures.

Table 2 summarizes the results of BiLD compared to the large baseline. Group 1 (2nd rows) and Group 2 (3rd rows) in the table correspond to BiLD models in the Pareto-frontier curves of Figure 4 that achieve minimal performance degradation and  $\sim\!1$  point performance degradation, respectively. The results in Group 1 demonstrate that BiLD achieves 1.52× speedup on average across benchmarks, and up to 2.13× speedup on the CNN/Dailymail summarization benchmark, with minimal performance loss from the large baseline. When allowing  $\sim\!1$  point accuracy degradation from the large baseline as in Group 2, BiLD is able to find more aggressive models, achieving 1.76× speedup on average and up to 2.38× speedup. Figure 4 also reveals that in the high-latency regime, BiLD performs even better than the baseline with shorter latency. This



**Figure 4:** Performance (i.e., text generation quality) and average end-to-end latency of processing a single sentence on 6 different combinations of benchmarks and models. We report BLEU, ROUGE-L, and Perplexity for translation, summarization, and language modeling, respectively, as performance metrics. The solid lines are BiLD, and the two X marks are the baselines (small and large on the left and right corners, respectively) that construct BiLD. The dashed lines represent the ablations of BiLD without rollback and fallback, respectively. For comparison, two horizontal lines are plotted to indicate the performance of the large baseline models and 1 point degradation from it. The latency on the x-axis is normalized by the latency of the large model.

**Table 2:** The summary of Figure 4 that compares the performance and average end-to-end latency per sentence of BiLD and the baseline. The first rows report the baseline, and the second and third rows report BiLD. The BiLD models in Group 1 (second rows) and Group 2 (third rows) are selected from the Pareto-frontier curves to have minimal performance degradation and  $\sim$ 1 point performance degradation, respectively. Results for BiLD additionally include performance degradation (negative sign indicating degradation) and latency speedup compared to the baseline. In the case of Perplexity for GPT ( $\dagger$ ), we have flipped the sign to avoid confusion, as lower values represent better performance, unlike the other metrics.

Model		IWSLT mT5 BLEU (↑)	WMT mT5 BLEU (†)	IWSLT FSMT BLEU (↑)	WMT FSMT BLEU (↑)	CNN/DM T5 ROUGE-L (↑)	<b>Wikitext GPT-2</b> Perplexity (↓)
Baseline	Performance	40.42	30.47	41.84	35.80	28.94	13.70
(Large)	Avg. latency (s/ex)	1.05	0.98	0.18	0.19	2.51	15.35
BiLD	Performance	40.23 (-0.19)	30.30 (-0.17)	41.83 (-0.01)	35.64 (-0.16)	28.98 (+0.04)	13.53 (+0.17 <sup>†</sup> )
Group 1	Avg. latency (s/ex)	0.64 (×1.64)	0.85 (×1.15)	0.11 (×1.61)	0.15 (×1.23)	1.18 (×2.13)	11.76 (×1.30)
BiLD	Performance	39.25 (-1.17)	29.26 (-1.21)	40.95 (-0.89)	34.73 (-1.07)	28.67 (-0.27)	14.56 (-0.86 <sup>†</sup> )
Group 2	Avg. latency (s/ex)	0.58 (×1.82)	0.70 (×1.39)	0.10 (×1.89)	0.12 (×1.59)	1.05 (×2.38)	9.69 (×1.59)

trend can be attributed to the ensembling effect of using two different models, which has been studied in prior work [36]. Overall, the results demonstrate the generalizability of BiLD across a wide range of tasks, models, and datasets.

We further conducted a performance comparison between our method and the speculative sampling method [5] on machine translation (IWSLT 2017 De-En and WMT 2014 De-En using mT5) and summarization (CNN/DailyMail using T5). We used a window size of {2, 3, 4, 5} for all cases. Compared to the speculative sampling,

BiLD achieves 0.42 higher BLEU score with the same speedup and 0.18× more latency gain with the same performance on the IWSLT benchmark. Similarly, on the WMT benchmark, BiLD achieves 0.06× additional latency gain with the same performance. Finally, for summarization on CNN/DailyMail, BiLD achieves 0.42 higher ROUGE-L score with the same speedup and 0.48× additional latency gain with similar performance as the speculative sampling. Overall, our empirical results demonstrate that the BiLD policy provides a

Ground Truth And Siftables are an example of a new ecosystem of tools for manipulating digital information.

Large And the Siftables are an example of a new generation of manipulation tools for digital data.

Small And the if you look at the ifleses are an example of a new generation of technologies for manipulation of digital data.

BLD (ours) And the Siftables are an example of a new generation of manipulation of digital data.

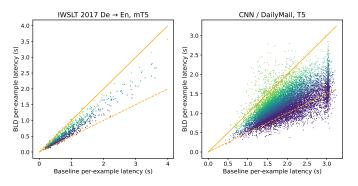
Ground Truth Which is great, because the Romans did not actually think that a genius was a particularly clever individual.

Large That's great. The Romans didn't really think that a genius was a particularly smart individual.

Small That's great. The tube didn't really think that a genius was a particularly lonely individual.

BLD (ours) That's great. The Romans didn't really think that a genius was a particularly smart individual.

Figure 5: Example text sequences that BiLD generates with the validation set of IWSLT 2017 De-En, compared to the ground truths and the outputs of the large and small baselines. For BiLD, tokens generated by the large model are highlighted in red, while all the other tokens are generated by the small model. This illustrates that with a small engagement of the large model, BiLD can correct not only inaccurate vocabulary but also wrong semantics of the text that the small model would have otherwise generated.



**Figure 6:** Comparison of per-example inference latency on (Left) IWSLT 2017 De-En translation and (Right) CNN/DailyMail summarization tasks between the baseline large model (x-axis) and BiLD (y-axis) on the entire validation sets. BiLD is chosen to be the model with the best text-generation quality (among different trade-offs in Fig. 4), which yields 0.18 better BLEU score and 0.70× of average latency for IWSLT and 0.14 better ROUGE-L score and 0.56× average latency for CNN/DailyMail compared to the baseline. More than 97% of the examples are faster with BiLD in both tasks despite improved BLEU or ROUGE-L scores.

more stable estimation of the larger model's prediction, leading to a better performance-latency tradeoff across various tasks.

4.2.2 **Per-example Latency Analysis.** We further analyze the latency of processing a single input using BiLD compared to the baseline large models. Figure 6 illustrates the latency comparison of BiLD and the large models for mT5 on IWSLT 2017 De-En and T5 on CNN/DailyMail. We select BiLD as the best (right-most) model on the Pareto-frontier in Figure 4. This performs 0.18 points better with 70% of the average latency for mT5 on IWSLT, and 0.14 points better with 56% of the average latency for T5 on CNN/DailyMail, as compared to the baseline. It can be observed from the figure that although one might be concerned that too many rollbacks would lead to longer latencies than the baseline, this is a rare occurrence, accounting for only 2.3% and 2.7% of the total examples for each task. The majority (more than 97%) of examples resulted in faster

latencies than the baseline, yielding an average latency reduction of  $0.70\times$  and  $0.56\times$  respectively, even with better text generation quality than the baseline.

4.2.3 **Examples of Generated Sequences.** Figure 5 provides examples of text sequences generated by BiLD on the validation set of IWSLT 2017 De-En, along with the ground truths (i.e., labels) and outputs of the large and small baselines. The tokens generated from the large model of BiLD are highlighted in red, while all other tokens are generated by the small model. The results illustrate that the small model often produces low-quality texts, by predicting inaccurate tokens which can be significant enough to change the meaning of the entire sentence. To contrast, it is observed from the examples that BiLD is able to improve the text generation quality by letting the large model interrupt when the small model generates incorrect tokens. In doing so, BiLD not only predicts valid tokens at the moment that the large model engages, but it also improves the subsequent prediction in terms of vocabulary choice and semantics.

#### 4.3 Ablation Studies

Figure 4 also illustrates two ablation studies: (1) BiLD without the rollback policy; and (2) BiLD without the fallback policy. The results indicate that the rollback policy results in consistently better text generation quality across all latency regimes in all benchmarks. In the case of the translation task, the gap between having and not having the rollback policy can be up to 1-2 points BLEU score. This demonstrates that, despite the additional latency overhead due to the duplicated computation for reverted tokens, the gain from improved text generation quality can outweigh this cost.

In addition, one may consider an alternative, where the small model periodically falls back to the large model after generating a fixed number of tokens, rather than having a fallback policy, instead relying on the large model's refinement based on the rollback policy. This approach corresponds to the ablation of the BiLD without the fallback policy. For the ablation, we keep the same rollback thresholds as the main experiments, while the fallback to the large model happens every fixed number of token generations. As can be seen in the figure, in most cases, the absence of the fallback policy results in substantial performance drop. Taken together, the

ablation studies indicate that it is not possible to rely on a single policy, but both of the policies are critical components of BiLD.

### 5 CONCLUSION

In this work, we have introduced Big Little Decoder (BiLD), a framework that reduces end-to-end inference latency for a wide variety of text generation tasks without the need for training or modifying the existing models. In essence, our framework couples a large and small decoder model together to generate text more efficiently. In particular, we start inference with a small model which runs autoregressively for the majority of the time to generate text with a low inference cost, while the large model is executed nonautoregressively to refine the small model's inaccurate predictions. BiLD incorporates two policies, the fallback policy, which hands control to the large model when the small model is uncertain, and the rollback policy, which allows the large model to revert the small model's inaccurate predictions. Our framework is evaluated across various text generation scenarios, including machine translation, summarization, and language modeling. Running on an NVIDIA Titan Xp GPU, with no performance drop BiLD achieved an average speedup of 1.52×, with improvements of up to 2.18× on some tasks. Furthermore, when a 1 point degradation in performance was allowed, BiLD achieved an average speedup of 1.76× with speedups of up to 2.38× on some tasks.

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### REFERENCES

- [1] https://www.arm.com/technologies/big-little.
- [2] Ondrej Bojar, Christian Buck, Christian Federmann, Barry Haddow, Philipp Koehn, Johannes Leveling, Christof Monz, Pavel Pecina, Matt Post, Herve Saint-Amand, Radu Soricut, Lucia Specia, and Ale s Tamchyna. Findings of the 2014 workshop on statistical machine translation. In Proceedings of the Ninth Workshop on Statistical Machine Translation, pages 12–58, Baltimore, Maryland, USA, June 2014. Association for Computational Linguistics.
- [3] Tom B Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. arXiv preprint arXiv:2005.14165, 2020
- [4] Mauro Cettolo, Marcello Federico, Luisa Bentivogli, Jan Niehues, Sebastian Stüker, Katsuhito Sudoh, Koichiro Yoshino, and Christian Federmann. Overview of the IWSLT 2017 evaluation campaign. In Proceedings of the 14th International Conference on Spoken Language Translation, pages 2–14, Tokyo, Japan, December 14-15 2017. International Workshop on Spoken Language Translation.
- [5] Charlie Chen, Sebastian Borgeaud, Geoffrey Irving, Jean-Baptiste Lespiau, Laurent Sifre, and John Jumper. Accelerating large language model decoding with speculative sampling. arXiv preprint arXiv:2302.01318, 2023.
- [6] Daoyuan Chen, Yaliang Li, Minghui Qiu, Zhen Wang, Bofang Li, Bolin Ding, Hongbo Deng, Jun Huang, Wei Lin, and Jingren Zhou. Adabert: Task-adaptive

- bert compression with differentiable neural architecture search. arXiv preprint arXiv:2001.04246, 2020.
- [7] Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, et al. Palm: Scaling language modeling with pathways. arXiv preprint arXiv:2204.02311, 2022.
- [8] Michiel de Jong, Yury Zemlyanskiy, Joshua Ainslie, Nicholas FitzGerald, Sumit Sanghai, Fei Sha, and William Cohen. Fido: Fusion-in-decoder optimized for stronger performance and faster inference. arXiv preprint arXiv:2212.08153, 2022.
- [9] Tim Dettmers, Mike Lewis, Younes Belkada, and Luke Zettlemoyer. Gpt3. int8 (): 8-bit matrix multiplication for transformers at scale. In Advances in Neural Information Processing Systems.
- [10] Nan Du, Yanping Huang, Andrew M Dai, Simon Tong, Dmitry Lepikhin, Yuanzhong Xu, Maxim Krikun, Yanqi Zhou, Adams Wei Yu, Orhan Firat, et al. Glam: Efficient scaling of language models with mixture-of-experts. In International Conference on Machine Learning, pages 5547-5569. PMLR, 2022.
- [11] Angela Fan, Edouard Grave, and Armand Joulin. Reducing transformer depth on demand with structured dropout. arXiv preprint arXiv:1909.11556, 2019.
- [12] Yarin Gal and Zoubin Ghahramani. Dropout as a bayesian approximation: Representing model uncertainty in deep learning. In international conference on machine learning, pages 1050–1059. PMLR, 2016.
- [13] Trevor Gale, Erich Elsen, and Sara Hooker. The state of sparsity in deep neural networks. arXiv preprint arXiv:1902.09574, 2019.
- [14] Marjan Ghazvininejad, Omer Levy, Yinhan Liu, and Luke Zettlemoyer. Maskpredict: Parallel decoding of conditional masked language models. arXiv preprint arXiv:1904.09324, 2019.
- [15] Jiatao Gu, James Bradbury, Caiming Xiong, Victor OK Li, and Richard Socher. Non-autoregressive neural machine translation. arXiv preprint arXiv:1711.02281, 2017.
- [16] Jiatao Gu, Changhan Wang, and Junbo Zhao. Levenshtein transformer. Advances in Neural Information Processing Systems, 32, 2019.
- [17] Chuan Guo, Geoff Pleiss, Yu Sun, and Kilian Q Weinberger. On calibration of modern neural networks. In *International conference on machine learning*, pages 1321–1330. PMLR, 2017.
- [18] Junliang Guo, Linli Xu, and Enhong Chen. Jointly masked sequence-to-sequence model for non-autoregressive neural machine translation. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 376–385, 2020.
- [19] Dan Hendrycks and Kevin Gimpel. A baseline for detecting misclassified and out-of-distribution examples in neural networks. arXiv preprint arXiv:1610.02136, 2016.
- [20] Karl Moritz Hermann, Tomas Kocisky, Edward Grefenstette, Lasse Espeholt, Will Kay, Mustafa Suleyman, and Phil Blunsom. Teaching machines to read and comprehend. In Advances in neural information processing systems, pages 1693–1701, 2015.
- [21] Geoffrey Hinton, Oriol Vinyals, and Jeff Dean. Distilling the knowledge in a neural network. Workshop paper in NIPS, 2014.
- [22] Jordan Hoffmann, Sebastian Borgeaud, Arthur Mensch, Elena Buchatskaya, Trevor Cai, Eliza Rutherford, Diego de Las Casas, Lisa Anne Hendricks, Johannes Welbl, Aidan Clark, et al. Training compute-optimal large language models. arXiv preprint arXiv:2203.15556, 2022.
- [23] Chris Hokamp, Demian Gholipour Ghalandari, Nghia The Pham, and John Glover. Dyne: Dynamic ensemble decoding for multi-document summarization. arXiv preprint arXiv:2006.08748, 2020.
- [24] Ngo Quang Huy, Tu Minh Phuong, and Ngo Xuan Bach. Autoencoding language model based ensemble learning for commonsense validation and explanation. arXiv preprint arXiv:2204.03324, 2022.
- [25] Forrest N Iandola, Albert E Shaw, Ravi Krishna, and Kurt W Keutzer. Squeezebert: What can computer vision teach nlp about efficient neural networks? arXiv preprint arXiv:2006.11316, 2020.
- [26] Xiaoqi Jiao, Yichun Yin, Lifeng Shang, Xin Jiang, Xiao Chen, Linlin Li, Fang Wang, and Qun Liu. Tinybert: Distilling bert for natural language understanding. arXiv preprint arXiv:1909.10351, 2019.
- [27] Jungo Kasai, Nikolaos Pappas, Hao Peng, James Cross, and Noah A Smith. Deep encoder, shallow decoder: Reevaluating non-autoregressive machine translation. arXiv preprint arXiv:2006.10369, 2020.
- [28] Alex Kendall and Yarin Gal. What uncertainties do we need in bayesian deep learning for computer vision? Advances in neural information processing systems, 30, 2017.
- [29] Sehoon Kim, Amir Gholami, Zhewei Yao, Michael W Mahoney, and Kurt Keutzer. I-bert: Integer-only bert quantization. arXiv preprint arXiv:2101.01321, 2021.
- [30] Nikita Kitaev, Lukasz Kaiser, and Anselm Levskaya. Reformer: The efficient transformer. In International Conference on Learning Representations, 2019.
- [31] Eldar Kurtic, Daniel Campos, Tuan Nguyen, Elias Frantar, Mark Kurtz, Benjamin Fineran, Michael Goin, and Dan Alistarh. The optimal bert surgeon: Scalable and accurate second-order pruning for large language models. arXiv preprint arXiv:2203.07259, 2022.

- [32] Woosuk Kwon, Sehoon Kim, Michael W Mahoney, Joseph Hassoun, Kurt Keutzer, and Amir Gholami. A fast post-training pruning framework for transformers. arXiv preprint arXiv:2204.09656, 2022.
- [33] Zhenzhong Lan, Mingda Chen, Sebastian Goodman, Kevin Gimpel, Piyush Sharma, and Radu Soricut. Albert: A lite bert for self-supervised learning of language representations. arXiv preprint arXiv:1909.11942, 2019.
- [34] Jason Lee, Elman Mansimov, and Kyunghyun Cho. Deterministic nonautoregressive neural sequence modeling by iterative refinement. arXiv preprint arXiv:1802.06901, 2018.
- [35] Zhuohan Li, Zi Lin, Di He, Fei Tian, Tao Qin, Liwei Wang, and Tie-Yan Liu. Hint-based training for non-autoregressive machine translation. arXiv preprint arXiv:1909.06708, 2019.
- [36] Yoshitomo Matsubara, Luca Soldaini, Eric Lind, and Alessandro Moschitti. Ensemble transformer for efficient and accurate ranking tasks: an application to question answering systems. arXiv preprint arXiv:2201.05767, 2022.
- [37] Stephen Merity, Caiming Xiong, James Bradbury, and Richard Socher. Pointer sentinel mixture models, 2016.
- [38] Paul Michel, Omer Levy, and Graham Neubig. Are sixteen heads really better than one? arXiv preprint arXiv:1905.10650, 2019.
- [39] Nathan Ng, Kyra Yee, Alexei Baevski, Myle Ott, Michael Auli, and Sergey Edunov. Facebook fair's wmt19 news translation task submission. arXiv preprint arXiv:1907.06616, 2019.
- [40] Liu Pai. Qiaoning at semeval-2020 task 4: Commonsense validation and explanation system based on ensemble of language model. In Proceedings of the Fourteenth Workshop on Semantic Evaluation, pages 415–421, 2020.
- [41] Adam Paszke, Sam Gross, Soumith Chintala, Gregory Chanan, Edward Yang, Zachary DeVito, Zeming Lin, Alban Desmaison, Luca Antiga, and Adam Lerer. Automatic differentiation in pytorch. 2017.
- [42] Reiner Pope, Sholto Douglas, Aakanksha Chowdhery, Jacob Devlin, James Bradbury, Anselm Levskaya, Jonathan Heek, Kefan Xiao, Shivani Agrawal, and Jeff Dean. Efficiently scaling transformer inference. arXiv preprint arXiv:2211.05102, 2022.
- [43] Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. Language models are unsupervised multitask learners. OpenAI blog, 1(8):9, 2019.
- [44] Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, Peter J Liu, et al. Exploring the limits of transfer learning with a unified text-to-text transformer. J. Mach. Learn. Res., 21(140):1–67, 2020.
- [45] Victor Sanh, Lysandre Debut, Julien Chaumond, and Thomas Wolf. Distilbert, a distilled version of bert: smaller, faster, cheaper and lighter. arXiv preprint arXiv:1910.01108, 2019.
- [46] Victor Sanh, Thomas Wolf, and Alexander Rush. Movement pruning: Adaptive sparsity by fine-tuning. Advances in Neural Information Processing Systems, 33:20378–20389, 2020.
- [47] Teven Le Scao, Angela Fan, Christopher Akiki, Ellie Pavlick, Suzana Ilić, Daniel Hesslow, Roman Castagné, Alexandra Sasha Luccioni, François Yvon, Matthias Gallé, et al. Bloom: A 176b-parameter open-access multilingual language model. arXiv preprint arXiv:2211.05100, 2022.
- [48] Tal Schuster, Adam Fisch, Jai Gupta, Mostafa Dehghani, Dara Bahri, Vinh Q Tran, Yi Tay, and Donald Metzler. Confident adaptive language modeling. arXiv preprint arXiv:2207.07061, 2022.
- [49] Chenze Shao, Jinchao Zhang, Yang Feng, Fandong Meng, and Jie Zhou. Minimizing the bag-of-ngrams difference for non-autoregressive neural machine translation. In *Proceedings of the AAAI conference on artificial intelligence*, volume 34, pages 198–205, 2020.
- [50] Sheng Shen, Zhen Dong, Jiayu Ye, Linjian Ma, Zhewei Yao, Amir Gholami, Michael W Mahoney, and Kurt Keutzer. Q-BERT: Hessian based ultra low precision quantization of bert. In AAAI, pages 8815–8821, 2020.
- [51] Shaden Smith, Mostofa Patwary, Brandon Norick, Patrick LeGresley, Samyam Rajbhandari, Jared Casper, Zhun Liu, Shrimai Prabhumoye, George Zerveas, Vijay Korthikanti, et al. Using deepspeed and megatron to train megatron-turing nlg 530b, a large-scale generative language model. arXiv preprint arXiv:2201.11990, 2022.
- [52] David So, Quoc Le, and Chen Liang. The evolved transformer. In International Conference on Machine Learning, pages 5877–5886. PMLR, 2019.
- [53] David R So, Wojciech Mańke, Hanxiao Liu, Zihang Dai, Noam Shazeer, and Quoc V Le. Primer: Searching for efficient transformers for language modeling. arXiv preprint arXiv:2109.08668, 2021.
- [54] Mitchell Stern, William Chan, Jamie Kiros, and Jakob Uszkoreit. Insertion transformer: Flexible sequence generation via insertion operations. In *International Conference on Machine Learning*, pages 5976–5985. PMLR, 2019.
- [55] Zhiqing Sun, Zhuohan Li, Haoqing Wang, Di He, Zi Lin, and Zhihong Deng. Fast structured decoding for sequence models. Advances in Neural Information Processing Systems, 32, 2019.
- [56] Zhiqing Sun, Hongkun Yu, Xiaodan Song, Renjie Liu, Yiming Yang, and Denny Zhou. Mobilebert: a compact task-agnostic bert for resource-limited devices. arXiv preprint arXiv:2004.02984, 2020.

- [57] Raphael Tang, Yao Lu, Linqing Liu, Lili Mou, Olga Vechtomova, and Jimmy Lin. Distilling task-specific knowledge from bert into simple neural networks. arXiv preprint arXiv:1903.12136, 2019.
- [58] Romal Thoppilan, Daniel De Freitas, Jamie Hall, Noam Shazeer, Apoorv Kulshreshtha, Heng-Tze Cheng, Alicia Jin, Taylor Bos, Leslie Baker, Yu Du, et al. Lamda: Language models for dialog applications. arXiv preprint arXiv:2201.08239, 2022.
- [59] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. In Advances in neural information processing systems, pages 5998–6008, 2017.
- [60] Elena Voita, David Talbot, Fedor Moiseev, Rico Sennrich, and Ivan Titov. Analyzing multi-head self-attention: Specialized heads do the heavy lifting, the rest can be pruned. arXiv preprint arXiv:1905.09418, 2019.
- [61] Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R Bowman. GLUE: A multi-task benchmark and analysis platform for natural language understanding. arXiv preprint arXiv:1804.07461, 2018.
- [62] Hanrui Wang, Zhanghao Wu, Zhijian Liu, Han Cai, Ligeng Zhu, Chuang Gan, and Song Han. Hat: Hardware-aware transformers for efficient natural language processing. arXiv preprint arXiv:2005.14187, 2020.
- [63] Sinong Wang, Belinda Li, Madian Khabsa, Han Fang, and Hao Ma. Linformer: Self-attention with linear complexity. arXiv preprint arXiv:2006.04768, 2020.
- [64] Wenhui Wang, Furu Wei, Li Dong, Hangbo Bao, Nan Yang, and Ming Zhou. Minilm: Deep self-attention distillation for task-agnostic compression of pretrained transformers. arXiv preprint arXiv:2002.10957, 2020.
- [65] Yiren Wang, Fei Tian, Di He, Tao Qin, ChengXiang Zhai, and Tie-Yan Liu. Non-autoregressive machine translation with auxiliary regularization. In Proceedings of the AAAI conference on artificial intelligence, volume 33, pages 5377–5384, 2019.
- [66] Bingzhen Wei, Mingxuan Wang, Hao Zhou, Junyang Lin, Jun Xie, and Xu Sun. Imitation learning for non-autoregressive neural machine translation. arXiv preprint arXiv:1906.02041, 2019.
- [67] Sean Welleck, Kianté Brantley, Hal Daumé Iii, and Kyunghyun Cho. Non-monotonic sequential text generation. In *International Conference on Machine Learning*, pages 6716–6726. PMLR, 2019.
- [68] Samuel Williams, Andrew Waterman, and David Patterson. Roofline: an insightful visual performance model for multicore architectures. Communications of the ACM, 52(4):65-76, 2009.
- [69] Thomas Wolf, Julien Chaumond, Lysandre Debut, Victor Sanh, Clement Delangue, Anthony Moi, Pierric Cistac, Morgan Funtowicz, Joe Davison, Sam Shleifer, et al. Transformers: State-of-the-art natural language processing. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations, pages 38–45, 2020.
- [70] Xiaoxia Wu, Zhewei Yao, Minjia Zhang, Conglong Li, and Yuxiong He. Extreme compression for pre-trained transformers made simple and efficient. arXiv preprint arXiv:2206.01859, 2022.
- [71] Zhanghao Wu, Zhijian Liu, Ji Lin, Yujun Lin, and Song Han. Lite transformer with long-short range attention. arXiv preprint arXiv:2004.11886, 2020.
- [72] Jin Xu, Xu Tan, Renqian Luo, Kaitao Song, Jian Li, Tao Qin, and Tie-Yan Liu. Nas-bert: task-agnostic and adaptive-size bert compression with neural architecture search. In Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining, pages 1933–1943, 2021.
- [73] Yige Xu, Xipeng Qiu, Ligao Zhou, and Xuanjing Huang. Improving bert finetuning via self-ensemble and self-distillation. arXiv preprint arXiv:2002.10345, 2020.
- [74] Linting Xue, Noah Constant, Adam Roberts, Mihir Kale, Rami Al-Rfou, Aditya Siddhant, Aditya Barua, and Colin Raffel. mt5: A massively multilingual pretrained text-to-text transformer. arXiv preprint arXiv:2010.11934, 2020.
- [75] Zhewei Yao, Reza Yazdani Aminabadi, Minjia Zhang, Xiaoxia Wu, Conglong Li, and Yuxiong He. Zeroquant: Efficient and affordable post-training quantization for large-scale transformers. arXiv preprint arXiv:2206.01861, 2022.
- [76] Yichun Yin, Cheng Chen, Lifeng Shang, Xin Jiang, Xiao Chen, and Qun Liu. Autotinybert: Automatic hyper-parameter optimization for efficient pre-trained language models. arXiv preprint arXiv:2107.13686, 2021.
- [77] Ali Hadi Zadeh, Isak Edo, Omar Mohamed Awad, and Andreas Moshovos. Gobo: Quantizing attention-based nlp models for low latency and energy efficient inference. In 2020 53rd Annual IEEE/ACM International Symposium on Microarchitecture (MICRO), pages 811–824. IEEE, 2020.
- [78] Ofir Zafrir, Guy Boudoukh, Peter Izsak, and Moshe Wasserblat. Q8BERT: Quantized 8bit bert. arXiv preprint arXiv:1910.06188, 2019.
- [79] Susan Zhang, Stephen Roller, Naman Goyal, Mikel Artetxe, Moya Chen, Shuohui Chen, Christopher Dewan, Mona Diab, Xian Li, Xi Victoria Lin, et al. Opt: Open pre-trained transformer language models. arXiv preprint arXiv:2205.01068, 2022.
- [80] Chunting Zhou, Graham Neubig, and Jiatao Gu. Understanding knowledge distillation in non-autoregressive machine translation. arXiv preprint arXiv:1911.02727, 2019.