Towards Efficient NLP: A Standard Evaluation and A Strong Baseline

Xiangyang Liu[1,2]*, **Tianxiang Sun**[1,2]*, **Junliang He**[1,2], **Jiawen Wu**[1,2], **Lingling Wu**[1,2], **Xinyu Zhang**[3], **Hao Jiang**[3], **Zhao Cao**[3], **Xuanjing Huang**[1,2], **Xipeng Qiu**[1,2] †

[1]School of Computer Science, Fudan University

[2]Shanghai Key Laboratory of Intelligent Information Processing, Fudan University

[3]Huawei Poisson Lab

{xiangyangliu20,txsun19,xjhuang,xpqiu}@fudan.edu.cn

{zhangxinyu35,jianghao66,caozhao1}@huawei.com

Abstract

Supersized pre-trained language models have pushed the accuracy of various natural language processing (NLP) tasks to a new state-of-the-art (SOTA). Rather than pursuing the reachless SOTA accuracy, more and more researchers start paying attention to model efficiency and usability. Different from accuracy, the metric for efficiency varies across different studies, making them hard to be fairly compared. To that end, this work presents **ELUE** (**E**fficient **L**anguage **U**nderstanding **E**valuation), a standard evaluation, and a public leaderboard for efficient NLP models. ELUE is dedicated to depicting the Pareto Frontier for various language understanding tasks, such that it can tell whether and how much a method achieves Pareto improvement. Along with the benchmark, we also release a strong baseline, **ElasticBERT**, which allows BERT to exit at any layer in both static and dynamic ways. We demonstrate the ElasticBERT, despite its simplicity, outperforms or performs on par with SOTA compressed and early exiting models. With ElasticBERT, the proposed ELUE has a strong Pareto Frontier and makes a better evaluation for efficient NLP models.

1 Introduction

Driven by the large-scale pre-training, today's NLP models have become much more powerful (Devlin et al., 2019; Yang et al., 2019; Lan et al., 2020; Raffel et al., 2020; Sun et al., 2020; Brown et al., 2020; Qiu et al., 2020). As a consequence of this drastic increase in performance, these pre-trained language models (PLMs) are notorious for becoming more and more computationally expensive due to the increasing number of parameters. Therefore, rather than pre-training a larger model to achieve a new state-of-the-art (SOTA) accuracy, most studies are pursuing improvement on other dimensions such as the number of parameters or FLOPs (Gordon et al., 2020; Sanh et al., 2019; Jiao et al., 2020; Lan et al., 2020; Shen et al., 2020). For these works, the goal has shifted from simple SOTA to "Pareto SOTA". A Pareto SOTA model means that there is no other model is currently better than it on all the dimensions of interest. For example, a model may claim to be Pareto SOTA as long as it achieves the best accuracy under the same number of parameters or FLOPs. For these efficient models with fewer parameters or FLOPs, it is unfair to get them evaluated on the accuracy-centric benchmarks such as GLUE (Wang et al., 2019b), and ranked among many large-scale models.

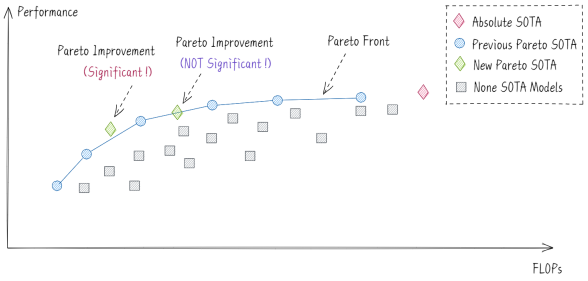

Figure 1: An illustration to show our motivation, that is, building the Pareto frontier can help recognizing whether and how much a method achieves Pareto improvement.

The shifted goal has outpaced the existing benchmarks, which cannot provide a comprehensive and intuitive comparison for efficient methods. In the absence of a proper benchmark, measures of efficiency in different studies cannot be standardized, and different methods cannot be fairly compared. As a result, it is difficult to say *whether* and *how much* a method achieves Pareto improvement. To that end, we aim to build the Pareto frontier for various tasks with standard evaluation for both performance and efficiency. Our motivation can be briefly illustrated by Figure 1.

Need for a standard evaluation As the goal has shifted, a new benchmark is urgently needed to

*Equal contribution.

†Corresponding author.

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comprehensively compare the NLP models in multiple dimensions. Currently, this multi-dimensional comparison is done in the individual papers, resulting in the following issues: **(a) Incomprehensive comparison.** The comparison is usually point-to-point, e.g. comparing model performance under the same FLOPs. The comparison in a broader range is usually missed, especially for works in conditional computation where the model performance varies with FLOPs. **(b) Unaccessible results.** Even if the comprehensive line-to-line comparison is conducted, the results are usually presented in form of figure, in which the data points are not accessible for the following work. As a result, the following work has to reproduce or estimate the results (e.g. Xin et al. (2021) estimate values from the figures of Zhou et al. (2020a)). **(c) Non-standard measurements.** Different works may adopt different metrics such as physical elapsed time, FLOPs, and executed model layers, making them hard to directly compare. Even if the adopted metrics are the same, there is no guarantee that they will be calculated in the same way (e.g. the hardware infrastructure, or the software to calculate FLOPs can be very different[1]). **(d) Inconvenience.** Recent studies usually choose GLUE (Wang et al., 2019b) as the main benchmark, which, however, is not suitable for dynamic methods due to its submission limitation that is designed to avoid overfitting on test sets.

Need for a strong baseline Currently, there are roughly two branches of efficient methods in NLP: static methods (e.g. distillation, pruning, quantization, etc.) and dynamic methods (e.g. early exiting). **(a) Static models** are obtained given an expected number of parameters or inference latency. These methods often use the first few layers (to keep the same number of parameters or FLOPs) of some pre-trained model followed by a classification head as their baseline, which, however, is too weak to serve as a baseline. **(b) Dynamic models** usually add multiple internal classifiers to the pre-trained LMs, and therefore allow flexible inference conditioned on the input. Nevertheless, the injected internal classifiers introduce a gap between pre-training and fine-tuning. Training the internal classifiers on downstream tasks often degenerates the performance of the entire model (Xin et al., 2021). Thus, static models need a strong baseline, and dynamic models need a strong backbone.

Contributions In this work, we address the above needs by contributing the following:

- **ELUE**(**E**fficient **L**anguage **U**nderstanding **E**valuation) – a standard benchmark for efficient NLP models. (1) ELUE supports online evaluation for model performance, FLOPs, and number of parameters. (2) ELUE is also an open-source platform that can facilitate future research. We reproduce and evaluate multiple compressed and early exiting methods on ELUE. All of the results are publicly accessible on ELUE. (3) ELUE provides an online leaderboard that uses a specific metric to measure how much a model oversteps the current Pareto frontier. ELUE leaderboard also maintains several separate tracks for models with different sizes. (4) ELUE covers six NLP datasets spanning sentiment analysis, natural language inference, similarity and paraphrase tasks. The ELUE benchmark is publicly available at `http://eluebenchmark.fastnlp.top/`.

- **ElasticBERT** – a strong baseline (backbone) for static (dynamic) models. ElasticBERT is a multi-exit Transformer (Vaswani et al., 2017) pre-trained on ∼160GB corpus. The pre-training objectives, MLM and SOP (Lan et al., 2020), are applied to multiple Transformer layers instead of only the last layer. Gradient equilibrium (Li et al., 2019) is adopted to alleviate the conflict of the losses at different layers. For static models, ElasticBERT is a strong baseline that can reach or even outperform distilled models. For dynamic models, ElasticBERT is a robust backbone that closes the gap between pre-training and fine-tuning. We release the pre-trained model weights of ElasticBERT[2] as well as code[3].

2 Related Work

NLP Benchmarks Evaluating the quality of language representations on multiple downstream tasks has become a common practice in the community. These evaluations have measured and

[1]We find that the FLOPs of Transformers calculated by different libraries (`thop`, `ptflops`, and `torchstat`) can be different. And besides, all of them missed FLOPs in some operations such as self-attention and layer normalization.

[2]https://huggingface.co/fnlp

[3]https://github.com/fastnlp/ElasticBERT

pushed the progress of NLP in recent years. SentEval (Conneau and Kiela, 2018) introduces a standard evaluation toolkit for multiple NLP tasks. Further, GLUE (Wang et al., 2019b) and SuperGLUE (Wang et al., 2019a) provide a set of more difficult datasets for model-agnostic evaluation. Another line of work is multi-dimensional evaluations. EfficientQA (Min et al., 2020) is an open-domain question answering challenge that evaluates both accuracy and system size. The system size is measured as the number of bytes required to store a Docker image that contains the submitted system. Dynabench (Kiela et al., 2021), an open-source benchmark for dynamic dataset creation and model evaluation, also supports multi-dimensional evaluation. In particular, Dynabench measures model performance, throughput, memory use, fairness, and robustness. Both EfficientQA and Dynabench require the user to upload the model along with the required environment to the server, which is costly for users to upload and also for the server to evaluate. In contrast, ELUE adopts a cheaper way to evaluate performance and efficiency of the model. Recently, Long-Range Arena (LRA) (Tay et al., 2021) is proposed to evaluate models under the long-context scenario. Different from ELUE, LRA mainly focuses on Xformers (Lin et al., 2021). Besides, some tasks included in LRA are not NLP tasks, or even not real-world tasks, while ELUE consists of common language understanding tasks. In addition, ELUE is also inspired by other well-known benchmarks, such as SQuAD (Rajpurkar et al., 2016), MultiNLI (Williams et al., 2018), DecaNLP (McCann et al., 2018), CLUE (Xu et al., 2020b), HotpotQA (Yang et al., 2018), GEM (Gehrmann et al., 2021), etc.

Efficient NLP Models Current efficient NLP models can be roughly categorized as two streams: model compression (static methods) and conditional computation (dynamic methods). Model compression is to reduce the number or precision of model parameters to achieve faster training and inference. Currently, there are several ways to achieve model compression: (1) *Knowledge Distillation*, which is to learn a compact student model that learns from the output distribution of a large-scale teacher model (Sanh et al., 2019; Jiao et al., 2020) (2) *Model Pruning*, which is to remove parts of parameters that are less important (Gordon et al., 2020), (3) *Weight Sharing* across different parts of the model (Lan et al., 2020) is also a common technique to significantly reduce parameters, (4) *Quantization*, which is to use low bit precision to store parameter and accelerate inference with low bit hardware operations (Shen et al., 2020), and (5) *Module Replacing*, which is to replace the modules of a big model with more compact substitutes (Xu et al., 2020a). In contrast, conditional computation is to selectively execute only parts of the model conditioned on a given input (Bengio et al., 2013; Davis and Arel, 2014). As a representative, an end-to-end halting approach, Adaptive Computation Time (ACT) (Graves, 2016), is developed to perform input-adaptive computation for recurrent networks. The idea of ACT is later adopted in Universal Transformer (Dehghani et al., 2019). Recently, as the rising of deep models for natural language processing, early exiting is widely used to speedup inference of transformer models (Liu et al., 2020a; Xin et al., 2020; Schwartz et al., 2020; Zhou et al., 2020b; Elbayad et al., 2020; Liao et al., 2021; Xin et al., 2021; Sun et al., 2021b; Zhu, 2021; Li et al., 2021a).

3 ELUE: A Standard Benchmark for Efficient NLP Models

ELUE aims to offer a standard evaluation for various efficient NLP models, such that they can be fairly and comprehensively compared. In Section 3.1, we list the design considerations to achieve this motivation. In Section 3.2, we describe the tasks and datasets included in ELUE. In Section A.1, we illustrate how to make a submission on ELUE, and how the submission is evaluated. In Section 3.3, we discuss the design of our leaderboard.

3.1 Design Considerations

Now we enumerate main considerations in the design of ELUE to ensure that it meets the needs mentioned early.

Multi-dimensional Evaluation The evaluation of ELUE should be multi-dimensional for comprehensive comparison. Instead of point-to-point comparison, methods can be compared in a line-to-line style in ELUE, where the "line" is a performance-efficiency trade-off curve.

Public Accessible All data points in ELUE should be publicly accessible such that the following work does not need to reproduce or estimate

results from previous work. To facilitate future research, some representative methods should be reproduced and evaluated in ELUE.

Standard Evaluation The measurement of model efficiency should be standardized in ELUE such that this line of methods can be fairly compared. Current studies usually use number of parameters (Lan et al., 2020; Jiao et al., 2020), FLOPs (Jiao et al., 2020; Liu et al., 2020a; Li et al., 2021b), actual inference time (Sanh et al., 2019; Schwartz et al., 2020), or number of executed layers (Zhou et al., 2020a; Sun et al., 2021b) to measure model efficiency. Among these metrics, measuring actual inference time is costly for both users and the server, and highly depends on the computation infrastructure and software implementation, while number of executed layers ignores the shape of input and hidden layers, therefore is inaccurate. Thus, ELUE adopts number of parameters and FLOPs as the metrics for model efficiency.

Easy-to-Use ELUE should be friendly to users, which means that the submission should be as simple as possible. Roughly speaking, there are currently two ways of submissions: (1) submitting the trained model such as SQuAD (Rajpurkar et al., 2016), Dynabench (Kiela et al., 2021), and (2) submitting the predicted test files such as GLUE (Wang et al., 2019b), SuperGLUE (Wang et al., 2019a), and CLUE (Xu et al., 2020b). The submission of ELUE lies in the latter way. Nevertheless, to evaluate number of parameters and FLOPs, the submitted test files should conform to a specific format, and besides, a Python file to define the used model is also required. For more details about submission and evaluation, see Appendix A.1.

3.2 Task and Dataset Selection

Following GLUE (Wang et al., 2019b), SuperGLUE (Wang et al., 2019a), and CLUE (Xu et al., 2020b), we collect tasks that can be formatted as single sentence classification or sentence pair classification. Since ELUE mainly focuses on efficient models, the difficulty of dataset is not a primary consideration. Instead, we collect tasks and datasets that are commonly used and publicly available in the community. The statistics of the collected datasets are listed in Table 1.

Sentiment Analysis Sentiment analysis, which is to classify the polarity of a given text, is a fundamental task in NLP. We select two well-known movie review datasets, Stanford Sentiment Treebank (SST) (Socher et al., 2013) and IMDb (Maas et al., 2011). For SST, we use the two-way class split, i.e. SST-2. Different from GLUE, SST-2 samples in ELUE are complete sentences instead of phrases. For IMDb, we randomly select 2.5k positive samples and 2.5k negative samples from training set to construct a development set.

Tasks	Datasets	|Train|	|Dev|	|Test|
Sentiment Analysis	SST-2	8,544	1,101	2,208
	IMDb	20,000	5,000	25,000
Natural Language Inference	SNLI	549,367	9,842	9,824
	SciTail	23,596	1,304	2,126
Similarity and Paraphrase	MRPC	3,668	408	1,725
	STS-B	5,749	1,500	1,379

Table 1: Statistics of datasets in ELUE.

Natural Language Inference Natural language inference (NLI) is a task to predict whether the premise entails the hypothesis, contradicts the hypothesis, or neither. NLI is often formulated as a sentence pair classification task (Devlin et al., 2019; Sun et al., 2021a). We select two NLI datasets, SNLI (Bowman et al., 2015) and SciTail (Khot et al., 2018). SNLI is a crowd-sourced collection of sentence pairs with balanced labels: *entailment*, *contradiction*, and *neutral*. We use the spell-checked version of the test and development sets[4]. The hard samples, which do not have golden labels due to the disagreement of annotators, are removed from the dataset and left for model diagnostic. SciTail is a two-way (*entail* or *neutral*) entailment classification dataset, which is derived from multiple-choice science exams and web sentences.

Similarity and Paraphrase For similarity and paraphrase tasks, we also select two datasets, Microsoft Research Paraphrase Corpus (MRPC) (Dolan and Brockett, 2005), and Semantic Textual Similarity Benchmark (STS-B) (Cer et al., 2017), both of which are also included in GLUE. MRPC is a collection of automatically extracted sentence pairs, each manually-labeled with a judgment to indicate whether the pair constitutes a paraphrase. STS-B is a corpus of sentence pairs, each of which is labeled with a score from 0 to 5 to represent the degree to which two sentences are semantically equivalent.

[4] https://nlp.stanford.edu/projects/snli/

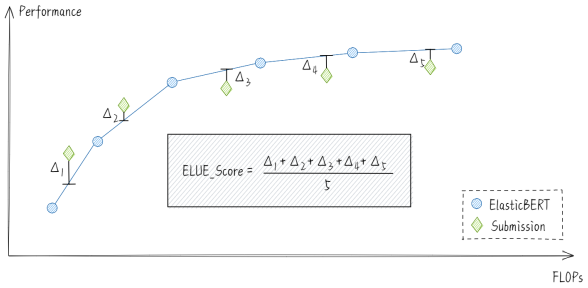


Figure 2: An illustration to show how ELUE score is computed.

3.3 Leaderboard

Following prior work (Yang et al., 2018; Wang et al., 2019b; Xu et al., 2020b), we also integrate a leaderboard in ELUE. For dynamic models that have multiple performance-FLOPs coordinates on each dataset, we need to sum up these coordinates as a score. A critical problem is to measure how good a coordinate is. In other words, to measure a coordinate (p, f), where p is performance and f is FLOPs, we need a baseline performance under the same FLOPs. We choose ElasticBERT as the baseline curve. We evaluate different layers of ElasticBERT, and obtained 12 coordinates $(p_i^{EB}, f_i^{EB})_{i=1}^{12}$, which are then used to interpolate to get a performance-FLOPs function $p^{EB}(f)$. With the baseline curve at hand, we can score a submission curve as

$$\text{ELUEScore} = \frac{1}{n}\sum_{i=1}^{n}[p_i - p^{EB}(f_i)]. \quad (1)$$

Note that the coordinates of ElasticBERT are separately interpolated on different datasets. The final ELUE score is an unweighted average of the scores on all the 6 datasets. Figure 2 gives an illustration of how ELUE score is computed. The ELUE score reflects the extent to which the submission oversteps the ElasticBERT.

In addition, following EfficientQA (Min et al., 2020), ELUE leaderboard also maintains four additional separate tracks, corresponding to models below 40M, 55M, 70M, 110M parameters. Models in these tracks are ranked by the average performance on all the datasets.

4 ElasticBERT: A Strong Baseline for Efficient Inference

Despite the encouraging results achieved by existing efficient models, we argue that a strong baseline (backbone) is needed for both static methods and dynamic methods. Static methods often choose the first few layers of some pre-trained models as their baseline (e.g. Sun et al. (2019); Jiao et al. (2020)), which can be weak. Dynamic methods that enable early exiting by training multiple internal classifiers usually introduce a gap between pre-training and fine-tuning, and therefore hurt the performance of the entire model (Xin et al., 2021). Thus, as illustrated in Figure 3, we present the ElasticBERT that bridges the gap between static and dynamic methods, and therefore can serve as a strong baseline for static methods and also a strong backbone for dynamic methods.

ElasticBERT is a multi-exit pre-trained language model with the following training objective:

$$\mathcal{L} = \sum_{l=1}^{L}(\mathcal{L}_l^{\text{MLM}} + \mathcal{L}_l^{\text{SOP}}), \quad (2)$$

where L is the total number of layers, $\mathcal{L}^{\text{MLM}}$ is the n-gram masked language modeling loss, $\mathcal{L}^{\text{SOP}}$ is the sentence order prediction loss (Lan et al., 2020). The two losses are applied to each layer of the model, such that the number of layers can be flexibly scaled on downstream tasks, and therefore it is named "ElasticBERT".

Bridge the Gap Between Static and Dynamic Methods As a baseline for static methods, the depth of ElasticBERT can be flexibly reduced on demand. Compared with the first l layer of BERT (Devlin et al., 2019), the l-layered ElasticBERT is a complete model (Turc et al., 2019; Li et al., 2021a) and can achieve better performance. It is worth noticing that ElasticBERT can be regarded as a special instance of LayerDrop (Fan et al., 2020) where the dropped layers are constrained to the top consecutive layers. As a backbone for dynamic methods, training classifiers injected in intermediate layers would be consistent with pre-training. Therefore, ElasticBERT can not only be used as a static complete model, but also be used as a backbone model of dynamic early exiting.

Gradient Equilibrium Pre-training with the simply summed loss in Eq. (2) could lead to a *gradient imbalance* issue (Li et al., 2019). In particular, due to the overlap of subnetworks, the variance of the gradient may grow overly large, leading to unstable training. To address this issue, we follow Li et al. (2019) and adopt the gradient equilibrium

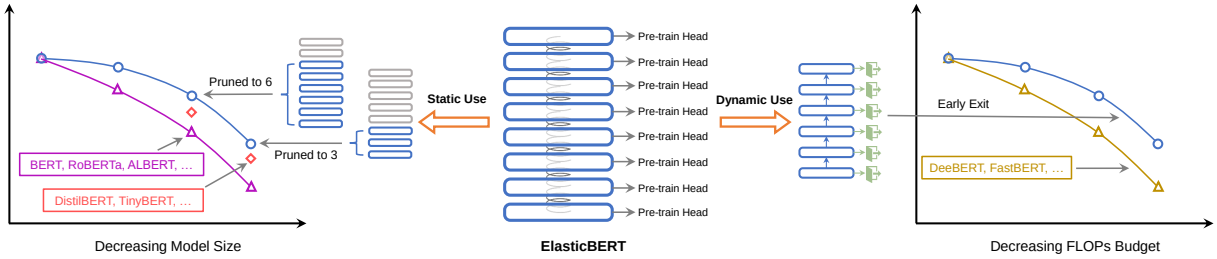


Figure 3: ElasticBERT is pre-trained with multiple pre-training heads attached at the intermediate layers. For static usage (left), it can be pruned on demand while outperforming previous pre-trained models with the same size. For dynamic usage (right), it can serve as the backbone for early exiting methods, achieving better performance-efficiency trade-off than early exiting models with other backbones.

(GE) strategy[5] in the pre-training of ElasticBERT.

Grouped Training In our preliminary experiments, we found that summing up losses at all layers could slow down pre-training and increase memory footprints. To alleviate this, we divide L exits into G groups. During training, we optimize the losses of the exits within each group by cycling alternately between different batches:

$$\mathcal{L} = \sum_{l \in \mathcal{G}_i} (\mathcal{L}_l^{\text{MLM}} + \mathcal{L}_l^{\text{SOP}}). \quad (3)$$

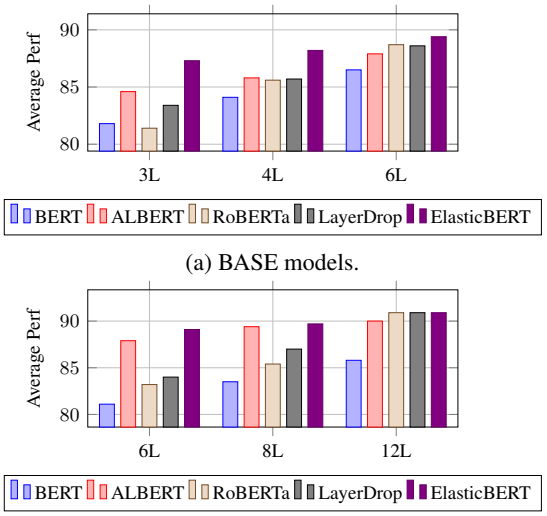
In Section B.3 we explore the performance of different grouping methods. As a result, we group the 12 exits of ElasticBERT$_{\text{BASE}}$ into $\mathcal{G}_1$={1, 3, 5, 7, 9, 11, 12} and $\mathcal{G}_2$={2, 4, 6, 8, 10, 12}, and group the 24 exits of ElasticBERT$_{\text{LARGE}}$ into $\mathcal{G}_1$={1, 4, 7, ..., 22, 24}, $\mathcal{G}_2$={2, 5, 8, ..., 23, 24}, and $\mathcal{G}_3$={3, 6, 9, ..., 21, 24}. Our experiments demonstrate that grouped training can significantly speedup the process of pre-training without a loss in performance.

5 Experiments

5.1 Experimental Setup

Pre-training Setup Following BERT (Devlin et al., 2019), we train ElasticBERT in two different configurations: ElasticBERT$_{\text{BASE}}$ and ElasticBERT$_{\text{LARGE}}$, which have the same model sizes with BERT$_{\text{BASE}}$ and BERT$_{\text{LARGE}}$, respectively. The detailed description can be found in Appendix B.1.

Downstream Evaluation We evaluate ElasticBERT on the ELUE benchmark, as a static model and as a dynamic model. As a static model, we evaluate different layers of ElasticBERT, denoted as ElasticBERT-nL. As a dynamic model, we inject and train internal classifiers in ElasticBERT$_{\text{BASE}}$ and adopt two strategies, entropy (Xin et al., 2020) and patience (Zhou et al., 2020a), to enable early exiting, denoted as ElasticBERT$_{\text{entropy}}$ and ElasticBERT$_{\text{patience}}$. To compare with previous work, we also evaluate ElasticBERT on the GLUE benchmark (Wang et al., 2019b). The comparison results is shown in Appendix B.2. For static usage, we fine-tune ElasticBERT and our baseline models for 10 epochs with early stopping using AdamW optimizer (Loshchilov and Hutter, 2019) with learning rates of {1e-5, 2e-5, 3e-5} and batch size of 32, and warm up the learning rate for the first 6 percent of total steps. In dynamic usage, for the models using two-stage training methods, we train for 3 epochs for each stage, and we train for 5 epochs for other models. Other optimization configurations are the same as those in static scenario.



(a) BASE models.

(b) LARGE models.

Figure 4: Comparison of the average performance on ELUE test sets between ElasticBERT and baselines.

[5]The reader is referred to the original paper for more details. In brief, the gradients of $\mathcal{L}_j$ w.r.t. the parameters of the i-th layer ($i < j$) would be properly rescaled.

Model	#Params	#FLOPs	SST-2	IMDb	MRPC	STS-B	SNLI	SciTail	Average
BASE Models									
$\text{BERT}_{\text{BASE}}$	109M	13399M	85.1	93.0	83.1	84.2	90.4	93.2	88.2
$\text{ALBERT}_{\text{BASE}}$	12M	13927M	86.6	92.9	87.8	88.3	90.1	93.4	89.9
$\text{RoBERTa}_{\text{BASE}}$	125M	13103M	88.3	**94.9**	88.0	**89.6**	91.3	92.8	**90.8**
$\text{LayerDrop}_{\text{BASE}}$	125M	13103M	88.5	94.2	**88.2**	87.1	90.7	92.8	90.3
ElasticBERT$_{\text{BASE}}$	109M	13399M	**88.6**	93.9	87.9	87.6	**91.3**	**93.8**	90.5
$\text{BERT}_{\text{BASE}}$-6L	67M	6700M	83.3	91.0	82.6	82.5	88.9	90.7	86.5
$\text{ALBERT}_{\text{BASE}}$-6L	12M	6972M	84.7	92.0	85.3	83.5	89.3	92.3	87.9
$\text{RoBERTa}_{\text{BASE}}$-6L	82M	6552M	86.8	92.6	86.7	84.5	**90.2**	91.3	88.7
$\text{LayerDrop}_{\text{BASE}}$-6L	82M	6552M	86.3	**92.9**	86.3	86.1	89.5	90.3	88.6
HeadPrune-$\text{BERT}_{\text{BASE}}$	86M	9249M	84.8	84.7	77.8	74.8	87.8	88.3	83.0
DistilBERT	67M	6700M	84.8	92.0	83.8	81.7	89.2	89.7	86.9
TinyBERT-6L	67M	6700M	85.3	89.0	86.2	85.7	89.3	90.0	87.6
BERT-of-Theseus	67M	6700M	84.4	90.7	82.4	85.0	89.4	92.1	87.3
ElasticBERT$_{\text{BASE}}$-6L	67M	6700M	**87.0**	92.7	**87.3**	**86.9**	90.1	**92.5**	**89.4**
LARGE Models									
$\text{BERT}_{\text{LARGE}}$	335M	47214M	87.9	94.0	85.9	86.7	90.8	93.9	89.9
$\text{ALBERT}_{\text{LARGE}}$	18M	48876M	87.7	93.8	88.1	89.3	90.2	93.6	90.5
$\text{RoBERTa}_{\text{LARGE}}$	355M	46042M	**90.5**	**95.7**	**89.9**	90.5	**91.6**	**95.8**	**92.3**
$\text{LayerDrop}_{\text{LARGE}}$	355M	46042M	90.4	95.3	89.5	**91.0**	91.4	95.2	92.1
ElasticBERT$_{\text{LARGE}}$	335M	47214M	89.8	95.0	89.8	90.9	91.4	95.7	92.1
$\text{BERT}_{\text{LARGE}}$-6L	108M	11922M	80.4	89.6	74.3	70.5	87.4	84.4	81.1
$\text{ALBERT}_{\text{LARGE}}$-6L	18M	12397M	84.5	92.0	84.7	85.1	89.4	90.8	87.8
$\text{RoBERTa}_{\text{LARGE}}$-6L	129M	11664M	83.5	91.7	77.9	72.7	88.6	84.7	83.2
$\text{LayerDrop}_{\text{LARGE}}$-6L	129M	11664M	85.4	92.5	77.3	75.9	88.8	84.1	84.0
ElasticBERT$_{\text{LARGE}}$-6L	108M	11922M	**86.8**	**92.9**	**86.2**	**86.3**	**89.8**	**92.4**	**89.1**

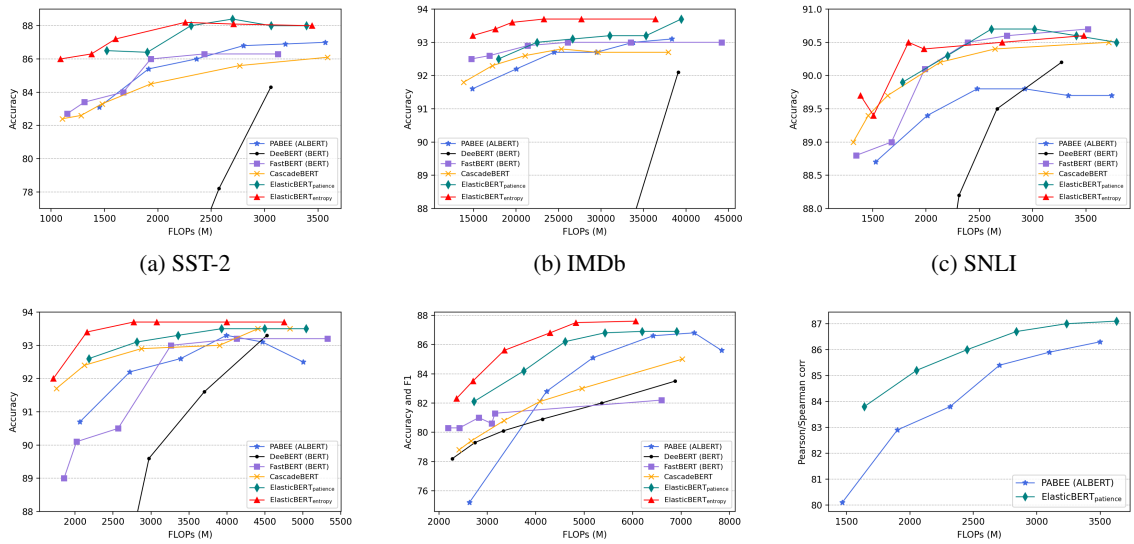
Table 2: ElasticBERT and static baseline performance on ELUE task test sets. We report the mean of Accuracy and F1 for MRPC, Pearson and Spearman correlation for STS-B and Accuracy for other tasks. The reported FLOPs is the average over all the datasets.

Baselines We compare ElasticBERT with three types of baselines: **(1)** Directly fine-tuning pre-trained models and their first n layers. We choose BERT (Devlin et al., 2019), ALBERT (Lan et al., 2020), RoBERTa (Liu et al., 2019) and LayerDrop (Fan et al., 2020) as our baselines. For the use of the first n layers, we simply add a linear classifier on top of the truncated model. **(2)** Compressed models. We choose two distilled models, DistilBERT (Sanh et al., 2019) and TinyBERT (Jiao et al., 2020), one pruned model, HeadPrune (Michel et al., 2019), and one model obtained by using *module replacing*, BERT-of-Theseus (Xu et al., 2020a) as our baseline models. **(3)** Dynamic early exiting models. To verify the effectiveness of ElasticBERT as a strong backbone of dynamic early exiting methods, we also compare $\text{ElasticBERT}_{\text{entropy}}$ and $\text{ElasticBERT}_{\text{patience}}$ which have the same early exiting strategy as DeeBERT (Xin et al., 2020) and PABEE (Zhou et al., 2020a) with four representative early exiting models: DeeBERT (Xin et al., 2020), FastBERT (Liu et al., 2020b), PABEE (Zhou et al., 2020a), and CascadeBERT (Li et al., 2021a).

5.2 Evaluating ElasticBERT on ELUE

ElasticBERT and our baselines are evaluated on ELUE tasks. For the BASE version of ElasticBERT, BERT, ALBERT, RoBERTa and LayerDrop, we evaluate the first 3/4/6/12 layers. For the LARGE version of the models, we evaluate the first 6/8/12/24 layers. For dynamic methods, we fine-tune ElasticBERT along with the injected internal classifiers using the gradient equilibrium (GE) strategy (Li et al., 2019), and adopt two different early exiting strategies: entropy-based strategy (Xin et al., 2020) and patience-based strategy (Zhou et al., 2020a).

Results of Static Models The performance of ElasticBERT and our baseline models on ELUE task test sets is shown in Table 2, where we find that $\text{ElasticBERT}_{\text{BASE}}$ and $\text{ElasticBERT}_{\text{LARGE}}$ outperform BERT and ALBERT with the same number of layers, but are slightly weaker than $\text{RoBERTa}_{\text{BASE}}$ and $\text{RoBERTa}_{\text{LARGE}}$. Besides, we find that the superiority of ElasticBERT over its baselines can be significant with fewer layers (See Figure 4 for the



(a) SST-2 (b) IMDb (c) SNLI

(d) SciTail (e) MRPC (f) STS-B

Figure 5: Performance-FLOPs trade-offs on ELUE task test sets. Because STS-B is a regression task, for which the entropy-based methods are not applicable, we only evaluate patience-based methods, i.e., PABEE and ElasticBERT$_{\text{patience}}$.

Model	SST-2	IMDb	MRPC	STS-B	SNLI	SciTail	Average
ElasticBERT$_{\text{BASE}}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Static Models							
BERT$_{\text{BASE}}$	-4.55	-2.15	-5.88	-4.75	-1.50	-3.35	-3.70
ALBERT$_{\text{BASE}}$	-2.41	-1.08	-2.34	-2.81	-1.55	-1.50	**-1.95**
RoBERTa$_{\text{BASE}}$	**-0.89**	**-0.11**	-2.95	-5.38	**-0.66**	-3.32	-2.22
LayerDrop$_{\text{BASE}}$	-1.17	-0.13	**-2.17**	-2.98	-1.36	-4.14	-1.99
HeadPrune-BERT$_{\text{BASE}}$	-3.81	-8.61	-9.73	-11.9	-2.89	-4.18	-6.85
DistilBERT	-2.20	-0.70	-3.50	-5.20	-0.90	-2.80	-2.55
TinyBERT-6L	-1.70	-3.70	-2.60	-1.90	-0.80	-2.50	-2.20
BERT-of-Theseus	-4.21	-2.61	-5.13	**-1.67**	-1.29	**-0.38**	-2.55
Dynamic Models							
PABEE	-1.33	-0.23	-2.93	-2.13	-0.85	-0.43	-1.50
DeeBERT	-12.1	-14.0	-4.88	-	-8.35	-6.19	-
FastBERT	-1.51	0.16	-3.70	-	-0.22	-1.23	-
CascadeBERT	-2.13	-0.12	-4.05	-	-0.23	0.14	-
ElasticBERT$_{\text{patience}}$	0.40	0.20	-1.00	**-0.44**	**0.03**	0.36	**-0.08**
ElasticBERT$_{\text{entropy}}$	**0.97**	**1.02**	**-0.14**	-	0.02	**0.64**	-

Table 3: ELUE scores calculated using Eq. (1) for static and dynamic baseline models. '-' denotes that the dataset/metric is not applicable to the model.

results of 3/4 (6/8) layers of the BASE (LARGE) models).

Results of Dynamic Models We compare ElasticBERT$_{\text{entropy}}$ and ElasticBERT$_{\text{patience}}$ with four dynamic models: DeeBERT (Xin et al., 2020), FastBERT (Liu et al., 2020b), PABEE (Zhou et al., 2020a), and CascadeBERT (Li et al., 2021a). The performance-FLOPs trade-off of the dynamic models on ELUE task test sets are shown in Figure 5, which demonstrates that ElasticBERT can achieve better performance-FLOPs trade-off.

Evaluating ELUE Scores According to Eq. (1), we also evaluate the ELUE scores of these baselines. As shown in Table 3, the ELUE score of ElasticBERT$_{\text{BASE}}$ is natural to be zero on all tasks. Among the other baselines, we find that ElasticBERT$_{\text{patience}}$ achieves the best ELUE score, while HeadPrune achieves the worst ELUE score. In addition, we find that dynamic models perform better than static models on average.

6 Conclusion and Future Work

In this work, we present ELUE, which is a public benchmark and platform for efficient models, and ElasticBERT, which is a strong baseline (backbone) for efficient static (dynamic) models. Both of the two main contributions are aimed to build the Pareto frontier for NLU tasks, such that the position of existing work can be clearly recognized, and future work can be easily and fairly measured.

Our future work is mainly in four aspects: (1) Including more baselines in ELUE, (2) Supporting the evaluation for more frameworks such as TensorFlow (Abadi et al., 2016), (3) Supporting diagnostics for submissions, (4) Supporting the evaluation of more different types of tasks.

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Ethical Considerations

The proposed ELUE benchmark aims to standardize efficiency measurement of NLP models. The collected datasets are widely used in previous work and, to our knowledge, do not have any attached privacy or ethical issues. Our proposed ElasticBERT is a pre-trained model to reduce computation cost and carbon emission. The pre-training data is public resources adopted in previous work, and therefore would not introduce new ethical concerns.

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Appendix

A Details of Evaluation

A.1 Submission and Evaluation

ELUE supports two kinds of submissions: submitting test files, or submitting from a paper.

Submit test files Users are required to submit two kinds of files: (1) predicted test files, and (2) a model definition file in Python. The predicted test files can be multiple, each indicates the prediction under a certain efficiency. The submitted test files should be in the following format:

index	pred	modules
0	1	(10),emb; (10,768),layer_1; (768),exit_1
1	0	(15),emb; (15,768),layer_1; (768),exit_1; (15,768),layer_2; (768),exit_2
2	1	(12),emb; (12,768),layer_1; (768),exit_1
...	...	...

Different from traditional predicted test files as in GLUE, an additional column "modules" is required to indicate the activated modules to predict each sample. The numbers before each module represent the input shape of that module, e.g. the "(10)" before "emb" indicates that the input of "emb" is a sequence of length 10. Note that this format is also compatible with token-level early exiting methods (Li et al., 2021b), where the sequence length is progressively reduced as the processing of layers.

Along with the test files, a Python file to define the model is also required. Figure 6 is an example Python file using PyTorch (Paszke et al., 2019) and Transformers (Wolf et al., 2020).

With the submitted Python file, ELUE is able to evaluate the average FLOPs on a dataset, and the number of parameters of the model.

In cases that the evaluation is not applicable, e.g. the programming language, or dependencies of the submitted Python file is not supported in ELUE, the user is allowed to evaluate FLOPs and number of parameters by themselves and upload their results along with the predictions to the ELUE website.

Submit from a paper Inspired by Paper with Code[6], we also expect that ELUE can serve as an open-source platform that can facilitate future research. Therefore, there is a track for the authors of

[6] https://paperswithcode.com/

```python
# import packages
import torch.nn as nn
from transformers import BertConfig
...

# module definitions
class ElasticBERTEmbeddings(nn.Module):
    def __init__():
        ...
    def forward(x):
        ...

class ElasticBERTLayer(nn.Module):
    def __init__():
        ...
    def forward(x)
        ...

class ElasticBERT(nn.Module):
    def __init__():
        ...
    def forward(x)
        ...

# module dict
config = BertConfig(num_labels=2)
module_list = {
    'emb': ElasticBertEmbeddings(config),
    'layer_1': ElasticBertLayer(config),
    'exit_1': nn.Linear(config.hidden_size, num_labels),
    'layer_2': ElasticBertLayer(config),
    'exit_2': nn.Linear(config.hidden_size, num_labels),
    ...
}
entire_model = ElasticBERT(config)
```

Figure 6: An example Python file for submission.

published papers to share their experimental results on ELUE datasets.

Performance Metrics Since the classes in MRPC are imbalanced, we report the unweighted average of accuracy and F1 score. For STS-B, we evaluate and report the Pearson and Spearman correlation coefficients. For other datasets, we simply adopt accuracy as the metric.

B Experimental Details and Additional Results

B.1 Details of Training ElasticBERT

The parameters of ElasticBERT are initialized with BERT, and therefore it has the same vocabulary and tokenizer as BERT. ElasticBERT is pre-trained on ∼160GB uncompressed English text corpora, which is comprised of English Wikipedia (12GB), BookCorpus (4GB) (Zhu et al., 2015), OpenWebText (38GB) (Gokaslan and Cohen, 2019), and part of the C4 corpus (110GB) (Raffel et al., 2020). We use Adam optimizer (Kingma and Ba, 2015) to pre-train ElasticBERT$_{\text{BASE}}$ and ElasticBERT$_{\text{LARGE}}$ and other hyperparameters are listed in Table 4. Our implementation is based on Huggingface's Transformers (Wolf et al., 2020) and the Megatron-LM toolkit (Shoeybi et al., 2019). ElasticBERT is trained on 64 32G NVIDIA Tesla V100 GPUs.

Hyperparameter	ElasticBERT$_{\text{BASE}}$	ElasticBERT$_{\text{LARGE}}$
Adam β_1	0.9	0.9
Adam β_2	0.999	0.999
Peak Learning Rate	2e-4	2e-4
Warm Up Type	Linear	Linear
Warm Up Rate	0.04	0.04
Weight Decay	0.01	0.01
Batch Size	4096	4096
Training Steps	125k	125k
Number of Layers	12	24
Hidden Size	768	1024
Attention Heads	12	16
FFN Intermediate Size	3072	4096

Table 4: Hyperparameters for ElasticBERT pre-training

B.2 Evaluating ElasticBERT on GLUE

To verify the effectiveness and the elasticity of ElasticBERT, we also evaluate ElasticBERT and our static baselines on the GLUE benchmark. We evaluate the first 6/12 layers of the BASE models, and the first 6/24 layers of the LARGE models.

Experimental results of ElasticBERT and our baseline models on GLUE are presented in Table 6, from which we find that ElasticBERT outperforms BERT and ALBERT with the same number of layers, but is weaker than RoBERTa in the 12/24 layers configuration. Compared with ElasticBERT that is trained for 125K steps with batch size of 4K, RoBERTa is trained for 500K steps with batch size of 8K, which makes its number of training samples 8 times larger than that of ElasticBERT. When using fewer layers (6 layers of BASE and LARGE models), ElasticBERT achieves the best performance among the static baselines, confirming its great elasticity.

Grouping	Accuracy
w/o Grouping	**76.7**
$\mathcal{G}_1$={1, 3, 5, 7, 9, 11, 12} $\mathcal{G}_2$={2, 4, 6, 8, 10, 12}	**76.7**
$\mathcal{G}_1$={1, 4, 7, 10, 12} $\mathcal{G}_2$={2, 5, 8, 11, 12} $\mathcal{G}_3$={3, 6, 9, 12}	75.7
$\mathcal{G}_1$={1, 2, 3, 4, 12} $\mathcal{G}_2$={5, 6, 7, 8, 12} $\mathcal{G}_3$={9, 10, 11, 12}	75.5
$\mathcal{G}_1$={1, 2, 3, 4, 5, 6, 12} $\mathcal{G}_2$={7, 8, 9, 10, 11, 12}	75.9

Table 5: The average accuracy acorss all the BERT exits on the MNLI dataset with different grouping.

Model	#Params	#FLOPs	CoLA	MNLI-m/mm	MRPC	QNLI	QQP	RTE	SST-2	STS-B	Average
BASE Models											
$\text{BERT}_{\text{BASE}}$	109M	6615M	56.5	84.6/84.9	87.6	91.2	89.6	69.0	92.9	89.4	82.9
$\text{ALBERT}_{\text{BASE}}$	12M	6861M	56.8	84.9/85.6	90.5	91.4	89.2	**78.3**	92.8	90.7	84.5
$\text{RoBERTa}_{\text{BASE}}$	125M	6727M	63.6	**87.5/87.2**	90.8	**92.7**	**90.3**	77.5	**94.8**	**90.9**	**86.1**
$\text{LayerDrop}_{\text{BASE}}$	125M	6727M	**64.5**	86.4/86.5	**91.6**	92.2	89.9	71.1	93.7	88.6	84.9
ElasticBERT$_{\text{BASE}}$	109M	6615M	64.3	85.3/85.9	91.0	92.0	90.2	76.5	94.3	90.7	85.6
$\text{BERT}_{\text{BASE}}$-6L	67M	3308M	44.6	81.4/81.4	84.9	87.4	88.7	65.7	90.9	88.1	79.2
$\text{ALBERT}_{\text{BASE}}$-6L	12M	3435M	52.4	82.6/82.2	89.0	89.8	88.7	70.4	90.8	89.6	81.7
$\text{RoBERTa}_{\text{BASE}}$-6L	82M	3364M	44.4	84.2/**84.6**	87.9	90.5	**89.8**	60.6	92.1	89.0	80.3
$\text{LayerDrop}_{\text{BASE}}$-6L	82M	3364M	53.7	83.8/83.8	87.6	89.8	89.4	64.3	91.3	88.1	81.3
$\text{HeadPrune-BERT}_{\text{BASE}}$	87M	4744M	48.7	71.0/79.7	80.2	86.1	84.7	62.5	89.4	85.2	76.4
DistilBERT	67M	3308M	**55.6**	82.1/82.0	86.5	89.2	88.8	63.9	91.3	86.7	80.7
TinyBERT-6L	67M	3308M	46.3	83.6/83.8	88.7	90.6	89.1	73.6	92.0	89.4	81.9
BERT-of-Theseus	67M	3308M	45.1	81.4/81.9	88.1	88.1	88.9	70.1	91.4	88.8	80.4
ElasticBERT$_{\text{BASE}}$-6L	67M	3308M	53.7	**84.3**/84.2	**89.7**	**90.8**	89.7	**74.0**	**92.7**	**90.2**	**83.3**
Test Set Results											
TinyBERT-6L	67M	3308M	42.5	83.2/82.4	86.2	89.6	79.6	**73.0**	91.8	85.7	79.3
ElasticBERT$_{\text{BASE}}$-6L	67M	3308M	**49.1**	**83.7/83.4**	**87.3**	**90.4**	**79.7**	68.7	**92.9**	**86.9**	**80.3**
LARGE Models											
$\text{BERT}_{\text{LARGE}}$	335M	23446M	61.6	86.2/86	90.1	92.2	90.1	72.9	93.5	90.4	84.8
$\text{ALBERT}_{\text{LARGE}}$	18M	24296M	60.1	86/86.1	90.4	91.6	89.6	83.0	95.2	91.4	85.9
$\text{RoBERTa}_{\text{LARGE}}$	355M	23840M	66.4	89/89.6	91.6	**94.2**	90.7	86.6	95.4	92.3	**88.4**
$\text{LayerDrop}_{\text{LARGE}}$	355M	23840M	**66.6**	**89.7/89.6**	91.2	93.9	88.5	**86.6**	**95.5**	**92.6**	88.2
ElasticBERT$_{\text{LARGE}}$	335M	23446M	66.3	88/88.5	**92.0**	93.6	**90.9**	83.1	95.3	91.7	87.7
$\text{BERT}_{\text{LARGE}}$-6L	108M	5863M	20.2	76.5/76.5	76.4	84.3	87.3	58.5	89.7	77.3	78.5
$\text{ALBERT}_{\text{LARGE}}$-6L	18M	6083M	51.7	82.2/82.9	86.5	89.4	88.6	66.4	**92.2**	89.4	81.0
$\text{RoBERTa}_{\text{LARGE}}$-6L	129M	5962M	43.3	80.4/80.9	80.0	86.1	88.9	54.9	90.1	80.5	76.1
$\text{LayerDrop}_{\text{LARGE}}$-6L	129M	5962M	44.3	81.4/81.0	79.8	87.1	88.5	53.1	91.4	83.0	76.6
ElasticBERT$_{\text{LARGE}}$-6L	108M	5863M	**53.9**	**83.5/84.3**	**89.6**	**90.8**	**90.1**	**71.1**	91.9	**90.1**	**82.8**
Test Set Results											
$\text{ALBERT}_{\text{LARGE}}$-6L	18M	6083M	46.5	81.9/82.2	84.7	88.5	78.9	62.3	91.3	85.1	77.9
ElasticBERT$_{\text{LARGE}}$-6L	108M	5863M	**47.2**	**83.2/82.6**	**86.2**	**90.4**	**80.2**	**67.0**	**92.5**	**86.3**	**79.5**

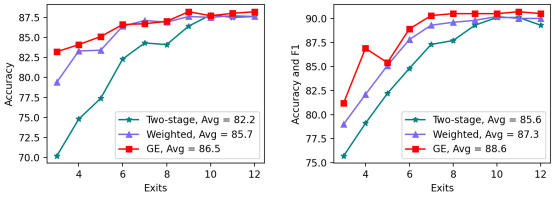
Table 6: ElasticBERT and static baseline performance on GLUE tasks. For MRPC, we report the mean of accuracy and F1. For STS-B, we report Pearson and Spearman correlation. For CoLA, we report Matthews correlation. For all other tasks we report accuracy.

B.3 Ablation Study

About the Training Strategy ElasticBERT adopts the gradient equilibrium (GE) to alleviate the conflict between the losses at different exits. Here, we compare GE with two other existing training strategies, two-stage training (Xin et al., 2020) and weighted training (Zhou et al., 2020a). Two-stage training is that, first training the top classifier along with the backbone model, and then freeze the parameters of the backbone model and train the injected internal classifiers. By this, two-stage training maintains the performance of the top classifier. Weighted training is to weight the loss of each exit according to the corresponding layer, which is

$$\mathcal{L} = \frac{\sum_{l=1}^{L} l \cdot \mathcal{L}_l}{\sum_{l=1}^{L} l}. \tag{4}$$

Experimental results of ElasticBERT with the three training strategies are shown in Figure 7. It



(a) SST-2 (b) MRPC

Figure 7: Performance of the ElasticBERT exits at different layers with different training strategies.

can be observed that training with GE strategy performs the best on both SST-2 and MRPC.

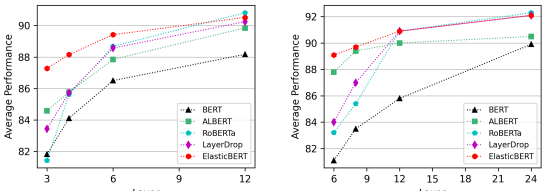
About the Grouped Exits As shown in Eq. (3), we divide the L exits into different groups to speedup the pre-training. Therefore, how to group these exits needs to be explored. Here we evaluate four different grouping methods, as described in Table 5. To keep the overall performance of the entire model, the exit classifier on the top of the model is included in each group. According to

Method	MNLI-m/mm	MRPC	QNLI	QQP	Average
		12 Layers			
ElasticBERT$_{\text{BASE}}$	85.4/**85.7**	89.2	91.9	**89.8**	**88.4**
w/o Grouped Training	85.3/85.1	**89.3**	**92.0**	89.8	88.3
w/o Grouped Training + GE	**85.5**/85.6	89.0	91.8	89.5	88.3
		6 Layers			
ElasticBERT$_{\text{BASE}}$	83.9/**83.6**	87.1	90.6	**89.6**	87.0
w/o Grouped Training	**84.5**/83.6	**87.5**	**90.7**	89.4	**87.1**
w/o Grouped Training + GE	83.5/83.3	87.2	90.7	88.3	86.6

Table 7: Comparison between ElasticBERT$_{\text{BASE}}$ with and without GE and Grouped Training. Here, ElastiBERT$_{\text{BASE}}$ is pre-trained using Wikipeida and BookCorpus data. ElasticBERT$_{\text{BASE}}$ denotes that model is pre-trained with GE and Grouped Training.

Method	Training Time (h)
ElasticBERT$_{\text{BASE}}$	106.0
-w/o Grouped Training	186.0
-w/o Grouped Training + GE	174.5

Table 8: The training time for different training strategies. All models are trained on the same GPU servers.



(a) ElasticBERT$_{\text{BASE}}$ (b) ElasticBERT$_{\text{LARGE}}$

Figure 8: Comparison of average performance on ELUE test sets between the ElasticBERT and other pre-trained models.

the experimental results in Table 5, we choose the odd/even grouping method for ElasticBERT$_{\text{BASE}}$. Similarly, our experiments demonstrate that grouping 24 exits into $\mathcal{G}_1$={1, 4, 7, ..., 22, 24}, $\mathcal{G}_2$={2, 5, 8, ..., 23, 24}, and $\mathcal{G}_3$={3, 6, 9, ..., 21, 24} works well for ElasticBERT$_{\text{LARGE}}$.

Effect of Gradient Equilibrium To verify that GE can enhance performance, we pre-train ElasticBERT$_{\text{BASE}}$ with and without GE using Wikipedia and BookCorpus data. As shown in Table 7, ElasticBERT with GE outperforms that without GE in two different configurations.

Effect of Grouped Training If we divide L exits into G groups, the number of samples used for training the remaining exits is $1/G$ of the last exit. To verify that this does not degrade the performance of the internal exits, we compare the performances of pre-training ElasticBERT$_{\text{BASE}}$ with and without Grouped Training. As shown in Table 7, we can observe that ElasticBERT with Grouped Training and GE does not suffer much performance loss compared with that training with only GE. In addition, as shown in the Table 8, using Grouped Training reduces $\sim$43% training time compared with that without Grouped Training.

B.4 Overall Comparison

We compare ElastiBERT with other large scale pre-trained models in Figure 8, from which we find that ElasticBERT is more robust to depth reduction. As the number of layers decreases, ElasticBERT offers greater advantages over other pre-trained models.

C ELUE Website

The ELUE website is built using Vue and Spring Boot. We use MySQL for data storage and our private servers to run the scoring script for each submission.