Sparse Distillation: Speeding Up Text Classification by Using Bigger Models

Qinyuan Ye†  Madian Khabsa Mike Lewis Sinong Wang Xiang Ren Aaron Jaech
1University of Southern California 2Facebook AI
{qinyuany,xiangren}@usc.edu
{mkhabsa,mikelewis,sinongwang,ajaech}@fb.com

Abstract
Distilling state-of-the-art transformer models into lightweight student models is an effective way to reduce computation cost at inference time. However, the improved inference speed may be still unsatisfactory for certain time-sensitive applications. In this paper, we aim to further push the limit of inference speed by exploring a new area in the design space of the student model. More specifically, we consider distilling a transformer-based text classifier into a billion-parameter, sparsely-activated student model with an embedding-averaging architecture. Our experiments show that the student models retain 97% of the RoBERTa-Large teacher performance on a collection of six text classification tasks. Meanwhile, the student model achieves up to 600x speed-up on both GPUs and CPUs, compared to the teacher models. Further investigation shows that our pipeline is also effective in privacy-preserving and domain generalization settings.

1 Introduction
Large pre-trained Transformers (Devlin et al., 2018; Liu et al., 2019) are highly successful, but their large inference costs means that people who host low-latency applications, or who are simply concerned with their cloud computing costs have looked for ways to reduce the costs. Prior work mainly achieves this by leveraging knowledge distillation (Hinton et al., 2015), which allows for the capabilities of a large well-performing model known as the teacher to be transferred to a smaller student model. For example, DistilBERT (Sanh et al., 2019) is a smaller transformer model distilled from BERT (Devlin et al., 2018), which reduces BERT’s size by 40% and becomes 60% faster during inference. However, such speed-up may be still insufficient for high-volume or low-latency inference tasks. In this paper, we aim to further push the limit of inference speed, by introducing Sparse Distillation, a framework that distills the power of state-of-the-art transformer models into a shallow, sparsely-activated, and over-parameterized student model.

Counter to the convention of using “smaller, faster, [and] cheaper” (Sanh et al., 2019) student models, our work explores a new area of the design space, where our fast and cheap student model is actually several times larger than the teacher. The student model we use is based on Deep Averaging Network (DAN) from Iyyer et al. (2015). DANs take a simple architecture by mapping the n-grams in the input sentence into embeddings, aggregating the embeddings with average pooling, and then using multiple linear layers to perform classification. This architecture is reminiscent of the high expressive power of billion parameter n-gram models (Buck et al., 2014; Brants et al., 2007) from before the existence of pre-trained language models. By selecting the n-gram vocabulary and the embedding dimension, DANs also scale up to bil-
lions of parameters. Meanwhile, the costs are kept low as DANs are sparsely-activated during training and inference.

One weakness of DANs is that they are restricted in modeling high-level meanings in long-range contexts, as compared to the self-attention operator in Transformers. However, recent studies have shown that large pre-trained Transformers are rather insensitive to word order (Sinha et al., 2021) and that they still work well when the learned self-attention is replaced with hard-coded localized attention (You et al., 2020). Taken together, these studies suggest that on some tasks it may be possible to get competitive results without computationally expensive operations such as self-attention.

To verify our hypothesis, we use an array of six text classification tasks\(^1\) and apply knowledge distillation to the large sparse DANs. Overall, we observe that the resulting student models retain 97% of the RoBERTa-Large teacher performance. We also show that our method falls outside of the Pareto frontier of existing methods; compared to a baseline of distilling to a LSTM student, our method gives higher accuracy at less than 1/35 the inference cost (see Fig. 1). Based on our empirical results, we conclude that faster and larger student models provide a valuable benefit over existing methods. We further examine our method in privacy-preserving settings (i.e., no access to task-specific data during distillation) and domain generalization settings (i.e., student models are applied and adapted to new data domains), where we find our method continue to bring improvements over baselines.

2 Sparse Distillation with DANs

2.1 Problem Definition

Our goal is to train an efficient text classification model \(M\) for a given task \(T\). In a \(n\)-way classification problem, the model \(M\) takes input text \(x\), and produces \(\hat{y} \in \mathbb{R}^n\), where \(\hat{y}_i\) indicates the likelihood that the input \(x\) belongs to category \(i\). The task \(T\) has a train set \(D_{\text{train}}\) and a validation set \(D_{\text{val}}\). Additionally, we assume access to a large unlabeled corpus \(C\) which is supposedly in a domain relevant to task \(T\). We comprehensively evaluate the efficiency of the model \(M\) by reporting: (1) accuracy on \(D_{\text{val}}\), (2) inference speed, and (3) the number of parameters in the model.

2.2 Method Overview

To train a text classifier that is both efficient and powerful, we employ knowledge distillation (Hinton et al., 2015), by having a powerful teacher model provide the supervision signal to an efficient student model. In particular, we are interested in using sparse n-gram based models as our student model. We explain the teacher and student model we use in §2.3, the training pipeline in §2.4, and implementation details in §2.5.

2.3 Models

**Teacher Model.** Fine-tuning a pre-trained transformer model is the predominant recipe for obtaining state-of-the-art results on various text classification tasks. Our teacher model is a RoBERTa-Large model (Liu et al., 2019) fine-tuned on the training set \(D_{\text{train}}\) of task \(T\).

**Student Model.** The student model is based on the Deep Averaging Network (DAN; Iyyer et al. 2015) with the modification that we operate on n-grams instead of words (Fig. 2). Specifically, for an input sentence \(x\), a list of n-grams \(g_1, g_2, \ldots, g_n\) are extracted from the sentence. These n-gram indices are converted into their embeddings (with dimension \(d_e\)) with an embedding layer \(\text{Emb}(.\)\). The sentence representation \(h\) will be computed as the average of all n-gram embeddings, i.e., \(h = \text{Mean}(\text{Emb}(g_1), \text{Emb}(g_2), \ldots, \text{Emb}(g_n)) \in \mathbb{R}^{d_e}\). The sentence representation then goes through two fully connected layers, \((W_1, b_1)\) and \((W_2, b_2)\) to produces the final logits \(\hat{\varepsilon}\), i.e., \(\hat{\varepsilon} = M_s(x) = \ldots\)

---

\(^1\)It’s well established that pre-trained Transformers are effective at many tasks beyond text classification. Supporting these use-cases is left for future work.
Figure 3: We adopt a three-stage pipeline for our study: (1) We fine-tune a RoBERTa-Large model on $D_{train}$ to get the teacher model. (2) We apply teacher model to the unlabeled corpus $C$ and $D_{train}$, and train the student model (DAN) to mimic the predictions of the teacher. This model is denoted as “DAN (KD)” (3) We further fine-tune the student model with $D_{train}$. This model is denoted as “DAN (KD+FT)”.

Remarks on Computation Complexity. The teacher model uses multiple transformer layers to capture the interactions between individual sub-word tokens, and aggregate such information into contextualized representations. Multi-headed self-attention is considered the most expensive operation in transformers, where the computation complexity is $O(m^2)$ for a sequence with $m$ sub-word tokens. The student model, Deep Averaging Network (DAN), can be considered as pre-computing word tokens, and aggregate such information into a large embedding table. By doing so, the computation complexity is reduced to $O(m)$. However, unlike the teacher, the context is limited to a small range, and no long range information (beyond n-gram) is taken into account by the student model.

2.4 Training Pipeline

Our training pipeline largely resembles the one introduced in Turc et al. (2019) and is illustrated in Fig. 3. It has three stages: (1) We first fine-tune a RoBERTa-Large model on the train set $D_{train}$ of task $T$, and use the resulting model as the teacher model. (2) We train the student model by aligning the predictions of the teacher ($\hat{y}$) and the predictions of the student ($\hat{y}$) on the union of unlabeled corpus $C$ and the train set $D_{train}$. We align the predictions by minimizing the KL divergence between the two distributions, i.e., $L = \sum_{j=1}^{n} \hat{y}_j \log \frac{\hat{y}_j}{\bar{y}_j}$. The resulting student model is denoted as “DAN (KD)”. (3) We further fine-tune the student model from step (2) with the task train set $D_{train}$, and get a new student model. This model is denoted as “DAN (KD+FT)”. This stage is optional.

2.5 Implementation Details

Determine N-gram Vocabulary. Our student model takes in n-grams as input. We determine the n-gram vocabulary by selecting the top $|V|$ frequent n-grams in $D_{train}$ and $C$. For each downstream dataset, we compute the vocabulary separately. We use CountVectorizer with default whitespace tokenization in sklearn (Pedregosa et al., 2011) to perform this task. We set n-gram range to be $(1, 4)$ and set $|V| = 1,000,000$, unless specified otherwise.

Optimization. The architecture of DAN is sparsely-activated, and thus can be sparsely-optimized to reduce memory footprint during training. To facilitate this, we design a hybrid Adam optimizer, where we use SparseAdam$^2$ for the sparse layers (i.e., the embedding table), and regular Adam for dense layers. SparseAdam is a modified version of the regular Adam optimizer. For Adam, the first and second moment for each parameter is updated at every step. This can be costly, especially for DAN, as most parameters in the embedding layer are not used during the forward pass. SparseAdam computes gradients and updates the moments only for parameters used in the forward pass. Our use of the hybrid Adam optimizer helps to improve speed and reduce memory usage. Notably, with the hybrid Adam optimizer, we can train a 1-billion parameter DAN with the batch size of 2048 at the speed of 8 batches/second, on a single GPU with 32 GB memory.

3 Experiment Settings

3.1 Data

Downstream Datasets. Following Tay et al. (2021), we use six text classification datasets, covering a wide range of applications, as the testbed
for our experiments and analysis. We use IMDB (Maas et al., 2011) and SST-2 (Socher et al., 2013) for sentiment analysis, TREC (Li & Roth, 2002) for question classification, AGNews (Zhang et al., 2015) for news classification. We use Civil Comments (Borkan et al., 2019) and Wiki Toxic (Wulczyn et al., 2017) dataset for toxicity detection.

### Knowledge Distillation Corpora
For each dataset, we manually select a relevant unlabeled corpus $C$ based on the task characteristics and text domain. For example, the IMDB and SST-2 models, which are tasked with classifying the sentiment of movie reviews, are paired with a corpus of unlabeled Amazon product reviews (Ni et al., 2019). TREC, a question classification task, is paired with PAQ (Lewis et al., 2021), a collection of 65 million questions. AGNews, a news classification task, is paired with CC-News corpus (Nagel, 2016). For Civil Comments, a dataset for detecting toxic news comments, we select the News subreddit corpus from ConvoKit (Chang et al., 2020), which is built from a previously existing dataset extracted and obtained by a third party and hosted by pushshift.io. Details of these datasets and the corpus are listed in Table 1.

### 3.2 Hyperparameters
For fine-tuning in stage 1, we select batch size from {16, 32} and learning rate from {1e-5, 2e-5, 5e-5} following the recommendations in (Liu et al., 2019). We train the model for 10 epochs on $D_{\text{train}}$. For knowledge distillation in stage 2, we set the batch size to be 2048, learning rate to be 5e-4, and total number of updates to be 1,000,000, as they work well in our preliminary experiments. The embedding table is randomly initialized and the embedding dimension $d_e$ is set to 1,000, unless specified otherwise. For further fine-tuning in stage 3, we set the batch size to be 32 and select the learning rate from {3e-4, 1e-4, 3e-5}. We train the model for 10 epochs on $D_{\text{train}}$. For all training procedures, we validate the model at the end of each epoch in the case of fine-tuning, or every 100,000 steps in the case of knowledge distillation. We save the best checkpoint based on dev accuracy.

### 3.3 Compared Methods
To comprehensively evaluate and analyze the n-gram student models, we additionally experiment with (1) training the student n-gram model from scratch, without knowledge distillation; (2) using other architectures for the student model, such as Bi-LSTM and Convolution Neural Networks; (3) directly fine-tuning compact transformers, e.g., DistilBERT (Sanh et al., 2019), MobileBERT (Sun et al., 2020).

### 4 Results and Analysis

#### 4.1 Main Results
How well can DANs emulate the performance of the teacher? In Table 2, we present the results on 6 text classification datasets. Firstly, we find that in 5 out of the 6 datasets, the gap between the teacher and the student model is within 3%. This suggests the power of simple n-gram models may be underestimated previously, as they are typically trained from scratch, without modern techniques such as pre-training and knowledge distillation. This also echoes with a series of recent work that questions the necessity of word order information (Sinha et al., 2021) and self-attention (You et al., 2020), in prevalent transformer architectures. Secondly, we observe that knowledge distillation help close more than half the gap between the teacher and the student model is within 3%. This suggests the power of simple n-gram models may be underestimated previously, as they are typically trained from scratch, without modern techniques such as pre-training and knowledge distillation. This also echoes with a series of recent work that questions the necessity of word order information (Sinha et al., 2021) and self-attention (You et al., 2020), in prevalent transformer architectures.

#### 4.2 How fast are DANs?
We have previously hypothesized that DANs will have superior inference speed due to its simple and sparse architecture.

### Table 1: Datasets and Distillation Corpus Used in Our Study.

| Dataset D | $|D_{\text{train}}|$ | $|D_{\text{dev}}|$ | Avg. l | Distillation Corpus C | $|C|$ |
|-----------|-------------------|-------------------|-------|----------------------|------|
| IMDB      | 25,000            | 25,000            | 300   | Amazon Reviews and * | 75m  |
| SST-2     | 67,349            | 872               | 11    | Amazon Reviews       | 75m  |
| TREC      | 5,452             | 500               | 11    | PAQ                  | 65m  |
| AGNews    | 120,000           | 7,600             | 55    | CC-News              | 418m |
| CCom      | 1,804,874         | 97,320            | 67    | Reddit News and *   | 60m  |
| WToxic    | 159,571           | 63,978            | 92    | *                    | 37m  |
Table 2: Performance Comparison on 7 Text Classification Tasks. We report accuracy for all datasets. In most cases, the gap between the teacher model (RoBERTa-Large) and the n-gram based student model (DAN(KD)/DAN(KD+FT)) is within 3%. Also, we observe that knowledge distillation help close more than half the gap between the teacher model and the n-gram model trained from scratch. †Knowledge distillation is performed without task data ($D_{train}$), assuming that the task data is private (see §4.2). ‡The dataset we obtain from public sources differs from the one in Tay et al. (2021).

| Model                      | IMDB | SST-2 | TREC | AGNews | CCom | WToxic |
|----------------------------|------|-------|------|--------|------|--------|
| DAN (from scratch)         | 88.3 | 79.5  | 78.4 | 91.1   | 95.7 | 92.2   |
| DAN (KD)†                  | 92.0 | 87.0  | 91.8 | 90.0   | 96.2 | 93.9   |
| DAN (KD)                   | 93.2 | 86.4  | 91.8 | 90.6   | 96.3 | 94.0   |
| DAN (KD+FT)                | 93.5 | 88.5  | 92.6 | 93.0   | 96.3 | 92.5   |
| Transformer-Base (Tay et al., 2021) | 94.2 | 92.1  | 93.6 | 93.5   |      | 91.5   |
| ConvNet (Tay et al., 2021) | 93.9 | 92.2  | 94.2 | 93.9   |      | 93.8   |
| RoBERTa-Large (Liu et al., 2019) | 96.3 | 96.2  | 94.8 | 95.4   | 96.3 | 94.1   |

Table 3: Model Size and Inference Speed Comparison. We report accuracy, inference speed (unit: samples per second) and relative speed compared to the teacher model (RoBERTa-Large). Our DAN model achieves competitive accuracy while achieving significant inference speed-up in multiple settings.

| Model            | Parameter Count | IMDB | SST-2 |
|------------------|-----------------|------|-------|
|                  | Total Sparse Dense | Acc. | GPU-fp32 | GPU-fp16 | CPU-fp32 | Acc. | GPU-fp32 | GPU-fp16 | CPU-fp32 |
| RoBERTa-Large    | 355M 51M 304M    | 96.3 | 28.9 (1x) | 92.3 (1x) | 1.4 (1x) | 96.2 | 267.3 (1x) | 92.3 (1x) | 1.4 (1x) |
| DistilBERT       | 66M 23M 43M      | 92.2 | 175.8 (6x) | 334.7 (4x) | 10.7 (8x) | 90.8 | 828.5 (3x) | 1117.3 (2x) | 60.6 (3x) |
| MobileBERT       | 25M 4M 21M       | 93.6 | 157.7 (5x) | 200.3 (2x) | 7.7 (6x) | 90.9 | 574.5 (2x) | 545.8 (1x) | 89.4 (4x) |
| LSTM (Layer-128d) | 53M 51M 2M        | 90.9 | 500.3 (17x) | 495.8 (5x) | 81.8 (59x) | 85.9 | 339.0 (13x) | 398.1 (7x) | 1002.6 (45x) |
| LSTM (Layer-256d) | 56M 51M 5M        | 91.2 | 489.1 (16x) | 486.7 (5x) | 57.1 (41x) | 86.8 | 3054.2 (11x) | 3938.4 (6x) | 615.7 (27x) |
| CNN (Layer-256d)  | 53M 51M 2M        | 89.2 | 3410.7 (109x) | 8427.1 (91x) | 251.2 (181x) | 82.8 | 1323.5 (5x) | 1563.9 (3x) | 3820.4 (172x) |

DAN (ours)        | 1001M 1000M 1M | 93.5 | 17557.9 (607x) | 20888.1 (226x) | 922.6 (663x) | 88.5 | 1745.7 (7x) | 1865.9 (3x) | 16478.6 (741x) |

In this section we quantify this advantage by comparing the n-gram model with the RoBERTa teacher model. We include two popular compact transformers, DistilBERT (Sanh et al., 2019) and MobileBERT (Sun et al., 2020), and two other popular student architectures, Bi-LSTM (Tang et al., 2019; Adhikari et al., 2020) and CNN (Chia et al., 2019) for a comprehensive comparison. For simplicity, we use BPE tokenizer and re-use the embedding table from RoBERTa for our student Bi-LSTM and CNN model. We use 2-layer Bi-LSTM with hidden dimension of 128, 256 and 512. For the CNN model, we use one 1D convolution layer with hidden dimension of 128 and context window of 7. All inference speed tests are done with the batch size of 32. GPU inference is performed with one Quadro RTX 8000 GPU, and CPU inference is performed with 56 Intel Xeon CPU E5-2690 v4 CPUs.

We provide more details and list the inference speed for IMDB and SST-2 in Table 3. We have previously visualized the speed comparison on IMDB dataset on in Fig. 1. DAN achieves the strong performance and inference efficiency among all different student model architectures. The speed-up is most significant on IMDB dataset (600x faster), as IMDB dataset has an average input length of 300 tokens, and the complexity of self-attention grows quadratically with sequence length. Moreover, DAN has an acceptable CPU inference speed, which greatly reduce the hardware cost for inference. We believe all these characteristics makes student DAN model as an ideal option for production or real-time use on text classification tasks.

How to achieve optimal performance with a fixed parameter budget? We explore how the configuration of vocabulary size and embedding dimension influence the student model performance. We test 19 different configurations with the IMDB dataset and list the results in Table 5. We also show the results graphically in Figure 4. All models in the table are trained with one single GPU, with the training scale described in §2.5. All else being equal, having more parameters in the student model is beneficial to the performance. For a fixed parameter budget, higher accuracy was achieved by increasing the embedding dimension and making a corresponding reduction in the vocabulary size.
Figure 4: Tradeoffs in IMDB dev set accuracy as the parameter budget is allocated to increasing either the n-gram vocabulary size or the embedding dimension.

![Graph showing tradeoffs in IMDB dev set accuracy](image)

| Parameter Count | IMDB Dev Accuracy |
|-----------------|-------------------|
| 500 million     | 93.2              |
| 1 billion       | 93.2              |
| 2 billion       | 93.2              |

Our best performing model has $|V| = 1,000,000$ and $d_e = 1,000$. Thus we keep this configuration for all other datasets.

**Simplest is the best: Exploring different design choices for DAN.** We try several modifications to our current experiment pipeline, including (1) replace average pooling with max pooling or taking sum in the DAN model; (2) pre-compute a n-gram representation by feeding the raw n-gram text to a RoBERTa-Large model, and using the representations to initialize the embedding table of the student model; (3) attach more dense layers in the DAN. We experiment with IMDB dataset and list the performance in Table 4. In general, we do not observe significant performance improvements brought by these variations. Thus, we keep the simplest design of DAN for all other experiments.

### 4.2 Privacy-preserving Settings

NLP datasets sometimes involve user generated text or sensitive information; therefore, data privacy can be a concern when training and deploying models with certain NLP datasets. In this section, we modify our experiment setting to a practical and privacy-preserving one. We assume the user has access to a public teacher model that is trained on private train dataset ($D_{train}$), but does not has access to $D_{train}$ itself. This is realistic nowadays with the growth of public model hubs such as TensorFlow Hub\(^4\) and Hugging Face Models\(^5\). After downloading the model, the user may wish to deploy a faster version of this model, or adapt the model to the user’s own application domain.

#### Knowledge Distillation without $D_{train}$

To simulate the privacy-preserving setting, we remove $D_{train}$ from the knowledge distillation stage in our experiment pipeline and only use the unlabeled corpus $C$. We use “DAN (KD)\(^†\)” to denote this model in Table 2. By comparing “DAN (KD)” and “DAN (KD)\(^†\)”, we found that the performance difference brought by task specific data $D_{train}$ is small in all cases, with the largest gap being 1.2% on IMDB dataset. This suggests that the proposed pipeline is still useful in the absence of task-specific data.

#### Domain Generalization and Adaptation

We select the two sentiment analysis tasks: IMDB and SST-2, and further explore the domain generalization/adaptation setting. Specifically, during stage 1, we fine-tune the RoBERTa-Large model on a source dataset; during stage 2, we apply knowledge distillation with unlabeled corpus $C$ and get the student model; during stage 3, we further fine-

\(^4\)https://www.tensorflow.org/hub
\(^5\)https://huggingface.co/models

---

**Table 4: Variations made to the student model and the performance on IMDB. \(^*\) represents the design choice we make in our main experiments.**

| Variations                  | Acc. |
|-----------------------------|------|
| 1. Pooling Methods          |      |
| Mean Pooling \((\ast)\)      | 93.2 |
| Max Pooling                 | 91.8 |
| Sum                         | 92.9 |
| 2. Embedding Initialization |      |
| With initialization         | 93.2 |
| Without initialization \((\ast)\) | 93.2 |
| 3. Dense Layers             |      |
| 1000 $\rightarrow$ 1000 $\rightarrow$ 2 \((\ast)\) | 93.2 |
| 1000 $\rightarrow$ 1000 $\rightarrow$ 256 $\rightarrow$ 2   | 93.1 |
| 1000 $\rightarrow$ 1000 $\rightarrow$ 256 $\rightarrow$ 64 $\rightarrow$ 2 | 93.0 |
Table 5: Domain Generalization and Adaptation Results. (1) We take the teacher model trained on the source dataset and evaluate it on the target dataset. (2) We obtain the student model “DAN (KD)” with unlabeled corpus $C$ and knowledge distillation. (3) We further fine-tune the student model on the target dataset to obtain “DAN (KD+FT)”. (4) “w. re-init.” represents that the classification head is re-initialized before further fine-tuning.

| Source | IMDB | SST-2 | Target | IMDB | SST-2 |
|--------|------|-------|--------|------|-------|
| DAN (from scratch, tar) | 79.5 | 88.3 | DAN (from scratch, tar) | 90.0 | 94.1 |
| (1) RoBERTa-Large (src) | 90.0 | 94.1 | (2) DAN (KD) | 81.9 | 92.0 |
| (3) DAN (KD+FT) | 89.4 | 93.0 | (4) DAN (KD+FT w. re-init.) | 86.7 | 92.8 |
| RoBERTa-Large (tar) | 96.2 | 96.3 | RoBERTa-Large (tar) | 96.2 | 96.3 |

4.3 Limitations and Discussions

Case study: What DANs are still not capable of. We take a closer look at the predictions made by our DAN model (student) and the RoBERTa-Large model (teacher). We list several representative cases in Table 6. These cases typically require understanding of complex language phenomena, such as irony, conditional clauses, and slang. In addition, these phenomena typically occur in contexts longer than 4 words, which DANs are not capable of modeling by design. For example, “bad actors” can mean “good actors” based on the later context “much funnier to watch”. We conclude that our proposed pipeline is not suitable to cases where modeling complex language phenomena has a higher priority than improving inference speed.

Understanding the performance gaps. Tay et al. (2021) advocate that architectural advances should not be conflated with pre-training. Our experiments further support this claim, if we consider knowledge distillation as a substitute for pre-training that provides the student model with stronger inductive biases, and consider the remaining teacher-student performance gap as the difference brought by architectural advances. On the other hand, we believe the power of DANs are previously undermined due to the challenges in optimizing large sparse models with limited supervision. Our experiments show that knowledge distillation effectively densify the supervision and greatly improve the performance of DANs.

5 Related Work

Efficient Transformers. Recent work attempts to improve computation or memory efficiency of transformer models mainly from the following perspectives: (1) Proposing efficient architectures or self-attention variants, e.g., Linformer (Wang et al., 2020), Longformer (Beltagy et al., 2020), BigBird (Zaheer et al., 2020). Tay et al. (2020) provide a detailed survey along this line of work. (2) Model compression using knowledge distillation, e.g., DistillBERT (Sanh et al., 2019), MobileBERT (Sun et al., 2020). These compressed models are typically task-agnostic and general-purpose, while in this work we focus on task-specific knowledge distillation. (3) Weight quantization and pruning, e.g., Gordon et al. (2020); Li et al. (2020).

Task-specific Knowledge Distillation in NLP. Researchers explored distilling a fine-tuned transformer into the following lightweight architectures, including smaller transformers (Turc et al., 2019; Jiao et al., 2019), LSTMs (Tang et al., 2019; Adhikari et al., 2020) and CNNs (Chia et al., 2019). Wasserblat et al. (2020) distill BERT into an architecture similar to DAN, however they restrict the model to only take unigrams (thus having small student models), and adopt a non-standard low-resource setting. To summarize, existing work typically focuses on reducing both number of parameter and the amount of computation, while in the paper we push the limit of inference speed and study an under-explored area in the design space, where the amount of computation is reduced by training a large embedding-based model.

Reducing Contextualized Representations to Static Embeddings. Related to our work, Ethayarajh (2019) and Bommasani et al. (2020) show how static word embeddings can be computed from BERT-style models. Ethayarajh (2019) suggest that less than 5% of the variance in a word’s contextualized representation can be explained by a static embedding, justifying the necessity of contextualized representation. Bommasani et al. (2020) found
Table 6: Case study on IMDB predictions. In these cases, the model can only make the correct predictions by understanding long contexts. Performance of DAN models are still limited as they only look at local n-grams and cannot model higher level interaction between words by design.

| Teacher | Student | Label | Sentence |
|---------|---------|-------|----------|
| Neg     | Pos     | Neg   | I really wanted to love this film. . . . |
| Neg     | Pos     | Neg   | This movie is a great movie ONLY if you need something to sit and laugh at the stupidity of it. . . . |
| Pos     | Neg     | Pos   | . . . They are such bad actors and it made this movie so much funnier to watch. . . . |

that static embeddings obtained by pooling over many contexts outperforms Word2Vec and GloVe in intrinsic evaluation. These two papers mainly focus on post-hoc interpretation of pre-trained transformer models using static embeddings. In our work we opt to use knowledge distillation techniques to learn n-gram embeddings. Meanwhile we acknowledge that the technique in Ethayarajh (2019) and Bommasani et al. (2020) could be used as an alternative method to convert transformer models to large but fast text classifiers.

Sparse Architectures. Our work starts with a fine-tuned Transformer model and distills it to a computationally efficient model with many more parameters. Alternatively, one could fix the computational cost at the same level as a full-sized Transformer while still greatly expanding the parameter count. This is the approach that is explored in the T5 Switch Transformer from Fedus et al. (2021) that makes use of a sparsely-activated mixture of experts. Both their work and ours agree in the conclusion that scaling up parameter count allows the model to memorize additional useful information.

6 Conclusions & Future Work

We investigated a new way of using knowledge distillation to produce a faster student model by reversing the standard practice of having the teacher be smaller than the teacher and instead allowed the student to have a large table of sparsely-activated embeddings. This enabled the student model to essentially memorize task-related information that if an alternate architecture were used would have had to be computed. We tested this method on six text classification tasks with models that were up to 1 billion parameters in size, approximately 3x as big as the RoBERTa-Large teacher model, and found that the student model was able to perform favorably. The relative drop in accuracy was less than 3% in five out of the six tasks.

We hope that our work can lead to further exploration of sparse architectures for faster and larger student models. There are multiple directions for future work, including scaling beyond 1 billion parameters and extending the DAN architecture to support tasks with long range dependencies like natural language inference or multiple inputs like text similarity. Additionally, we have only tested our methods on English tasks. More work is needed to test the idea on other languages where n-gram statistics can be different than English.

Acknowledgments

We would like to thank Robin Jia, Christina Sauper, and USC INK Lab members for the insightful discussions.

References

Ashutosh Adhikari, Achyudh Ram, Raphael Tang, William L. Hamilton, and Jimmy Lin. Exploring the limits of simple learners in knowledge distillation for document classification with DocBERT. In 5th Workshop on Representation Learning for NLP, pp. 72–77, Online, July 2020. ACL. doi: 10.18653/v1/2020.repl4nlp-1.10. URL https://aclanthology.org/2020.repl4nlp-1.10.

Iz Beltagy, Matthew E Peters, and Arman Cohan. Longformer: The long-document transformer. arXiv preprint arXiv:2004.05150, 2020.

Rishi Bommasani, Kelly Davis, and Claire Cardie. Interpreting pretrained contextualized representations via reductions to static embeddings. In ACL, pp. 4758–4781, 2020.

Daniel Borkan, Lucas Dixon, Jeffrey Sorensen, Nithum Thain, and Lucy Vasserman. Nuanced metrics for measuring unintended bias with real data for text classification. In Companion proceedings of the 2019 world wide web conference, pp. 491–500, 2019.

Thorsten Brants, Ashok C. Popat, Peng Xu, Franz J. Och, and Jeffrey Dean. Large language models in machine translation. In Proceedings of the 2007 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning (EMNLP-CoNLL), pp. 858–867, Prague, Czech Republic, June 2007. Associ-
Christian Buck, Kenneth Heafield, and Bas Van Ooyen. N-gram counts and language models from the common crawl. In LREC, volume 2, pp. 4. Citeseer, 2014.

Jonathan P Chang, Caleb Chiam, Liye Fu, Andrew Z Wang, Justine Zhang, and Cristiana Danescu-Niculescu-Mizil. Convokit: A toolkit for the analysis of conversations. arXiv preprint arXiv:2005.04246, 2020.

Yew Ken Chia, Sam Witteveen, and Martin Andrews. Transformer to CNN: Label-scarce distillation for efficient text classification. arXiv preprint arXiv:1909.03508, 2019.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805, 2018.

William Fedus, Barret Zoph, and Noam Shazeer. Switch transformers: Scaling to trillion parameter models with simple and efficient sparsity. arXiv preprint arXiv:2101.03961, 2021.

Mitchell A Gordon, Kevin Duh, and Nicholas Andrews. Compressing BERT: Studying the effects of weight pruning on transfer learning. arXiv preprint arXiv:2002.08307, 2020.

Geoffrey Hinton, Oriol Vinyals, and Jeff Dean. Distilling the knowledge in a neural network. arXiv preprint arXiv:1503.02531, 2015.

Mohit Iyyer, Varun Manjunatha, Jordan Boyd-Graber, and Hal Daumé III. Deep unordered composition rivals syntactic methods for text classification. In ACL, pp. 1681–1691, 2015.

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.

Patrick Lewis, Yuxiang Wu, Linqing Liu, Pasquale Minervini, Heinrich Küttler, Aleksandra Piktus, Pontus Stenetorp, and Sebastian Riedel. Paq: 65 million probably-asked questions and what you can do with them. arXiv preprint arXiv:2102.07033, 2021.

Xin Li and Dan Roth. Learning question classifiers. In COLING, 2002. URL https://aclanthology.org/C02-1150.

Zhuohan Li, Eric Wallace, Sheng Shen, Kevin Lin, Kurt Keutzer, Dan Klein, and Joseph E Gonzalez. Train large, then compress: Rethinking model size for efficient training and inference of transformers. arXiv preprint arXiv:2002.11794, 2020.

Yinhao Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. Roberta: A robustly optimized BERT pretraining approach. arXiv preprint arXiv:1907.11692, 2019.

Andrew L. Maas, Raymond E. Daly, Peter T. Pham, Dan Huang, Andrew Y. Ng, and Christopher Potts. Learning word vectors for sentiment analysis. In ACL, pp. 142–150, Portland, Oregon, USA, June 2011. URL https://aclanthology.org/P11-1015.

Sebastian Nagel. Cc-news. URL: http://web.archive.org/save/http://commoncrawl.org/2016/10/newsdatasetavailable, 2016.

Jianmo Ni, Jiacheng Li, and Julian McAuley. Justifying recommendations using distantly-labeled reviews and fine-grained aspects. In EMNLP, pp. 188–197, 2019.

F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. Scikit-learn: Machine learning in Python. Journal of Machine Learning Research, 12:2825–2830, 2011.

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.

Koustuv Sinha, Robin Jia, Dieuwke Hupkes, Joelle Pineau, Adina Williams, and Douwe Kiela. Masked language modeling and the distributional hypothesis: Order word matters pre-training for little. arXiv preprint arXiv:2104.06644, 2021.

Richard Socher, Alex Perelygin, Jean Wu, Jason Chuang, Christopher D. Manning, Andrew Ng, and Christopher Potts. Recursive deep models for semantic compositionality over a sentiment treebank. In EMNLP, pp. 1631–1642, Seattle, Washington, USA, October 2013. Association for Computational Linguistics. URL https://aclanthology.org/D13-1170.

Zhiqing Sun, Hongkun Yu, Xiaodan Song, Renjie Liu, Yiming Yang, and Denny Zhou. Mobiebert: a compact task-agnostic BERT for resource-limited devices. arXiv preprint arXiv:2004.02984, 2020.

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.
Yi Tay, Mostafa Dehghani, Dara Bahri, and Donald Metzler. Efficient transformers: A survey. *arXiv preprint arXiv:2009.06732*, 2020.

Yi Tay, Mostafa Dehghani, Jai Gupta, Dara Bahri, Vansi Arribandi, Zhen Qin, and Donald Metzler. Are pre-trained convolutions better than pre-trained transformers? *arXiv preprint arXiv:2105.03322*, 2021.

Iulia Turc, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Well-read students learn better: On the importance of pre-training compact models. *arXiv preprint arXiv:1908.08962*, 2019.

Sinong Wang, Belinda Z Li, Madian Khabsa, Han Fang, and Hao Ma. Linformer: Self-attention with linear complexity. *arXiv preprint arXiv:2006.04768*, 2020.

Moshe Wasserblat, Oren Pereg, and Peter Izsak. Exploring the boundaries of low-resource bert distillation. In *Proceedings of SustaiNLP: Workshop on Simple and Efficient Natural Language Processing*, pp. 35–40, 2020.

Ellery Wulczyn, Nithum Thain, and Lucas Dixon. Ex machina: Personal attacks seen at scale. In *WWW, WWW ’17*, pp. 1391–1399, Republic and Canton of Geneva, CHE, 2017. International World Wide Web Conferences Steering Committee. doi: 10.1145/3038912.3052591. URL https://doi.org/10.1145/3038912.3052591.

Weiqiu You, Simeng Sun, and Mohit Iyyer. Hard-coded gaussian attention for neural machine translation. *arXiv preprint arXiv:2005.00742*, 2020.

Manzil Zaheer, Guru Guruganesh, Kumar Avinava Dubey, Joshua Ainslie, Chris Alberti, Santiago Ontanon, Philip Pham, Anirudh Ravula, Qifan Wang, Li Yang, et al. Big bird: Transformers for longer sequences. In *NeurIPS*, 2020.

Xiang Zhang, Junbo Zhao, and Yann LeCun. Character-level convolutional networks for text classification. *Advances in neural information processing systems*, 28:649–657, 2015.