XtremeDistilTransformers: Task Transfer for Task-agnostic Distillation

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Abstract
While deep and large pre-trained models are the state-of-the-art for various natural language processing tasks, their huge size poses significant challenges for practical uses in resource constrained settings. Recent works in knowledge distillation propose task-agnostic as well as task-specific methods to compress these models, with task-specific ones often yielding higher compression rate. In this work, we develop a new task-agnostic distillation framework XtremeDistilTransformers that leverages the advantage of task-specific methods for learning a small universal model that can be applied to arbitrary tasks and languages. To this end, we study the transferability of several source tasks, augmentation resources and model architecture for distillation. We evaluate our model performance on multiple tasks, including the General Language Understanding Evaluation (GLUE) benchmark, SQuAD question answering dataset and a massive multi-lingual NER dataset with 41 languages.

1 Introduction
Large-scale pre-trained models have become the standard starting point for various natural language processing tasks (Devlin et al., 2019a). Several NLP tasks have achieved significant progress utilizing these pre-trained models reaching previously unattainable performance (Clark et al., 2020; Liu et al., 2019b). The size of these models have been also steadily growing to hundreds of millions (Devlin et al., 2019a; Yang et al., 2019) to billions of parameters (Raffel et al., 2019; Brown et al., 2020).

The huge size poses significant challenges for downstream applications in terms of energy consumption and cost of inference (Strubell et al., 2019). As such, it could be a deterrent to using them in practice limiting their usage in on-the-edge scenarios and under constrained computational training or inference budgets.

Several research directions have considered compressing large-scale models including work on pruning (Gordon et al., 2020), quantization (Han et al., 2016) and distillation (Sanh, 2019). Knowledge distillation, in particular, has shown strong results in pre-trained transformer-based language model compression. With knowledge distillation, we train a student network (with smaller capacity) to mimic the full output distribution of the teacher network (Hinton et al., 2015). Knowledge distillation has been applied to pre-trained language model compression in two different settings: (1) before task-specific fine tuning (i.e. task-agnostic distillation) or (2) after task-specific fine tuning (i.e. task-specific distillation).

Task-agnostic distillation (Sanh, 2019; Sun et al., 2019, 2020) has the advantage that the model needs to be distilled only once and can be reused for fine-tuning on multiple down-stream tasks. It also allows us to achieve speedup in both fine-tuning and inference. On the other hand, task-specific distillation (Tang et al., 2019; Jiao et al., 2019; Mukherjee and Hassan Awadallah, 2020) has been shown to achieve significantly higher compression rate and inference speedup (Fu et al., 2020; Mukherjee and Hassan Awadallah, 2020).

In this work, we first study the transferability of pre-trained models across several source tasks to select the optimal one for transfer. We then aim to create universally distilled models that can be used with any downstream task while leveraging the benefits of the techniques and augmentation resources developed for the source transfer task. We
show that distilled models that use task-specific data transfer to varying degrees and their transferability depends on choices of the source task, data augmentation strategy and distillation techniques.

**Contributions:** More specifically, this work makes the following contributions:

(a) Studies the transferability of several source tasks and augmentation resources for task-agnostic knowledge distillation.

(b) Develops a distillation framework to learn a massively compressed student model leveraging deep hidden representations and attention states from multiple layers of the teacher model with progressive knowledge transfer.

(c) Extensive experiments on several datasets in GLUE benchmark and for massive multilingual NER demonstrate the effectiveness of task and language transfer. Finally, we will release the task-agnostic checkpoints for the distilled models.

2 Exploring Tasks for Transfer

2.1 Role of Tasks for Distillation

*Task-specific* distillation assumes the presence of human labeled data to fine-tune the teacher for the underlying task and provide the student with corresponding logits for learning. Such techniques have shown massive compression (e.g., 7.5x compression in LRC-BERT (Fu et al., 2020) and 35x compression in XtremeDistil (Mukherjee and Hasan Awadallah, 2020)) without performance loss. An obvious disadvantage is the need to distil for each and every task which is resource-intensive.

In contrast, *task-agnostic* methods rely on objectives like masked language modeling (MLM) and representation transfer over unlabeled data. These do not require human labels allowing them to learn from massive amounts of text. This allows the model to retain general information applicable to arbitrary tasks, but results in much less compression (e.g., $2x^3$ in MiniLM (Wang et al., 2020), (Sanh, 2019) and TinyBERT (Jiao et al., 2019)).

This begs the question of whether we can use more specific tasks, other than language modeling, that can harness human labels to provide task-specific logits and representations, while also transferring well to arbitrary tasks. This would allow us to leverage the relative strength of both of the above families of techniques to obtain high compression rate of task-specific methods as well as wide applicability of task-agnostic ones.

2.2 Transferability of Tasks

In order to leverage task-specific distillation techniques, we need to select a source task that transfers well to other tasks such that: a model distilled for the source task can obtain a good performance on fine-tuning with labeled data from arbitrary target tasks. We perform the following analysis with the pre-trained teacher model with the assumption that the benefits will be transferred to the student model.

A recent work (Chen et al., 2020a) studies the notion of task transferability for BERT in the context of lottery ticket hypothesis (Frankle and Carbin, 2019). Specifically, the authors study if subnetworks obtained for one task obtained by network pruning transfer to other tasks and if there are universal subnetworks that train well for many tasks.

The authors observe that while masked language modeling (MLM) is the most universal task, there are other candidate tasks like natural language inference and question-answering that allow us to transfer meaningful representations to other tasks.

**Task transfer.** Consider a pre-trained neural network model (e.g., BERT) $f(x; \theta)$ with encoder parameters $\theta \in \mathbb{R}^{d_1}$. Given a source task $S$ with ground-truth labeled data $D_S = \{x, y\}$, we first fine-tune the pre-trained model $f(x; \theta, \gamma_S)$ by adding task-specific classification parameters $\gamma_S \in \mathbb{R}^{d_2}$. We now extract the encoder $f(x; \theta_S)$ where the parameters $\theta_S \in \mathbb{R}^{d_1}$ have been adapted to the source task ($\theta \rightarrow \theta_S$). Now, given a target task $T$ with labeled data $D_T$, we further fine-tune the encoder $f(x; \theta_S, \gamma_T)$ where $\gamma_T \in \mathbb{R}^{d_2}$ represents task-specific parameters for the target task.

**Selection criteria for the best source task.** Given a set of source $S$ and target $T$ tasks, consider $\text{eval}(s \in S \rightarrow t \in T)$ to be the performance of a pre-trained language model that is adapted from $s$ to $t$, measured with some evaluation metric (e.g., accuracy, F1). We define the best source transfer task as $\argmax_{s \in S} \frac{1}{|T|} \sum_{t \in T} \text{eval}(s \rightarrow t)$ depicting the best transfer performance obtained on an average on transferring a pre-trained model from the source to a set of different target tasks.

While this definition simplifies the transfer
Table 1: Transfer performance on fine-tuning BERT on labeled data for several source tasks in the rows (e.g., MNLI), extracting the encoder (e.g., MNLI-BERT) and further fine-tuning on labeled data for several target tasks in the columns. We observe MNLI to obtain the best performance for task transfer on an average.

| Task       | MRPC | MNLI  | RTE  | QQP  | QNLI | SST-2 | SQuADv1 | Avg  |
|------------|------|-------|------|------|------|-------|---------|------|
| #Labels    | 3.7K | 393K  | 2.5K | 364K | 108K | 67K   | 87K     | -    |
| BERT       | 83.8 | 84.4  | 66.8 | 91.2 | 91.4 | 92.2  | 88.3    | 85.4 |
| MNLI-BERT  | 88.2 | 84.2  | 79.1 | 91.1 | 91.1 | 93.6  | 87.2    | 87.8 |
| QNLI-BERT  | 87.0 | 84.8  | 73.3 | 91.6 | 91.3 | 93.4  | 87.6    | 85.1 |
| SST2-BERT  | 81.6 | 84.7  | 66.1 | 91.1 | 91.3 | 93.4  | 87.6    | 85.1 |
| SQuADv1-BERT | 86.3 | 84.6  | 69.7 | 87.1 | 91.6 | 92.9  | 88.3    | 85.4 |

problem ignoring task difficulty (e.g., ternary MNLI is harder than binary SST), domain overlap (SQuAD and QNLI are both question-answering datasets), task setup (e.g., span extraction in SQuAD and pairwise-classification in MNLI) and variable amount of training labels per task, we defer a more controlled study of this problem as future work.

Candidate tasks for transfer. We consider a sub-set of source tasks from lottery ticket hypothesis for BERT (Chen et al., 2020a) for which transfer performance is at least as high as same-task performance on at least two target tasks. We ignore MLM since the pre-trained encoder (BERT) is intrinsically trained with MLM objective that provides no additional information in our transfer setup.

Transfer evaluation. Table 1 shows the performance of pre-trained BERT-base with task transfer, where each row depicts a source task $S$ and each column represents the target task $T$. We observe that MNLI as the source task, followed by QNLI, has the best performance on an average on transferring to several target tasks, especially those with limited training labels for fine-tuning. Similar improvements with MNLI for tasks like RTE (textual entailment) and MRPC (paraphrase) have been reported in recent work like RoBERTa (Liu et al., 2019b). Therefore, we adopt MNLI as the source task for transfer distillation and evaluate its effectiveness for several target tasks and languages.

2.3 Transfer Set for Knowledge Distillation

Task-agnostic methods can learn from large unlabeled general-purpose text using self-supervision objectives like MLM. Task-specific distillation, on the other hand, rely on large-scale task-specific transfer data that is often difficult to obtain for many tasks. Prior works show large-scale task-specific transfer data to be instrumental in minimizing the performance gap of the teacher and student (Turc et al., 2019; Mukherjee and Has-san Awadallah, 2020). However, these works primarily explore instance-classification tasks like sentiment classification (e.g., IMDB and SST2) or topic classification (e.g., AG News and Dblpedia) with readily available in-domain transfer data. For example, sentiment classification in IMDB can benefit from large amounts of unlabeled user reviews from the forum. However, this is difficult to obtain for pair-wise classification tasks like NLI. Additionally, NLI being a ternary classification task (entail / contradict / neutral) requires a transfer set with a similar label distribution for effective transfer. To address these issues, we explore techniques to automatically generate large-scale task-specific transfer sets leveraging a very large bank of web sentences from Common Crawl in Section 4.1.

3 Distillation Framework

Overview. Given a pre-trained model fine-tuned on the source task as teacher, our objective is to distil its knowledge in a compressed (both in terms of width and depth) student. Given a wide teacher and a narrow student, we employ embedding factorization to align their widths for knowledge transfer. Given a deep teacher and a shallow student, we align all the layers of the student to the topmost layers of the teacher. To this end, we transfer both the hidden representations as well as attention states from multiple layers of the teacher to the student with progressive knowledge transfer. The above techniques in combination allow us to transfer knowledge from any teacher to any student of arbitrary architecture. Finally, XtremeDistilTransformers supports for both task and language transfer (refer to Section 4.4) in contrast to many prior work. Table 2 contrasts XtremeDis-
Table 2: Contrasting XtremeDistilTransformers with state-of-the-art task-agnostic distilled models. XtremeDistilTransformers leverages embedding factorization, hidden representations and attention states of the teacher from multiple layers with progressive knowledge transfer for distillation while accommodating arbitrary student architecture and languages.

| Embedding Factorization | Hidden Representation | Attention Multi-layer Transfer | Student-arch. -agnostic | Multi-lingual |
|-------------------------|-----------------------|-------------------------------|------------------------|--------------|
| DistilBERT              |                       |                               |                        |              |
| TinyBERT                |                       |                               |                        |              |
| MiniLM                  |                       |                               |                        |              |
| MobileBERT              | ✓                     | ✓                             | ✓                      | ✓            |
| XtremeDistilTransformers| ✓                     | ✓                             | ✓                      | ✓            |

tilTransformers against existing distillation techniques, namely, DistilBERT (Sanh, 2019), TinyBERT (Jiao et al., 2019), MiniLM (Wang et al., 2020) and MobileBERT (Sun et al., 2020).

**Input Representation.** XtremeDistilTransformers uses the tokenizer and special tokens as used in the teacher model. For instance, it uses Wordpiece tokenization (Wu et al., 2016) with a fixed vocabulary $V$ (e.g., $30k$ tokens) for distilling BERT and adds special symbols “[CLS]” and “[SEP]” to mark the beginning and end of a text sequence respectively.

**Teacher model.** Given pre-trained models with variable performance across tasks, we want to choose the best teacher for the best source transfer task (i.e. MNLI). We experiment with base and large versions of BERT (Devlin et al., 2019b) and Electra (Clark et al., 2020) as teachers. Table 3 shows a comparison of their performance and parameters on MNLI. Given the same parameter complexity, we find Electra to be the best on MNLI.

Table 3: Performance of fine-tuning pre-trained teacher models of different sizes on the MNLI task.

| Model            | Params (MM) | Accuracy |
|------------------|-------------|----------|
| BERT-Base        | 109         | 84.24    |
| Electra-Base     | 109         | 88.21    |
| BERT-Large       | 335         | 87.11    |
| Electra-Large    | 335         | 90.73    |

**Student model.** We compare the performance of state-of-the-art distilled models in terms of parameters, compression and performance gap (after distillation) with respect to the teacher (reported in Table 4). We observe MiniLM (Wang et al., 2020) to have the closest performance to the teacher BERT. Correspondingly, we choose miniature versions of MiniLM (23 MM and 14 MM parameters) as candidate students. We investigate different student initialization strategies (including initialization with a task-agnostic distilled model) and show that their performance can be improved further in the XtremeDistilTransformers framework. We also study the trade-off between different architectural aspects (parameters, layers, attention heads and hidden dimension) against its performance.

**In the following section, superscript $T$ always represents the teacher and $S$ denotes the student.**

Table 4: Comparing distilled models from prior work based on average GLUE score, parameters (MM) and performance gap with respect to the teacher.

| Models         | GLUE Score | Params (MM) | %Gap |
|----------------|------------|-------------|------|
| BERT-Base      | 81.5       | 109         | -    |
| DistilBERT     | 75.2       | 66          | 7.73 |
| BERT-Truncated | 76.2       | 66          | 6.50 |
| TinyBERT       | 79.1       | 66          | 2.94 |
| MiniLM         | 80.4       | 66          | 1.35 |

3.1 Word Embedding Factorization

Our student and teacher model consist of the word embedding layer with embedding matrices $W^S \in \mathbb{R}^{|V| \times d^S}$ and $W^T \in \mathbb{R}^{|V| \times d^T}$, where $d^S < d^T$ depicting a thin student and a wide teacher.

A large number of parameters reside in the word embeddings of pre-trained models. For instance, multilingual BERT with WordPiece vocabulary of $V = 110K$ tokens and embedding dimension of $D = 768$ contains $92MM$ word embedding parameters. We use a dimensionality reduction algorithm, namely, Singular Value Decomposition (SVD) to project the teacher word embeddings of dimension $\mathbb{R}^{|V| \times d^T}$ to a lower dimensional space $\mathbb{R}^{|V| \times d^S}$. Given the teacher word embedding matrix of dimension $\mathbb{R}^{|V| \times d^T}$, SVD finds the best $d^S$ dimensional representation that minimizes sum of
The student and teacher models consist of $L^S$ and $L^T$ repeated transformer blocks, where $L^S < L^T$. Considering an input sequence of $n$ tokens $x = \{x_1, x_2, \ldots x_n\}$, the token embedding $W$ is added to the position $PE$ and segment $SE$ embeddings as $z_i(x_i) = W(x_i) + PE(i) + SE(i)$. The input to the network is given by $H^0 = [z_1, z_2, \ldots z_{|x|}]$. In case of the student, the token embedding is obtained from the SVD-decomposed token embedding of the teacher model as $W^S$, whereas the position and segment embeddings are learnable embeddings of dimension $d^S$. Transformer blocks repeatedly compute hidden state representations from the output of the previous layer, where hidden states from the $l$th layer of the teacher and student are given by,

$$H^T_l = \text{Transformer}_T^T(H^T_{l-1}), l \in [1, \ldots L^T]$$  
(1)

$$H^S_l = [h^S_{l,1}, h^S_{l,2}, \ldots, h^S_{l,|x|}], l \in [1, 2 \ldots L^T]$$  
(2)

$$H^S_l = \text{Transformer}_T^S(H^S_{l-1}), l \in [1, \ldots L^S]$$  
(3)

$$H^S_l = [h^S_{l,1}, h^S_{l,2}, \ldots, h^S_{l,|x|}], l \in [1, 2 \ldots L^S]$$  
(4)

3.2 Hidden Layer Representations

Transformers view the input representation as a set of key-value pairs $\{K, V\}$ of dimension same as input sequence length $|x|$. Each of the key and values are obtained from hidden state representations of the encoder. Transformers compute the weighted sum of the values, where the weight for each value is obtained by dot-product of the query with the key values as $\text{Attention}(Q, K, V) = \text{softmax}(\frac{Q^T K}{\sqrt{n}})V$. In the context of multi-head attention with several attention heads, the above is computed as follows. Consider $A_{l,a}, a \in [1, 2, \ldots AH]$, where $AH$ is the number of attention heads of the teacher and student. Consider the query, key and values obtained by $Q_{l,a} = H_{l-1}^S W^S, K_{l,a} = H_{l-1}^T W^T, V_{l,a} = H_{l-1}^T W^T$.

Each multi-head attention state of dimension $|x| \times |x|$ from the $l$th layer is given by:

$$A_{l,a}(Q_{l,a}, K_{l,a}, V_{l,a}) = \text{softmax}(\frac{Q_{l,a}^T K_{l,a}}{\sqrt{n}})V_{l,a}$$  
(5)

Since our teacher and student are both transformers with similar multi-head attention mechanism, we obtain the corresponding attention states:

$$A^T_{l,a}, l \in [1, 2, \ldots L^T], a \in [1, 2, \ldots AH]$$  
(6)

$$A^S_{l,a}, l \in [1, 2, \ldots L^S], a \in [1, 2, \ldots AH]$$  
(7)

3.3 Multi-head Self-attention

Multi-layer hidden state transfer. We leverage deep representations from multiple layers of the teacher that capture different forms of features to aid the student in learning. In order to align multiple layers of the student to those of the teacher as a form of mimic learning, we train the student with the following multi-layer representation loss objective. Given a deep teacher with $L^T$ layers and a shallow student with $L^S$ layers, where $L^T > L^S$, we align the last $L^S$ layers of each model. Given a wide teacher and narrow student with corresponding dimensions $d^T > d^S$, we perform a linear transformation to upscale and align the corresponding hidden state representations of the student such that $H^S_l(x) = W^f \cdot H^T_l(x) + b^f$, where $W^f \in R^{d^T \times d^S}$ is the transformation matrix, $b^f \in R^{d^T}$ is the bias.

$$\text{layer loss} = -\sum_{t'=L^S}^{L^T} \sum_{t=1}^{L^S} \frac{|H^T_l(x_t) - H^S_l(x_{t'})|^2}{2 \cdot L^S \cdot |x|}$$  
(8)

Multi-layer attention transfer. We also leverage the self-attention signals from the different teacher layers to guide the student. Similar to previous loss objective, we align the attention states of the last $L^S$ layers of the teacher and student from multiple attention heads with the following objective:

$$\text{attnt loss} = -\sum_{t'=L^S}^{L^T} \sum_{a=1}^{AH} \frac{|A^H_{l,a}(x_t) - A^T_{l,a}(x_{t'})|^2}{2 \cdot L^S \cdot |AH| \cdot |x|}$$  
(9)

Task-specific logit transfer. Given hidden state representations from last layer $L^S$ and $L^T$ of the student and teacher, we can obtain the task-specific logits for source transfer task (e.g., MNLI) from:

$$z^S_l(x) = H^S_{L^S}(x) \cdot W^S$$  
(10)

$$z^T_l(x) = H^T_{L^T}(x) \cdot W^T$$  
(11)
where $W^S \in R^{dS \times C}$, $W^T \in R^{dT \times C}$, and $C$ is the number of classes. The prior computations of multi-layer hidden state and attention loss are performed over large amounts of unlabeled transfer data from the source task. To explicitly adapt these models to the source task, we leverage some amount of source-task-specific labeled data to align the logits of the teacher and student. To this end, we minimize the following task-specific logit loss:

$$\text{logit}_{l,a,x} = \frac{1}{2} || z^S(x) - z^T(x) ||^2 \quad (12)$$

Finally, we fine-tune the student on task-specific labeled data with the cross-entropy loss:

$$\text{ce}_{l,a,x} = \sum_{c=1}^{C} I(x, c) \log \text{softmax}(z^S_c(x)) \quad (13)$$

where $I(x, c)$ is a binary indicator (0 or 1) if class label $c$ is the correct classification for $x$ and $z^S_c(x)$ is the predicted logit corresponding to class $c$.

### Progressive knowledge transfer

Multi-layer joint optimization of the above loss functions bears the risk of error propagation from lower layers impacting the knowledge transfer from upper layers. Recent works (Sun et al., 2020; Mukherjee and Hassan Awadallah, 2020) demonstrate the benefit of progressive knowledge transfer by gradual freezing and unfreezing of neural network layers for mitigation. We adopt a similar principle in our work with the training recipe in Algorithm 1.

Instead of jointly optimizing all the loss functions, we first minimize the multi-layer representation and attention loss to align the last $L^S$ layers of the teacher and student. Then we freeze the student encoder, learn task-specific parameters by optimizing task-specific logit loss and cross-entropy loss. For any loss function, we freeze the parameters learned from the previous stage, learn new parameters (e.g., softmax for task-specific loss) introduced by a new loss function, and finally perform end-to-end fine-tuning based on cross-entropy loss. Error propagation from lower layers is mitigated by freezing lower part of the network while learning additional task-specific parameters.

### Algorithm 1 Progressive knowledge transfer

**Input:** (a) Transformer teacher model (e.g., BERT) fine-tuned on hard labels on task $S$ (e.g., MNLI). (b) Initial pre-trained student model (e.g., MiniLM)

1. Optimize student params $\theta = \{H_l^S\}_{l=1}^{L^S}, \{A_l^{i,a}\}_{a=1}^{A_l}$ optimizing losses in Eqn. 8 and 9
2. Freeze $\theta$ and optimize task-specific parameters $W^S$ optimizing logit loss in Eqn. 12 with soft labels
3. Update $\theta$ and $W^S$ optimizing logit loss in Eqn. 12 with soft labels
4. Freeze $\theta$ and optimize task-specific parameters $W^S$ optimizing cross-entropy loss in Eqn. 13 with hard labels
5. Update $\theta$ and $W^S$ optimizing cross-entropy loss in Eqn. 13 with hard labels

### 4 Experiments

We first explore several augmentation resources for knowledge transfer. Then we compare distillation performance and compression rate of XtremeDistilTransformers with existing models on GLUE (Wang et al., 2018), SQuAD (Rajpurkar et al., 2016) and massive multilingual NER on 41 languages in WikiAnn (Pan et al., 2017). All experiments are performed on 4 Tesla V-100 GPUs.

| Model       | Params | Aug. Data | #Samples | Acc  |
|-------------|--------|-----------|----------|------|
| Electra     | 109    | -         | -        | 88.12|
| Xtreme      | 22     | MNLI      | 392K     | 82.56|
| DistilTransf. |      | SNLI      | 550K     | 82.57|
|             |        | PAWS      | 695K     | 82.58|
|             |        | ParaNMT   | 5.4MM    | 83.70|
|             |        | SentAug   | 4.3MM    | 84.52|

### 4.1 Unlabeled Augmentation Data

Given the best source transfer task as MNLI, we choose the best teacher from Table 3 as Electra and the best student from Table 4 as MiniLM for initializing the student model in XtremeDistilTransformers. We explore the following augmentation resources:

(a) **MNLI** (Williams et al., 2018): We use training data as the transfer set, ignoring the labels.

(b) **SNLI** (Bowman et al., 2015) is similar to MNLI with human-written English sentence-pairs categorized in three classes (entail / contradict / neutral).

(c) **PAWS** (Zhang et al., 2019): This contains human-labeled pairs generated from both word swapping and back translation which feature the importance of modeling structure, context, and word order for identifying paraphrases.

(d) **ParaNMT** (Wieting and Gimpel, 2018) consists of a large number of English-English senten-
Table 6: Comparing the performance of distilled models DistilBERT (Sanh, 2019), TinyBERT (Jiao et al., 2019), MiniLM (Wang et al., 2020) and XtremeDistilTransformers on the development set for several GLUE tasks. R denotes reported published results and HF denotes the performance obtained with our HuggingFace implementations.

| Models                  | Params | Speedup | MNL1  | QNLI  | QQP   | RTE   | SST   | MRPC  | SQuADv2 | Avg |
|------------------------|--------|---------|-------|-------|-------|-------|-------|-------|---------|-----|
| BERT (R)               | 109    | 1x      | 84.5  | 91.7  | 91.3  | 68.6  | 93.2  | 87.3  | 76.8    | 84.8|
| BERT-Trun (R)          | 66     | 2x      | 81.2  | 87.9  | 90.4  | 65.5  | 90.8  | 82.7  | 69.9    | 81.2|
| DistilBERT (R)         | 66     | 2x      | 82.2  | 89.2  | 88.5  | 59.9  | 91.3  | 87.5  | 70.7    | 81.3|
| TinyBERT (R)           | 66     | 2x      | 83.5  | 90.5  | 90.6  | 72.2  | 91.6  | 88.4  | 73.1    | 84.3|
| MiniLM (R)             | 66     | 2x      | 84.0  | 91.0  | 91.0  | 71.5  | 92.0  | 88.4  | 76.4    | 84.9|
| MiniLM (R)             | 22     | 5.3x    | 82.8  | 90.3  | 90.6  | 68.9  | 91.3  | 86.6  | 72.9    | 83.3|
| BERT (HF)              | 109    | 1x      | 84.4  | 91.4  | 91.2  | 66.8  | 93.2  | 83.8  | 74.8    | 83.7|
| MiniLM (HF)            | 22     | 5.3x    | 82.7  | 89.4  | 90.3  | 64.3  | 90.8  | 84.1  | 71.5    | 81.9|
| XtremeDistilTransf. (HF)| 22    | 5.3x    | 84.5  | 90.2  | 90.4  | 77.3  | 91.6  | 89.0  | 74.4    | 85.3|
| XtremeDistilTransf. (HF)| 14   | 9.4x    | 81.8  | 86.9  | 89.5  | 74.4  | 89.9  | 86.5  | 63.0    | 81.7|

4.2 Distillation Performance in GLUE

Given a model distilled from MNLI, we extract the encoder $f(x; \theta_S)$, add task-specific parameters $\gamma_T$ and fine-tune $f(x; \theta_S, \gamma_T)$ on labeled data for several tasks with results in Table 6. We report results from both published works and our results built on top of HuggingFace (HF) (Wolf et al., 2020).

We observe XtremeDistilTransformers to obtain the best performance on an average closely followed by MiniLM and TinyBERT. Since the performance of pre-trained models vary with careful calibrations, in our implementations with HF default hyper-parameters (marked as HF in Table 6), we observe XtremeDistilTransformers initialized with MiniLM to outperform MiniLM by 4.3% given same hyper-parameters and random seeds, and outperform BERT by 2% with 5.3x inference speedup. In a similar setup, the most compressed version of XtremeDistilTransformers with 14MM parameters performs within 2.4% of BERT with 9.4x inference speedup.

4.3 What is more important for distillation, bigger or better teacher?

Table 7 shows the performance of XtremeDistilTransformers distilled from teachers of different sizes and pre-training schemes. Refer to Table 3 for teacher performances on MNLI. We observe that a better teacher (e.g., Electra-base > BERT-base, and Electra-large > BERT-large) leads to a better student. However, we also observe teacher model complexity to play a significant role in distillation. For instance, although BERT-large is better than Electra-base, we observe a slight degradation in distillation performance when distilled from BERT-large with 3x parameters compared to...
Electra-base — given the student model of same capacity. We conjecture this to be an artifact of model capacity as it becomes increasingly difficult for a shallow student to mimic a much bigger and deeper teacher.

### 4.4 Transfer Distillation for Massive Multilingual Named Entity Recognition

We experiment with XtremeDistilTransformers distilled from a monolingual task (MNLI-English) and adapt it for the multilingual setting to perform joint named entity recognition (NER) on 41 languages.

Consider XtremeDistilTransformers encoder with hidden layers \( \{H_t\} \in \mathcal{R}^{|x| \times d} \), attention states \( \{A_{t,a}\} \in \mathcal{R}^{|x| \times |x|} \) and word embeddings \( \mathcal{W} \in \mathcal{R}^{|V| \times d} \), where \(|x|\), \(d\) and \(|V|\) denote sequence length, embedding dimension and vocabulary size. The only factor dependent on the vocabulary size is the word embedding matrix \( \mathcal{W} \).

In principle, we can retain learned hidden layers \( \{H_t\} \) and attention states \( \{A_{t,a}\} \), and only adapt word embeddings to transfer to other languages with different vocabulary.

To this end, we leverage word embeddings from multilingual BERT for target adaptation. Specifically, we use word embedding factorization using Singular Value Decomposition (SVD) (as outlined in Section 3.1) to project \( \mathcal{R}^{|V| \times d_T} \rightarrow \mathcal{R}^{|V| \times d_S} \) from the mBERT word embedding space to that of XtremeDistilTransformers, where \( d_T \) and \( d_S \) represent the embedding dimension of the teacher and student.

Now, we **switch word embedding parameters** in XtremeDistilTransformers (distilled from English) with the SVD-decomposed mBERT word embeddings while **retaining prior encoder parameters** \( \{H_t\}, \{A_{t,a}\} \) and further distil it on the multilingual WikiAnn data from 41 languages in WikiAnn (Pan et al., 2017). Table 8 compares the performance of XtremeDistilTransformers against multilingual models MMNER (Rahimi et al., 2019) and XtremeDistil (Mukherjee and Hassan Awadallah, 2020). We observe the most compressed version of XtremeDistilTransformers with 14 million parameters to obtain a similar performance to XtremeDistil but with \( 2x \) additional compression and within \( 4\% \) F1 of mBERT. Note that, in contrast to XtremeDistil, we transfer encoder parameters from a monolingual distilled model. With progressive knowledge transfer, we further freeze the word embedding parameters and fine-tune the encoder parameters on downstream task.

### 4.5 Ablation Study

Table 9 shows ablation results on removing different components from XtremeDistilTransformers for multilingual NER. We observe performance degradation on removing multi-layer attention and hidden state losses from distillation objective (a and b). When we remove both multi-layer components in (b), we use hidden-states from only last layer of the teacher. This also demonstrates the benefit of multi-layer distillation. We observe significant degradation without embedding factorization using SVD (c) i.e. the student uses monolingual (English) word embeddings and vocabulary. Without progressive transfer, and fine-tuning model end-to-end result in some degradation (d). Finally, we observe that distilling a student model from scratch (i.e. randomly initialized) without
transferring multilingual word embeddings or encoder parameters (e) result in significant performance loss, thereby, demonstrating the benefit of transfer distillation.

Table 1 in Appendix shows the variation in performance of XtremeDistilTransformers with different architecture (number of attention heads, hidden layers and embedding dimension), compression and performance gap against multilingual BERT — with the smallest version obtaining 87x encoder compression (or, 1 million encoder parameters) with 9% F1 gap against mBERT for NER on 41 languages.

Table 9: Ablation of XtremeDistilTransformers (22MM params) on WikiAnn for NER on 41 languages.

| Distillation Features | F1  |
|-----------------------|-----|
| All: w/ multi-layer attn. & hidden state, embed. factor, w/ freezing | 89.38 |
| (a) w/o multi-layer attn. | 87.86 |
| (b) w/o multi-layer attn., w/o hidden state | 87.61 |
| (c) w/o embed. factor. (monoling. vocab.) | 78.90 |
| (d) w/ embed. factor & w/o freezing | 87.76 |
| (e) init. from scratch | 83.40 |

5 Related Work

**Distillation.** Prior works on task-specific distillation (Liu et al., 2019a; Zhu et al., 2019; Tang et al., 2019; Turc et al., 2019) leverage soft logits from teachers for distilling students. (Sun et al., 2019; Sanh, 2019; Aguilar et al., 2019) leverage teacher representations as additional signals. These methods are often constrained by embedding dimension, width and depth of models. Some recent works leverage embedding (Sun et al., 2020) and shared word (Zhao et al., 2019) projection to address these limitations. Task-agnostic methods like (Jiao et al., 2019; Wang et al., 2020; Sun et al., 2020) leverage hidden states and attention states from teachers but not task-specific logics (refer to Table 2 for a contrast). Finally, another line of work in model compression use quantization (Gong et al., 2014), low-precision training and network pruning (Han et al., 2016) to reduce the memory footprint.

**Augmentation.** Unsupervised contrastive learning techniques like SimCLR (Chen et al., 2020b,c) leverage semantic equivalence of images to train models to differentiate between images and perturbed versions while obtaining parity with fully-supervised models. Similarly UDA (Xie et al., 2019) leverages consistency learning between texts and backtranslations to improve few-shot text classification. Finally, self-training and pretraining with SentAugment (Du et al., 2020) improves text classification with task-specific augmentation.

6 Conclusions

We develop a novel distillation framework XtremeDistilTransformers to leverage the advantages of task-specific distillation for high compression as well as wide applicability of task-agnostic ones. We study transferability of tasks for pretrained models and demonstrate NLI to be a great source task to obtain a better teacher that transfers well across several tasks. This, in turn, is used to distil a better student obtaining significant improvements over state-of-the-art task-agnostic distilled models over several tasks. Finally, we demonstrate techniques to obtain large-scale task-specific augmentation data from the web to facilitate this knowledge transfer.

7 Appendix

**Hyper-parameters.** XtremeDistilTransformers is built over HuggingFace with most of the default hyper-parameters. Please refer to the ReadMe for the attached code for details.

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| # Layer | # Attn | # Dim | F1   | #Enc. | #Word Emb. | #Enc Compress. | F1 Gap(%) |
|---------|--------|-------|------|-------|-----------|----------------|-----------|
| 2       | 2      | 128   | 82.05| 1     | 15        | 87             | 11.49     |
| 6       | 12     | 192   | 83.29| 8     | 23        | 11             | 10.15     |
| 6       | 12     | 216   | 83.40| 9     | 26        | 10             | 10.03     |
| 2       | 4      | 256   | 84.30| 2     | 31        | 44             | 9.06      |
| 4       | 2      | 128   | 84.43| 1     | 15        | 87             | 8.92      |
| 6       | 2      | 128   | 85.44| 2     | 15        | 44             | 7.83      |
| 4       | 4      | 256   | 86.26| 3     | 31        | 29             | 6.95      |
| 4       | 12     | 312   | 86.69| 5     | 37        | 17             | 6.48      |
| 4       | 12     | 312   | 86.74| 5     | 37        | 17             | 6.43      |
| 6       | 4      | 256   | 86.82| 5     | 31        | 17             | 6.34      |
| 6       | 12     | 384   | 88.00| 11    | 46        | 8              | 5.07      |
| 12      | 12     | 768   | 92.70| 87    | 92        | 1              | 0         |

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