**AutoDistil**: Few-shot Task-agnostic Neural Architecture Search for Distilling Large Language Models

**Abstract**

Knowledge distillation (KD) methods compress large models into smaller students with manually-designed student architectures given pre-specified computational cost. This requires several trials to find a viable student, and further repeating the process for each student or computational budget change. We use Neural Architecture Search (NAS) to automatically distill several compressed students with variable cost from a large model. Current works train a single SuperLM consisting of millions of subnetworks with weight-sharing, resulting in interference between subnetworks of different sizes. Our framework AutoDistil addresses above challenges with the following steps: (a) Incorporates inductive bias and heuristics to partition Transformer search space into $K$ compact sub-spaces ($K=3$ for typical student sizes of base, small and tiny); (b) Trains one SuperLM for each sub-space using task-agnostic objective (e.g., self-attention distillation) with weight-sharing of students; (c) Lightweight search for the optimal student without re-training. Fully task-agnostic training and search allow students to be reused for fine-tuning on any downstream task. Experiments on GLUE benchmark against state-of-the-art KD and NAS methods demonstrate AutoDistil to outperform leading compression techniques with up to 2.7x reduction in computational cost and negligible loss in task performance.

**1 Introduction**

While large pre-trained language models (e.g., BERT [Devlin et al., 2019], GPT-3 [Brown et al., 2020]) are effective, their huge size poses significant challenges for downstream applications in terms of energy consumption and cost of inference [Strubell et al., 2019], limiting their usage in on the edge scenarios and under constrained computational inference budgets. Knowledge distillation [Wang et al., 2020a], [Sanh et al., 2019], [Jiao et al., 2020], [Sun et al., 2020] has shown strong results in compressing pre-trained language models, where we train a small student model to mimic the full output distribution of the large teacher model. However, these works require pre-specification of the student model architecture and corresponding computational cost (e.g., number of parameters, FLOPs) before they can perform distillation. This poses two significant challenges: (i) since the architectures are hand-engineered, it requires several trials to come up with viable architectures and to define a myriad of hyper-parameters (e.g., number of layers, hidden dimension, number of attention heads, etc.); (ii) one has to re-run the distillation process with any change in specification for either the student architecture or the desired computational cost for using the student in a target environment.
Few-shot Task-agnostic Neural Architecture Search

AutoDistil uses few-shot task-agnostic Neural Architecture Search to distill several compressed students with variable #FLOPs (x-axis) from $K=3$ SuperLMs (corresponding to each point cloud) trained on $K$ sub-spaces of Transformer search space. Each student (blue dot) extracted from the SuperLM is fine-tuned on MNLI with accuracy on y-axis. The best student from each SuperLM is marked in red. Given any state-of-the-art distilled model, AutoDistil generates a better candidate with less #FLOPs and improved task performance from corresponding search space.

To address these challenges, Neural Architecture Search (NAS) provides a natural solution to automatically search through a large space of candidate models while accounting for often conflicting objectives like computational cost vs. task performance. The dominant paradigm for NAS comprises of two main components: (a) Super model training which combines all possible architectures into a single graph and jointly training them via weight-sharing; and (b) Searching for optimal architecture from Super model with the best possible accuracy on a downstream task, satisfying a user-specified latency constraint for a specific device.

NAS has demonstrated promising results in some recent explorations in the natural language understanding domain. However, these works suffer from the following drawbacks.

(D1) All of these works train one single large Super Language Model (SuperLM) consisting of millions of diverse student architectures. This results in some undesirable effects of co-adaptation like conflicts in weight-sharing where bigger student models converge faster in contrast to the smaller ones converging slower. Also, a single SuperLM may not have sufficient capacity to encode a large search space. As a result, these works use a multi-stage training process, where they first conduct NAS to identify candidate student models and then perform further pre-training and knowledge distillation of the candidates.

(D2) Additionally, these works are not fully task-agnostic. For instance, performs task-agnostic SuperLM training, but task-specific search for the student with proxy tasks like SQuAD and MNLI.

We address these challenges with few-shot task-agnostic NAS consisting of the following three steps.

(S1) **Search space design.** We partition the Transformer search space into $K$ sub-spaces ($K = 3$ in our work for typical student model sizes like base, small and tiny) considering important architectural hyper-parameters like the network depth, width and number of attention heads. We further leverage inductive bias and heuristics to limit the number of student architectures in each sub-space.

(S2) **Task-agnostic SuperLM training.** We train $K$ SuperLM, one for every sub-space. This allows each SuperLM more capacity to encode a sub-space as opposed to a single large one. We train each SuperLM with a task-agnostic objective like deep self-attention distillation, where we transfer knowledge from the self-attention module (including keys, queries and values) of a pre-trained teacher (e.g., BERT) to the student and use weight-sharing to train the SuperLM.

(S3) **Lightweight optimal student search.** We obtain optimal student(s) directly from well-trained SuperLM(s) without any re-training. We propose two strategies to find the optimal student with task-agnostic or task-proxy search.

Overall, our contributions can be summarized as:

1. We develop a few-shot task-agnostic Neural Architecture Search framework to distill several compressed models with variable computational cost. We address the challenge of co-adaptation and weight-sharing of compressed models by few-shot NAS and a compact search space design.
Table 1: Comparing AutoDistil with existing KD and NAS methods on aspects as task-agnostic training and search; generating multiple students with variable compression cost; single-stage training without additional adaptation; SuperLM training with compact search space to mitigate interference (\(P\) denotes partial).

| Method           | Task-agnostic | Variable Compression | NAS | Single SuperLM | Compact | Training | Search |
|------------------|---------------|----------------------|-----|----------------|---------|----------|--------|
| BERT-PKD         | ×             | ×                    |     |                |         |          |        |
| SparseBERT       | ×             | ×                    |     |                |         |          |        |
| DistilBERT       | ✓             | ✗                    |     |                | ✗       | One-shot | ✗      |
| TinyBERT         | ✓             | ✗                    |     |                | ✗       | One-shot | ✗      |
| MOBILEBERT       | ✓             | ✗                    |     |                | ✗       | One-shot | ✗      |
| MINILM           | ✓             | ✗                    |     |                | ✗       | One-shot | ✗      |
| DynaBERT         | ✗             | ✓                    |     |                |         | Few-shot | ✗      |
| NAS-BERT         | \(P\)         | ✓                    |     |                | ✗       | One-shot | ✗      |
| AutoTinyBERT     | \(P\)         | ✓                    |     |                | ✗       | One-shot | ✗      |
| AutoDistil       | ✓             | ✓                    |     |                | ✓       | Few-shot | ✓      |

(2) We use self-attention distillation to train the SuperLM and demonstrate this to be better than masked language modeling objective for task-agnostic SuperLM training.

(3) We perform extensive experiments in the GLUE benchmark where our method achieves 62.4% reduction in computational cost and 59.7% reduction in model size over state-of-the-art task-agnostic distillation methods with similar downstream task performance, with a comprehensive summary of the results in Figure 1.

2 Background

We present an overview of Transformers [Vaswani et al., 2017], especially its two main sub-layers, multi-head self-attention (MHA) and feed-forward network (FFN). Transformer layers are stacked to encode contextual information for input tokens as:

\[
X^l = \text{Transformer}(X^{l-1}), \quad l \in [1, L]
\]  

where \(L\) is the number of Transformer layers, \(X^l \in \mathbb{R}^{s \times d_{\text{hid}}}\), \(s\) is the sentence length, and \(d_{\text{hid}}\) is the hidden dimension. In the following, we omit the layer indices for simplicity.

**Multi-Head Self-Attention (MHA).** Given the previous Transformer layer’s output \(X\), the MHA output is given as:

\[
Q_h, K_h, V_h = XW_h^Q, XW_h^K, XW_h^V,
\]

\[
\text{Attention}(Q_h, K_h, V_h) = \text{softmax} \left( \frac{Q_hK_h^\top}{\sqrt{d_{\text{head}}}} \right)V_h,
\]

\[
\text{MHA}(X) = \text{Concat}(\text{head}_1, \ldots, \text{head}_H)W^O,
\]

where \(W_h^Q, W_h^K, W_h^V \in \mathbb{R}^{d_{\text{hid}} \times d_{\text{head}}}, W^O \in \mathbb{R}^{d_{\text{hid}} \times d_{\text{hid}}}\) are linear transformations. \(Q_h, K_h, V_h \in \mathbb{R}^{s \times d_{\text{head}}}\) are called queries, keys, and values, respectively. \(H\) is the number of heads. \(\text{head}_h = \text{Attention}(Q_h, K_h, V_h)\) denotes the \(h\)-th attention head. Concat is the concatenating operation. \(d_{\text{head}} = d_{\text{hid}}/H\) is the dimension of each head.

**Feed-Forward Network (FFN).** Each Transformer layer contains an FNN sub-layer, which is stacked on the MHA. FFN consists of two linear transformations with a ReLU activation as:

\[
\text{FFN}(x) = \max(0, xW^1 + b_1)W^2 + b_2,
\]

where \(W^1 \in \mathbb{R}^{d_{\text{hid}} \times d_{\text{f}}}, W^2 \in \mathbb{R}^{d_{\text{f}} \times d_{\text{hid}}}, b_1 \in \mathbb{R}^{d_{\text{f}}}, \text{ and } b_2 \in \mathbb{R}^{d_{\text{hid}}}\). In addition, there are residual connection and layer normalization on top of MHA and FFN (denoted by \(\oplus\) in Figure 2), which are formulated as \(\text{LayerNorm}(x + \text{MHA}(x))\) and \(\text{LayerNorm}(x + \text{FFN}(x))\), respectively.
Given a large pre-trained language model (e.g., BERT) as teacher, AutoDistil distills several compressed models with variable computational cost in a task-agnostic fashion. In the following, we describe our major components.

### 3.1 Search Space Design

**Searchable transformer components.** We presented an overview of Transformers in Section 2 and our framework in Figure 2. We observe that four important hyper-parameters for the Transformer building blocks, include:

- Number of layers \( L \) to capture the network depth
- Hidden dimension \( d_{hid} \) to encode input representation
- Attention heads \( H \) for multi-head self-attention
- Feed-forward network (FFN) dimension: we encode this by the MLP (multi-layer perceptron) ratio defined as \( r = \frac{d_f}{d_{hid}} \) with \( d_f \) and \( d_{hid} \) representing the intermediate dimension of the FFN and hidden dimension respectively

All of the above factors are important for model capacity and have a significant impact on the model size and computational cost. For instance, different layers have different feature representation capabilities. Recent works show
that Transformer models are overparameterized \cite{Michel2019a, Voita2019a}, such as the feed-forward layer (FFN), which is one of the most computation intensive components \cite{Ganesh2020}. Therefore, we search for the optimal MLP ratio and hidden dimension that reduce computational cost resulting from the FFN layers. Furthermore, studies \cite{Michel2019b, Voita2019b} show that attention heads can be redundant when they learn to encode similar relationships and nuances for each word. Thus, we make the number of attention heads searchable as well.

**Inductive bias.** Prior work \cite{Romero2015} demonstrate that thinner and deeper neural networks with improved representation capacity perform better than wider and shallower ones. We incorporate this as an inductive bias to decide the number of layers to consider for the students in each of our \( K \) sub-spaces (base, small, tiny), where we prefer deeper students in terms of the number of layers. Furthermore, we constrain all the Transformer layers in a given student model to share identical and homogeneous structures, i.e., the same number of attention heads, hidden dimension, etc. This not only reduces the size of the search space, it is also more friendly to hardware and software frameworks \cite{Yin2021}. \n
**Search space partition.** Existing works \cite{Yin2021, Xu2021a} train a single large SuperLM containing millions of student architectures by weight-sharing. This leads to performance degradation due to optimization interference and convergence of subnetworks with very different sizes \cite{Yu2020}. To mitigate such interference, we employ a few-shot learning strategy \cite{Chen2021, Zhao2021} as follows: we partition the whole Transformer search space into \( K \) sub-spaces such that each sub-space covers different sizes of student models given by the number of parameters. We set \( K = 3 \) to cover typical student sizes, namely base, small and tiny versions. Table \ref{tab:search_space} shows the parameter ranges for the \( K \) sub-spaces, along with the student configurations contained in each.

We now encode each sub-space into a SuperLM, where each student model in the space is a subnetwork of the SuperLM. Furthermore, all the student subnetworks share the weights of their common dimensions, with the SuperLM being the largest one in the search space. Considering \( K \) independent SuperLMs, each one now has more capacity to encode a sub-space, in contrast to a limited capacity single SuperLM in prior works. Furthermore, our choices for the heuristic partition and inductive bias result in less number of student models of comparable size in each sub-space which alleviates conflicts in weight-sharing.

The student subnetworks are extracted from the SuperLM via bottom-left extraction. In particular, given a specific architecture \( \alpha = \{ l, d_{hid}, r, h \} \), (i) we first extract alternate \( l \) Transformer layers from the SuperLM; (ii) then extract bottom-left sub-matrices in terms of \( d_{hid} \) and \( r \) from the original matrices that represent the hidden dimension and the MLP ratio respectively; (iii) finally, for the attention heads, we extract the leftmost \( h \) heads and retain the dimension of each head as the SuperLM.

### 3.2 Task-agnostic SuperLM Training

We illustrate the SuperLM training process in Algorithm \ref{alg:superlm_training}. Given a large pre-trained language model (e.g., BERT) as the teacher, we initialize the SuperLM with the weights of teacher. In each step of SuperLM training, we randomly sample several student subnetworks from the search space; apply knowledge distillation between the sampled subnetworks and the teacher to accumulate the gradients; and then update the SuperLM. We leverage deep self-attention distillation \cite{Wang2020} for task-agnostic training. To this end, we employ multi-head self-attention relation distillation to align the attention distributions as well as the scaled dot-product of keys, queries and values of the teacher and sampled student subnetworks.

Consider \( A_1, A_2, A_3 \) to denote the queries, keys and values of multiple relation heads of teacher model, and \( B_1, B_2, B_3 \) respectively for a sampled subnetwork. The mean squared error (\( \text{MSE}(\cdot) \)) between multi-head self-attention relation of the teacher and sampled subnetwork is used as the distillation objective:

\[
\mathcal{L} = \sum_{i=1}^{3} \beta_i \mathcal{L}_i
\]  

\[
\mathcal{L}_i = \frac{1}{H} \sum_{k=1}^{H} \text{MSE}(R^T_{ik}, R^S_{ik})
\]  

\[
R^T_i = \text{softmax}(\frac{A_i A^T_i}{\sqrt{d_k}}), \quad R^S_i = \text{softmax}(\frac{B_i B^T_i}{\sqrt{d_k}})
\]  

where \( H \) is the number of attention heads; \( R^T_{ik} \) represents the teacher’s \( Q \) and \( K \) relation; or \( V \) relation; \( R^S_{ik} \) represents the same for student. \( R^T_{ik} \) is the relation information based on one attention head, and \( d_k \) is the attention head size.

Relation knowledge distillation avoids the introduction of additional parameters to transform the student’s representations with different dimensions to align to that of the teacher. For the teacher model and subnetworks with different
Algorithm 1 Few-shot Task-agnostic Knowledge Distillation with AutoDistil.

Input: Partitioned $K$ sub-spaces $A_k$; initialized $K$ SuperLMs $S_k$ on $A_k$; pre-trained teacher model $T$; unlabeled data $D$; training epochs $E$; sampling steps $M$

Output: Trained SuperLMs $\{S_k\}$

for $k = 1$ to $K$
    for $i = 1$ to $E$
        Get a batch of data from $D$
        for batch in $D$
            Clear gradients in SuperLM $S_k$
            for $m = 1$ to $M$
                Randomly sample a subnetwork $s$ from $S_k$
                Calculate self-attention distil. loss between subnetwork $s$ and teacher $T$ with Eqn. (6)
                Accumulate gradients
            end for
            Update $S_k$ with the accumulated gradients
        end for
    end for
end for

number of attention heads, we first concatenate the self-attention vectors of different attention heads of the subnetwork and then split them according to the number of relation heads of the teacher model. Then, we align their queries with the same number of relation heads for distillation. In addition, we only transfer the self-attention knowledge from the last layer of the teacher model to the last layer of the student model. Automatically selecting which layers to align is an interesting research direction that we defer to future work.

Formally, the SuperLM for sub-space $A_k$ is trained as:

$$W_{A_k}^* = \arg\min_{W} \mathbb{E}_{\alpha \in A}[L(W_\alpha; U; D_{train})],$$

where, $K$ is the number of sub-space partitions; $W$ are the weights of the SuperLM; $W_\alpha$ are the weights in $W$ specified by the architecture $\alpha$; $U$ are the weights of the teacher model including the self-attention module used for distillation; $D_{train}$ is the training data set, and $L(\cdot)$ is the self-attention loss function from Eqn. (6).

3.3 Lightweight Optimal Student Search

We outline two search strategies for selecting the optimal student subnetwork.

Task-agnostic search. We compute the task-agnostic self-attention distillation loss for all student subnetworks using Eqn. (6) on a heldout validation set from the unlabeled training corpus. The student subnetworks are directly obtained by bottom-left extraction from the well-trained SuperLM (outlined in Section 3.1). This process is lightweight since it does not require any training or adaptation of the student and the number of subnetworks is limited.

The optimal student is given by the subnetwork with the least validation loss subject to the following constraint.

$$\alpha^*_A = \arg\min_{\alpha \in A_1, 2, \ldots, K} L(W^*_\alpha; D_{val}), \quad s.t. \quad g(\alpha) < c,$$

where $W^*_\alpha$ is the weights of architecture $\alpha$ obtained from $W^*_A$, $D_{val}$ is the validation data set, $L$ is the self-attention distillation loss, and $g(\cdot)$ is a function to calculate the computational cost (e.g., #FLOPs, #parameters) of the subnetwork subject to a given constraint $c$.

Task-proxy search. This strategy considers a proxy task (e.g., MNLI [Williams et al. 2018]) with label information to fine-tune each of the 256 candidate subnetworks in each of the $K=3$ sub-spaces. The optimal student in each sub-space is given by the one with the best downstream task performance (e.g., accuracy). Although this strategy is more resource expensive than the task-agnostic one, we demonstrate this to obtain better trade-off in computational cost vs. task performance given the auxiliary task label information.
Table 3: Performance comparison between models distilled by AutoDistil against several task-agnostic students (6 layer, 768 hidden size, 12 heads) distilled from BERT\textsubscript{BASE}. We report the relative reduction in computational cost (#FLOPs and #Parameters) and improvement in average task performance on GLUE (dev) over all baselines. AutoDistil\textsubscript{Agnostic} is obtained by task-agnostic search. AutoDistil\textsubscript{Proxy\textsubscript{B}} and AutoDistil\textsubscript{Proxy\textsubscript{S}} are obtained by task-proxy search from SuperLM\textsubscript{base} and SuperLM\textsubscript{small} respectively.

| Model         | AutoDistil\textsubscript{Agnostic} | AutoDistil\textsubscript{Proxy\textsubscript{B}} | AutoDistil\textsubscript{Proxy\textsubscript{S}} |
|---------------|-------------------------------------|-----------------------------------------------|-----------------------------------------------|
|               | \Delta\text{FLOPs} \text{ΔPara} \text{ΔAvg.} | \Delta\text{FLOPs} \text{ΔPara} \text{ΔAvg.} | \Delta\text{FLOPs} \text{ΔPara} \text{ΔAvg.} |
| BERT\textsubscript{BASE} Devlin et al. [2019] (teacher) | 81.1% 75.5% -2.6 | 60.9% 54.3% -0.5 | 82.0% 76.2% -2.3 |
| BERT\textsubscript{SMALL} Turc et al. [2019] | 62.4% 59.7% -0.3 | 22.3% 24.7% +1.8 | 64.3% 60.8% -0.02 |
| Truncated BERT Williams et al. [2018] | 62.4% 59.7% +2.5 | 22.3% 24.7% +4.6 | 64.3% 60.8% +2.8 |
| DistilBERT Sanh et al. [2019] | 62.4% 59.7% +1.1 | 22.3% 24.7% +3.2 | 64.3% 60.8% +1.4 |
| TinyBERT Jiao et al. [2020] | 62.4% 59.7% -0.3 | 22.3% 24.7% +1.8 | 64.3% 60.8% +0.0 |
| MINILM Williams et al. [2018] | 62.4% 59.7% -1.4 | 22.3% 24.7% +0.7 | 64.3% 60.8% -1.1 |

4 Experiments

4.1 Setup

Datasets. We conduct experiments on the General Language Understanding Evaluation (GLUE) benchmark [Wang et al. [2018]]. We compare our method with the baseline methods on two single-sentence classification tasks (CoLA [Wang et al. [2018]], SST-2 [Socher et al. [2013]]), two similarity and paraphrase tasks (MRPC [Dolan and Brockett [2005]], QQP [Chen et al. [2018]]), and three inference tasks (MNLI [Williams et al. [2018]], QNLI [Rajpurkar et al. [2016]], RTE [Dagan et al. [2005]], Haim et al. [2006], Giampiccolo et al. [2007], Bentivogli et al. [2009]). We report accuracy for MNLI, QNLI, QQP, SST-2, RTE, report f1 for MRPC, and report Matthew’s correlation for CoLA.

Baselines. We compare against several task-agnostic methods\(^2\) generating compressed models from BERT\textsubscript{base}, teacher, using (i) knowledge distillation like BERT\textsubscript{SMALL} Turc et al. [2019], Truncated BERT Williams et al. [2018], DistilBERT Sanh et al. [2019], TinyBERT Jiao et al. [2020], MINILM Williams et al. [2018], as well as those based on Neural Architecture Search, like AutoTinyBERT Yin et al. [2021], and NAS-BERT Xu et al. [2021a].

AutoDistil configuration. We use uncased BERT\textsubscript{BASE} as the teacher consisting of 12 Transformer layers, 12 attention heads; with the hidden dimension and MLP ratio being 768 and 4, respectively. It consists of 100M parameters with 11.2G FLOPs. We use English Wikipedia and BookCorpus data for SuperLM training with WordPiece tokenization. We use 16 V100 GPUs to train the SuperLM, with 128 as the batch size and 4e-5 as the peak learning rate for 10 epochs. The maximum sequence length is set to 128. The coefficients in distillation objective (Eqn. (6)), \(\beta_1, \beta_2, \) and \(\beta_3\), are all set to 1. We distill the self-attention knowledge of the last layer to train the SuperLM. Both the teacher and SuperLM are initialized with pre-trained BERT\textsubscript{BASE}. Other hyper-parameter settings are shown in Appendix.

4.2 Finding the Optimal Compressed Models

We use the following search strategies and constraints to find the optimal compressed models by AutoDistil.

AutoDistil\textsubscript{Agnostic} is obtained by task-agnostic search without any task label information. We set a constraint in Eqn. (10) such that the #FLOPs of the optimal compressed model is at least 50% less than the teacher model. We rank all the subnetworks contained in all the partitions of the trained SuperLM by their self-attention distillation loss on the heldout validation set, and select the one that meets the constraint with the minimum loss.

AutoDistil\textsubscript{Proxy\textsubscript{B}} uses MNLI Williams et al. [2018] as a proxy to estimate downstream task performance of different subnetworks. Prior work Chen et al. [2020] has demonstrated performance improvements in MNLI to be correlated to other GLUE tasks. To this end, we fine-tune all subnetworks in each partition of the trained SuperLMs, and select corresponding subnetworks with the best trade-off between task performance (accuracy) and computational cost (#FLOPs). This results in \(K=3\) optimal students, corresponding to AutoDistil\textsubscript{Proxy\textsubscript{B}}, AutoDistil\textsubscript{Proxy\textsubscript{S}}, and AutoDistil\textsubscript{Proxy\textsubscript{T}} obtained from the corresponding sub-spaces with SuperLM\textsubscript{base}, SuperLM\textsubscript{small} and SuperLM\textsubscript{tiny} respectively.

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\(^1\)We ignore STS-B for a fair comparison with our strongest baseline MinILM Wang et al. [2020a] that do not report the task.

\(^2\)For a fair comparison, we do not include DynaBERT Hou et al. [2020] with task-specific search, and MobileBERT Sun et al. [2020] that uses BERT\textsubscript{large} as teacher in our main result tables.
Table 4: Performance comparison between AutoDistil students, and popular task-agnostic students distilled from BERT\textsubscript{BASE} (6 layer, 768 hidden size, 12 attention heads). Our results are averaged over 5 runs. Baseline numbers are reported from corresponding papers.

| Model | #FLOPs | #Para | MNLI-m | QNLI | QQP | SST-2 | CoLA | MRPC | RTE | Average (Metric) |
|-------|--------|-------|--------|------|------|-------|------|------|-----|-----------------|
| BERT\textsubscript{BASE} Devlin et al. [2019] (teacher) | 11.2G 109M | | 84.5 91.7 91.3 93.2 58.9 87.3 | | | | | | | 68.6 82.2 |
| BERT\textsubscript{SMALL} Turc et al. [2019] | 5.66G 66.5M | | 81.8 89.8 90.6 91.2 53.5 84.9 | 67.9 | | | | | | 80.0 |
| Truncated BERT Williams et al. [2018] | 5.66G 66.5M | | 81.2 87.9 90.4 90.8 41.4 82.7 | 65.5 | | | | | | 77.1 |
| DistilBERT Sanh et al. [2019] | 5.66G 66.5M | | 82.2 89.2 88.5 91.3 51.3 87.5 | 59.9 | | | | | | 78.6 |
| TinyBERT Jiao et al. [2020] | 5.66G 66.5M | | 83.5 90.5 90.6 91.6 42.8 | 88.4 | 72.2 | | | | | 79.9 |
| MINILM Williams et al. [2018] | 5.66G 66.5M | | 84.0 91.0 91.0 92.0 49.2 | 88.4 | 71.5 | 81.0 |
| AutoDistil\textsubscript{Agnostic} | 2.13G 26.8M | | 82.8 89.9 90.8 90.6 47.1 | 87.3 | 69.0 | | | | | 79.6 |
| AutoDistil\textsubscript{ProxyB} | 4.40G 50.1M | | 83.8 90.8 91.1 91.1 55.0 | 88.8 | 71.9 | 81.7 |
| AutoDistil\textsubscript{ProxyS} | 2.02G 26.1M | | 83.2 90.0 90.6 90.1 48.3 | 88.3 | 69.4 | 79.9 |
| AutoDistil\textsubscript{ProxyT} | 0.27G 6.88M | | 79.0 86.4 89.1 85.9 24.8 | 78.5 | 64.3 | 72.6 |

Table 5: Architecture comparison between the optimal compressed students searched by AutoDistil with state-of-the-art hand-engineered students distilled from BERT\textsubscript{BASE}.

| Model | #Layers | #Hid | Ratio | #Heads | #FLOPs | #Para |
|-------|---------|------|-------|--------|--------|-------|
| BERT\textsubscript{BASE} | 12 | 768 | 4 | 12 | 11.2G | 109M |
| MINILM | 6 | 768 | 4 | 6 | 5.66G | 66.5M |
| AutoDistil\textsubscript{Agnostic} | 11 | 352 | 4 | 10 | 2.13G | 26.8M |
| AutoDistil\textsubscript{ProxyB} | 12 | 544 | 3 | 9 | 4.40G | 50.1M |
| AutoDistil\textsubscript{ProxyS} | 11 | 352 | 4 | 8 | 2.02G | 26.1M |
| AutoDistil\textsubscript{ProxyT} | 7 | 160 | 3.5 | 10 | 0.27G | 6.88M |

respectively. We visualize the selected subnetworks for each superLM in Figure 3 with the architectures of the optimal compressed models shown in Table 5.

4.2.1 Comparison with Baselines

We compare the above AutoDistil compressed models against state-of-the-art KD and NAS models distilled from the same teacher BERT\textsubscript{BASE}. We present the relative performance improvement of AutoDistil over several baselines in Table 3 with respect to the following measures: savings in computational cost in the form of (i) FLOPs and (ii) parameter reduction, along with (iii) improvement in the average task performance aggregated over all the GLUE tasks with detailed results in Table 4.

From Table 3 we observe that the compressed model AutoDistil\textsubscript{Agnostic} generated via our SuperLM training and task-agnostic search has 80% less FLOPs and 75% less parameters, while incurring 2.6 point accuracy drop in comparison to the large teacher model. When compared to all other baseline models distilled from BERT\textsubscript{BASE}, AutoDistil\textsubscript{Agnostic} leads to 62.4% less FLOPs with 59.7% less parameters while incurring a maximum accuracy drop of less than 1.5 points – demonstrating the effectiveness of AutoDistil in obtaining a better trade-off between task performance and computational cost.

4.2.2 Search Strategy and Architectures

From Table 3 we observe that both the task-agnostic and task-proxy search strategies achieve better trade-off between performance and cost than the baselines. The compressed model AutoDistil\textsubscript{ProxyB} obtained from SuperLM\textsubscript{base} by the task-proxy search strategy reduces FLOPs and parameters by 22.3% and 24.7%, respectively, while obtaining better task performance than all the baselines. Moreover, by comparing AutoDistil\textsubscript{Agnostic} and AutoDistil\textsubscript{ProxyB} from SuperLM\textsubscript{small}, we observe that task-proxy search obtains better trade-off in cost vs. performance than the task-agnostic one by making use of task label information.
Figure 3: Computational cost vs. task (MNLI) performance trade-off for all 256 subnetworks contained in each of K SuperLMs (base, small and tiny). 3(a)-3(c) show the trade-off between accuracy (Y-axis) and #FLOPs (X-axis), and 3(d)-3(f) show the trade-off between accuracy (Y-axis) and #Para (X-axis). We show the optimal compressed AutoDistil student for each SuperLM marked in red, along with other state-of-the-art KD and NAS techniques for comparison.

From Table 5 we observe that optimal compressed models have thin-and-deep structure which is consistent with findings that thinner and deeper models perform better than wider and shallower ones. While we use this as an inductive bias for sub-space partitioning, our search space (Table 2) also contains diverse subnetworks with different depth and width. Non-maximal MLP ratio and attention heads for optimal compression indicate that self-attention and feed-forward layers of Transformers are overparameterized.

4.2.4 Task-agnostic Training Strategies

We study different task-agnostic strategies for SuperLM training in AutoDistil. Specifically, we compare three strategies in Table 6: (i) Replacing the KD loss in Eqn. 6 with masked language modeling (MLM) loss to calculate gradients. (ii) KDatt+Cont further continues training the searched compressed models on the large language corpus. (iii) KDatt is the strategy adopted in AutoDistil for self-attention distillation. We evaluate subnetworks with the same architecture (6 layers, 768 hidden, 12 heads, MLP ratio 4) from the trained SuperLM.

We fine-tune the subnetworks on RTE and MRPC tasks, and report accuracy and f1 respectively. First, we observe self-attention distillation to perform better than MLM, for SuperLM training. Second, we observe limited performance gains with continued training demonstrating the effectiveness of our single-stage training protocol.
Table 6: Comparing task-agnostic SuperLM training strategies.

| Strategy    | MRPC | RTE |
|-------------|------|-----|
| MLM         | 89.4 | 68.2|
| KD\textsubscript{att} + Cont. | 91.0 | 71.8|
| KD\textsubscript{att} | 91.2 | 71.5|

Table 7: Comparing search space design strategies.

| Task  | Search Space Size (number of subnetworks) | One-shot | K=3-shot |
|-------|------------------------------------------|----------|----------|
| MRPC  | 27 | 864 | 11232 | 256*3 |
| RTE   | 88.2 | 87.5 | 85.1 | 91.2 |
|       | 67.2 | 64.5 | 62.8 | 71.8 |

4.2.5 Search Space Design Strategies

In Table 7, we compare one-shot NAS versus few-shot NAS training for our SuperLM. For one-shot NAS, we consider a single search space containing different numbers of subnetworks (e.g., 27, 864, 11232). For few-shot NAS, we consider $K=3$ sub-spaces containing 256 subnetworks each. We extract subnetworks with the same architecture (6 layers, 768 hidden, 12 heads, MLP ratio 4) from trained SuperLM for each strategy for evaluation. We fine-tune the subnetworks on RTE and MRPC tasks, and report accuracy and F1 respectively. We observe fewer subnetworks contained in a single search space for one-shot NAS result in a better performance. This results from optimization interference as the number and size of subnetworks increase. Finally, we observe our design strategy with few-shot NAS to perform the best while containing lesser number of subnetworks.

5 Related Work

Task-specific knowledge distillation. Knowledge distillation (KD) [Hinton et al. 2015] is one of the most widely used techniques for model compression, which transfers knowledge from a large teacher to a smaller student model. Task-specific distillation aims to generate smaller student models by using downstream task label information. Typical task-specific distillation works include BERT-PKD [Sun et al. 2019], BERT\textsubscript{SMALL} [Turc et al. 2019], TinyBERT [Jiao et al. 2020], DynaBERT [Hou et al. 2020], and SparseBERT [Xu et al. 2021b]. While task-specific KD methods often achieve good task performance, a typical drawback is that it is resource-consuming to run distillation for each and every task, and also not scalable.

Task-agnostic knowledge distillation. In contrast to task-specific distillation, we explore task-agnostic KD that does not use any task label information. The distilled task-agnostic models can be re-used by simply fine-tuning on downstream tasks. They can also be used to initialize students for task-specific distillation. Task-agnostic distillation leverages knowledge from soft target probabilities, hidden states, layer mappings and self-attention distributions of teacher to train student models. Typical task-agnostic distillation works include DistilBERT [Sanh et al. 2019], MobileBERT [Sun et al. 2020], and MiniLM [Wang et al. 2020a]. MobileBERT assumes that students have the same number of layers as the teacher for layer-by-layer distillation. MiniLM transfers self-attention knowledge from the last layer of the teacher to that of the student. These works rely on hand-designed architecture for the student models for KD that requires several trials, and needs to be repeated for a new student with a different cost. In contrast, we develop techniques to automatically design and distill several student models with variable cost using NAS.

Neural Architecture Search. While NAS has been extensively studied in computer vision [Pham et al. 2018], [Tan et al. 2019], [Cai et al. 2020], [Yu et al. 2020], there has been relatively less exploration in natural language processing. Evolved Transformer [So et al. 2019] and HAT [Wang et al. 2020b] search for efficient sub-networks from the Transformer architecture for machine translation tasks. Some recent approaches closest to our method include, DynaBERT [Hou et al. 2020], AutoTinyBERT [Yin et al. 2021] and NAS-BERT [Xu et al. 2021a]. While DynaBERT performs task-specific distillation, AutoTinyBERT uses task-agnostic KD and MLM strategies for SuperLM training, but task-specific search for the compressed models. NAS-BERT uses a different search space, and performs two-stage knowledge distillation with pre-training and fine-tuning of the candidates. Both of these approaches employ one-shot NAS as a single large search space containing millions of subnetworks that result in co-adaptation and weight-sharing challenges between them for SuperLM training. In contrast, our method employs few-shot NAS with a compact search
space design to address the above challenges. This further allows us to do a lightweight search for the optimal student without re-training in a fully task-agnostic fashion.

6 Conclusion

We develop a few-shot task-agnostic NAS framework, namely AutoDistil for distilling large language models into compressed students with variable computational cost. To address the co-adaptation and weight-sharing challenges for SuperLM training, we partition the Transformer search space into $K=3$ compact sub-spaces covering important architectural components like the network depth, width, and number of attention heads. We leverage deep self-attention distillation for fully task-agnostic SuperLM training and lightweight optimal student search without re-training. This allows our students to be re-used by simply fine-tuning on downstream tasks. Experiments in the GLUE benchmark demonstrate that AutoDistil outperforms state-of-the-art task-agnostic distillation methods with 62.4% less computational cost and 59.7% less parameters while obtaining a similar downstream task performance.

References

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: Pre-training of deep bidirectional transformers for language understanding. In NAACL, pages 4171–4186, Minneapolis, Minnesota, June 2019. Association for Computational Linguistics. doi:10.18653/v1/N19-1423.

Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel Ziegler, Jeffrey Wu, Clemens Winter, Chris Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. Language models are few-shot learners. In H. Larochelle, M. Ranzato, R. Hadsell, M. F. Balcan, and H. Lin, editors, Advances in Neural Information Processing Systems, volume 33, pages 1877–1901. Curran Associates, Inc., 2020.

Emma Strubell, Ananya Ganesh, and Andrew McCallum. Energy and policy considerations for deep learning in NLP. In ACL, pages 3645–3650, Florence, Italy, July 2019. Association for Computational Linguistics. doi:10.18653/v1/P19-1355.

Wenhui Wang, Furu Wei, Li Dong, Hangbo Bao, Nan Yang, and Ming Zhou. Minilm: Deep self-attention distillation for task-agnostic compression of pre-trained transformers. In H. Larochelle, M. Ranzato, R. Hadsell, M. F. Balcan, and H. Lin, editors, Advances in Neural Information Processing Systems, volume 33, pages 5776–5788. Curran Associates, Inc., 2020a.

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.

Xiaoqi Jiao, Yichun Yin, Lifeng Shang, Xin Jiang, Xiao Chen, Linlin Li, Fang Wang, and Qun Liu. Tinybert: Distilling bert for natural language understanding. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: Findings, pages 4163–4174, 2020.

Zhiqing Sun, Hongkun Yu, Xiaodan Song, Renjie Liu, Yiming Yang, and Denny Zhou. Mobilebert: a compact task-agnostic bert for resource-limited devices. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 2158–2170, 2020.

Hieu Pham, Melody Guan, Barret Zoph, Quoc Le, and Jeff Dean. Efficient neural architecture search via parameters sharing. In International Conference on Machine Learning, pages 4095–4104. PMLR, 2018.

Mingxing Tan, Bo Chen, Ruoming Pang, Vijay Vasudevan, Mark Sandler, Andrew Howard, and Quoc V Le. Mnasnet: Platform-aware neural architecture search for mobile. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 2820–2828, 2019.

Han Cai, Chuang Gan, Tianzhe Wang, Zhekai Zhang, and Song Han. Once for all: Train one network and specialize it for efficient deployment. In International Conference on Learning Representations, 2020.

Jiahui Yu, Pengchong Jin, Hanxiao Liu, Gabriel Bender, Pieter-Jan Kindermans, Mingxing Tan, Thomas Huang, Xiaodan Song, Ruoming Pang, and Quoc Le. Bignas: Scaling up neural architecture search with big single-stage models. In European Conference on Computer Vision, pages 702–717. Springer, 2020.

Lu Hou, Zhiqi Huang, Lifeng Shang, Xin Jiang, Xiao Chen, and Qun Liu. DynaBERT: Dynamic bert with adaptive width and depth. In H. Larochelle, M. Ranzato, R. Hadsell, M. F. Balcan, and H. Lin, editors, Advances in Neural Information Processing Systems, volume 33, pages 9782–9793. Curran Associates, Inc., 2020. URL https://proceedings.neurips.cc/paper/2020/file/6f5216f8d89b088e18298e043bfe48ed-Paper.pdf
Yichun Yin, Cheng Chen, Lifeng Shang, Xin Jiang, Xiao Chen, and Qun Liu. AutoTinyBERT: Automatic hyperparameter optimization for efficient pre-trained language models. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 5146–5157. Association for Computational Linguistics, August 2021.

Jin Xu, Xu Tan, Renqian Luo, Kaitao Song, Jian Li, Tao Qin, and Tie-Yan Liu. NAS-BERT: task-agnostic and adaptive-size BERT compression with neural architecture search. In Feida Zhu, Beng Chin Ooi, and Chunyan Miao, editors, KDD ’21: The 27th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, Virtual Event, Singapore, August 14-18, 2021, pages 1933–1943. ACM, 2021a. doi:10.1145/3447548.3467262.

Gabriel Bender, Pieter-Jan Kindermans, Barret Zoph, Vijay Vasudevan, and Quoc Le. Understanding and simplifying one-shot architecture search. In International Conference on Machine Learning, pages 550–559. PMLR, 2018.

Yiyang Zhao, Linnan Wang, Yuandong Tian, Rodrigo Fonseca, and Tian Guo. Few-shot neural architecture search. In International Conference on Machine Learning, pages 12707–12718. PMLR, 2021.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. In Advances in neural information processing systems, pages 5998–6008, 2017.

Paul Michel, Omer Levy, and Graham Neubig. Are sixteen heads really better than one? In NeurIPS, pages 14014–14024, 2019a.

Elena Voita, David Talbot, Fedor Moisseev, Rico Sennrich, and Ivan Titov. Analyzing multi-head self-attention: Specialized heads do the heavy lifting, the rest can be pruned. arXiv preprint arXiv:1905.09418, 2019a.

Prakhar Ganesh, Yao Chen, Xin Lou, Mohammad Ali Khan, Yin Yang, Deming Chen, Marianne Winslett, Hassan Sajjad, and Preslav Nakov. Compressing large-scale transformer-based models: A case study on bert. arXiv preprint arXiv:2002.11985, 2020.

Paul Michel, Omer Levy, and Graham Neubig. Are sixteen heads really better than one? In H. Wallach, H. Larochelle, A. Beygelzimer, F. d’Alché-Buc, E. Fox, and R. Garnett, editors, Advances in Neural Information Processing Systems, volume 32. Curran Associates, Inc., 2019b.

Elena Voita, David Talbot, Fedor Moisseev, Rico Sennrich, and Ivan Titov. Analyzing multi-head self-attention: Specialized heads do the heavy lifting, the rest can be pruned. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 5797–5808, Florence, Italy, July 2019b. Association for Computational Linguistics.

Adriana Romero, Nicolas Ballas, Samira Ebrahimi Kahou, Antoine Chassang, Carlo Gatta, and Yoshua Bengio. Fitnets: Hints for thin deep nets. In Yoshua Bengio and Yann LeCun, editors, 3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings, 2015.

Minghao Chen, Houwen Peng, Jianlong Fu, and Haibin Ling. Autoformer: Searching transformers for visual recognition. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 12270–12280, 2021.

Adina Williams, Nikita Nangia, and Samuel Bowman. A broad-coverage challenge corpus for sentence understanding through inference. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 1112–1122, New Orleans, Louisiana, June 2018. Association for Computational Linguistics. doi:10.18653/v1/N18-1101.

Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel Bowman. GLUE: A multi-task benchmark and analysis platform for natural language understanding. In Proceedings of the 2018 EMNLP Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP, pages 353–355, Brussels, Belgium, November 2018. Association for Computational Linguistics.

Alex Warstadt, Amanpreet Singh, and Samuel R. Bowman. Neural network acceptability judgments, 2018.

Richard Socher et al. Recursive deep models for semantic compositionality over a sentiment treebank. In Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing, pages 1631–1642, Seattle, Washington, USA, October 2013. Association for Computational Linguistics.

William B Dolan and Chris Brockett. Automatically constructing a corpus of sentential paraphrases. In Proceedings of the Third International Workshop on Paraphrasing (IWP2005), 2005.

Zihan Chen, Hongbo Zhang, Xiaojie Zhang, and Leqi Zhao. Quora question pairs. URL https://www.kaggle.com/c/quora-question-pairs, 2018.

Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. Squad: 100,000+ questions for machine comprehension of text. arXiv preprint arXiv:1606.05250, 2016.
Ido Dagan, Oren Glickman, and Bernardo Magnini. The pascal recognising textual entailment challenge. In *Machine Learning Challenges Workshop*, pages 177–190. Springer, 2005.

R Bar Haim, Ido Dagan, Bill Dolan, Lisa Ferro, Danilo Giampiccolo, Bernardo Magnini, and Idan Szpektor. The second pascal recognising textual entailment challenge. In *Proceedings of the Second PASCAL Challenges Workshop on Recognising Textual Entailment*, 2006.

Danilo Giampiccolo, Bernardo Magnini, Ido Dagan, and William B Dolan. The third pascal recognizing textual entailment challenge. In *Proceedings of the ACL-PASCAL workshop on textual entailment and paraphrasing*, pages 1–9, 2007.

Luisa Bentivogli, Peter Clark, Ido Dagan, and Danilo Giampiccolo. The fifth pascal recognizing textual entailment challenge. In *TAC*, 2009.

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.

Tianlong Chen, Jonathan Frankle, Shiyu Chang, Sijia Liu, Yang Zhang, Zhangyang Wang, and Michael Carbin. The lottery ticket hypothesis for pre-trained bert networks. In L. Larochelle, M. Ranzato, R. Hadsell, M. F. Balcan, and H. Lin, editors, *Advances in Neural Information Processing Systems*, volume 33, pages 15834–15846. Curran Associates, Inc., 2020.

Geoffrey Hinton, Oriol Vinyals, and Jeffrey Dean. Distilling the knowledge in a neural network. In *NIPS Deep Learning and Representation Learning Workshop*, 2015. URL [http://arxiv.org/abs/1503.02531](http://arxiv.org/abs/1503.02531).

Siqi Sun, Yu Cheng, Zhe Gan, and Jingjing Liu. Patient knowledge distillation for bert model compression. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 4323–4332, 2019.

Dongkuan Xu, Ian EH Yen, Jinxi Zhao, and Zhibin Xiao. Rethinking network pruning—under the pre-train and fine-tune paradigm. In *Proceedings of the Human Language Technology Conference of the NAACL*, 2021b.

David So, Quoc Le, and Chen Liang. The evolved transformer. In Kamalika Chaudhuri and Ruslan Salakhutdinov, editors, *Proceedings of the 36th International Conference on Machine Learning*, volume 97 of *Proceedings of Machine Learning Research*, pages 5877–5886. PMLR, 09–15 Jun 2019.

Hanrui Wang, Zhanghao Wu, Zhijian Liu, Han Cai, Ligeng Zhu, Chuang Gan, and Song Han. Hat: Hardware-aware transformers for efficient natural language processing. In *Annual Conference of the Association for Computational Linguistics*, 2020b.

Hassan Sajjad, Fahim Dalvi, Nadir Durrani, and Preslav Nakov. On the effect of dropping layers of pre-trained transformer models. *arXiv preprint arXiv:2004.03844*, 2020.

John Wie廷 and Kevin Gimpel. ParaNMT-50M: Pushing the limits of paraphrastic sentence embeddings with millions of machine translations. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 451–462, Melbourne, Australia, July 2018. Association for Computational Linguistics.

Yukun Zhu, Ryan Kiros, Rich Zemel, Ruslan Salakhutdinov, Raquel Urtasun, Antonio Torralba, and Sanja Fidler. Aligning books and movies: Towards story-like visual explanations by watching movies and reading books. In *Proceedings of the IEEE international conference on computer vision*, pages 19–27, 2015.
A Appendix

A.0.1 Comparison with Baselines

We compare AutoDistil with state-of-the-art distilled models in terms of the trade-off between model size (#Para) and performance (accuracy). The results are shown in Figure 4. AutoDistil uses few-shot task-agnostic Neural Architecture Search to distill several compressed students with variable #Para (x-axis) from $K=3$ SuperLMs (corresponding to each point cloud) trained on $K$ sub-spaces of Transformer search space. Each student extracted from the SuperLM is fine-tuned on MNLI with y-axis showing accuracy. The best student from each SuperLM is marked in red. Given any state-of-the-art distilled model, AutoDistil generates a better candidate with less #Para and improved task performance from corresponding search space.

Figure 4: Comparison between AutoDistil and state-of-the-art distilled models.

A.0.2 Layer Selection Strategies

Table 8: Effects of layer selection strategies.

| Strategy             | MRPC | RTE |
|----------------------|------|-----|
| Alternate_Dropping   | 91.2 | 71.8|
| Top_Dropping         | 90.6 | 68.5|
| Alternate_Top_Dropping | 85.7 | 62.7|

We study different strategies to construct subnetwork layers by selecting layers from the superLM model. Alternate_Dropping is the strategy adopted in AutoDistil such that we drop alternating odd layers from the superLM model to construct subnetwork layers. Top_Dropping means that we drop top layers of superLM to construct subnetwork layers. Alternate_Top_Dropping means that we first perform Alternate_Dropping in superLM training stage and then perform Top_Dropping in fine-tuning stage (please refer to Sajjad et al. [2020] for more details of different layer selection strategies). For all strategies, we perform knowledge distillation between the last layer of the teacher model and the last layer of the subnetworks. We evaluate the subnetworks with the same architecture (#layer=6, #hid=768, R=4, #heads=12) after superLM is trained. We report accuracy and f1 for RTE and MRPC, respectively.

We report the results in Table 8. We observe that the strategy of Alternate_Dropping achieves the best performance on both MRPC and RTE tasks, which demonstrates the effectiveness of the layer selection strategy used in AutoDistil. Alternate_Top_Dropping performs the worst due to interference when different layer selection strategies are used in the superLM training stage and the fine-tuning stage of compressed models. This indicates that the knowledge contained in the superLM model and the compressed model is structured and that it is non-trivial to select layers from superLM to extract subnetwork layers.
A.0.3 Scaling of Training Data

We investigate the effects of data sets of different sizes used for superLM training. In particular, we compare MNLI [Williams et al. 2018], ParaNMT [Wieting and Gimpel 2018] (we sampled 5 million samples from the original 50 million data), Wiki, and Wiki+Book [Zhu et al. 2015]. We report the size of each data set and the performance of AutoDistil with each training data set in Table 9. We observe that AutoDistil performs the best with Wiki+Book data set, and the larger the data set, the better the performance. Moreover, we observe similar performance for MNLI and ParaNMT data sets, especially on MRPC task. This is because MNLI is correlated to other GLUE tasks. In addition, we observe that an increase in the amount of data does not guarantee to bring an equivalent increase in performance. For example, Wiki data set is more than five times larger than ParaNMT data set, but our method performs only about 1% better with Wiki data set than with ParaNMT. These observations illustrate that while using a larger data set does improve the performance of the method, the improvement could be quite limited.

A.0.4 Hyper-parameter Settings for Fine-Tuning

Table 10: Hyper-parameters used for fine-tuning on GLUE.

| Tasks  | Learning Rate | Batch Size | Epochs |
|--------|---------------|------------|--------|
| MNLI-m | 2e-5          | 32         | 5      |
| QNLI   | 2e-5          | 32         | 5      |
| QQP    | 2e-5          | 32         | 5      |
| SST-2  | 2e-5          | 32         | 10     |
| CoLA   | 1e-5          | 32         | 20     |
| MRPC   | 2e-5          | 32         | 10     |
| RTE    | 2e-5          | 32         | 10     |

We report the fine-tuning hyper-parameter settings of GLUE benchmark in Table 10. AutoDistil and baselines follow the same settings.