One Student Knows All Experts Know: From Sparse to Dense

Fuzhao Xue 1  Xiaoxin He 1  Xiaozhe Ren 2  Yuxuan Lou 1  Yang You 1

Abstract

Human education system trains one student by multiple experts. Mixture-of-experts (MoE) is a powerful sparse architecture including multiple experts. However, sparse MoE model is hard to implement, easy to overfit, and not hardware-friendly. In this work, inspired by human education model, we propose a novel task, knowledge integration, to obtain a dense student model (OneS) as knowledgeable as one sparse MoE. We investigate this task by proposing a general training framework including knowledge gathering and knowledge distillation. Specifically, we first propose Singular Value Decomposition Knowledge Gathering (SVD-KG) to gather key knowledge from different pretrained experts. We then refine the dense student model by knowledge distillation to offset the noise from gathering. On ImageNet, our OneS preserves 61.7% benefits from MoE. OneS can achieve 78.4% top-1 accuracy with only 15M parameters. On four natural language processing datasets, OneS obtains 88.2% MoE benefits and outperforms SoTA by 51.7% using the same architecture and training data. In addition, compared with the MoE counterpart, OneS can achieve 3.7× inference speedup due to the hardware-friendly architecture.

1. Introduction

Revisiting how we grow up and become a researcher, most people learn from multiple teachers. Existing work (Bransford et al., 1999) in education also shows that experts from different subjects can help students reach deep understanding and train more talents for society. The students who integrate knowledge from experts can become as knowledgeable as the set of these teachers fast. Inspired by such a human education model, this work focuses on training a powerful deep learning model by collecting knowledge from a set of teachers (i.e., experts).

Recent study in deep learning proposed mixture-of-experts (MoE) to make a deep learning model include multiple experts. Each expert is a sub-neural network in the whole model. The key idea of MoE is to divide and conquer the task. MoE encourages each expert to learn from a task-specific subset of the input. For each subset of the input, there would be only a sub-network activated. The gating function introduced by Fedus et al. (2021) enables us to scale model to trillions of parameters with comparable computation cost. However, MoE is hard to implement. For MoE with trillions of parameters, training and inference require expert parallelism. That is, we need to deploy different experts on different devices to reduce the memory consumption on device (e.g., GPU, TPU). In addition, MoE is easy to overfit. We usually pretrain an MoE on a large dataset and then fine-tune it on various downstream tasks. In most cases, these downstream tasks are actually the target problem we want to solve. Compared with dense models, more trainable parameters and sparse conditional computation introduce overfitting (Xue et al., 2021; Lou et al., 2021) during fine-tuning, especially when the scale of dataset is not large enough. Third, MoE model is not hardware-friendly. Expert parallelism is communication expensive. For GPU clusters, all-to-all operation is too slow to scale the MoE model up. Besides, the gating function...
includes numerous operations to create token-masks, select top-k experts, and perform cumulative-sum to find the token-id going to each expert and sparse matrix-multiply (Rajbhandari et al., 2022). All these operations are wasteful due to the sparse tensor representation. More importantly, they are extremely slow due to many kernel call invocations. In summary, the sparse MoE model is powerful, but it is hard to use. The dense model is widely used but weaker than the sparse model. Then, is it possible to combine the strength of sparse and dense model to train a model that is both effective and easy to use?

In this work, inspired by human education model, we propose a new task, i.e., knowledge integration. As a general training framework, knowledge integration includes knowledge gathering and knowledge distillation. In knowledge gathering, we treat each expert in MoE as a teacher in human education. The student is a dense model, and we are to collect of knowledge from all experts and assign the knowledge to the student. To gather knowledge from experts, we propose Singular Value Decomposition Knowledge Gathering (SVD-KG) for the student. Specifically, we use SVD to extract key knowledge from different experts of a pretrained MoE, and then, we initialize the feed-forward network (FFN) layers for a dense model to approximate the MoE. To further refine the model from noise, we use knowledge distillation (Hinton et al., 2015) to fine-tune the student. Please note the teacher is the whole MoE model in knowledge distillation. The final student model has the same architecture as a normal dense model, but, it would cover the knowledge of MoE with many experts and much more trainable parameters. The framework described above matches well with the human education model, one student integrates knowledge from multiple experts so that the student can learn fast.

Our contributions are summarized as follows:

- We propose a new task, knowledge integration. The goal is to combine the effectiveness of the sparse MoE model and the usability of the dense model. To our best knowledge, this is the first work focusing on learning a dense model from a pretrained MoE model.

- We propose to solve knowledge integration in two steps, knowledge gathering and knowledge distillation. To gather, we propose Singular Value Decomposition Knowledge Gathering, a new approach to extract key knowledge from experts of a pretrained MoE, and we then use the knowledge to initialize a dense model.

- We evaluate our general training framework on different areas, i.e., computer vision and natural language processing. On ImageNet, our OneS preserve 23.1% more benefits from MoE than SoTA. On natural language processing benchmarks, we achieve 88.2% MoE benefits with only 46% parameters, and we outperforms SoTA (e.g., ALBERT, Switch) using almost the same architecture and training data. Also, due to the hardware-friendly model architecture, OneS can achieve $3.7 \times$ inference speedup over MoE counterpart.

2. Preliminary

2.1. Mixture-of-Experts

Mixture-of-experts is a typical conditional computation model. In this work, we use a pretrained MoE model as a teacher, and a dense model as a student to imitate the human education model. Therefore, we briefly review MoE first. Given one MoE model with $E$ trainable experts and input representation $x \in \mathbb{R}^D$, the output of MoE model can be formulated as (Shazeer et al., 2017):

$$\text{MoE}(x) = \sum_{i=1}^{E} G(x)_{i} e_{i}(x)$$

where $e_{i}(\cdot)$ is a non-linear transformation $\mathbb{R}^D \rightarrow \mathbb{R}^D$ of the $i$th expert, and $G(\cdot) : \mathbb{R}^D \rightarrow \mathbb{R}^E$ is the gating network, $G(x)_i$ is the routing weights of $x$ to the $i$-th expert. Usually, both $e(\cdot)$ and $G(\cdot)$ are parameterized by neural networks. Please note the output of $G(\cdot)$ should be activated by softmax function:

$$G(x) = \text{topK}(\omega(h(x) + \epsilon))$$

where $\omega$ is the softmax function, $h(\cdot)$ is a linear layer mapping $\mathbb{R}^D \rightarrow \mathbb{R}^E$, and $\epsilon \sim \mathcal{N}(0, \frac{1}{m^2})$ is a Gaussian noise for exploration of expert routing. The top-K selection is a key module to activate sub-network sparsely. We usually set $K$ as 1 or 2 for comparable computation cost with corresponding dense model.

When training MoE model, if we have no regularization, most tokens may be dispatched to a small portion of experts, and other experts receive few tokens. Such imbalanced assignment would lead to lower efficiency and inferior accuracy (Lepikhin et al., 2020; Fedus et al., 2021). Therefore, to achieve balanced workload for different experts, we usually combines router $g(\cdot)$ with load balance loss (Lepikhin et al., 2020) $L_{\text{balance}}$:

$$L_{\text{balance}} = E \cdot \sum_{i=1}^{E} m_{i} \cdot P_{i}$$

where $m$ is a vector and the $i$th element of $m$ represents the
The overall training framework is knowledge integration, and it includes two stages, knowledge gathering and knowledge distillation.

### 2.2. Problem Formulation

We have two stages in the knowledge integration framework proposed in this work: (1) knowledge gathering from MoE; (2) knowledge distillation to further refine the new dense model (i.e., student). For the first stage, given $E$ experts $\{e_1(\cdot), e_2(\cdot), \ldots, e_E(\cdot)\}$, we are to maximize the knowledge covered in the dense model $s(\cdot)$. We use transformer-based MoE to introduce our framework due to its popularity. Given input representation $x$, within one transformer block, each expert is an FFN, which can be formulated as:

$$ e_i(x) = f^2_i(\sigma(f^1_i(x))) $$

where $f^1_i(\cdot)$ and $f^2_i(\cdot)$ and linear transformations of $i^{th}$ expert, $\sigma(\cdot)$ is the activation functions (e.g., ReLU or GELU). For the dense student, we have the same architecture but different trainable parameters:

$$ s(x) = g^2(\sigma(g^1(x))) $$

where $\sigma(\cdot)$ would be the same activation function as experts. The only difference is the trainable parameters in linear transformations. Then, our target is to approximate the trainable parameters of $g^1$ and $g^2$ according to $\{f^1_1, \ldots, f^1_E\}$ and $\{f^2_1, \ldots, f^2_E\}$, respectively. We define this target as knowledge gathering from MoE.

The second stage is fine-tuning the dense student to minimize the difference between teacher output and student output. We can easily find this task closer to knowledge distillation (Hinton et al., 2015), so in this paper, we follow the typical KD approaches as our solution.

Our goal is to preserve MoE’s benefits by a dense student as much as possible. So, we define a metric, MoE benefits, to measure the ability of a dense student to integrate knowledge from the MoE counterpart. The MoE benefits can be written as:

$$ \text{MoE benefits} = \frac{\text{score}_{\text{student}} - \text{score}_{\text{dense}}}{\text{score}_{\text{MoE}} - \text{score}_{\text{dense}}} $$

where score can be everything to evaluate the model. For instance, score is accuracy for image classification. The $\text{score}_{\text{dense}}$ here denotes the dense model’s performance without knowledge integration proposed.
3. Approach

In general, the final target of this work is to obtain a dense student model that is easy to use and as effective as the sparse MoE. To this end, we propose a general training framework, knowledge integration, to integrate knowledge from sparse MoE teacher to dense student. The proposed knowledge integration includes two stages: knowledge integration from MoE and knowledge distillation to refine the student. An overview of the proposed general training framework is shown in Figure 2. The first step is to initialize the dense student. For most trainable layers (e.g., embedding layer, attention layer, normalization layer), the teacher and the student have the same structure, so we can copy the weights from teachers following Switch Transformer (Fedus et al., 2021). The challenging part is the MoE layer. MoE layer has much more trainable parameters than the single FFN layer in dense model, and each expert is actually an FFN layer with unique weights and bias. The core issue is to incorporate knowledge from different FFN experts and assign the knowledge to one single FFN in student. To this end, we propose SVD Knowledge Gathering (SVD-KG) to gather knowledge from MoE. Then, knowledge distillation is to fine-tune the initialized model to further improve performance.

3.1. Knowledge Gathering from MoE

After copying the weights and bias in the perfectly matched layers, we initialize the dense student model by sparse MoE. In this work, we propose SVD-KG to extract key knowledge from different experts of a pretrained MoE.

3.1.1. SVD Knowledge Gathering

Given a MoE layer with E experts, the target here is to gather knowledge from all experts for one student. According to Eq. 6 and Eq. 7, each expert comprises two linear layers and the student share the same model structure with one expert. For brevity, we treat each expert as one linear transformation to show our idea, which can be expanded to multiple linear layers easily. For E linear layers \{f^1, f^2, \ldots, f^E\}, each linear layer \(f^i(\cdot): \mathbb{R}^{d_1} \rightarrow \mathbb{R}^{d_2}\) with weights \(W^i_f \in \mathbb{R}^{d_1 \times d_2}\) and bias \(b^i_f \in \mathbb{R}^{d_2}\),

\[
\text{SVD-KG}(f^1, f^2, \ldots, f^E) = \text{SVD-KG}(W^1_f, W^2_f, \ldots, W^E_f; b^1_f, b^2_f, \ldots, b^E_f) \approx (W_g; b_g) = g
\]

where \(g(\cdot): \mathbb{R}^{d_1} \rightarrow \mathbb{R}^{d_2}\) is a linear layer with \(W_g \in \mathbb{R}^{d_1 \times d_2}\) and bias \(b_g \in \mathbb{R}^{d_2}\).

We name such layers as perfectly matched layers in this work.

We first consider to initialize \(b_g\). Since it has much less trainable parameters, we simply average the bias vector from different experts:

\[
b_g = \frac{1}{E} \sum_{i=1}^{E} b^i_f
\]

We employ such a simple policy because knowledge stored in bias is much less than in weights, due to fewer trainable parameters.

For weights, in MoE, a wide over-parameterized model with much more trainable parameters, it is challenging to cover all knowledge in a narrow dense model. Instead, we propose to collect the key knowledge from different experts instead, and then merge them into a single dense model. Thus, the question is, how can we extract the key knowledge of each trainable matrix (i.e., weights)? Low-rank compression (CHen et al., 2021) has shown promising results in capturing key knowledge, which was used to convert a not low-rank matrix to a rank-\(k\) decomposition of the weight matrix. In this work, obtaining rank-\(k\) decomposition is not our target. We are to use SVD to extract key knowledge and merge them to initialize another dense model. The low-rank approximation with singular value decomposition (SVD) algorithm can be written as:

\[
W^i_f = U^i_f S^i_f V^T_f \approx U^{i_k}_f S^{i_k}_f V^{T_k}_f
\]

where \(U^i_f \in \mathbb{R}^{d_1 \times d_1}\) and \(V^i_f \in \mathbb{R}^{d_2 \times d_2}\) are unitary matrices, \(S^i_f \in \mathbb{R}^{d_1 \times d_2}\) is a diagonal matrix. We usually select the top-K elements in \(S^i_f\) and then construct \(U^{i_k}_f, S^{i_k}_f, V^{T_k}_f \in \mathbb{R}^{d_1 \times K}, \mathbb{R}^{d_1 \times K}, \mathbb{R}^{d_2 \times K}\) to approximate \(W^i_f\).

When \(k\) is fixed, every matrix has the rank-\(k\) decomposition to approximate the original matrix. However, we cannot guarantee the key knowledge in every expert can be covered by a fixed rank-\(k\) decomposition. Thus, we define a SVD ratio \(\lambda \in (0, 1]\) to ensure:

\[
\rho(S^{i_k}_f) \approx \lambda \rho(S^i_f)
\]

where \(\rho(S^i_f)\) denotes the sum of diagonal elements of \(S^i_f\). If \(\lambda = 1\), all ranks would be preserved for a full-rank matrix.

We then collect the decomposition of each expert and con-
We can then obtain $W_g$ as:

$$W_g = U_g S_g V_g^T$$ (14)

$W_g$ is a rank-$K_g$ matrix, where $K_g = \sum_{i=1}^{E} K^i$, covering the key knowledge of every expert.

After SVD-KG, knowledge has been integrated from pretrained MoE. However, during knowledge gathering, it is unavoidable to induce noise when we move conditional computation. Detailed analysis about the induced noise during gathering can be found in Appendix A.1.

### 3.2. Knowledge Distillation

To mine the knowledge from noise, we adopt knowledge distillation to fine-tune the dense student. We investigated two types of knowledge distillation approaches, soft distillation (Hinton et al., 2015) and hard-label distillation (Touvron et al., 2021). Soft distillation minimizes the Kullback-Leibler divergence between the output of the teacher and the student. The corresponding distillation loss can be written as:

$$L^\text{soft}_{\text{distill}} = T^2 L_{KL}(\omega(z_s/T), \omega(z_t/T))$$ (15)

where $\omega$ is the softmax function, $L_{KL}$ is Kullback-Leibler divergence loss, $z_s$ and $z_t$ are the logits of student and teacher, respectively, and $T$ is the softmax temperature.

The hard-label distillation takes the hard decision of the teacher as a true label. In other words, it treats the knowledge distillation task as a typical classification task, supervised by both the prediction from the teacher and ground truth.

$$L^\text{hard}_{\text{distill}} = L_{CE}(\omega(z_s), \text{argmax}(z_t))$$ (16)

where $L_{CE}$ is the cross-entropy loss, argmax is used to obtain the hard label of teacher’s prediction.

### 3.3. Optimization

Our final loss function is simple:

$$L_{\text{total}} = \alpha L_{\text{main}} + (1 - \alpha) L_{\text{distill}}$$ (17)

where $\alpha$ is used to balance the main loss\(^2\) and the distillation loss can be either soft distillation loss or hard-label distillation loss. For hard-label distillation, $\alpha$ is usually set as 0.5.

In Section 4.3, we found there is no significant difference in performance when using different types of distillation loss. Therefore, we adapt soft distillation, a more widely used approach as our default choice. Since our pretrained MoE is fixed during knowledge distillation, we do not need the load balance loss of MoE.

### 4. Experiments

To evaluate our general training framework, we conduct two sets of experiments on two different areas, computer vision and natural language processing.

#### 4.1. Computer Vision

**4.1.1. Experimental Settings**

**Datasets** We select two widely-used image classification benchmarks, ILSVRC-2012 ImageNet (Deng et al., 2009) and Cifar10 (Krizhevsky et al., 2009), as platforms to evaluate our framework on computer vision. ILSVRC-2012 ImageNet dataset we used in this work has 1k classes and 1.3M images. We denote it as ImageNet in the following experiments for brevity.

**Baselines** As we are the first work, to our best knowledge, focusing on integrating knowledge from a pretrained MoE, the only two existing strong baselines are the knowledge distillation framework proposed in Meta AI MoE (Artetxe et al., 2021) and Switch Transformer (Fedus et al., 2021). The first one simply initializes the student dense model randomly. The second work initializes the dense model with the non-expert weights. That is, they simply copy the layer which can be perfectly matched into the dense model. For the weights that cannot be matched (i.e., experts), they skip the initialization and train these layers from scratch instead. In our work, for brevity, we denote these two approaches as Distill and Switch, respectively. We also report the result of Vision Transformer (ViT) on the same setting to compare the parameter efficiency.

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\(^2\)The main loss depends on the task. For instance, to classify images, it is cross-entropy. For BERT pretraining, it should be the masked language modeling loss and next sentence prediction loss.
Teacher In our training framework, we need an MoE model to initialize our student dense model (i.e., knowledge gathering) and perform knowledge distillation. In this work, we apply the pretrained WideNet (Xue et al., 2021) as the platform. The reason is, every transformer block of this MoE model has one sparse MoE layer instead of one dense layer. It can verify the effectiveness of our approach in a more straightforward manner.

Hyper-parameters For a fair comparison, we follow the data augmentation used in teacher model: Inception-style pre-processing, Mixup (Zhang et al., 2017), RandAugment (Cubuk et al., 2020) and label smoothing (Szegedy et al., 2016; Yuan et al., 2020). We use LAMB (You et al., 2019) optimizer. Batch-size and learning rate are set as 4096 and 0.004, respectively. All settings of WideNet (Xue et al., 2021) are the same as reported in their paper. Please note we freeze all trainable weights of the teacher model (i.e., WideNet) in the training stage of OneS. For distillation hyper-parameters, we set $\alpha$ as 0.25 and temperature $T$ as 1.0. Linear learning rate decay is applied. Please see Appendix for other training details.

We also fine-tune our pretrained student model on Cifar10. The fine-tune setting is the same as ViT and WideNet. We use SGD optimizer with momentum. Compared with pretraining on ImageNet, label smoothing and warm-up are removed.

4.1.2. Results on ImageNet

We report the top-1 accuracy and MoE benefits on ImageNet in Table 1. The MoE benefits is the metric we defined in Eq. 8. We observe that OneS-L achieves 78.4% top-1 accuracy with only 15M parameters. Compared with the strongest baseline, Switch-L, our model has 0.6 points improvement. Compared with the teacher model, OneS-L outperforms WideNet-B by 0.9% with half of the parameters. As a final result, OneS-L achieves comparable performance with ViT-B with only 17% trainable parameters. More importantly, in (Xue et al., 2021), without MoE, WideNet-L can only achieve 76.9% top-1 accuracy. Our OneS-L has the totally same architecture with the WideNet without MoE, but we can achieve 78.4% accuracy. That is, our OneS-L preserves 61.7% improvement (i.e., MoE benefits) from WideNet. In addition, our OneS-B achieves 57.7 MoE benefits, which outperforms the SoTA (i.e., Switch) by 23.1 points. Such results show the effectiveness of knowledge integration.

4.1.3. Results on Cifar10

We further fine-tune our dense student model, OneS on Cifar10 in this part. As shown in Table 2, our OneS-L outperforms our baselines, Switch-B and Switch-L, by 0.3% and 0.6% respectively. The OneS-L can even achieve comparable performance with WideNet-B with 0.33 × trainable parameters. OneS-B also achieves better performance than Switch-B due to gathering knowledge from MoE by SVD-KG. In summary, the results on Cifar10 show the improvement of pretraining on ImageNet can propagate to downstream tasks.

4.2. Natural Language Processing

4.2.1. Experimental Settings

Similar to experiments on computer vision tasks, we still have two stages of training in natural language processing. The difference is, following existing works (Lan et al., 2019; Devlin et al., 2019; Xue et al., 2021), we focus on the performance of downstream tasks instead of pretraining.

Datasets We use English Wikipedia (Devlin et al., 2019) and BOOKCORPUS (Zhu et al., 2015) as our pretraining corpus. For fine-tuning, we evaluate our work on General Language Understanding Evaluation (GLUE) benchmark (Wang et al., 2018), two different versions of the
Table 3. Results of fine-tuning on MNLI, SST-2 and two versions of SQuAD datasets. The two numbers of F1 and EM for each SQuAD dataset are first averaged. The FLOPs here means the floating-point operations in FFN layer or MoE layer. We only report the FLOPs in FFN or MoE layer because FLOPs at other layers are same. We also compare the inference speed on TPU v3-8 to show the usability of dense model. The benefits here is the MoE benefits we proposed in Eq. 8.

| Model     | #para | FLOPs | Speedup | SQuAD1.1 | SQuAD2.0 | MNLI | SST-2 | Avg | Benefits(%) |
|------------|-------|-------|---------|----------|----------|------|-------|-----|-------------|
| Teacher    |       |       |         |          |          |      |       |     |             |
| WideNet    | 26M   | 2.4x  | 1.0x    | 89.6/82.7| 80.6/77.4| 82.6 | 91.1  | 84.71 | -           |
| Baseline   |       |       |         |          |          |      |       |     |             |
| ALBERT     | 12M   | 1.0x  | 3.7x    | 89.3/82.3| 80.0/77.1| 81.5 | 90.3  | 84.03 | 0.0         |
| Distill    | 12M   | 1.0x  | 3.7x    | 89.4/82.7| 79.8/76.6| 81.9 | 90.7  | 84.21 | 26.5        |
| Switch     | 12M   | 1.0x  | 3.7x    | 89.5/82.6| 79.9/77.0| 82.0 | 90.3  | 84.20 | 25.0        |
| Ours       | 12M   | 1.0x  | 3.7x    | 89.7/83.0| 80.2/77.1| 82.3 | 91.2  | 84.63 | 88.2        |

Stanford Question Answering (SQUAD) dataset (Rajpurkar et al., 2016; 2018).

Table 4. Top-1 Accuracy of ablation study on ImageNet to investigate the contributions of our two key components (i.e., knowledge gathering (KG) and knowledge distillation (KD)).

| Model | ImageNet |
|-------|----------|
| OneS-B | 75.7     |
| w/o KG | 73.8     |
| w/o KD | 75.0     |
| w/o KG & KD | 72.8 |
| OneS-L | 78.4     |
| w/o KG | 77.3     |
| w/o KD | 77.6     |
| w/o KG & KD | 76.9 |

Baselines Similar to the experiments on computer vision, we still select Distill and Switch as our direct baselines. The student model also has the same architecture as ALBERT except for the individual layer normalization (Xue et al., 2021). Therefore, another strong baseline is the ALBERT. We expect our OneS can outperform ALBERT with the almost same architecture, comparable number of parameters, and the same pretraining dataset.

Hyper-parameters After initialization, we further train OneS by a linear combination of masked language modeling loss, sentence order prediction loss and soft knowledge distillation loss. Following (Sanh et al., 2019), we only feed the logits of masked language modeling loss to $L_{distill}$. We still freeze all trainable weights of the teacher model (i.e., WideNet with 4 experts) in the training stage of OneS. The learning rate of LAMB optimizer is set as 0.00352. $\alpha$ is set as 0.75, and $\lambda$ is 0.25 in this part. Other detailed hyper-parameters can be found in Appendix A.2.2.

4.2.2. Results on NLU benchmarks

After pretraining on Wikipedia and BOOKCORPUS by knowledge distillation, we fine-tune our OneS without distillation loss. Such a setting is different from existing work on distilling language models. The reason is, one of our goals is to obtain an easy-to-use model without expert routing. If we still have an MoE teacher, the downstream fine-tuning still requires complicated hardware and software co-design for MoE. The results on downstream natural language understanding tasks are shown in Table 3. In general, observe OneS outperforms ALBERT and SoTA (i.e., Distill and Switch) on all tasks by achieving 88.2% MoE benefits. For instance, on four tasks, OneS surpass Switch by 0.42 in average. Also, we achieve 53.2% and 51.7% MoE benefits over Switch and Distill, respectively. On a few tasks, e.g., SQUAD1.1 and SST-2, OneS can even outperform the teacher MoE model, WideNet. We suggest that MoE model tends to overfit on small datasets. OneS has MoE’s knowledge but a dense structure, so that the benefits from pretraining can propagate to downstream tasks easier.

Compared with MoE model, another strength of our OneS is the inference speed. MoE model has gating function and sparse einsum operators due to conditional computation, which would reduce the computational efficiency. However, our model can achieve 3.7x inference speedup. Please note WideNet only uses 2.4x FLOPs at MoE layers. One reason why OneS can achieve such a high efficiency is less FLOPs. Another important reason is, the dense model is more hardware-friendly than sparse MoE model.

4.3. Ablation Study

We conduct three sets of ablation studies in this work. The first set is to investigate the contributions of knowledge gathering and knowledge distillation. As shown in Table 4, there is a significant performance drop without knowledge gathering, which shows the knowledge included in pretrained sparse model is critical to improving the student model’s performance. For the model without KD, in this experiments, we adopt the $L_{main}$ in Eq. 17 as the only loss function. We can see the knowledge distillation is helpful, as the prediction of teacher can instruct the student to mine knowledge in noisy weights gathered. In addition, when the dense model does not gather knowledge from MoE, the KD enables the
5. Related Work

5.1. Mixture-of-Experts

MoE has shown promising results on various tasks. Recent works scaled a dense model to a sparse one by MoE. Faster convergence speed of MoE can save the global computation cost. One typical way to use MoE is, replacing the FFN layer in transformer (Vaswani et al., 2017) by an MoE layer. (Lepikhin et al., 2020) first scale machine translation transformer model to 600 million parameters using automatic sharding. After that, Fedus et al. (2021) further scales the transformer to trillion parameter models with simple and efficient sparsity and shows promising results on natural language understanding. In computer vision, ViT-MoE (Ruiz et al., 2021) matches SoTA performance on ImageNet using 14.7 billion of parameters, while requiring as little as half of the computation at inference time. Recent work (Lou et al., 2021) investigated the MoE usage on MLP-Mixer, which also achieved better effectiveness and efficiency than the dense model. Instead of scaling up, this work use and fix the pretrained MoE models as a teacher. The core target is to combine the effectiveness of MoE and usability of dense model.

5.2. Knowledge Integration

Knowledge inheritance (Qin et al., 2021) is related to our knowledge integration. Knowledge inheritance usually inherits knowledge from small pretrained model and then speed-up the training of large models. Contrastively, our work is integrating knowledge from a large MoE model. Sun et al. (2019) proposed to integrate knowledge by using knowledge masking strategies. Please note our knowledge integration is different from theirs. Instead of a self-supervised learning approach to integrate knowledge from data, our work is to integrate knowledge from pretrained MoE. There are a few works focusing on inheriting knowledge from a dense model to initialize a MoE model, which is the opposite of our work. For instance, Zhang et al. (2022) duplicated dense model multiple times to initialize MoE models. Zhang et al. (2021) proposed MoEfication. The proposed approach is to inherit knowledge from a dense model and obtain an MoE model with comparable parameters to reduce the computation cost. In general, MoEfication is a sparsification approach. In Switch Transformer (Fedus et al., 2021), authors tried to initialize trainable parameters except for MoE layers to speed-up MoE training, although their main purpose is to scale transformer to trillions of parameters.

6. Conclusion and Future Work

In this paper, inspired by the human education model, we propose knowledge integration, a new task to combine the ef-
effective\textsuperscript{ness} of MoE model and the usability of dense model. As the first work focusing on this task, our solution is integrating knowledge in two steps (\textit{i.e.}, knowledge gathering and knowledge distillation). Knowledge gathering focuses on gathering knowledge from pretrained MoE to initialize dense student models. Knowledge distillation is to further refine the dense one. Experiments show that our OneS achieves outstanding effectiveness and efficiency on computer vision and natural language processing tasks. It is noteworthy our OneS can even preserve 88.2\% benefits from MoE with 0.42\times FLOPs per transformer block, 3.7\times inference speedup and 46\% trainable parameters.

In the future, we plan to further investigate advanced knowledge distillation approaches to better integrate knowledge of MoE into a dense student. Also, we expect to adapt our approach to the extremely huge MoE model like GLaM (Du et al., 2021) to obtain the most powerful dense student.

### References

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A. Appendix

A.1. Knowledge Gathering Noise Analysis

We are to discuss and analyze the noise induced during SVD knowledge gathering in this section. Given one MoE layer \( \text{MoE}(\cdot) \), the target of SVD-KG is to integrate its knowledge to a student dense layer \( g(\cdot) \). For brevity, we set every expert and the dense student layer as the single linear layer. There are \( E \) experts in MoE layer: \( \{f^1, \ldots, f^E\} \) with weights \( \{W_1^f, \ldots, W_E^f\} \) and bias \( \{b_1^f, \ldots, b_E^f\} \). The dense student layer is \( g \) with weights \( W_g \) and bias \( b_g \). According to Eq. 1, the MoE layer can be written as:

\[
\text{MoE}(x) = \sum_{i=1}^{E} G(x)_i c_i(x) = \sum_{i=1}^{E} p_i h_i(W^j_i x + b^j_i)
\]

where \( p \) is the routing score of router, \( h \) is an index vector. For the selected experts, \( h_i = 1 \), and \( h_i = 0 \) for other unselected experts. Due to the load balance loss during MoE training, we can assume \( p_i \approx 1.0 \) when \( h_i = 1 \). Then, we can approximate MoE layer by SVD:

\[
\text{MoE}(x) \approx \sum_{i=1}^{E} h_i(U^j_i S^j_i V^T_j K_i x + b^j_i)
\]

\[
\approx \sum_{i=1}^{E} h_i \sum_{j=1}^{K^i} a^i_{jf} K_i s^i_{jf} K_i v^i_{jf} K_i x + b^j_i
\]

where \( K^i \) is the selected rank of \( i \)-th expert.

According to Eq. 14, \( g(\cdot) \) can be formulated as:

\[
g(x) = \sum_{i=1}^{E} \sum_{j=1}^{K^i} a^i_{jf} K_i s^i_{jf} K_i v^i_{jf} K_i x + \frac{1}{E} \sum_{i=1}^{E} b^j_i
\]

For brevity, to analyze, we assume MoE layer here is to select the 1-st expert, and then the MoE layer can be written as:

\[
\text{MoE}(x) \approx \sum_{j=1}^{K^1} a^1_{jf} K_1 s^1_{jf} K_1 v^1_{jf} K_1 x + b^j_1
\]

and the student dense layer:

\[
g(x) = \sum_{j=1}^{K^1} a^1_{jf} K_1 s^1_{jf} K_1 v^1_{jf} K_1 x + b^j_1 + \frac{1}{E} \sum_{i=2}^{E} b^j_i - \frac{E-1}{E} b^j_1
\]
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Since the non-selected experts do not interact with the current input token $x$, we assume, for the non-selected experts, we let $\epsilon_1 = f^j(x)$ and $\epsilon_1 \sim \mathcal{N}(\mu_1, \sigma_1^2)$ and $\epsilon_2 = b^j_x$ and $\epsilon_2 \sim \mathcal{N}(\mu_2, \sigma_2^2)$. According to Eq. 12, $g(x)$ can be written as:

$$g(x) = \sum_{j=1}^{K_1} u^j_{f} K_1^s_f K_1^v_f K_1 T x + \lambda [(E - 1)\epsilon_1 - \frac{E - 1}{E} \epsilon_2]$$  \hfill (23)

The low-rank approximation ensures $\sum_{j=1}^{K_1} u^j_{f} K_1^s_f K_1^v_f K_1 T x + b^j_1$ cover most informative knowledge in the selected expert, and noise reduced linearly along $\lambda$. When we are integrating knowledge from experts, a smaller $\lambda$ is required to reduce noise.

A.2. Hyper-parameters

A.2.1. Computer Vision

Table 6. Hyper-parameters on ImageNet pretraining and Cifar10 finetuning. $\alpha$ and $\lambda$ are from Eq. 17 and Eq. 12

| Parameter               | ImageNet | Cifar10 |
|-------------------------|----------|---------|
| Epoch                   | 300      | 100     |
| Warmup Epochs           | 30       | 0       |
| Batch Size              | 4096     | 512     |
| Learning rate           | 0.004    | 0.03    |
| Weight Decay            | 0.1      | 0       |
| Dropout                 | 0.1      | 0.1     |
| Label smoothing         | 0.1      | 0       |
| Mixup prob.             | 0.5      | 0.5     |
| $\alpha$                | 0.25     | -       |
| $\lambda$               | 0.75     | -       |

Most hyper-parameters are set following existing works (e.g., ViT, WideNet). The main difference is the learning rate. Since we are training from a dense model initialized by a MoE model. We observe that a too large learning rate harms the accuracy. We therefore set a smaller learning rate 0.004 (0.01 in WideNet).

A.2.2. Natural Language Processing

The pretraining hyper-parameters is shown in

Table 7. Hyper-parameters on NLP downstream tasks fine-tuning.

| Parameter   | SQuAD1.1/2.0 | MNLI  | SST2  |
|-------------|--------------|-------|-------|
| Steps       | 3649/8144    | 10000 | 5234  |
| Warmup      | 365/814      | 1000  | 314   |
| Batch Size  | 48           | 128   | 128   |
| LR          | 5e-5/3e-5    | 3e-5  | 4e-5  |
| Dropout     | 0/0          | 0     | 0     |
| Max Length  | 384/512      | 512   | 512   |

We follow the hyper-parameters in (Devlin et al., 2019; Lan et al., 2019; Xue et al., 2021) and the final hyper-parameters are reported in Table 7.