Partial to Whole Knowledge Distillation: Progressive Distilling Decomposed Knowledge Boosts Student Better

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Abstract

Knowledge distillation field delicately designs various types of knowledge to shrink the performance gap between compact student and large-scale teacher. These existing distillation approaches simply focus on the improvement of knowledge quality, but ignore the significant influence of knowledge quantity on the distillation procedure. Opposed to the conventional distillation approaches, which extract knowledge from a fixed teacher computation graph, this paper explores a non-negligible research direction from a novel perspective of knowledge quantity to further improve the efficacy of knowledge distillation. We introduce a new concept of knowledge decomposition, and further put forward the Partial to Whole Knowledge Distillation (PWKD) paradigm. Specifically, we reconstruct teacher into weight-sharing sub-networks with same depth but increasing channel width, and train sub-networks jointly to obtain decomposed knowledge (sub-networks with more channels represent more knowledge). Then, student extract partial to whole knowledge from the pre-trained teacher within multiple training stages where cyclic learning rate is leveraged to accelerate convergence. Generally, PWKD can be regarded as a plugin to be compatible with existing offline knowledge distillation approaches. To verify the effectiveness of PWKD, we conduct experiments on two benchmark datasets: CIFAR-100 and ImageNet, and comprehensive evaluation results reveal that PWKD consistently improve existing knowledge distillation approaches without bells and whistles.

Introduction

To make deep neural networks (DNNs) practically applied, the demand for developing compact DNNs came into being. Shrinking the performance gap between compact models and large-scale models is of paramount importance. Knowledge distillation (KD) (Hinton, Vinyals, and Dean 2015) is one of the representative schemes to develop compact models by distilling knowledge from teacher (large-scale models) to student (compact models). Up to now, there have derived many different paradigms, such as offline distillation (Hinton, Vinyals, and Dean 2015; Romero et al. 2014), online distillation (Zhang et al. 2018b; Anil et al. 2018) etc. More importantly, these derivative knowledge distillation paradigms have been widely used in computer vision (Peng et al. 2019b; Wu et al. 2020; Zhang et al. 2020; Li, Jin, and Yan 2017; Mullapudi et al. 2019) and natural language processing (NLP) tasks (Kim and Rush 2016; Zhou, Neubig, and Gu 2019; Tan et al. 2019; Sun et al. 2019). KD community attributes the success of knowledge distillation to dark knowledge (Hinton, Vinyals, and Dean 2015) and hence mainly focuses on boosting student’s performance from the perspective of knowledge quality. To capture the nature of teacher representation, various types of knowledge, such as response-based knowledge (Hinton, Vinyals, and Dean 2015; Tian, Krishnan, and Isola 2019), feature-based knowledge (Romero et al. 2014; Zagoruyko and Komodakis 2016; Wang et al. 2020a), relation-based knowledge (Yim et al. 2017; Tung and Mori 2019; Passalis, Tzelepi, and Tefas 2020) and etc are designed to improve knowledge quality.

Despite the great success of KD, there are a few works to interpret what student benefits from dark knowledge. Cheng et al. (2020) explains the working mechanism of knowledge distillation by quantifying the knowledge encoded in the intermediate layer, and they find out that knowledge distillation makes student learn more visual concepts. In this paper, we do not intend to further demystify dark knowledge, but this interesting observation motivates us to rethink knowledge distillation schemes from the perspective of knowledge quantity.

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quantity rather than knowledge quality. Orange arrows in Figure 1 represents the feature information corresponding to different knowledge quantity with one given knowledge type. Cho and Haribaran (2019) empirically finds that the teacher accuracy is a poor predictor of student performance, which implies that teacher consisting of more knowledge may not be a better teacher. TAKD (Mirzadeh et al. 2020) introduces a teacher assistant with intermediate less knowledge to make the students learn better. Thus, we suppose that knowledge quantity of teacher has a great influence on the efficacy of knowledge distillation.

Based on the above observation, we survey most knowledge distillation literature whether it is offline or online paradigms. Then, we find out that teacher transfer the whole knowledge (logits, intermediate feature maps, etc obtained with the whole feed-forward computation graph) to student at once, which is counter-intuitive in the view of human beings. Imagining that a human teacher imparts all of what he has learned throughout his life to student, is it easy for student to accept it, especially in the early learning phases with poor cognitive ability? Hinton describes GLOM (Hinton 2021) to parse an image into a part-whole hierarchy, which motivates us to model the knowledge quantity of teacher into the partial-whole paradigm. We further make an intuitive hypothesis that progressively distilling knowledge from teacher with a partial-whole paradigm boosts student better (named partial-whole hypothesis for short).

To verify partial-whole hypothesis, we propose a partial to whole knowledge distillation (PWKD) paradigm as Figure 1 shows. We define a new setup of knowledge decomposition to parse knowledge of teacher into partial-whole knowledge. Different from GLOM (Hinton 2021) parsing image into independent partial representation, our goal is much simpler and aims to decompose knowledge representation into monotonically increasing fragments. Specifically, we reconstruct teacher into multiple weight-shared sub-networks with the same layer depth but different channel width, which preserves that knowledge quantity positively correlates with channel width (e.g., knowledge of 1.0× teacher is more than the one of 0.5× teacher). Then, all sub-networks are trained jointly to obtain decomposed knowledge pieces. In the distillation process, we split the distillation into multiple training stages, in which student extract different knowledge fragments. To converge to a local minimum in each stage, cyclic learning rate scheduler (Smith 2017) is leveraged to student to accelerate convergence in the distillation process.

We empirically evaluate PWKD on two benchmark datasets: CIFAR-100 and ImageNet, and PWKD is used as a general plugin compatible with nine mainstream offline distillation approaches (e.g., FitNet (Romero et al. 2014), AT (Sun et al. 2019), CRD (Tian, Krishnan, and Isola 2019) and etc). Comprehensive experiments show that knowledge distillation plugged with PWKD consistently improves performance with a substantial margin across various datasets, distillation approaches, and teacher-student pairs.

We summary the main contributions of this paper as follows:

1. For the first time, we analyze knowledge distillation from a new perspective of teacher knowledge quantity instead of obsessing over knowledge quality.

2. We present the partial-whole hypothesis and put forward a PWKD scheme to verify this hypothesis. Without loss of generality, PWKD is compatible with almost all offline distillation approaches.

3. Comprehensive experiment results demonstrate that PWKD is such a simple yet effective distillation paradigm, which consistently improves distillation baseline with a substantial margin. The ablation study also strongly supports the intuition of this paper. We believe these results will further inspire a new understanding of knowledge distillation.

Related Work

Knowledge Distillation (KD). KD (Hinton, Vinyals, and Dean 2015) has developed to present and mainly consists of two distillation schemes: offline distillation (Hinton, Vinyals, and Dean 2015; Romero et al. 2014; Huang and Wang 2017; Heo et al. 2019; Passalis and Tefas 2018) and online distillation (self-distillation is regarded as a special online distillation) (Zhang et al. 2018b; Anil et al. 2018; Zhang et al. 2019; Hou et al. 2019). Online distillation is the earliest distillation scheme and it includes two sequential training phases: firstly, training a teacher model before distillation; secondly, the pre-trained teacher is used to guide the optimization of student. However, teacher with higher performance is not always available or training teacher costs large computation. Thus online distillation came into being. Online distillation has only one training phase, during which both teacher and student are optimized from scratch and updated simultaneously. To obtain decomposed knowledge, teacher must be pre-trained, and hence we mainly focus on the offline distillation scheme.

For offline distillation, it is inevitable to consider two questions: (i) what knowledge to distill? and (ii) how to distill knowledge? To answer the first question, there are three categories of knowledge from teacher: output logits (Hinton, Vinyals, and Dean 2015; Chen et al. 2017; Huang, Zhu, and Ye 2019), intermediate feature map (Romero et al. 2014; Huang and Wang 2017; Passalis and Tefas 2018) and relation-based knowledge (Yim et al. 2017; Lee and Song 2019). Although the three types of knowledge represent different information, they share the same pattern that knowledge is obtained from the whole computation graph of teacher. There are few literatures that try to better distill knowledge. Opposed to the all-in distillation paradigm, we follow a similar rationale of curriculum distillation and propose a novel partial to whole knowledge distillation (PWKD) paradigm to answer the second question in this paper.

Adaptive Neural Networks (ANNs). ANNs have attracted increasing attention because of their advantages in computation efficiency, representation power and etc (Han et al. 2021). Opposed to static ones, ANNs dynamically adjust structures according to input samples (Wang et al. 2018; Huang et al. 2017) or constrained computation budgets (Yu et al. 2018; Wang et al. 2020b). More specifically, ANNs
adjust structures from the perspective of depth ([Wang et al. 2018] [Huang et al. 2017], channel width ([Yu et al. 2018] [Gao et al. 2018]), spatial resolution ([Wang et al. 2020b] [Yang et al. 2020]) or dynamic routing ([Li et al. 2020]). To answer the second question above (how to distill knowledge?), we instantiate knowledge decomposition with the adjusted attribute of ANNs in the channel dimension. Different from most ANNs, which aim for the trade-off between accuracy and computation efficiency, we reconstruct static teacher into ANNs to obtain decomposed knowledge. Sub-networks preserve both coarse-grained and fine-grained features, and the relationship between the amount of knowledge and the number of sub-network channel widths can be clearly defined.

Methodology
We clarify the goal of this paper is to build a new distillation setup: partial to whole knowledge distillation (PWKD) framework. To achieve this goal, we introduce the concept of knowledge decomposition. To our best knowledge, it is the first time to involve knowledge decomposition in the field of knowledge distillation. We reconstruct teacher into weight-sharing sub-networks with increasing channel widths and train these networks jointly to obtain decomposed knowledge. Then, we specify the interaction between student and teacher. At last, we put forward the overall PWKD framework that student progressively extracts partial to whole knowledge from teacher.

Knowledge Decomposition
Before introducing knowledge decomposition, we first define the knowledge contained in a neural network. To keep the definition simple, we take the classical image classification as an example. Given a training dataset consisting of image and label tuples \((x, y) \in \mathcal{X} \times \mathcal{Y}\), a neural network \(f(x, \mathbf{W})\) with learnable weights \(\mathbf{W}\) is build to fit the mapping \(\mathcal{X} \rightarrow \mathcal{Y}\). Cross entropy is used as the loss function \((\mathcal{L})\) and \(\mathbf{W}^*\) is achieved with Stochastic Gradient Descent (SGD) optimization:

\[
\mathbf{W}^* = \arg \min_{\mathbf{W}} \mathcal{L}(f(x, \mathbf{W}), y). 
\] (1)

Then, the well-optimized neural network \(f(x, \mathbf{W}^*)\) is used for inference. Given an input \(x\), \(f(x, \mathbf{W}^*)\) propagates forward and the output logits, intermediate feature maps, and relationships between layers or samples can be defined as the knowledge \(\Phi\).

Because \(\Phi\) is obtained with the whole network computation graph before the knowledge output node, we further define \(\Phi\) as the ‘whole knowledge’. In the knowledge distillation field, the conventional distillation approaches transfer ‘whole knowledge’ directly to student in the whole student optimization procedure (name all-in scheme for short). We argue that the all-in scheme is much simpler but counterintuitive. Knowledge distillation should obey the rule of curriculum learning from easy to difficult, just like humans. Intuitively, we can quantify the difficulty of learning from the perspective of knowledge quantity. Thus, it is necessary to decompose teacher’s knowledge before knowledge distillation.

Adaptive neural networks (ANNs) adapt structures to the input or computation constrain, which implies that network representation can be split into multiple parts. Inspired by the partial activation property of ANNs, we can also decompose the knowledge of teacher by reconstructing teacher into multiple sub-networks. To clearly quantify knowledge, we need to explicitly define the correspondence between the sub-networks and the amount of knowledge. In general, model representation ability and model computational complexity are positively correlated. Therefore, an intuitive way to reconstruct teacher is to divide teacher into multiple sub-networks with the same depth but different channel widths and parameters are shared between different sub-networks. As Figure 2 shows, we decompose the knowledge of vanilla teacher in four channel width groups (0.25×, 0.5×, 0.75×, and 1.0× channel width of full model). The knowledge quantity of four sub-networks is \(\Phi_{0.25\times}\), \(\Phi_{0.5\times}\), \(\Phi_{0.75\times}\) and \(\Phi_{1.0\times}\) respectively.

Figure 2: The framework of knowledge decomposition. Teacher is split into four sub-networks with same layer depth but different channel width (scale 0.25×, 0.5×, 0.75× and 1.0× channel width of full model). The knowledge quantity of four sub-networks is \(\Phi_{0.25\times}\), \(\Phi_{0.5\times}\), \(\Phi_{0.75\times}\) and \(\Phi_{1.0\times}\) respectively.
Distillation with Decomposed Knowledge

Given the pre-trained teacher optimized with Eq.2 and Eq.3, student can extract the decomposed knowledge $\Phi_{p\times}$ from the sub-networks with pre-defined channel width. Because the only difference between sub-networks and the full model is the channel width in each layer, the decomposed knowledge can be applied to almost all off-line distillation approaches. The whole loss function can be formulated as:

$$\mathcal{L} = \beta \star \mathcal{L}_{cls}(f_s(x, W_s), y) + (1 - \beta) \star \mathcal{L}_{kd}(f_s(x, W_s), f_t(x, W_{p\times}), T),$$

where $\beta$ represents $\mathcal{L}_{cls}$ weighted factor in student training phase and $\mathcal{L}_{kd}$ stands for a general distillation loss, such as similarity loss (Tung and Mori 2019), contrastive loss (Tian, Krishnan, and Isola 2019) and etc. The detailed distillation process can be described as Figure 3(a).

Overall Partial to Whole Distillation

Partial to whole multiple stage distillation. Although students can distill decomposed knowledge arbitrarily, we argue that progressively knowledge extraction boosts student better. In the above subsection, we have explicitly quantified knowledge through model capability: the more channels there are, the more knowledge the sub-network includes. Sequentially, we only need to divide the student distillation process into multiple stages and each stage distills knowledge gradually in ascending order. We keep the student training epochs as the vanilla distillation process and just split the total training epochs to each piece of knowledge with equal epochs. As Figure 3(b) shows, teacher transfers knowledge to student from $\Phi_{p\times}$ to $\Phi_{1.0\times}$ progressively.

Cyclical learning rate scheduler. During most knowledge distillation approaches, they use the learning rate scheduler with a fixed value that monotonically decreases during the whole training procedure of students. That makes sense, because student just needs to mimic teacher with a piece of knowledge. However, in the PWKD framework, there are multiple pieces of knowledge and student need to mimic different pieces of knowledge in each distillation stage. The conventionally monotonous learning rate schedulers make student optimized with a bigger learning rate in early distillation stages and yet smaller learning rate in later distillation stages, which prevents students from fully absorbing knowledge and further limits the performance improvement.

To fully take advantage of each piece of knowledge, student must converge to a local minimum in each distillation stage. Cyclical learning rate (CLR) scheduler can make model converge fast (Smith 2017) and we equip PWKD with CLR to converge to multiple local minimums. To make a fair comparison, we use the same training epochs as with other knowledge distillation approaches. Thus, each local minimum could be achieved with only $1/G$ ($G$ represents the number of knowledge pieces) of the total training epochs. Specifically, CLR consists of multiple cycles with the same learning rate policy. In each cycle, the learning rate is constrained with a range and varies between the minimum and maximum boundary with a certain functional form. In this paper, we instantiate the cyclical function form as the triangular window, which linearly increases from the minimum to the maximum bound and then linearly decreases to the minimum with equal window size.
Experiments

We evaluate partial to whole knowledge distillation (PWKD) on CIFAR-100 (Krizhevsky, Hinton et al. 2009) and ImageNet (Deng et al. 2009). We compare PWKD with standard KD on both datasets and to claim the generality, we extend PWKD to nine popular knowledge distillation methods on CIFAR-100. At last, we ablate the effect of PWKD and hyper-parameters.

Main Results

Results on CIFAR-100 In this section, we aim to verify the effectiveness of PWKD on CIFAR-100 dataset. Firstly, we reconstruct teacher into 4 weight-sharing sub-networks with channel width 0.25×, 0.5×, 0.75× and 1.0× respectively. Then, all sub-networks are trained jointly in each iteration to obtained knowledge fragments. Specifically, we set ResNet-20×4, ResNet-32×4, ResNet-44×4 and ResNet-56×4 as teacher (×4 means that channel width of each layer expands 4 times), and the test accuracy of sub-networks are reported in Table 1. For each teacher, test accuracy of sub-networks increase monotonically with channel width. Further compared with test accuracy of teacher without reconstruction, we observe that all sub-networks has inferior performance even for sub-networks with channel width 1.0×. This phenomenon may be caused by conflicted optimization goals of sub-networks in weight-sharing strategy.

With the pre-trained sub-networks, we split the distillation process into four stages, which equals to the number of sub-networks. In each distillation stage, student distill from one sub-network, and sub-networks are applied to each stage in the order of channel width from 0.25× to 1.0×. Besides, the cyclical learning rate also consist of four cycles, each distillation stage share the same learning rate decay policy to converge to local minimum.

We apply the above four teachers to five students: ResNet-20, ResNet-32, ResNet-44, ResNet-56 and ResNet-110. We define test accuracy of student trained from scratch and distilled from teacher with KD (Hinton, Vinyals, and Dean 2015) as baselines. We sum up the evaluation results in Figure 4 with four sub-figures. As Figure 4 shows, PWKD consistently outperforms the two baselines for all teacher-student pairs. An interesting observation is that in Figure 4 (c) and Figure 4 (d), ResNet-20 with KD has inferior performance (drop by 1.08% and 1.16%) than vanilla performance (this phenomenon is interpreted as teacher-student gap in Mirzadeh et al. (2020)), but PWKD can still improve ResNet-20 distilled from ResNet-44×4 and ResNet-56×4 with 1.01% and 1.42% respectively. To be most important, as Table 1 shows, all sub-networks in PWKD under-perform vanilla teacher, but distill various students outperform the ones distilled from vanilla teacher. These promising results demonstrate that PWKD boosts students better.

Extend to various distillation approaches As described in the methodology, PWKD can be used as a general plugin to be applied to various knowledge distillation approaches. To support the generality, we extend PWKD to existing distillation approaches in this section from the perspectives of teacher-student architecture styles and distillation methods. For teacher-student architecture styles, we mainly consider teacher-student pairs with homogeneous architectures (e.g., ResNet/ResNet (He et al. 2016) and heterogeneous architectures (e.g., ResNet/ShuffleNet (Zhang et al. 2018a), ResNet/MobileNet (Sandler et al. 2018), VGGNet (Simonyan and Zisserman 2014)/ShuffleNet and VGGNet/ResNet). For distillation methods, we introduce nine popular algorithms, consisting of KD (Hinton, Vinyals, and Dean 2015), FitNet (Romero et al. 2014), AT (Zagoruyko and Komodakis 2016), SP (Tung and Mori 2019), CC (Peng et al. 2019a), VLD (Ahn et al. 2019), RKD (Park et al. 2019), PTK (Passalis and Tefas 2018), NST (Huang and Wang 2018).

Table 1: Results of sub-networks on CIFAR-100. Each network is reconstructed into 4 sub-networks with channel width 0.25×, 0.5×, 0.75× and 1× respectively. Knowledge quantity of sub-networks increase monotonically with channel width, and all sub-networks consistently have inferior performance compared with vanilla teacher.
We further evaluate PWKD on ImageNet. ResNet-50 is adopted as the teacher, and we reconstruct ResNet-50 into 4 sub-networks with also 50 layers but 0.25×, 0.5×, 0.75× and 1× channel width respectively. We train the four sub-networks jointly to obtain knowledge $\Phi_{0.25\times}$, $\Phi_{0.5\times}$, $\Phi_{0.75\times}$ and $\Phi_{1\times}$. Top-1 accuracy of sub-networks are reported in Table 4. There are some different from sub-networks results on CIFAR-100 that sub-network ResNet-50 with 1× channel width outperforms vanilla ResNet-50 trained from scratch independently.

When applying KD to student, we find default KD setting $\beta=0.9$ and $T=6.0$ can not improve student as observed in Cho and Hariharan (2019). After comparative analysis with networks are reported in Table 4. There are some different from sub-networks results on CIFAR-100 that sub-network ResNet-50 with 1× channel width outperforms vanilla ResNet-50 trained from scratch independently.

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CIFAR-100, we guess this phenomenon is caused by inferior training accuracy and larger image category. Thus we try to assign more credit to ground truth labels may improve the efficacy of KD. Specifically, we set $\beta$ in Eq.4 to 0.1. As Table 4 shows, vanilla KD improve student ResNet10, ResNet-18 and ResNet-34 0.32%, 0.80% and 0.79%. Following this hyper-parameter setting, we plug vanilla KD with PWKD, and maximum and minimum boundary of CLR are 0.1 and 0.0001. The performance of students can be further improved by 0.85%, 0.68% and 0.60% compared with vanilla KD methods.

Ablation study

Effects of PWKD and cyclical scheduler  Our proposed distillation scheme consists of PWKD and cyclical learning rate scheduler. We choose ResNet-20×4/ResNet-20 as teacher/student pair to ablate the effect of PWKD and cyclical learning rate (CLR) in this section. As Table 5 shows, vanilla KD improves ResNet-20 with 0.47%, but PWKD without cyclical learning rate scheduler obtains 2.29% improvement compared with baseline. Further, we introduce cyclical learning rate scheduler to PWKD and PWKD improve ResNet-20 2.61%, which imply convergence to multiple local minimums prompt student better.

| Teacher/student | KD   | PWKD | CLR | Top1 (\Delta) |
|----------------|------|------|-----|---------------|
| None/ResNet-20 (baseline) | 68.15 (+0.00) | 66.07 (+0.00) |
| None/ResNet-20 | √ | 66.32 (+0.47) | |
| ResNet-20×4/ResNet-20 | √ | 70.76 (+2.61) | |

Table 6: Ablate effects of PWKD and cyclical learning rate scheduler on knowledge distillation efficacy.

Considering the benefit of CLR, we further investigate more possibility of learning rate decay form in each cycle. Besides the rectangular form presented in [Smith 2017], we instantiate other custom learning rate decay policy, multi-step scheduler, linear scheduler and cosine scheduler into CLR. We report the comparison results of different CLR in Table 7. We observe that all four CLR can gain with at least 1.48% improvement. CLR with the rectangular form works best with PWKD and improve ResNet-44 and ResNet-56 with 2.37% and 2.23% respectively.

Varying knowledge distillation order  As claimed in the introduction, curriculum learning in distillation process is such significant, and we further investigate the knowledge distillation order in this section. We consider two types of distillation order in PWKD, that is curriculum order (distilling knowledge from $\Phi_{0.25\times} \rightarrow \Phi_{0.5\times} \rightarrow \Phi_{0.75\times} \rightarrow \Phi_{1.0\times}$) and reversed order (distilling knowledge from $\Phi_{1.0\times} \rightarrow \Phi_{0.75\times} \rightarrow \Phi_{0.5\times} \rightarrow \Phi_{0.25\times}$). We set ResNet-20×4 as teacher, and ResNet-20, ResNet-32, ResNet-44, ResNet-56 and ResNet-110 as student. We compare PWKD and reversed PWKD in Figure 6 and results show that PWKD consistently outperform reversed PWKD across five teacher-student pairs. In some cases (e.g., ResNet-20×4/ResNet-56 and ResNet-20×4/ResNet-110), reversed PWKD even has inferior performance than vanilla KD [Hinton, Vinyals, and Dean 2015]. We conclude that curriculum learning from partial to whole is such promising for knowledge distillation.

| Method             | ResNet-44×4/ResNet-44 | ResNet-56×4/ResNet-56 |
|--------------------|-----------------------|-----------------------|
| Vanilla student    | 71.17 (+0.00)         | 72.07 (+0.00)         |
| PWKD (multi-step)  | 72.65 (+1.48)         | 73.55 (+1.48)         |
| PWKD (cosine)      | 72.89 (+1.72)         | 73.92 (+1.85)         |
| PWKD (linear)      | 73.25 (+2.08)         | 74.14 (+2.07)         |
| PWKD (rectangle)   | 73.54 (+2.37)         | 74.30 (+2.23)         |

Table 7: Ablate effects of different cyclical learning rate scheduler on the efficacy of PWKD on CIFAR-100.

Varying groups of knowledge decomposition  Knowledge decomposition is one of the key components in PWKD framework, and the groups of knowledge decomposition have great influence on the efficacy of knowledge distillation. Therefore, we investigate the effects of knowledge decomposition by varying groups of knowledge decomposition. Given a teacher, we change the number of sub-networks $G \in \{2, 4, 8\}$ and train sub-networks jointly to obtain decomposed knowledge. As Figure 5 shows, given four teacher-student pairs, the test accuracy of student is positive correlated with G. These results seems make sense, and further support the intuition of this paper that smoother distillation boosts student better. However, considering the trade-off between teacher training computation and student distillation performance, we set G to 4 in default.

**Conclusion**

We analyze knowledge distillation from a new perspective of teacher knowledge quantity and propose PWKD paradigm. Comprehensive evaluation results across datasets, distillation approaches and teacher-student pairs demonstrate the generality and effectiveness of PWKD. We further conclude that partial-whole hypothesis actually makes sense and knowledge quantity has the potential to improve the efficacy of knowledge distillation. In the future, we plan to explore more knowledge decomposition paradigms from the angle

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[^Channel width list]: [0.5×, 1.0×], [0.25×, 0.5×, 0.75×, 1.0×] and [0.25×, 0.35×, 0.45×, 0.55×, 0.65×, 0.75×, 0.85×, 1.0×] corresponds to $G=2,4,8$ respectively.
of feature resolution, network depth and etc. Relating knowledge distillation and adaptive neural networks is an interesting topic.
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