HINT-DYNAMIC KNOWLEDGE DISTILLATION

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ABSTRACT

Knowledge Distillation (KD) transfers the knowledge from a high-capacity teacher model to promote a smaller student model. Existing efforts guide the distillation by matching their prediction logits, feature embedding, etc., while leaving how to efficiently utilize them in junction less explored. In this paper, we propose Hint-dynamic Knowledge Distillation, dubbed HKD, which excavates the knowledge from the teacher’s hints in a dynamic scheme. The guidance effect from the knowledge hints usually varies in different instances and learning stages, which motivates us to customize a specific hint-learning manner for each instance adaptively. Specifically, a meta-weight network is introduced to generate the instance-wise weight coefficients about knowledge hints in the perception of the dynamical learning progress of the student model. We further present a weight ensembling strategy to eliminate the potential bias of coefficient estimation by exploiting the historical statistics. Experiments on standard benchmarks of CIFAR-100 and Tiny-ImageNet manifest that the proposed HKD well boost the effect of knowledge distillation tasks.

Index Terms— Knowledge Distillation; Dynamic Network; Meta-Learning

1. INTRODUCTION

Whilst deep neural networks (DNNs) have achieved remarkable success in computer vision, most of these well-performed models are difficult to deploy on edge devices in practical scenarios due to the high computational costs. To alleviate this, light-weight DNNs have been investigated a lot. The typical approaches mainly include parameter quantization \cite{1}, network pruning \cite{2}, knowledge distillation (KD) \cite{3}, etc. Among them, the KD topic has gained increasing popularity in various vision tasks due to its simplicity to be integrated into other model compression pipelines.

The core idea of KD \cite{3} is to distill the knowledge from the cumbersome teacher model to strengthen the compressed student by matching their posterior distribution of class labels as knowledge hints. Numerous subsequent works further explore various new forms of matching hints, such as intermediate representation \cite{4, 5, 6}, attention maps \cite{7}, mutual information \cite{8, 9, 10}, structural knowledge \cite{11, 12, 13}, etc. By extracting knowledge from the soft labels as coarse distillation, most of these methods further leverage more fine-grained distillation from the explored novel knowledge hints. Concretely, they combine the guidance from various grains with pre-defined weight coefficients and maintain their consistency across instances throughout the training procedure. Nevertheless, the dynamical capacity of the student model is neglected by most of these methods \cite{14}. In this regard, the current KD paradigm tends to fail in modeling and perceiving the dynamical distillation effect of different knowledge hints.

To ameliorate the above issue, we present a novel hint-dynamic scheme from the insight of efficiently utilizing diverse knowledge hints. Fig. 1 depicts the motivation of our proposed framework. The learning progress of the student differs in instances across the distillation procedure. For the plain instances which are certain for the student, simply the coarse knowledge from the rudimentary soft labels is enough to guide the distillation. In contrast, for those critical ones who are not well-learned, more fine-grained knowledge from other hints like feature embedding is introduced.

Our insight is to dynamically generate a customized learning fashion to handle different knowledge hints according to

Fig. 1: Motivation of the proposed HKD. Unlike the existing KD paradigm that exploits different knowledge hints in a pre-defined fashion, our HKD adaptively customizes the learning fashion on each instance at different training iteration $t$. 

The study is supported partly by the National Natural Science Foundation of China under Grants 52105126, 82172033, U19B2031, 82272071, 62271430, and 61971369.\textsuperscript{*} Corresponding author: Xiaotong Tu, xttu@xmu.edu.cn}
the aptitude of student. To this end, we formulate the importance of each knowledge hint as a variable dependent on the input instance and model the learning fashion as weight coefficients of the KD loss from different hints. A meta-weight network (meta-net) is further leveraged, where an inner loop is set up to train the meta-net to generate weights for each instance, while an outer loop uses the updated meta-net to guide the standard KD. To alleviate the estimation bias of optimal weights, we further propose a weight ensembling strategy utilizing historical statics.

Our contribution can be summarized as:

- We propose a novel Hint-dynamic Knowledge Distillation framework that enables dynamic learning for various knowledge hints adaptively.
- We introduce a meta-learning based method that dynamically assigns the weight coefficients about distillation loss for each sample.
- We derive an uncertainty-based weight ensembling strategy, which alleviates the adverse effect of the unreliable estimation of meta-weight via historical statics.
- Experiments demonstrate the superior performance of the proposed HKD on benchmark datasets.

2. METHOD

2.1. Preliminaries

In the task of KD, given a pre-trained teacher model $T$ and a student model $S$ on a training data set $\mathcal{X}$, the KL divergence between the student output $p_S(x)$ and $p_T(x)$ is minimized as the vanilla KD version [3]:

$$
\mathcal{L}_{\text{KD}}^{\text{van}} = \sum_{x \in \mathcal{X}} p_T(x) \cdot \log \frac{p_T(x)}{p_S(x)}
$$

Subsequently, the community further explores a extensive variety of hint forms for knowledge transfer beyond the prediction labels, like intermediate layers [4], attention maps [7], etc. Specifically, they leverage an auxiliary guidance signals from the teacher by using the matching loss $\mathcal{L}_{\text{KD}}^{\text{aux}}$ for the exploited hints, which is utilized to update the student $S$ over training data set $\mathcal{X}$:

$$
\mathcal{L}(S; \mathcal{X}) = \sum_{x \in \mathcal{X}} \mathcal{L}_{\text{CE}}(x) + \beta \mathcal{L}_{\text{KD}}^{\text{aux}}(x) + \gamma \mathcal{L}_{\text{KD}}^{\text{van}}(x)
$$

where $\mathcal{L}_{\text{CE}}$ is the cross entropy loss whereas $\beta, \gamma$ are the weight coefficients for different distillation losses of each sample, respectively, which are designed empirically to keep fixed for all the instances across the whole training procedure in conventional KD methods, despite the different learning progress of the student model for each sample. As a core distinction, we propose to dynamically adjust the guidance manner from the teacher, which emphasizes the varying demand for different knowledge hints for each instance at different iterations.
2.2. Hint-dynamic Knowledge Distillation

Overview. To dynamically utilize the different knowledge hints for each instance, one naive solution is to utilize an uncertainty-based metric [15, 16] that however can be unreliable. To ameliorate this issue, we draw the inspiration from meta-learning [17] and leverage a meta-weight network (meta-net) to encode each instance’s importance. In this regard, the meta-net and the knowledge distillation framework can promote each other. Fig.2 depicts the workflow of the proposed HKD.

Meta-Weight Network. To perform the instance-wise dynamic estimation of the optimal learning fashion, we design a meta-net \( W \) to generate the weight coefficients for different knowledge hints on each instance, which is prior to every learning iteration of the student model. We feed the prediction logits of both student and teacher into meta-net, so the weight for sample \( x \) can be written as:

\[
\beta(x), \gamma(x) = \mathcal{W}(p_S(x), p_T(x))
\]

Practically, the meta-net is easy to implement, e.g., a 2-layer Multi-Layer Perception (MLP) with a given weight range. In what follows, we further leverage a pseudo student to perform the inner-loop optimization for our HKD, which is inspired by the insight of meta-learning [17, 18].

Inner Loop via Pseudo Student Generation. In the utilization of a meta-net, we exploit a technique to update pseudo student to make perception of the model performance. Specifically, a meta-set \( \mathcal{X}_{\text{meta}} \) is held out from the whole training data set \( \mathcal{X} \), i.e., \( |\mathcal{X}_{\text{meta}}| \ll |\mathcal{X}| \), and we perform a one-step gradient update for the student as a pseudo version \( S_p \):

\[
L(S_p; \mathcal{X}) = \sum_{x \in \mathcal{X}_{\text{meta}}} L_{CE}(x) + \beta(x)L_{\text{KD}}^\text{aux}(x) + \gamma(x)L_{\text{KD}}(x)
\]

The mean-square error (MSE) of pseudo student on the meta-set reflects the quality of weight estimation of the meta-net, which can be further utilized to optimize the meta-net \( \mathcal{W} \):

\[
L(\mathcal{W}; \mathcal{X}_{\text{meta}}^\text{err}) = \sum_{x \in \mathcal{X}_{\text{meta}}^\text{err}} L_{\text{MSE}}(p_{S_p}(x), GT(x))
\]

where \( \mathcal{X}_{\text{meta}}^\text{err} \) denotes the incorrect results of pseudo student’s output in the meta-set [19], \( p_{S_p}(x) \) is the prediction probability of the pseudo student, and \( GT(x) \) returns the ground-truth probability value of the corresponding sample.

Outer Loop Optimization via Second-order Gradient. In the outer loop, student selectively acquire knowledge hints from the teacher under the guidance of the meta-net. In this regard, a standard knowledge distillation process is introduced as Eq. 2. Then, by iteratively executing the two preceding loops, we can formulate a nested optimization problem:

\[
\begin{align*}
\min_S & \quad L(S; \mathcal{X}) \\
\text{s.t.} & \quad W = \arg\min_W L(\mathcal{W}; \mathcal{X}_{\text{meta}}^\text{err})
\end{align*}
\]

where the outer loop is formulated as a problem to search for the optimal hint weights while constrained by the inner loop.

2.3. Meta-Weight Ensembling

The effect of the proposed meta-learning based framework relies on the accurate estimation of the hint coefficients, i.e., the output of the meta-net, whereas the transient state of this weight is not always reliable. To address this issue, we further propose a strategy to generate a more robust hint weights via the temporal ensembling:

\[
(\beta^t(x), \gamma^t(x)) = \begin{cases} 
\epsilon \cdot (\beta^{t-1}(x), \gamma^{t-1}(x)) + (1 - \epsilon) (\beta(x), \gamma(x)) & u(x) < u_{th} \\
(\beta(x), \gamma(x)) & u(x) \geq u_{th}
\end{cases}
\]

where \( t \) denotes the current step and \( t - 1 \) is the previous step. \( \epsilon \) controls the ratio between the weight of \( t \) and \( t - 1 \). \( u_{th} \) is the threshold value of uncertainty. This mechanism is applied to the updating of student in the outer loop, which means \( \beta^t_S, \gamma^t_S \) are calculated by Eq. 7. \( u(x) \) representing the uncertainty of sample \( x \), can be modeled by the prediction entropy: \( u(x) = -p_S(x)\log(p_S(x)) \).

3. EXPERIMENTS

Datasets. Experiments are conducted on the benchmark datasets of CIFAR-100 [20] and Tiny-ImageNet [21]. CIFAR-100 contains 50K 32×32 training images with 500 images per class and 10K test images with 100 images per class. Tiny-ImageNet is a subset version of ImageNet with 200 classes, where each image is down-sampled to 64×64. The images in each class are split as 500/50 for training and testing, respectively.

Implementation Details. Following the common practice in KD [13, 22], we set the total number of training epochs to 240 while the batch size to 64. We use stochastic gradient descent (SGD) as the optimizer for the student model. Except for ShuffleNet V1, which is set to 0.01, the initial learning rate is 0.05. Weight decay is set to \( 5 \times 10^{-4} \). For meta-net, we adopt an Adam optimizer with the initial learning rate \( 1 \times 10^{-3} \). For the meta-set, we set size to 1000 on CIFAR-100 and 2000 on Tiny-ImageNet considering 10 samples per class. The training interval of the inner loop is 100. We search for the optimal dynamic weights \( \beta \) and \( \gamma \) with a searching range \( t = 0.5 \) around the initial value 1. For the weight ensembling, an uncertainty threshold of 0.6 is adopted, and \( \epsilon \) is 0.5.

3.1. Comparisons with State-of-the-art Methods

Results on CIFAR-100. We test the performance of our method when combined with three SOTA KD works, including Fitnet [4], VID [8] and CRD [13]. We directly cite the quantitative results reported in their papers [13]. The results are shown in Tab.1. \( T \) and \( S \) denote the accuracy of the
Table 1: Top-1 Test Acc. (%) of the student networks on CIFAR-100.

| Model         | ResNet3x32 → ResNet32 | WRN_40_2 → WRN_40_2 | ResNet100 → ResNet32 |
|---------------|-----------------------|---------------------|----------------------|
| T             | 78.92                 | 78.67               | 59.35                |
| S             | 71.14                 | 70.59               | 58.93                |
| Fitnet [1]    | 72.35                 | 72.63               | 59.93                |
| VDD [1]       | 72.29                 | 72.55               | 59.36                |
| CRD [1]       | 72.22                 | 72.57               | 59.41                |

Table 2: Top-1 Test Acc. (%) of the student networks on Tiny-ImageNet.

| Model         | Vgg13 → Vgg8 | WRN_32x4 → WRN_32x4 | ResNet1010 → ResNet20 |
|---------------|--------------|---------------------|-----------------------|
| Sol           | 60.00        | 61.26               | 58.46                 |
| S             | 56.01        | 57.17               | 51.49                 |
| Fitnet        | 58.33        | 58.86               | 59.06                 |
| VDD           | 58.55        | 58.85               | 59.15                 |
| CRD           | 58.88        | 59.65               | 59.81                 |

Table 3: Computational cost (s/epoch) and Top-1 Test Acc. (%) of different distillation methods on CIFAR-100.

| Model         | ResNet3x32 → ResNet32 | ResNet50 → Vgg8 | WRN_40_2 → WRN_40_2 | ResNet1010 → ResNet20 |
|---------------|-----------------------|-----------------|---------------------|----------------------|
| Vanilla KD    | 56.96                 | 56.32            | 46.95               | 75.88                |
| HKD (ours)    | 46.86                 | 72.94            | 46.95               | 75.88                |
| SAKD [23]     | 99.88                 | 72.85            | 73.92               | 76.21                |

Table 4: Top-1 Test Acc. (%) of ablation studies on CIFAR-100.

| Model         | R32x2→R32 | W40-2→SN11 | Time cost |
|---------------|-----------|------------|-----------|
| Static Un-Dy  | 73.92     | 73.30      | 73.78     |
| MWN (l = 1)   | 73.94     | 73.77      | 73.78     |
| MWN (l = 0.5) | 73.94     | 73.77      | 73.78     |
| MWN+MWE (full)| 73.94     | 73.77      | 73.78     |

The dynamic weight in different searching range $l$ of 0.5 and 1 around the initial value. It can be seen that an appropriate searching range leads to a better distillation effect. (4) When equipped with meta-weight ensembling strategy as $MWE$ to facilitate a more robust estimation of dynamic weight, the accuracy of the student model distilled by our full HKD method achieves the best accuracy, which indicates each component of our HKD plays its own role.

Visualization on Meta-weight Estimation. Fig. 3 shows the curves of the batch-wise average of weight variation on TinyImageNet. We can see that most samples are uncertain to the student during the initial stage of distillation, thus the vanilla KD loss and CRD loss weights are relatively large. As the distillation goes on, the student’s capacity increases, which requires more guidance from vanilla KD. Consequently, the weight of vanilla KD loss increases while the weight of CRD loss decreases. Finally, the student tends to choose a stable learning fashion compared with the initial state.

Fig. 3: The curves of the learned hint weights in two experiments on Tiny-ImageNet.

4. CONCLUSION

This paper proposes Hint-dynamic Knowledge Distillation (HKD) to promote knowledge transfer in a dynamic and active fashion. Instead of using fixed weight coefficients for knowledge hints from the teacher, HKD dynamically customize instance-wise learning to promote the distillation process. Specifically, a meta-weight network is leveraged to generate the estimation of optimal learning manner regarding knowledge hints, utilizing a meta-learning-based optimization framework. To address weight estimation bias, a meta-weight ensembling strategy is explored, which adaptively ensembles hint weights based on historical statistics. Extensive experiments on benchmark datasets show that HKD outperforms state-of-the-art and off-the-shelf distillation methods.

3.2. Further Empirical Analysis

Ablation Study. We conduct ablation studies on CIFAR-100 to validate the effect of each component in HKD. The results are shown in Tab. 4. Note that the experiments here are based on the feature hints from CRD. (1) **Static** denotes the baseline which adopts a fixed weight of knowledge hints during the whole training procedure. (2) **Un-Dy** models the dynamic property w.r.t. the knowledge hints using an uncertainty-based approach as in [15]. We can see the performance gain brought by utilizing the dynamic modeling for the weight. (3) **MWN** further exploits the meta-weight network to generate teacher and student models when they are trained individually. We can see that HKD significantly enhances the modern KD methods and outperforms two other adaptive distillation methods [15, 22] in most experiments.

Results on Tiny-ImageNet. Following KD on Tiny-ImageNet common practice [22], experiments are conducted with three sets of $T$ and $S$. Tab. 2 presents the results, which indicate that HKD continues to outperform other works.

Computation cost. Tab. 3 shows the computational cost and top1 test accuracy when combined with VID [8], all experiments are conducted on RTX 2080Ti. We can observe that: Compared to SAKD [22], the existing SOTA for adaptive distillation, our HKD reduces the average computation cost by 54.33% percent. Despite slightly inferior than SAKD in one set of results in Tab. 3, HKD has a far lower computational cost than SAKD. This marginal performance improvement, which requires a substantial time cost is not worthwhile.
5. REFERENCES

[1] Jiaxiang Wu, Cong Leng, Yuhang Wang, Qinghao Hu, and Jian Cheng, “Quantized convolutional neural networks for mobile devices,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 4820–4828.

[2] Mingbao Lin, Rongrong Ji, Yan Wang, Yichen Zhang, Baobao Zhang, Yonghong Tian, and Ling Shao, “‘Hrank: Filter pruning using high-rank feature map,” in Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2020, pp. 1529–1538.

[3] Geoffrey Hinton, Oriol Vinyals, Jeff Dean, et al., “Distilling the knowledge in a neural network,” arXiv preprint arXiv:1503.02531, vol. 2, no. 7, 2015.

[4] Adriana Romero, Nicolas Ballas, Samira Ebrahimi Kahou, Antoine Chassang, Carlo Gatta, and Yoshua Bengio, “Fitnets: Hints for thin deep nets,” arXiv preprint arXiv:1412.6550, 2014.

[5] Pengguang Chen, Shu Liu, Hengshuang Zhao, and Jiaya Jia, “Distilling knowledge via knowledge review,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2021, pp. 5008–5017.

[6] Gustavo Aguilar, Yuan Ling, Yu Zhang, Benjamin Yao, Xing Fan, and Chenlei Guo, “Knowledge distillation from internal representations,” in Proceedings of the AAAI Conference on Artificial Intelligence, 2020, vol. 34, pp. 7350–7357.

[7] Sergey Zagoruyko and Nikos Komodakis, “Paying more attention to attention: Improving the performance of convolutional neural networks via attention transfer,” arXiv preprint arXiv:1612.03928, 2016.

[8] Sungsoo Ahn, Shell Xu Hu, Andreas Damianou, Neil D Lawrence, and Zhenwen Dai, “Variational information distillation for knowledge transfer,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2019, pp. 9163–9171.

[9] Baoyun Peng, Xiao Jin, Jiaheng Liu, Dongsheng Li, Yichao Wu, Yu Liu, Shunfeng Zhou, and Zhaoning Zhang, “Correlation congruence for knowledge distillation,” in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2019, pp. 5007–5016.

[10] Frederick Tung and Greg Mori, “Similarity-preserving knowledge distillation,” in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2019, pp. 1365–1374.

[11] Wonpyo Park, Dongju Kim, Yan Lu, and Minsu Cho, “Relational knowledge distillation,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2019, pp. 3967–3976.

[12] Jinguo Zhu, Shixiang Tang, Dapeng Chen, Shijie Yu, Yakun Liu, Mingzhe Rong, Aijun Yang, and Xiaohua Wang, “Complementary relation contrastive distillation,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2021, pp. 9260–9269.

[13] Yonglong Tian, Dilip Krishnan, and Phillip Isola, “Contrastive representation distillation,” arXiv preprint arXiv:1910.10699, 2019.

[14] Chenxin Li, Mingbao Lin, Zhiyuan Ding, Nie Lin, Yihong Zhuang, Yue Huang, Xinghao Ding, and Lujuan Cao, “Knowledge condensation distillation,” in Computer Vision–ECCV 2022: 17th European Conference, Tel Aviv, Israel, October 23–27, 2022, Proceedings, Part XI. Springer, 2022, pp. 19–35.

[15] Lei Li, Yankai Lin, Shuhuai Ren, Peng Li, Jie Zhou, and Xu Sun, “Dynamic knowledge distillation for pre-trained language models,” in Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, 2021, pp. 379–389.

[16] Chenxin Li, Wena Ma, Liyan Sun, Xinghao Ding, Yue Huang, Guisheng Wang, and Yizhou Yu, “Hierarchical deep network with uncertainty-aware semi-supervised learning for vessel segmentation,” Neural Computing and Applications, pp. 1–14, 2022.

[17] Chelsea Finn, Pieter Abbeel, and Sergey Levine, “Model-agnostic meta-learning for fast adaptation of deep networks,” in International conference on machine learning. PMLR, 2017, pp. 1126–1135.

[18] Chenxin Li, Xin Lin, Yijin Mao, Wei Lin, Qi Qi, Xinghao Ding, Yue Huang, Dong Liang, and Yizhou Yu, “Domain generalization on medical imaging classification using episodic training with task augmentation,” Computers in biology and medicine, vol. 141, pp. 105144, 2022.

[19] Jihao Liu, Boxiao Liu, Hongsheng Li, and Yu Liu, “Meta knowledge distillation,” arXiv preprint arXiv:2202.07940, 2022.

[20] Alex Krizhevsky, Geoffrey Hinton, et al., “Learning multiple layers of features from tiny images,” 2009.

[21] Ya Le and Xuan Yang, “Tiny imagenet visual recognition challenge,” CS 231N, vol. 7, no. 7, pp. 3, 2015.

[22] Jie Song, Ying Chen, Jingwen Ye, and Mingli Song, “Spot-adaptive knowledge distillation,” IEEE Transactions on Image Processing, vol. 31, pp. 3359–3370, 2022.