MUTUAL DISTILLATION OF CONFIDENT KNOWLEDGE

Ziyun Li$^1$ Xinshao Wang$^{2,6}$ Di Hu$^3$ Neil M. Robertson$^{4,6}$
David A. Clifton$^{2,5}$ Christoph Meinel$^1$ Haojin Yang$^1$

$^1$Hasso Plattner Institute, Germany
$^2$Institute of Biomedical Engineering, University of Oxford, UK
$^3$Renmin University of China, China
$^4$Queen’s University Belfast, UK
$^5$Oxford Suzhou Centre for Advanced Research, China
$^6$Zenith Ai, UK

ABSTRACT

Mutual knowledge distillation (MKD) improves a model by distilling knowledge from another model. However, not all knowledge is certain and correct, especially under adverse conditions. For example, label noise usually leads to less reliable models due to undesired memorization [1, 2]. Wrong knowledge misleads the learning rather than helps. This problem can be handled by two aspects: (i) improving the reliability of a model where the knowledge is from (i.e., knowledge source’s reliability); (ii) selecting reliable knowledge for distillation. In the literature, making a model more reliable is widely studied while selective MKD receives little attention. Therefore, we focus on studying selective MKD. Concretely, a generic MKD framework, Confident knowledge selection followed by Mutual Distillation (CMD), is designed. The key component of CMD is a generic knowledge selection formulation, making the selection threshold either static (CMD-S) or progressive (CMD-P). Additionally, CMD covers two special cases: zero knowledge and all knowledge, leading to a unified MKD framework. Extensive experiments are present to demonstrate the effectiveness of CMD and thoroughly justify the design of CMD. For example, CMD-P obtains new state-of-the-art results in robustness against label noise.

1. INTRODUCTION

“What knowledge to be selected for distillation” is an essential question of mutual knowledge distillation (MKD) but has received little attention. Existing MKD methods treat all knowledge of a deep model equally, i.e., all knowledge is distilled into another model without selection. However, there was no study on the knowledge selection, which could be a key, as empirically indicated in Table [1]. This research question can also be expressed as:

Should all knowledge or partial knowledge of a model be distilled into another model?

In clean scenarios, the knowledge source is generally reliable. Thus, simply distilling all knowledge is reasonable, and it has widespread use in existing KD works. However, in label-noise scenarios, the knowledge source is less reliable. The distilled incorrect knowledge would mislead the learning

Table 1: The interactions between how each model is trained and what knowledge should be distilled. Zero: no distilled knowledge, two models are trained independently; All knowledge: distilled without selection, as MKD does; We proposed CMD-S and CMD-P. Vertically, CMD-S and CMD-P are better than "Zero" and "All" consistently no matter how each model is trained. This empirically demonstrates that selecting confident knowledge for distillation is better. Horizontally, methods with self confidence label correction (MyLC) outperforms those without self confident label correction (cross entropy(CE), label smooth(LS), confidence penalty(CP)) consistently across all distillation types. This empirically proves the importance of improving knowledge source when noisy labels exist. Experiments are done on CIFAR-100 using ResNet34. The symmetric label noise rate is 40%. The average final test accuracies (%) of two models are reported. The performance difference between the two models is negligible.

| Distilled Knowledge | CE | LS | CP | MyLC (ours) |
|---------------------|----|----|----|-------------|
| Zero                | 47.20 | 51.53 | 51.09 | 65.04       |
| All(MKD)            | 51.42 | 53.63 | 53.18 | 61.11       |
| CMD-S(ours)         | 52.52 | 55.10 | 53.86 | 68.45       |
| CMD-P(ours)         | 54.28 | 56.73 | 56.47 | 69.09       |

1The bidirectional mutual knowledge distillation (MKD), where two models can have the same or different architectures, is a combination of two single-direction KD. Bidirectional MKD has the potential to improve both models dynamically and progressively. Thus, this work focuses on MKD.

2We remark that the label-noise setting is typical and challenging in real-world machine learning applications, where the given datasets have non-perfect annotations. Additionally, in some recent work, it is shown that the
rather than help. Therefore, it is vital to note “not all knowledge is created equal” and identify “what knowledge could be distilled?”. We work on this problem from two aspects: (i) making the knowledge source more reliable, (ii) selecting the certain knowledge to distill. For the first aspect, many algorithms have been proposed, e.g., Tf-KD [11] and ProSelfLC [3]. For simplicity, we exploit them and focus more on the second aspect: selective knowledge distillation.

To explore the knowledge selection problem, we design a selective MKD framework, i.e., Mutual distillation of confident knowledge, which is shown in Figure 1. We propose to only distill confident knowledge. Specifically, we design a generic knowledge selection formulation, so that we can either fix the knowledge selection threshold (CMD-Static, shortened as CMD-S) or change it progressively as the training progresses (CMD-Progressive, abbreviated as CMD-P). In CMD-P, we leverage the training time to adjust how much knowledge would be selected dynamically considering that a model’s knowledge improves along with time. CMD-P performs slightly better than CMD-S, according to our empirical studies, e.g., Table 1, more detail in Section 4.1.

We summarise our contributions as follows:

- To the best of our knowledge, we are the first one to study what knowledge to be selected for distillation in MKD. Correspondingly, we propose a generic knowledge selection formulation, including the variants of zero-knowledge, all knowledge, CMD-S, and CMD-P.
- Thorough studies on the models’ learning curves, knowledge selection criterion’s settings, and hyperparameters justify the rationale of our selective MKD design and its effectiveness.
- Our proposed CMD-P obtains new state-of-the-art results in deep robustness against label noise.

2. RELATED WORK AND PRELIMINARY

KD is an effective method for distilling the knowledge of complex ensembles or a cumbersome model (usually named teacher models) to a small model (usually named a student) [7][8]. Recently, many deep KD variants have been proposed, e.g., self knowledge distillation (Self KD) which trains a single learner and leverages its own knowledge [3][4], MKD with knowledge transfer between two learners [9][10][11], ensemble-based KD methods [12][13], and born-again networks with knowledge distilling from multiple student generations [14]. Since we focus on training two learners, Teacher→Student KD (T2S KD) and Mutual KD are more relevant. We present more of them in supplementary.

Table 2: Summary of LS, CP, Boot-soft, ProSelfLC, and MyLC from the angle of self KD. ϵ measures how much we trust the prediction and ϵ ∈ [0, 1]. It can be static or progressive and adaptive as the training progresses. p and q represent model prediction and annotated label respectively.

|              | LS     | CP     | Boot-soft | ProSelfLC |
|--------------|--------|--------|-----------|-----------|
| Refined label| (1 - ϵ)q | (1 - ϵ)q | (1 - ϵ)q | (1 - ϵ)q |
| Self-trust ϵ | Fixed  | Fixed  | Dynamic   | Dynamic   |

2.1. Revisiting independent self label correction methods

We explore and apply some Self Label Correction (i.e., Self KD) algorithms to train models independently so that their knowledge is more reliable, especially when noisy labels exist. We summarise LS together with some highly relevant self KD methods, including confidence penalty (CP) [15], Boot-soft [16] and ProSelfLC [3] in Table 2.

According to the Table 2, LS applies a uniform distribution (u) to smooth the annotated label. CP penalizes highly confident predictions. Boot-soft and ProSelfLC refine the learning target by combining a corresponding prediction. ϵ is fixed manually in LS, CP, and Boot-soft. While in ProSelfLC, ϵ changes dynamically during training based on training time and sample confidence calculated by prediction’s entropy as l(p) = 1 - H(p)/H(u), where l(p) represents a model’s predictive confidence w.r.t x (i.e., sample confidence).
2.2. MyLC: An alternative for self LC

MyLC is designed for demonstrating the effectiveness and extensiveness of CMD. MyLC considers self-trust $\epsilon$ into two parts, local confidence $l(p)$ and global confidence $g(r)$, similar to ProSelfLC. We apply sample confidence w.r.t. each sample $x$ as local confidence, as ProSelfLC does. For global confidence, MyLC computes it based on a model’s predictive confidence w.r.t. all samples, shown as following:

$$g(r) = h(r - \rho, b_1), \quad \text{where} \quad r = 1 - \frac{\sum^n_{i=1} H(p_i)}{n + H(u)}, \quad (1)$$

$h(\lambda, b_1) = 1/(1 + e^{\exp(-\lambda \times b_1)})$ is a logistic function, where $b_1$ is a hyperparameter for controlling the smoothness of $h$. $r$ represents a model’s overall certainty of all examples. A higher $r$ implies that a model is more reliable. Intuitively, if $r$ is higher than a threshold $\rho$, we assign more trust to the model. We simply set $\rho = 0.5$ in all our experiments. Consequently, $\epsilon = g(r) \times l(p)$. And the loss becomes:

$$L_{MyLC} = H(\hat{q}_{MyLC}|p) = E_{\hat{q}_{MyLC}}(-\log p),$$

where $\hat{q}_{MyLC} = (1 - \epsilon)q + \epsilon p$. \hfill (2)

3. MUTUAL DISTILLATION OF CONFIDENT KNOWLEDGE

CMD improves MKD by distilling confident knowledge into each other rather than all knowledge, as shown in the Figure[1]. Conventional MKD transfers all knowledge between two models while our CMD selects confident knowledge to distill. We design a generic knowledge selection formulation that unifies zero knowledge, all knowledge, and partial knowledge selection in a static and progressive fashion (CMD-S and CMD-P).

3.1. Learning objectives

To distill model B’s confident knowledge into model A, we optimise A’s predictions towards B’s confident predictions:

$$L_{B2A} = \begin{cases} H(\hat{q}_B, p_A), & \text{if } H(p_B) < \chi, \\ 0, & \text{if } H(p_B) \geq \chi. \end{cases} \quad (3)$$

We use the entropy $H(p_B)$ to measure the confidence of $p_B$ since entropy as a solid measure in noise label scenarios, there have been some studies on it and proved its effectiveness [15, 17, 8]. Low entropy indicates high confidence, and vice versa. $\chi$ is a threshold to decide whether a label prediction is confident enough or not. Specifically, only when $H(p_B) < \chi$, the model B’s knowledge w.r.t. $x$ is confident enough. $\hat{q}_B$ is the learning target, which can be from a self KD method as it is more reliable.

Analogously, we distill model A’s confident knowledge into model B:

$$L_{A2B} = \begin{cases} H(\hat{q}_A, p_B), & \text{if } H(p_A) < \chi, \\ 0, & \text{if } H(p_A) \geq \chi. \end{cases} \quad (4)$$

The final loss functions for models A and B are:

$$L_A = L_{A\rightarrow B \rightarrow A} + L_{B2A} = \begin{cases} H(\hat{q}_A, p_A) + H(\hat{q}_B, p_A), & \text{if } H(p_B) < \chi; \\ H(\hat{q}_A, p_A), & \text{if } H(p_B) \geq \chi; \end{cases}$$

$$L_B = L_{B\rightarrow A \rightarrow B} + L_{A2B} = \begin{cases} H(\hat{q}_B, p_B) + H(\hat{q}_A, p_B), & \text{if } H(p_A) < \chi; \\ H(\hat{q}_B, p_B), & \text{if } H(p_A) \geq \chi; \end{cases}$$

3.2. A generic design for knowledge selection

As aforementioned, we use an entropy threshold $\chi$ to decide whether a piece of knowledge is certain enough or not. We design a generic formation for $\chi$ as follows:

$$\chi = \frac{H(u)}{\eta} + 2h(\frac{t}{\Gamma} - 0.5, b_2),$$

where $h(\cdot, \cdot)$ is a logistic function. $u$ is a uniform distribution, thus $H(u)$ is a constant. $t$ and $\Gamma$ denote the current epoch and the total number of epochs, respectively. For a wider unification, we make the design of Eq. (5) generic and flexible. Therefore, we use $\eta$ to control the starting point. While $b_2$ controls how the knowledge selection changes along with $t$. $\chi$ has two different modes:

- **Static (CMD-S).** The confidence threshold $\chi$ is a constant when $b_2 = 0$. Concretely, $2h(\frac{t}{\Gamma} - 0.5, 0) = 1 \rightarrow \chi = \frac{H(u)}{\eta}$. This mode covers two special cases:
  (i) One model’s all knowledge is distilled into the other when $\eta \in (0, 1) \rightarrow \chi \geq \frac{H(u)}{\eta}$, which degrades to be the conventional MKD.
  (ii) Zero knowledge is distilled between two models when $\eta \in \{-\infty, \infty\} \rightarrow \chi \leq 0$.

- **Progressive (CMD-P).** When $b_2 \neq 0$, $\chi$ changes as the training progresses. To make it comprehensive, $\chi$ can be either increasing or decreasing at training:
  (i) If $b_2 > 0$, $\chi$ increases as $t$ increases. Since the knowledge selection criteria is relaxed, more knowledge will be transferred between the two models at the later learning phase.
  (ii) On the contrary, $\chi$ gradually decreases when setting $b_2 < 0$. This only allows knowledge with higher confidence (lower entropy) to be distilled.

It is worth highlighting that compared to sample selection methods, CMD can correct the supervision in loss computation and optimisation stages when the supervision (label) is noisy. In other word, instead of discarding
noisy samples, CMD can correct supervision and distill reliable knowledge. Both models’ knowledge becomes more confident at the later stage even the knowledge selection criterion becomes stricter (i.e., $b_2 < 0$). And we can clearly observe that almost all the training samples are distilled in the later training phase in Figure 2. In our empirical studies (e.g., Figure 4), in the noisy scenario, CMD-P with $b_2 < 0$ performs the best. Therefore, when comparing with prior relevant methods, we use CMD-P with $b_2 < 0$ by defaults.

4. EXPERIMENTS

In this section, we first demonstrate that CMD is effective in robust learning against an adverse condition, i.e., label noise (Section 4.1). Then we empirically verify that CMD, as a selective MKD, outperforms prior MKD approaches for training two models collaboratively no matter whether they are of the same architecture or not (Section 4.2). We subsequently present a comprehensive ablation study and hyper-parameters analysis (Section 4.3 and Supplementary). Different network architectures are evaluated. For all experiments, we report the final results when the training terminates. More implementation details are provided in the supplementary material. The code will be released once this work is accepted.

4.1. CMD for robust learning against noisy labels

Label noise generation. We verify the effectiveness of our proposed CMD on both synthetic and real-world label noise. For synthetic label noise, we consider symmetric noise and pair-flip noise [18]. For symmetric label noise, a sample’s original label is uniformly changed to one of the other classes with a probability of noise rate $r$. The noise rates are set to 20%, 40%, 60%, and 80%. For pair-flip noise, the original label is flipped to its adjacent class with noise rates of 20% and 40%, respectively.

4.1.1. The interaction between self label correction and CMD

As shown in Tables 1 and 3, CMD, as a new selective MKD method, can be easily added to existing self label correction methods as a collaborative mutual enhancer. Table 3 is an extension of Table 1. Since ProSelfLC and MyLC always performs better than the other approaches, therefore we only apply CMD over them to explore how much CMD can enhance stronger baselines. We can see that after applying CMD-P/CMD-S, we achieve 1-5% improvement among different noise types and rates compared to ProSelfLC and MyLC.

4.1.2. Outperforming recent state-of-the-art methods for handling label noise

Results on one synthetically noisy CIFAR-100 and two real-world noisy datasets, Food-101 and Webvision. As shown in Table 4, CMD-P+MyLC outperform all the recent label-noise-oriented methods under both pair-flip and symmetric noisy labels. Notably, their improvements are more significant when noise rate rises. For Food-101, As this dataset is more challenging, thus the performance gap is smaller over all methods. For Webvision, our experiments follow the “Mini” setting in [20]. The first 50 classes of the Google resized image subset is treated as training set and evaluate the trained networks on the same 50 classes on the ILSVRC12 validation set. The results of CMD-P+MyLC are around 5-6% higher than the latest methods including Co-teaching, APL, CDR, and ProSelfLC.

4.2. Comparing with recent state-of-the-art MKD methods

MKD for two networks of the same architecture. In Table 5, as same part, we present the results of the baseline CE, self distillation methods (Ti-KD$_{reg}$ [4], ProSelfLC and ProSelfLC + ProSelfLC) and the proposed CMD-P/CMD-S methods.
Table 4: Recent state-of-the-art approaches for label noise are compared. All methods apply ResNet50 as the network architecture. For Food-101, we use a ResNet50 pre-trained on ImageNet. For Webvision, we follow the "Mini" setting in [19, 20, 21, 22]. The top two results of each column are bolded.

| Method       | CIFAR-100 | Real-world noise |
|--------------|-----------|------------------|
|              | Pair-flip label noise | Symmetric label noise | Food-101 | Webvision (Mini) |
|              | 20% | 40% | 20% | 40% | ~20% | ~50% |
| CE           | 64.10 | 52.77 | 63.93 | 56.82 | 84.03 | 57.34 |
| GCE [23]     | 62.32 | 55.03 | 65.62 | 57.97 | 83.73 | 61.22 |
| Co-teaching [18] | 58.11 | 48.46 | 61.47 | 53.44 | 76.89 | 33.26 |
| Co-teaching+ [24] | 56.31 | 38.03 | 64.13 | 59.92 | 83.10 | 47.60 |
| Joint [25]   | 67.35 | 52.22 | 54.88 | 45.64 | 85.52 | 56.33 |
| Forward [26] | 58.37 | 39.82 | 66.12 | 59.45 | 81.25 | 57.66 |
| MentorNet [20] | 54.73 | 45.31 | 57.27 | 49.01 | 76.89 | 33.26 |
| T-revision [27] | 62.69 | 52.31 | 64.67 | 57.15 | 85.97 | 60.58 |
| DMI [28]     | 58.77 | 42.89 | 62.77 | 57.42 | 85.52 | 56.93 |
| APL [22]     | 71.93 | 56.94 | 68.68 | 62.72 | 86.36 | 61.85 |
| CDR [19]     | 73.11 | 69.49 | 71.17 | 60.38 | 86.97 | 62.40 |
| MyLC         | 72.25 | 70.84 | 69.92 | 62.80 | 86.70 | 64.44 |
| CMD-P+MyLC   | **74.38** | **73.86** | **72.23** | **64.30** | **87.60** | **67.48** |

Table 5: In the different part, MKD for training two models of different net architectures, all networks are trained for 200 epochs; In the same part, MKD for training two networks of the same architecture. For self distillation, we train single model. For each algorithm, we train ResNet34 for 100 epochs. Experiments are done on CIFAR-100 with 40% symmetric noisy labels. For each case, the best result is bolded. SfNetV2* represents ShufflenetV2.

| Method       | Different | Same |
|--------------|-----------|------|
|              | ResNet18  | SfNetV2* | ResNet34 |
| Baseline CE  | 50.63     | 44.06 | 47.20 |
| Self KD     | Ti-KD     | 51.05 | 44.70 | 47.39 |
|             | ProselfLC | 58.51 | 58.89 | 64.07 |
|             | MyLC      | 55.94 | 61.21 | 65.04 |
| Offline     | SSKD      | 52.83 | 57.17 | 55.21 |
|             | KDC L     | 55.45 | 46.10 | 51.20 |
| MKD         | SyncMKD+  | 60.38 | 47.72 | 51.42 |
|             | CMD-P     | **68.10** | **64.37** | **69.09** |
|             | +MyLC     |       |       |       |

Fig. 3: Learning curves on CIFAR-100 using ResNet34. The training set has 40% symmetric noisy labels.

MyLC), offline KD (SSKD [30]), ensemble KD (KDC L, here we use two same nets) and mutual distillation algorithms (SyncMKD, and CMD-P+MyLC) under noisy scenarios. SyncMKD and KDCL distill all knowledge without selection. CMD-P+MyLC achieve 17%-18% absolute improvement compared to SyncMKD and KDCL under the same architecture, ResNet34.

MKD for two networks of different architectures. For self KD methods, we train each model individually while together for MKD methods(with mutual distillation). In Table 5's different part, we show CMD's effectiveness for training two different networks, ResNet18 and ShufflenetV2. CMD improves for around 8% for ResNet18 and 1-3% for ShufflenetV2 compared to the second place.

4.3. Analysis on dynamic learning behaviours

Figure 3 shows the accuracy curves of different methods on CIFAR-100 with 40% symmetric noisy labels. Here, we only show the promoter CMD-P because CMD-P is slightly better than CMD-S. We observe that CMD-P dramatically boosts the performance of CE, ProselfLC and MyLC.

As the training goes, without CMD-P, the test accuracies of CE, ProselfLC and MyLC drop a lot after around 50 epochs, due to the undesired memorisation. However,
when CMD-P is exploited, their generalisation is improved significantly. This indicates that CMD-P is great at avoiding overfitting and learning robustly under noisy labels. In summary, CMD not only boosts self label correction methods but also promotes robust learning against adverse conditions.

5. CONCLUSION

We study knowledge selection in MKD and propose a unified knowledge selection framework, named CMD. CMD improves MKD by distilling only confident knowledge to guide the peer model. By extensive experiments, we empirically demonstrate the effectiveness of CMD. Furthermore, CMD outperforms related MKD methods and obtains new state-of-the-art results in handling the label noise problem.

6. REFERENCES

[1] Chiyuan Zhang, Samy Bengio, Moritz Hardt, Benjamin Recht, and Oriol Vinyals, “Understanding deep learning requires rethinking generalization,” in ICLR, 2017.
[2] Devansh Arpit, Stanislaw Jastrzbski, Nicolas Ballas, David Krueger, Emmanuel Bengio, Maxinder S. Kanwal, Tegan Maharaj, Asja Fischer, Aaron Courville, Yoshua Bengio, and Simon Lacoste-Julien, “A closer look at memorization in deep networks,” in ICML, 2017.
[3] Xinshao Wang, Yang Hua, Elyor Kodirov, David A Clifton, and Neil M Robertson, “ProSelILC: Progressive self label correction for training robust deep neural networks,” in CVPR, 2021.
[4] Li Yuan, Francis EH Tay, Guilin Li, Tao Wang, and Jiashi Feng, “Revisiting knowledge distillation via label smoothing regularization,” in CVPR, 2020.
[5] Yisen Wang, Xingjun Ma, Zaiyi Chen, Yuan Luo, Jinfeng Yi, and James Bailey, “Symmetric cross entropy for robust learning with noisy labels,” in ICCV, 2019.
[6] Eric Arazo, Diego Ortego, Paul Albert, Noel O’Connor, and Kevin Mcguinness, “Unsupervised label noise modeling and loss correction,” in ICML, 2019.
[7] Cristian Buicla, Rich Caruana, and Alexandru Niculescu-Mizil, “Model compression,” in KDDM, 2006.
[8] Geoffrey Hinton, Oriol Vinyals, and Jeffrey Dean, “Distilling the knowledge in a neural network,” in NeurIPS Deep Learning and Representation Learning Workshop, 2015.
[9] Ying Zhang, Tao Xiang, Timothy M Hospedales, and Huchuan Lu, “Deep mutual learning,” in CVPR, 2018.
[10] Adriana Romero, Nicolas Ballas, Samira Ebrahimi Kahou, Antoine Chassang, Carlo Gatta, and Yoshua Bengio, “Fitnets: Hints for thin deep nets,” in ICLR, 2015.
[11] Jimmy Ba and Rich Caruana, “Do deep nets really need to be deep?,” in NeurIPS, 2014.
[12] Qishan Guo, Xinjiang Wang, Yichao Wu, Zhipeng Yu, Ding Liang, Xiaolin Hu, and Ping Luo, “Online knowledge distillation via collaborative learning,” in CVPR, 2020.
[13] Guile Wu and Shaogang Gong, “Peer collaborative learning for online knowledge distillation,” arXiv preprint arXiv:2006.04147, 2020.
[14] Tommaso Furlanello, Zachary Lipton, Michael Tschannen, Laurent Itti, and Anima Anandkumar, “Born again neural networks,” in ICML, 2018.
[15] Gabriel Pereyra, George Tucker, Jan Chorowski, Lukasz Kaiser, and Geoffrey Hinton, “Regularizing neural networks by penalizing confident output distributions,” in ICLR Workshop, 2017.
[16] Scott Reed, Honglak Lee, Dragomir Anguelov, Christian Szegedy, Dumitru Erhan, and Andrew Rabinovich, “Training deep neural networks on noisy labels with bootstrapping,” in ICLR Workshop, 2015.
[17] Christian Szegedy, Vincent Vanhoucke, Sergey Ioffe, Jon Shlens, and Zbigniew Wojna, “Rethinking the inception architecture for computer vision,” in CVPR, 2016.
[18] Bo Han, Quanming Yao, Xingrui Yu, Gang Niu, Miao Xu, Weihua Hu, Ivor Tsang, and Masashi Sugiyama, “Co-teaching: Robust training of deep neural networks with extremely noisy labels,” in NeurIPS, 2018.
[19] Xiaobo Xia, Tongliang Liu, Bo Han, Chen Gong, Nannan Wang, Zongyuan Ge, and Yi Chang, “Robust early-learning: Hindering the memorization of noisy labels,” in ICLR, 2021.
[20] Lu Jiang, Zhengyuan Zhou, Thomas Leung, Li-Jia Li, and Li Fei-Fei, “Mentornet: Learning data-driven curriculum for very deep neural networks on corrupted labels,” in ICML, 2018.
[21] Pengfei Chen, Ben Ben Liao, Guangyong Chen, and Shengyu Zhang, “Understanding and utilizing deep neural networks trained with noisy labels,” in NeurIPS, 2018.
[22] Xingjun Ma, Hanxun Huang, Yisen Wang, Simone Romano, Sarah Erfani, and James Bailey, “Normalized loss functions for deep learning with noisy labels,” in ICLR, 2020.
[26] Giorgio Patrini, Alessandro Rozza, Aditya Krishna Menon, Richard Nock, and Lizhen Qu, “Making deep neural networks robust to label noise: A loss correction approach,” in CVPR, 2017.

[27] Xiaobo Xia, Tongliang Liu, Nannan Wang, Bo Han, Chen Gong, Gang Niu, and Masashi Sugiyama, “Are anchor points really indispensable in label-noise learning?,” in NeurIPS, 2019.

[28] Yilun Xu, Peng Cao, Yuqing Kong, and Yizhou Wang, “L_dmi: A novel information-theoretic loss function for training deep nets robust to label noise.,” in NeurIPS, 2019.

[29] Yu Yao, Tongliang Liu, Bo Han, Mingming Gong, Jiankang Deng, Gang Niu, and Masashi Sugiyama, “Dual t: Reducing estimation error for transition matrix in label-noise learning,” in NeurIPS, 2020.

[30] Guodong Xu, Ziwei Liu, Xiaoxiao Li, and Chen-Change Loy, “Knowledge distillation meets self-supervision,” in ECCV, 2020.

[31] Helong Zhou, Liangchen Song, Jiajie Chen, Ye Zhou, Guoli Wang, Junsong Yuan, and Qian Zhang, “Rethinking soft labels for knowledge distillation: A bias-variance tradeoff perspective,” in ICLR, 2021.

[32] Alex Krizhevsky, “Learning multiple layers of features from tiny images,” 2009.

[33] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun, “Deep residual learning for image recognition,” in CVPR, 2016.

[34] Lukas Bossard, Matthieu Guillaumin, and Luc Van Gool, “Food-101–mining discriminative components with random forests,” in ECCV. Springer, 2014, pp. 446–461.

[35] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei, “Imagenet: A large-scale hierarchical image database,” in CVPR, 2009.

[36] Christian Szegedy, Sergey Ioffe, Vincent Vanhoucke, and Alexander Alemi, “Inception-v4, inception-resnet and the impact of residual connections on learning,” in AAAI, 2017.
Supplementary Material for CMD

7. RELATED WORK

Notations. For a multi-class classification problem, $x$ is a data point, and $q \in \mathbb{R}^C$ is its annotated label distribution, also seen as annotated knowledge. $C$ is the number of training classes. In the traditional practice, $q$ is a one-hot representation, a.k.a., hard label. Mathematically, $q(j|x) = 1$ only if $j = y$, and 0 otherwise. Here, $y$ denotes the semantic class of $x$. $f$ is a deep neural network that predicts the probabilities of $x$ being different training classes. We denote them using a vector $p \in \mathbb{R}^C$, which can be seen as a model’s self knowledge.

7.1. T2S KD and MKD

T2S KD \cite{2} transfers knowledge from a teacher model to a student model and can be formulated as:

$$L_{T2SKD}(q, p_t, p_s) = (1 - \epsilon)H(q, p) + \epsilon D_{KL}(p_t, p),$$ (6)

where $p$ is the prediction by a student model while $p_t$ is the output of a teacher model, $H(q, p)$ represents the cross entropy loss between target $q$ and prediction $p$.

Mutual KD (MKD) \cite{9} trains two models $A$ and $B$, making them learn from each other. Therefore, we have $L_A(q, p_A, p_B) = (1 - \epsilon)H(q, p_A) + \epsilon D_{KL}(p_B, p_A)$ and $L_B(q, p_B, p_A) = (1 - \epsilon)H(q, p_B) + \epsilon D_{KL}(p_A, p_B)$. In the original proposal, $A$ and $B$ are trained iteratively in an asynchronous fashion, and we called it asynchronous Mutual KD (AsyncMKD). In our experiments, for non-selective MKD, we implement Synchronous Mutual KD (SyncMKD) because its training pipeline is the same as other methods, so that the comparison becomes more exact. Their overall loss can be represented as follows, and $t$ is an iteration counter.

$$L_{AsyncMKD} = \begin{cases} L_A(q, p_A, p_B), & t \% 2 = 1, \\ L_B(q, p_B, p_A), & t \% 2 = 0. \end{cases}$$ (7)

$$L_{SyncMKD} = L_A(q, p_A, p_B) + L_B(q, p_B, p_A).$$ (8)

7.2. The relationship between KD and label modification

As mentioned in \cite{3}, the learning target modification is to replace a one-hot label representation by its convex combination with a predicted distribution $\bar{p}$: $\tilde{q} = (1 - \epsilon)q + \epsilon \bar{p}$. This is a generic formulation of label modification: (i) $\bar{p}$ can come from different sources, e.g., uniform distributions, a current model, a pretrained model of the same net architecture, a teacher model of a different net architecture, an ensemble of multiple expert models, etc; (ii) $\epsilon$ can be fixed in Boot-soft \cite{16}, Joint-soft \cite{25}, or adaptive as in ProSelfLC \cite{3}.

As $D_{KL}(p_t, p) = H(p_t, p) - H(p_t)$, and $H(p_t)$ is a constant for a fixed teacher model. Hence, we can omit $H(p_t)$ and rewrite Eq. (6) as:

$$L_{T2SKD}(q, p, p_t) = E_{(1-\epsilon)q + \epsilon p_t}(-\log p)$$

$$\rightarrow \tilde{q}_{T2SKD} = (1 - \epsilon)q + \epsilon p_t.$$ (9)

Thus, $\tilde{q}_{T2SKD}$ is a new label that contains the distilled knowledge from another model. Similar reformulation of Eq. (7) and Eq. (8) can be done for AsyncMKD and SyncMKD, respectively.

7.3. The relationship between KD and sample selection

As demonstrated in section \cite{7}, when KD is exploited, only the label of a sample may be changed. Therefore, the biggest difference between KD and sample selection (e.g., Co-teaching \cite{18} \cite{24}) is that KD uses all samples. Symmetrically but differently, our proposed CMD, as a selective MKD method, selects knowledge to distill while sample selection methods select training data points to train. SSKD \cite{30} combines self-supervision and KD, and the extremely inaccurate predictions would be removed when performing contrastive predictions in the teacher model. The sample selection process happens in producing predictions but not in distillation. \cite{31} focuses on sample selection and example weighting techniques by filtering out regularization samples, and assigning a lower weight to regularization samples and a larger weight to the others.
8. IMPLEMENTATION DETAILS

8.1. Datasets and data augmentation

• CIFAR100 [32] has 50,000 training images and 10,000 test images of 100 classes. The image size is $32 \times 32 \times 3$. Simple data augmentation is applied following [33], i.e., we pad 4 pixels on every side of the image and then randomly crop it with a size of $32 \times 32$.

• Food-101 [34] has 75,750 images of 101 classes. The training set contains real-world noisy labels. In the test set, there are 25,250 images with clean labels. For data augmentation, training images are randomly cropped with a size of $224 \times 224$.

• Webvision [20] has 2.4 million images crawled from the websites using the 1,000 concepts in ImageNet ILSVRC12 [35]. For data augmentation, we first resize the training images to $320 \times 320$ and then randomly cropped with a size of $299 \times 299$.

8.2. Training details

• On CIFAR100, we train on 90% training data (corrupted in synthetic cases) and use 10% clean training data as a validation set to search hyperparameters, e.g., $b_1$, $b_2$. Finally, we retrain a model on the entire training data and report its accuracy on the test data for a fair comparison. We train CIFAR100 on three net architectures including ResNet34, ResNet50, ResNet18 and ShuffleNetV2. For ResNet34, the initial learning rate is 0.1 and then divided by 10 at the 50th and 80th epoch, respectively. The number of total epochs is 100. For ShuffleNetV2 and ResNet28, the initial learning rate is 0.1 and then divided by 5 at the 50th, 120th, and 160th epoch, respectively. We train 200 epochs in total. For all the training, we use an SGD optimizer with a momentum of 0.9, a weight decay of 5e-4, and a batch size of 128. For ResNet50, for a fair comparison, we use the same training settings as [19].

• On Food-101, we also separate the training data into two parts, 90% for training and 10% for validation. We use the validation set to search hyper-parameters. Finally, we report its accuracy on the clean test data. We train ResNet50 (initialised by a pretrained model on ImageNet) using a batch size of 32, due to GPU memory limitation. And we use the SGD as an optimizer with a momentum of 0.9, and a weight decay of 5e-4. The learning rate starts at 0.01 and then is divided by 10 at the 50th and 80th epoch, respectively in total 100 epochs.

• On Webvision, we follow the “Mini” setting in [20]. We take the first 50 classes of the Google resized image subset as the training set and the same 50 classes of the ILSVRC12 validation set as the test set and apply inception-resnet v2 [36] as training architecture with batch size of 32. We use SGD as an optimizer with a momentum of 0.9, and a weight decay of 5e-4. The learning rate starts at 0.01 and then is divided by 10 in each epoch after the 40th epoch with a total number of 80 epochs.

All models are trained on multiple 2080 Ti GPUs between 2 and 4, which is adjusted according to model size and batch size.

9. LABEL NOISE METHODS IN THE LITERATURE

We compare with classical and latest label correction methods, including CE, LS, CP, Bootsoft, and ProSelfLC. We use the same training settings for all methods as mentioned in 8.2. We also compare with the classical and latest label noise methods, including CE, GCE [23], Co-teaching [18] (maintaining two identical networks simultaneously and transferring small-loss instances to the peer model), Co-teaching+ [24] (transferring the small-loss samples among the disagreement predictions to the peer model), Joint [25], Forward [26] (correcting the training loss by estimating the noise-transition matrix), MentorNet [20] (providing a curriculum for StudentNet to focus on the samples whose labels are probably correct), T-revision [27] (reweighting samples based on importance and revising the noise-transition matrix by a slack variable), S2E [29] (managing noisy labels by automated machine learning), DMI [28] (introducing an information-theoretic loss function), APL [22] (combining two robust loss functions that mutually boost each other), CDR [19] (reducing the side effect of noisy labels before early stopping), and ProSelfLC.
Fig. 4: Analysis of $b_2$ under CIFAR-100.

Table 6: The results of CMD-S with different $\eta$. We train on CIFAR-100 using ResNet-34.

| CMD-S         | Symmetric label noise |
|---------------|-----------------------|
|               | 20%       | 40%       | 60%       | 80%       |
| $H(u)$ ($\eta = 1$) | 70.37     | 59.26     | 36.18     | 16.17     |
| 1/2 $H(u)$ ($\eta = 2$) | 72.11     | 65.04     | 46.15     | 18.62     |
| 1/3 $H(u)$ ($\eta = 3$) | 72.83     | 66.42     | 51.34     | 19.84     |
| 1/4 $H(u)$ ($\eta = 4$) | 73.25     | 67.26     | 54.34     | 22.45     |

10. HYPER-PARAMETERS ANALYSIS

10.1. Analysis of $b_2$

Mathematically, according to section 3.2, $b_2$ decides how the knowledge selection threshold changes along with the training epoch $t$.

In Figure 4a, we fix $\eta = 2$ and study the effect of $b_2$ under different noise rates. We observe that the accuracy increases as $b_2$ decreases for all noise rates. The trend becomes more obvious as the noise rate increases. This empirically verifies the effectiveness of confident knowledge selection again. Furthermore, progressively increasing the confidence criterion leads to better performance. In Figure 4b, we further study $b_2$ under different $\eta$. The accuracy keeps increasing as $b_2$ decreases for all $\eta$. Additionally, the trend is more significant when $\eta$ becomes smaller.

10.2. Analysis of $\eta$

As presented in section 3.2, $\eta$ is a parameter to linearly scale the knowledge selection criteria. To study $\eta$, we first analyze the static mode. Table 6 shows the results of CMD-S with different $\eta$. We can see that a lower threshold (i.e., larger $\eta$) has higher accuracy for all noise rates. This further demonstrates the effectiveness of distilling more confident knowledge.

We then analyse the dynamic mode. In Figure 4b, the green line ($\eta = 4$) has the highest accuracy for most $b_2$ values. Overall, the blue line ($\eta = 3$) is the second best, while the red line ($\eta = 2$) has the lowest accuracy. Therefore, we conclude that a smaller $\eta$ is better in both static and progressive modes.
class CMDWithLoss(nn.Module):
    def __init__(self):
        super(CMDWithLoss, self).__init__()

    def forward(self, qA, qB, pA, pB, threshold):
        # qA, corrected label from model A
        # qB, corrected label from model B
        # pA, knowledge from model A
        # pB, knowledge from model B

        # calculate the entropy of pA
        hpA = torch.sum(-pA * torch.log(pA + 1e-6), 1)
        # calculate the entropy of pB
        hpB = torch.sum(-pB * torch.log(pB + 1e-6), 1)

        threshold_l = threshold * torch.ones(len(hpA)).cuda()

        # select the low entropy sample from model B
        indexA = (hpB < threshold_l).nonzero()
        # select the low entropy sample from model A
        indexB = (hpA < threshold_l).nonzero()

        # distill knowledge from model B to model A
        lossB2A = torch.sum(qB[indexA].squeeze(1) * 
                            (-torch.log(pA[indexA].squeeze(1) + 1e-6)), 1)

        # distill knowledge from model A to model B
        lossA2B = torch.sum(qA[indexB].squeeze(1) * 
                            (-torch.log(pB[indexB].squeeze(1) + 1e-6)), 1)

        lossB2A = sum(lossB2A) / len(hpA)
        lossA2B = sum(lossA2B) / len(hpB)

        return lossB2A, lossA2B