Reducing Flipping Errors in Deep Neural Networks

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Abstract

Deep neural networks (DNNs) have been widely applied in various domains in artificial intelligence including computer vision and natural language processing. A DNN is typically trained for many epochs and then a validation dataset is used to select the DNN in an epoch (we simply call this epoch “the last epoch”) as the final model for making predictions on unseen samples, while it usually cannot achieve a perfect accuracy on unseen samples. An interesting question is “how many test (unseen) samples that a DNN missclassifies in the last epoch were ever correctly classified by the DNN before the last epoch?”. In this paper, we empirically study this question and find on several benchmark datasets that the vast majority of the misclassified samples in the last epoch were ever classified correctly before the last epoch, which means that the predictions for these samples were flipped from “correct” to “wrong”. Motivated by this observation, we propose to restrict the behavior changes of a DNN on the correctly-classified samples so that the correct local boundaries can be maintained and the flipping error on unseen samples can be largely reduced. Extensive experiments on different benchmark datasets with different modern network architectures demonstrate that the proposed flipping error reduction (FER) approach can substantially improve the generalization, the robustness, and the transferability of DNNs without introducing any additional network parameters or inference cost, only with a negligible training overhead.

Introduction

The superior performances of deep neural networks (DNNs) have driven their wide deployment in varieties of applications in artificial intelligence such as medical diagnosis (Miotti et al. 2016), automated vehicle control (Levinson et al. 2011), and financial business (Ozbayoglu, Gudelek, and Sezer 2020). Despite the remarkable performances, it is appealing and necessary to further improve them, thus benefiting these applications and extending the application horizon to more accuracy-critical or safety-critical domains. However, furthering improving the performance of a DNN usually needs to substantially, even exponentially, increase the number of its parameters (Simonyan and Zisserman 2015). which leads to a large amount of computation and memory costs. In this work, we aim to enhance the performance of a DNN classifier without introducing any additional network parameters, without increasing inference cost, and almost without training overhead by exploring the learning dynamics of DNNs.

Currently, DNNs are typically trained for many epochs and then a validation dataset is used to select the DNN in the best epoch as the final model for making predictions on unseen samples or the validation dataset is used to set up the total number of training epochs and then the DNN at the last epoch is selected as the final model. Without losing generality, we simply denote the selected epoch in both cases by the last epoch. An interesting question regarding the generalization of a DNN classifier is “how many misclassified test samples in the last epoch were ever correctly classified by the DNN before the last epoch?”. To quantitatively study this question, we first introduce several novel metrics and definitions: (1) Wrongly Flipped Samples (WFSs) are the samples that are misclassified by the DNN in the last epoch but were ever classified correctly by the DNN before the last epoch?’. (2) Relative Flipping Error (RFE) is the ratio of WFSs to the total number of misclassified test samples (MTSs) in the last epoch, i.e., \( RFE = \frac{\#WFSs}{\#MTSs} \). We report the RFEs of various modern networks on two different benchmark datasets including a regular classification dataset, i.e., CIFAR-100 (Krizhevsky and Hinton 2009) and a fine-grained classification dataset, i.e., Standford Dogs (Khosla et al. 2011). As shown in Figure [I] across different modern network architectures on both datasets, a large percentage of the wrongly-classified test samples in the last...
epoch were ever correctly classified before the last epoch, e.g., the RFEs of ResNet-18 are over 90% on both datasets. This indicates that the DNN has ever learned the correct local boundaries for these samples but then flipped them to the wrong directions.

Inspired by the observation, we propose a novel framework, i.e., flipping error reduction (FER), to reduce the number of wrongly-flipped samples and thus to enhance DNN performances. FER is based on the idea that once a DNN has made a correct prediction on a sample, we limit the behavior change of the DNN on this sample with the goal of maintaining the correct local classification boundaries near this sample to avoid wrong flipping. To capture the local boundaries, we define the behavior of a DNN on a sample as its output soft distribution over different classes which captures the distances between a sample and different class boundaries. Since a DNN may make correct predictions in many epochs for a sample, we maintain a weighted average of these correct behaviors based on their confidences and epoch numbers. A behavior with a higher confidence or in a later epoch contributes more to the average. The weighted average behavior is more stable and accurate than a single behavior for restricting the DNN behavior changes on well-learned samples.

FER is a simple and easy-to-implement yet effective approach for training DNNs. Extensive experiments on different types of benchmark datasets demonstrate that FER can improve the generalization, the robustness, and the transferability of DNNs without introducing any additional network parameters, without increasing inference cost but only with a negligible training overhead for maintaining the average behaviors of a DNN on correctly-classified samples.

Our contributions are summarized as follows:

- We study a novel problem about “how many wrongly-classified test samples in the last epoch were ever correctly classified before the last epoch?” and define novel metrics to quantitatively investigate this question and further propose a solution to this problem. To our best knowledge, this is the first work to address this issue.
- To reduce flipping errors, we propose a novel framework, i.e., FER, that restricts the behavior changes of a DNN on correctly-classified samples and thus maintains the correct local boundaries near these samples.
- We empirically show on different types of benchmark datasets that FER is able to improve the generalization, the robustness, and the transferability of modern DNNs, without introducing any network parameters or inference cost, only with a negligible training overhead.

**Related Work**

In this paper, we study the wrongly flipped predictions on unseen samples. This phenomenon also happens to training (seen) samples (Toneva et al. 2019). However, as current DNNs are powerful enough to memorize the whole training dataset, these wrongly-flipped predictions on training samples can almost always be corrected by the DNNs through memorization in the later epochs. Memorization does not mean generalization and thus the wrong flipping issue on unseen samples is more challenging. FER is designed to solve this problem by restricting the soft output distribution changes of a DNN on correctly-classified samples to maintain local correct classification boundaries. Hence, it is technically related to label smoothing (Szegedy et al. 2016) and knowledge distillation (KD) techniques (Hinton, Vinyals, and Dean 2015; Deng and Zhang 2021a) which are also based on soft distribution.

**Label Smoothing** Szegedy et al. (2016) propose the label smoothing regularizer (LSR) that linearly interpolates between a one-hot label and a uniform distribution to generate a soft distribution as the label for training DNNs, and empirically show that it is able to improve the performance of the Inception architecture on image classification. Ever since then, LSR has been used in various advanced image classification models (Zoph et al. 2018; Real et al. 2019; Huang et al. 2019) and has also been introduced to other domains. In speech recognition, Chorowski and Jaitly (2016) show that label smoothing reduces the word error rate on the WSJ dataset. In machine translation, Vaswani et al. (2017) show that label smoothing improves the BLEU score but hurts the perplexity. Muller et al. (2019) empirically demonstrate that LSR leads to a better calibration for DNNs. Recently, Yuan et al. (2020) propose a new manually designed label smoothing based regularizer, i.e., TF-Reg, that combines LSR and a temperature. These label smoothing techniques manually assign the same small probability to the non-ground-truth classes and thus fail to take into account sample-to-class similarities and cannot fully utilize the advantages of soft labels.

**Knowledge Distillation** Knowledge distillation (KD) (Hinton, Vinyals, and Dean 2015) overcomes the limitations of the manually designed soft labels by taking advantage of a pretrained teacher network to generate soft labels which contain sample-to-class similarity (distance) information. However, it also brings several times of training cost over the manually designed soft labels due to the two facts: (1) KD first requires training a large DNN as the teacher; (2) when training the student, KD needs to process each sample twice in each iteration, once by the teacher and once by the student. To reduce the cost of training a large teacher, many self-distillation approaches including but not limited to (Xu and Liu 2019; Zhang et al. 2019; Yang et al. 2019b) in-
We denote the training dataset by \( D \). In this section, we introduce Flipping Error Reduction (FER) for improving DNN performances by reducing this kind of flipping errors. Inspired by this observation, we propose to improve DNN performances by reducing this kind of flipping errors.

Framework

In this section, we introduce FER for improving DNN performances by exploring the learning dynamics of DNNs. To show the connection between FER and the standard training procedure, we first review the standard procedure and then make further derivations to present FER.

Standard Training Procedure

We denote the training dataset by \( D = \{(x_i, y_i)\}_{i=1}^{n} \) of \( n \) samples where \( x_i \) denotes an input sample and \( y_i \) represents the corresponding one-hot label. The standard training (STD) procedure trains a DNN \( f \) by minimizing the cross-entropy loss between the DNN output and the one-hot label:

\[
L_{CE}(x) = H(f(x), y) \tag{1}
\]

where \( H \) denotes cross-entropy.

At the beginning of the training process, a DNN with initial weights makes wrong predictions on most samples. The DNN is then trained for multiple epochs with the goal of making correct predictions on data samples. However, we find that the behaviors of a DNN on many test samples are flipped from correct predictions to wrong predictions as the training progresses, which is opposite to the learning goal. Inspired by this observation, we propose to improve DNN performances by reducing this kind of flipping errors.

Flipping Error Reduction

To reduce flipping errors, we propose to regularize the behavior changes of a DNN on the samples that are already classified correctly. Note that we do not restrict the behavior of a DNN on the misclassified samples, since the local boundaries near these samples are still wrong and cannot be used to make correct predictions on unseen samples. The behavior of a DNN on a sample is defined as a soft distribution:

\[
b(x) = \sigma\left(\frac{f(x)}{\tau}\right) \tag{2}
\]

where \( \sigma \) denotes the softmax function and \( \tau \) is a temperature to soften the outputs. The advantage of using a soft distribution is that soft labels are able to capture the sample-to-class-margin distances, i.e., sample-to-class similarities. By restricting the behavior changes of a DNN on correctly-classified samples, the correct local boundaries near these samples can be maintained, thus reducing wrong flipping.

Since a DNN is typically trained for many epochs, there can be multiple correct behaviors of a DNN on a sample. These correct behaviors are generated in different epochs and may also have different confidences. Here the confidence means the probability for the ground-truth class, i.e., \( c = \sigma(f(x))[y] \) where \( y \) is the ground-truth class index. A natural question is “which correct behavior should be used for restricting the DNN behavior on a sample?”. As shown in Figure 2, we maintain a weighted average of all these correct behaviors based on the confidence and the epoch number of each behavior for each sample. Specifically, in epoch \( k \), suppose that the DNN has made correct predictions in \( j \) epochs for sample \( x \) where \( 0 \leq j \leq k - 1 \). We denote the behaviors in these \( j \) epochs with correct predictions by \( b_1(x), b_2(x), \ldots, b_j(x) \) where \( b_j(x) \) is the behavior of the DNN on sample \( x \) in the \( j \)th behavior-correct epoch. For the behavior in a later epoch or with a high confidence, we assign a larger weight as the DNN has learned more information or is more confident. The weighted average behavior in epoch \( k \) is calculated with:

\[
\hat{b}_k(x) = e^{-\mu c_j} \hat{b}_{k-1}(x) + (1 - e^{-\mu c_j}) b_j(x) \tag{3}
\]

where \( c_j \) is the confidence of \( b_j(x) \) and \( \mu \) is a coefficient to scale the contribution of confidence \( c_j \). Besides \( b_j(x) \), all the other behaviors with correct predictions also contribute to the current average behavior \( \hat{b}_k(x) \) as they are involved in computing \( \hat{b}_{k-1}(x) \). We then restrict the behavior changes...
of the DNN on correctly-classified samples with a regularizer:

\[ \mathcal{L}_{\text{cor}}(x) = \alpha \mathcal{L}_{CE}(x) + \beta \Kappa(\sigma\left(\frac{f(x)}{\tau}\right), \hat{b}_k(x)) \]  

(4)

where \( \alpha \) and \( \beta \) are two balancing weights; \( \Kappa \) denotes KL-divergence. The gradients do not flow through \( \hat{b}_k(x) \) as it is the record of the past behaviors of a DNN. In most cases, we simply set \( \alpha \) and \( \beta \) to \( 1.0 - 0.9 \frac{k}{M} \) and \( 0.9 \frac{k}{M} \) (where \( M \) is the number of total training epochs), respectively, based on the fact that the average behavior becomes more accurate in the later epoch with the DNN learning more information.

FER restricts the behaviors of a DNN on correctly-classified samples but gives the totally free space for the DNN on learning misclassified samples, thus the final objective is written as:

\[ \mathcal{L}_{\text{FER}}(x) = 1_{[T(x)]} \mathcal{L}_{\text{cor}}(x) + (1 - 1_{[T(x)]}) \mathcal{L}_{CE}(x) \]  

(5)

where \( 1_{[\cdot]} \) is the indicator function which equals to one if the argument in the subscript \([\cdot]\) is true and zero otherwise; \( T(x) \) denotes the argument that sample \( x \) has been ever classified correctly before the current epoch. As we can see, the training overhead of FER is the cost for maintaining a soft behavior average (i.e., \( \hat{b}_k(x) \)) for each correctly-classified sample, which is negligible as these soft behaviors do not need to be stored in the GPU memory.

### Analysis of FER

**Label Smoothing Effects**

FER is highly related to LSR as it defines the DNN behavior as a soft distribution. LSR assigns a small probability to the non-ground-truth classes as it defines the DNN behavior as a soft distribution. LSR and should inherit the advantage of LSR such as a better generalization. The advantage of FER over LSR is that FER can capture the sample-to-class distance information which is accumulated from the past behaviors of the DNN, while LSR fails to provide this kind of information as it assigns the same small probability to all the non-ground-truth classes. To further illustrate this point, we provide an intuitive example in Figure 3.

**Maintaining Correct Local Classification Boundaries**

FER defines the the DNN behavior as the soft output distribution over different classes which contains sample-to-class distance information. It restricts the DNN behavior changes

![Figure 3: Due to the body type differences, the dog in the first row is more visually similar to a cat while the the dog in the second row is more visually similar to a wolf. Different from LSR that assigns them the same soft label, FER uses the weighted average behavior that assigns different probabilities to different classes.](image)

|                | ShuffleNetV2 | ResNet-18 |
|----------------|--------------|-----------|
| **CIFAR-100**  |              |           |
| FER            | 74.82±0.24   | 80.29±0.12|
| FER w/o S1     | 74.48±0.33   | 80.00±0.18|
| FER w/o S2     | 74.46±0.19   | 79.90±0.07|
| LWR            | 73.53±0.33   | 79.73±0.32|
| **Standford**  |              |           |
| FER            | 68.75±0.17   | 70.64±0.25|
| FER w/o S1     | 68.01±0.40   | 70.25±0.25|
| FER w/o S2     | 67.82±0.10   | 70.08±0.18|
| LWR            | 67.39±0.42   | 69.84±0.45|

Table 1: Ablation studies regarding the strategies in FER.

|                | \( \mu = 0.5 \) | \( \mu = 1.0 \) | \( \mu = 1.5 \) |
|----------------|-----------------|-----------------|-----------------|
| \( \tau = 5 \) | 79.95±0.14      | 80.29±0.12      | 79.91±0.16      |
| \( \tau = 10 \)| 79.40±0.33      | 79.63±0.15      | 79.64±0.09      |

Table 2: Effects of \( \tau \) and \( \mu \) with ResNet-18 on CIFAR-100.

on the correctly-classified samples and gives free space for learning wrongly-classified samples. FER thus mitigates wrong flipping through maintaining the correct local boundaries while allowing correct flipping (i.e., from wrong predictions to correct predictions) for wrongly-classified samples. We empirically validate the flipping error reduction effects of FER in the ablation studies.

### Experiments

We first conduct ablation studies and then compare FER with cost-comparable label-smoothing approaches.

### Ablation Studies

**Can FER Reduce Flipping Errors?**

FER is developed from the STD training procedure with the goal of reducing the number of wrongly flipped samples. In this part, we aim to empirically validate that FER indeed reduces the flipping errors of DNNs. The flipping error (FE) is quantitatively defined as the ratio of the number of wrongly flipped test samples (WFSs) to the total number of test samples (TSs):

\[ FE = \frac{\#WFSs}{\#TSs} \]  

(7)
We conduct experiments on two different types of datasets including one regular classification dataset and one fine-grained dataset, i.e., CIFAR-100 (Krizhevsky and Hinton 2009) and Standard Dogs (Khosla et al. 2011).

Figure 4 and Figure 5 report the FEs on CIFAR-100 and Standard Dogs, respectively. It is observed that by simply restricting the DNN behaviors on correctly-classified samples, FER consistently and substantially reduces the FEs across different networks and datasets, which demonstrates the ability of FER to mitigate wrong flipping.

FER v.s. LWR. There are two strategies in FER: (1) only restricting the DNN behavior changes on correctly-classified samples while giving the DNN totally free space for learning on misclassified samples, instead of restricting the DNN behavior on all the samples; (2) using the weighted average of multiple correct behaviors instead of one single behavior to restrict a DNN. In this part, we empirically examine the effects of the two strategies. We denote FER without strategy (1) by FER w/o S1, without strategy (2) by FER w/o S2. Without both of the two strategies, FER is reduced to LWR (Deng and Zhang 2021c) that is a special case of FER.

Table 1 reports the performances on CIFAR-100 and Standard Dogs. As expected, without either of the two strategies or without both (i.e., LWR), the performances drop significantly on both datasets, which demonstrates the effectiveness of the two strategies and the superiority of FER over LWR.

Effects of $\tau$ and $\mu$. $\tau$ in FER controls the softness of the behavior while $\mu$ scales the contribution of the confidence of each behavior to the weighted average. Their effects on the performances of FER are reported in Table 2. It is observed that $\tau = 5$ consistently outperforms $\tau = 10$. The reason is that as seen from Eq. (2), a large $\tau$ makes the behavior too flat to contain sample-to-class distance information. On the other hand, we observe that the performance of FER is not sensitive to $\mu$.

Generalization on Test Data
We use the test accuracy to measure the generalization of different methods on test data.

Datasets We adopt different kinds of datasets across different domains including two regular classification datasets, i.e., CIFAR-100 (Krizhevsky and Hinton 2009) and Tiny-ImageNet [1] three fine-grained classification datasets, i.e.,

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1https://tiny-imagenet.herokuapp.com
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lar datasets, i.e., Arcene (Dua and Graff 2017), and Iris (Dua et al. 2011), and FGVC-Aircraft (Maji et al. 2013), two tabu-

deration studies.

Architecture To examine whether FER works on different modern architectures, we adopt ResNet (He et al. 2016a,b), WRN (Zagoruyko and Komodakis 2016), ShuffleNet (Ma et al. 2018), and MobileNet (Sandler et al. 2018).

Baseline As FER is modified from the the standard training procedure (STD), STD is considered as one of the most important baselines. In addition, since FER uses soft distribution, we also compare FER with label smoothing based methods including cost-comparable self-distillation approaches, i.e., LSR (Müller, Kornblith, and Hinton 2019), Max-Entropy (Pereyra et al. 2017), SD (Yang et al. 2019b), CS-KD (Yun et al. 2020), and TF-Reg (Yuan et al. 2020). The comparison and discussion with LWR (Deng and Zhang 2021c) are given in the above ablation studies.

More specific details regarding these datasets, baselines, and hyper-parameters are given in Appendix due to space limitation.

| Architectures | ResNet-10 | ResNet-18 | MobileNetV2 | ShuffleNetV2 |
|---------------|-----------|-----------|-------------|--------------|
| Arcene        | 58.96±0.12| 61.09±0.49| 67.20±0.21 | 61.67±0.85  |
| LSR           | 59.31±0.21| 63.57±0.50| 67.97±0.43 | 62.66±0.11  |
| Max-Entropy   | 59.00±0.30| 61.23±0.37| 66.56±0.30 | 61.10±0.15  |
| SD            | 59.28±0.34| 64.19±0.24| 68.15±0.32 | 63.99±0.29  |
| CS-KD         | 60.70±0.21| 64.57±0.29| 67.48±0.32 | 63.32±0.25  |
| TF-Reg        | 58.84±0.60| 62.04±0.28| 67.20±0.43 | 61.19±0.58  |
| FER (Ours)    | 64.86±0.45 (↑ 5.90) | 67.65±0.25 (↑ 6.56) | 69.08±0.47 (↑ 1.88) | 65.60±0.26 (↑ 3.93) |

Table 4: Test accuracies (%) on fine-grained classification datasets. ↑ denotes the absolute improvement over the STD procedure.

| Dataset       | Arcene (%) | Iris (%) |
|---------------|------------|----------|
| STD           | 83.00±2.16 | 90.00±2.72 |
| LSR           | 81.00±4.55 | 92.22±1.57 |
| Max-Entropy   | 79.67±3.77 | 94.44±1.57 |
| SD            | 81.00±1.63 | 93.33±2.72 |
| CS-KD         | 83.67±0.94 | 94.44±1.57 |
| TF-Reg        | 80.00±2.16 | 90.00±2.72 |
| FER (Ours)    | 86.33±0.94 (↑ 3.33) | 95.56±1.57 (↑ 5.56) |

Table 5: Test accuracies (%) on tabular datasets.

Regular Classification The regular classification is conducted on CIFAR-100 and Tiny ImageNet. The comparison results are reported in Table [3]. It is clearly observed that by simply restricting the DNN behavior changes on correctly-classified samples to maintain correct local boundaries, FER consistently outperforms the standard training procedure (i.e., STD) by a large margin with different network architectures across different datasets, e.g., the absolute accuracy improvements with ResNet-18 are 2.98% and 2.15% on CIFAR-100 and Tiny ImageNet, respectively, which demonstrates the effectiveness of FER. On the other hand, FER also beats the other competitors significantly with different architectures on different datasets, which demonstrates the superiority of FER over these label smoothing based approaches.

Fine-Grained Classification We further evaluate FER on fine-grained classification which is a more challenging task due to the small intra-class differences but large inter-class differences. Table [4] reports the comparison results on three fine-grained classification benchmark datasets. We observe that the superiority of FER over the baselines is more obvious on the fine-grained datasets than on regular datasets, e.g., the absolute accuracy improvements over STD with ResNet-18 are 6.56%, 4.08%, and 2.80% on CUB, Stanford Dogs, and FGVC-Aircraft, respectively. The reason is that the samples in different classes of the fine-grained classification share more visual similarities, which leads to more wrong flipping. FER mitigates this issue by maintaining local correct boundaries and thus obtains a much better performance.

Classification on Non-Image Data To investigate the applicability of FER on non-image data, we conduct several
We investigate the transferability of the representations learned by FER, as one goal of deep representation learning is to learn general representations that can be transferred to different datasets. Specifically, we first train ResNet-18 on CIFAR-100, and then freeze the feature encoder and train a linear classifier on STL-10 (Coates, Ng, and Lee 2011) and Tiny ImageNet. All images in STL-10 and Tiny ImageNet are resized to 32×32 to match the input size of the ResNet-18 pretrained on CIFAR-100.

The transferability performances are reported in Table 7. The representations learned by FER have a much better cross-dataset performance than those of the other baselines. The reason can be that FER takes into account the sample-to-class-margin distance information when learning the representations, thus avoiding overfitting the dataset and leading to more general representations.

| Cross-dataset       | STD           | LSR           | SD            | CS-KD         | TF-Reg        | FER (Ours)   |
|---------------------|---------------|---------------|---------------|---------------|---------------|--------------|
| CIFAR-100 to STL-10 | 69.71±0.14    | 68.85±0.23    | 69.27±0.13    | 69.96±0.02    | 69.13±0.07    | 70.80±0.15   |
| CIFAR-100 to Tiny ImageNet | 33.47±0.25 | 32.66±0.10 | 31.87±0.05 | 33.46±0.05 | 33.07±0.07 | 34.20±0.12 |

Conclusion

In this paper, we study a novel problem about “how many misclassified unseen samples in the last epoch were ever correctly classified by the DNN?” and then propose a simple yet effective framework FER to mitigate the wrong flipping issue, which is to our best knowledge the first work to address this problem. This is achieved by restricting the DNN behavior changes on correctly-classified samples with the goal of maintaining the correct local classification boundaries to avoid wrongly flipping on unseen samples. Extensive experiments on several benchmark datasets with different modern network architectures demonstrate that FER consistently improves the generalization, the robustness, and the transferability of DNNs substantially.

1https://github.com/pluskid/fitting-random-labels
References

Arpit, D.; Jastrzebski, S. K.; Ballas, N.; Krueger, D.; Bengio, E.; Kanwal, M. S.; Maharaj, T.; Fischer, A.; Courville, A. C.; Bengio, Y.; et al. 2017. A Closer Look at Memorization in Deep Networks. In ICML.

Bagherinezhad, H.; Horton, M.; Rastegari, M.; and Farhadi, A. 2018. Label refinery: Improving imagenet classification through label progression. arXiv preprint arXiv:1805.02641.

Chorowski, J.; and Jaitly, N. 2016. Towards better decoding and language model integration in sequence to sequence models. arXiv preprint arXiv:1612.02695.

Coates, A.; Ng, A.; and Lee, H. 2011. An analysis of single-layer networks in unsupervised feature learning. In Proceedings of the fourteenth international conference on artificial intelligence and statistics, 215–223. JMLR Workshop and Conference Proceedings.

Deng, X.; and Zhang, Z. 2021a. Comprehensive Knowledge Distillation with Causal Intervention. Advances in Neural Information Processing Systems, 34.

Deng, X.; and Zhang, Z. 2021b. Graph-Free Knowledge Distillation for Graph Neural Networks. In The 30th International Joint Conference on Artificial Intelligence.

Deng, X.; and Zhang, Z. 2021c. Learning with Retrospection. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 35, 7201–7209.

Dua, D.; and Graff, C. 2017. UCI Machine Learning Repository.

Furlanello, T.; Lipton, Z. C.; Tschannen, M.; Itti, L.; and Anandkumar, A. 2018. Born again neural networks. arXiv preprint arXiv:1805.04770.

Han, B.; Yao, Q.; Yu, X.; Niu, G.; Xu, M.; Hu, W.; Tsang, I.; and Sugiyama, M. 2018. Co-teaching: Robust training of deep neural networks with extremely noisy labels. In Advances in neural information processing systems, 8527–8537.

He, K.; Zhang, X.; Ren, S.; and Sun, J. 2016a. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, 770–778.

He, K.; Zhang, X.; Ren, S.; and Sun, J. 2016b. Identity mappings in deep residual networks. In European conference on computer vision, 630–645. Springer.

Hinton, G.; Vinyals, O.; and Dean, J. 2015. Distilling the knowledge in a neural network. arXiv preprint arXiv:1503.02531.

Huang, G.; Li, Y.; Pleiss, G.; Liu, Z.; Hopcroft, J. E.; and Weinberger, K. Q. 2017. Snapshot ensembles: Train 1, get m for free. arXiv preprint arXiv:1704.00109.

Huang, Y.; Cheng, Y.; Bapna, A.; Firat, O.; Chen, D.; Chen, M.; Lee, H.; Ngiam, J.; Le, Q. V.; Wu, Y.; et al. 2019. Gpipe: Efficient training of giant neural networks using pipeline parallelism. In Advances in neural information processing systems, 103–112.

Ji, M.; Shin, S.; Hwang, S.; Park, G.; and Moon, I.-C. 2021. Refine Myself by Teaching Myself: Feature Refinement via Self-Knowledge Distillation. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 10664–10673.

Khosla, A.; Jayadevaprakash, N.; Yao, B.; and Li, F.-F. 2011. Novel dataset for fine-grained image categorization: Stanford dogs. In Proc. CVPR Workshop on Fine-Grained Visual Categorization (FGVC).

Krizhevsky, A.; and Hinton, G. 2009. Learning multiple layers of features from tiny images. Technical report, Citeseer.

Levinson, J.; Askeland, J.; Becker, J.; Dolson, J.; Held, D.; Kammel, S.; Kolter, J. Z.; Langer, D.; Pink, O.; Pratt, V.; et al. 2011. Towards fully autonomous driving: Systems and algorithms. In 2011 IEEE Intelligent Vehicles Symposium (IV), 163–168. IEEE.

Loshchilov, I.; and Hutter, F. 2017. Sgdr: Stochastic gradient descent with warm restarts. International Conference for Learning Representations.

Ma, N.; Zhang, X.; Zheng, H.-T.; and Sun, J. 2018. Shufflenet v2: Practical guidelines for efficient cnn architecture design. In Proceedings of the European conference on computer vision (ECCV), 116–131.

Maji, S.; Rahtu, E.; Kannala, J.; Blaschko, M.; and Vedaldi, A. 2013. Fine-grained visual classification of aircraft. arXiv preprint arXiv:1306.5151.

Miotto, R.; Li, L.; Kidd, B. A.; and Dudley, J. T. 2016. Deep patient: an unsupervised representation to predict the future of patients from the electronic health records. Scientific reports, 6(1): 1–10.

Müller, R.; Komblith, S.; and Hinton, G. E. 2019. When does label smoothing help? In Advances in Neural Information Processing Systems, 4694–4703.

Ozbayoglu, A. M.; Gudelek, M. U.; and Sezer, O. B. 2020. Deep learning for financial applications: A survey. Applied Soft Computing, 93: 106384.

Pereyra, G.; Tucker, G.; Chorowski, J.; Kaiser, Ł.; and Hinton, G. 2017. Regularizing neural networks by penalizing confident output distributions. arXiv preprint arXiv:1701.06548.

Real, E.; Aggarwal, A.; Huang, Y.; and Le, Q. V. 2019. Regularized evolution for image classifier architecture search. In Proceedings of the aaai conference on artificial intelligence, volume 33, 4780–4789.

Sandler, M.; Howard, A.; Zhu, M.; Zhmoginov, A.; and Chen, L.-C. 2018. Mobilenetv2: Inverted residuals and linear bottlenecks. In Proceedings of the IEEE conference on computer vision and pattern recognition, 4510–4520.

Simonyan, K.; and Zisserman, A. 2015. Very deep convolutional networks for large-scale image recognition. In International Conference for Learning Representations.

Szegedy, C.; Vanhoucke, V.; Ioffe, S.; Shlens, J.; and Wojna, Z. 2016. Rethinking the inception architecture for computer vision. In Proceedings of the IEEE conference on computer vision and pattern recognition, 2818–2826.
Toneva, M.; Sordoni, A.; Combes, R. T. d.; Trischler, A.; Bengio, Y.; and Gordon, G. J. 2019. An empirical study of example forgetting during deep neural network learning. In International Conference for Learning Representations.

Vaswani, A.; Shazeer, N.; Parmar, N.; Uszkoreit, J.; Jones, L.; Gomez, A. N.; Kaiser, L.; and Polosukhin, I. 2017. Attention is all you need. In Advances in neural information processing systems, 5998–6008.

Wah, C.; Branson, S.; Welinder, P.; Perona, P.; and Belongie, S. 2011. The caltech-ucsd birds-200-2011 dataset. California Institute of Technology.

Xu, T.-B.; and Liu, C.-L. 2019. Data-distortion guided self-distillation for deep neural networks. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 33, 5565–5572.

Yang, C.; Xie, L.; Qiao, S.; and Yuille, A. L. 2019a. Training deep neural networks in generations: A more tolerant teacher educates better students. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 33, 5628–5635.

Yang, C.; Xie, L.; Su, C.; and Yuille, A. L. 2019b. Snapshot distillation: Teacher-student optimization in one generation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2859–2868.

Yuan, L.; Tay, F. E.; Li, G.; Wang, T.; and Feng, J. 2020. Revisiting Knowledge Distillation via Label Smoothing Regularization. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 3903–3911.

Yun, S.; Park, J.; Lee, K.; and Shin, J. 2020. Regularizing class-wise predictions via self-knowledge distillation. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 13876–13885.

Zagoruyko, S.; and Komodakis, N. 2016. Wide Residual Networks. In BMVC.

Zhang, C.; Bengio, S.; Hardt, M.; Recht, B.; and Vinyals, O. 2017. Understanding deep learning requires rethinking generalization. International Conference for Learning Representations.

Zhang, H.; Cisse, M.; Dauphin, Y. N.; and Lopez-Paz, D. 2018. mixup: Beyond empirical risk minimization. International Conference for Learning Representations.

Zhang, L.; Song, J.; Gao, A.; Chen, J.; Bao, C.; and Ma, K. 2019. Be your own teacher: Improve the performance of convolutional neural networks via self distillation. In Proceedings of the IEEE International Conference on Computer Vision, 3713–3722.

Zoph, B.; Vasudevan, V.; Shlens, J.; and Le, Q. V. 2018. Learning transferable architectures for scalable image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, 8697–8710.