ExpertNet: Adversarial Learning and Recovery Against Noisy Labels

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Abstract

Today’s available datasets in the wild, e.g., from social media and open platforms, present tremendous opportunities and challenges for deep learning, as there is a significant portion of tagged images, but often with noisy, i.e. erroneous, labels. Recent studies improve the robustness of deep models against noisy labels without the knowledge of true labels. In this paper, we advocate to derive a stronger classifier which proactively makes use of the noisy labels in addition to the original images - turning noisy labels into learning features. To such an end, we propose a novel framework, ExpertNet, composed of Amateur and Expert, which iteratively learn from each other. Amateur is a regular image classifier trained by the feedback of Expert, which imitates how human experts would correct the predicted labels from Amateur using the noise pattern learnt from the knowledge of both the noisy and ground truth labels. The trained Amateur and Expert proactively leverage the images and their noisy labels to infer image classes. Our empirical evaluations on noisy versions of CIFAR-10, CIFAR-100 and real-world data of Clothing1M show that the proposed model can achieve robust classification against a wide range of noise ratios and with as little as 20-50% training data, compared to state-of-the-art deep models that solely focus on distilling the impact of noisy labels.

1 Introduction

The ever-increasing self-generated contents on social media, e.g., Instagram images, power up the deep neural networks, but also aggravate the challenge of noisy data. Large portion of images accessible on the public domain come with labels which are unfortunately noisy due to careless annotations [1, 28] or even adversary strategies [4, 13, 22]. The learning capacity of deep neural networks is shown to be hindered by such noisy labels [30] due to the memorization effect of networks. Classification accuracy on standard image benchmarks degrades drastically in the presence of dirty labels. For example, the accuracy of a trained AlexNet to classify CIFAR-10 images drops from 77% to 10%, when trained on noisy labels [30].
Motivated by the significant impact of noisy labels, the prior art [7] derives different robust deep networks with a central theme to distill the influence of noisy labels in the model training process without the knowledge of the label ground truth. As a result, the learned networks can robustly classify images in a stand-alone manner. D2L [26] estimates the Local Intrinsic Dimension (LID) at each epoch as a proxy to indicate the existence and impact of dirty labels. Co-teaching [5] trains two networks simultaneously by exchanging the weights updated from possibly clean data. Forward [19] uses a noise-aware correction matrix to correct labels and train the network. Bootstrap [20] has a loss function which combines predicted and noisy labels.

While prior art significantly improves the robustness of deep networks, the pre-assumed scenarios overlook the opportunity of noisy labels. On the one hand, today’s image data are often bundled with labels of questionable quality and detrimental impact on the learning. On the other hand, such labels provide auxiliary information which can compliment the learnt knowledge of deep networks trained solely on image inputs. The core idea behind visual-semantic models, e.g., DeVise [2], is to combine the learning capacities of labeled images and annotated data. C-GAN [12] (conditional generative adversarial network) improves the quality of images synthesized by the generator network via additional label information and RC-GAN [23] further addresses the challenge of dirty labels for C-GAN.

In this paper, we advocate to leverage the noisy labels as an additional feature to derive a stronger classifier. We consider learning scenarios where at training time both the ground truth and noisy labels are available, and only noisy labels at inference time. In particular difficult classification problems, whose labels require a high degree of expertise, can fit this scenario well. One such example is cancer detection from medical images. This is a daunting task, and even trained experts are prone to make errors. Hence, these images are evaluated by multiple doctors of varying expertise. In such a setting, both noisy (first evaluation by one expert) and true labels (e.g., stemming from a committee or subsequent in-depth exams) are available at the same time.

We derive a robust network, namely ExpertNet, composed of Amateur and Expert, where the former classifies images based on the feedback from Expert and the latter learns how to correct the output of Amateur like human experts. Both models are trained simultaneously at each minibatch. Amateur learns to classify the input images to the corrected labels from Expert, and the softmax output of Amateur plus the given labels are inputs to train Expert to match the ground truth. Amateur can be seen as a regular image classifier, which Expert helps it to be aware of the presence of noisy labels. Such trained Amateur and Expert can then classify images based on the image and corresponding noisy label.

We empirically evaluate ExpertNet on synthetic noise injected into CIFAR-10 and CIFAR-100, and noise drawn from real world contained in Clothing1M. For a fair comparison with state-of-the-art robust deep models, we present the classification accuracy in both Amateur only and complete ExpertNet model under different subsets of training inputs. ExpertNet consistently outperforms existing image-only models, i.e., D2L, Co-teaching, Forward and Bootstrap, especially for CIFAR-100. When using the same amount of training data, ExpertNet can achieve absolute accuracy improvements of 5% up to 30%. ExpertNet reaches similar or higher accuracy than image-only models even with just 20% of training data in the case of CIFAR-100.

Our contribution can be summarized as follows. First, we derive a novel network framework, i.e., ExpertNet, that turns noisy labels into auxiliary learning advantages via imitating human experts. Secondly, we significantly improve the robustness of deep networks against noisy labels compared to models based on images only.
1.1 Problem statement

The problem considered here is as follows. Images collected in the public domain are tagged with pre-existing noisy labels, whose true classes can be corrupted. We assume label noises follow random distribution. We illustrate in Fig. 1 (black elements only) the learning procedure that is commonly deployed by robust deep networks [5, 19, 20, 26]. The deep networks are trained by a set of images and labels, which are noisy, meaning with incorrect label classes. The objective of the training process is to minimize the loss function, which may be modified to be noise tolerant [26]. The network architecture may consist of different components, e.g., two networks that parallelly [5] or sequentially [19] train each other via stochastic gradient descent. In the inference phase, images are then fed into the trained network, and the prediction accuracy is computed based on true labels. The core idea behind such a learning process is to filter out the negative impact of noisy labels during training and learn a model from clean information.

In contrast to indirectly learn the label noise dynamics, our core idea is to leverage noisy labels as part of the training and inference input, as shown in Fig. 1 (including green elements), to directly learn the noisy label dynamics and incorporate that as auxiliary input into the training process. To such an end, the ground truth of labels is assumed from human experts or oracles and provided as part of the training input. Essentially, the networks are trained by three inputs: images, their noisy labels, and the ground truth labels. Afterward, the trained network will be tested on images and their noisy labels. The classifier can then classify images based on image inputs and limited label info.

2 Related Work

The central theme of learning on noisy labels is to increase the robustness of networks by distilling the impact of noisy labels during training. We categorize the proposed solutions into three approaches. In addition, we review adversarial learning.

**Smart sampling selection.** An intuitive solution is to select clean samples or to cleanse the (noisy) labels such that models are trained on selective clean labels [20, 21]. MentorNet [7] pre-trains a neural network as a teacher and provides a curriculum (sample weighting scheme) for the student network to select clean samples. The curriculum is dynamically learned from the data, instead of pre-defined by human experts. Decoupling [16] designs an algorithm that selectively updates the weights of two base deep networks, only when there is disagreement between the two networks’ predictions. Co-teaching [5] and Co-teaching+ [29] relies on two neural networks teaching each other the curriculum for clean data selection and training. Such approaches are inherently limited by the sample-selection bias.

**Modifying loss function.** Designing loss function that is tolerant to label noise can fundamentally strengthen the robustness of the classifier. [23] derives an unbiased estimator of
any loss functions for binary classification, e.g., SVM and logistic regression, in the presence of random classification noise. A simple weighted loss function is proposed to differentiate the noisy and clean label distributions, where the weights are label-dependent. Ghosh et. al [3] extend the necessary condition of unbiased estimator of loss function [18] from binary classification to multi-class classification. D2L [26] uses Local Intrinsic Dimensionality (LID) score as a proxy to indicate when the memorization effect on dirty labels becomes dominant. [31] proposes to incorporate use mean absolute error as a generalization to the cross entropy loss function for deep neural networks.

**Noise transition model.** Incorporating the model of the noise patterns as part of the training process of the classifier is a semi-supervised approach for estimating the label quality. Patrini et. al [19] estimate the noise transition matrix by manual labeling and try to minimize the distance between classification outputs and transition matrix. [8] connects the last layer of softmax with the given labels and indirectly learns the patterns of noisy labels. Different from the other studies, [6] utilizes the trusted data (around 10% of training) by introducing a loss correction technique and estimating a label corruption matrix.

**Adversarial training with noisy labels** The essence of adversarial learning is to train networks with adversarial examples, such as noisy images, so that trained networks can defend against unseen adversaries. Such learning strategies [4] are commonly realized by a min-max game between attackers and classifiers. The adversarial images can be iteratively generated by another network [15, 24] or disturbed by Gaussian noises [10], so called zero-knowledge attacks. Most existing adversarial learning methods focus on corrupted images, except [9, 23] that focus on corrupted labels via conditional generative adversarial networks.

To the best of our knowledge, adversarial learning is yet to be explored in the problem space of noisy labels. ExpertNet presents a novel learning framework to explore the potential of adversarial learning in classification problems encountering noisy labels.

### 3 Methodology

Consider the classification problem having training set \( D = \{(x_1, y_1, t_1), (x_2, y_2, t_2), \ldots, (x_N, y_N, t_N)\} \) where \( x_i \) denotes the \( i^{th} \) observed sample, and \( t_i \in \{0, 1\}^K \) and \( y_i \in \{0, 1\}^K \) the corresponding label vectors over \( K \) classes representing the clean ground truth and noisy given classes, respectively. Traditional classification problems only use the sample \( x_i \) and its true label \( t_i \). However, real-world datasets are typically affected to various degrees by label noise. Hence, for some samples, the given label \( y_i \) is different from the true label \( t_i \) even in the training set. The core contribution of the paper is a model, named ExpertNet, which leverages both \( x_i \) and \( y_i \) to predict \( t_i \), instead of only \( x_i \). Using this additional information enables the model to significantly boost the accuracy as demonstrated in §4.

#### 3.1 ExpertNet Architecture

We address this problem via ExpertNet comprising two neural networks complete with a traditional softmax output layer named Amateur \( A \) and Expert \( E \). Figure 2 shows how the two networks are interconnected. The goal of the Amateur is to predict the label \( \hat{y}_i^A \) of an observed sample \( x_i \) while Expert aims at correcting, if necessary, this prediction based on the output of the Amateur and the given label \( y_i \). The label corrected by the Expert \( \hat{y}_i^E \) is provided as feedback to the Amateur during training closing the loop.
Expert acts as a supervisor which reviews and corrects the predictions of Amateur by comparing it to another label source: the given labels $y$. We need Expert because both label sources are affected by errors stemming from an imperfect model for the former and from label noise for the latter. From this point of view, we can consider the given labels $y$ as the output of a second external independent imperfect model which is prone to make different errors than Amateur. The idea of having Expert is to leverage not only the intrinsic properties of single models, as most related work does, but also the differences across the models. In the simplest case, if model A is good at classifying dogs and model B in classifying cats, we could learn to trust more model A when predicting dogs and model B when predicting cats. However, cases are rarely as easy, and we resort to the Expert model to learn these patterns.

To decide the type of information to exchange between Amateur and Expert, we consider that the output layer of neural networks is traditionally a softmax transformation $\sigma(z_k) = e^{z_k}/\sum_{j=1}^{K} e^{z_j}$. This ensures that the output vector elements are all in the range $z_j \in [0, 1], j = 1...K$ and their sum is $\sum_{j=1}^{K} z_j = 1$ satisfying the properties of a probability distribution. This probability distribution is more informative about the correctness of the prediction because it intrinsically includes information on how confident, i.e. how sharp, or how insecure, i.e. spread out, the model is on the prediction of the most likely class. Hence, we use this as the input to Expert from Amateur rather than the sole predicted class.

The task of Amateur is to classify images. This fits well the classic state-of-the-art DNN vision-models. In our evaluation, we use the CNN defined in [25] having three blocks of two convolutional layers plus one pooling layer followed by a fully connected layer and the softmax output layer. Instead, the task of Expert is to decide the correct label based on the concatenation of the class probability and given label vectors. Here we use a shallower multilayer perceptron. More details on the two submodels of ExpertNet are given in §4.

### 3.2 ExpertNet Training

Let $g^A(\cdot; \phi)$ parameterized by $\phi$ and $g^E(\cdot; \omega)$ parameterized by $\omega$ be the prediction functions. $g^A(\cdot)$ and $g^E(\cdot)$ output the class probabilities predicted by the final softmax layer of Amateur and Expert, respectively. The training loss functions can be written as follows:

$$l^A = \min_{\phi} \sum_{i=1}^{N} \mathcal{L}(g^E(<g^A(x_i), y_i>; \omega), g^A(x_i; \phi))$$

(1)

$$l^E = \min_{\omega} \sum_{i=1}^{N} \mathcal{L}(t_i, g^E(<g^A(x_i), y_i>; \omega))$$

(2)
Algorithm 1: Training ExpertNet

**Input**: Training set $D$ made of: Observed samples $x$, Given labels $y$, True labels $t$

**Output**: Trained Amateur $A$ and Expert $E$

1. Initialize $A$ and $E$ with random $\phi$ and $\omega$

2. for training iteration do

3. for each batch $B\{x,y,t\}$ from $D$ do

4. $\hat{y}_A :=$ Predict label probabilities of $x$ by $A$

5. $z := \text{concatenate } <\hat{y}_A, y>$

6. Train $E$ with pair $(z,t)$ updating $\omega$

7. $\hat{y}_E :=$ Predict corrected label probabilities from $z$ by $E$

8. Train $A$ with pair $(x,\hat{y}_E)$ updating $\phi$

end

end

where $\langle \cdot, \cdot \rangle$ is the concatenation function of two vectors and $\mathcal{L}$ the loss over the $K$ classes. For both networks we use $\mathcal{L}$ equal to the cross-entropy loss fitting well the probabilistic output of softmax layer. $\mathcal{L}$ increases as predicted probability diverges from expected label.

To train the model we use the alternating minimization approach on batches of data. We first train the Expert based on the output of the Amateur then the Amateur based on the feedback from the Expert. Algorithm 1 details this process. After random initialization of the weights $\phi$ and $\omega$ (Step 1) for each training step and data batch, we use $A$ to predict the labels $\hat{y}_A$ of the observed images $x$ (Step 4). $\hat{y}_A$ is concatenated with the given labels $y$ (Step 5) as input to train $E$ together with the true labels $t$ (Step 6). After that in turn we use $E$ to predict the corrected labels $\hat{y}_E$ (Step 7) and train $A$ based on the pair $(x,\hat{y}_E)$ (Step 8). We use stochastic gradient descent with momentum and learning rate decay to update $\omega$ and $\phi$.

4 Evaluation

4.1 Experiments Setup

**Datasets.** Our evaluation is based on three benchmarking datasets: CIFAR-10 [21], CIFAR-100 [22] and Clothing1M [27]. CIFAR-10 and CIFAR-100 include $32 \times 32$-pixel color images organized in 10 and 100 classes, respectively. The image classes range from animals to vehicles. Both datasets contain 50000 training and 10000 validation images. Clothing1M contains images scrapped from the Internet classified into 14 classes based on the surrounding text. It is representative of real world noise (average noise rate of 39.5%). Here we use the cleansed training, validation and testing sets of 47K, 14K and 10K samples, respectively.

**Label noise.** For CIFAR-10 and CIFAR-100 we use the original labels as true labels $t$. We generate the noisy given labels $y$ by injecting symmetric label noise where the original label is flipped to one of the other classes with uniform probability. We use different noise ratios corresponding to flipping probabilities of 0.2, 0.3, 0.4, and 0.5. Such generating principles are applied for both training and inferences images. Since the ground truth of 1 million training image labels in Clothing1M is not available, we use cleansed labels (47K samples) available in the dataset and then generate given (noisy) labels by using the estimated noise confusion matrix which is provided by [27].
ExpertNet parameters. For CIFAR-10 and CIFAR-100 Amateur is the 12-layer CNN architecture used in [25] with ReLU activation functions. Expert is a feed-forward 4-layer neural network with Leaky ReLU activation functions in the hidden layers and sigmoid in the last layer. Both networks are implemented using Keras v2.2.4 and Tensorflow v1.13 and trained using stochastic gradient descent with momentum 0.9, weight decay $10^{-4}$, and learning rate 0.01. We train our model for 120 and 200 epochs for CIFAR-10 and CIFAR-100, respectively. For Clothing1M, we resize each image to $256 \times 256$ pixels and crop the center to $224 \times 224$. We use ResNet50 for Amateur with SGD optimizer and momentum of 0.9. The weight decay factor is $5 \times 10^{-3}$, and the batch size is 16. The initial learning rate is 0.002 and decreased by 10 every 5 epochs. The total training epochs are 50. The Expert architecture remains the same. All experiments run on servers equipped with 8-cores @ 2.4GHz, 64GB of RAM, and an NVIDIA TITAN X GPU.

4.2 Competing Methods

We consider the following four methods, which aim to filter out the (impact of) noisy labels by altering the loss function, selecting the clean labels, and inferring the noise transition matrix. Competing models are based on their original code and settings.

- **D2L** [26]: uses the Local Intrinsic Dimensionality (LID) to detect points of noisy data and modifies the loss function based on the LID score.
- **Co-teaching** [5]: uses two neural networks to teach each other by selecting and exchanging the more informative data batches where the selection leverages the memory effect of neural networks.
- **Bootstrap** [20]: uses a weighted combination of the original label and prediction of the model as the final prediction.
- **Forward** [19]: uses the noise transition matrix to correct the labels before training.

Comparison modes For a fair comparison, we compare the competing models against ExpertNet under two scenarios: without and with using the given labels $y$ during inference. In the case without $y$, the predictions are taken from Amateur, and Expert is used only during training. In the case with $y$, we consider the whole ExpertNet, including Expert in both training and inference, and the predictions are taken from Expert. Additionally, we evaluate the effect of decreasing amounts of training data which range from randomly selected 100% to 20% of the training samples for each dataset. Experiment across competing models all use the same training and validation sets.

Metrics of interests We present the inference accuracy of ExpertNet and all four competing methods. As a performance metric, we use the accuracy evaluated on the validation data computed as the ratio of the number of correct predictions, i.e. equal to the original true labels $t$, divided by the total number of validation samples. For ExpertNet, we present two sets of accuracy results from ExpertNet: one is based on the inference from the sole trained Amateur network, and the other is based on the joint inference from Amateur and Expert. Such convention are used in Table 1 and 2. The difference between the accuracy values represents the auxiliary learning capacity of Expert.

4.3 Results

CIFAR-10 We report accuracy results under all noise levels and amounts of training data in Table 1. Starting with 100% training data, one can see that ExpertNet achieves the accuracy of 89.23%, 88.30%, 84.36%, and 80.73% for the cases of 20%, 30%, 40%, and 50% noise
### Table 1: Inference accuracy on CIFAR-10

| Noise Ratio | Amateur | Expert | D2L  | Co-Teach | Bootstrap | Forward | Amateur | Expert | D2L  | Co-Teach | Bootstrap | Forward |
|-------------|---------|--------|------|----------|-----------|---------|---------|--------|------|----------|-----------|---------|
| 100%        | 82.29   | 89.23  | 84.75| 82.45    | 81.80     | 83.11   | 79.53   | 84.36  | 80.69| 77.28    | 72.44     | 78.12   |
| 80%         | 81.74   | 88.61  | 82.85| 81.57    | 79.98     | 81.43   | 76.16   | 81.76  | 79.11| 75.74    | 71.50     | 72.76   |
| 60%         | 79.18   | 86.27  | 79.73| 79.30    | 74.19     | 75.40   | 73.35   | 79.33  | 76.63| 73.95    | 58.02     | 55.67   |
| 40%         | 75.11   | 86.01  | 77.94| 77.09    | 63.82     | 60.31   | 67.32   | 74.78  | 71.84| 73.95    | 25.11     | 31.88   |
| 20%         | 67.45   | 82.23  | 70.47| 70.37    | 23.82     | 31.35   | 56.33   | 67.88  | 63.08| 18.91    | 21.16     |         |
| Noise Ratio |         |        |      |          |           |         |         |        |      |           |           |         |
| 30%         | 100%    | 81.85  | 88.30| 82.45    | 80.29     | 77.14   | 81.68   | 76.45   | 80.73| 78.94    | 74.47     | 76.23   |
| 80%         | 79.87   | 85.83  | 81.27| 79.16    | 75.60     | 79.38   | 72.24   | 78.48  | 76.43| 71.52    | 57.84     | 63.33   |
| 60%         | 77.73   | 86.32  | 79.14| 76.87    | 70.09     | 68.35   | 69.91   | 75.06  | 73.73| 68.80    | 31.98     | 37.01   |
| 40%         | 71.88   | 82.12  | 75.68| 72.87    | 35.13     | 37.87   | 61.86   | 69.34  | 68.63| 64.25    | 22.95     | 26.87   |
| 20%         | 61.06   | 75.44  | 70.78| 67.37    | 20.99     | 28.99   | 50.96   | 61.37  | 59.08| 57.11    | 15.63     | 17.89   |

CIFAR-100 is significantly more difficult than CIFAR-10. First, the number of classes increase by a factor 10. Second, the training samples per class reduce by a factor 10. Consequently, the achieved accuracy scores shown in Table 2 are lower. Even so ExpertNet achieves 86.72%, 79.92%, 73.87%, and 66.11% for noise ratios of 20%, 30%, 40%, and 50%, respectively. Moreover, the advantage of using Expert as guidance is more pronounced. Not only no other model except ExpertNet is able to reach 60% accuracy, but also Amateur consistently reaches similar performance as D2L except under amounts of training data below 60%. However, Amateur is in line with Forward. Another positive result is that ExpertNet seems to be the least affected by diminishing training data. Unfortunately, the same does not hold for increasing noise levels. For a fair comparison, we identify the minimum required training data for ExpertNet to achieve similar or higher accuracy as the other four
## Table 2: Inference accuracy on CIFAR-100

| Noise Ratio | ExpertNet Amateur | D2L | Co-Teach | Bootstrap | Forward | ExpertNet Amateur | D2L | Co-Teach | Bootstrap | Forward |
|-------------|--------------------|-----|----------|-----------|---------|--------------------|-----|----------|-----------|---------|
| 100%        | 59.24              | 86.72 | 55.70    | 52.74     | 52.58   | 59.87              | 53.04 | 73.87    | 49.50     | 41.87   |
| 80%         | 54.56              | 85.38 | 51.26    | 50.01     | 48.95   | 55.51              | 49.91 | 71.06    | 45.17     | 39.88   |
| 60%         | 50.01              | 84.85 | 48.33    | 42.82     | 41.62   | 50.76              | 41.76 | 68.80    | 39.89     | 33.54   |
| 40%         | 44.13              | 82.51 | 42.48    | 36.75     | 32.68   | 48.04              | 34.96 | 64.33    | 36.82     | 28.33   |
| 20%         | 31.11              | 80.74 | 31.19    | 27.93     | 24.01   | 32.65              | 23.12 | 61.89    | 24.33     | 19.92   |

## Table 3: Inference accuracy on Clothing1M (affected by real world noise)

| Noise Ratio | 50% | 100% |
|-------------|-----|------|
| ExpertNet   | 69.83 | 83.42 |
| D2L         | 49.05 | 69.43 |
| Co-Teaching | 50.11 | 70.04 |
| Forward     | 51.26 | 68.94 |
| Bootstrap   | 48.94 | 68.77 |

ExpertNet achieves remarkable inference accuracy in the presence of noise labels on significantly smaller sets of training data, compared to state-of-the-art methods. The effective design of ExpertNet is particularly evident for more difficult benchmarks, such as CIFAR-100. The combined architecture of Amateur and Expert outperforms other methods even when learning from just 20% of training data used for the others.

**Clothing1M** We summarize results in Table 3 with full training data and randomly selected 50% data. When using all the training set, ExpertNet achieves 83.42% accuracy, which is 13 points higher than the second best approach, i.e., forward at 70.04%. This is due to the capacity of Expert to learn the real world noise pattern. When halving the training set, ExpertNet still achieves 69.83%, which is roughly the result the four competing methods reach using 100% training data. In other words, having the ground truth for half of the data ExpertNet can outperform other approaches which do not leverage the knowledge of noise patterns. ExpertNet has the best relative performance on CIFAR-100, followed by Clothing1M, and CIFAR-10, reflecting the decreasing importance and difficulty to learn the noise patterns. Clothing1M results further accentuate the idea of ExpertNet that learning from both images and (noisy) labels can strengthen the robustness and efficiency of deep neural networks.

## 5 Conclusion

Motivated by the observation that images in the public domain are often bundled with pre-existing noisy labels, this paper presents a novel and effective learning paradigm, called ExpertNet, which infers the images by both inputs of images and noisy labels via two networks, i.e., Amateur and Expert. The core idea of ExpertNet is to train Amateur, and Expert...
with each other, where Amateur is a deep CNN and Expert imitates how human experts correct the output of Amateur by the ground truth. As such, ExpertNet can effectively classify images via auxiliary information of noisy labels - proactively turning dirty labels to a learning advantage. Our empirical results show that ExpertNet can be generalized on extensive and challenging scenarios, i.e., the combinations of noise ratios and training data reduction, and significantly outperforms existing robust network classifiers on both CIFAR benchmarks and real world dataset.

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