Understanding and Utilizing Deep Neural Networks Trained with Noisy Labels

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1 Summary

Deep Neural networks, especially Convolutional Neural Networks has the ability to learn and memorize specific patterns in the images-label pair. This can be exploited to memorize the noisy labels in a critical systems or for noise removal in general. The author proposes a co-teaching strategy which takes full advantage of the identified samples to train DNNs robustly against noisy labels. Compared to other extensive state-of-the-art DNNs, the proposed model was able to generalize better and to improve the noise generalization when performed in both synthetic and real-world noisy samples.

2 Strengths of the proposal

1. They are using noise transition matrix, T to quantify the generalization performance of DNN trained with noisy labels and since generalization occurs in *generalization in distribution* with the proposed novel co-teaching strategy with the INCV method. This makes the model robust and to identify clean labels accurately.
2. Test accuracy is quantitatively calculated in terms of noise ratio in the given sample set. Given test accuracy is a quadratic function of the noise ration(symmetric noise), the performance is robust for the system.
3. The proposed model outperforms all the state of the art techniques like MentorNet, D2L, etc. both in symmetrical and asymmetrical noisy labels. Also in real world dataset such as WebVision and ILSVRC2012. They provide theoretical guarantees for the INCV and the technique they use.

3 Weaknesses of the proposal

1. Author was not provide sufficient experiment to prove that the a deep NN if trained many epochs can fit/generalize the data distribution of the training set even if there are noisy labels if the training accuracy is low. This should be proved to hypothesis that converging to an extremely low value does not contradict their findings.

4 Results

The proposed model takes advantage of the generalization of the distribution of the noisy labels and accurate labels and by co-teaching method with INCV performs superior to all other state-of-the-art deep learning techniques for noisy samples. They outperforms other models like MentorNet, D2L, Co-teaching, De-coupling and F-correction. They uses a hybrid model of co-teaching and INCV taking advantage of the generalization of distribution in noisy labels. Thus they are able to get state of the art results in the noisy label detection.

5 Discussion

How can we use improve upon the technique to extent the work to identify noisy labels in detection or segmentation data-set?
It is interesting to find that the CIFAR10 dataset has wrongly labeled samples. Imagenet and MS COCO will have many such wrongly annotated samples. How much do they affect the performance of the CNN network we use, let say VGG-16/YOLO that we use?
How much Bayes theorem governs learning and generalization of deep neural network?