How does Disagreement Help Generalization against Label Corruption?

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Outline

1. Introduction to Learning with Label Corruption/Noisy Labels.

2. Related works
   - Learning with small-loss instances
   - Decoupling

3. Co-teaching: From Small-loss to Cross-update

4. Co-teaching+: Divergence Matters

5. Experiments

6. Summary
Big and high quality data drives the success of deep models.

**Figure:** There is a steady reduction of error every year in object classification on large scale dataset (1000 object categories, 1.2 million training images) [Russakovsky et al., 2015].

- However, what we usually have in practice is **big data with noisy labels**.
Noisy labels from crowdsourcing platforms.

Unreliable labels may occur when the workers have limited domain knowledge.
Noisy labels from web search/crawler.

- The keywords may not be relevant to the image contents.
How to model noisy labels?

- **Class-conditional noise (CCN):**
  Each label $y$ in the training set (with $c$ classes) is flipped into $\tilde{y}$ with probability $p(\tilde{y}|y)$. Denote by $T \in [0, 1]^{(c \times c)}$ the noise transition matrix specifying the probability of flipping one label to another, so that $\forall i,j \ T_{ij} = p(\tilde{y} = j | y = i)$.

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**Figure**: Illustration of noisy labels.
What happens when learning with noisy labels?

**Figure:** Accuracy of neural networks on noisy MNIST with different noise rate (0., 0.2, 0.4, 0.6, 0.8). (Solid is train, dotted is validation.) [Arpit et al., 2017]

**Memorization:** Learning easy patterns first, then (totally) over-fit noisy training data.

**Effect:** Training deep neural networks directly on noisy labels results in accuracy degradation.
How can we robustly learn from noisy labels?

Current progress in three orthogonal directions:

- **Learning with noise transition:**
  - Forward Correction (Australian National University, CVPR’17)
  - S-adaptation (Bar Ilan University, ICLR’17)
  - Masking (RIKEN-AIP/UTS, NeurIPS’18)

- **Learning with selected samples:**
  - MentorNet (Google AI, ICML’18)
  - Learning to Reweight Examples (University of Toronto, ICML’18)
  - **Co-teaching** (RIKEN-AIP/UTS, NeurIPS’18)

- **Learning with implicit regularization:**
  - Virtual Adversarial Training (Preferred Networks, ICLR’16)
  - Mean Teachers (Curious AI, NIPS’17)
  - Temporal Ensembling (NVIDIA, ICLR’17)
A promising research line: Learning with small-loss instances

- **Main idea:** regard **small-loss instances** as “correct” instances.

**Figure:** Self-training MentorNet [Jiang et al., 2018].

- **Benefit:** easy to implement & free of assumptions.
- **Drawback:** **accumulated error** caused by sample-selection bias.
A promising research line: Learning with small-loss instances

Consider the standard class-conditional noise (CCN) model.

- We can learn a reliable classifier if a set of clean data is available.
- Then, we can use the reliable classifier to filter out the noisy data, where “small loss” serves as a gold standard.
- However, we usually only have access to noisy training data. The selected small-loss instances are only likely to be correct, instead of totally correct.
- (Problem) There exists accumulated error caused by sample-selection bias.
- (Solution 1) In order to select more correct samples, can we design a “small-loss” rule by utilizing the memorization of deep neural networks?
Related work: Decoupling

- Easy samples can be quickly learnt and classified (memorization effect).
- Decoupling focus on hard samples, which can be more informative.
- Decoupling use samples in each mini-batch that two classifiers have disagreement in predictions to update networks.
- (Solution 2) Can we further attenuate the error from noisy data by utilizing two networks?

Figure: Decoupling [Malach and Shalev-Shwartz, 2017].
Co-teaching: Cross-update meets small-loss

- Co-teaching maintains two networks (A & B) simultaneously.
- Each network samples its small-loss instances based on memorization of neural networks.
- Each network teaches such useful instances to its peer network. (Cross-update)

Figure: Co-teaching[Han et al., 2018].
Two networks in Co-teaching will converge to a consensus gradually.
However, two networks in Disagreement will keep diverged.
We bridge the “Disagreement” strategy with Co-teaching to achieve Co-teaching+.
How does Disagreement Benefit Co-teaching?

- **Disagreement-update step:** Two networks feed forward and predict all data first, and only keep prediction disagreement data.
- **Cross-update step:** Based on disagreement data, each network selects its small-loss data, but back propagates such data from its peer network.
Co-teaching+ Paradigm

1: Input $w^{(1)}$ and $w^{(2)}$, training set $\mathcal{D}$, batch size $B$, learning rate $\eta$, estimated noise rate $\tau$, epoch $E_k$ and $E_{\text{max}}$;
for $e = 1, 2, \ldots, E_{\text{max}}$ do

2: Shuffle $\mathcal{D}$ into $\frac{|\mathcal{D}|}{B}$ mini-batches; //noisy dataset
for $n = 1, \ldots, \frac{|\mathcal{D}|}{B}$ do

3: Fetch $n$-th mini-batch $\tilde{\mathcal{D}}$ from $\mathcal{D}$;
4: Select prediction disagreement $\tilde{\mathcal{D}}' = \{(x_i, y_i) : \tilde{y}_i^{(1)} \neq \tilde{y}_i^{(2)}\}$;
5: Get $\tilde{\mathcal{D}}'(1) = \arg \min_{\mathcal{D}':|\mathcal{D}'|\geq \lambda(e)|\tilde{\mathcal{D}}'|} \ell(\mathcal{D}'; w^{(1)})$; //sample $\lambda(e)$% small-loss instances
6: Get $\tilde{\mathcal{D}}'(2) = \arg \min_{\mathcal{D}':|\mathcal{D}'|\geq \lambda(e)|\tilde{\mathcal{D}}'|} \ell(\mathcal{D}'; w^{(2)})$; //sample $\lambda(e)$% small-loss instances
7: Update $w^{(1)} = w^{(1)} - \eta \nabla \ell(\tilde{\mathcal{D}}'(2); w^{(1)})$; //update $w^{(1)}$ by $\tilde{\mathcal{D}}'(2)$;
8: Update $w^{(2)} = w^{(2)} - \eta \nabla \ell(\tilde{\mathcal{D}}'(1); w^{(2)})$; //update $w^{(2)}$ by $\tilde{\mathcal{D}}'(1)$;
end

9: Update $\lambda(e) = 1 - \min\{\frac{e}{E_k} \tau, \tau\}$ or $1 - \min\{\frac{e}{E_k} \tau, (1 + \frac{e-E_k}{E_{\text{max}}-E_k})\tau\}$; (memorization helps)
end

10: Output $w^{(1)}$ and $w^{(2)}$.

Co-teaching+: Step 4: disagreement-update; Step 5-8: cross-update.
Relations to other approaches

Table: Comparison of state-of-the-art and related techniques with our Co-teaching+ approach.

“small loss”: regarding small-loss samples as “clean” samples;
“double classifiers”: training two classifiers simultaneously;
“cross update”: updating parameters in a cross manner;
“divergence”: keeping two classifiers diverged during training.

<table>
<thead>
<tr>
<th></th>
<th>MentorNet</th>
<th>Co-training</th>
<th>Co-teaching</th>
<th>Decoupling</th>
<th>Co-teaching+</th>
</tr>
</thead>
<tbody>
<tr>
<td>small loss</td>
<td>✓</td>
<td>×</td>
<td>✓</td>
<td>×</td>
<td>✓</td>
</tr>
<tr>
<td>double classifiers</td>
<td>×</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>cross update</td>
<td>×</td>
<td>✓</td>
<td>✓</td>
<td>×</td>
<td>✓</td>
</tr>
<tr>
<td>divergence</td>
<td>×</td>
<td>✓</td>
<td>×</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>
## Datasets for CCN model

**Table**: Summary of data sets used in the experiments.

<table>
<thead>
<tr>
<th>Dataset</th>
<th># of train</th>
<th># of test</th>
<th># of class</th>
<th>size</th>
</tr>
</thead>
<tbody>
<tr>
<td>MNIST</td>
<td>60,000</td>
<td>10,000</td>
<td>10</td>
<td>28×28</td>
</tr>
<tr>
<td>CIFAR-10</td>
<td>50,000</td>
<td>10,000</td>
<td>10</td>
<td>32×32</td>
</tr>
<tr>
<td>CIFAR-100</td>
<td>50,000</td>
<td>10,000</td>
<td>100</td>
<td>32×32</td>
</tr>
<tr>
<td>NEWS</td>
<td>11,314</td>
<td>7,532</td>
<td>7</td>
<td>1000-D</td>
</tr>
<tr>
<td>T-ImageNet</td>
<td>100,000</td>
<td>10,000</td>
<td>200</td>
<td>64×64</td>
</tr>
</tbody>
</table>
Noise Transitions for CCN model

We manually generate class-conditional noisy labels using two types of noise transitions:

(a) Pair ($\epsilon = 45\%$).

(b) Symmetry ($\epsilon = 50\%$).

Figure: Different noise transitions (using 5 classes as an example) [Han et al., 2018].
Baselines

- MentorNet: small-loss trick;
- Co-teaching: small-loss and cross-update trick.
- Decoupling: instances that have different predictions;
- F-correction: loss correction on transition matrix;
- Standard: directly training on noisy datasets.
Network structures

**Table:** MLP and CNN models used in our experiments on *MNIST, CIFAR-10, CIFAR-100/Open-sets,* and *NEWS.*

<table>
<thead>
<tr>
<th>MLP on MNIST</th>
<th>CNN on CIFAR-10</th>
<th>CNN on CIFAR-100/Open-sets</th>
<th>MLP on NEWS</th>
</tr>
</thead>
<tbody>
<tr>
<td>28×28 Gray Image</td>
<td>32×32 RGB Image</td>
<td>32×32 RGB Image</td>
<td>1000-D Text</td>
</tr>
<tr>
<td>Dense 28×28 → 256, ReLU</td>
<td>5×5 Conv, 6 ReLU, 2×2 Max-pool</td>
<td>3×3 Conv, 64 BN, ReLU, 2×2 Max-pool</td>
<td>300-D Embedding</td>
</tr>
<tr>
<td>Dense 2×2 Conv, 64 BN, ReLU</td>
<td>3×3 Conv, 128 BN, ReLU</td>
<td>Flatten → 1000×300</td>
<td>Adaptive avg-pool → 16×300</td>
</tr>
<tr>
<td>Dense 2×2 Max-pool</td>
<td>3×3 Conv, 16 ReLU, 2×2 Max-pool</td>
<td>Dense 16×300 → 4×300</td>
<td>BN, Softsign</td>
</tr>
<tr>
<td>5×5 Conv, 196 BN, ReLU</td>
<td>3×3 Conv, 196 BN, ReLU</td>
<td>Dense 4×300 → 300</td>
<td>BN, Softsign</td>
</tr>
<tr>
<td>Dense 16×5×5 → 120, ReLU, Dense 120 → 84, ReLU</td>
<td>3×3 Conv, 196 BN, ReLU, 2×2 Max-pool</td>
<td>Dense 300 → 7</td>
<td></td>
</tr>
<tr>
<td>Dense 256 → 10</td>
<td>Dense 84 → 10</td>
<td>Dense 256 → 100/10</td>
<td></td>
</tr>
<tr>
<td>Dense 256 → 84, ReLU</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

(RIKEN & UTS) Co-teaching+ Jun 12th, 2019 20 / 30
**MNIST**

- **Standard**
- **Decoupling**
- **F-correction**
- **MentorNet**
- **Co-teaching**
- **Co-teaching+**

**Figure**: Test accuracy vs number of epochs on *MNIST* dataset.

(a) **Pair-45%**.

(b) **Symmetry-50%**.

(c) **Symmetry-20%**.
**CIFAR-10**

Figure: Test accuracy vs number of epochs on CIFAR-10 dataset.
CIFAR-100

Figure: Test accuracy vs number of epochs on CIFAR-100 dataset.
Figure: Test accuracy vs number of epochs on NEWS dataset.
T-ImageNet

**Table:** Averaged/maximal test accuracy (%) of different approaches on *T-ImageNet* over last 10 epochs. The best results are in blue.

<table>
<thead>
<tr>
<th>Flipping-Rate(%)</th>
<th>Standard</th>
<th>Decoupling</th>
<th>F-correction</th>
<th>MentorNet</th>
<th>Co-teaching</th>
<th>Co-teaching+</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pair-45%</td>
<td>26.14/26.32</td>
<td>26.10/26.61</td>
<td>0.63/0.67</td>
<td>26.22/26.61</td>
<td>27.41/27.82</td>
<td>26.54/26.87</td>
</tr>
<tr>
<td>Symmetry-50%</td>
<td>19.58/19.77</td>
<td>22.61/22.81</td>
<td>32.84/33.12</td>
<td>35.47/35.76</td>
<td>37.09/37.60</td>
<td>41.19/41.77</td>
</tr>
<tr>
<td>Symmetry-20%</td>
<td>35.56/35.80</td>
<td>36.28/36.97</td>
<td>44.37/44.50</td>
<td>45.49/45.74</td>
<td>45.60/46.36</td>
<td>47.73/48.20</td>
</tr>
</tbody>
</table>
Open-sets

**Open-set noise:**
An open-set noisy label occurs when a noisy sample possesses a true class that is not contained within the set of known classes in the training data.

**Open-sets:** CIFAR-10 noisy dataset with 40% open-set noise from CIFAR-100, ImageNet32, and SVHN.

![Figures](RIKEN & UTS)

**Figure:** Examples of open-set noise for “airplane” in CIFAR-10 [Wang et al., 2018].
Open-sets

Table: Averaged/maximal test accuracy (%) of different approaches on Open-sets over last 10 epochs. The best results are in blue.

<table>
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</thead>
<tbody>
<tr>
<td>CIFAR-10 + CIFAR-100</td>
<td>62.92</td>
<td>79.27/79.33</td>
<td>79.28</td>
<td>79.43/79.58</td>
<td>79.28/79.74</td>
</tr>
<tr>
<td>CIFAR-10 + ImageNet-32</td>
<td>58.63</td>
<td>79.27/79.40</td>
<td>79.38</td>
<td>79.42/79.60</td>
<td>79.89/80.52</td>
</tr>
<tr>
<td>CIFAR-10 + SVHN</td>
<td>56.44</td>
<td>79.72/79.81</td>
<td>77.73</td>
<td>80.12/80.33</td>
<td>80.62/80.95</td>
</tr>
</tbody>
</table>
Conclusion:

- This paper presents Co-teaching+, a robust model for learning on noisy labels.
- Three key points towards robust training on noisy labels:
  1) use small-loss trick based on memorization effects of deep networks;
  2) cross-update parameters of two networks;
  3) keep two networks diverged during training.

Future work:

- Investigate the theory of Co-teaching+ from the view of disagreement-based algorithms [Wang and Zhou, 2017].
Link to our paper:

Our poster will be:
Wed Jun 12th 06:30 – 09:00 PM@Pacific Ballroom #21

Thank you very much for your attention!
References


