How does Disagreement Help Generalization against Label Corruption?

Center for Advanced Intelligence Project, RIKEN, Japan
Centre for Artificial Intelligence, University of Technology Sydney, Australia

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Outline

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

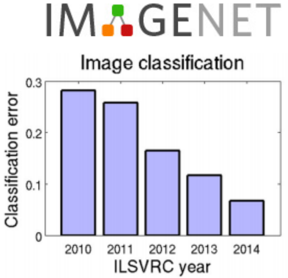
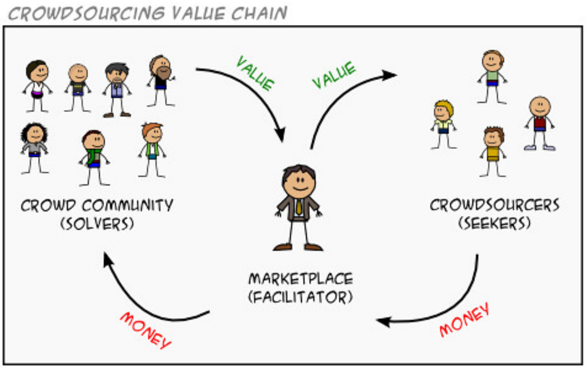


Figure: There is a steady reduction of error every year in object classification on large scale dataset (1000 object categories, 1.2 million training images) [Russakovsky et al., 2015].

- However, what we usually have in practice is big data with noisy labels.

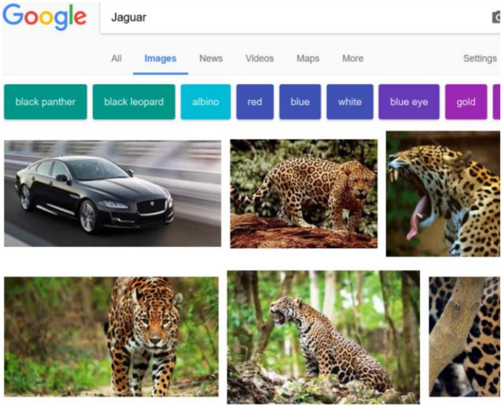
Noisy labels from crowdsourcing platforms.



Credit: *Torbjørn Marø*

- Unreliable labels may occur when the workers have limited domain knowledge.

Noisy labels from web search/crawler.



Screenshot of Google.com

- 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 $\forall_{i,j} T_{ij} = p(\tilde{y}=j|y=i)$.

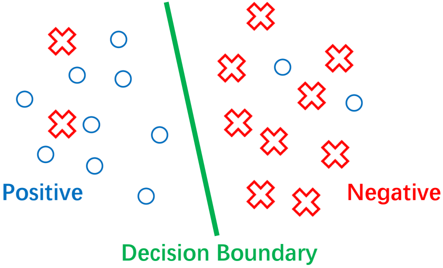


Figure: Illustration of noisy labels.

What happens when learning with noisy labels?

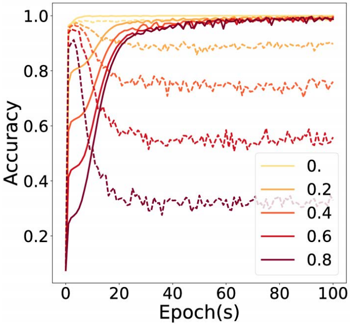


Figure: Accuracy of neural networks on noisy MNIST with different noise rate (0., 0.2, 0.4, 0.6, 0.8). (Solid is train, dotted is validation.) [Arpit et al., 2017]

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 wen 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.

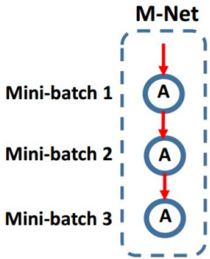


Figure: Self-training MentorNet[Jiang et al., 2018].

- 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

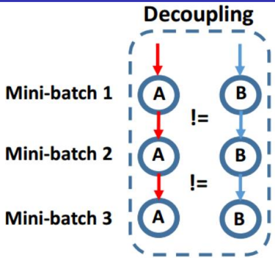


Figure: Decoupling[Malach and Shalev-Shwartz, 2017].

- 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?

Co-teaching: Cross-update meets small-loss

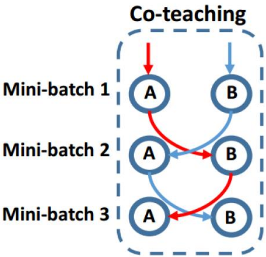


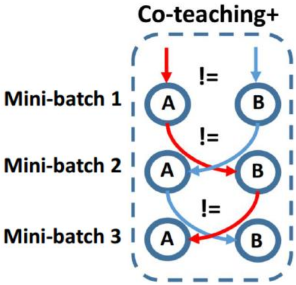
Figure: Co-teaching[Han et al., 2018].

- 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)

Divergence

- 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 η, estimated noise rate τ, epoch E_k and $E_{\max}$;

for $e = 1, 2, \ldots, E_{\max}$ 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 $\bar{\mathcal{D}}$ from $\mathcal{D}$;

    4: Select prediction disagreement $\bar{\mathcal{D}}' = \{(x_i, y_i) : \bar{y}_i^{(1)} \neq \bar{y}_i^{(2)}\}$;

    5: Get $\bar{\mathcal{D}}'^{(1)} = \arg\min_{\mathcal{D}':|\mathcal{D}'| \geq \lambda(e)|\bar{\mathcal{D}}'|} \ell(\mathcal{D}'; w^{(1)})$; //sample $\lambda(e)$% small-loss instances

    6: Get $\bar{\mathcal{D}}'^{(2)} = \arg\min_{\mathcal{D}':|\mathcal{D}'| \geq \lambda(e)|\bar{\mathcal{D}}'|} \ell(\mathcal{D}'; w^{(2)})$; //sample $\lambda(e)$% small-loss instances

    7: Update $w^{(1)} = w^{(1)} - \eta \nabla \ell(\bar{\mathcal{D}}'^{(2)}; w^{(1)})$;//update $w^{(1)}$ by $\bar{\mathcal{D}}'^{(2)}$;

    8: Update $w^{(2)} = w^{(2)} - \eta \nabla \ell(\bar{\mathcal{D}}'^{(1)}; w^{(2)})$;//update $w^{(2)}$ by $\bar{\mathcal{D}}'^{(1)}$;

  end

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

	MentorNet	Co-training	Co-teaching	Decoupling	Co-teaching+
small loss	✓	×	✓	×	✓
double classifiers	×	✓	✓	✓	✓
cross update	×	✓	✓	×	✓
divergence	×	✓	×	✓	✓

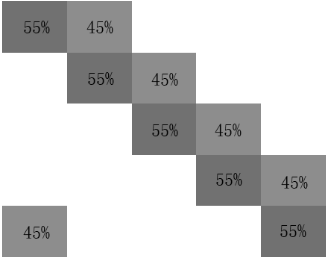
Datasets for CCN model

Table: Summary of data sets used in the experiments.

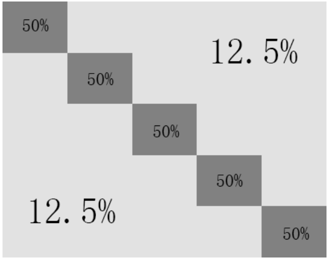
	# of train	# of test	# of class	size
MNIST	60,000	10,000	10	28×28
CIFAR-10	50,000	10,000	10	32×32
CIFAR-100	50,000	10,000	100	32×32
NEWS	11,314	7,532	7	1000-D
T-ImageNet	100,000	10,000	200	64×64

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

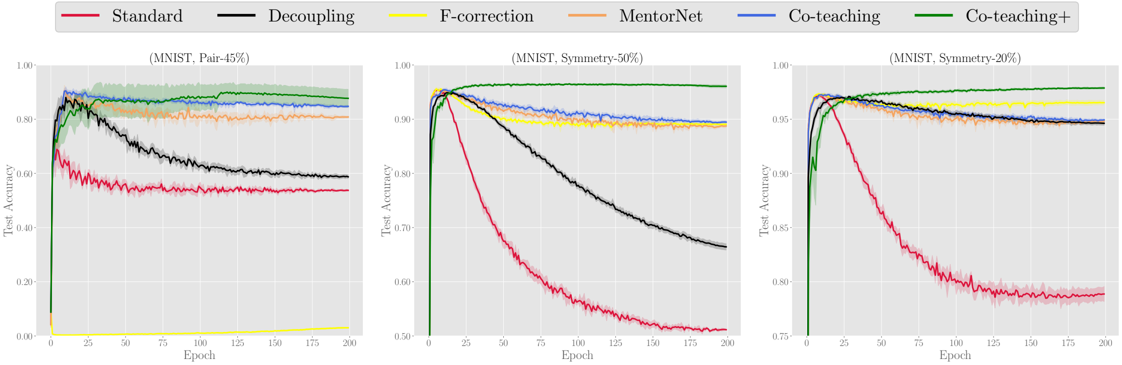
- MentorNet: small-loss trick;
- Co-teaching: small-loss and cross-update trick.
- Decoupling: instances that have different predictions;
- F-correction: loss correction on transition matrix;
- Standard: directly training on noisy datasets.

Network structures

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

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

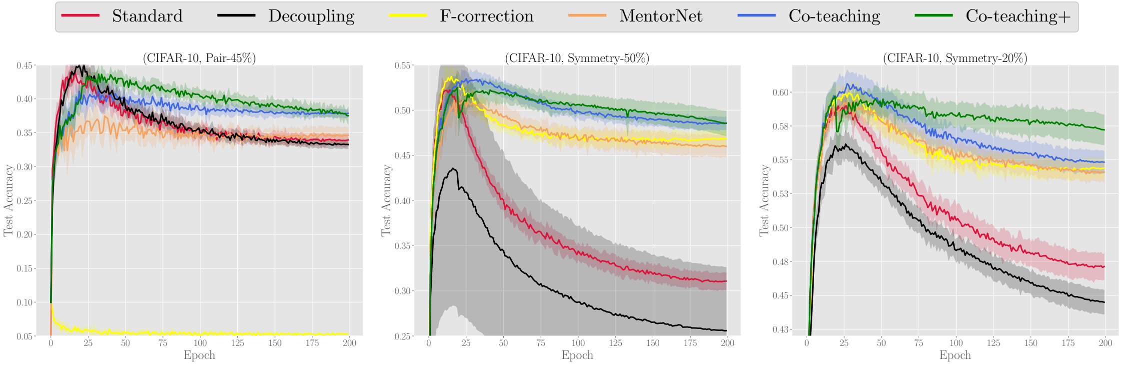
MNIST



(a) Pair-45%. (b) Symmetry-50%. (c) Symmetry-20%.

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

CIFAR-10



(a) Pair-45%. (b) Symmetry-50%. (c) Symmetry-20%.

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

CIFAR-100

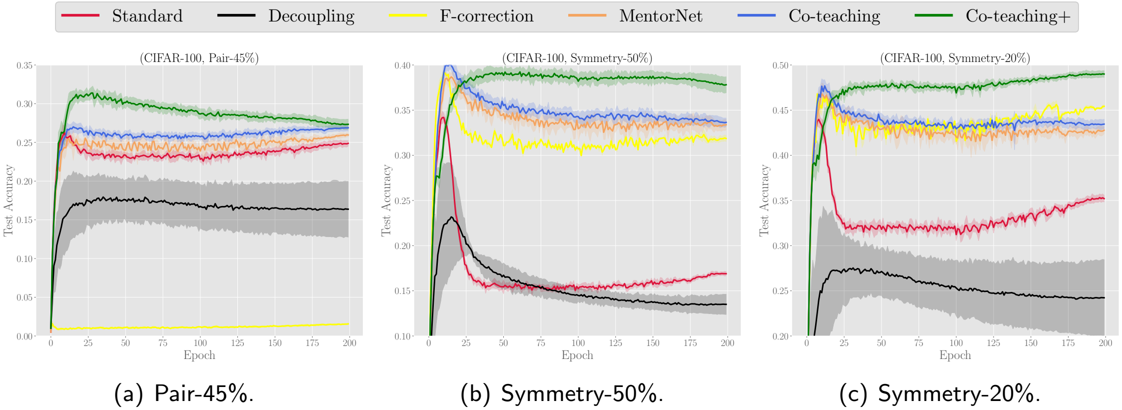
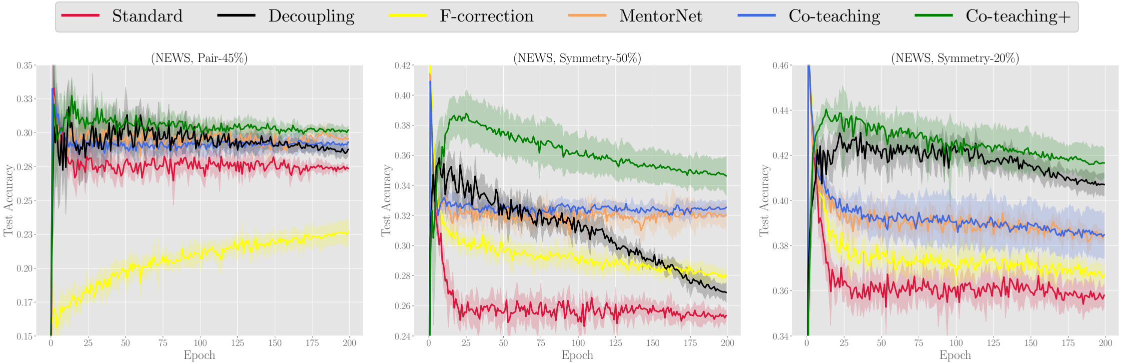


Figure: Test accuracy vs number of epochs on *CIFAR-100* dataset.

NEWS



(a) Pair-45%. (b) Symmetry-50%. (c) Symmetry-20%.

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.

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

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.

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.

Open-set noise	Standard	MentorNet	Iterative[Wang et al., 2018]	Co-teaching	Co-teaching+
CIFAR-10+CIFAR-100	62.92	79.27/79.33	79.28	79.43/79.58	79.28/79.74
CIFAR-10+ImageNet-32	58.63	79.27/79.40	79.38	79.42/79.60	79.89/80.52
CIFAR-10+SVHN	56.44	79.72/79.81	77.73	80.12/80.33	80.62/80.95

Summary

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!

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