Learning with Noisy Supervision

Part II: Statistical Learning with Noisy Supervision

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Structure

Basics

Consistent algorithms

Transition matrix

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Learning without label noise

Problem setup:

Data: $S = \{(\boldsymbol{x}_1, y_1), \ldots, (\boldsymbol{x}_n, y_n)\} \sim D^n$.

Aim: Learn a classifier $f \in F$, such that $\forall (\boldsymbol{x}, y) \sim D$,
$f(\boldsymbol{x})$ is a good prediction for y.

What is the best classifier we can obtain?

w.r.t. accuracy

To measure the accuracy, we define loss function

$$\ell(\boldsymbol{x}, y), f \mapsto \ell\big(y, f(\boldsymbol{x})\big) \in \mathbb{R}.$$

For example, 0-1 loss: $\mathbf{1}(y \neq \mathrm{sign}(f(\boldsymbol{x})))$.

The best classifier should be the one that has the smallest loss on all the possible data from the domain.

Theoretically,

$$R_{D,0-1}(f) = \mathbb{E}_{(X,Y)\sim D}[\mathbf{1}(Y \neq \operatorname{sign}(f(X)))]$$
$$= \iint P(X = \boldsymbol{x}, Y = y)\, \mathbf{1}(y \neq \operatorname{sign}(f(\boldsymbol{x})))d\boldsymbol{x}dy$$
$$= 1 - \iint P(X = \boldsymbol{x}, Y = y)\, \mathbf{1}(y = \operatorname{sign}(f(\boldsymbol{x})))d\boldsymbol{x}dy.$$

$$f_\rho(\boldsymbol{x}) = \arg\max_y P(Y = y | X = \boldsymbol{x}).$$

Expected risk, Bayes classifier

The expected risk:

$$R_{D,0-1}(f) = \mathbb{E}_{(X,Y)\sim D}[\mathbf{1}(Y \neq \text{sign}(f(X)))].$$

Bayes risk: $R^*_{D,0-1} = \inf_f R_{D,0-1}(f).$

The Bayes decision rule (Bayes classifier):

$$f_\rho = \arg\inf_f R_{D,0-1}(f) \,.$$

Restricted Bayes risk: $f^* = \inf_{f\in\mathcal{F}} R_{D,0-1}(f) \,.$

Empirically,

In reality, we can only observe a sample of data
$S = \{(\boldsymbol{x}_1, y_1), \ldots, (\boldsymbol{x}_n, y_n)\} \sim D^n$.

We approximate the expected risk $R(f)$ via the empirical risk: $\widehat{R}_{D,\ell}(f) = \frac{1}{n}\sum_{i=1}^{n} \ell\big(y_i, f(\boldsymbol{x}_i)\big)$.

We minimize the empirical risk to find a predictor:

$$f_n = \arg\min_{f \in \boldsymbol{\mathcal{F}}} \widehat{R}_{D,\ell}(f).$$

Statistically consistent classifier [1,2]:

With high probability, as $n \longrightarrow \infty$,
we have: $R_{D,\ell}(f_n) \longrightarrow R_{D,\ell}(f^*)$.

[1] Mohri et al. *Foundations of machine learning*. MIT press, 2018.
[2] Devroye, et al. *A probabilistic theory of pattern recognition*. Vol. 31. Springer Science & Business Media, 2013.

Aim:

Designing algorithms whose outputs will approach $f_\rho(\boldsymbol{x}) = \arg\max_y P(Y = y | X = \boldsymbol{x})$.

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Learning with label noise

Noisy sample: $\tilde{S} = \{(\boldsymbol{x}_1, \tilde{y}_1), \ldots, (\boldsymbol{x}_n, \tilde{y}_n)\} \sim \widetilde{D}^n$,
where $\tilde{y}$ stands for noisy labels and $\widetilde{D}$ the noisy distribution.

What is the best classifier we can learn?

Can we approach $f_\rho(\boldsymbol{x}) = \arg\max_y P(Y = y | X = \boldsymbol{x})$?

Learning with label noise

One category: extracting confident examples or correct labels.

SOTA, e.g., Co-teaching [3]; Joint Optim [4].

Another category: label-noise learning [5].

Methodology, i.e., statistically consistent algorithms.

[3] Han, Bo, et al. "Co-teaching: Robust training of deep neural networks with extremely noisy labels." *NeurIPS* 2018.
[4] Tanaka, Daiki, et al. "Joint optimization framework for learning with noisy labels." *CVPR* 2018.
[5] Xia, Xiaobo, et al. "Are anchor points really indispensable in label-noise learning?." *NeurIPS* 2019.

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Why called "label-noise learning"?

Model label noise

Transition matrix:

$$\begin{bmatrix} P(\tilde{Y} = 1|Y = 1, \boldsymbol{x}) & \cdots & P(\tilde{Y} = 1|Y = C, \boldsymbol{x}) \\ \vdots & \ddots & \vdots \\ P(\tilde{Y} = C|Y = 1, \boldsymbol{x}) & \cdots & P(\tilde{Y} = C|Y = C, \boldsymbol{x}) \end{bmatrix}.$$

Transition matrix

$$\begin{bmatrix} P(\tilde{Y}=1|\boldsymbol{x}) \\ \vdots \\ P(\tilde{Y}=C|\boldsymbol{x}) \end{bmatrix} = \underbrace{\boxed{\begin{bmatrix} P(\tilde{Y}=1|Y=1,\boldsymbol{x}) & \cdots & P(\tilde{Y}=1|Y=C,\boldsymbol{x}) \\ \vdots & \ddots & \vdots \\ P(\tilde{Y}=C|Y=1,\boldsymbol{x}) & \cdots & P(\tilde{Y}=C|Y=C,\boldsymbol{x}) \end{bmatrix}}}_{T^\top(\boldsymbol{x})} \begin{bmatrix} P(Y=1|\boldsymbol{x}) \\ \vdots \\ P(Y=C|\boldsymbol{x}) \end{bmatrix}$$

Why called “label-noise learning”?

- Label-noise learning [5]
- Noisy-label learning
- Learning with noisy labels [6]

[5] Xia, Xiaobo, et al. “Are anchor points really indispensable in label-noise learning?.” *NeurIPS* 2019.
[6] Natarajan, Nagarajan, et al. “Learning with noisy labels.” *NeurIPS* 2013.

Model Label Noise

(1)Random Classification Noise (RCN) [7]:

$$\rho_{\tilde{Y},Y}(X) = P\left(\tilde{Y} \middle| Y, X\right) = P\left(\tilde{Y} \middle| Y\right) = \rho, \forall\, Y \neq \tilde{Y}.$$

(2)Class-conditional Noise (CCN) [6]:

$$\rho_{\tilde{Y},Y}(X) = P\left(\tilde{Y} \middle| Y, X\right) = P\left(\tilde{Y} \middle| Y\right).$$

(3) Instance-dependent Noise (IDN) [8,9]:

$$\rho_{\tilde{Y},Y}(X) = P\left(\tilde{Y} \middle| Y, X\right).$$

[7] Angluin, Dana, and Philip Laird. "Learning from noisy examples." *Machine Learning* 2.4: 343-370, 1988.
[8] Cheng, Jiacheng, et al. "Learning with bounded instance and label-dependent label noise." *ICML* 2020.
[9] Berthon, Antonin, et al. "Confidence scores make instance-dependent label-noise learning possible." *ICML*, 2021

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[9] Berthon, Antonin, et al. "Confidence scores make instance-dependent label-noise learning possible." *ICML*, 2021

Random Classification Noise (RCN)

Theorem 1. The losses satisfying the following symmetric criterion is robust to RCN:

$$L(f(X),+1) + L(f(X),-1) = C,$$

where C is a constant. That is

$$\arg\min_f R_{D,L}(f) = \arg\min_f R_{\tilde{D},L}(f).$$

Because: $R_{\tilde{D},L}(f) = \mathbb{E}_{(X,\tilde{Y})\sim\tilde{D}}[L(f(X),\tilde{Y})] = (1-2\rho)R_{D,L}(f) + \rho C.$

$\approx \hat{R}_{\tilde{D},L}(f)$

[10] Du Plessis, Marthinus C. et al. "Analysis of learning from positive and unlabeled data." *NeurIPS* 2014

Random Classification Noise (RCN)

The symmetric losses that are robust to RCN:

(1) 0-1 Loss: $L(f(X), Y) = \mathbf{1}(\text{sign}(f(X)) \neq Y)$;

(2) Unhinged Loss: $L(f(X), Y) = 1 - Yf(X)$;

(3) Sigmoid Loss: $L(f(X), Y) = \frac{1}{1+e^{Yf(X)}}$;

(4) Ramp Loss: $L(f(X), Y) = \frac{1}{2}\max(0, \min(2, 1 - Yf(X)))$ …

Class-conditional Noise (CCN)

The loss correction method:
Modify ℓ to be $\tilde{\ell}$ such that

$$\mathbb{E}_{(X,\tilde{Y})\sim\tilde{D}}\left[\tilde{\ell}\left(f(X),\tilde{Y}\right)\right] = \mathbb{E}_{(X,Y)\sim Y}\left[\ell(f(X),Y)\right]$$

By exploiting the model of label noise:

$$\begin{bmatrix} P(\tilde{Y}=1|\boldsymbol{x}) \\ \vdots \\ P(\tilde{Y}=C|\boldsymbol{x}) \end{bmatrix} = \begin{bmatrix} P(\tilde{Y}=1|Y=1) & \cdots & P(\tilde{Y}=1|Y=C) \\ \vdots & \ddots & \vdots \\ P(\tilde{Y}=C|Y=1) & \cdots & P(\tilde{Y}=C|Y=C) \end{bmatrix} \begin{bmatrix} P(Y=1|\boldsymbol{x}) \\ \vdots \\ P(Y=C|\boldsymbol{x}) \end{bmatrix}$$

$$\begin{bmatrix} P(\tilde{Y}=1|\boldsymbol{x}) \\ \vdots \\ P(\tilde{Y}=C|\boldsymbol{x}) \end{bmatrix} = \begin{bmatrix} P(\tilde{Y}=1|Y=1) & \cdots & P(\tilde{Y}=1|Y=C) \\ \vdots & \ddots & \vdots \\ P(\tilde{Y}=C|Y=1) & \cdots & P(\tilde{Y}=C|Y=C) \end{bmatrix} \begin{bmatrix} P(Y=1|\boldsymbol{x}) \\ \vdots \\ P(Y=C|\boldsymbol{x}) \end{bmatrix}$$

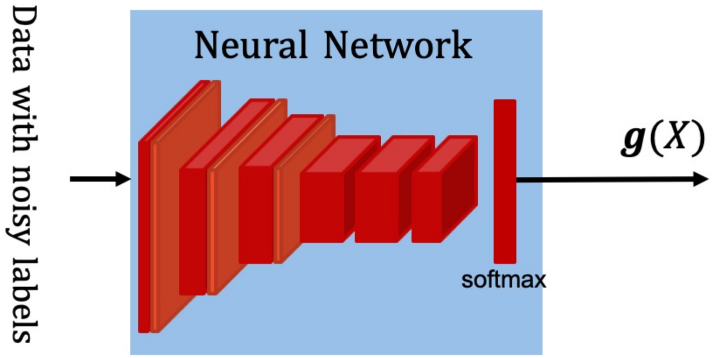
Unbiased estimator（binary classification）[6]:

$$\tilde{\ell}_{ue}(f(\boldsymbol{x}), y) = \frac{(1-\rho_{y,-y})\ell(f(\boldsymbol{x}), y) - \rho_{-y,y}\ell(f(\boldsymbol{x}), -y)}{1-\rho_{-1,+1}-\rho_{+1,-1}}$$

The idea is that $\mathbb{E}_{\tilde{y}|\mathrm{y}}\left[\tilde{\ell}_{ue}(f(\boldsymbol{x}), \tilde{y})\right] = \ell(f(\boldsymbol{x}), y)$.

Thus, $\mathbb{E}_{(X,\tilde{Y})\sim\tilde{D}}\left[\tilde{\ell}_{ue}\left(f(X), \tilde{Y}\right)\right] = \mathbb{E}_{(X,Y)\sim D}[\ell(f(X), Y)]$

[6] Natarajan, Nagarajan, et al. “Learning with noisy labels.” *NeurIPS* 2013.



$$\begin{bmatrix} P(\tilde{Y}=1|\boldsymbol{x}) \\ \vdots \\ P(\tilde{Y}=C|\boldsymbol{x}) \end{bmatrix} = \begin{bmatrix} P(\tilde{Y}=1|Y=1) & \cdots & P(\tilde{Y}=1|Y=C) \\ \vdots & \ddots & \vdots \\ P(\tilde{Y}=C|Y=1) & \cdots & P(\tilde{Y}=C|Y=C) \end{bmatrix} \begin{bmatrix} P(Y=1|\boldsymbol{x}) \\ \vdots \\ P(Y=C|\boldsymbol{x}) \end{bmatrix}$$

Importance reweighting [11]:

$$\tilde{\ell}_{ir}(f(\boldsymbol{x}), y) = \frac{P(\boldsymbol{x}, y)}{\tilde{P}(\boldsymbol{x}, y)} \ell(f(\boldsymbol{x}), y) = \frac{\boldsymbol{g}_y(\boldsymbol{x})}{(T^\top \boldsymbol{g})_y(\boldsymbol{x})} \ell(f(\boldsymbol{x}), y),$$

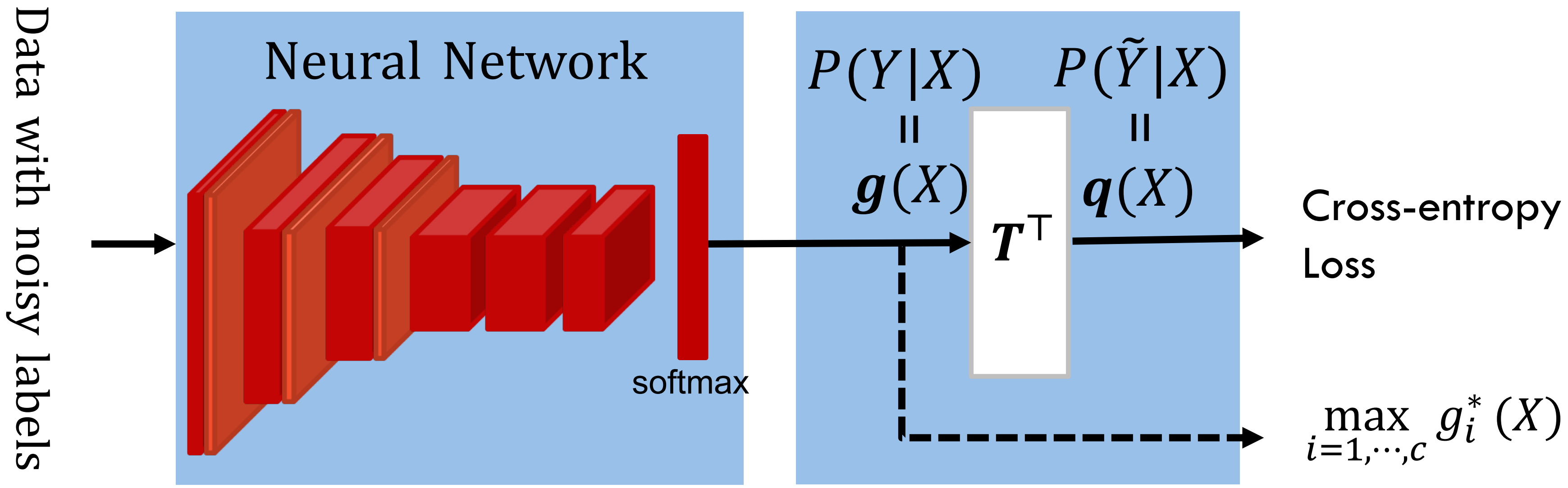
where $f(\boldsymbol{x}) = \arg\max_{j \in \{1,\ldots,C\}} \boldsymbol{g}_j(\boldsymbol{x})$.

Thus, $\mathbb{E}_{(X,\tilde{Y})\sim\tilde{D}}\left[\tilde{\ell}_{ir}\left(f(X), \tilde{Y}\right)\right] = \mathbb{E}_{(X,Y)\sim D}[\ell(f(X), Y)]$

[11] Liu, Tongliang, and Dacheng Tao. "Classification with noisy labels by importance reweighting." *IEEE Transactions on pattern analysis and machine intelligence* 38.3 (2015): 447-461..

$$\begin{bmatrix} P(\tilde{Y}=1|\boldsymbol{x}) \\ \vdots \\ P(\tilde{Y}=C|\boldsymbol{x}) \end{bmatrix} = \begin{bmatrix} P(\tilde{Y}=1|Y=1) & \cdots & P(\tilde{Y}=1|Y=C) \\ \vdots & \ddots & \vdots \\ P(\tilde{Y}=C|Y=1) & \cdots & P(\tilde{Y}=C|Y=C) \end{bmatrix} \begin{bmatrix} P(Y=1|\boldsymbol{x}) \\ \vdots \\ P(Y=C|\boldsymbol{x}) \end{bmatrix}$$

Forward correction [12]:



[12] Patrini, Giorgio, et al. "Making deep neural networks robust to label noise: A loss correction approach." *CVPR* 2017.

A summary of consistent algorithms

- Many methods for dealing with noisy labels

  Loss correction, Sample selection, label correction, …

- Model label noise

  Random Classification Noise (RCN)

  Class-conditional Noise (CCN)

  Instance-dependent Noise (IDN)

- Symmetric loss functions are robust to RCN

  A loss function is symmetric if $\sum_y \ell(f(\boldsymbol{x}), y) = c$

- Three loss correction methods

  Unbiased estimator, importance reweighting, forward correction

Structure

Basics

Consistent algorithms

Transition matrix

How to estimate the transition matrix

Given the noisy data
$\tilde{S} = \{(\boldsymbol{x}_1, \tilde{y}_1), \ldots, (\boldsymbol{x}_n, \tilde{y}_n)\} \sim \widetilde{D}$.

How to estimate the transition matrix T?

Anchor point assumption [11]

Rearrange the relationship among the noisy class posterior, the clean class posterior, and the transition matrix, we have

$$P(\tilde{Y} = 1|\boldsymbol{x}) = (1 - \beta_{+1,-1} - \beta_{-1,+1})\boxed{P(Y = 1|\boldsymbol{x})} + \beta_{-1,+1}$$

$$P(\tilde{Y} = -1|\boldsymbol{x}) = (1 - \beta_{+1,-1} - \beta_{-1,+1})\boxed{P(Y = -1|\boldsymbol{x})} + \beta_{+1,-1}$$

We designed the following estimator:

$$\beta_{-y,+y} = \min_{\boldsymbol{x} \in X} P(\tilde{Y} = y|\boldsymbol{x}).$$

[11] Liu, Tongliang, and Dacheng Tao. "Classification with noisy labels by importance reweighting." *IEEE Transactions on pattern analysis and machine intelligence* 38.3 (2015): 447-461..

Definition

If $P(Y = i | \boldsymbol{x}^i) = 1$, then $\boldsymbol{x}^i$ is called the anchor point for the i-th class.

[11] Liu, Tongliang, and Dacheng Tao. "Classification with noisy labels by importance reweighting." *IEEE Transactions on pattern analysis and machine intelligence* 38.3 (2015): 447-461..

Anchor point assumption

$$\begin{bmatrix} P(\tilde{Y}=1|X) \\ \vdots \\ P(\tilde{Y}=C|X) \end{bmatrix} = \underbrace{\boxed{\begin{bmatrix} P(\tilde{Y}=1|Y=1) & \cdots & P(\tilde{Y}=1|Y=C) \\ \vdots & \ddots & \vdots \\ P(\tilde{Y}=C|Y=1) & \cdots & P(\tilde{Y}=C|Y=C) \end{bmatrix}}}_{T} \begin{bmatrix} P(Y=1|X) \\ \vdots \\ P(Y=C|X) \end{bmatrix}$$

$$\begin{bmatrix} P(\tilde{Y}=1|X=\boldsymbol{x}^1) \\ \vdots \\ P(\tilde{Y}=C|X=\boldsymbol{x}^1) \end{bmatrix} = \begin{bmatrix} \boxed{\begin{matrix} P(\tilde{Y}=1|Y=1) \\ \vdots \\ P(\tilde{Y}=C|Y=1) \end{matrix}} & \begin{matrix} \cdots \\ \ddots \\ \cdots \end{matrix} & \begin{matrix} P(\tilde{Y}=1|Y=C) \\ \vdots \\ P(\tilde{Y}=C|Y=C) \end{matrix} \end{bmatrix} \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} P(\tilde{Y}=1|X=\boldsymbol{x}^i) \\ \vdots \\ P(\tilde{Y}=C|X=\boldsymbol{x}^i) \end{bmatrix} = \begin{bmatrix} P(\tilde{Y}=1|Y=i) \\ \vdots \\ P(\tilde{Y}=C|Y=i) \end{bmatrix}$$

[11] Liu, Tongliang, and Dacheng Tao. "Classification with noisy labels by importance reweighting." *IEEE Transactions on pattern analysis and machine intelligence* 38.3 (2015): 447-461..

How to find anchor points

Binary classification, find the anchor points:

$$\boldsymbol{x}^y = \underset{\boldsymbol{x} \in X}{\mathrm{argm}ax}\, P\left(\tilde{Y} = y \middle| \boldsymbol{x}\right).$$

Multi-classification, approximate the anchor points for multi-class learning:

$$\boldsymbol{x}^y \approx \underset{\boldsymbol{x} \in X}{\mathrm{argm}ax}\, P\left(\tilde{Y} = y \middle| \boldsymbol{x}\right).$$

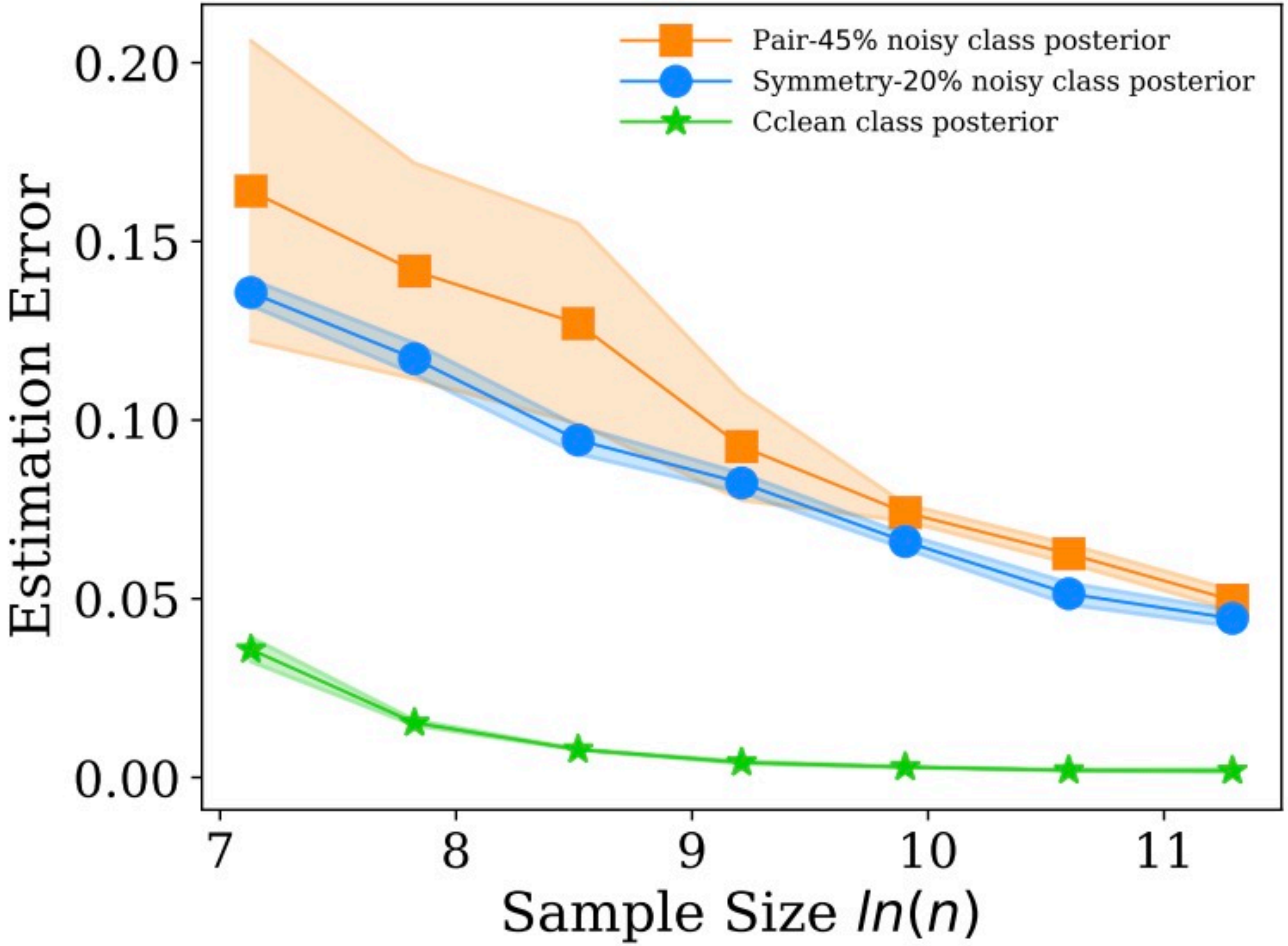
[11] Liu, Tongliang, and Dacheng Tao. "Classification with noisy labels by importance reweighting." *IEEE Transactions on pattern analysis and machine intelligence* 38.3 (2015): 447-461..

T estimator vs Dual-T estimator [13]

T estimator: $\begin{bmatrix} P(\tilde{Y} = 1|X = \boldsymbol{x}^i) \\ \vdots \\ P(\tilde{Y} = C|X = \boldsymbol{x}^i) \end{bmatrix} = \begin{bmatrix} P(\tilde{Y} = 1|Y = i) \\ \vdots \\ P(\tilde{Y} = C|Y = i) \end{bmatrix}$

Estimation error: $\left|P\left(\tilde{Y} = c \middle| \boldsymbol{x}\right) - \hat{P}\left(\tilde{Y} = c \middle| \boldsymbol{x}\right)\right| = \Delta_1.$

[13] Yao Y, et al. Dual T: Reducing estimation error for transition matrix in label-noise learning. NeurIPS 2020.



[13] Yao Y, et al. Dual T: Reducing estimation error for transition matrix in label-noise learning. NeurIPS 2020.

T estimator vs Dual-T estimator

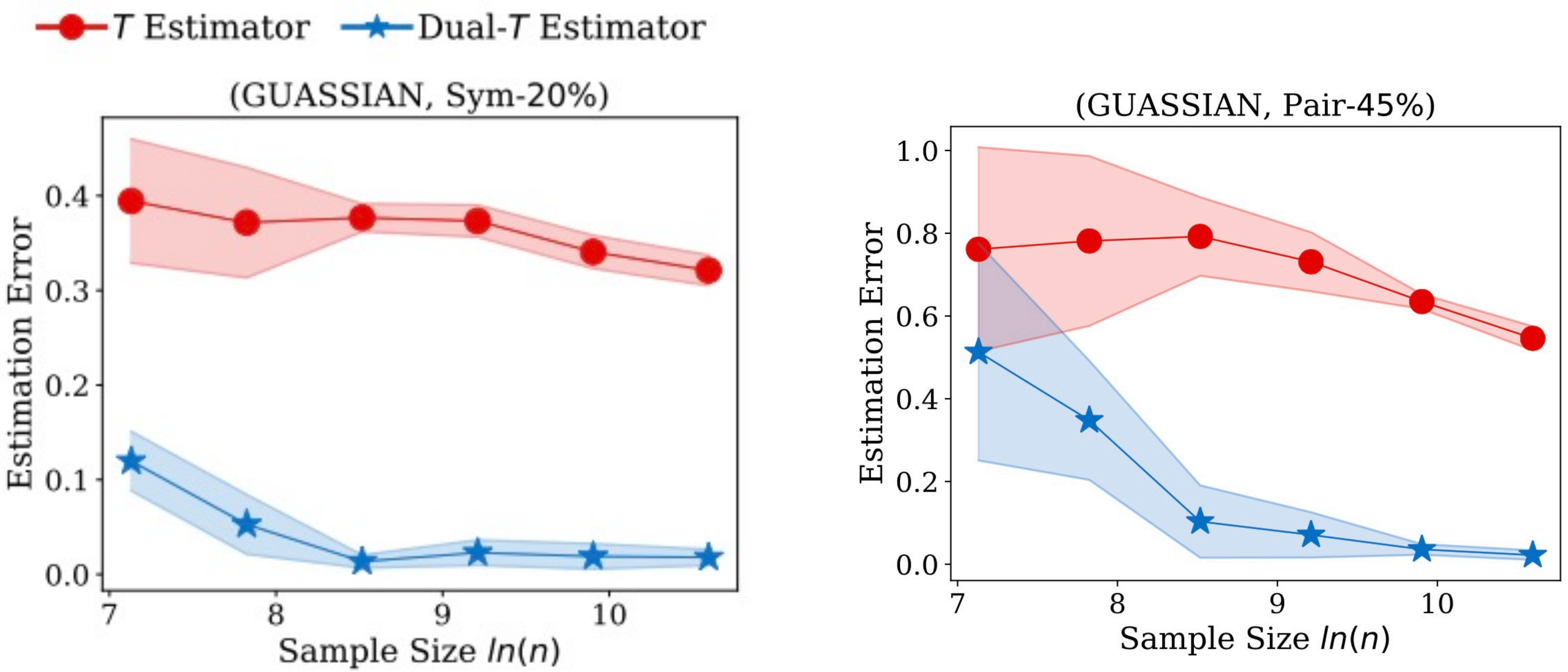
We let $P(Y' = y|\boldsymbol{x}) = \hat{P}(\tilde{Y} = y|\boldsymbol{x})$, where Y' is a variable for intermediate class.

Dual-T estimator:

$$T_{ij} = P(\tilde{Y} = j|Y = i) = \sum_{l=1}^{C} P(\tilde{Y} = j|Y' = l, Y = i)\ \boxed{P(Y' = l|Y = i)}$$
$$= \sum_{l=1}^{C} T_{lj}^{\spadesuit}(Y = i) T_{il}^{\clubsuit}.$$

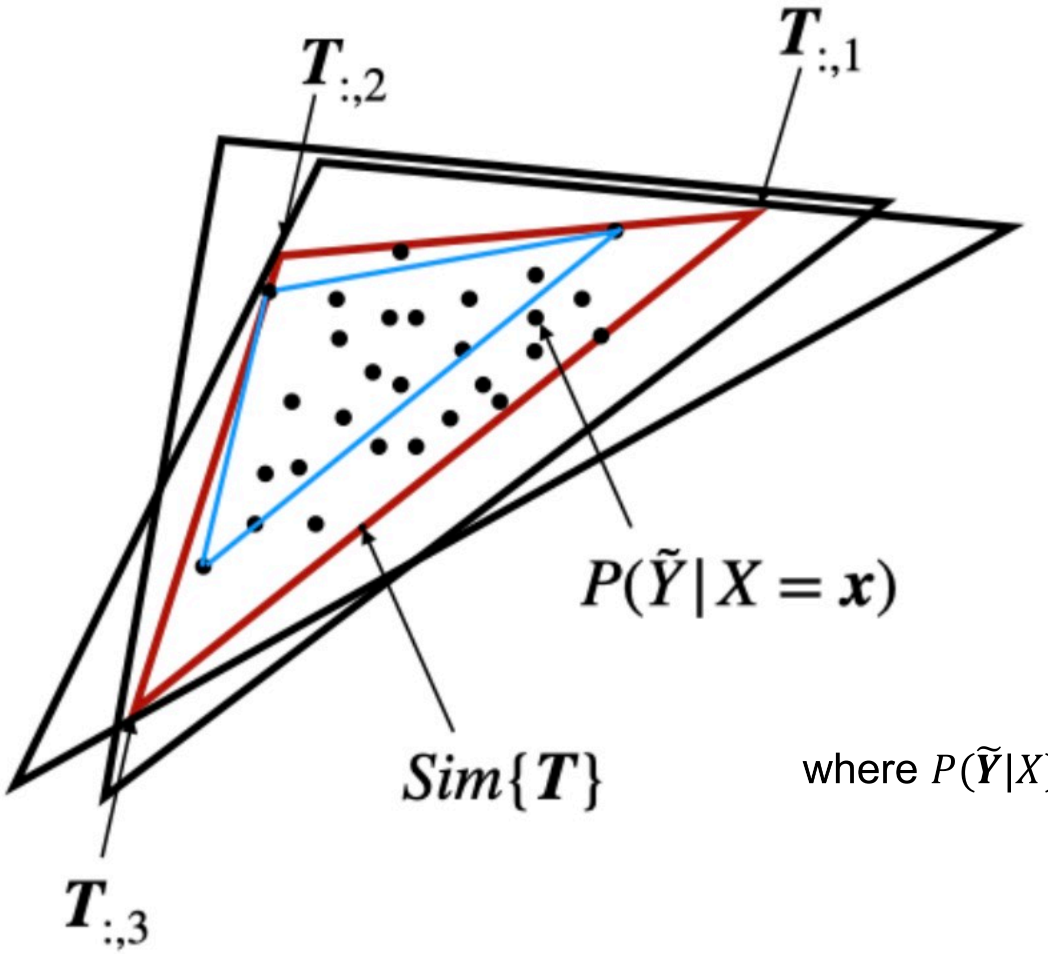
[13] Yao Y, et al. Dual T: Reducing estimation error for transition matrix in label-noise learning. NeurIPS 2020.

Estimation error of transition matrix



[13] Yao Y, et al. Dual T: Reducing estimation error for transition matrix in label-noise learning. NeurIPS 2020.

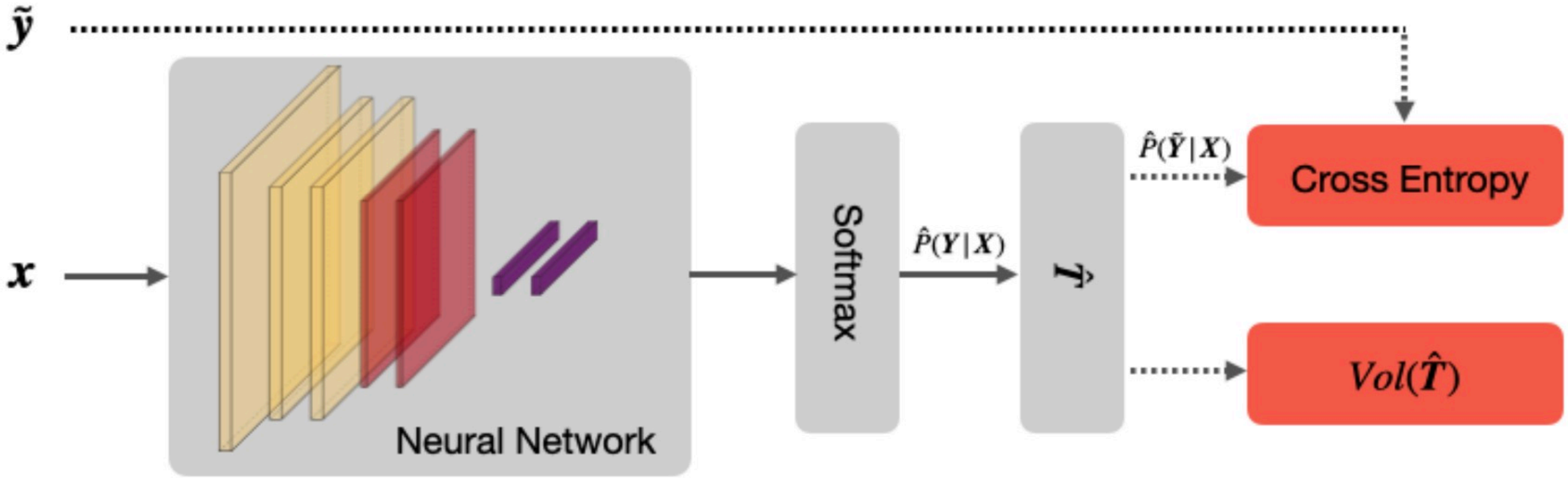
Sufficiently scattered assumption vs anchor point assumption



where $P(\tilde{\boldsymbol{Y}}|X) = \begin{bmatrix} P(\tilde{Y}=1|X) \\ \vdots \\ P(\tilde{Y}=C|X) \end{bmatrix} = \underbrace{\boxed{\begin{bmatrix} P(\tilde{Y}=1|Y=1) & \cdots & P(\tilde{Y}=1|Y=C) \\ \vdots & \ddots & \vdots \\ P(\tilde{Y}=C|Y=1) & \cdots & P(\tilde{Y}=C|Y=C) \end{bmatrix}}}_{T} \begin{bmatrix} P(Y=1|X) \\ \vdots \\ P(Y=C|X) \end{bmatrix}$

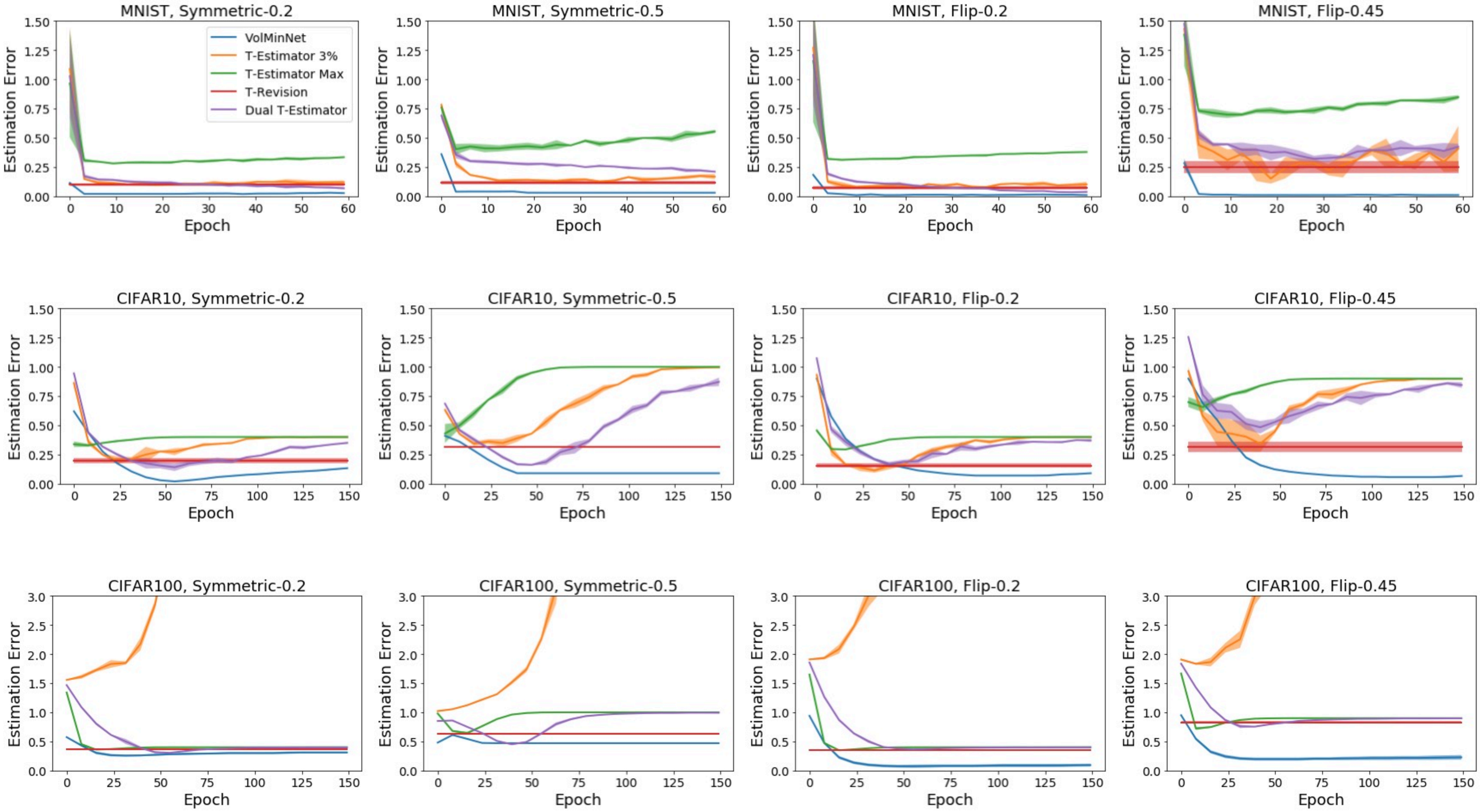
[14] Li, Xuefeng, et al. "Provably end-to-end label-noise learning without anchor points." *ICML* 2021.

VolMinNet [14]



$$\min_{\hat{T}\in\mathbb{T}} \operatorname{vol}(\hat{T})$$
$$\text{s.t.}\ \hat{T}h_\theta = P(\widetilde{\boldsymbol{Y}}|X)$$

[14] Li, Xuefeng, et al. "Provably end-to-end label-noise learning without anchor points." *ICML* 2021.



[14] Li, Xuefeng, et al. "Provably end-to-end label-noise learning without anchor points." *ICML* 2021.

T revision [15]

$$T = \begin{matrix} 0.5 & 0.3 & 0.2 & & \\ & 0.5 & .25 & .25 & \\ & & 0.5 & 0.3 & 0.2 \\ 0.2 & & & 0.5 & 0.3 \\ 0.3 & 0.2 & & & 0.5 \end{matrix} \qquad \tilde{T} = \begin{matrix} 0.5 & 0.3 & 0.2 & & \\ & 0.5 & 0.3 & 0.2 & \\ & & 0.5 & 0.3 & 0.2 \\ 0.2 & & & 0.5 & 0.3 \\ 0.3 & 0.2 & & & 0.5 \end{matrix}$$

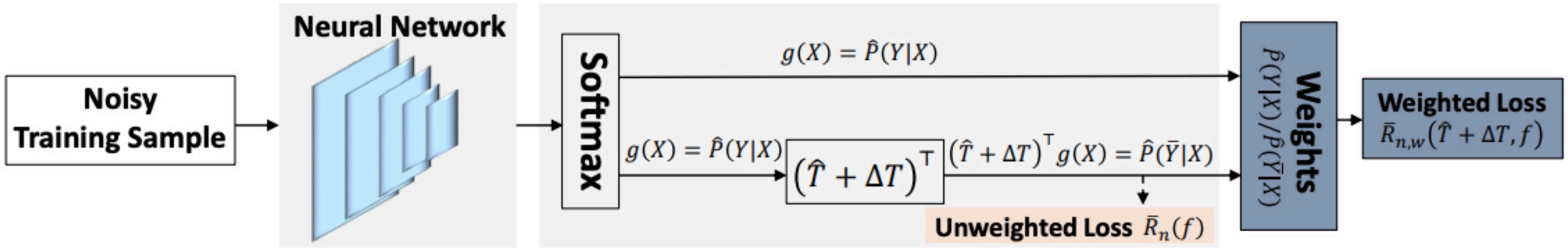
If $P(\widetilde{\boldsymbol{Y}}|X = \boldsymbol{x}) = [0.141; 0.189; 0.239; 0.281; 0.15]$,

then, $P(\boldsymbol{Y}|X = \boldsymbol{x}) = (T^\top)^{-1} P(\widetilde{\boldsymbol{Y}}|X = \boldsymbol{x}) =$
$[0.15; 0.28; 0.25; \boxed{0.3;} 0.02]$.

$$P(\boldsymbol{Y}|X = \boldsymbol{x}) = (\tilde{T}^\top)^{-1} P(\widetilde{\boldsymbol{Y}}|X = \boldsymbol{x})$$
$$= [0.1587; 0.2697; \boxed{0.2796;} 0.2593; 0.0325].$$

[15] Xia X, et al. Are Anchor Points Really Indispensable in Label-Noise Learning? NeurIPS. 2019

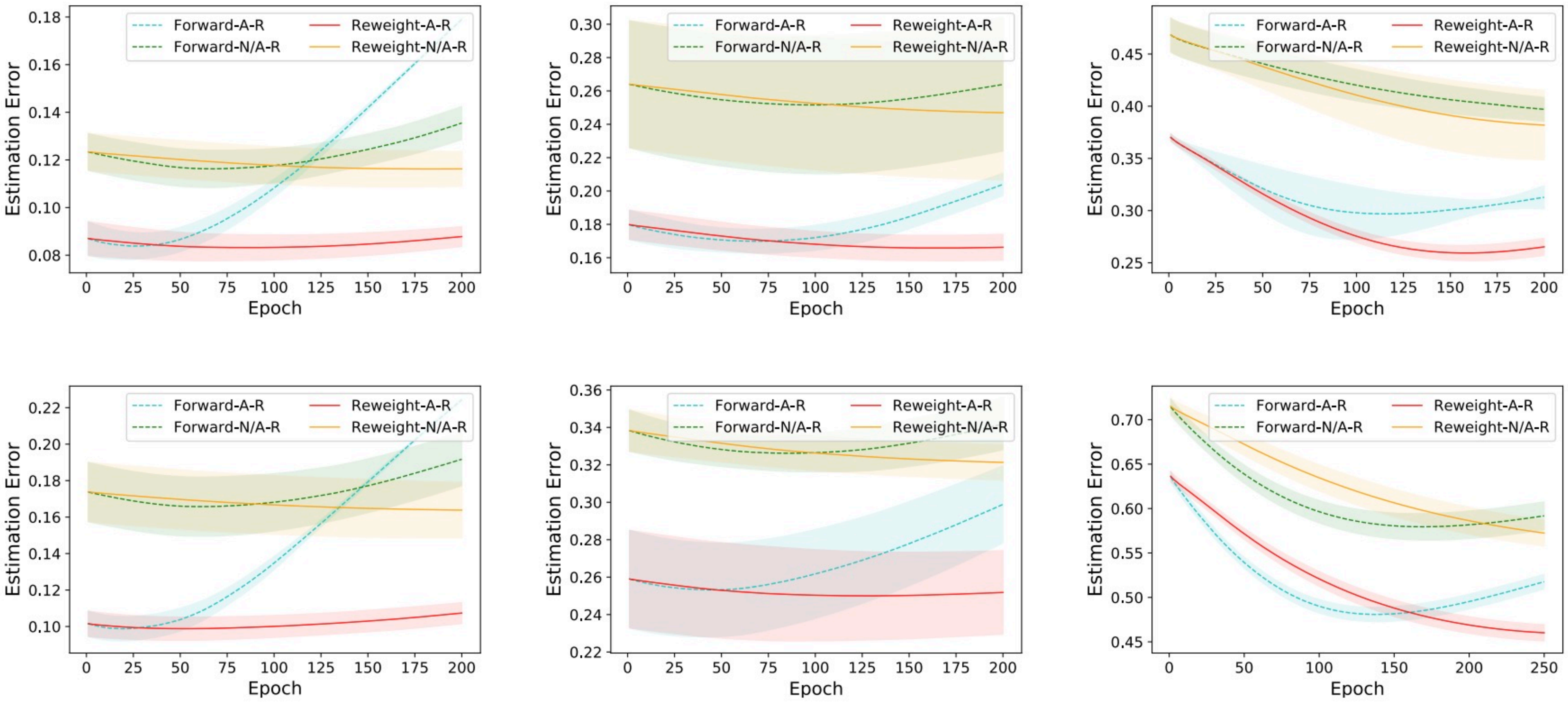
T revision [15]



$$\tilde{L}(\boldsymbol{x}, \tilde{y}) = \beta(\boldsymbol{x}, \tilde{y}) L(f(\boldsymbol{x}), \tilde{y}) = \frac{\boldsymbol{g}_{\tilde{Y}}(\boldsymbol{x})}{(\boldsymbol{T}^{\top}\boldsymbol{g})_{\tilde{Y}}(\boldsymbol{x})} L(f(\boldsymbol{x}), \tilde{y}).$$

$$f(\boldsymbol{x}) = \mathrm{argmax}_{i \in \{1,\dots,C\}} \boldsymbol{g}_i(\boldsymbol{x}).$$

[15] Xia X, et al. Are Anchor Points Really Indispensable in Label-Noise Learning? NeurIPS. 2019



(a) *MNIST* (b) *CIFAR-10* (c) *CIFAR-100*

[15] Xia X, et al. Are Anchor Points Really Indispensable in Label-Noise Learning? NeurIPS. 2019

A summary of estimating transition matrix

- How to estimate the transition matrix given only noisy data?
  Method: T estimator (by exploiting anchor points)

- Large estimation error of the noisy class posterior
  Method: Dual-T estimator (by decomposing the matrix)

- How about if there is no anchor points?
  Method: VolMinNet (using the sufficiently scattered assumption)

- How to deal with poorly estimated transition matrix
  Method: T revision (revising the matrix by using a slack variable)

Conclusion and future directions

- Conclusion
  - Statistically consistent algorithms: the classifier learned by using noisy data will converge to the optimal one defined by using clean data
  - Statistically consistent algorithms are robust to the data distribution and label noise type
  - Modelling the label noise and estimating the transition matrix are cores in label-noise learning
- Future directions
  - Design effectively loss correction methods for deep learning
  - How to address the finite/small sample problem
  - How to use a small set of clean data to better estimate the transition matrix
  - How to model and estimate the instance-dependent label noise (IDN)