Learning under Noisy Supervision

https://wsl-workshop.github.io/acml21-tutorial

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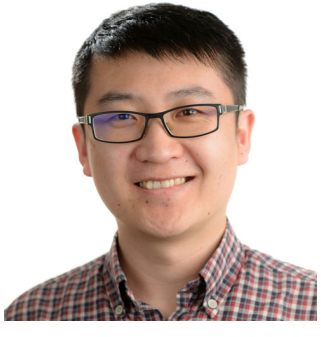
Schedule at a Glance

UTC+9

16:00-16:15	Overview of Learning with Noisy Supervision Masashi Sugiyama (RIKEN/U Tokyo)
16:15-16:50	Statistical Learning with Noisy Supervision Tongliang Liu (U Sydney)
16:50-17:25	Deep Learning with Noisy Supervision Bo Han (Hong Kong Baptist U)
17:25-18:00	Automated Learning from Noisy Supervision Quanming Yao (Tsinghua U)
18:00-18:30	Beyond Class-Conditional Noise Gang Niu (RIKEN)


Overview of Learning with Noisy Supervision

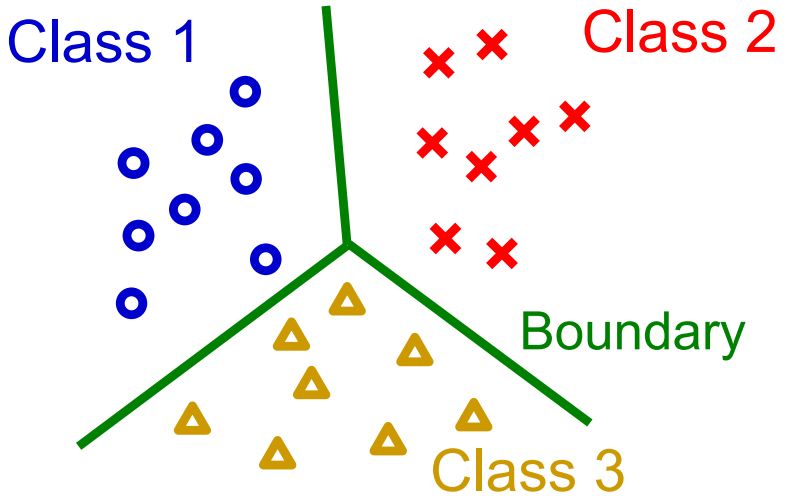
Masashi Sugiyama

RIKEN Center for Advanced Intelligence Project/
The University of Tokyo

http://www.ms.k.u-tokyo.ac.jp/sugi/

Ordinary Classification

- (Clean) training data: $\{(\boldsymbol{x}_i, y_i)\}_{i=1}^n \overset{\text{i.i.d.}}{\sim} p(\boldsymbol{x}, y)$



$\boldsymbol{x} \in \mathbb{R}^d$: Input pattern

$y \in \{1, \ldots, c\}$: Clean class label

$p(\boldsymbol{x}, y)$: Clean data density

- Training error minimization: $\min_{\boldsymbol{g}} \widehat{R}(\boldsymbol{g})$

$$\widehat{R}(\boldsymbol{g}) = \frac{1}{n} \sum_{i=1}^{n} \ell\Big(y_i, \boldsymbol{g}(\boldsymbol{x}_i)\Big)$$

$\boldsymbol{g}(\boldsymbol{x}) \in \mathbb{R}^c$: Classifier

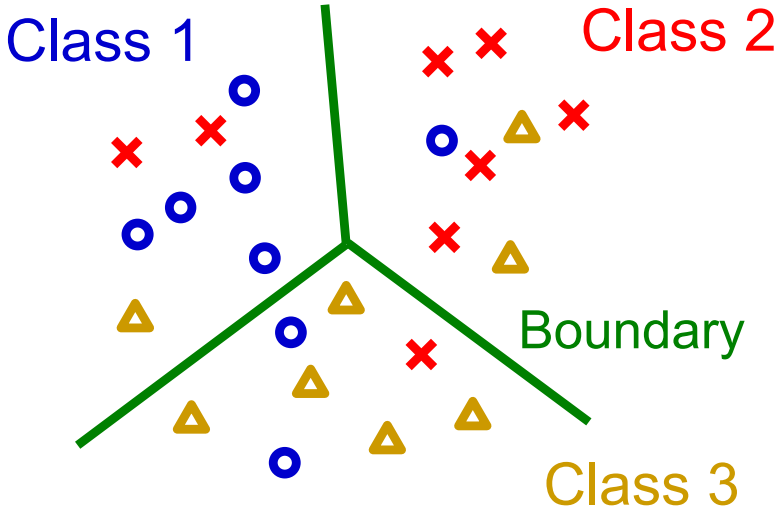
$\ell(y, \boldsymbol{g}(\boldsymbol{x})) \in \mathbb{R}$: Loss

  - Statistically consistent and work well.

$$\operatorname*{argmin}_{\boldsymbol{g}} \widehat{R}(\boldsymbol{g}) \overset{n \to \infty}{\to} \operatorname*{argmin}_{\boldsymbol{g}} R(\boldsymbol{g}) \qquad R(\boldsymbol{g}) = \mathbb{E}_{p(\boldsymbol{x}, y)} \Big[\ell\Big(y, \boldsymbol{g}(\boldsymbol{x})\Big)\Big]$$

Classification with Noisy Supervision

- Noisy training data: $\{(\boldsymbol{x}_i, \widetilde{y}_i)\}_{i=1}^{n} \overset{\text{i.i.d.}}{\sim} \widetilde{p}(\boldsymbol{x}, \widetilde{y})$



$\widetilde{y} \in \{1, \ldots, c\}$: Noisy class label

$\widetilde{p}(\boldsymbol{x}, \widetilde{y})$: Noisy data density

- Training error minimization: $\min_{\boldsymbol{g}} \widetilde{R}(\boldsymbol{g})$

$$\widetilde{R}(\boldsymbol{g}) = \frac{1}{n} \sum_{i=1}^{n} \ell\left(\widetilde{y}_i, \boldsymbol{g}(\boldsymbol{x}_i)\right)$$

$$\operatorname*{argmin}_{\boldsymbol{g}} \widetilde{R}(\boldsymbol{g}) \overset{n \to \infty}{\not\to} \operatorname*{argmin}_{\boldsymbol{g}} R(\boldsymbol{g})$$

  - No longer consistent and does not work well.

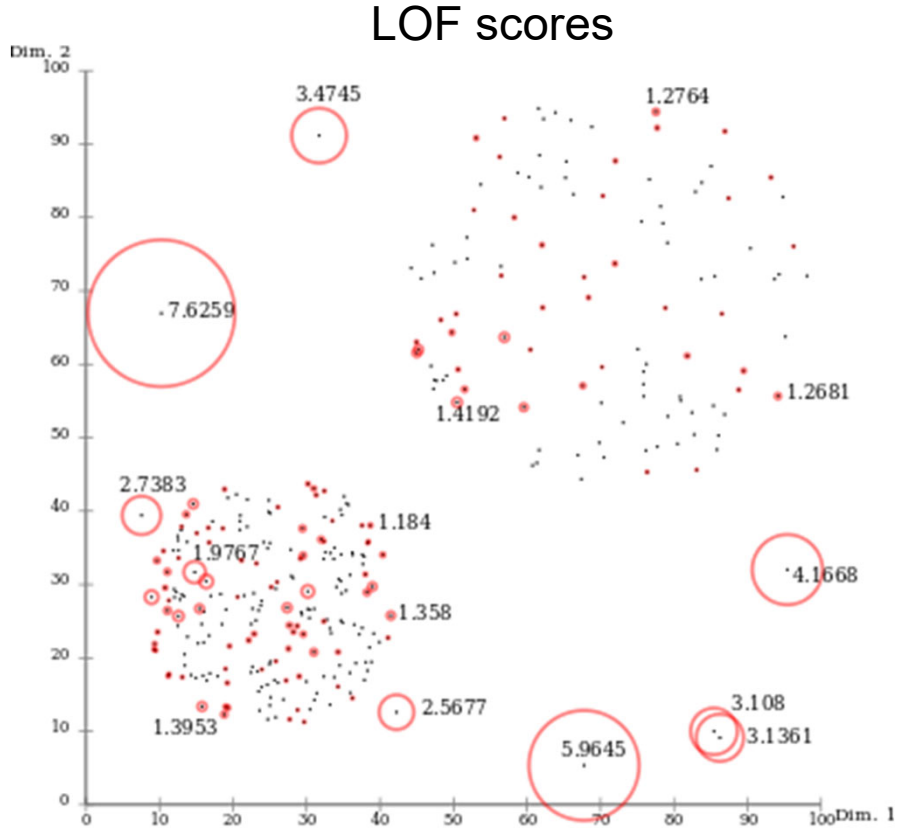
- How can we handle noisy data?

Generic Approach (1)

- Unsupervised noisy data removal:
  - Hotelling's T^2 statistics,
  - k-means clustering,
  - local outlier factor (LOF).

Breunig et al. (SIGMOD2000)

https://en.wikipedia.org/wiki/Harold_Hotelling

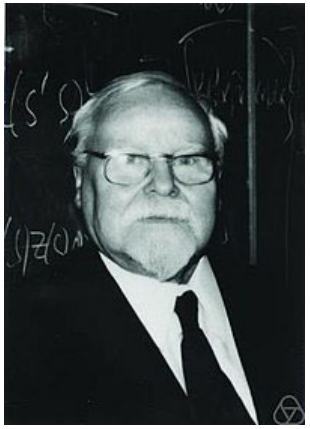


https://en.wikipedia.org/wiki/Local_outlier_factor

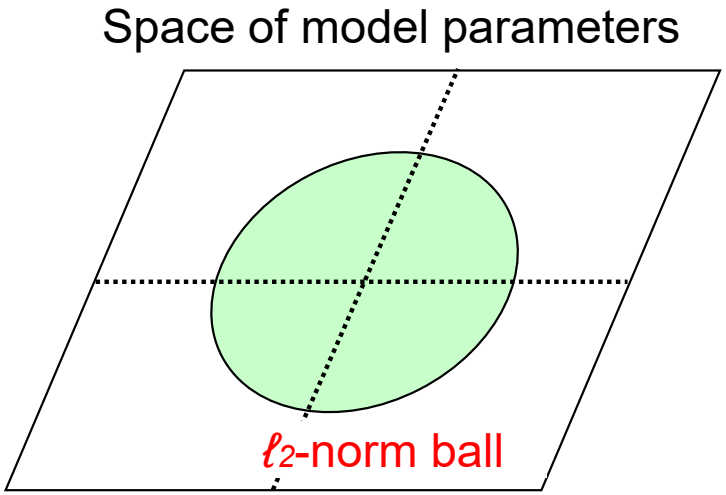
- Easy to use, but this is completely heuristic and no supervision is used.

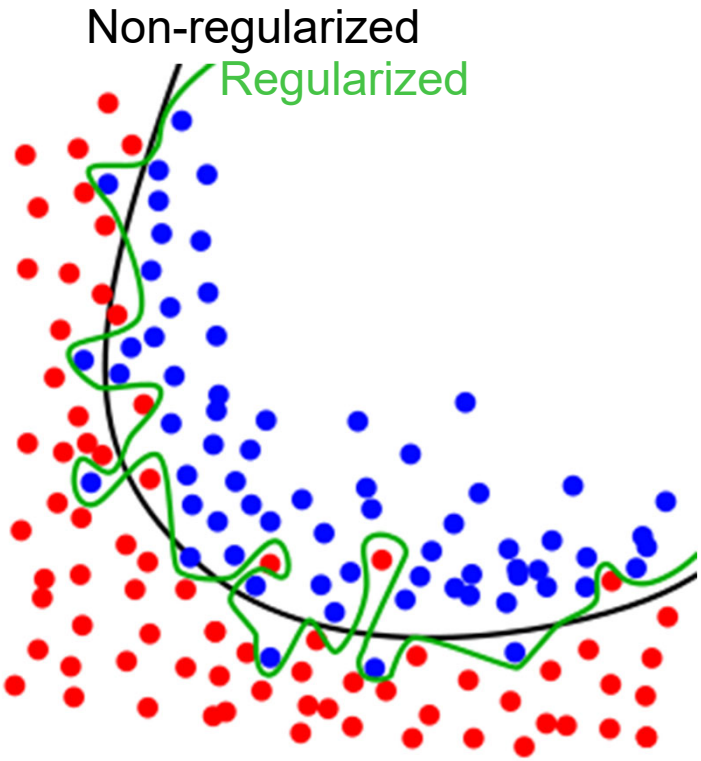
Generic Approach (2)

- Regularization: keeping the norm of the model parameters small for preventing overfitting.
  - Tikhonov regularization



https://en.wikipedia.org/wiki/Andrey_Nikolayevich_Tikhonov



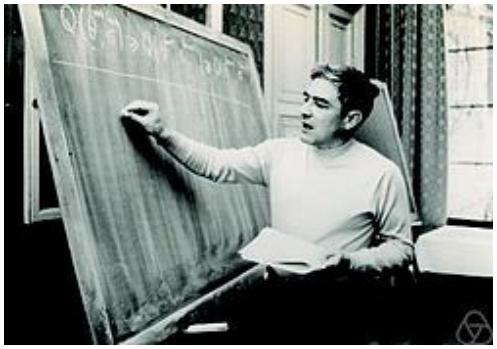


https://en.wikipedia.org/wiki/Overfitting

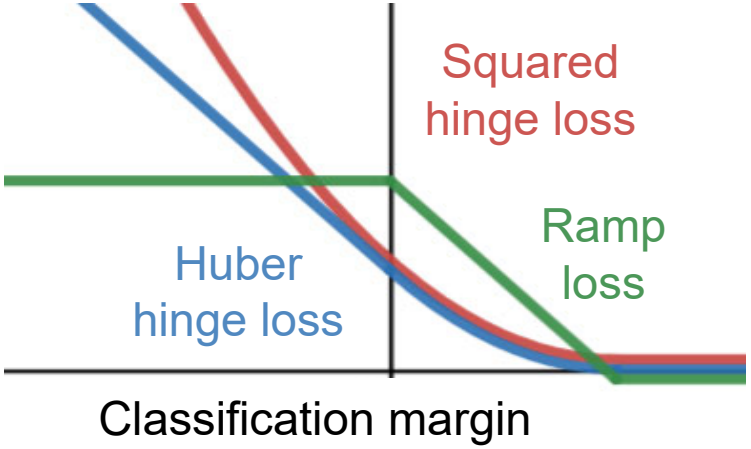
- Nice theory, but smoothing is not enough to cope with strong label noise.

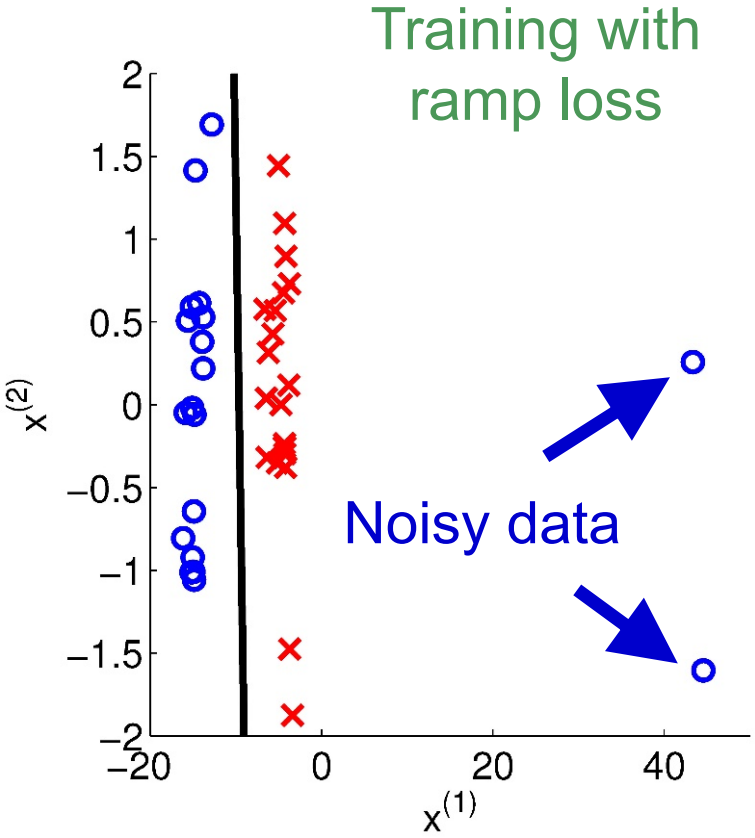
Generic Approach (3)

- Robust statistics: suppressing the influence of noisy data by a gentle loss
  - Huber loss,
  - Ramp loss.



https://en.wikipedia.org/wiki/Peter_J._Huber





- Nice theory for regression (additive noise), but not very robust in classification (flipping noise).

Aim of This Tutorial

- The generic approaches were NOT specially designed for handling label noise.
- In this tutorial, we introduce recent advances in multi-class classification that explicitly handle noisy supervision:
  - Explicit modeling of label noise and systematic elimination of its influence.
  - Selecting clean samples/correcting noisy labels for robust deep learning.
  - Various industrial applications.
  - Advanced topics beyond class-conditional noise.

Reference for This Tutorial

- Bo Han, Quanming Yao, Tongliang Liu, Gang Niu, Ivor W. Tsang, James T. Kwok, and Masashi Sugiyama:

  A Survey of Label-noise Representation Learning: Past, Present and Future.

  https://arxiv.org/pdf/2011.04406.pdf

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Enjoy the tutorial!