Virtual Tea Hour, UCL

Jan. 8, 2021

Recent Advances in Robust Machine Learning

Masashi Sugiyama

RIKEN Center for Advanced Intelligence Project/
The University of Tokyo

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

About Myself

My jobs:

- Director: RIKEN AIP
- Professor: University of Tokyo
- Consultant: several local startups

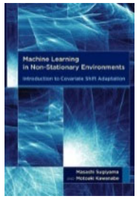
Interests: Machine learning (ML)

- Weakly-supervised learning,
- Robust learning,
- Transfer learning,
- Density ratio estimation,
- Reinforcement learning,
- Variational inference…

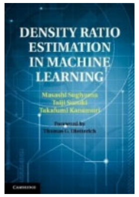
Academic activities:

- Program Chairs for NeurIPS2015, AISTATS2019, ACML2010/2020…

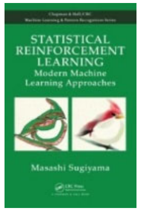
Sugiyama & Kawanabe, Machine Learning in Non-Stationary Environments, MIT Press, 2012



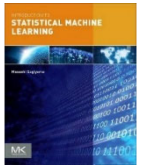
Sugiyama, Suzuki & Kanamori, Density Ratio Estimation in Machine Learning, Cambridge University Press, 2012



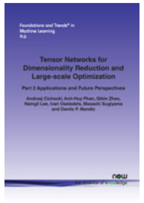
Sugiyama, Statistical Reinforcement Learning, Chapman and Hall/CRC, 2015


STATISTICAL REINFORCEMENT LEARNING
Modern Machine Learning Approaches
Masashi Sugiyama

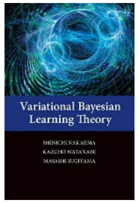
Sugiyama, Introduction to Statistical Machine Learning, Morgan Kaufmann, 2015



Cichocki, Phan, Zhao, Lee, Oseledets, Sugiyama & Mandic, Tensor Networks for Dimensionality Reduction and Large-Scale Optimizations, Now, 2017

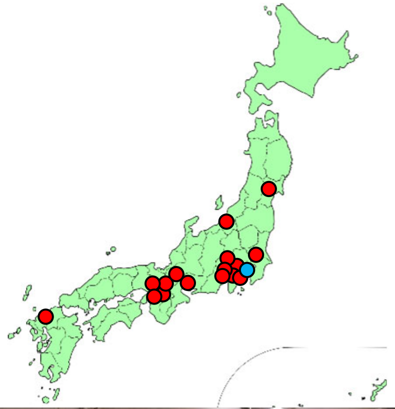

Tensor Networks for Dimensionality Reduction and Large-scale Optimization
now

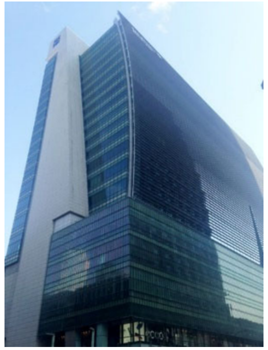
Nakajima, Watanabe & Sugiyama, Variational Bayesian Learning Theory, Cambridge University Press, 2019



RIKEN Center for Advanced Intelligence Project (AIP)

- 10-year national project in Japan (2016-2025):
  - Develop next-generation AI technology (learning and optimization theory, etc.)
  - Accelerate scientific research (material, cancer, stem cells, genomics, etc.)
  - Solve socially critical problems (natural disaster, elderly healthcare, etc.)
  - Study of ethical, legal and social issues of AI (ethical guideline, privacy protection, etc.)
  - Human resource development (150+ researchers, 200+ students, 150+ interns, 300+ visiting scientists, 40+ industry projects)





Today’s Topic: Robust Machine Learning

- In real-world applications, it becomes increasingly important to consider robustness:
  - Noise: sensor error, human error
  - Insufficient information: weak supervision
  - Bias: sample selection bias, changing environments
  - Attack: adversarial noise, distribution shift
- In this talk, I will give an overview of our recent advances in robust machine learning.

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

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3. Transfer learning
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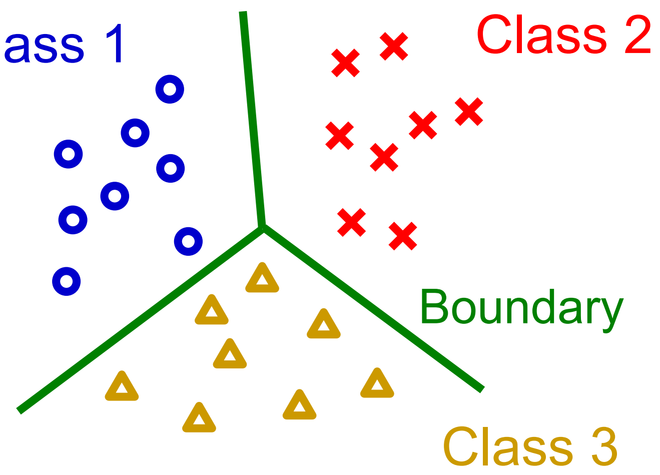
Ordinary Classification

- Clean training data: $\{(\boldsymbol{x}_i, y_i)\}_{i=1}^{n}$



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

$y \in \{1, \ldots, c\}$: Clean class label (not necessarily separable)

- Training error minimization is statistically consistent and work well:

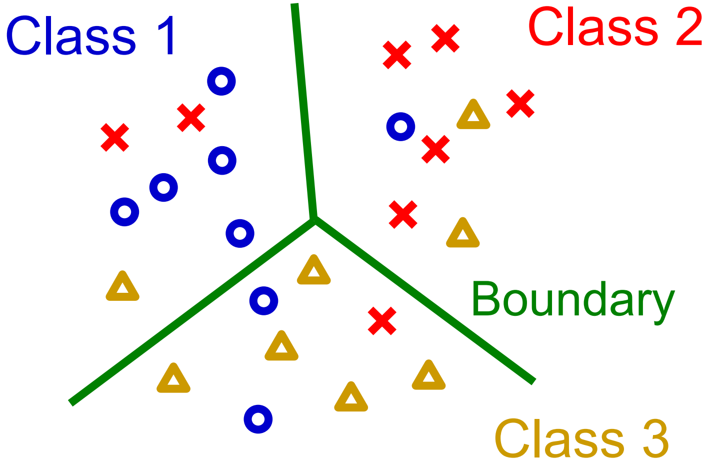
$$\frac{1}{n}\sum_{i=1}^{n} \ell\Big(y_i, \boldsymbol{g}(\boldsymbol{x}_i)\Big)$$

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

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

Noisy Classification

- Noisy training data: $\{(\boldsymbol{x}_i, \widetilde{y}_i)\}_{i=1}^{n}$



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

$\widetilde{y} \in \{1, \ldots, c\}$: Noisy class label (clean labels are corrupted)

- Training error minimization is no longer consistent and does not work well:

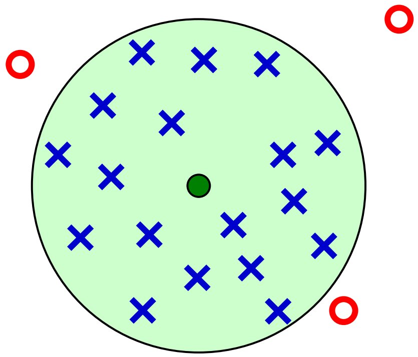
$$\frac{1}{n}\sum_{i=1}^{n} \ell\Big(\widetilde{y}_i, \boldsymbol{g}(\boldsymbol{x}_i)\Big)$$

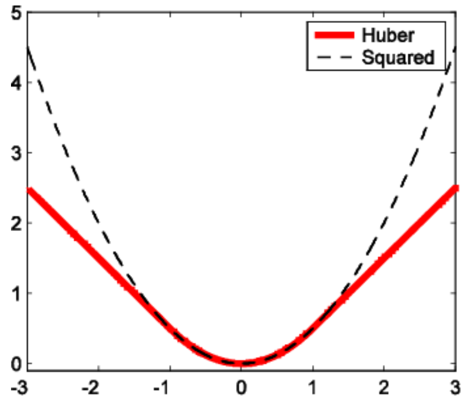
$\boldsymbol{g}(\boldsymbol{x}) \in \mathbb{R}^c$: Classifier

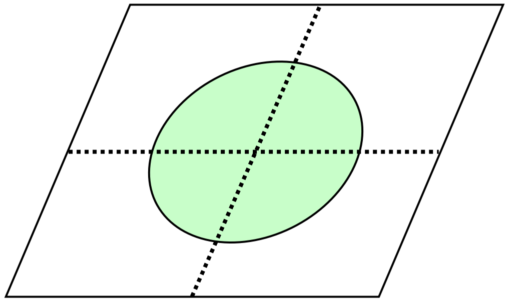
$\ell(y, \boldsymbol{g}(\boldsymbol{x})) \in \mathbb{R}$: Loss

Standard Approaches

- Unsupervised outlier removal:
  - Substantially difficult
- Robust loss, regularization:
  - Not robust enough
- We want to go beyond the limitations of existing approaches!
  - Noise transition correction
  - Noiseless sample selection
  - Model capacity control







(1-1) Noise Transition Correction

- Noise transition matrix $\boldsymbol{T}$:
  - Flipping probability from y to $\widetilde{y}$.

$$\boldsymbol{T}^\top = \underset{y}{\begin{array}{|c|c|c|}\hline 1 & 0.1 & 0.5 \\ \hline 0 & 0.8 & 0.5 \\ \hline 0 & 0.1 & 0 \\ \hline \end{array}}\ \widetilde{y}$$

- Major approaches: Patrini et al. (CVPR2017)
  - Loss correction by $\boldsymbol{T}^{-1}$ to eliminate noise.
  - Classifier correction by $\boldsymbol{T}^\top$ to simulate noise.
- We want to estimate $\boldsymbol{T}$ only from noisy data:
  - Use human cognition as a “mask” for $\boldsymbol{T}$.

    Han, Yao, Niu, Zhou, Tsang, Zhang & Sugiyama (NeurIPS2018)
  - Learn $\boldsymbol{T}$ and a classifier simultaneously.

    Xia, Liu, Wang, Han, Gong, Niu & Sugiyama (NeurIPS2019)
  - Decompose $\boldsymbol{T}$ into simpler components.

    Yao, Liu, Han, Gong, Deng, Niu, Sugiyama & Tao (NeurIPS2020)
  - Extension to input-dependent noise $\boldsymbol{T}(\boldsymbol{x})$.

    Xia, Liu, Han, Wang, Gong, Liu, Niu, Tao & Sugiyama (NeurIPS2020)

(1-2) Co-teaching

- Memorization of neural nets:

Arpit et al. (ICML2017)
Zhang et al. (ICLR2017)

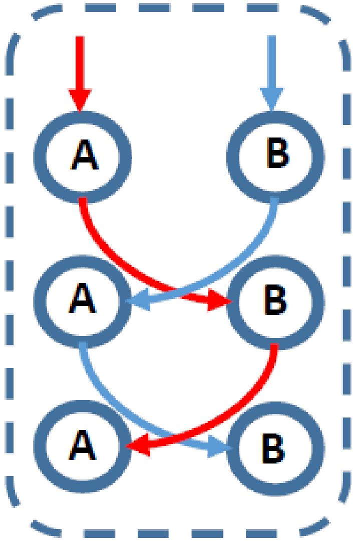
  - Stochastic gradient descent fits clean data faster.
  - However, naïve early stopping does not work well.

- “Co-teaching” between two neural nets:
  - Teach small-loss data each other.

    Han, Yao, Yu, Niu, Xu, Hu, Tsang & Sugiyama (NeurIPS2018)
  - Teach only disagreed data.

    Yu, Han, Yao, Niu, Tsang & Sugiyama (ICML2019)
  - Gradient ascent for large-loss data.

    Han, Niu, Yu, Yao, Xu, Tsang & Sugiyama (ICML2020)

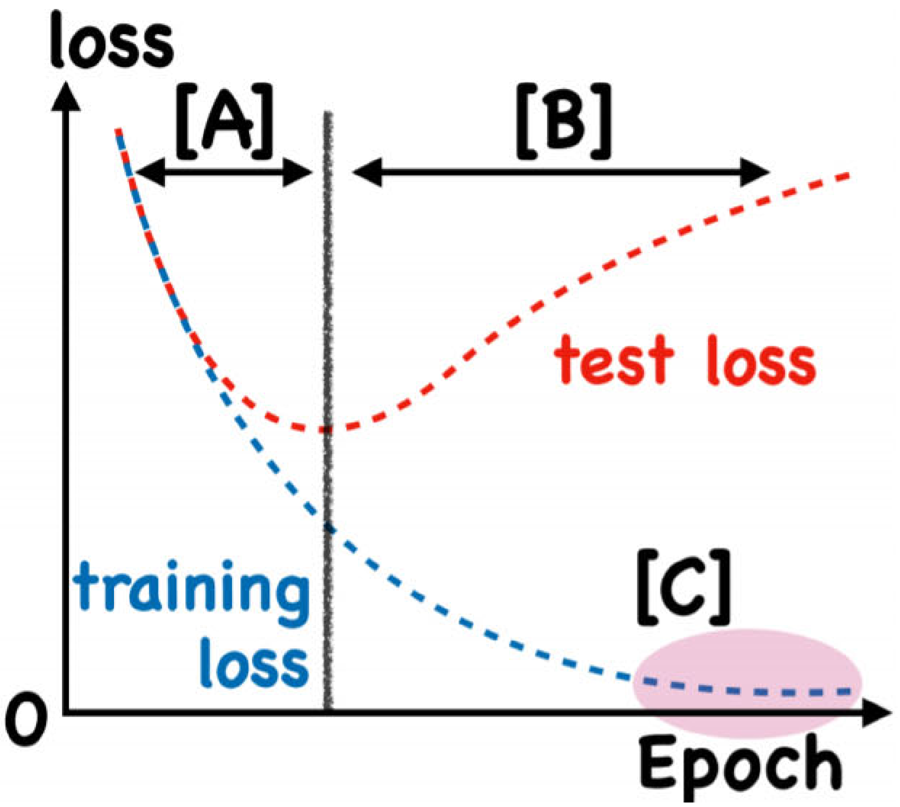


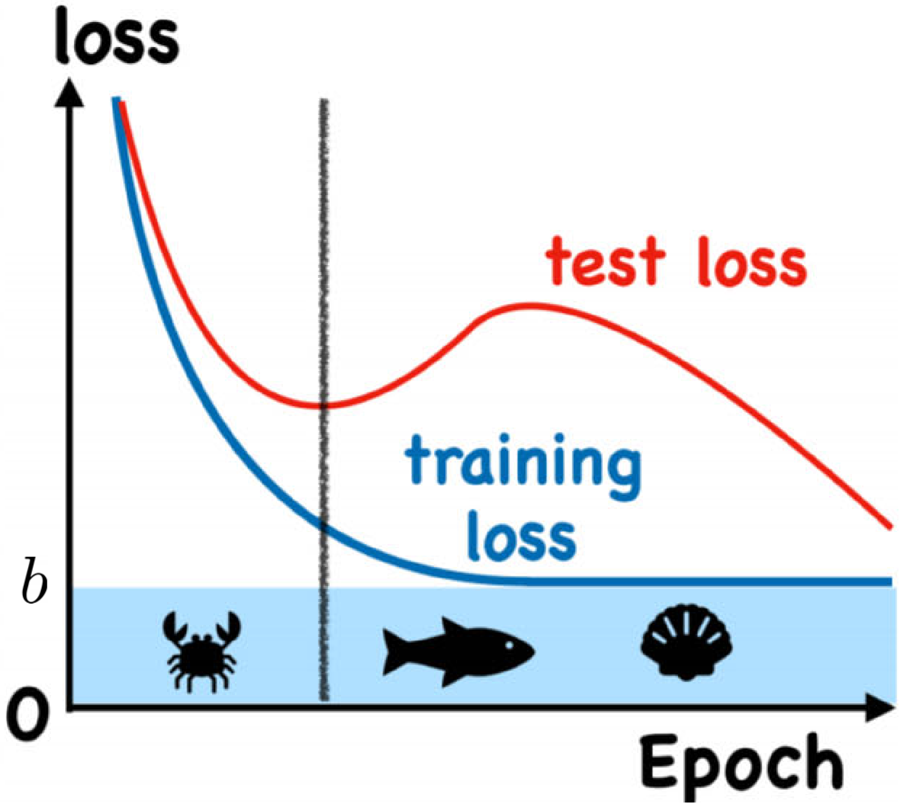
- No theory but very robust in experiments:
  - Works well even if 50% labels are randomly flipped.

(1-3) Flooding

- Neural nets tend to overfit.
- “Flooding” the training error prevents overfitting.
  - It induces double descent? $|R(f) - b| + b$

Ishida, Yamane, Sakai, Niu & Sugiyama (ICML2020)





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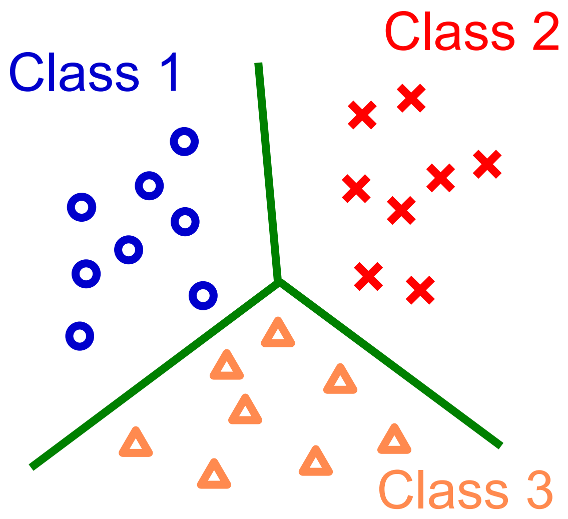
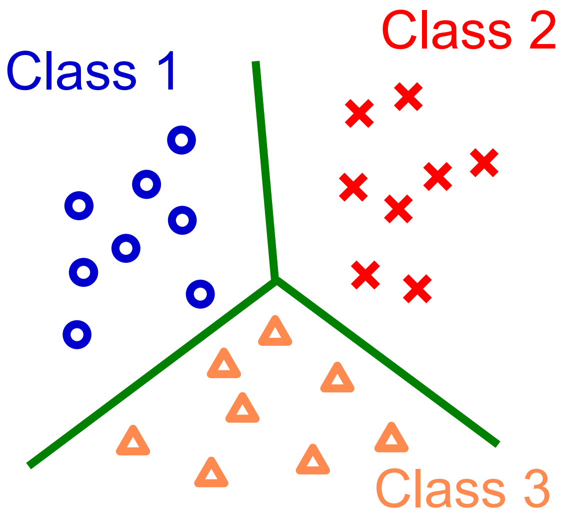
Weakly Supervised Learning

- Ordinary supervised learning requires fully labeled data (input-output pairs).
- But collecting fully labeled data can be expensive in practice.
- Can we utilize "weakly" labeled data?
  - Complementary classification
  - Partial-label classification
  - Various weakly supervised classification methods for binary problems



(2-1) Complementary Classification

- **Complementary label**: a class the pattern does not belong to.
  - E.g., “not class 1”, “not a cat”.
  - Cheaper than ordinary labels.



- Classifiers can be trained only from complementary labels.
  - Unbiased risk estimation

    Ishida, Niu & Sugiyama (NIPS2017)
    Ishida, Niu, Menon & Sugiyama (ICML2019)

  - Multiple complementary labels

    Feng, Kaneko, Han, Niu, An & Sugiyama (ICML2020)

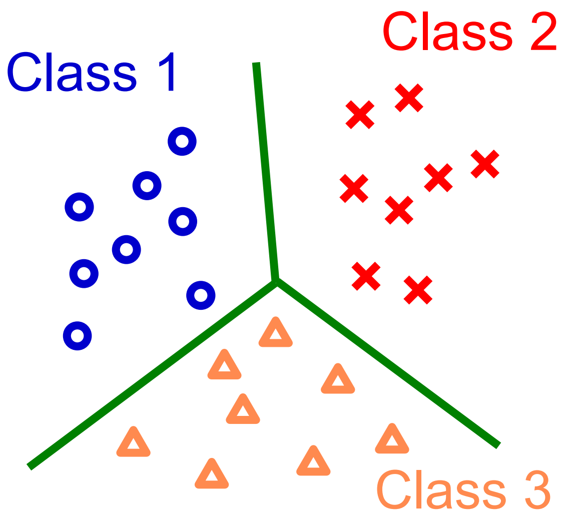
  - Beyond unbiased risk estimation

    Chou, Niu, Lin & Sugiyama (ICML2020)

$1/\sqrt{n}$

(2-2) Partial-Label Classification

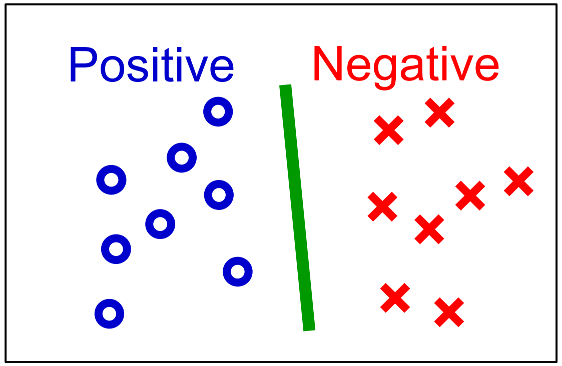
- Partial label: Nguyen and Caruana (KDD2008)
  a subset of labels containing the true one
  - E.g., “Either 1 or 2”, “dog or cat”
  - Cheaper than ordinary labels



- Classifiers can be trained only from partial labels. $1/\sqrt{n}$
  - Progressive identification of correct labels.
    Lv, Xu, Feng, Niu, Geng & Sugiyama (ICML2020)
  - Explicit modeling of partial label generation.
    Feng, Lv, Han, Xu, Niu, Geng, An & Sugiyama (NeurIPS2020)

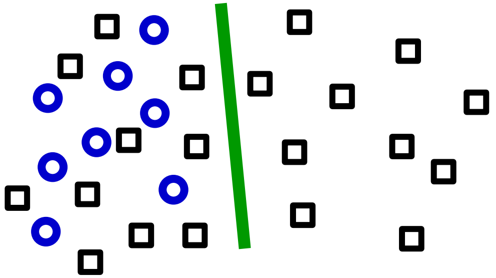
(2-3) More for Binary Problems

- Binary classification is possible only from weakly supervised data!



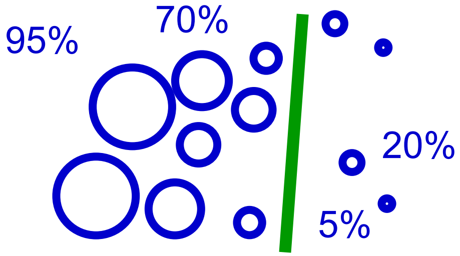
$1/\sqrt{n}$

Positive-Unlabeled



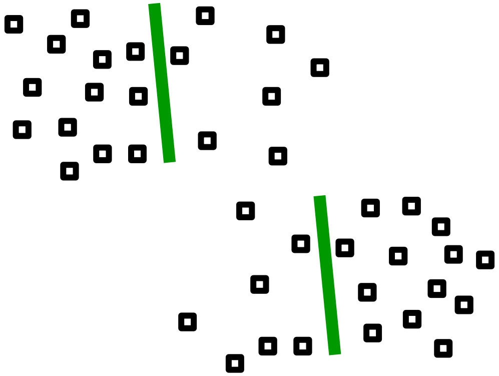
du Plessis, Niu & Sugiyama (NIPS2014, ICML2015)
Niu, du Plessis, Sakai, Ma & Sugiyama (NIPS2016)
Kiryo, du Plessis, Niu & Sugiyama (NIPS2017)
Hsieh, Niu & Sugiyama (ICML2019)

Positive confidence



Ishida, Niu & Sugiyama (NeurIPS2018)

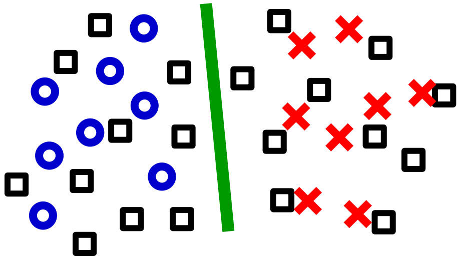
Unlabeled-Unlabeled



du Plessis, Niu & Sugiyama (TAAI2013)
Lu, Niu, Menon & Sugiyama (ICLR2019)
Charoenphakdee, Lee & Sugiyama (ICML2019)
Lu, Zhang, Niu & Sugiyama (AISTATS2020)

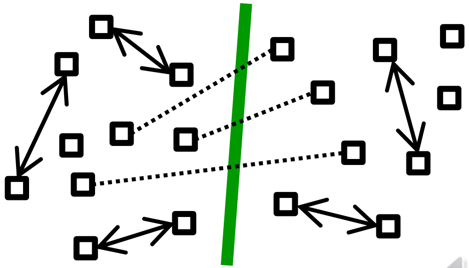
Sugiyama, Sakai, Ishida, Nan, Bao & Niu,
Machine Learning from Weak Supervision,
MIT Press, 2021?

Positive-Negative-Unlabeled



Sakai, du Plessis, Niu & Sugiyama (ICML2017)
Sakai, Niu & Sugiyama (MLJ2018)

Similar-Dissimilar-Unlabeled



Bao, Niu & Sugiyama (ICML2018)
Shimada, Bao, Sato & Sugiyama (arXiv2019)
Dan, Bao & Sugiyama (arXiv2020)

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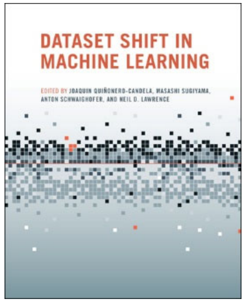
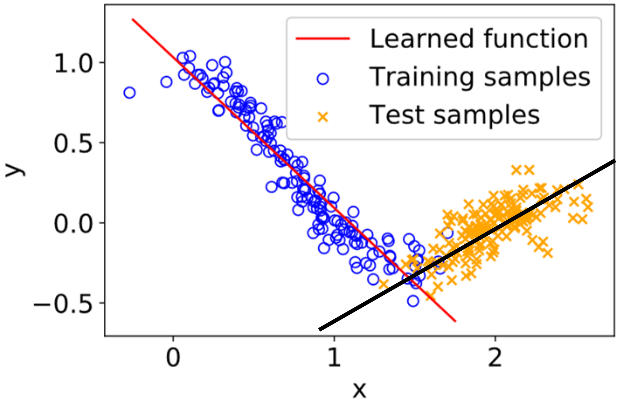
Transfer Learning


DATASET SHIFT IN MACHINE LEARNING
EDITED BY JOAQUIN QUIÑONERO-CANDELA, MASASHI SUGIYAMA, ANTON SCHWAIGHOFER, AND NEIL D. LAWRENCE

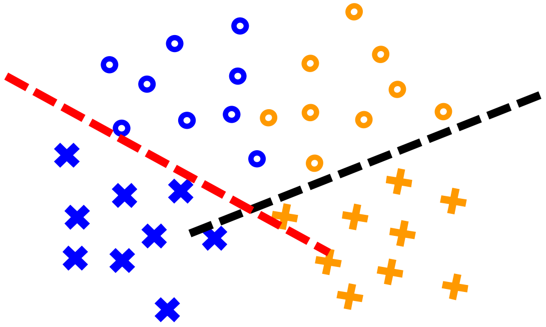
Quiñonero-Candela, Sugiyama, Schwaighofer & Lawrence (MIT Press 2009)

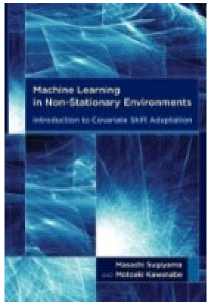
- Training and test data often have different distributions, due to
  - changing environments,
  - sample selection bias.
- Transfer learning (domain adaptation):
  - Match the distributions so that training data resemble test data.

Regression



Classification




Machine Learning in Non-Stationary Environments
Introduction to Covariate Shift Adaptation
Masashi Sugiyama and Motoaki Kawanabe

Sugiyama & Kawanabe,
Machine Learning in Non-Stationary Environments,
MIT Press, 2012

Unsupervised Transfer Learning

- Given training input-output and test input, match the training and test distributions:
  - Better discrepancy measures for distribution matching:

    Kuroki, Charoenphakdee, Bao, Honda, Sato & Sugiyama (AAAI2019)
    Lee, Charoenphakdee, Kuroki & Sugiyama (arXiv2019)
  - Handling noisy labels in the source domain:

    Liu, Lu, Han, Niu, Zhang & Sugiyama (arXiv2019)
  - No/incomplete unlabeled data from the test domain:

    Ishii, Takenouchi & Sugiyama (ACML2019)
    Ishii, Takenouchi & Sugiyama (WACV2020)
  - Transferring data generation mechanism:

    Teshima, Sato & Sugiyama (ICML2020)
    Teshima, Ishikawa, Tojo, Oono, Ikeda & Sugiyama (NeurIPS2020)
  - Simultaneous learning of a classifier and importance weights:

    Zhang, Yamane, Lu & Sugiyama (ACML2020)
    Fang, Lu, Niu & Sugiyama (NeurIPS2020)

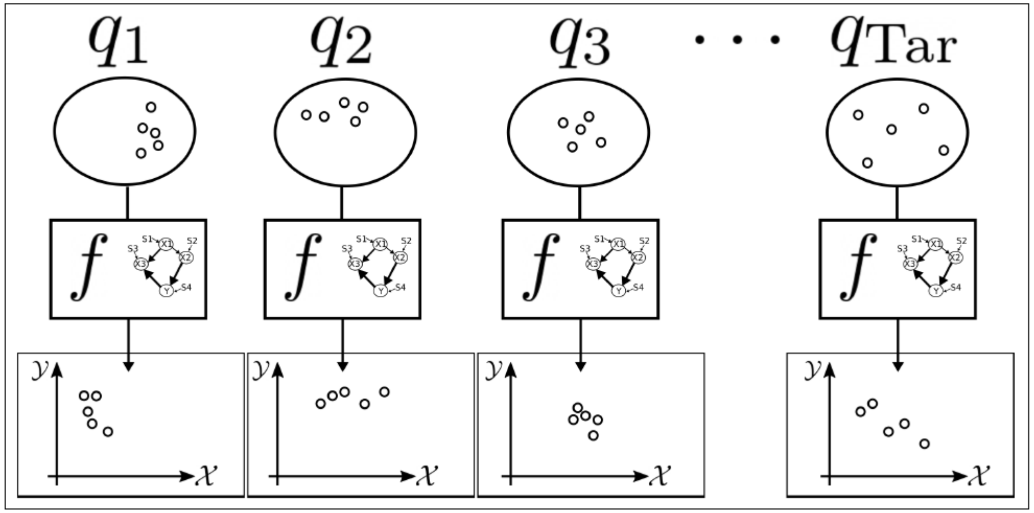
(3-1) Mechanism Transfer

- Is transfer learning possible when data distributions are seemingly very different?
- Yes, if data generation mechanisms are shared:
  - Use invertible neural networks (INNs) to invert the data generation mechanism.
    Teshima, Sato & Sugiyama (ICML2020)
  - INNs are universal approximators.
    Teshima, Ishikawa, Tojo, Oono, Ikeda & Sugiyama (NeurIPS2020)

Independent components

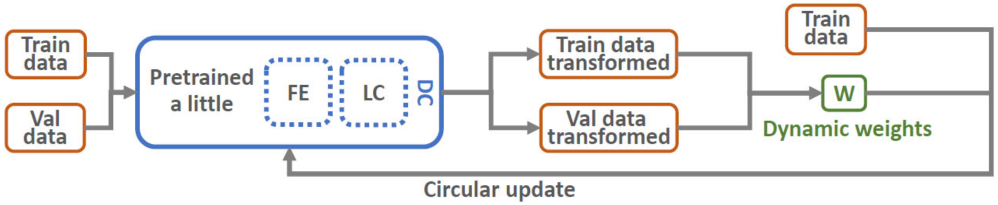
“Mechanism”

Observed data



(3-2) One-Step Adaptation

- Standard approach: 2 steps
  - Weight estimation: $\min_{w} D(w, p_{\mathrm{te}}/p_{\mathrm{tr}})$
  - Weighted classifier training: $\min_{f} \mathbb{E}_{p_{\mathrm{tr}}}[w(x,y)\ell(f(x),y)]$
- Proposed methods: 1 step
  - With a common feature extractor for w and f, learn them dynamically in mini-batch training.



Fang, Lu, Niu & Sugiyama (NeurIPS2020)

  - Minimize an upper bound of the risk w.r.t. w and f under covariate shift $p_{\mathrm{tr}}(y|x) = p_{\mathrm{te}}(y|x)$:

Zhang, Yamane, Lu & Sugiyama (ACML2020)

$$\min_{w,f} J(w,f) \qquad J(w,f) \geq R^2(f)$$

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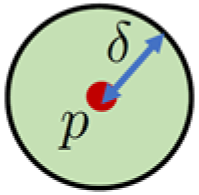
Adversarial Change in Test Input

- An adversary changes test input points to confuse our predictor.
  - We want to be robust against such change.
- Various studies of adversarial learning:
  1. Distributionally robust learning.
  2. Adversarial training for pointwise attack.
  3. Rejection of adversarial data.

(4-1) Distributionally Robust Learning

- Setting: an adversary changes the test distribution arbitrarily.
- Approach: Learn a predictor such that it still works well for the worst test distribution.
  - Well studied in regression (output is continuous) and works well.
  - In classification (output is categorical), additional condition is needed to enhance the robustness, e.g., latent prior probability change.



$$\boxed{\min_{\theta} \sup_{q \in \mathcal{Q}_p} \mathbb{E}_{q(x,y)}[\ell(g_\theta(x), y)]}$$

$$\mathcal{Q}_p = \{q \mid \mathrm{D}_f(q \| p) \leq \delta\}$$

"f-divergence ball"

[Bagnell 2005, Ben-Tal+ 2013, Namkoong+ 2016, 2017]

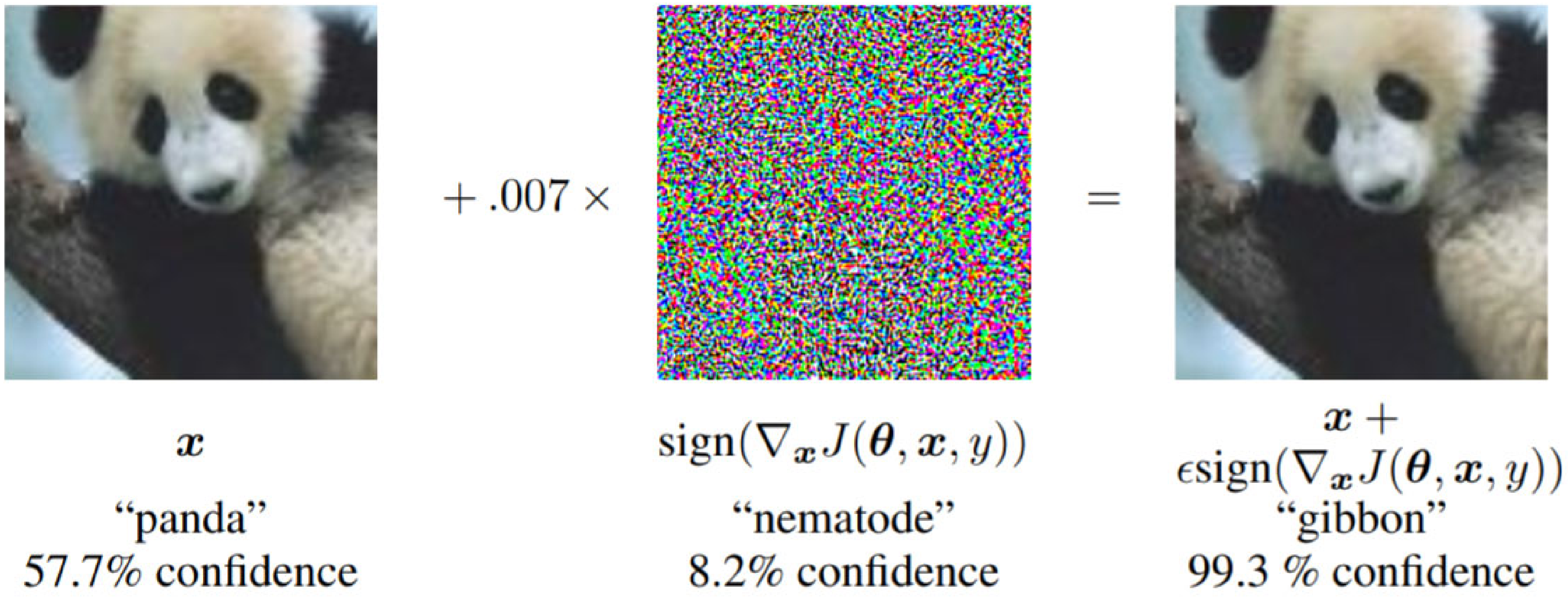
Hu, Niu, Sato & Sugiyama (ICML2018)

Storkey & Sugiyama (NIPS2007)

(4-2) Pointwise Attack

- Deep neural networks are vulnerable to small perturbations in test input.

Goodfellow et al. (ICLR2015)



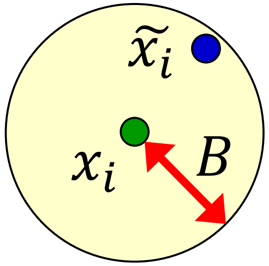
$\boldsymbol{x}$
"panda"
57.7% confidence

$\text{sign}(\nabla_{\boldsymbol{x}} J(\boldsymbol{\theta}, \boldsymbol{x}, y))$
"nematode"
8.2% confidence

$\boldsymbol{x} + \epsilon\text{sign}(\nabla_{\boldsymbol{x}} J(\boldsymbol{\theta}, \boldsymbol{x}, y))$
"gibbon"
99.3 % confidence

- We want to make deep neural networks stable for such test input perturbations.

(4-2a) Adversarial Training for Pointwise Attack



- Setting: an adversary changes test input points arbitrarily.
- Approach: Consider the worst test input $\tilde{x}_i$:

$$\min_f \frac{1}{\mathrm{n}} \sum_{i=1}^{n} \ell(f\,(\tilde{x}_i), y_i)$$

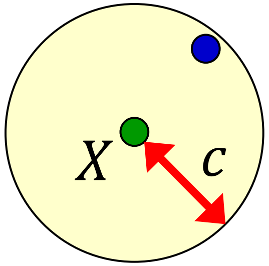
$$\tilde{x}_i = \underset{\tilde{x} \in B(x_i)}{\arg\max}\, \ell(f(\tilde{x}), y_i)$$

  - Conditions for the calibration of surrogate classification loss has been elucidated.

Bao, Scott & Sugiyama (COLT2020)

- However,
  - There is no theoretical guarantee for robustness.
  - Minimax training is too conservative.

(4-2b) Guaranteed Defense to Pointwise Attack



- Stabilize output of the neural net:

$$\forall \epsilon, \left(\|\epsilon\|_2 < c \;\Rightarrow\; t_X = \operatorname*{argmax}_i \{F(X+\epsilon)_i\} \right)$$

- Lipchitz-margin training:

Tsuzuku, Sato & Sugiyama (NeurIPS2018)

- ● Compute the Lipchitz constant for the entire network :

$$\|F(X) - F(X+\epsilon)\|_2 \leq L_F \|\epsilon\|_2$$

- ● Train the neural net to have large prediction margins:

$$\forall i \neq t_X, (F_{t_X} \geq F_i + \sqrt{2} c L_F)$$

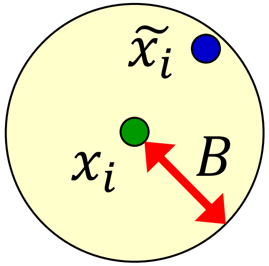
- Robustness is theoretically guaranteed.
  - ● However, the guarded area is not so large.

(4-2c) Friendly Adversarial Training

- Minimax training is too conservative:

$$\min_{f} \frac{1}{\mathrm{n}} \sum_{i=1}^{n} \ell(f\,(\widetilde{x_i}), y_i)$$

$$\widetilde{x_i} = \arg\max_{\tilde{x} \in B(x_i)} \ell(f(\tilde{x}), y_i)$$



- "Friendly" adversarial training:

Zhang, Xu, Han, Niu, Cui, Sugiyama & Kankanhalli (ICML2020)

  - Among adversarial inputs, consider the one with margin ρ.

$$\widetilde{x_i} = \arg\min_{\tilde{x} \in B(x_i)} \ell(f(\tilde{x}), y_i)$$
$$\text{s.t. } \ell(f(\tilde{x}), y_i) - \min_{y} \ell(f(\tilde{x}), y\,) \geq \rho$$

  - Considering the geometry can further improve the robustness experimentally.

Zhang, Zhu, Niu, Han, Sugiyama & Kankanhalli (arXiv2020)

  - Theoretical analysis is still open.

4-3) Classification with Reject Option

- In severe applications, better to reject difficult test inputs and ask human to predict instead.
- Standard approach: Test points having low-confidence prediction are rejected.
  - Logistic loss results in weak performance.
  - New rejection criteria for general losses with guaranteed theoretical convergence and better experimental performance.
- However,

  Ni, Charoenphakdee, Honda & Sugiyama (NeurIPS2019)
  Charoenphakdee, Cui, Zhang & Sugiyama (arXiv2020)

  - Adversarial input gives high-prediction confidence.
  - Not possible to handle real-time applications.

Contents

1. Noisy label learning
2. Weakly supervised learning
3. Transfer learning
4. Adversarial learning
5. Future outlook

Summary

- Nowadays, ML systems are deployed in various societal problems, where reliability is extremely important.
- We explored robustness to different factors:
  - Noise: sensor error, human error
  - Insufficient information: weak supervision
  - Bias: sample selection bias, changing environments
  - Attack: adversarial noise, distribution shift

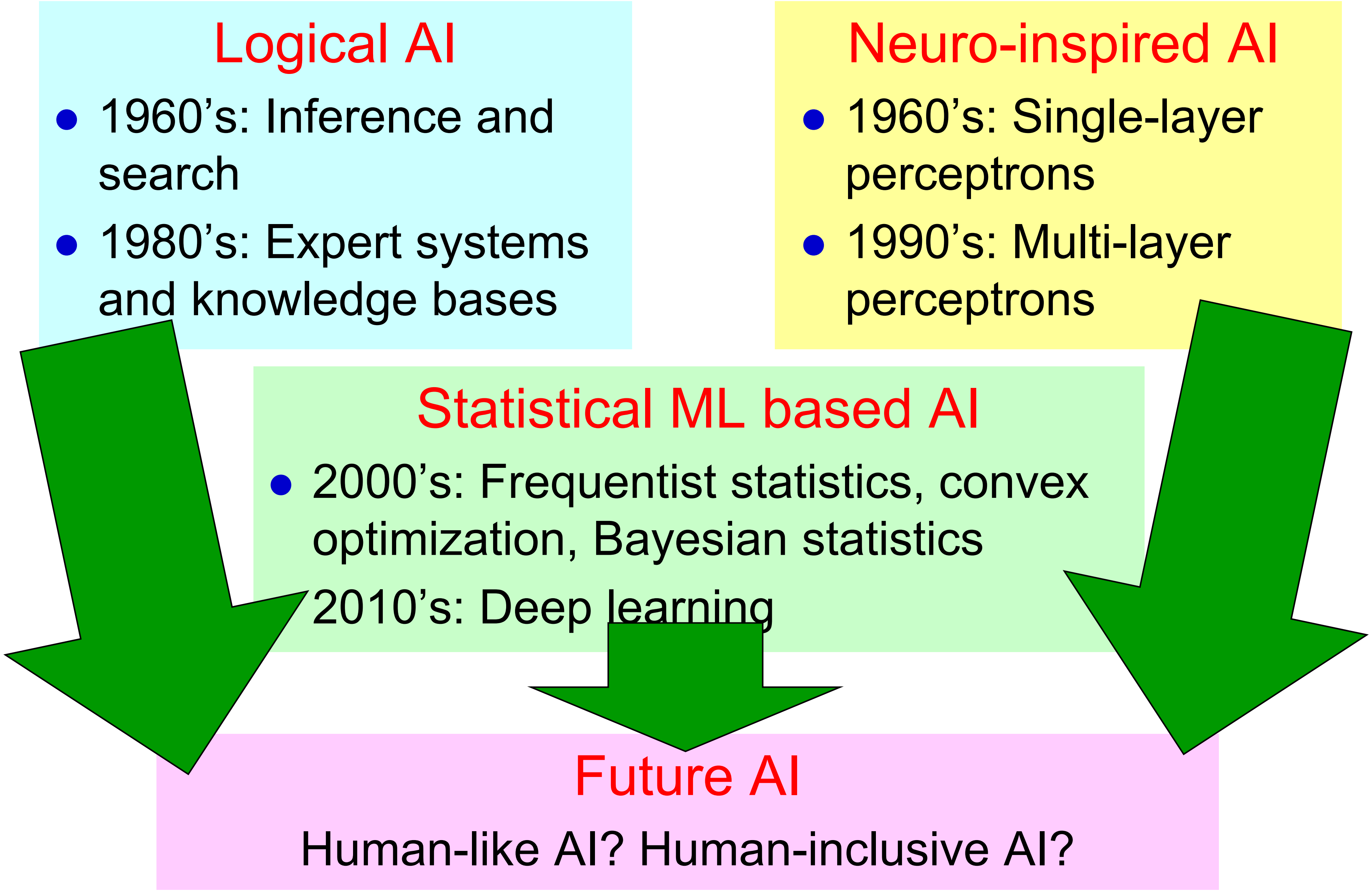
Challenges in Reliable ML

- Reliable ML in expectable situations:
  - Model the corruption process explicitly and correct the solution.
- Reliable ML in unexpected situations:
  - Consider worst-case robustness.
  - Include human support.
- Exploring somewhere in the middle would be practically useful and important.
  - Partial knowledge of the corruption process.

Challenges in Reliable ML

- In reliable ML research, the choice of performance metrics is crucial.
  - Simply improving the accuracy is not the goal.
- Since humans use ML systems, performance metrics should reflect human cognitive bias.
  - Ex: in image evaluation, MSE is not natural, but we care edges, texture, faces, etc.
- “Designing” appropriate performance metrics is an important challenge.

Past and Future of AI Research



Logical AI

- 1960’s: Inference and search
- 1980’s: Expert systems and knowledge bases

Neuro-inspired AI

- 1960’s: Single-layer perceptrons
- 1990’s: Multi-layer perceptrons

Statistical ML based AI

- 2000’s: Frequentist statistics, convex optimization, Bayesian statistics

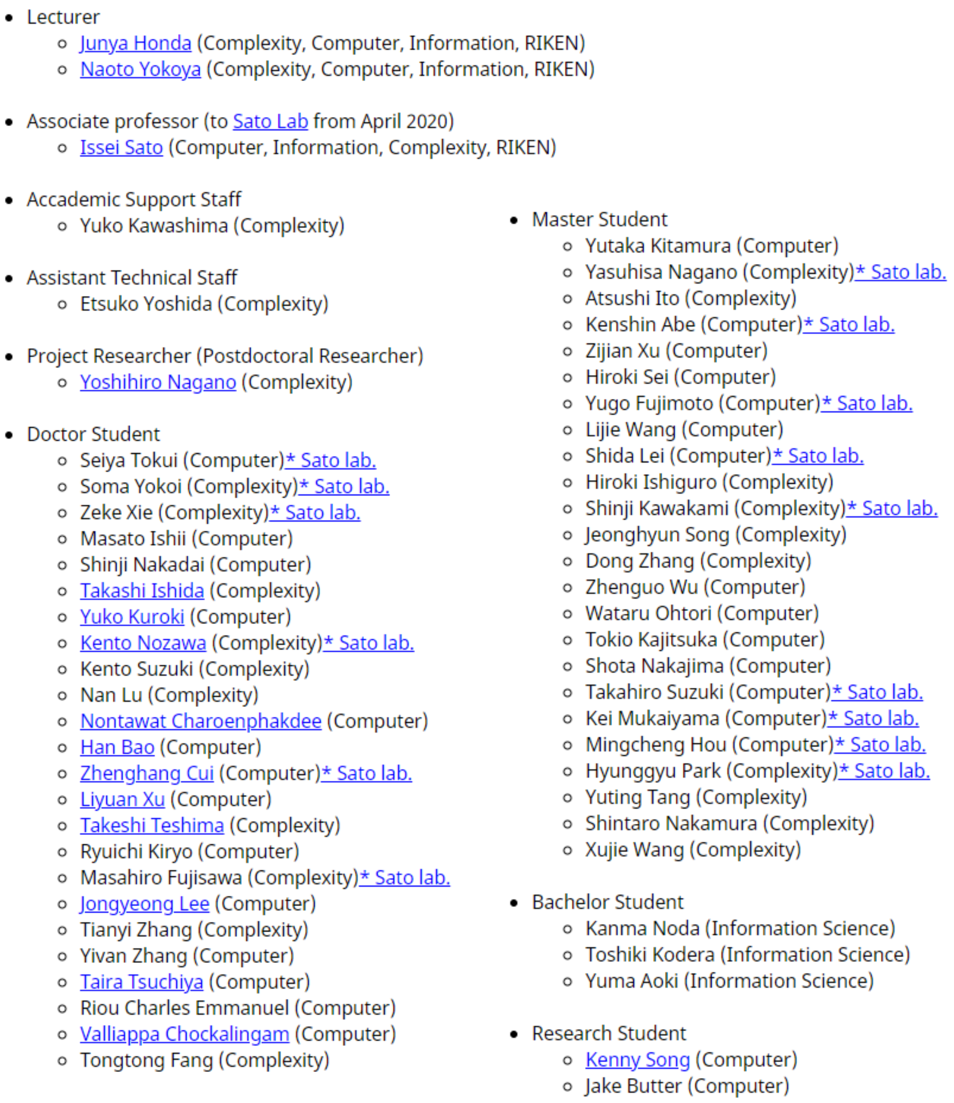
2010’s: Deep learning

Future AI

Human-like AI? Human-inclusive AI?

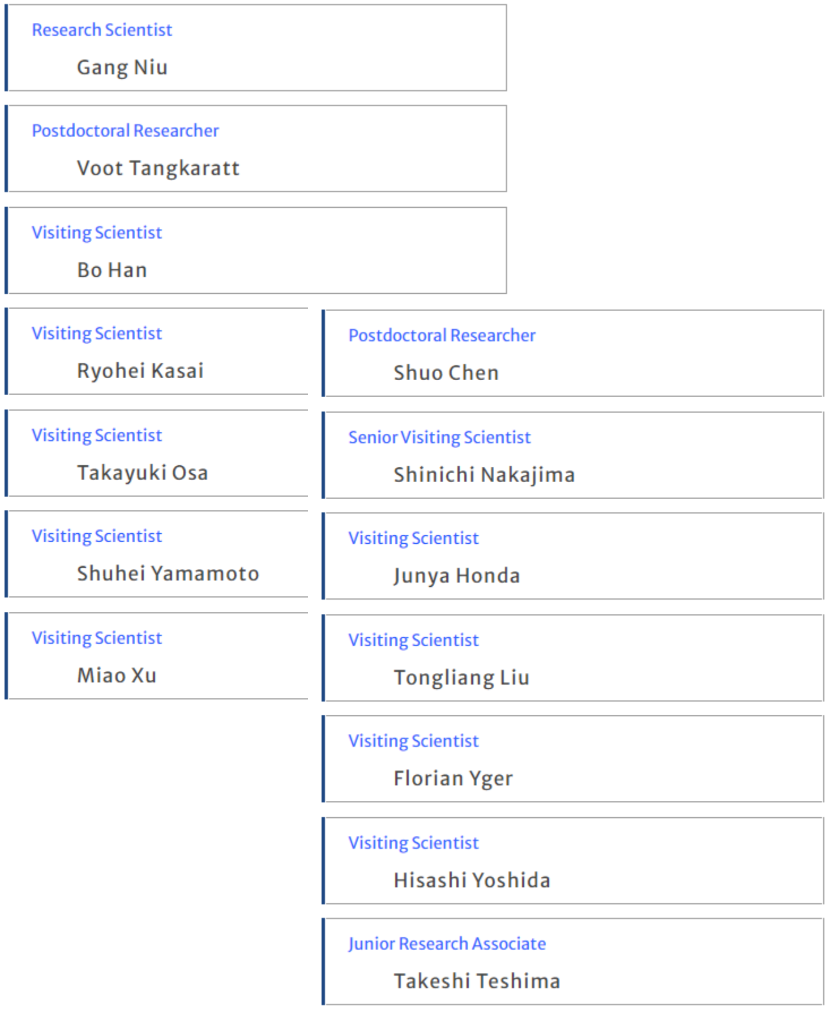
Thanks to Great Collaborators!

The University of Tokyo



- Lecturer
  - Junya Honda (Complexity, Computer, Information, RIKEN)
  - Naoto Yokoya (Complexity, Computer, Information, RIKEN)
- Associate professor (to Sato Lab from April 2020)
  - Issei Sato (Computer, Information, Complexity, RIKEN)
- Accademic Support Staff
  - Yuko Kawashima (Complexity)
- Assistant Technical Staff
  - Etsuko Yoshida (Complexity)
- Project Researcher (Postdoctoral Researcher)
  - Yoshihiro Nagano (Complexity)
- Doctor Student
  - Seiya Tokui (Computer)* Sato lab.
  - Soma Yokoi (Complexity)* Sato lab.
  - Zeke Xie (Complexity)* Sato lab.
  - Masato Ishii (Computer)
  - Shinji Nakadai (Computer)
  - Takashi Ishida (Complexity)
  - Yuko Kuroki (Computer)
  - Kento Nozawa (Complexity)* Sato lab.
  - Kento Suzuki (Complexity)
  - Nan Lu (Complexity)
  - Nontawat Charoenphakdee (Computer)
  - Han Bao (Computer)
  - Zhenghang Cui (Computer)* Sato lab.
  - Liyuan Xu (Computer)
  - Takeshi Teshima (Complexity)
  - Ryuichi Kiryo (Computer)
  - Masahiro Fujisawa (Complexity)* Sato lab.
  - Jongyeong Lee (Computer)
  - Tianyi Zhang (Complexity)
  - Yivan Zhang (Computer)
  - Taira Tsuchiya (Computer)
  - Riou Charles Emmanuel (Computer)
  - Valliappa Chockalingam (Computer)
  - Tongtong Fang (Complexity)
- Master Student
  - Yutaka Kitamura (Computer)
  - Yasuhisa Nagano (Complexity)* Sato lab.
  - Atsushi Ito (Complexity)
  - Kenshin Abe (Computer)* Sato lab.
  - Zijian Xu (Computer)
  - Hiroki Sei (Computer)
  - Yugo Fujimoto (Computer)* Sato lab.
  - Lijie Wang (Computer)
  - Shida Lei (Computer)* Sato lab.
  - Hiroki Ishiguro (Complexity)
  - Shinji Kawakami (Complexity)* Sato lab.
  - Jeonghyun Song (Complexity)
  - Dong Zhang (Complexity)
  - Zhenguo Wu (Computer)
  - Wataru Ohtori (Computer)
  - Tokio Kajitsuka (Computer)
  - Shota Nakajima (Computer)
  - Takahiro Suzuki (Computer)* Sato lab.
  - Kei Mukaiyama (Computer)* Sato lab.
  - Mingcheng Hou (Computer)* Sato lab.
  - Hyunggyu Park (Complexity)* Sato lab.
  - Yuting Tang (Complexity)
  - Shintaro Nakamura (Complexity)
  - Xujie Wang (Complexity)
- Bachelor Student
  - Kanma Noda (Information Science)
  - Toshiki Kodera (Information Science)
  - Yuma Aoki (Information Science)
- Research Student
  - Kenny Song (Computer)
  - Jake Butter (Computer)

RIKEN



Research Scientist
Gang Niu

Postdoctoral Researcher
Voot Tangkaratt

Visiting Scientist
Bo Han

Visiting Scientist
Ryohei Kasai

Visiting Scientist
Takayuki Osa

Visiting Scientist
Shuhei Yamamoto

Visiting Scientist
Miao Xu

Postdoctoral Researcher
Shuo Chen

Senior Visiting Scientist
Shinichi Nakajima

Visiting Scientist
Junya Honda

Visiting Scientist
Tongliang Liu

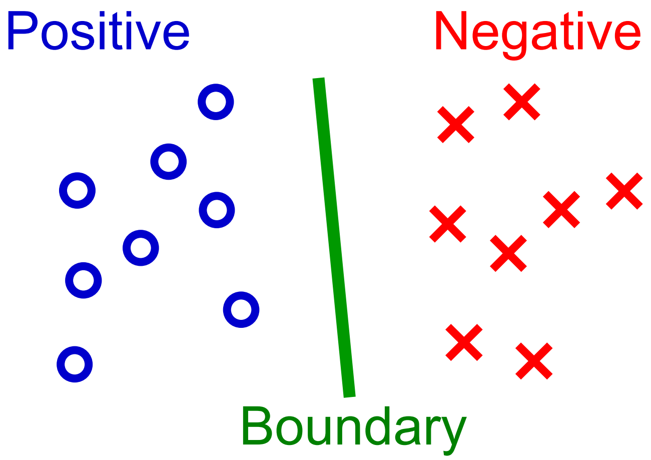
Visiting Scientist
Florian Yger

Visiting Scientist
Hisashi Yoshida

Junior Research Associate
Takeshi Teshima

Weakly Supervised Learning

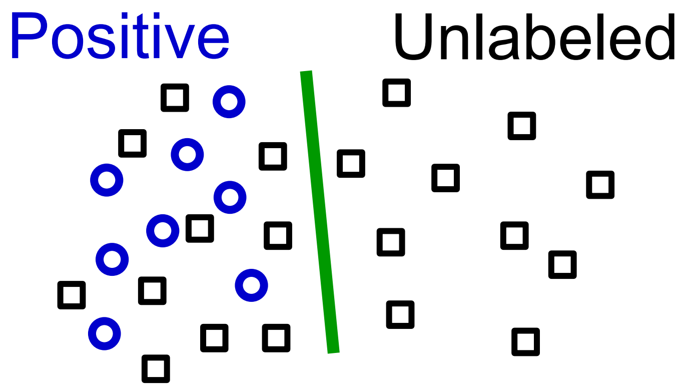
- Ordinary supervised learning requires fully labeled data (input-output pairs).
- But collecting fully labeled data can be expensive in practice.
- Can we utilize “weakly” labeled data?
  - No negative data
  - Positive confidence data
  - Similar/dissimilar data
  - Complementary data
  - Partial-label data



P: Positive, N: Negative, U: Unlabeled

(2-1) PU Classification

- Only positive and unlabeled data is available; negative data is completely missing:
  - Click vs. non-click
  - Friend vs. non-friend



- We want to minimize the risk of classifier f only from PU data:

$$\pi = p(y=+1)$$

$$R(f) = \mathbb{E}_{p(\boldsymbol{x},y)}\Big[\ell\Big(yf(\boldsymbol{x})\Big)\Big]$$

$$= \underbrace{\pi\mathbb{E}_{p(\boldsymbol{x}|y=+1)}\Big[\ell\Big(f(\boldsymbol{x})\Big)\Big]}_{\text{Risk for P data}} + \underbrace{(1-\pi)\mathbb{E}_{p(\boldsymbol{x}|y=-1)}\Big[\ell\Big(-f(\boldsymbol{x})\Big)\Big]}_{\text{Risk for N data}}$$

- But N-risk cannot be estimated directly.

Key Trick

du Plessis, Niu & Sugiyama (NIPS2014, ICML2015)
Niu, du Plessis, Sakai, Ma & Sugiyama (NIPS2016)
Kiryo, du Plessis, Niu & Sugiyama (NIPS2017)
Hsieh, Niu & Sugiyama (ICML2019)

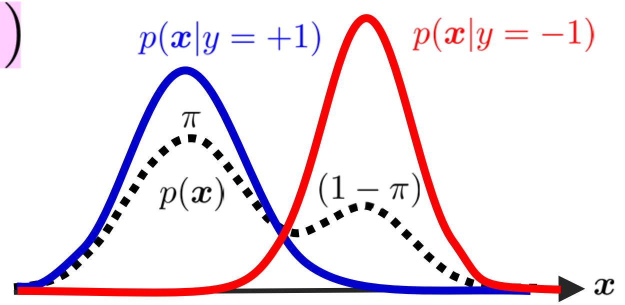
Risk for P data　　　　　　Risk for N data

$$R(f) = \pi \mathbb{E}_{p(\boldsymbol{x}|y=+1)}\left[\ell\Big(f(\boldsymbol{x})\Big)\right] + (1-\pi)\mathbb{E}_{p(\boldsymbol{x}|y=-1)}\left[\ell\Big(-f(\boldsymbol{x})\Big)\right]$$

- Use “U-density is mixture of P- and N-densities”:

$$p(\boldsymbol{x}) = \pi p(\boldsymbol{x}|y=+1) + (1-\pi)p(\boldsymbol{x}|y=-1)$$

$$\pi = p(y=+1)$$



- Then

$$R(f) = \pi \mathbb{E}_{p(\boldsymbol{x}|y=+1)}\left[\ell\Big(f(\boldsymbol{x})\Big)\right]$$

$$+\mathbb{E}_{p(\boldsymbol{x})}\left[\ell\Big(-f(\boldsymbol{x})\Big)\right] - \pi \mathbb{E}_{p(\boldsymbol{x}|y=+1)}\left[\ell\Big(-f(\boldsymbol{x})\Big)\right]$$

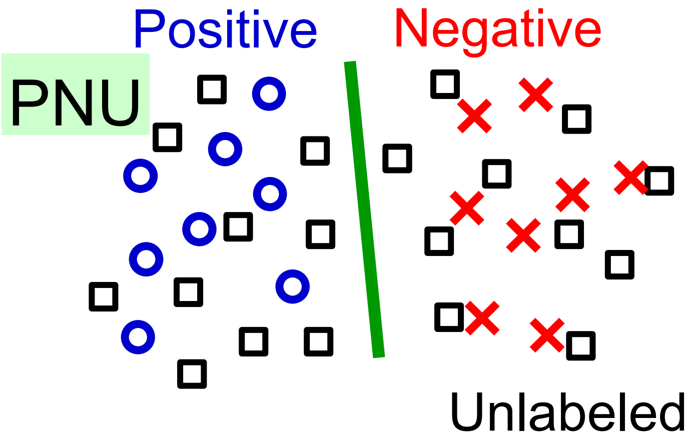
- Empirical risk minimization (ERM) is possible from PU data, just by replacing expectations by sample averages!

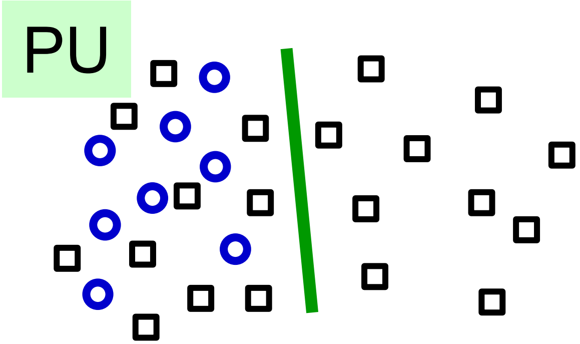
$$R(\widehat{f}_{\mathrm{PU}}) - R(f^*) \leq C(\delta)\left(\frac{2\pi}{\sqrt{n_{\mathrm{P}}}} + \frac{1}{\sqrt{n_{\mathrm{U}}}}\right)$$

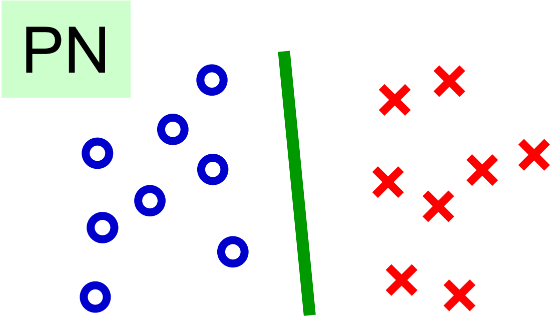
(2-2) PNU Classification (Semi-Supervised Classification)

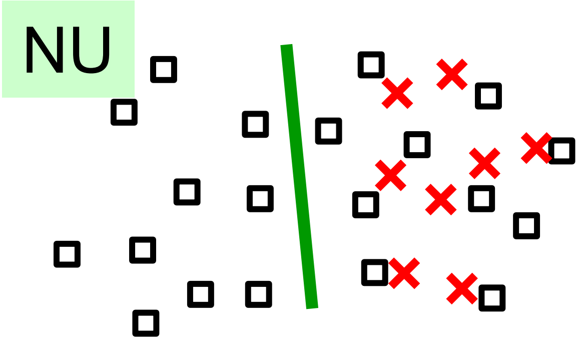
Sakai, du Plessis, Niu & Sugiyama (ICML2017)
Sakai, Niu & Sugiyama (MLJ2018)

- Let’s decompose PNU into PU, PN, and NU:
  - Each is solvable.
  - Let’s combine them!
- Without cluster assumptions, PN classifiers are trainable!









$$R_{0/1}(f) \leq 2\widehat{R}^{\gamma}_{\mathrm{PN+PU}}(f) + \mathcal{O}(1/\sqrt{n_{\mathrm{P}}} + 1/\sqrt{n_{\mathrm{N}}} + 1/\sqrt{n_{\mathrm{U}}})$$

(2-3) Pconf Classification

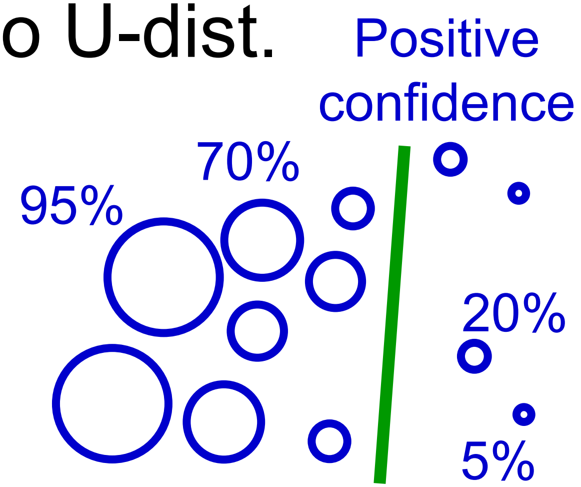
Ishida, Niu & Sugiyama (NeurIPS2018)

- Only P data is available, even not U data:
  - Data from rival companies cannot be obtained.
  - Only positive results are reported (publication bias).
- "Only-P learning" is unsupervised.
- From positive-confidence data, ERM is possible!
  - Augment r-Pconf samples to (1-r)-Nconf samples.
  - Importance sampling from P-dist. to U-dist.

$$R(f) = \pi \mathbb{E}_{p(\boldsymbol{x}|y=+1)}\left[\ell\Big(f(\boldsymbol{x})\Big) + \frac{1-r(\boldsymbol{x})}{r(\boldsymbol{x})}\ell\Big(-f(\boldsymbol{x})\Big)\right]$$

$\pi = p(y=+1)$ $r(\boldsymbol{x}) = P(y=+1|\boldsymbol{x})$

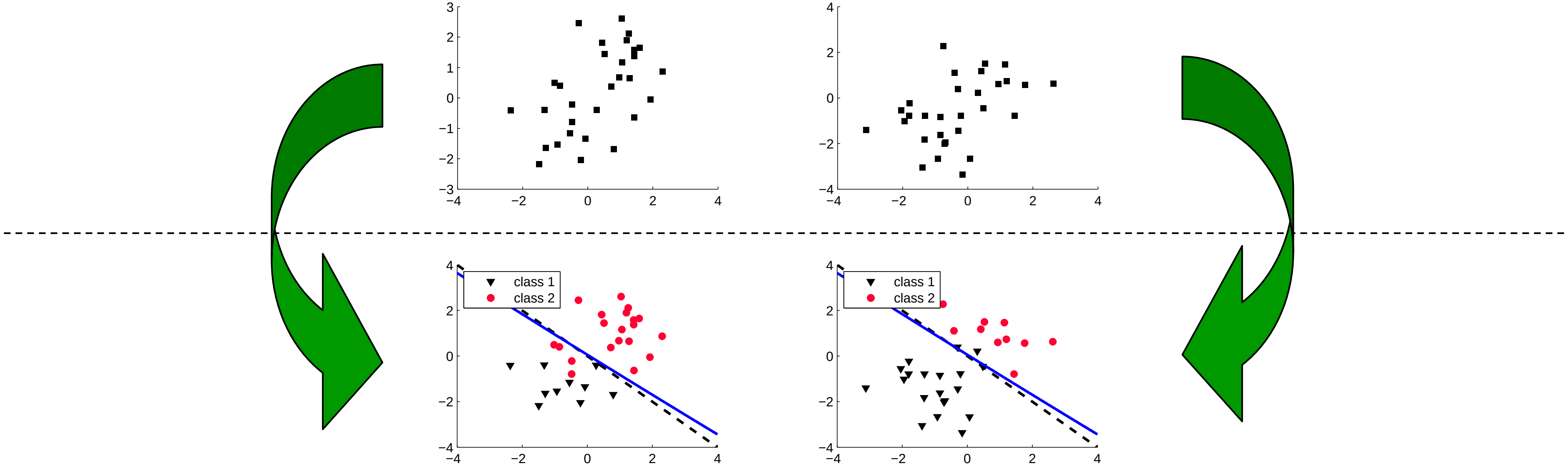
$$R\Big(f^*\Big) - R\Big(\widehat{f}\Big) = \mathcal{O}_p\Big(1/\sqrt{n}\Big)$$



(2-4) UU Classification

du Plessis, Niu & Sugiyama (TAAI2013)
Lu, Niu, Menon & Sugiyama (ICLR2019)
Charoenphakdee, Lee & Sugiyama (ICML2019)
Lu, Zhang, Niu & Sugiyama (AISTATS2020)

- From two sets of unlabeled data with different class priors, PN classifiers are trainable by ERM!



- In PU, we regarded U as noisy N.
- In UU, we use noisy P and noisy N!

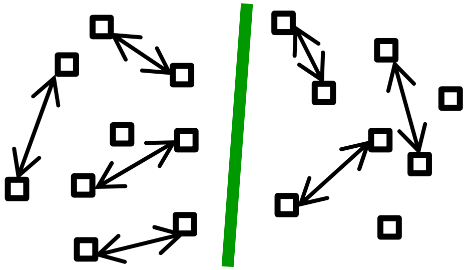
$$\mathcal{O}_p\left(1/\sqrt{n}\right)$$

(2-5) SU Classification

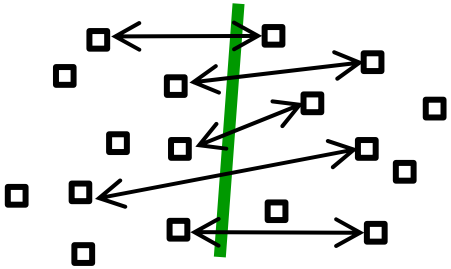
Bao, Niu & Sugiyama (ICML2018)

- Delicate classification (money, religion…):
  - Highly hesitant to directly answer questions.
  - Less reluctant to just say “same as him/her”.
- From similar data pairs and unlabeled data, PN classifiers are trainable!

  $1/\sqrt{n}$



  - Decoupling S-pairs results in UU classification!
- Learning from dissimilar data pairs is also possible.



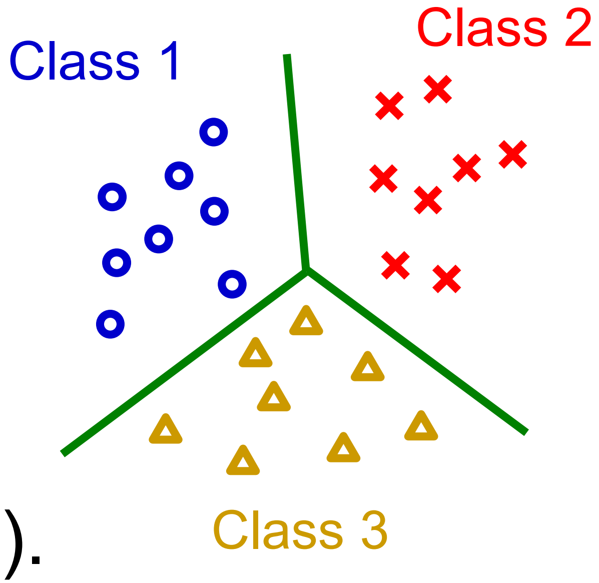
  - SDU classification is also possible.

Shimada, Bao, Sato & Sugiyama (NeCo2021)
Dan, Bao & Sugiyama (arXiv2020)

(2-6) Complementary Classification

Ishida, Niu & Sugiyama (NIPS2017)
Ishida, Niu, Menon & Sugiyama (ICML2019)
Chou, Niu, Lin & Sugiyama (ICML2020)

- Labeling patterns in multi-class problems:
  - Selecting the collect class from a long class list is extremely painful.



- Complementary labels:
  - Specify a class that a pattern does not belong to (“not class 1”).
  - This is much easier and faster to collect!
- From complementary labels, classifiers are trainable by ERM!

$1/\sqrt{n}$

  - Noisy labels with uniform transition to other classes.

Incorporating Ordinary Labels

- Convert multiclass labeling into yes-no labeling:

http://www.softbank.jp/corp/group/sbr/news/press/2014/20141029_01/

https://www.bostondynamics.com/atlas

Is this Softbank Pepper?
Yes! (ordinary label)

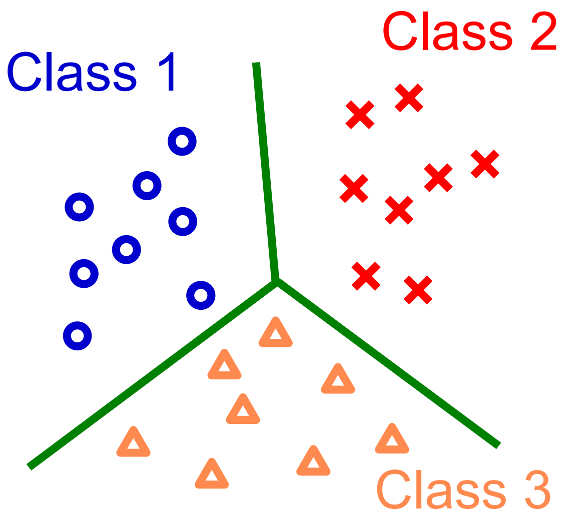
Is this iRobot Roomba?
No! (complementary label)

- Use both of ordinary and complementary labels!

$$R(f) = \mathbb{E}_{p(\boldsymbol{x},y)}\left[\mathcal{L}\Big(f(\boldsymbol{x}),y\Big)\right] + \left\{(c-1)\mathbb{E}_{\bar{p}(\boldsymbol{x},\bar{y})}\left[\bar{\mathcal{L}}\Big(f(\boldsymbol{x}),\bar{y}\Big)\right] + \mathrm{Const.}\right\}$$

(2-7) Partial-Label Classification

- **Partial label**: Nguyen and Caruana (KDD2008)
  a subset of labels containing the true one
  - "Either 1 or 2"
  - Cheaper than ordinary labels

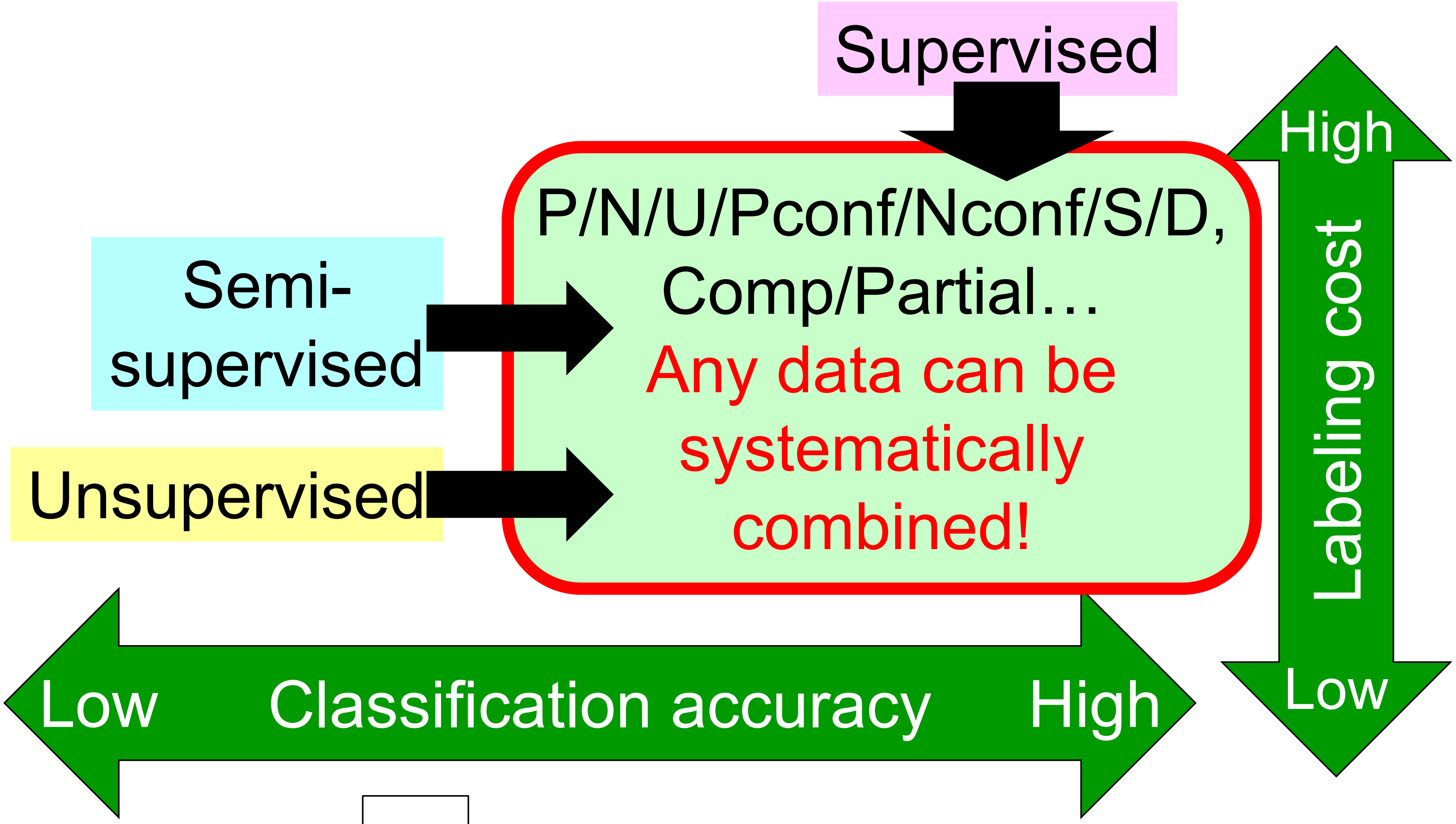


- From partial labels, classifiers are trainable by ERM!

Feng, Kaneko, Han, Niu, An & Sugiyama (ICML2020)
Lv, Xu, Feng, Niu, Geng & Sugiyama (ICML2020)
Feng, Lv, Han, Xu, Niu, Geng, An & Sugiyama (NeurIPS2020)

  - Complementary label is equivalent to partial label with size k-1.

Weakly Supervised Learning



Supervised

Semi-supervised

Unsupervised

P/N/U/Pconf/Nconf/S/D, Comp/Partial…

Any data can be systematically combined!

Low Classification accuracy High

High Labeling cost Low

Sugiyama, Ishida, Lu, Bao, Sakai & Niu,
Machine Learning from Weak Supervision
MIT Press, 2021(?)