

Masking: A New Perspective of Noisy Supervision

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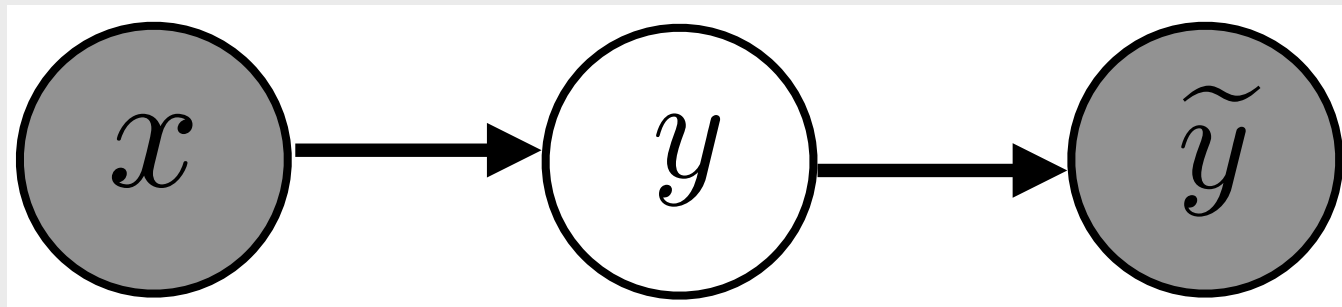
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Overview

TL;DR: The masking conveys **human cognition** of invalid class transitions, and speculates the **structure** of the noise transition matrix. Therefore, we only learn the noise **transition probability** to reduce the estimation burden.

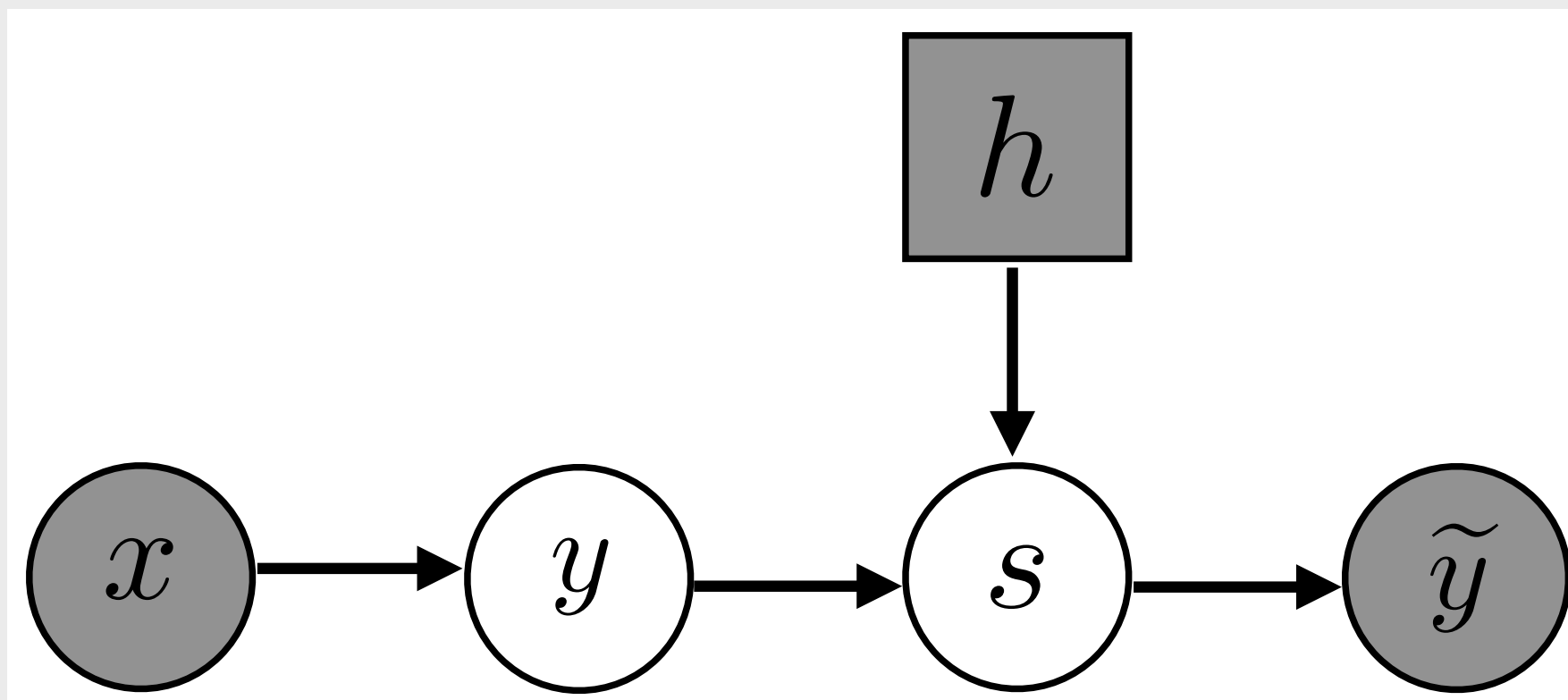
- **Noisy labels** are corrupted from ground-truth labels, which degenerates the robustness of learning models.
- **Deep neural networks** have the high capacity to fit any noisy labels. The solutions are as follows.
 - ◊ Noise **transition** matrix estimation. E.g., F-correction.
 - ◊ **Regularization**. E.g., VAT and Mean teacher.
 - ◊ Training on **selected** samples. E.g., MentorNet.
- We present a human-assisted approach called **Masking** combating with noisy labels.
 - ◊ Conveying human cognition of invalid class transitions.
 - ◊ Speculating the structure of the noise transition matrix.
 - ◊ Deriving a **structure-aware probabilistic model**, which incorporates a **structure prior**.
- Empirical results on **CIFAR10**, **CIFAR100** with three noise structures and **Clothing1M** demonstrate that, our approach can improve the robustness of classifiers.

Deficiency of Benchmarks



- Independent framework: not for **agnostic** noisy data.
- Unified framework: suffer from **local** minimums.

Structure-aware Probabilistic Model (MASKING)



- Human cognition **masks** the invalid class transitions.
- The model focuses on the noise **transition probability**.
- The estimation burden will be **largely reduced**.

ELBO of MASKING

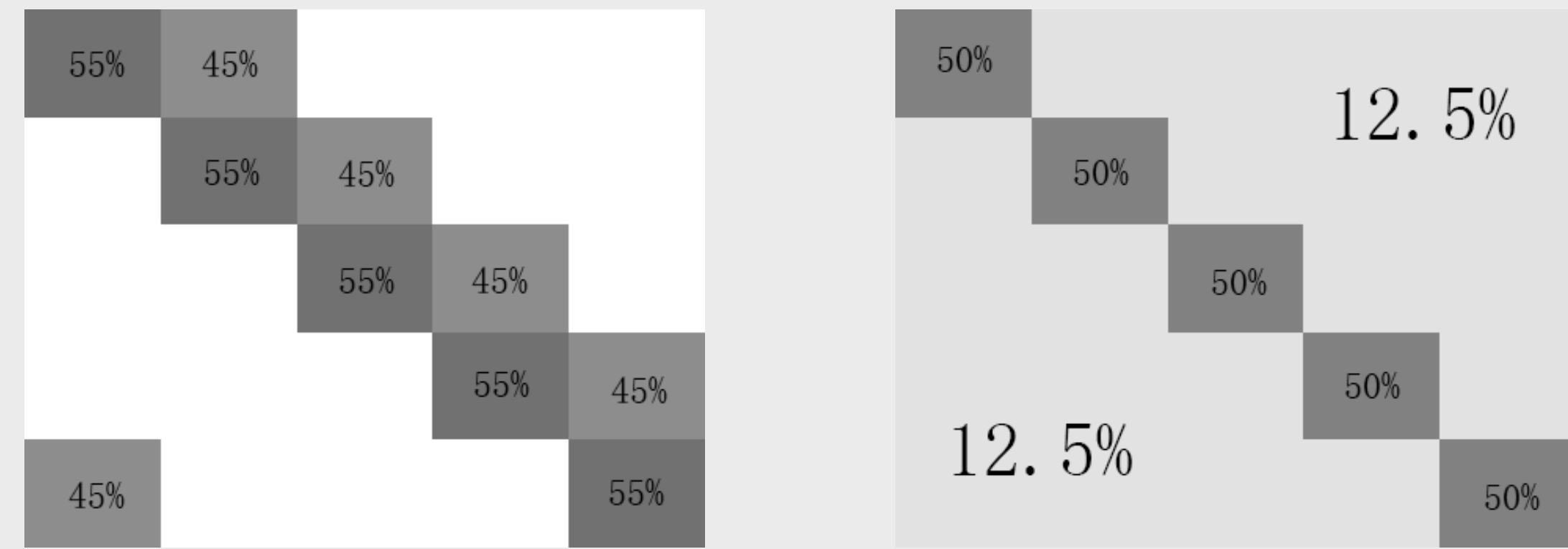
$$\ln P(\tilde{y}|x) \geq \mathbb{E}_{Q(s)} \left[\underbrace{\ln \sum_y P(\tilde{y}|y, s) P(y|x)}_{\text{previous model}} - \ln \left(Q(s_o) / \underbrace{P(s_o)}_{\text{structure prior}} \right) \right]_{s_o=f(s)},$$

where $Q(s)$ is the variational distribution to approximate the **posterior** of the noise transition matrix s , and $Q(s_o) = Q(s) \frac{ds}{ds_o} \big|_{s_o=f(s)}$ is the corresponding variational distribution of the **structure** s_o .

QR Code

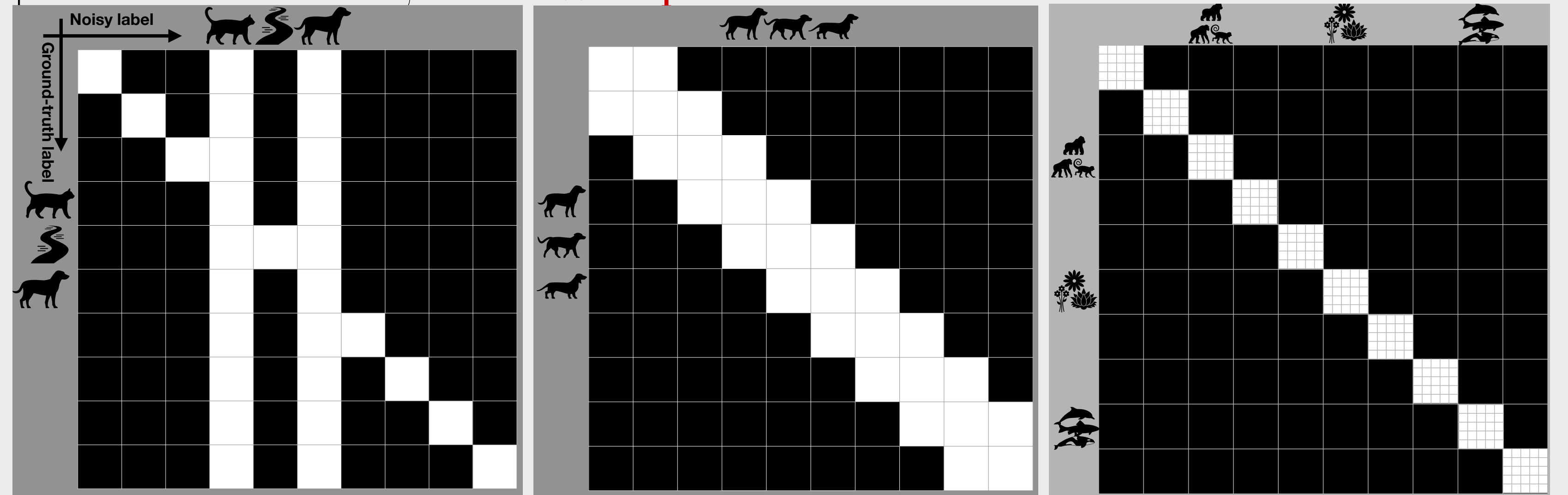


Estimating Noise Transition Matrix



Motivation: Data Perspective

- (a) beach \leftrightarrow mountain; **beach** \leftrightarrow **dog**.
- (b1) Australian terrier \leftrightarrow Norwich terrier; (b2) **Norfolk terrier** \leftrightarrow **Norwich terrier** \leftrightarrow **Irish terrier**.
- (c) aquatic mammals \leftrightarrow flowers; **beaver** \leftrightarrow **dolphin**.



Principled Realization

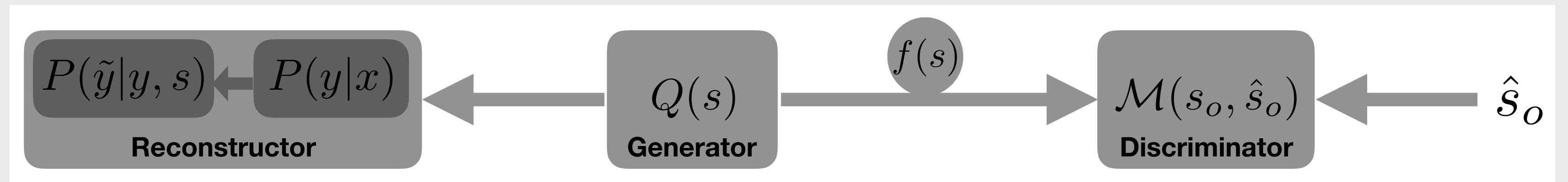
Q1: Challenge from **structure extraction**.

A1: the **tempered sigmoid func** as $f(\cdot)$ to map from s to s_o ,

$$f(s) = \frac{1}{1 + \exp(-\frac{s-\alpha}{\beta})}, \quad \text{where } \alpha \in (0, 1), \beta \ll 1.$$

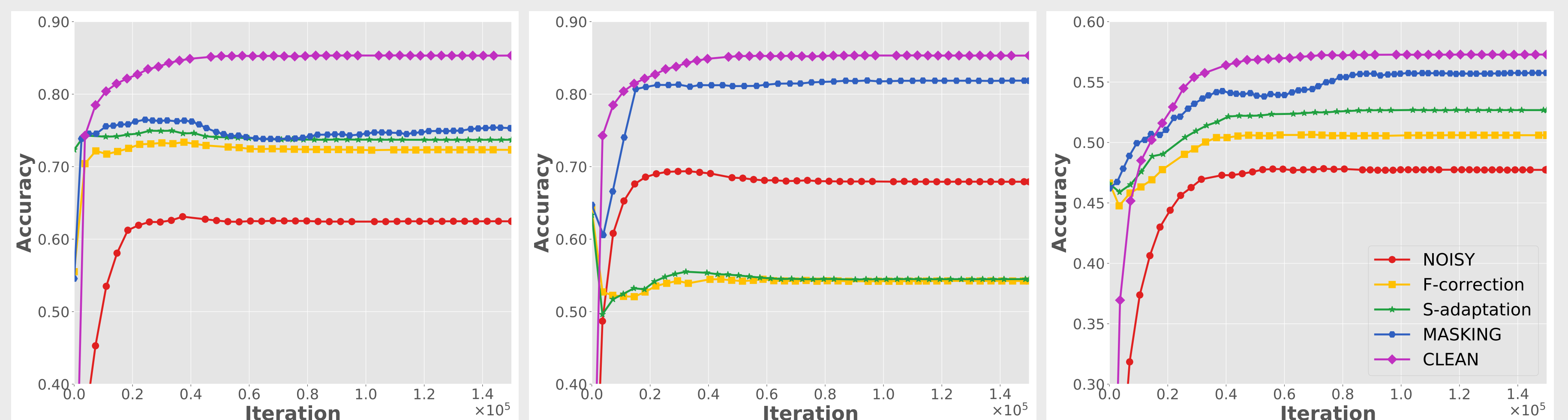
Q2: Challenge from **structure alignment**.

A2: **GAN-like structure** to model the structure instillation.



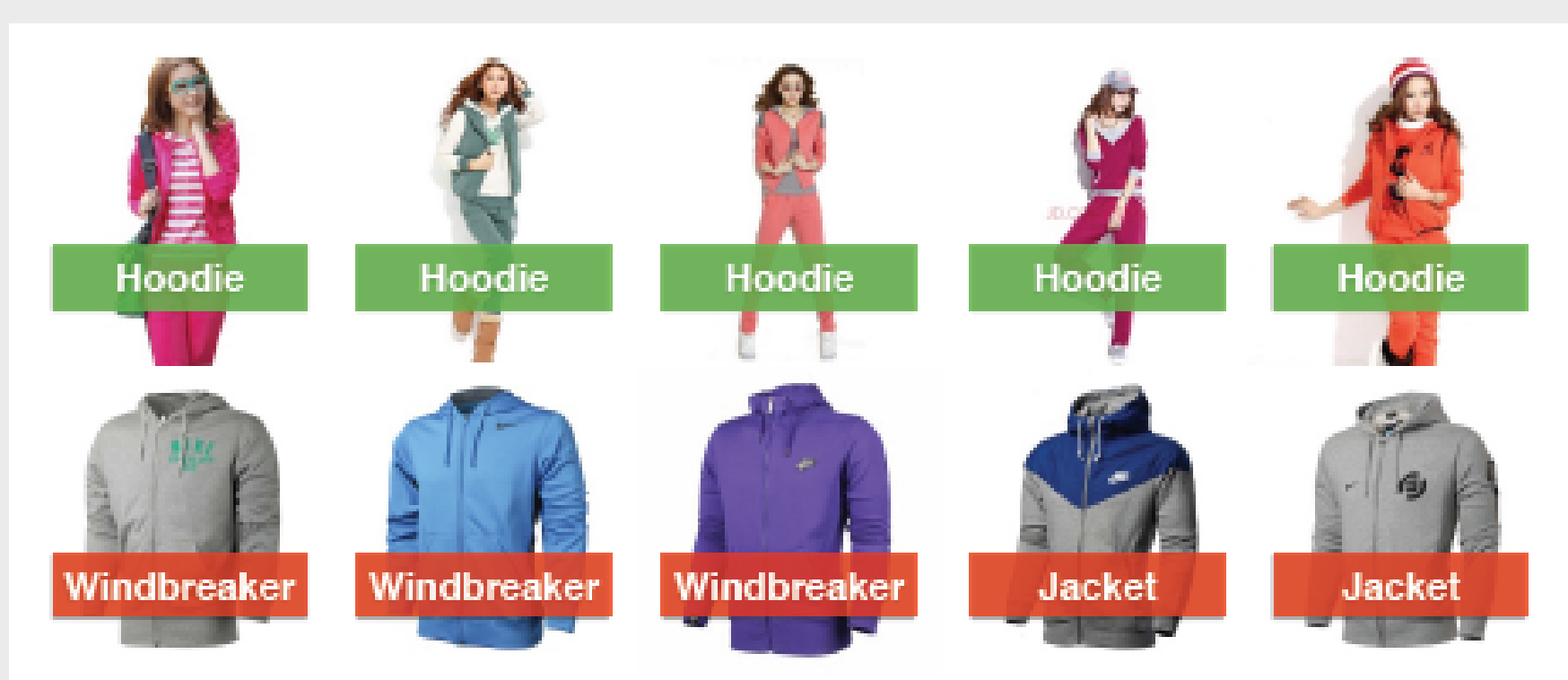
CIFAR10 and CIFAR100

- The test accuracy vs iterations on **benchmark** datasets.



Clothing1M

- The test accuracy on **Clothing1M** from Taobao.com.



Models	Performance(%)
NOISY	68.9
F-correction	69.8
S-adaption	70.3
MASKING	71.1
CLEAN	75.2