Cross-Domain Self-supervised Learning

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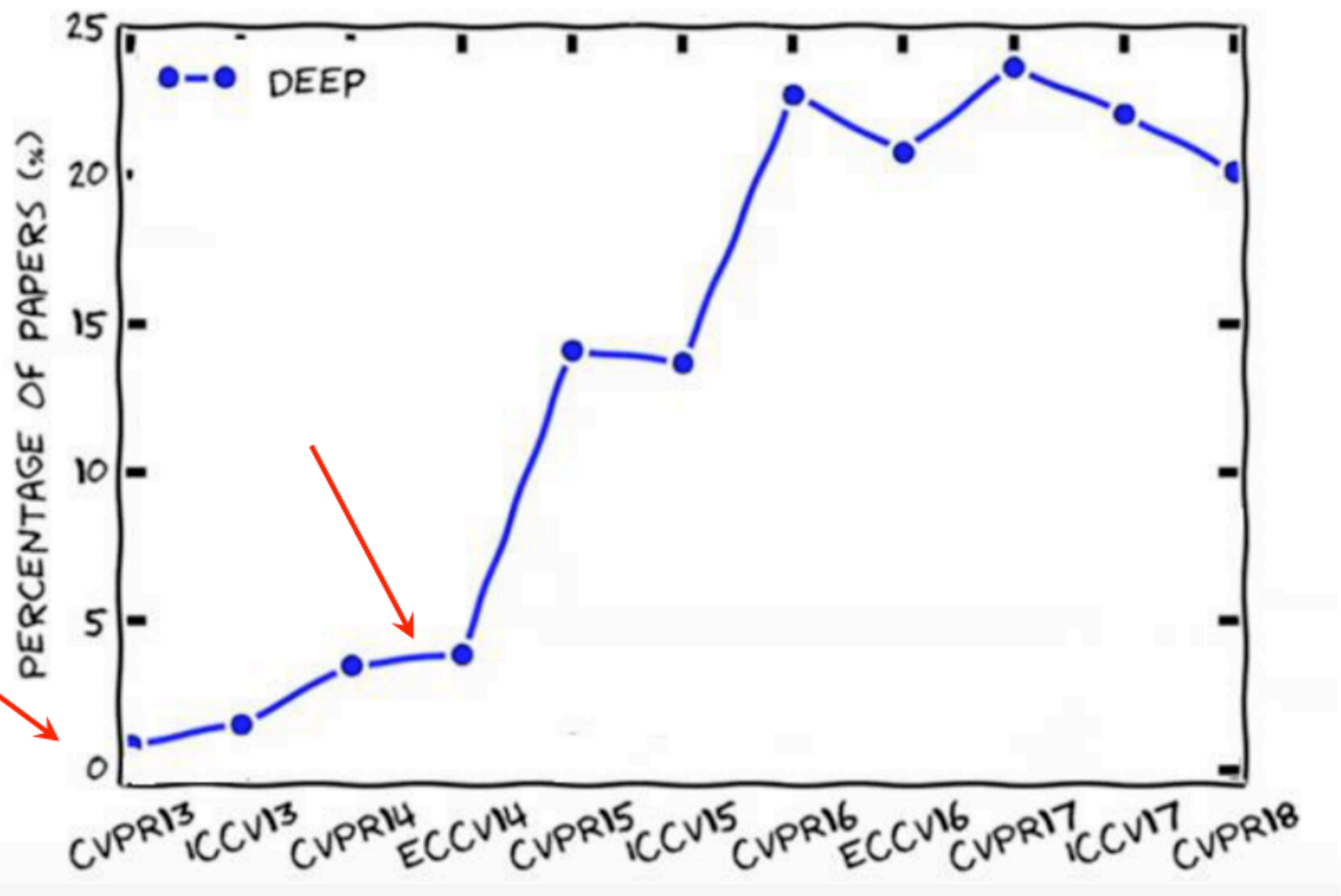
A Story about Cake (in Yann LeCun's Turing Talk)

- **"Pure" Reinforcement Learning (cherry)**
  - The machine predicts a scalar reward given once in a while.
  - **A few bits for some samples**
- **Supervised Learning (icing)**
  - The machine predicts a category or a few numbers for each input
  - Predicting human-supplied data
  - **10→10,000 bits per sample**
- **Self-Supervised Learning (cake génoise)**
  - The machine predicts any part of its input for any observed part.
  - Predicts future frames in videos
  - **Millions of bits per sample**

Credit by Yann LeCun

A Story about ImageNet

AlexNet



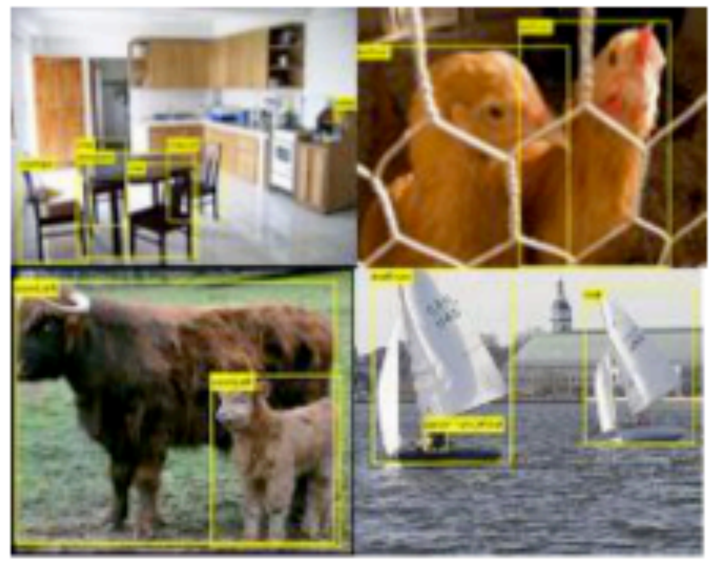
Supervised Pretraining + Finetuning (2014)

- A kind of transfer learning paradigm

Pretraining on ImageNet Classification

Finetuning

Semantic Segmentation



Object Detection

Fine-grained Classification

Two Stories Meet Each Other

- Unsupervised Pretraining + Finetuning

Momentum Contrast for Unsupervised Visual Representation Learning

Kaiming He Haoqi Fan Yuxin Wu Saining Xie Ross Girshick

Facebook AI Research (FAIR)

Code: https://github.com/facebookresearch/moco

2019.11

MoCo

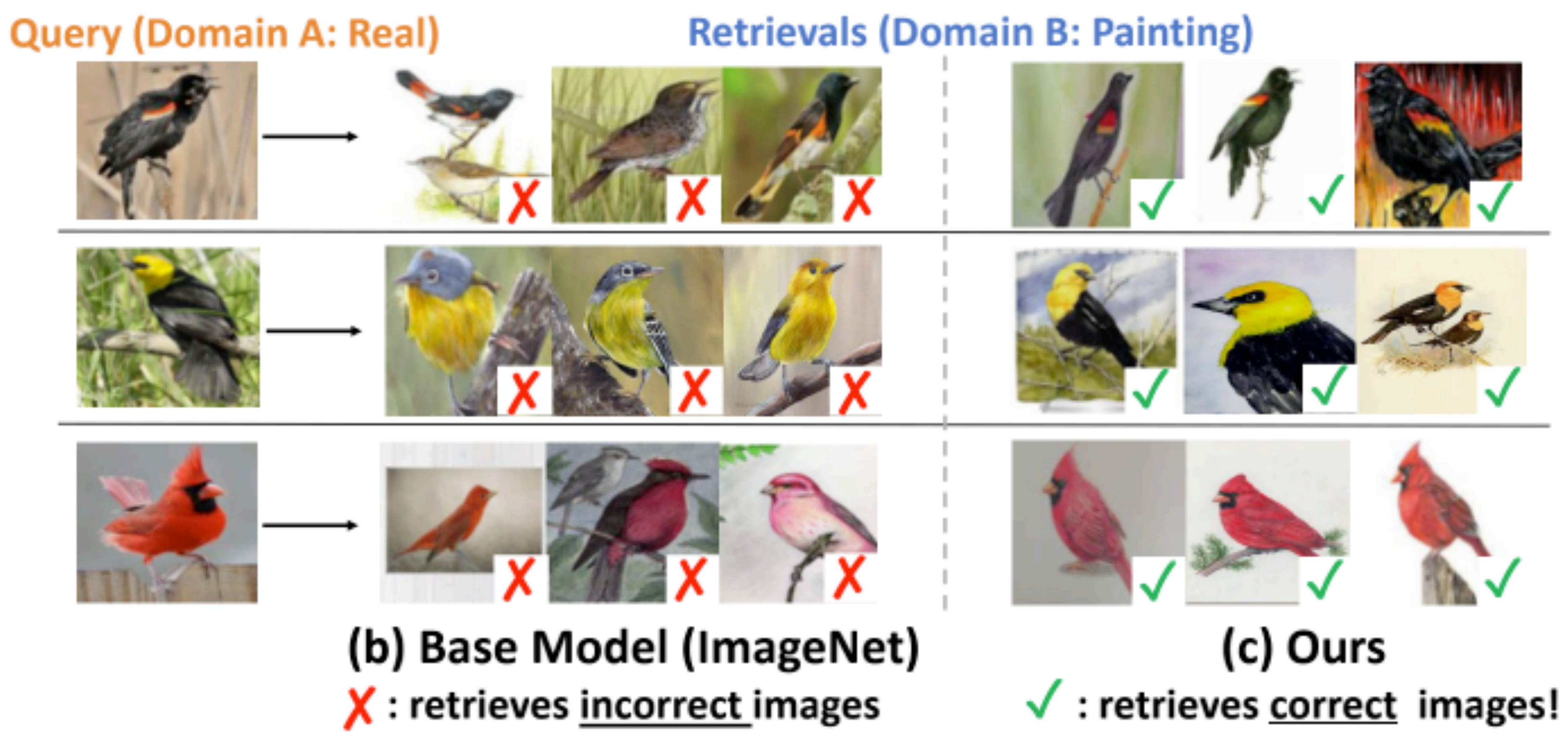
FAIR

- For the first time, unsupervised pretraining outperform supervised pretraining on 7 down-stream tasks

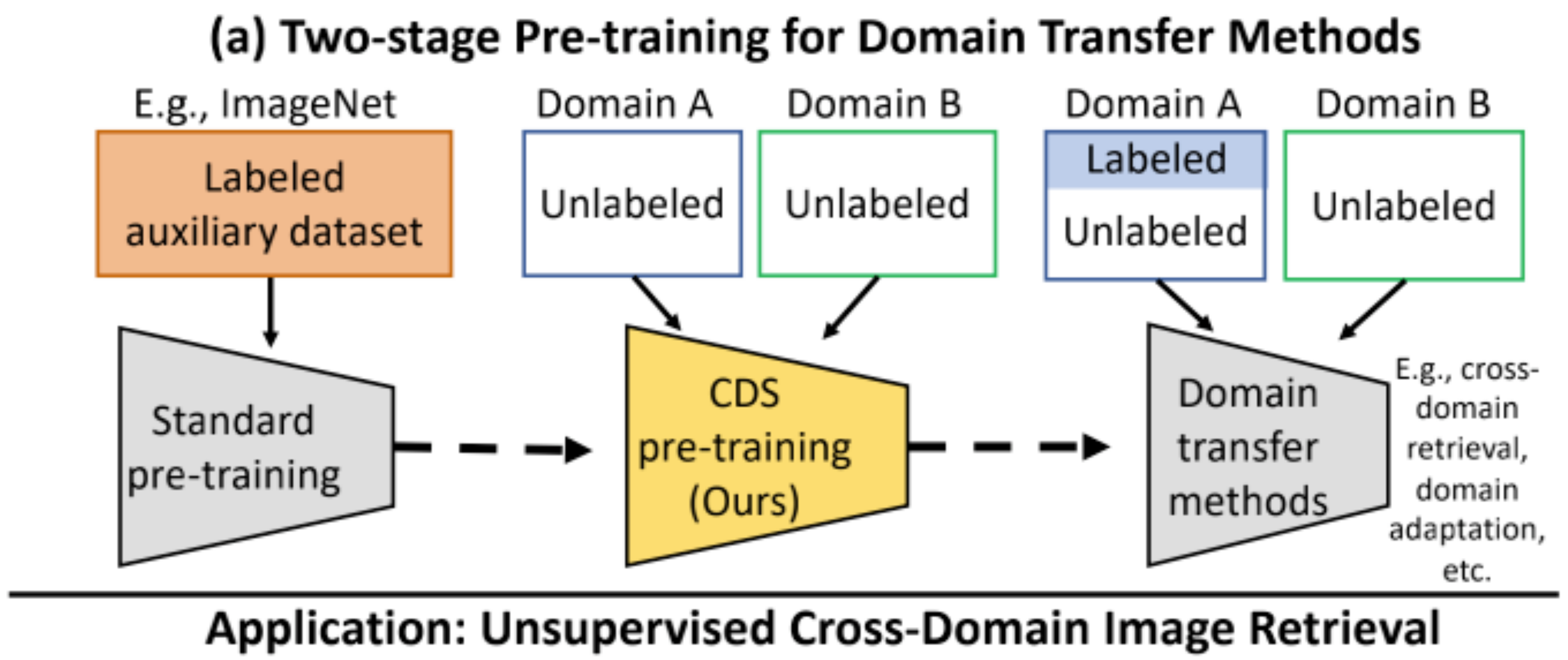
ICCV 2021: CDS: Cross-Domain Self-supervised Pre-training

Donghyun Kim, Kuniaki Saito, Tar-Hyun Oh, Bryan A. Plummer, Stan Sclaroff, Kate Sarnko
Boston University, POSTECH, MIT-IBM Watson AI Lab

Motivation：
- ImageNet上的预训练模型在表示学习上具有偏向性
- SSL在单域无监督表示学习上具有很好的效果



Method：
- 在预训练模型迁移到下游跨域任务的过程中，额外增加SSL Pre-Training作为过渡



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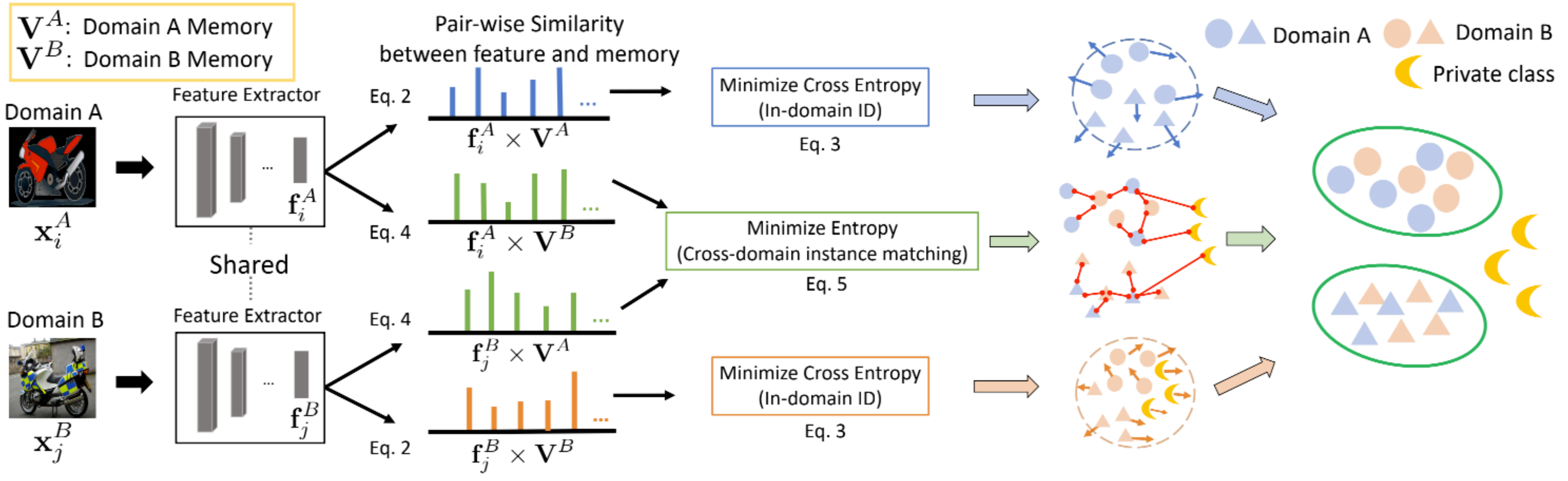

Step1: $P_i^A = \frac{\exp((\mathbf{v}_i^A)^\top \mathbf{f}_i^A/\tau)}{\sum_{k=1}^{N_A} \exp((\mathbf{v}_k^A)^\top \mathbf{f}_i^A/\tau)}, P_j^B = \frac{\exp((\mathbf{v}_j^B)^\top \mathbf{f}_j^B/\tau)}{\sum_{k=1}^{N_B} \exp((\mathbf{v}_k^B)^\top \mathbf{f}_j^B)/\tau)},$ $\mathcal{L}_{I\text{-}ID} = -\frac{1}{|\mathbb{B}|}(\sum_{i\in\mathbb{B}} \log P_i^A + \sum_{j\in\mathbb{B}} \log P_j^B)),$

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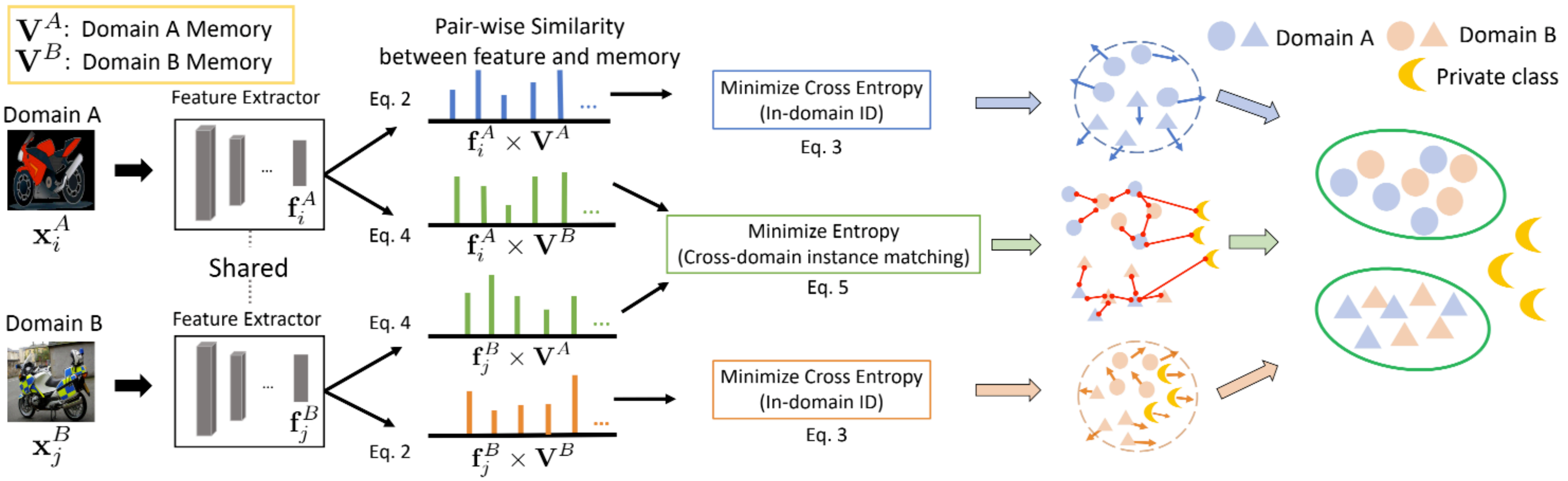

$$\mathcal{L}_{CDM} = \frac{1}{|\mathbb{B}|}\left(\sum_{i\in\mathbb{B}} H(P_i^{A\to B}) + \sum_{j\in\mathbb{B}} H(P_j^{B\to A})\right),$$

Step2:

$$P_{j',i}^{A\to B} = \frac{\exp((\mathbf{v}_{j'}^B)^\top \mathbf{f}_i^A/\tau)}{\sum_{k=1}^{N_B}\exp((\mathbf{v}_k^B)^\top \mathbf{f}_i^A/\tau)}, P_{i',j}^{B\to A} = \frac{\exp((\mathbf{v}_{i'}^A)^\top \mathbf{f}_j^B/\tau)}{\sum_{k=1}^{N_A}\exp((\mathbf{v}_k^A)^\top \mathbf{f}_j^B/\tau)}$$

$$H(P_i^{A\to B}) = -\sum_{j'}^{N_A} P_{j',i}^{A\to B}\log P_{j',i}^{A\to B},$$

$$H(P_j^{B\to A}) = -\sum_{i'}^{N_B} P_{i',j}^{B\to A}\log P_{i',j}^{B\to A},$$

CVPR 2021: Prototypical Cross-domain Self-supervised Learning for Few shot Unsupervised Domain Adaptation

Xiangyu Yue, Zangwei Zheng, Shanghang Zhang, Yang Gao
Trevor Darrell, Kurt Keutzer, Alberto Sangiovanni Vincentelli
UC Berkeley, Nanjing University, Tsinghua University

Motivation：

- CDS的域内损失减弱了数据的语义信息；域间损失在某些场景下受abnormal样本的影响
- two-stage pre-training在下游任务上的表现与DA方法有关

Method：

- 引入类原型思想，加强语义表示
- 设置自适应原型分类器，实现端到端训练

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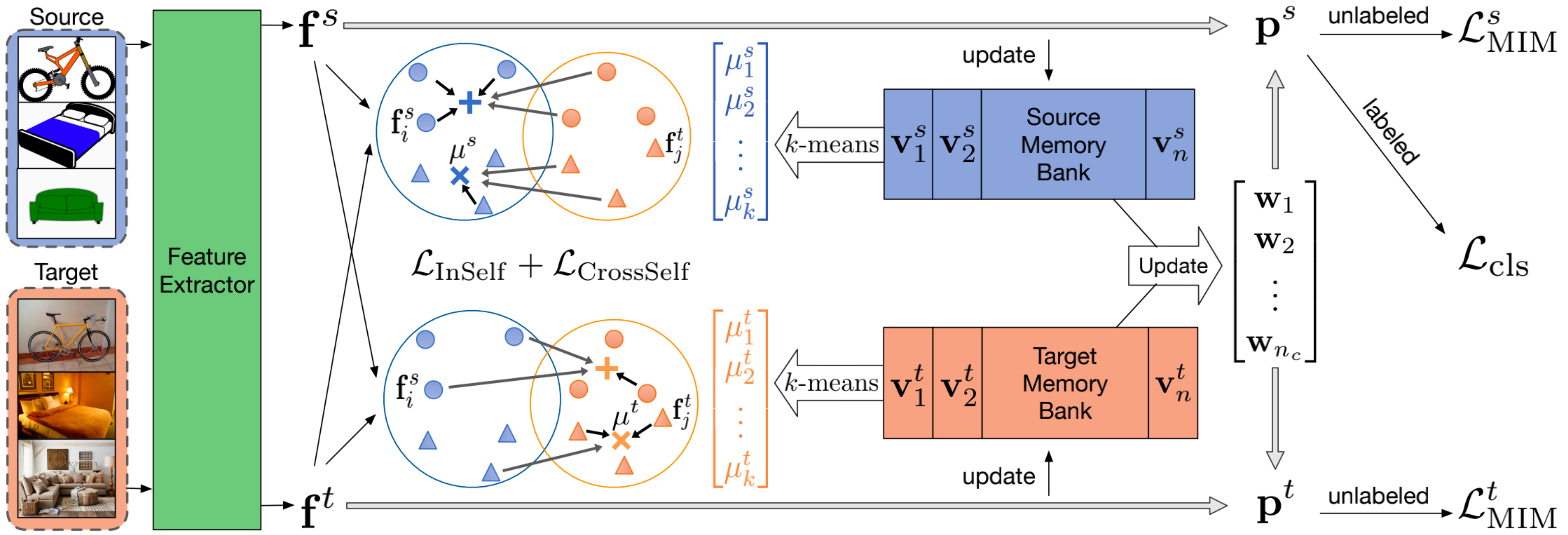
$$\mathcal{D}_s = \{(\mathbf{x}_i^s, y_i^s)\}_{i=1}^{N_s}$$

$$\mathcal{D}_{su} = \{(\mathbf{x}_i^{su})\}_{i=1}^{N_{su}}$$

$$\mathcal{D}_{tu} = \{(\mathbf{x}_i^{tu})\}_{i=1}^{N_{tu}}$$



In domain

$$P_{i,j}^s = \frac{\exp(\mu_j^s \cdot \mathbf{f}_i^s/\phi)}{\sum_{r=1}^k \exp(\mu_r^s \cdot \mathbf{f}_i^s/\phi)},$$

$$\mathcal{L}_{\text{PC}} = \sum_{i=1}^{N_s+N_{su}} \mathcal{L}_{CE}(P_i^s, c_s(i)) + \sum_{i=1}^{N_{tu}} \mathcal{L}_{CE}(P_i^t, c_t(i))$$

$$\mathcal{L}_{\text{InSelf}} = \frac{1}{M}\sum_{m=1}^{M} \mathcal{L}_{\text{PC}}^{(m)}$$

Cross domain

$$P_{i,j}^{s\to t} = \frac{\exp(\mu_j^t \cdot \mathbf{f}_i^s/\tau)}{\sum_{r=1}^k \exp(\mu_r^t \cdot \mathbf{f}_i^s/\tau)}.$$

$$H(P_i^{s\to t}) = -\sum_{j=1}^{k} P_{i,j}^{s\to t} \log P_{i,j}^{s\to t}.$$

$$\mathcal{L}_{\text{CrossSelf}} = \sum_{i=1}^{N_s+N_{su}} H(P_i^{s\to t}) + \sum_{i=1}^{N_{tu}} H(P_i^{t\to s})$$

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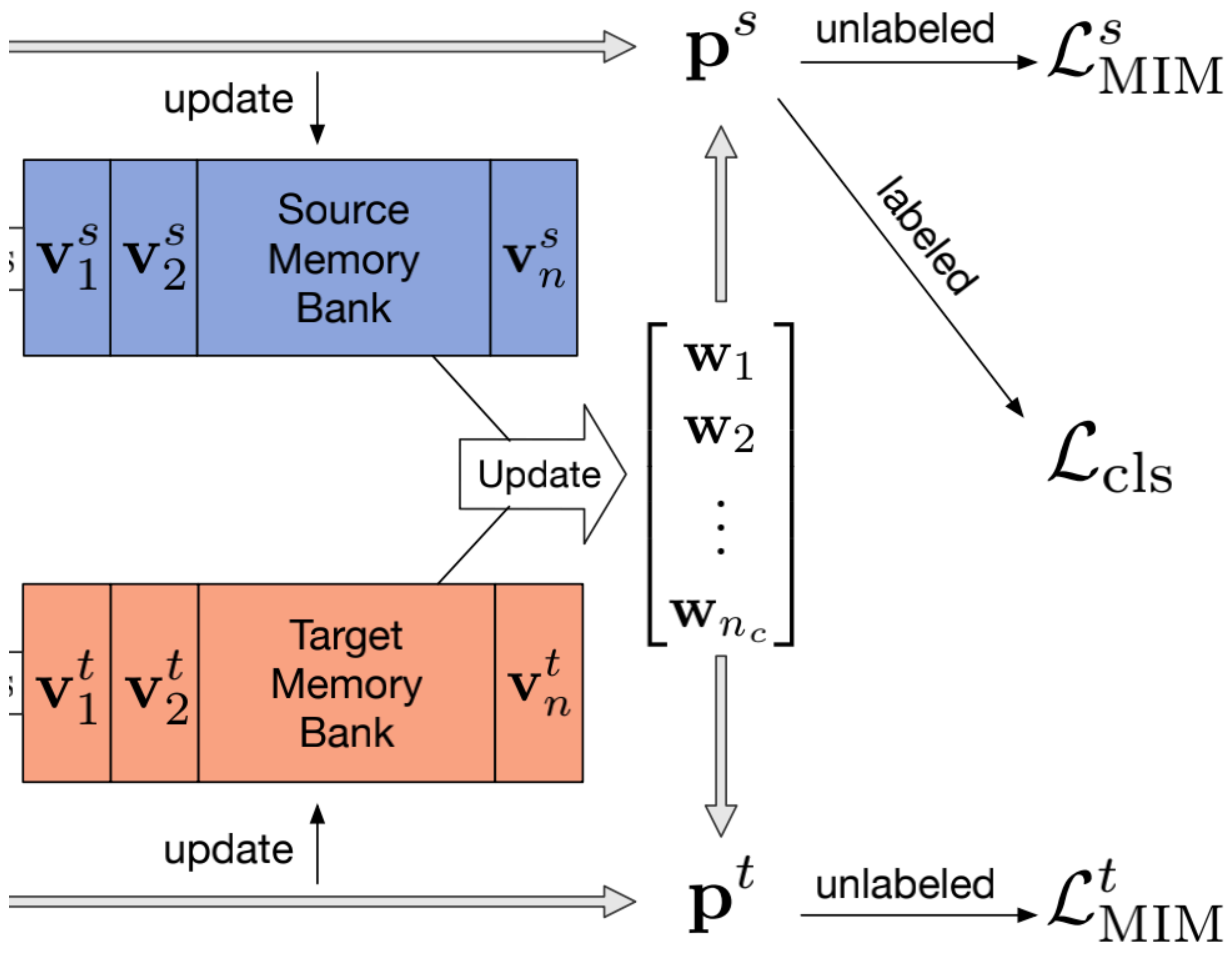
Adaptive Prototype-Classifier Learning

$$\mathbf{p}(\mathbf{x}) = \sigma(\tfrac{1}{T}\dot{\mathbf{W}}^{\mathrm{T}}\mathbf{f}).$$

$$\mathcal{L}_{\mathrm{cls}} = \mathbb{E}_{(\mathbf{x},y)\in\mathcal{D}_s}\mathcal{L}_{CE}(\mathbf{p}(\mathbf{x}), y)$$

$$\hat{\mathbf{w}}_i^s = \frac{1}{|\mathcal{D}_{s+}^{(i)}|}\sum_{\mathbf{x}\in\mathcal{D}_{s+}^{(i)}} \boldsymbol{V}^s(\mathbf{x});\ \hat{\mathbf{w}}_i^t = \frac{1}{|\mathcal{D}_{tu}^{(i)}|}\sum_{\mathbf{x}\in\mathcal{D}_{tu}^{(i)}} \boldsymbol{V}^t(\mathbf{x})$$

$$\mathbf{w}_i = \begin{cases} unit(\hat{\mathbf{w}}_i^s) & \text{if } |\mathcal{D}_{tu}^{(i)}| < t_w \\ unit(\hat{\mathbf{w}}_i^t) & \text{otherwise} \end{cases}$$



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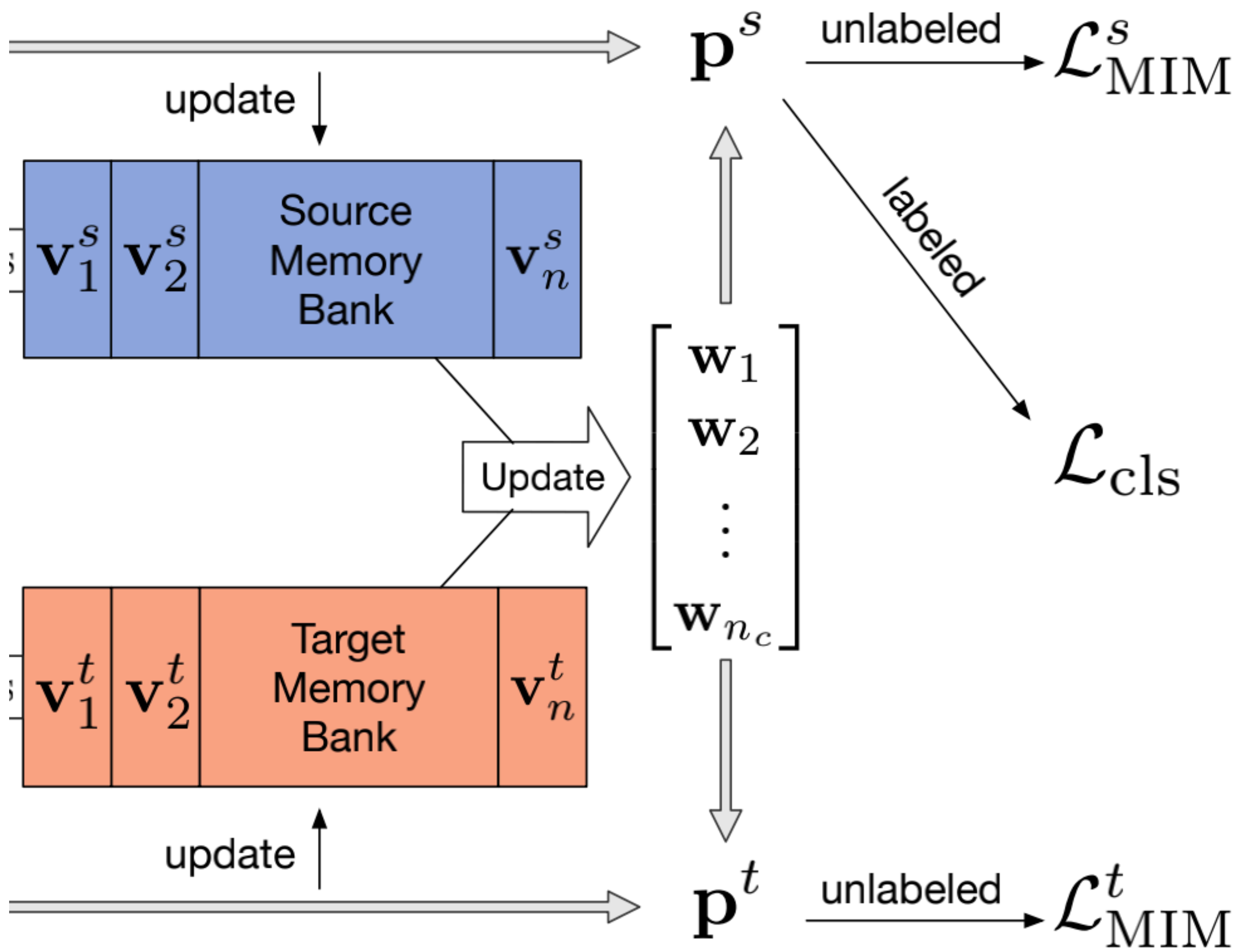
Adaptive Prototype-Classifier Learning

$$\mathcal{I}(y;\mathbf{x}) = \mathcal{H}(\mathbf{p}_0) - \mathbb{E}_{\mathbf{x}}[\mathcal{H}(p(y|\mathbf{x};\theta))],$$

$$\mathcal{L}_{\text{MIM}} = -\mathcal{I}(y;\mathbf{x})$$

$$\mathcal{L}_{PCS} = \mathcal{L}_{\text{cls}} + \lambda_{\text{in}} \cdot \mathcal{L}_{\text{InSelf}} + \lambda_{\text{cross}} \cdot \mathcal{L}_{\text{CrossSelf}} + \lambda_{\text{mim}} \cdot \mathcal{L}_{\text{MIM}}$$



总结

- Cross-domain Self-supervised Learning将SSL扩展到了跨域场景下
- 用Prototype思想代替传统分类器在OOD场景下有更多发挥的空间