领域适配前沿研究

场景、方法与模型选择

大数据系统软件国家工程实验室 游凯超

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自我介绍

- 清华大学软件学院 2016 级
- 大数据系统软件国家工程实验室
- 师从 龙明盛老师
- 研究领域：迁移学习
- 个人主页 youkaichao.github.io

目录

- **领域适配问题概述**

- 部分领域适配
  - Learning to Transfer Examples for Partial Domain Adaptation @CVPR2019

- 通用领域适配
  - Universal Domain Adaptation @CVPR2019

- 领域适配中的模型选择
  - Towards Accurate Model Selection in Deep Unsupervised Domain Adaptation @ICML2019

Learner: $f: x \rightarrow y$ **Distribution:** $(x, y) \sim P(x, y)$

fish

bird

mammal

tree

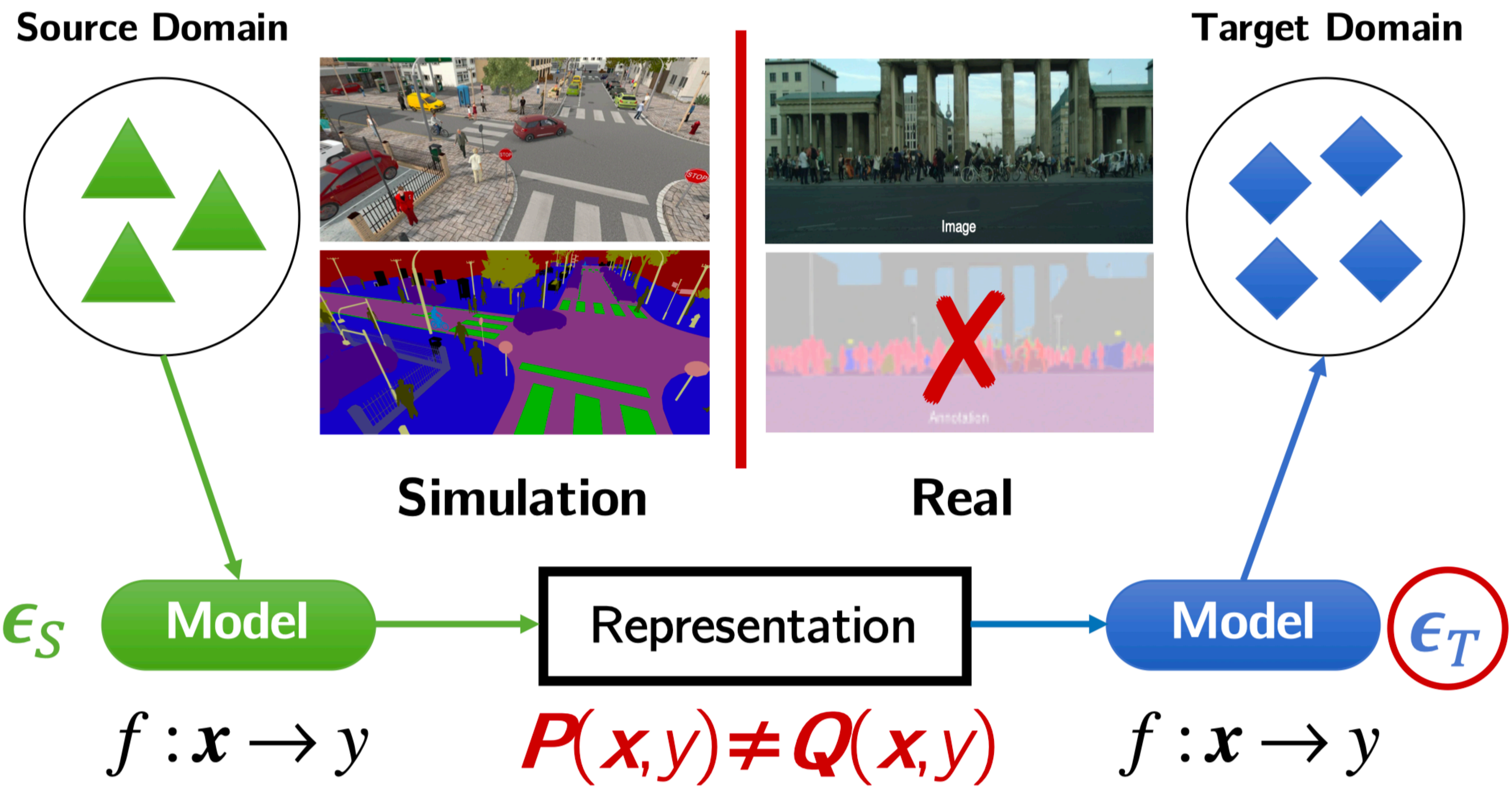
flower

……

Error Bound: $\epsilon_{\text{test}} \leq \hat{\epsilon}_{\text{train}} + \sqrt{\dfrac{\text{complexity}}{n}}$

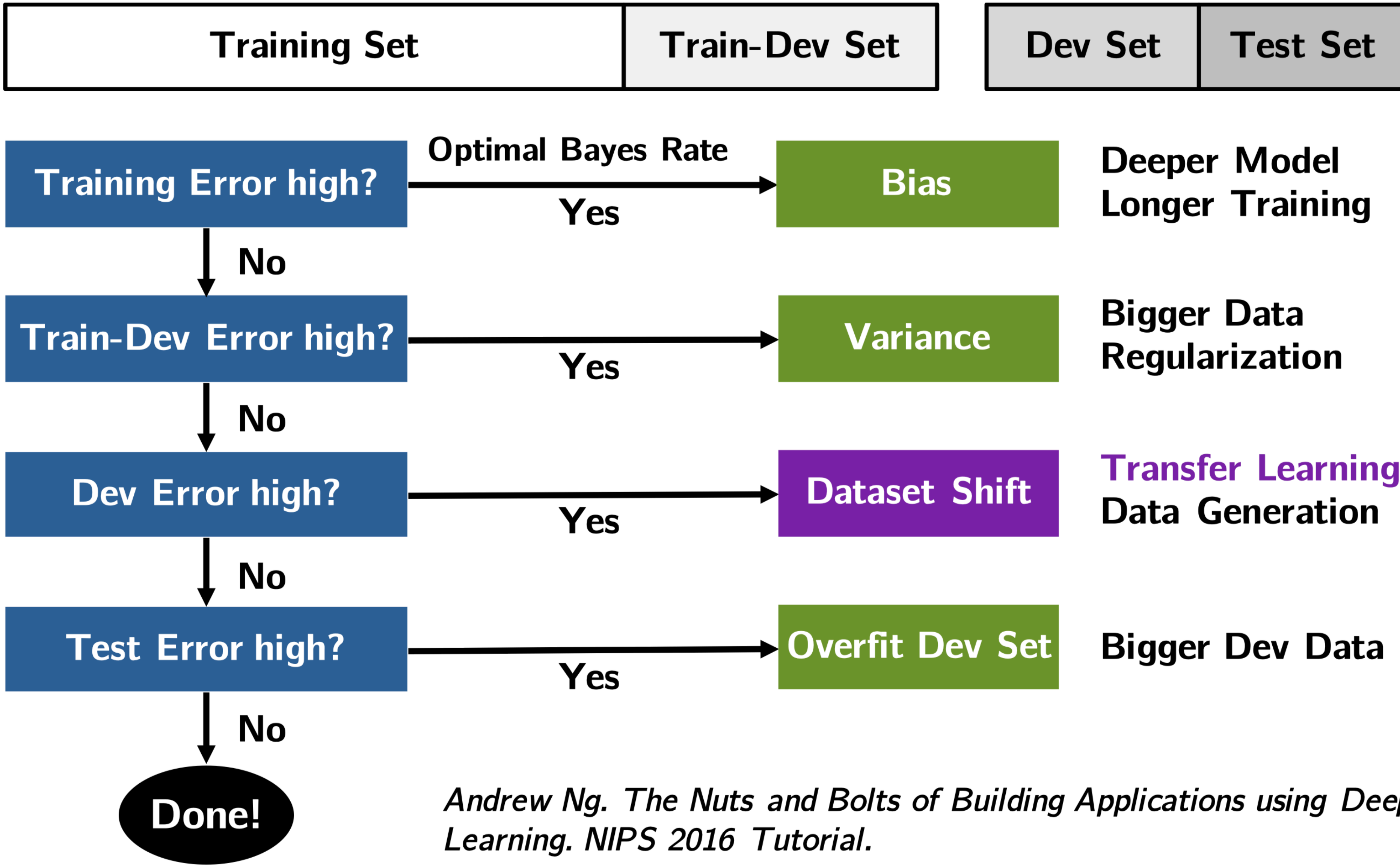
shuffle → 独立同分布（IID, independently and identically distributed）

迁移学习



独立不同分布（IDD, independently and **differently** distributed）

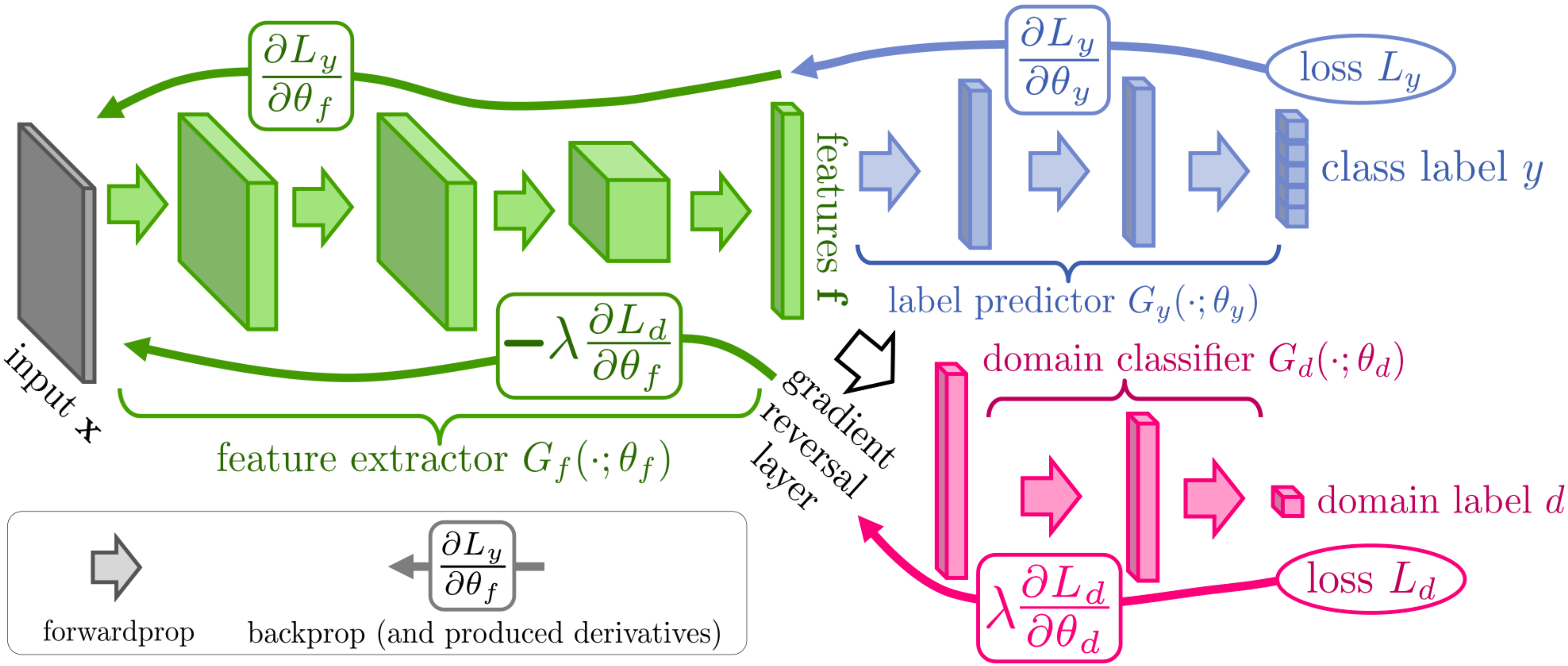
迁移学习



Andrew Ng. The Nuts and Bolts of Building Applications using Deep Learning. NIPS 2016 Tutorial.

领域适配

- 源领域 $\mathcal{D}_s = \{(\mathbf{x}_i^s, \mathbf{y}_i^s)\}_{i=1}^{n_s}$
- 目标领域 $\mathcal{D}_t = \{\mathbf{x}_j^t\}_{j=1}^{n_t}$



Ganin et al, Unsupervised Domain Adaptation by Backpropagation, ICML 2015

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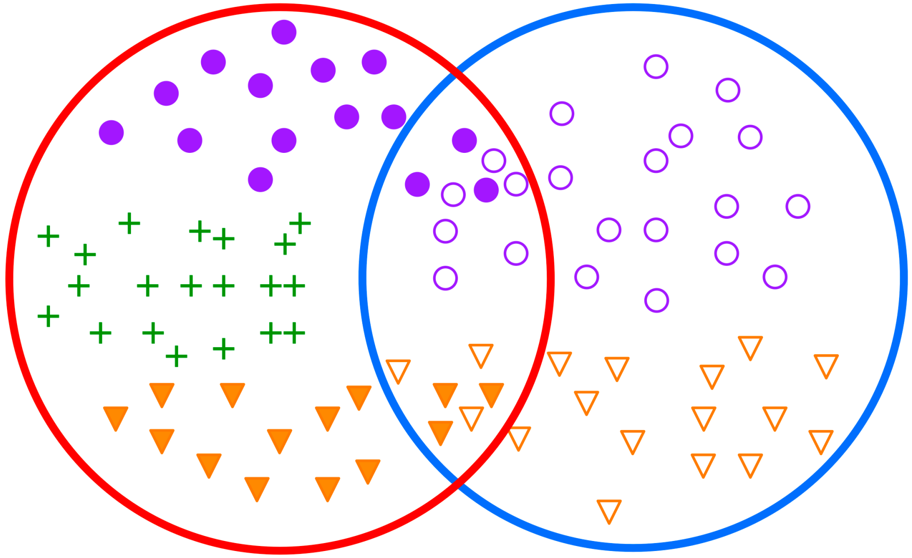
部分领域适配

- 从大领域迁移到小领域

- 识别出小领域的类别 → 转化成标准领域适配问题



部分领域适配

- Leaky-softmax 函数

$$\tilde{\sigma}(\mathbf{z}) = \frac{\exp(\mathbf{z})}{|\mathcal{C}_s| + \sum_{c=1}^{|\mathcal{C}_s|} \exp(z_c)}$$

$$\tilde{G}_d(G_f(\mathbf{x}_i)) = \sum_{c=1}^{|\mathcal{C}_s|} \tilde{G}_y^c(G_f(\mathbf{x}_i))$$

$$\begin{aligned} E_{\tilde{G}_y} = & -\frac{\lambda}{n_s} \sum_{i=1}^{n_s} \sum_{c=1}^{|\mathcal{C}_s|} \Big[y_{i,c}^s \log \tilde{G}_y^c(G_f(\mathbf{x}_i^s)) \\ & + (1 - y_{i,c}^s) \log \left(1 - \tilde{G}_y^c(G_f(\mathbf{x}_i^s))\right) \Big] \end{aligned}$$

$$\begin{aligned} E_{\tilde{G}_d} = & -\frac{1}{n_s} \sum_{i=1}^{n_s} \log \left(\tilde{G}_d(G_f(\mathbf{x}_i^s)) \right) \\ & - \frac{1}{n_t} \sum_{j=1}^{n_t} \log \left(1 - \tilde{G}_d(G_f(\mathbf{x}_j^t))\right) \end{aligned}$$

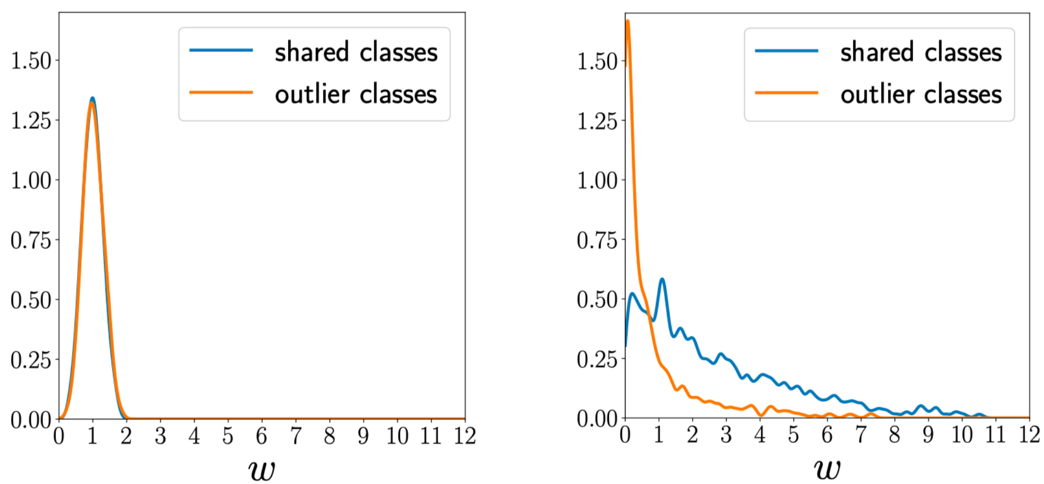
- 判断源领域的样本的类别是否属于目标领域

$$w(\mathbf{x}_i^s) = 1 - \tilde{G}_d(G_f(\mathbf{x}_i^s))$$

- 减少只出现在源领域中的类别的权重

部分领域适配

Method	Office-31						
	A→W	D→W	W→D	A→D	D→A	W→A	Avg
ResNet [15]	75.59±1.09	96.27±0.85	98.09±0.74	83.44±1.12	83.92±0.95	84.97±0.86	87.05±0.94
DAN [21]	59.32±0.49	73.90±0.38	90.45±0.36	61.78±0.56	74.95±0.67	67.64±0.29	71.34±0.46
DANN [10]	73.56±0.15	96.27±0.26	98.73±0.20	81.53±0.23	82.78±0.18	86.12±0.15	86.50±0.20
ADDA [37]	75.67± 0.17	95.38±0.23	99.85±0.12	83.41± 0.17	83.62±0.14	84.25±0.13	87.03±0.16
RTN [22]	78.98±0.55	93.22±0.52	85.35±0.47	77.07±0.49	89.25±0.39	89.46±0.37	85.56±0.47
IWAN [43]	89.15±0.37	99.32±0.32	99.36±0.24	90.45±0.36	95.62±0.29	94.26±0.25	$\boxed{94.69\pm0.31}$
SAN [5]	93.90±0.45	99.32±0.52	99.36±0.12	94.27±0.28	94.15±0.36	88.73±0.44	94.96±0.36
PADA [6]	86.54±0.31	99.32±0.45	**100.00**±.00	82.17±0.37	92.69±0.29	**95.41**±0.33	92.69±0.29
ETN	**94.52**±0.20	**100.00**±.00	**100.00**±.00	**95.03**±0.22	**96.21**±0.27	94.64±0.24	$\boxed{\mathbf{96.73}\pm0.16}$



(a) IWAN (b) ETN

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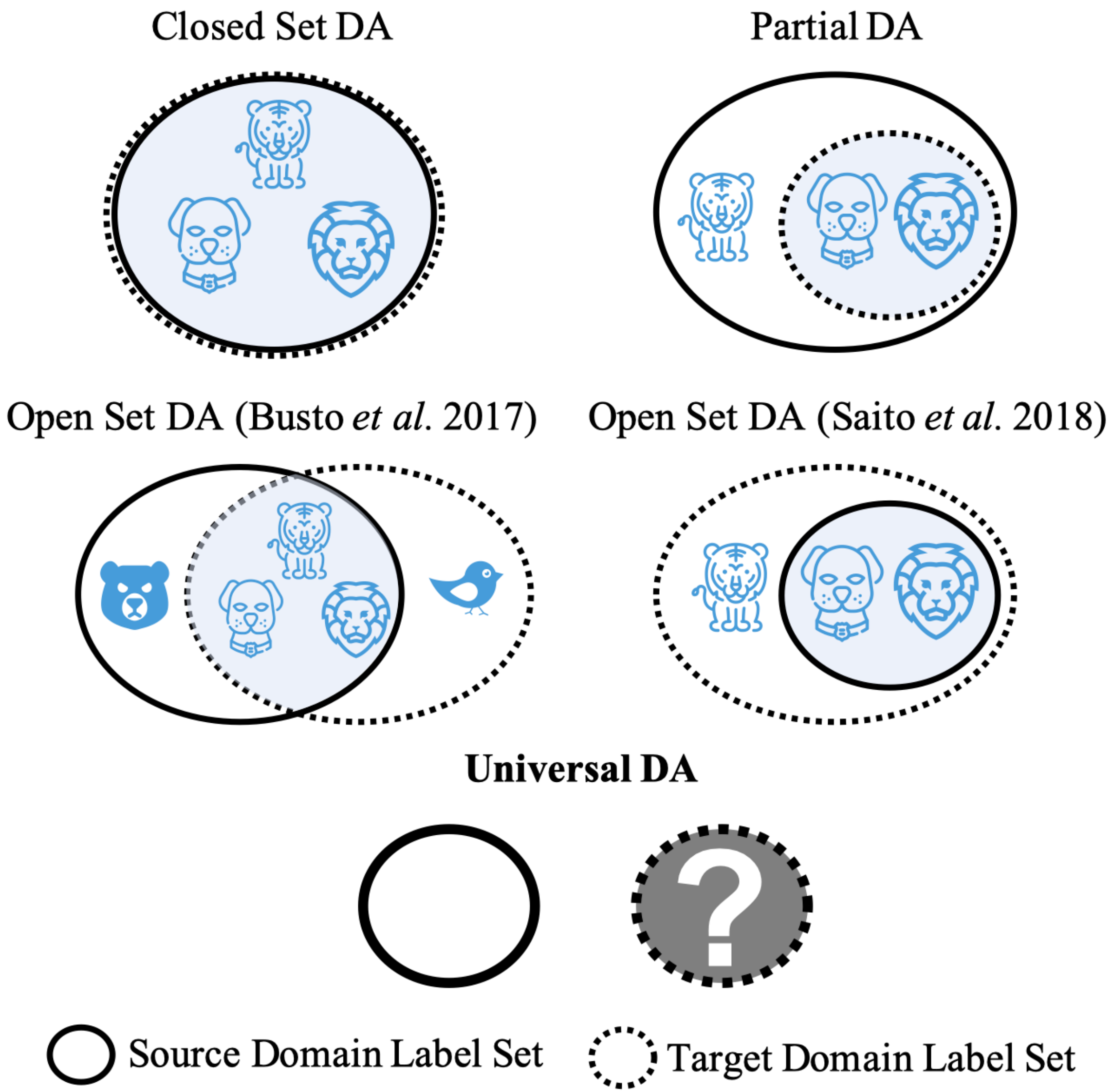
通用领域适配



Closed Set DA
Partial DA
Open Set DA (Busto *et al.* 2017)
Open Set DA (Saito *et al.* 2018)
Universal DA
Source Domain Label Set
Target Domain Label Set

通用领域适配

- 类别差异
  - 目标领域类别未知

    $$\mathcal{C} = \mathcal{C}_s \cap \mathcal{C}_t \quad \overline{\mathcal{C}}_s = \mathcal{C}_s \setminus \mathcal{C} \quad \overline{\mathcal{C}}_t = \mathcal{C}_t \setminus \mathcal{C}$$

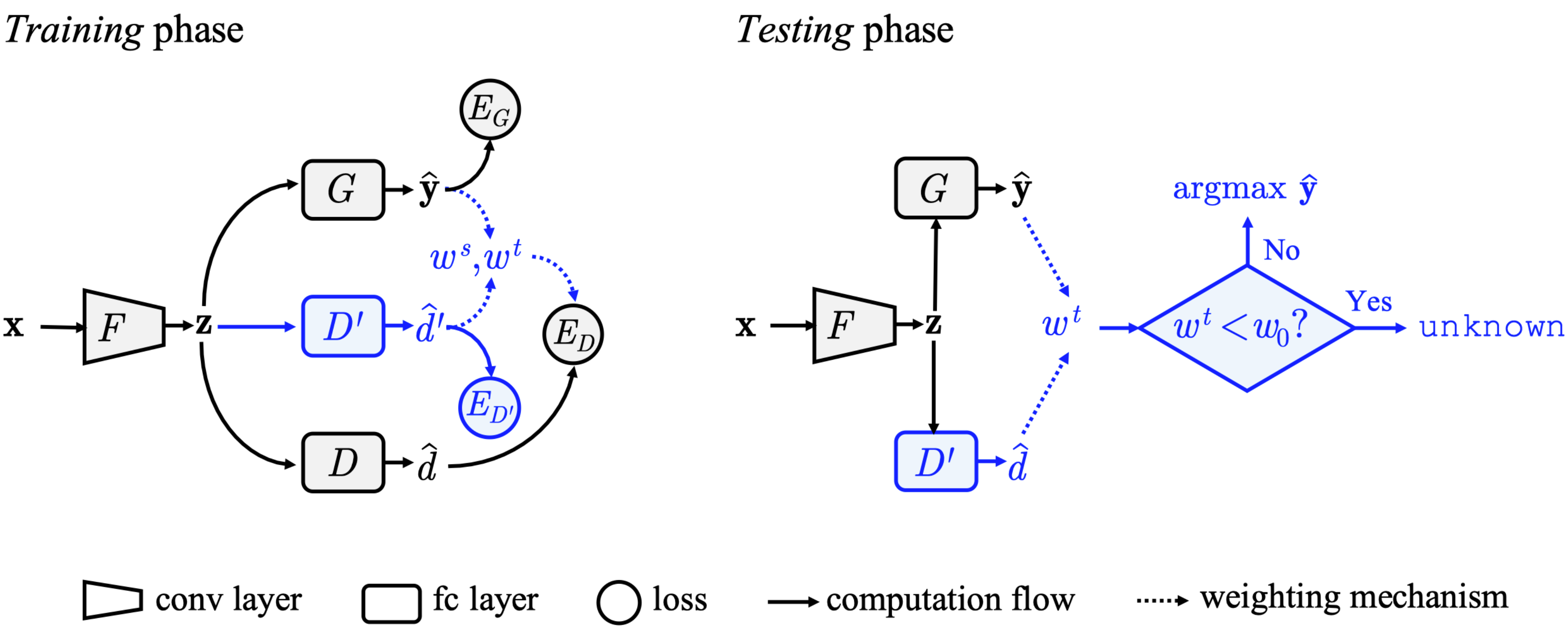
  - 类别公共性

    $$\xi = \frac{|\mathcal{C}_s \cap \mathcal{C}_t|}{|\mathcal{C}_s \cup \mathcal{C}_t|}$$

- 领域差异
  - 标准领域适配做法

- 未知类别
  - 置信度低于一定阈值时认为是未知类别

通用领域适配



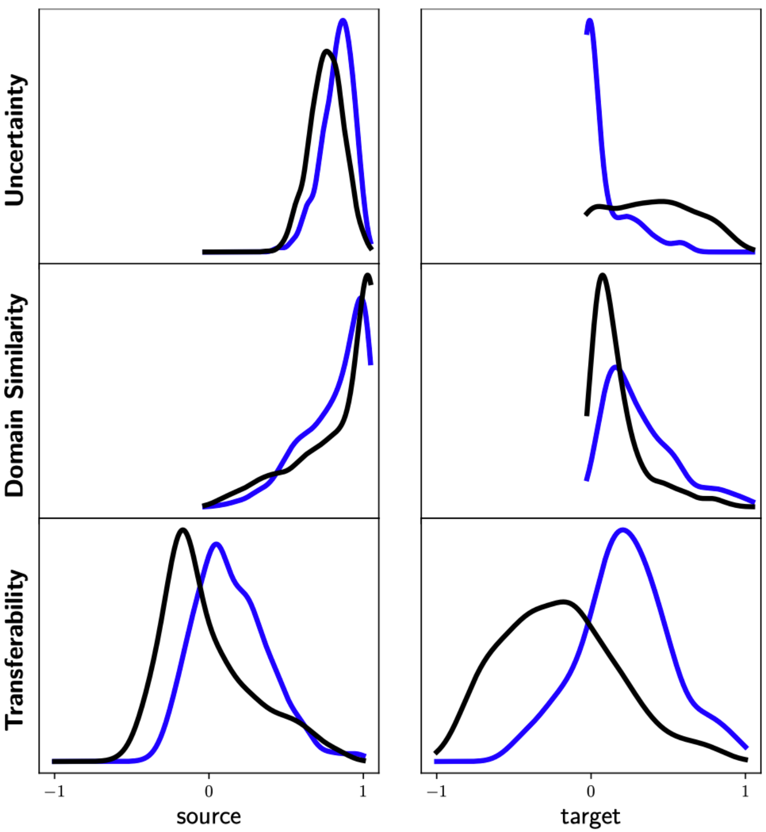
需要合适的计算w的方法

通用领域适配

- 权重计算方式
  - 综合利用熵以及领域判别器的输出
  - 熵越小，越倾向于是源领域的数据
  - 领域判别器的输出越大，越倾向于是源领域的数据

$$w^s(\mathbf{x}) = \frac{H(\hat{\mathbf{y}})}{\log|\mathcal{C}_s|} - \hat{d}'(\mathbf{x})$$

$$w^t(\mathbf{x}) = \hat{d}'(\mathbf{x}) - \frac{H(\hat{\mathbf{y}})}{\log|\mathcal{C}_s|}$$



通用领域适配

Table 1. Average class accuracy (%) of universal domain adaptation tasks on **Office-Home** $(\xi = 0.15)$ dataset (ResNet)

Method	Office-Home												
	Ar → Cl	Ar → Pr	Ar → Rw	Cl → Ar	Cl → Pr	Cl → Rw	Pr → Ar	Pr → Cl	Pr → Rw	Rw → Ar	Rw → Cl	Rw → Pr	Avg
ResNet [13]	59.37	76.58	87.48	69.86	71.11	81.66	73.72	56.30	86.07	78.68	59.22	78.59	73.22
DANN [6]	56.17	81.72	86.87	68.67	73.38	83.76	69.92	56.84	85.80	79.41	57.26	78.26	73.17
RTN [23]	50.46	77.80	86.90	65.12	73.40	85.07	67.86	45.23	85.50	79.20	55.55	78.79	70.91
IWAN [45]	52.55	81.40	86.51	70.58	70.99	85.29	74.88	57.33	85.07	77.48	59.65	78.91	73.39
PADA [45]	39.58	69.37	76.26	62.57	67.39	77.47	48.39	35.79	79.60	75.94	44.50	78.10	62.91
ATI [28]	52.90	80.37	85.91	71.08	72.41	84.39	74.28	57.84	85.61	76.06	60.17	78.42	73.29
OSBP [35]	47.75	60.90	76.78	59.23	61.58	74.33	61.67	44.50	79.31	70.59	54.95	75.18	63.90
UAN w/o d	61.60	81.86	87.67	74.52	73.59	84.88	73.65	57.37	86.61	81.58	62.15	79.14	75.39
UAN w/o y	56.63	77.51	87.61	71.96	69.08	83.18	71.40	56.10	84.24	79.27	60.59	78.35	72.91
UAN	**63.00**	**82.83**	**87.85**	**76.88**	**78.70**	**85.36**	**78.22**	**58.59**	**86.80**	**83.37**	**63.17**	**79.43**	**77.02**

Table 2. Average class accuracy (%) on **Office-31** $(\xi = 0.32)$ **ImageNet-Caltech** $(\xi = 0.07)$ and **VisDA2017** $(\xi = 0.50)$ (ResNet)

Method	Office-31							ImageNet-Caltech		VisDA
	A → W	D → W	W → D	A → D	D → A	W → A	Avg	I → C	C → I	
ResNet [13]	75.94	89.60	90.91	80.45	78.83	81.42	82.86	70.28	65.14	52.80
DANN [6]	80.65	80.94	88.07	82.67	74.82	83.54	81.78	71.37	66.54	52.94
RTN [23]	85.70	87.80	88.91	82.69	74.64	83.26	84.18	71.94	66.15	53.92
IWAN [45]	85.25	90.09	90.00	84.27	84.22	86.25	86.68	72.19	66.48	58.72
PADA [45]	85.37	79.26	90.91	81.68	55.32	82.61	79.19	65.47	58.73	44.98
ATI [28]	79.38	92.60	90.08	84.40	78.85	81.57	84.48	71.59	67.36	54.81
OSBP [35]	66.13	73.57	85.62	72.92	47.35	60.48	67.68	62.08	55.48	30.26
UAN	**85.62**	**94.77**	**97.99**	**86.50**	**85.45**	**85.12**	**89.24**	**75.28**	**70.17**	**60.83**

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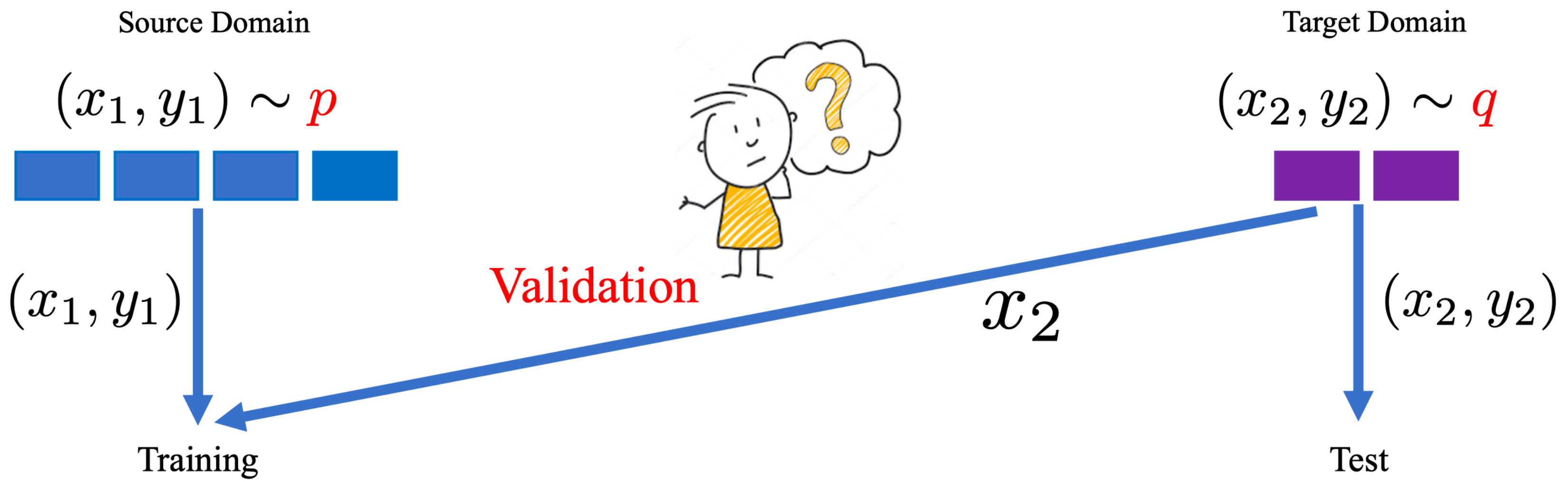
领域适配中的模型选择

- Supervised Learning

$(x_1, y_1) \sim \color{red}{p}$	$(x_2, y_2) \sim \color{red}{p}$	$(x_3, y_3) \sim \color{red}{p}$
Training	Validation	Test

- Semi-Supervised Learning (SSL)?
- Unsupervised Domain Adaptation (UDA)?



领域适配中的模型选择

- 领域适配
  - 有标注源领域 $p(x, y)$
  - 无标注目标领域 $q(x, y)$
  - $p(x, y) \neq q(x, y)$

- 协变量假设

$$p(y|x) = q(y|x), p(x) \neq q(x)$$

$$\Longrightarrow p(x, y) \neq q(x, y)$$

- 目标估计量（验证方法）

$$\mathbb{E}_{\mathbf{x} \sim q} \ell(g(\mathbf{x}), y)$$

领域适配中的模型选择

- 期望无偏

$$
\begin{aligned}
\mathbb{E}_{\mathbf{x}\sim p} w(\mathbf{x})\ell(g(\mathbf{x}), y) &= \mathbb{E}_{\mathbf{x}\sim p} \frac{q(\mathbf{x})}{p(\mathbf{x})}\ell(g(\mathbf{x}), y) \\
&= \int_p \frac{q(\mathbf{x})}{p(\mathbf{x})}\ell(g(\mathbf{x}), y)p(\mathbf{x})\mathrm{d}\mathbf{x} \\
&= \int_q \ell(g(\mathbf{x}), y)q(\mathbf{x})\mathrm{d}\mathbf{x} \\
&= \mathbb{E}_{\mathbf{x}\sim q}\ell(g(\mathbf{x}), y) \\
&= \mathcal{R}(g)
\end{aligned}
$$

领域适配中的模型选择

- 方差控制

$$\mathbb{E}[z] = \zeta, \mathbb{E}[t] = \tau$$

$$z^\star = z + \eta(t - \tau).$$

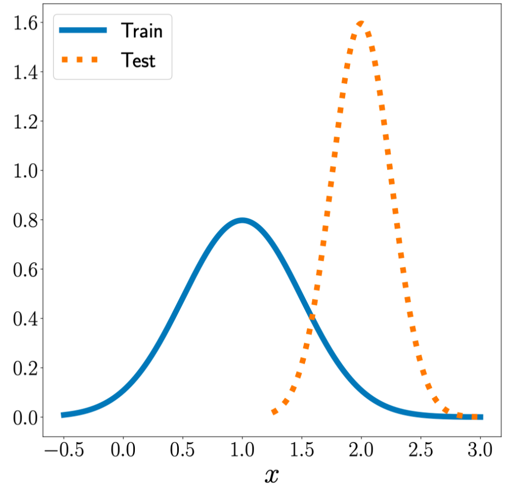
$$\mathbb{E}[z^\star] = \mathbb{E}[z] + \eta\mathbb{E}[t - \tau] = \zeta + \eta(\mathbb{E}[t] - \mathbb{E}[\tau]) = \zeta.$$

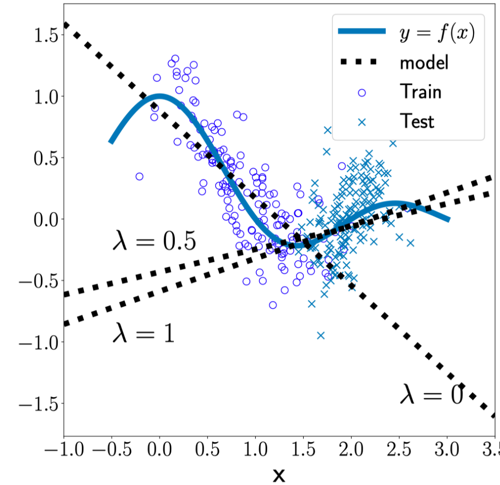
$$\mathrm{Var}[z^\star] = \mathrm{Var}[z + \eta(t - \tau)] = \eta^2\mathrm{Var}[t] + 2\eta\mathrm{Cov}(z, t) + \mathrm{Var}[z]$$

$$\min \mathrm{Var}[z^\star] = {\color{red}(1 - \rho_{z,t}^2)}\mathrm{Var}[z], \text{ when } \hat{\eta} = -\frac{\mathrm{Cov}(z, t)}{\mathrm{Var}[t]}$$

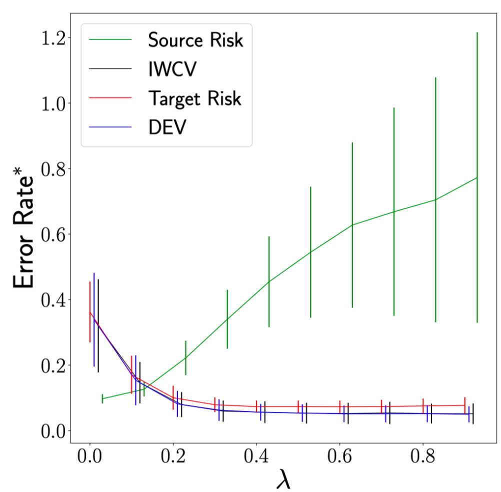
领域适配中的模型选择

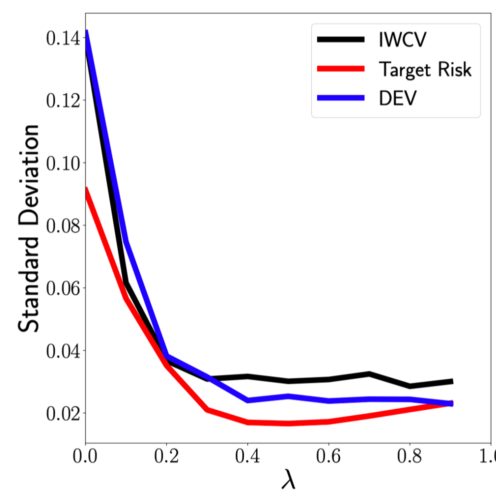
- 在人造数据集上





- 在实际数据集上
  - VisDA/Office/Digits
  - CDAN, MCD, GTA
  - √





代码

- Learning to Transfer Examples for Partial Domain Adaptation @CVPR2019
  - https://github.com/thuml/ETN

- Universal Domain Adaptation @CVPR2019
  - https://github.com/thuml/Universal-Domain-Adaptation

- Towards Accurate Model Selection in Deep Unsupervised Domain Adaptation @ICML2019
  - https://github.com/thuml/Deep-Embedded-Validation

Q&A

游凯超

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