ETH zürich

Domain Generalization and Adaptation using Low Rank Exemplar Classifiers

报告人：李文
苏黎世联邦理工学院 计算机视觉实验室

Outline

- Problems
  - Domain Adaptation and Domain Generalization
- Low Rank Exemplar Classifiers
  - Low Rank Exemplar Classifiers (LRE-SVMs and LRE-LSSVMs)
  - Domain Generalization and Adaptation
- Experiments
  - Domain Generalization
  - Domain Adaptation
- Summary

Outline

- Problems
  - Domain Adaptation and Domain Generalization
- Low Rank Exemplar Classifiers
  - Low Rank Exemplar Classifiers (LRE-SVMs and LRE-LSSVMs)
  - Domain Generalization and Adaptation
- Experiments
  - Domain Generalization
  - Domain Adaptation
- Summary

Domain Adaptation: Examples

- Examples

Web <-> Consumer

Sketch <-> Photo

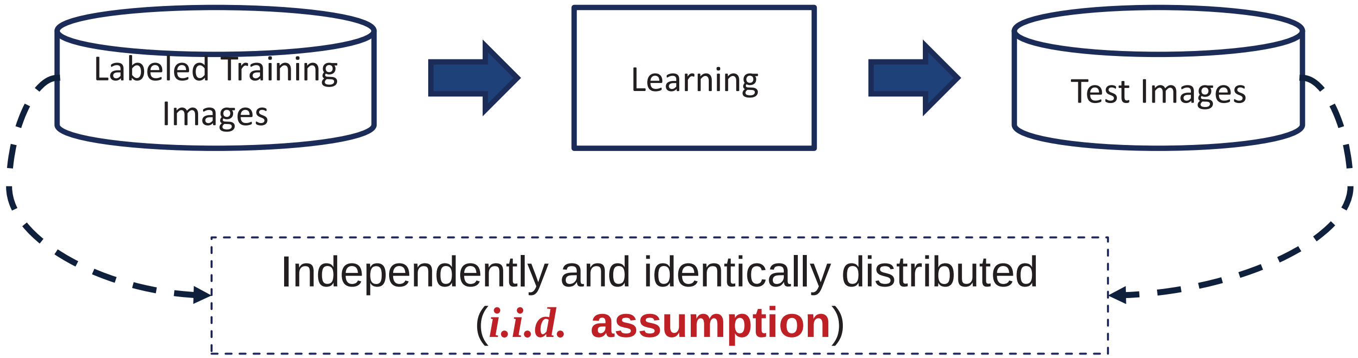
Synthetic <-> Real

Fall <-> Winter

K. Saenko, B. Kulis, M. Fritz and T. Darrell. Adapting Visual Category Models to New Domains. In ECCV, 2010.
T. Kim M. Cha, H. Kim, J. Lee J. Kim. Learning to Discover Cross-Domain Relations with Generative Adversarial Networks. In ICCV 2017
X. Peng, K. Saenko. Synthetic to Real Adaptation with Generative Correlation Alignment Networks. Arxiv 1701.05524, 2017.
J. Hoffman, D. Wang, F. Yu, T. Darrel. FCNs in the Wild: Pixel-level Adversarial and Constraint-based Adaptation. Arxiv 1612.02649, 2016。

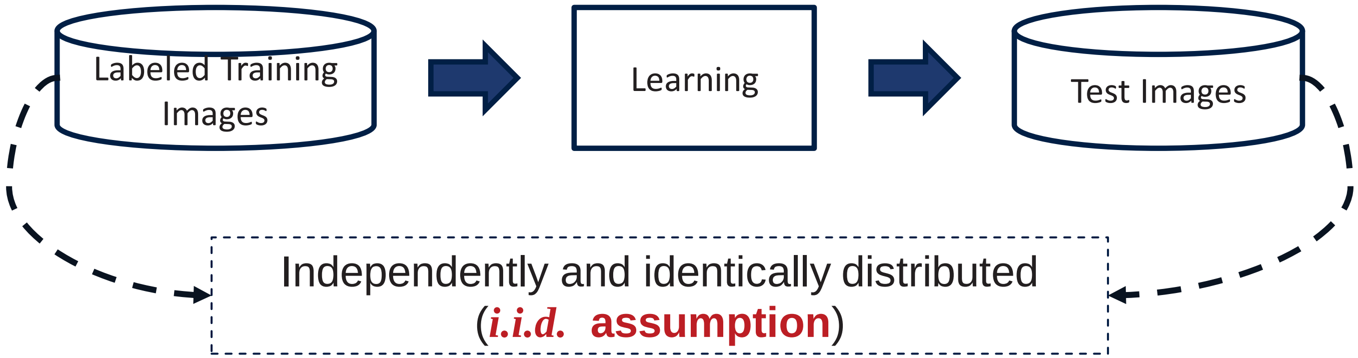
Visual Recognition System

- Visual Recognition System



Visual Recognition System

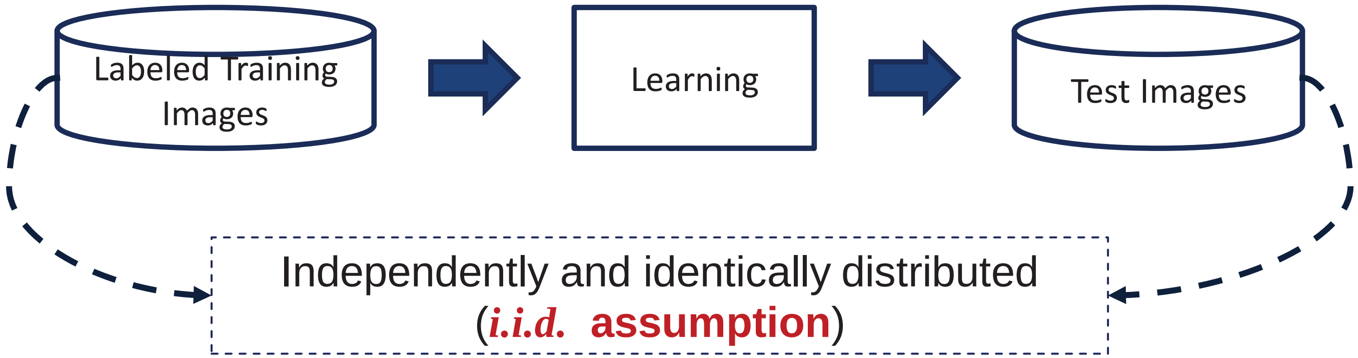
- Visual Recognition System



- "*i.i.d*" assumption may not always hold
  - Data collection bias is inevitable
  - The real-world test data changes easily

Visual Recognition System

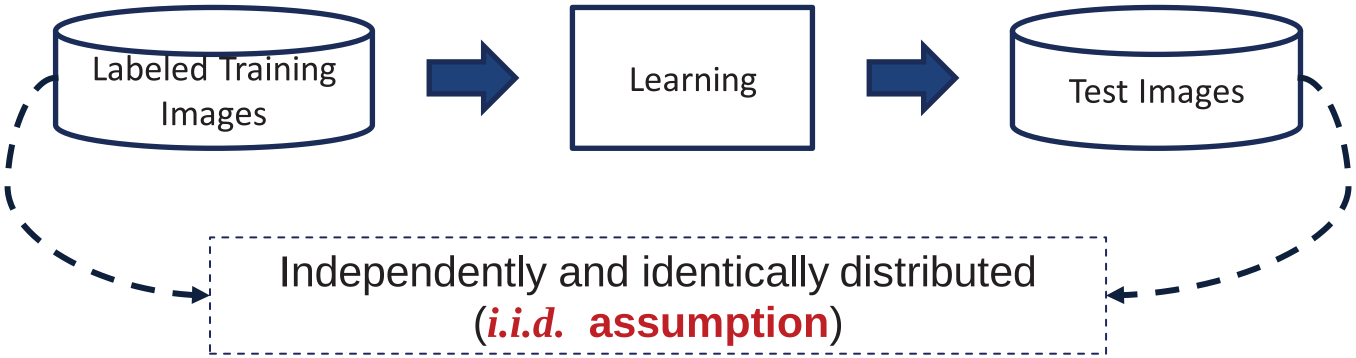
- Visual Recognition System



- "*i.i.d*" assumption may not always hold
  - Data collection bias is inevitable
  - The real-world visual data varies a lot

Visual Recognition System

- Visual Recognition System



- "*i.i.d*" assumption may not always hold
  - **Data collection bias is inevitable**
  - The real-world visual data varies a lot

Dataset Bias

- **Name that dataset!**

Caltech-101 ____ Tiny ____

LabelMe ____ 15 Scenes ____

MSRC ____ Corel ____

COIL-100 ____ Caltech-256 ____

UIUC____ PASCAL 07 ____

ImageNet ____ SUN09 ____

A. Torralba, and A. Efros. Unbiased Look at Dataset Bias. In CVPR 2011.

Dataset Bias

- **Name that dataset!**

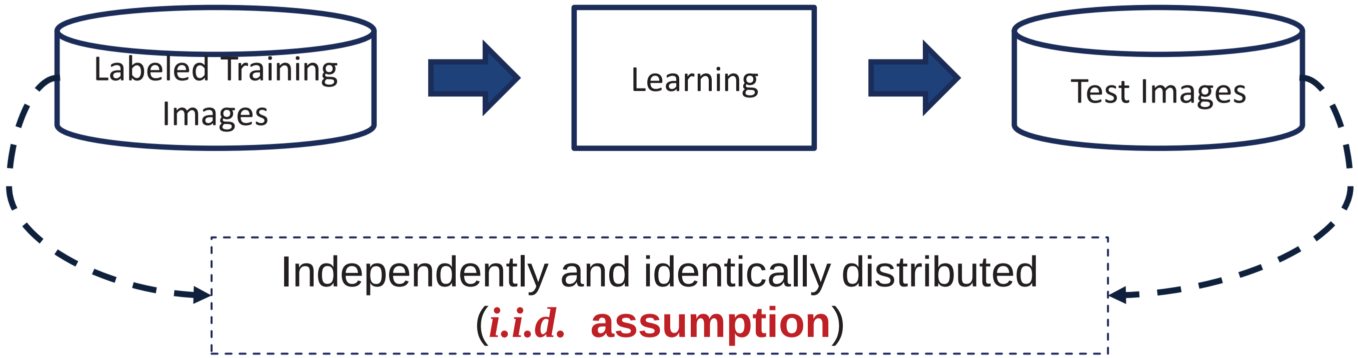
Caltech-101 __1__	Tiny Images __4__
LabelMe __7__	15 Scenes __9__
MSRC __3__	Corel __10__
COIL-100 __12__	Caltech-256 __11__
UIUC__2__	PASCAL 07 __6__
ImageNet __5__	SUN09 __8__

Current vision datasets contains their own **biases**, regardless of their semantic categories.

A. Torralba, and A. Efros. Unbiased Look at Dataset Bias. In CVPR 2011.

Visual Recognition System

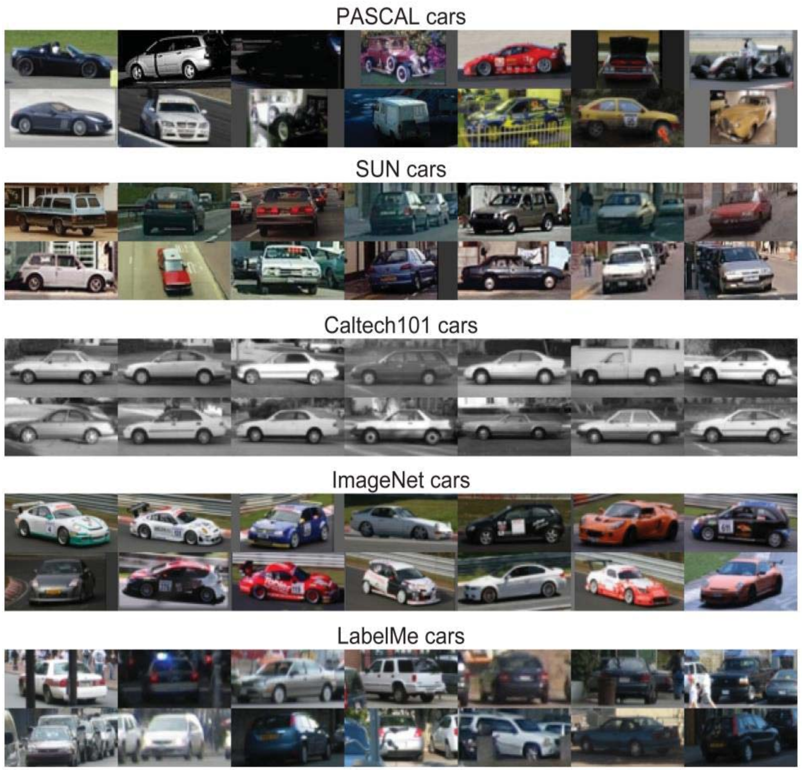
- Visual Recognition System



- "*i.i.d*" assumption may not always hold
  - Data collection bias is inevitable
  - **The real-world visual data varies a lot**

Dataset Bias

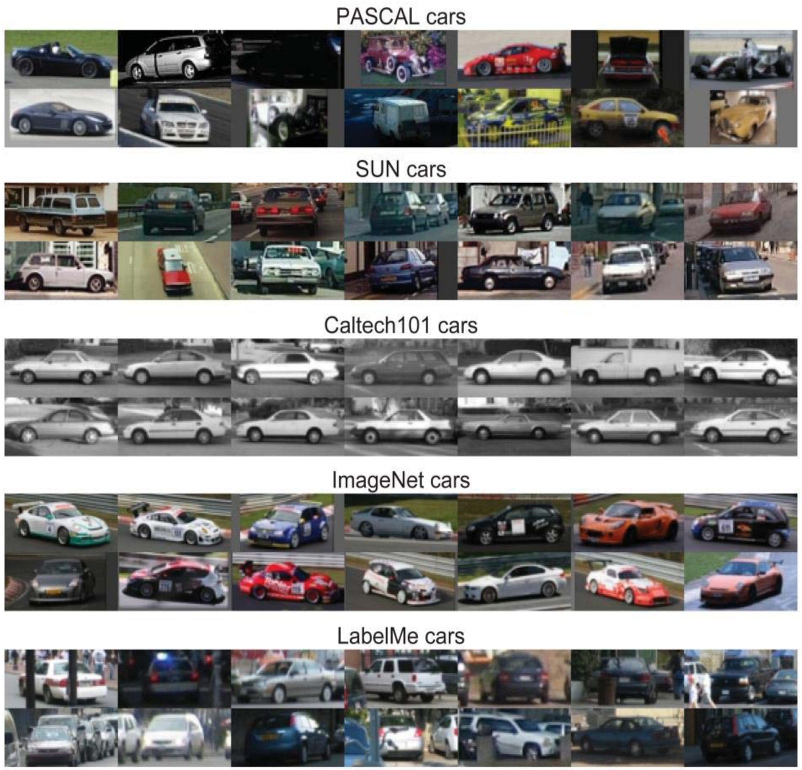
- **Real-world objects vary a lot**



A. Torralba, and A. Efros. Unbiased Look at Dataset Bias. In CVPR 2011.

Dataset Bias

- ## Impact of Dataset Bias



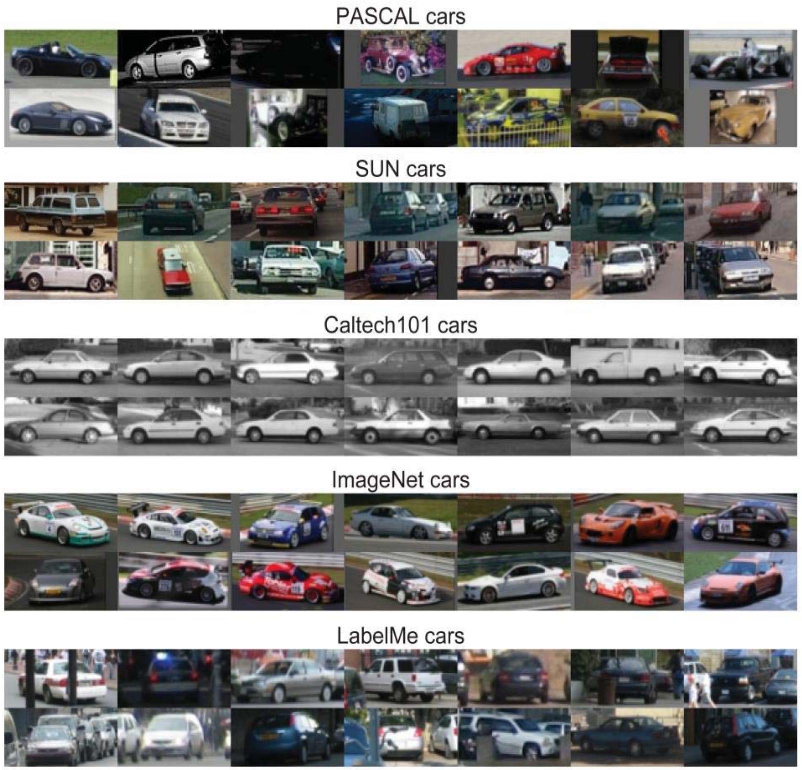
Cross-dataset Classification Performance
"*Car*" Classification

	S	L	P	I	C	M	drop
S	**28.2**	29.5	16.3	14.6	16.9	21.9	30%
L	14.7	**34.0**	16.7	22.9	43.6	24.5	28%
P	10.1	25.5	**35.2**	43.9	44.2	39.4	7%
I	11.4	29.6	36.0	**57.4**	52.3	42.7	40%
C	7.5	31.1	19.5	33.1	**96.9**	42.1	73%
M	9.3	27.0	24.9	32.6	40.3	**68.4**	61%

A. Torralba, and A. Efros. Unbiased Look at Dataset Bias. In CVPR 2011.

Dataset Bias

▪ Impact of Dataset Bias



Cross-dataset Classification Performance
"*Car*" Classification

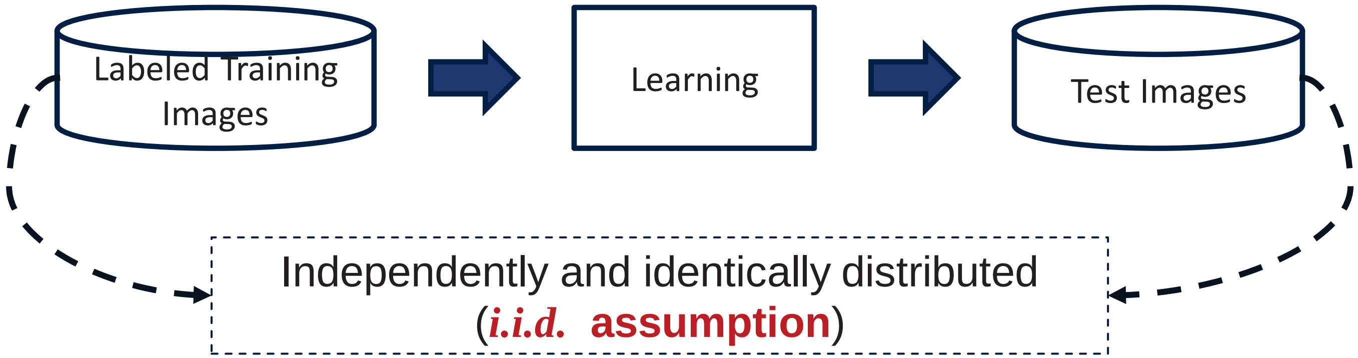
	S	L	P	I	C	M	drop
S	**28.2**	29.5	16.3	14.6	16.9	21.9	30%
L	14.7	**34.0**	16.7	22.9	43.6	24.5	28%
P	10.1	25.5	**35.2**	43.9	44.2	39.4	7%
I	11.4	29.6	36.0	**57.4**	52.3	42.7	40%
C	7.5	31.1	19.5	33.1	**96.9**	42.1	73%
M	9.3	27.0	24.9	32.6	40.3	**68.4**	61%

Dataset bias harms the **cross-dataset classification** performance.

A. Torralba, and A. Efros. Unbiased Look at Dataset Bias. In CVPR 2011.

Visual Recognition System

- Visual Recognition System



- "*i.i.d*" assumption may not always hold
  - Data collection bias is inevitable
  - The real-world visual data varies a lot
  - **Re-collect data? Cost money and time!**

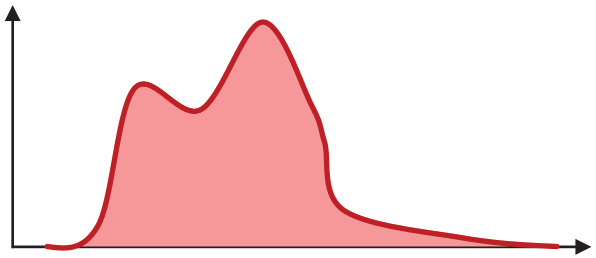
Domain Adaptation: Problem Description

- Domain Adaptation

bike:

cup:

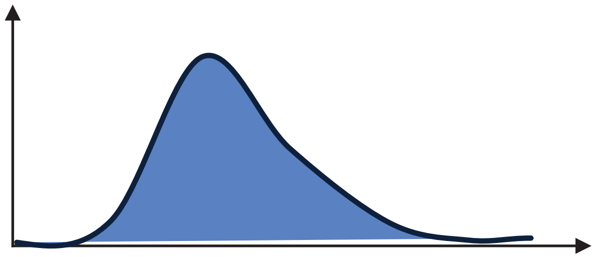
Source Domain



$P_s(\mathbf{x}, y)$

$$\boxed{P_s(\mathbf{x}, y) \neq P_t(\mathbf{x}, {\color{red}y})}$$

Target Domain



$P_t(\mathbf{x}, {\color{red}y})$

Domain Adaptation: Problem Description

- (Unsupervised) Domain Adaptation
  - Source domain: $\{(\mathbf{x}_i^s, y_i^s)|_{i=1}^{n_s}\}$
  - Target domain: $\{\mathbf{x}_i^t|_{i=1}^{n_t}\}$
  - Data distribution mismatch: $P_s(\mathbf{x}^s, y^s) \neq P_t(\mathbf{x}^t, y^t)$ or $P_s(\mathbf{x}^s) \neq P_t(\mathbf{x}^t)$
  - Feature space and label space are consistent: $\mathbf{x}^s, \mathbf{x}^t \in \mathbb{R}^D \quad y^s, y^t \in \mathcal{L}$

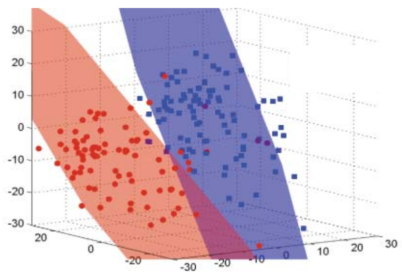
Domain Adaptation: Problem Description

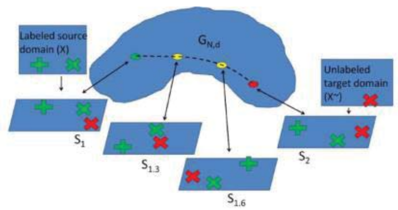
- (Unsupervised) Domain Adaptation
  - Source domain: $\{(\mathbf{x}_i^s, y_i^s)|_{i=1}^{n_s}\}$
  - Target domain: $\{\mathbf{x}_i^t|_{i=1}^{n_t}\}$
  - Data distribution mismatch: $P_s(\mathbf{x}^s, y^s) \neq P_t(\mathbf{x}^t, y^t)$ or $P_s(\mathbf{x}^s) \neq P_t(\mathbf{x}^t)$
  - Feature space and label space are consistent: $\mathbf{x}^s, \mathbf{x}^t \in \mathbb{R}^D \quad y^s, y^t \in \mathcal{L}$

- Related Concepts:
  - Transfer Learning
    - Label space are different (cross-task)
  - Heterogeneous Domain Adaptation
    - Feature space are different (cross-feature)

Domain Adaptation: Related Works

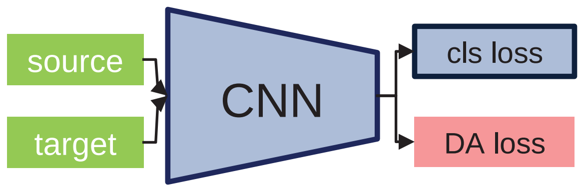
- Feature-Level Methods
  - Strategy: $P_s(\mathbf{x}^s) \neq P_t(\mathbf{x}^t) \Rightarrow P_s(g(\mathbf{x}^s)) \approx P_t(\mathbf{x}^t)$
- Traditional methods
  - For example, TCA, SGF, GFK, SA, DIP, based on subspace and manifold principles.





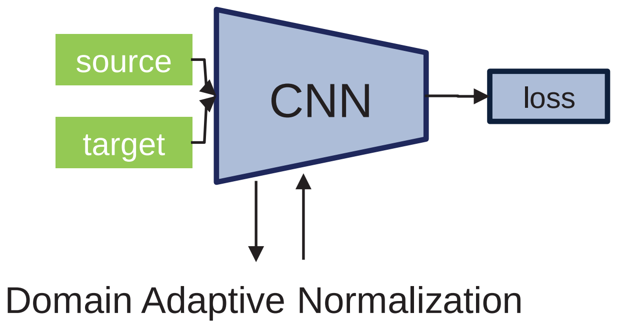
Domain Adaptation: Related Works

- Feature-Level Methods
  - Strategy: $P_s(\mathbf{x}^s) \neq P_t(\mathbf{x}^t) \Rightarrow P_s(g(\mathbf{x}^s)) \approx P_t(\mathbf{x}^t)$
- Traditional methods
  - For example, TCA, SGF, GFK, SA, DIP, based on subspace and manifold principles.
- CNN based methods
  - Top-down: DAN, JAN, GRL, DRCN,
  - Bottom-Up: AdaBN, AutoDIAL



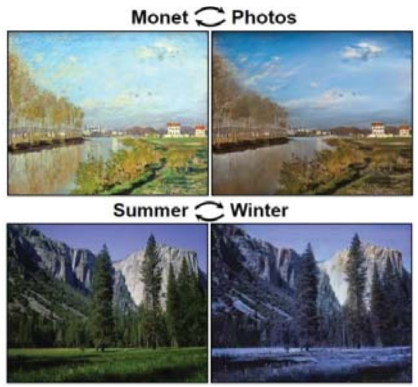
Domain Adaptation: Related Works

- Feature-Level Methods
  - Strategy: $P_s(\mathbf{x}^s) \neq P_t(\mathbf{x}^t) \Rightarrow P_s(\mathrm{g}(\mathbf{x}^s)) \approx P_t(\mathbf{x}^t)$
- Traditional methods
  - For example, TCA, SGF, GFK, SA, DIP, based on subspace and manifold principles.
- CNN based methods
  - Top-down: DAN, JAN, GRL, DRCN,
  - Bottom-Up: AdaBN, AutoDIAL



Domain Adaptation: Related Works

- Feature-Level Methods
  - Strategy: $P_s(\mathbf{x}^s) \neq P_t(\mathbf{x}^t) \Rightarrow P_s(g(\mathbf{x}^s)) \approx P_t(\mathbf{x}^t)$
- Traditional methods
  - For example, TCA, SGF, GFK, SA, DIP, based on subspace and manifold principles.
- CNN based methods
  - Top-down: DAN, JAN, GRL, DRCN,
  - Bottom-Up: AdaBN, AutoDIAL
- Image-Level
  - CycleGAN, DiscoGAN, DualGAN, UNIT



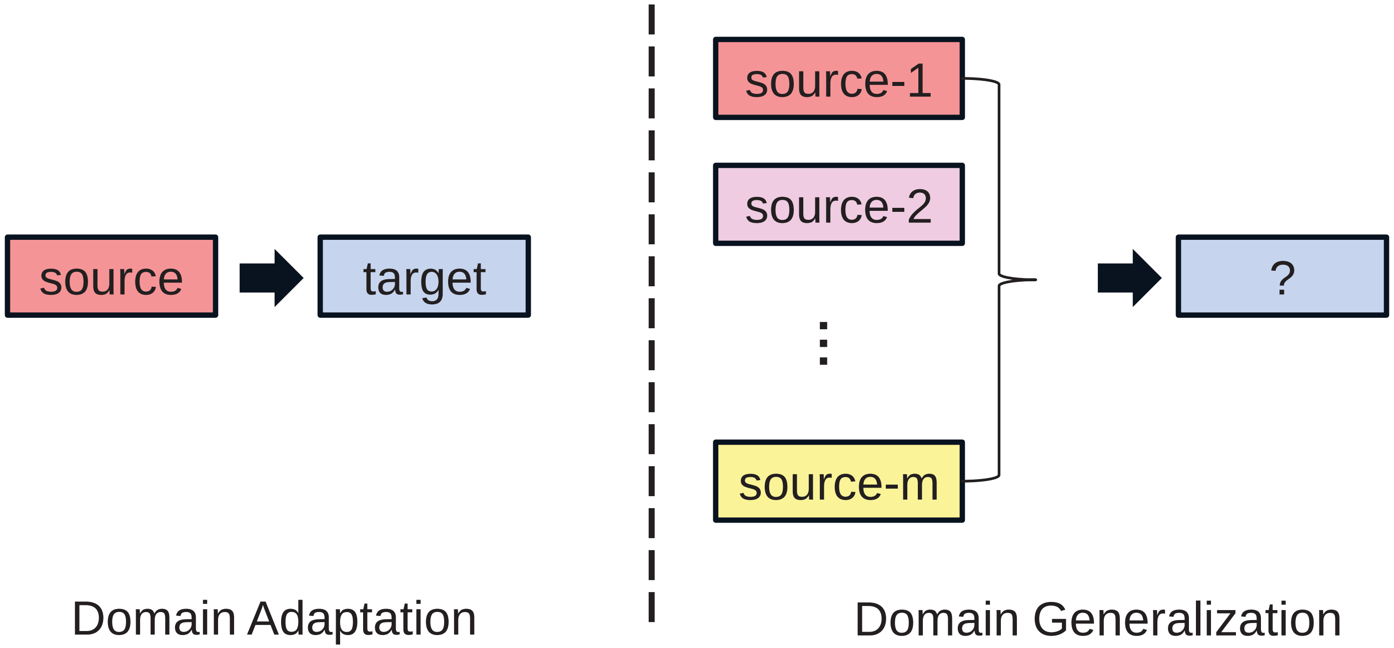
ETH zürich

Domain Adaptation: Related Works

- Instance-Level Methods
  - Strategy: $P_s(\mathbf{x}^s) \neq P_t(\mathbf{x}^t)$ ➡ $g(\mathbf{x}^s)P_s(\mathbf{x}^s) \neq P_t(\mathbf{x}^t)$
- Methods
  - KMM, DA-SVM
- Deep Methods
  - Transductive DA, Associative DA

Domain Generalization

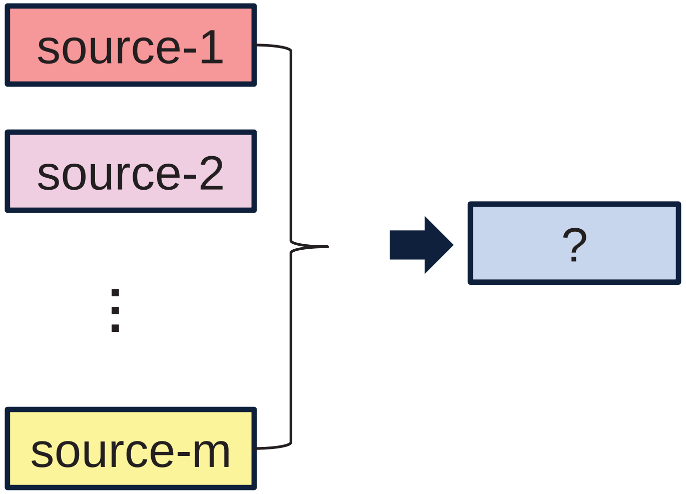
- What if we do not know about target domain?
  - Multi-source domain generalization



K. Muandet, D. Balduzzi, B. Scholkopf. Domain generalization via invariant feature representation. In ICML, 2013.

Domain Generalization

- Problems
  - Real world domains are not distinctive



Domain Generalization

- Problems
  - A more common case, single but diverse source domain

source domain

source-1

source-2

⋮

source-m

→ ?

Domain Generalization

- Latent Domain Discovery
  - Partition one source domain into multiple latent domains

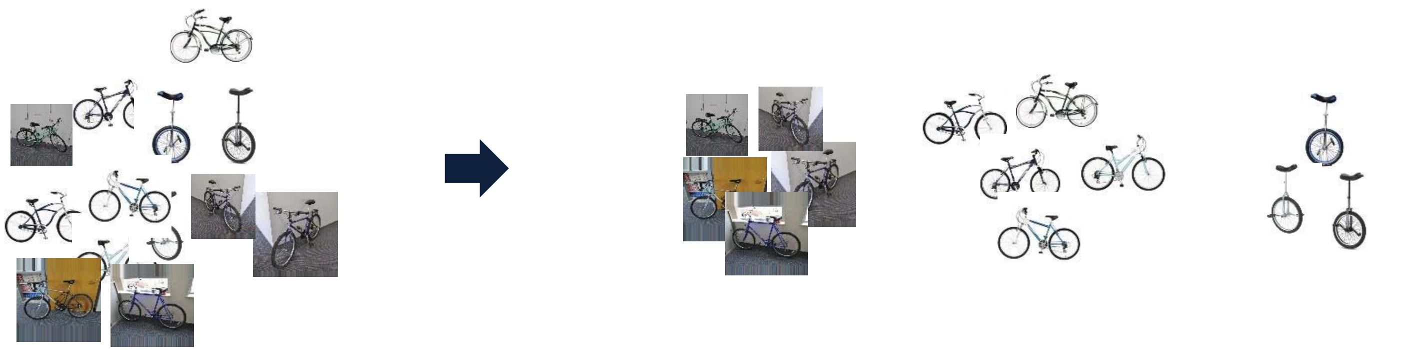
source domain latent-1 latent-2 latent-3

J. Hoffman, B. Kulis, T. Darrell, K. Saenko. Discovering Latent Domains For Multisource Domain Adaptation. In ECCV 2012.

B. Gong, K. Grauman, and F. Sha. Reshaping Visual Datasets for Domain Adaptation. In NIPS 2013

Domain Generalization

- Latent Domain Discovery
  - Partition one source domain into multiple latent domains



source domain

latent-1 latent-2 latent-3

- **How many** latent domains?
- Non-trivial to **disentangle** correlated variances

J. Hoffman, B. Kulis, T. Darrell, K. Saenko. Discovering Latent Domains For Multisource Domain Adaptation. In ECCV 2012.

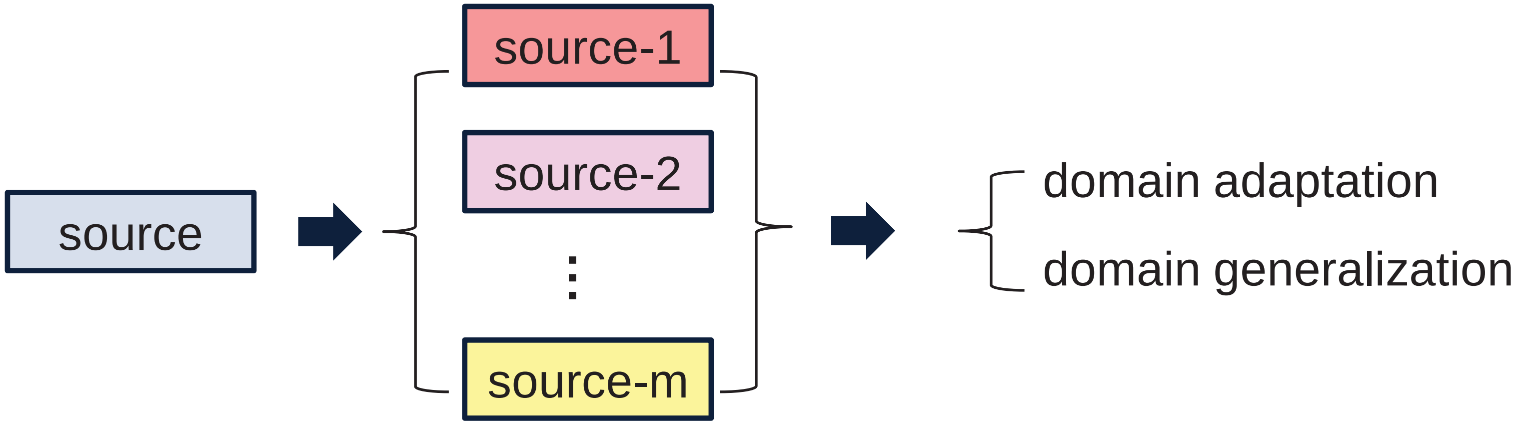
B. Gong, K. Grauman, and F. Sha. Reshaping Visual Datasets for Domain Adaptation. In NIPS 2013

Outline

- Problems
  - Domain Adaptation and Domain Generalization
- Low Rank Exemplar Classifiers
  - Low Rank Exemplar Classifiers (LRE-SVMs and LRE-LSSVMs)
  - Domain Generalization and Adaptation
- Experiments
  - Domain Generalization
  - Domain Adaptation
  - Evolving Domain Adaptation
- Conclusions and Future Work

Low-Rank Exemplar Classifiers for Domain Generalization

- One-stage Approach



Low-Rank Exemplar Classifiers for Domain Generalization

- One-stage Approach

source → domain adaptation / domain generalization