Towards Visual Recognition *in the Wild*: *Long-Tailed* Sources & Open *Compound* Targets

Boqing Gong
Google

Learning To Detect Unseen Object Classes by Between-Class Attribute Transfer

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CVPR 2009

50 classes

85 attributes

Abstract

We study the problem of object classification when training and test classes are disjoint, i.e. *no training examples of the target classes are available. This setup has hardly been studied in computer vision research, but it is the rule rather than the exception, because the world contains tens of thousands of different object classes and for only a very few of them image, collections have been formed and annotated with suitable class labels.*

In this paper, we tackle the problem by introducing attribute-based classification. *It performs object detection*

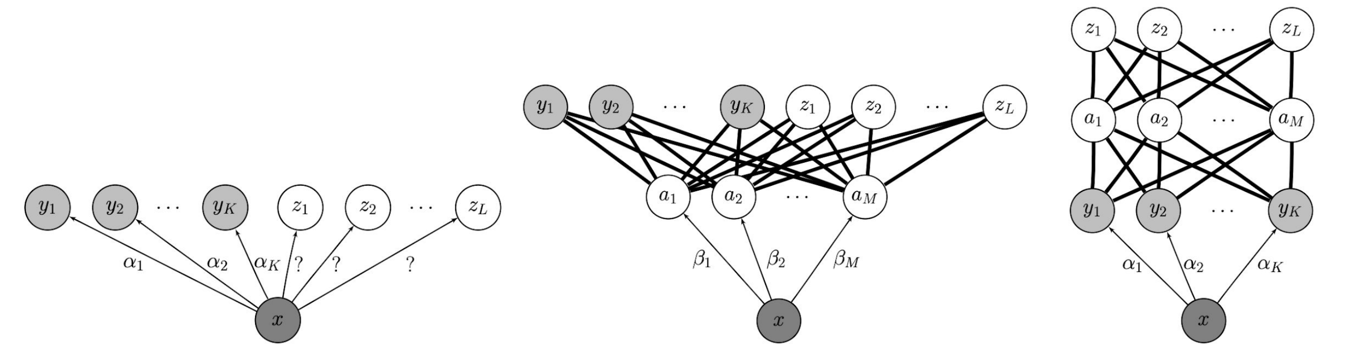
otter

black: yes
white: no
brown: yes
stripes: no
water: yes
eats fish: yes

polar bear

black: no
white: yes
brown: no
stripes: no
water: yes
eats fish: yes

zebra



(a) Flat multi-class classification (b) Direct attribute prediction (DAP) (c) Indirect attribute prediction (IAP)

Abstract form: *unsupervised* domain adaptation (DA)

Setup

Source domain (with labeled data)

$$D_{\mathcal{S}} = \{(x_m, y_m)\}_{m=1}^{\mathsf{M}} \sim \boxed{P_{\mathcal{S}}(X, Y)}$$

Target domain (no labels for training)

$$D_{\mathcal{T}} = \{(x_n, \textbf{?}\ \}_{n=1}^{\mathsf{N}} \sim \boxed{P_{\mathcal{T}}(X, Y)}$$

Different distributions

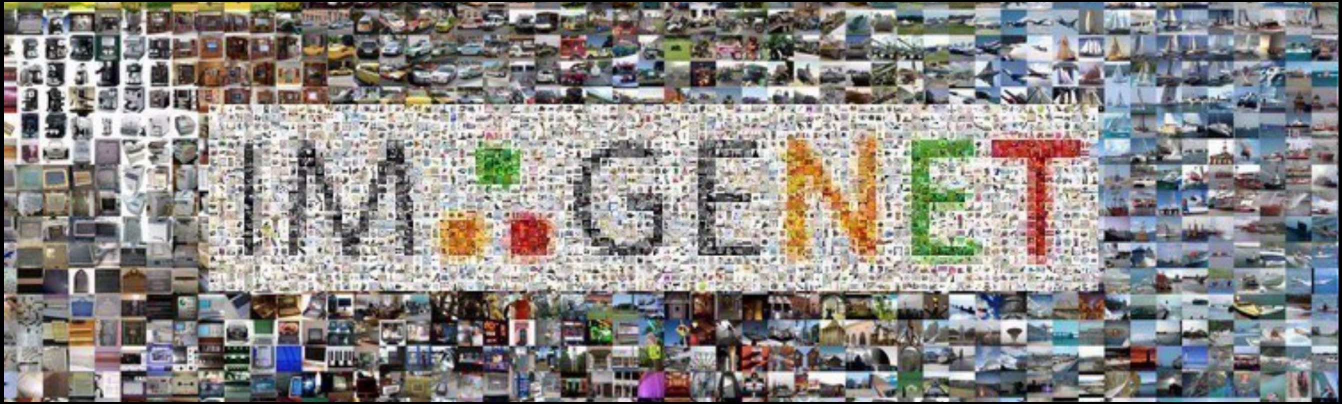
Objective

Learn models to work well on target

Kernel Methods for Unsupervised Domain Adaptation

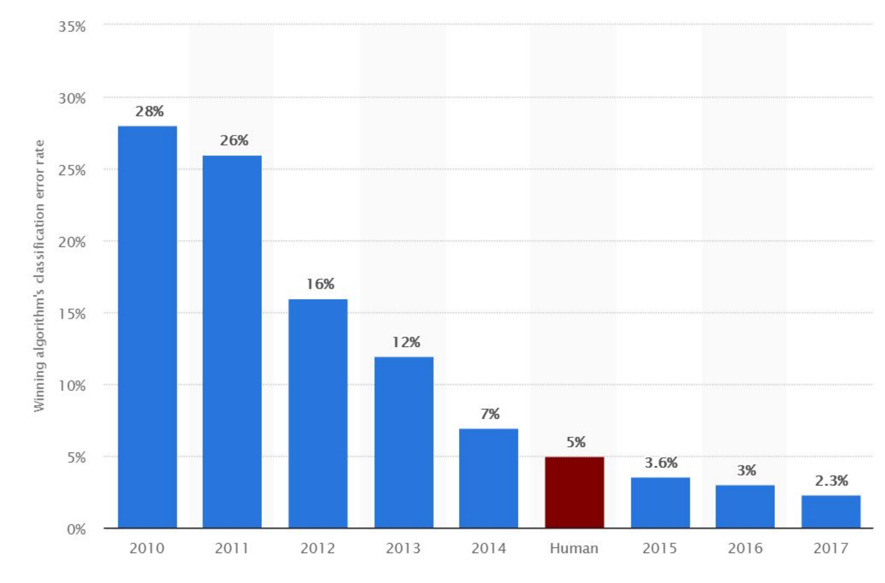
10~100 classes

2011-2015



ILSVRC
2010-2017

~1000 classes



Bottom image credit:
http://www.thegreenmedium.com/blog/2019/5/24/why-robots-will-help-you-rather-than-try-to-take-over-the-world-a-brief-history-of-ai

DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition

Jeff Donahue*, Yangqing Jia*, Oriol Vinyals, Judy Hoffman, Ning Zhang, Eric Tzeng, Trevor Darrell
{JDONAHUE,JIAYQ,VINYALS,JHOFFMAN,NZHANG,ETZENG,TREVOR}@EECS.BERKELEY.EDU
UC Berkeley & ICSI, Berkeley, CA, USA

Abstract

We evaluate whether features extracted from the activation of a deep convolutional network trained in a fully supervised fashion on a large, fixed set of object recognition tasks can be re-purposed to novel generic tasks. Our generic tasks may differ significantly from the originally trained tasks and there may be insufficient labeled or unlabeled data to conventionally train or

pects of a given domain through discovery of salient clusters, parts, mid-level features, and/or hidden units (Hinton & Salakhutdinov, 2006; Fidler & Leonardis, 2007; Zhu et al., 2007; Singh et al., 2012; Krizhevsky et al., 2012). Such models have been able to perform better than traditional hand-engineered representations in many domains, especially those where good features have not already been engineered (Le et al., 2011). Recent results have shown that moderately deep unsupervised models outperform the

ICML 2014

Deep features!

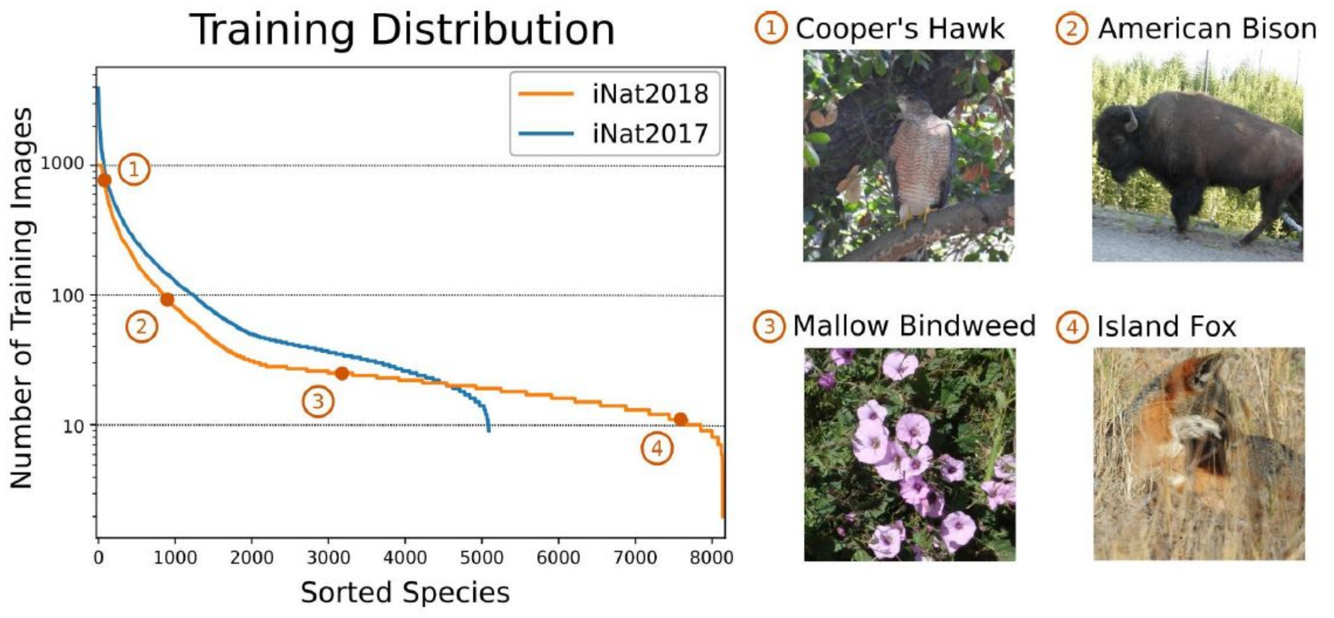
COCO
Common Objects in Context

places
THE SCENE RECOGNITION DATABASE

ACTIVITYNET

Kinetics

Training Image Distribution



The iNaturalist Species Classification and Detection Dataset

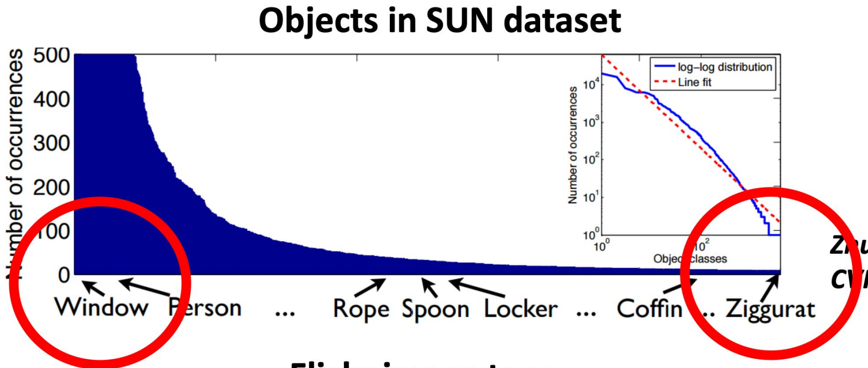
Grant Van Horn[1] Oisin Mac Aodha[1] Yang Song[2] Yin Cui[3] Chen Sun[2]
Alex Shepard[4] Hartwig Adam[2] Pietro Perona[1] Serge Belongie[3]

Object recognition

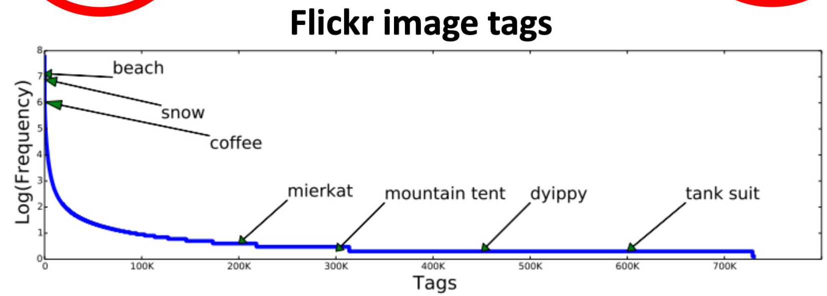
in the wild

5k~8k classes

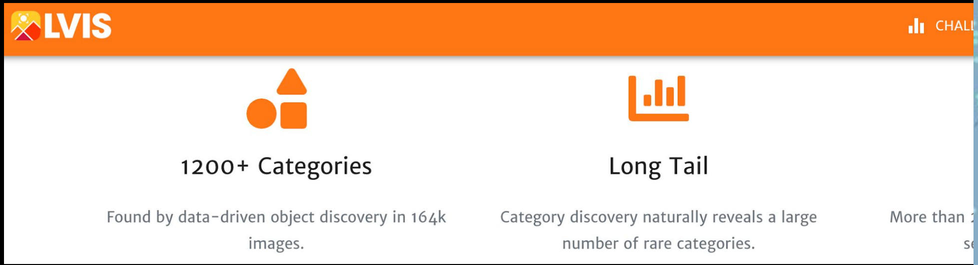
in the wild

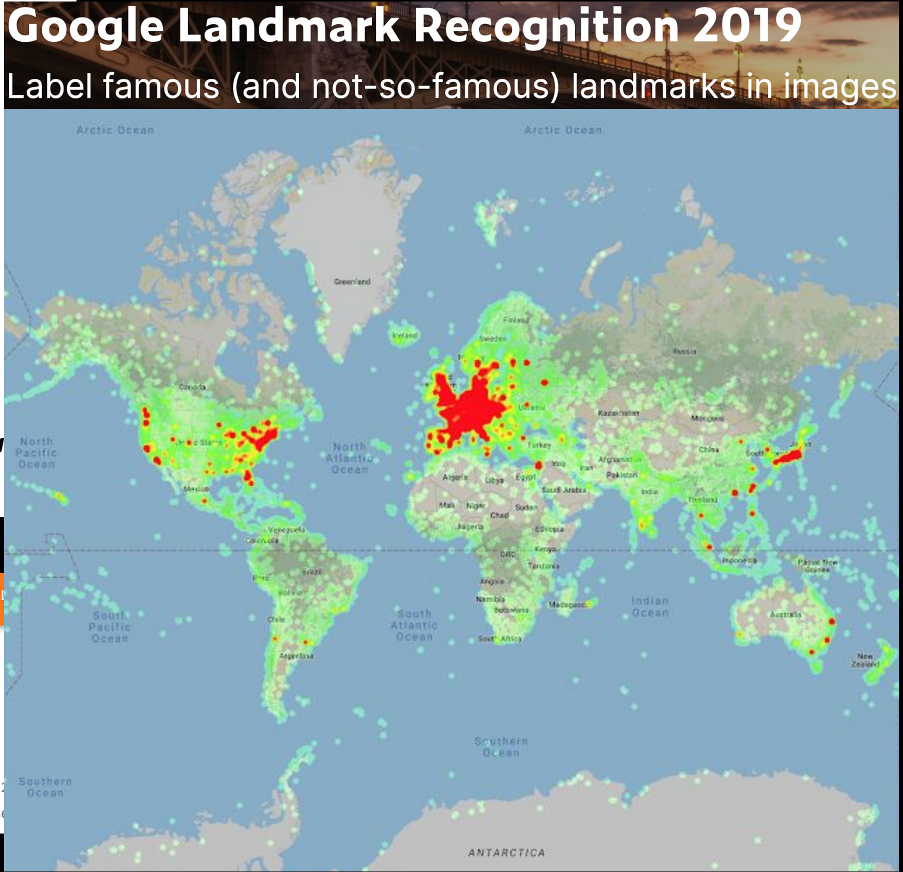


Zhu et al. CVPR 2014



Kordumova MM 2015





in the wild

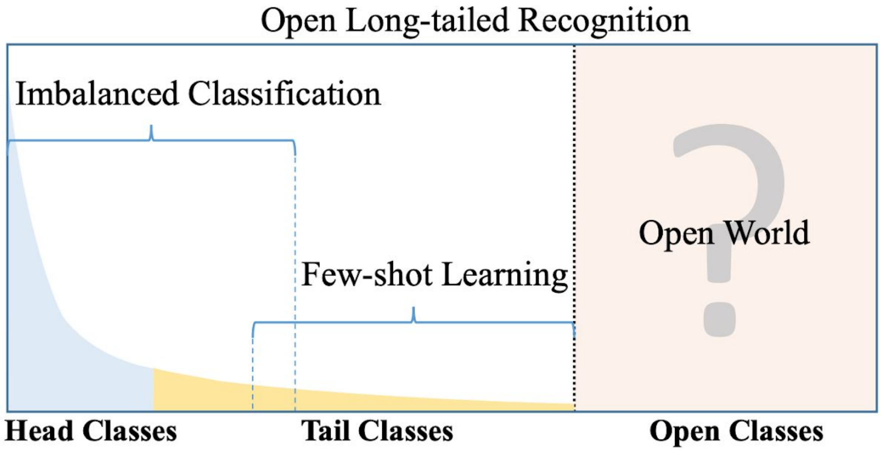
Right image credit: https://natureneedsmore.org/the-elephant-in-the-room/

Large-Scale Long-Tailed Recognition in an Open World

Ziwei Liu[1,2*] Zhongqi Miao[2*] Xiaohang Zhan[1] Jiayun Wang[2] Boqing Gong[2†] Stella X. Yu[2]
[1] The Chinese University of Hong Kong [2] UC Berkeley / ICSI
{zwliu,zx017}@ie.cuhk.edu.hk, {zhongqi.miao,peterwg,stellayu}@berkeley.edu, bgong@outlook.com

Abstract

Real world data often have a long-tailed and open-ended distribution. A practical recognition system must classify among majority and minority classes, generalize from a few known instances, and acknowledge novelty upon a never seen instance. We define Open Long-Tailed Recognition (OLTR) as learning from such naturally distributed data and optimizing the classification accuracy over a balanced test set which include head, tail, and open classes.



CVPR 2019 (oral), improving neural architectures

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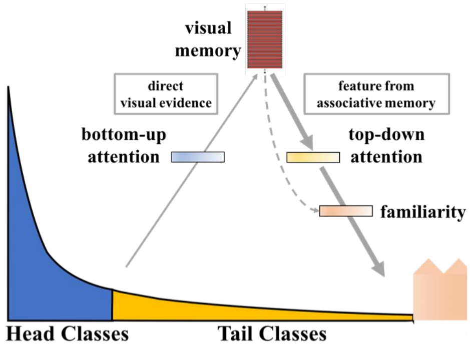
Long-tailed ImageNet (1000 classes)

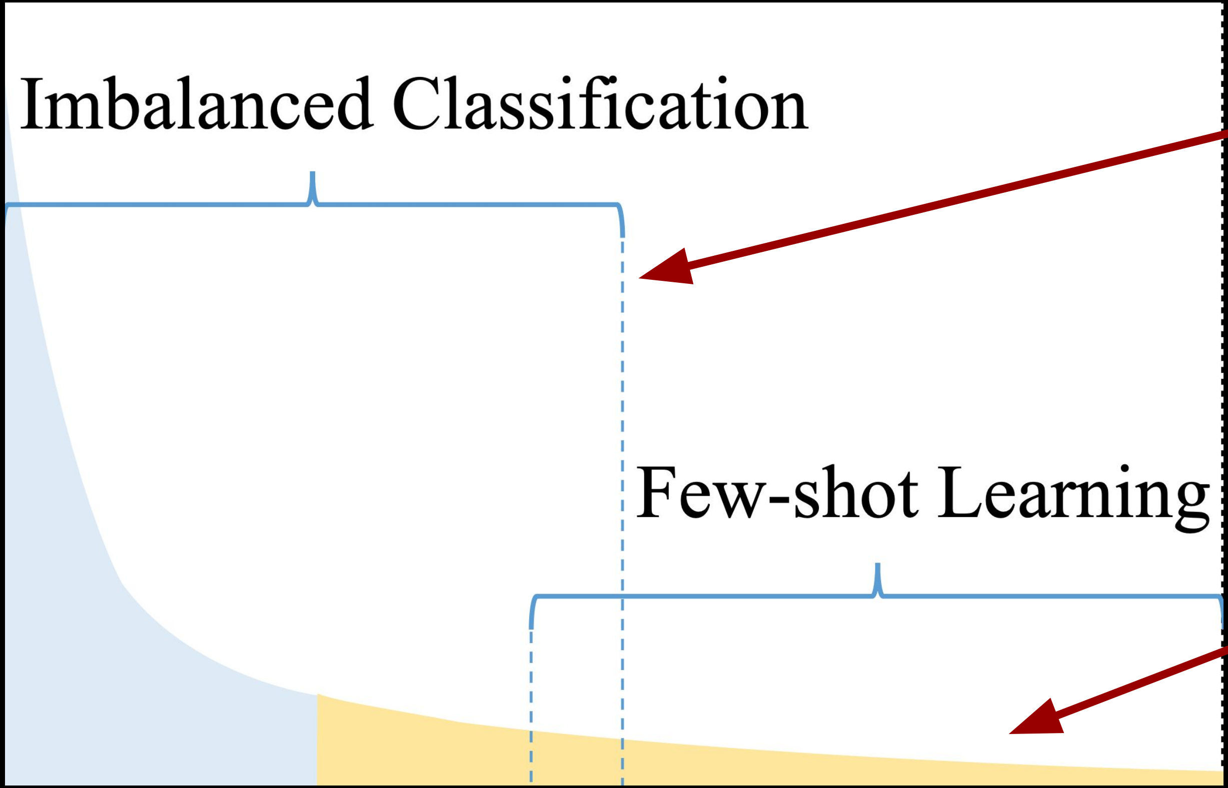
Long-tailed Places-365

Long-tailed MS1M ArcFace (74.5k ids)



A memory bank to enhance tail classes

CVPR 2019 (oral), improving neural architectures



An old AI problem

A new AI problem (meta-learning, transfer learning, zero-shot learning)

Acknowledgement: Matthew Brown @Google

Existing work

Class-wise weighting, over/under-sampling, etc.

[CVPR'18] Large Scale Fine-Grained Categorization and Domain-Specific Transfer Learning

[CVPR'19] Class-Balanced Loss Based on Effective Number of Samples

[NeurIPS'19] Learning Imbalanced Datasets with Label-Distribution-Aware Margin Loss

[ICLR'20] Decoupling Representation and Classifier for Long-Tailed Recognition

DECOUPLING REPRESENTATION AND CLASSIFIER FOR LONG-TAILED RECOGNITION

Bingyi Kang[1,2], Saining Xie[1], Marcus Rohrbach[1], Zhicheng Yan[1], Albert Gordo[1], Jiashi Feng[2], Yannis Kalantidis[1]

Abstract form: *unsupervised* domain adaptation (DA)

Setup

Source domain (with labeled data)

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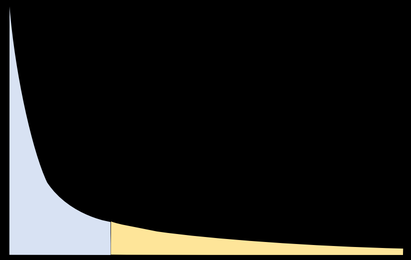
Different distributions



Objective

Learn models to work well on target

Existing work

Class-wise weighting, over/under-sampling, etc.

[CVPR'18] Large Scale Fine-Grained Categorization and Domain-Specific Transfer Learning

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[ICLR'20] Decoupling Representation and Classifier for Long-Tailed Recognition

… as domain adaptation

Target

$$\mathtt{error} = \mathbb{E}_{P_t(x,y)} L(f(x;\theta), y),$$

$$= \mathbb{E}_{P_s(x,y)} L(f(x;\theta), y) P_t(x,y)/P_s(x,y)$$

Source

$$= \mathbb{E}_{P_s(x,y)} L(f(x;\theta), y) \frac{P_t(y) P_t(x|y)}{P_s(y) P_s(x|y)}$$

$$= \mathbb{E}_{P_s(x,y)} L(f(x;\theta), y) w_y (1 + \tilde{\epsilon}_{x,y}),$$

Existing work assumes ϵ=0

Head vs. tail

Many training images in a **head** class: ϵ=0

$$\text{Training cats} \sim P_t(x|\text{cat})$$

Few-shot training images in a **tail** class: ϵ≠0

$$\text{Training tacs} \nsim P_t(x|\text{tac})$$

… as domain adaptation

$$= \mathbb{E}_{P_s(x,y)} L(f(x;\theta), y) \frac{P_t(y) P_t(x|y)}{P_s(y) P_s(x|y)}$$

$$:= \mathbb{E}_{P_s(x,y)} L(f(x;\theta), y) w_y (1 + \tilde{\epsilon}_{x,y}),$$

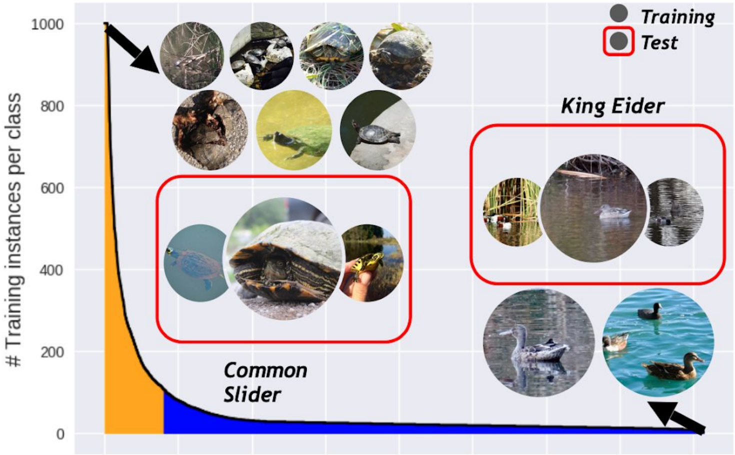
Existing work assumes ϵ=0

Rethinking Class-Balanced Methods for Long-Tailed Visual Recognition from a Domain Adaptation Perspective

Muhammad Abdullah Jamal[1*] Matthew Brown[3] Ming-Hsuan Yang[2,3] Liqiang Wang[1] Boqing Gong[3]
[1]University of Central Florida [2]University of California at Merced [3]Google

Abstract

Object frequency in the real world often follows a power law, leading to a mismatch between datasets with long-tailed class distributions seen by a machine learning model and our expectation of the model to perform well on all classes. We analyze this mismatch from a domain adaptation point of view. First of all, we connect existing class-balanced methods for long-tailed classification to target shift, a well-studied scenario in domain adaptation. The connection reveals that these methods implicitly assume



CVPR 2020 (oral), long-tailed recognition ≅ domain adaptation

Our approach

Estimating both w_y & $\tilde{\epsilon}_{x,y}$

by unifying [CVPR'19] & an improved meta-learning method

SOTA on six datasets

- CIFAR-LT-10
- CIFAR-LT-100
- ImageNet-LT
- Places-LT
- **iNaturalist 2017**
- **iNaturalist 2018**

Long-tailed visual recognition (LTVR)

Emerging challenge as the datasets grow in scale

Timely topic

Datasets: iNaturalist, LVIS, ImageNet, COCO, etc.

Tasks: almost all

... as domain adaptation

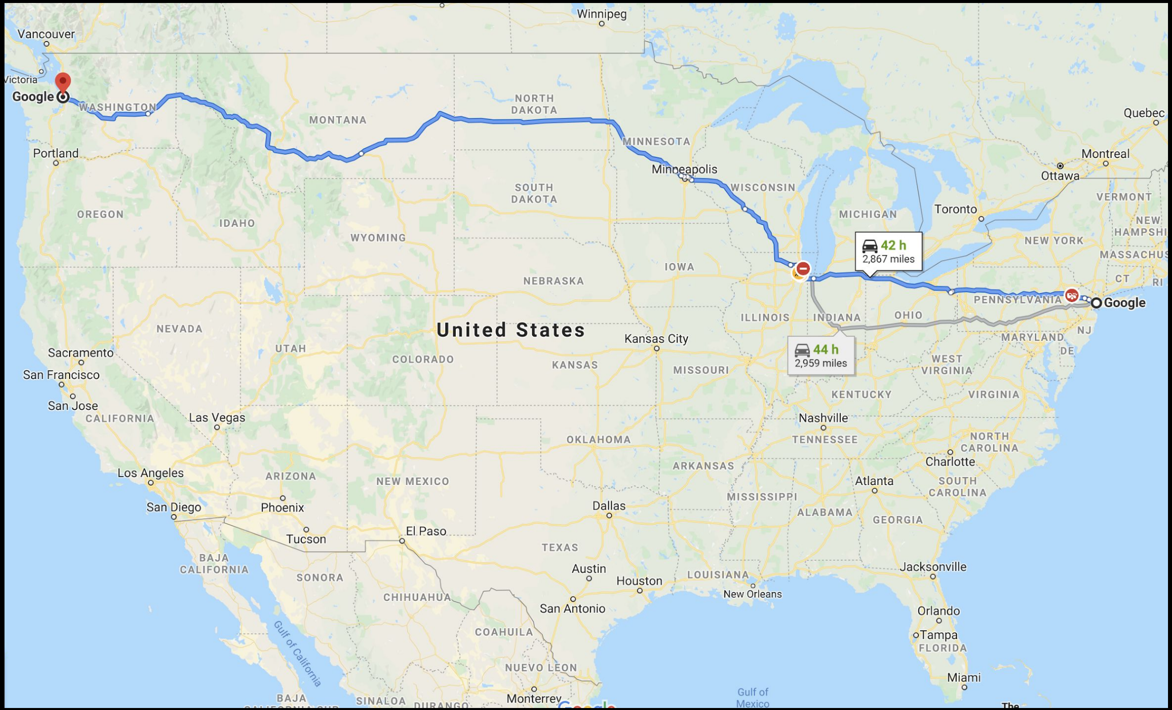
New perspective to LTVR

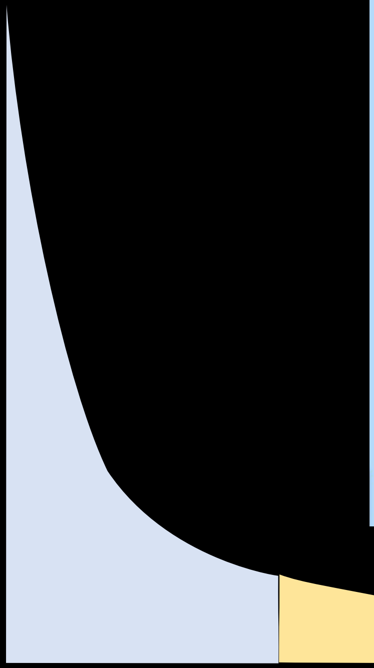
New powerhouse of methods

- Domain-invariant representation learning
- Curriculum domain adaptation
- Adversarial learning
- Classifier discrepancy
- Data augmentation & synthesis, etc.

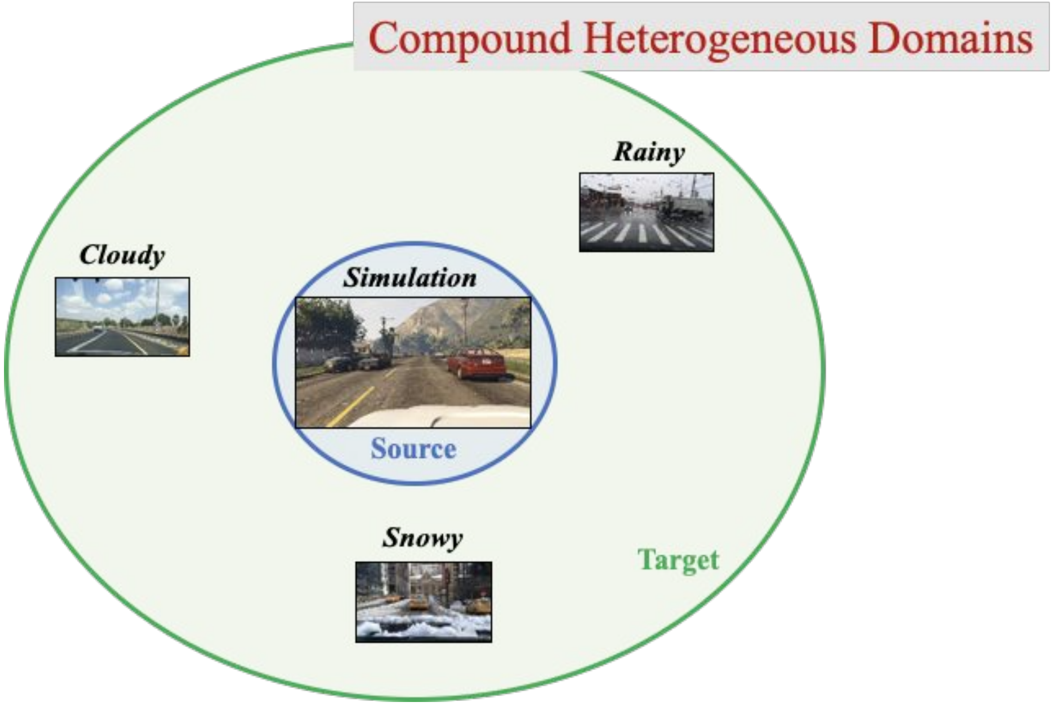
Diff: no access to target data

in the wild


Google
Google
42 h
2,867 miles
44 h
2,959 miles
United States
Vancouver
Winnipeg
Portland
Minneapolis
Kansas City
Nashville
Sacramento
San Francisco
San Jose
Las Vegas
Los Angeles
San Diego
Phoenix
Tucson
El Paso
Dallas
Austin
Houston
San Antonio
New Orleans
Atlanta
Charlotte
Jacksonville
Orlando
Tampa
Miami
Toronto
Ottawa
Montreal
Quebec
WASHINGTON
OREGON
IDAHO
MONTANA
WYOMING
NORTH DAKOTA
SOUTH DAKOTA
NEBRASKA
MINNESOTA
IOWA
WISCONSIN
MICHIGAN
ILLINOIS
INDIANA
OHIO
PENNSYLVANIA
NEW YORK
NEVADA
UTAH
COLORADO
KANSAS
MISSOURI
KENTUCKY
WEST VIRGINIA
VIRGINIA
MARYLAND
CALIFORNIA
ARIZONA
NEW MEXICO
OKLAHOMA
ARKANSAS
TENNESSEE
NORTH CAROLINA
SOUTH CAROLINA
MISSISSIPPI
ALABAMA
GEORGIA
TEXAS
LOUISIANA
FLORIDA
VERMONT
MASSACHUS
CT
NJ
DE
BAJA CALIFORNIA
SONORA
CHIHUAHUA
COAHUILA
NUEVO LEON
SINALOA
Monterrey
Gulf of California
Gulf of Mexico



Open compound test cases (target)



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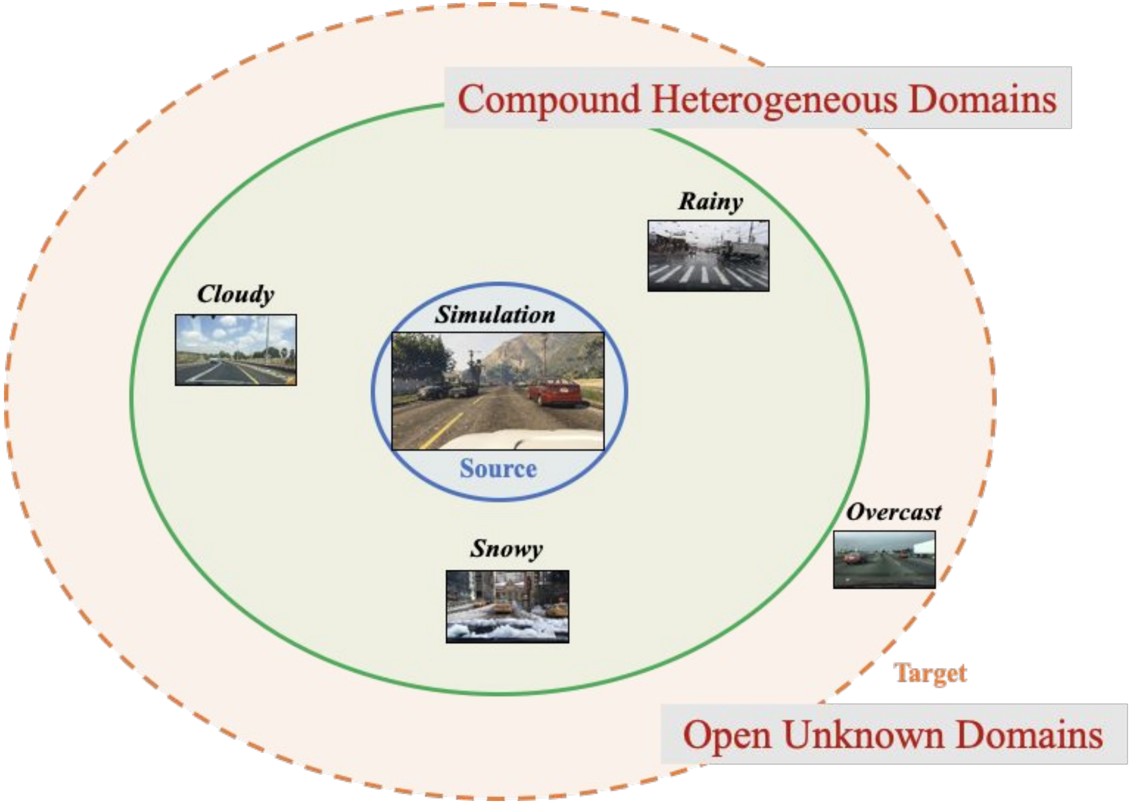
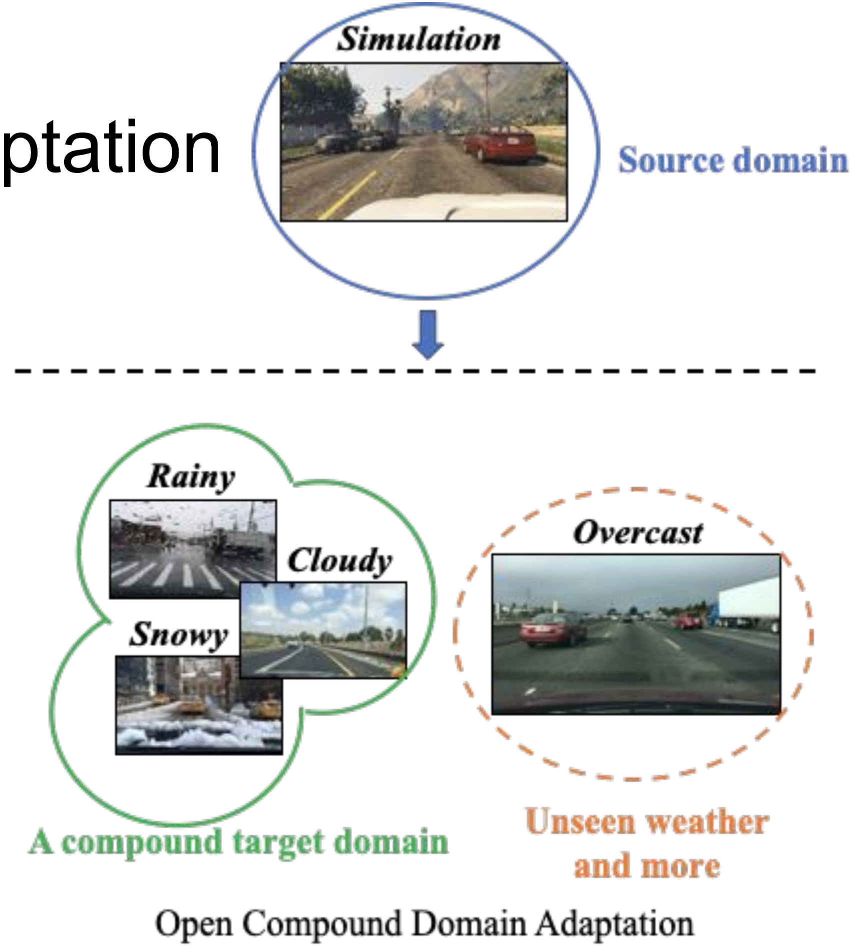


Open compound domain adaptation



Training:

Labeled source domain data

Unlabeled data of the compound target

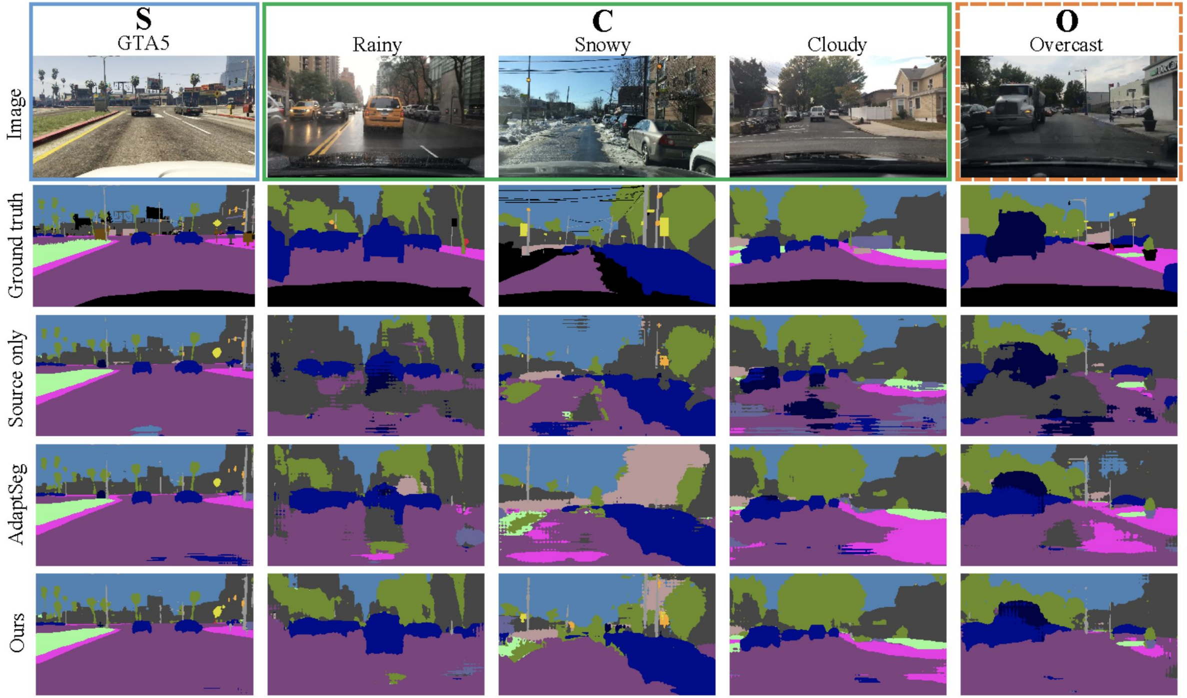
Testing:

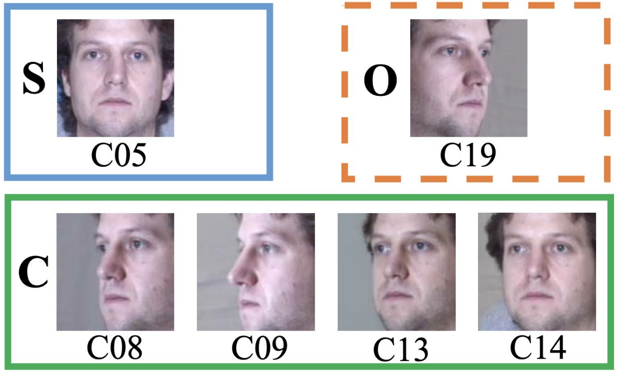
in the compound target domain and

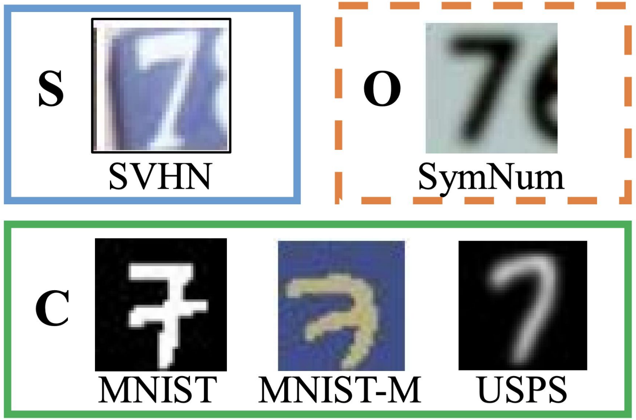
in previously unseen domains

Liu, Ziwei, Zhongqi Miao, Xingang Pan, Xiaohang Zhan, Stella X. Yu, Dahua Lin, and Boqing Gong. "Compound domain adaptation in an open world." *CVPR 2020.* (oral)

Experiments

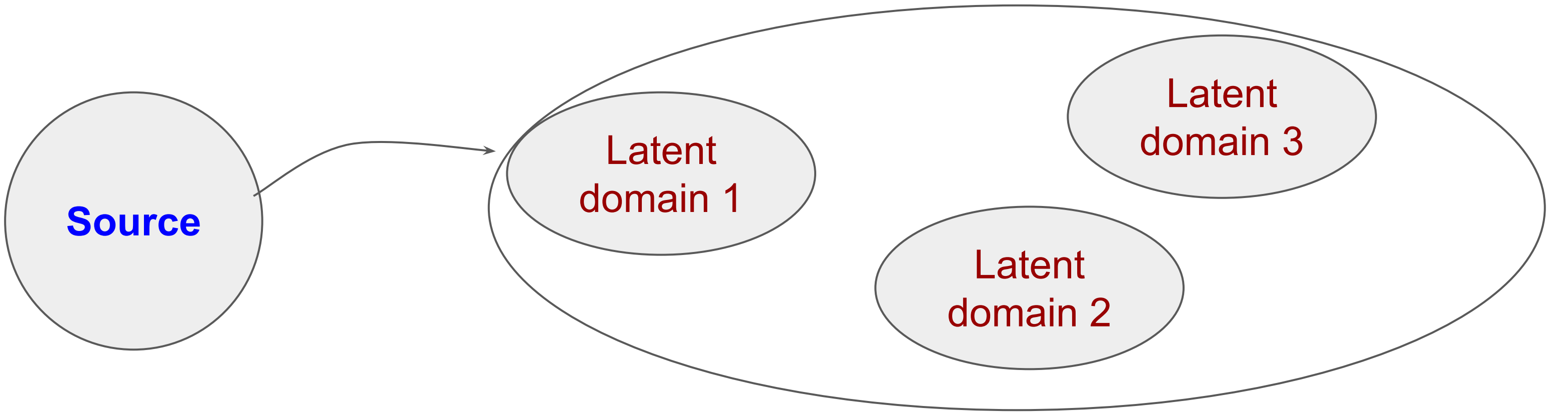






Our approach to break the compound target domain

into a series of bi-domain adaptation problems by “domain distances” between the source and latent domains in the target (curriculum training)



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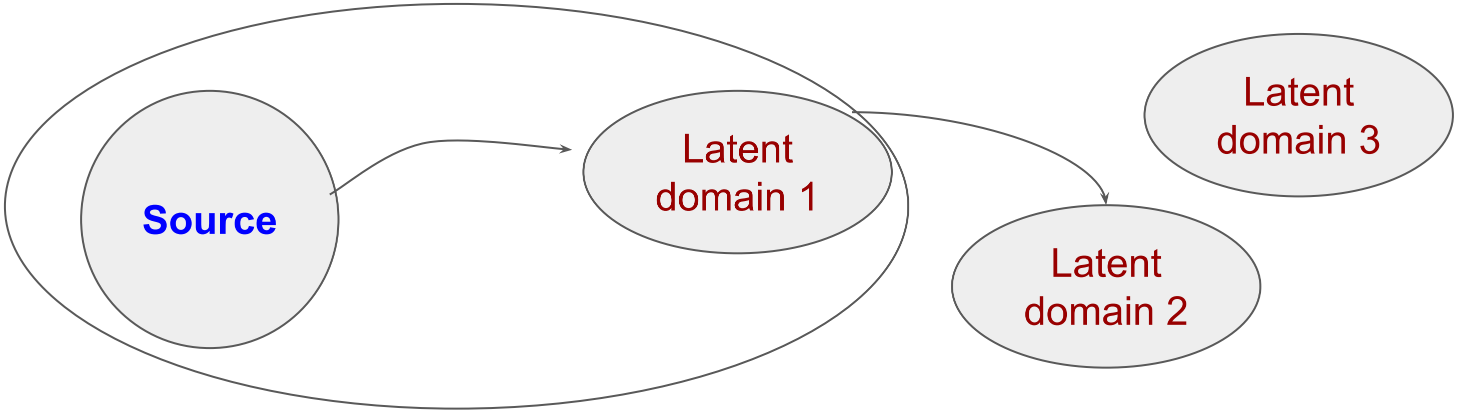

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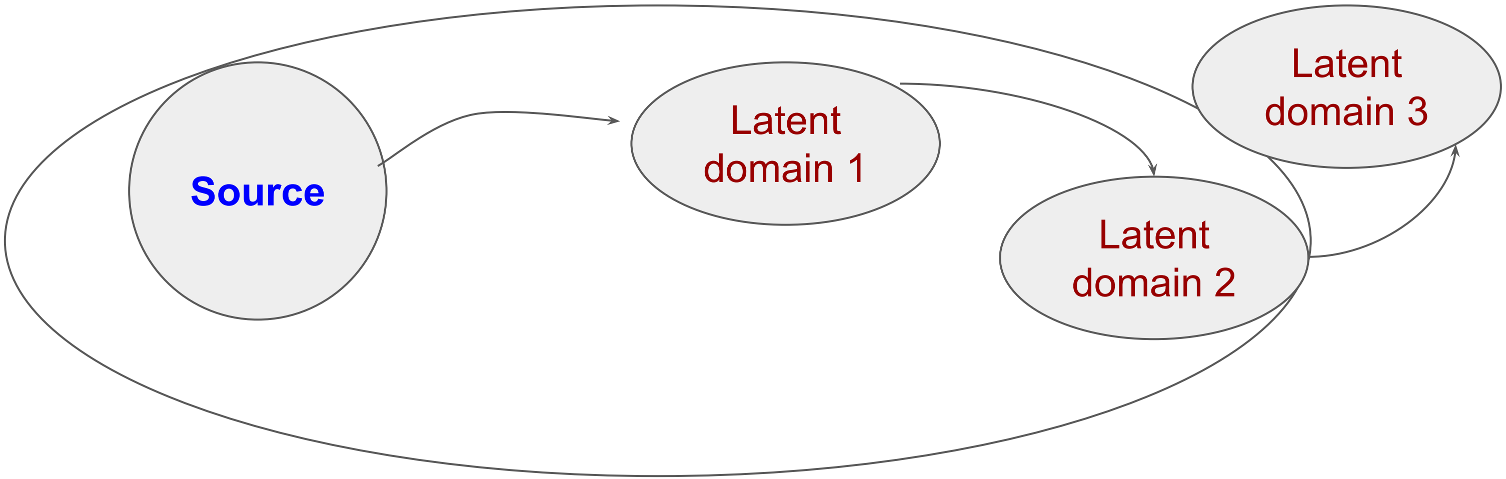

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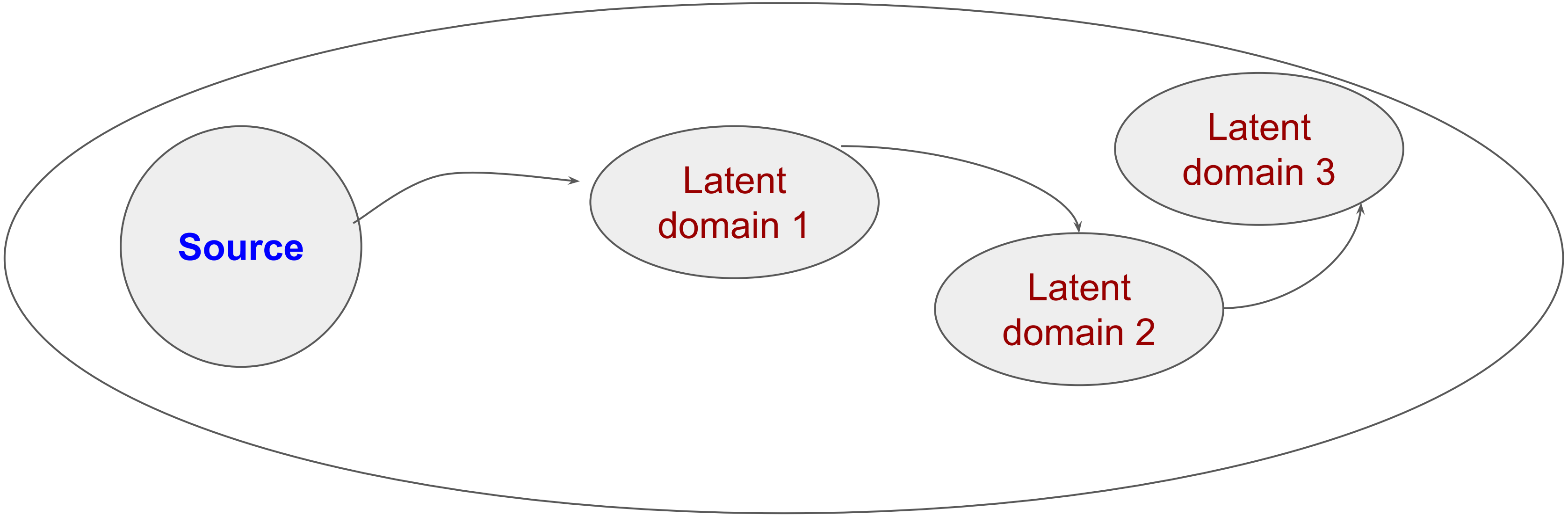

Pushing the boundary of visual recognition

Long-tailed source domains

- The elephant in the room as we scale up classes / study the wild data
- Memory bank to enhance tail classes (CVPR’19, oral)
- Domain adaptation: a new powerhouse of techniques (CVPR’20, oral)
- *Improved meta-learning for long-tailed recognition (undergoing)*

Open compound target domains (CVPR’20, oral)

- *Learning from unlabeled, noisy data in the wild (undergoing)*