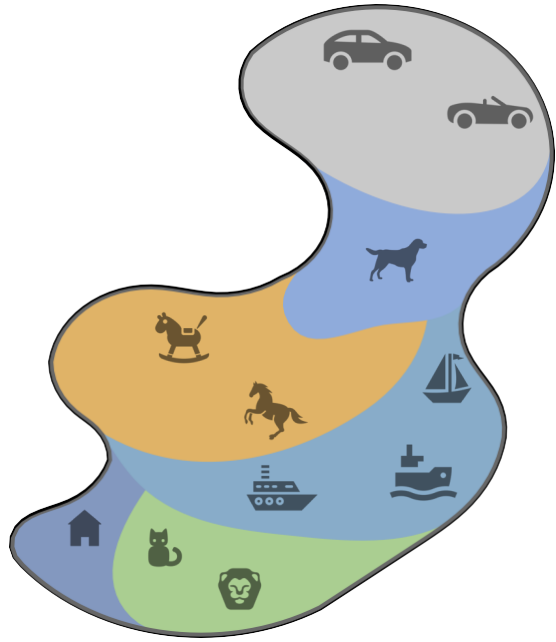


Lecture 6: Domain Adaptation



A Limitation of the (Supervised) ML Framework



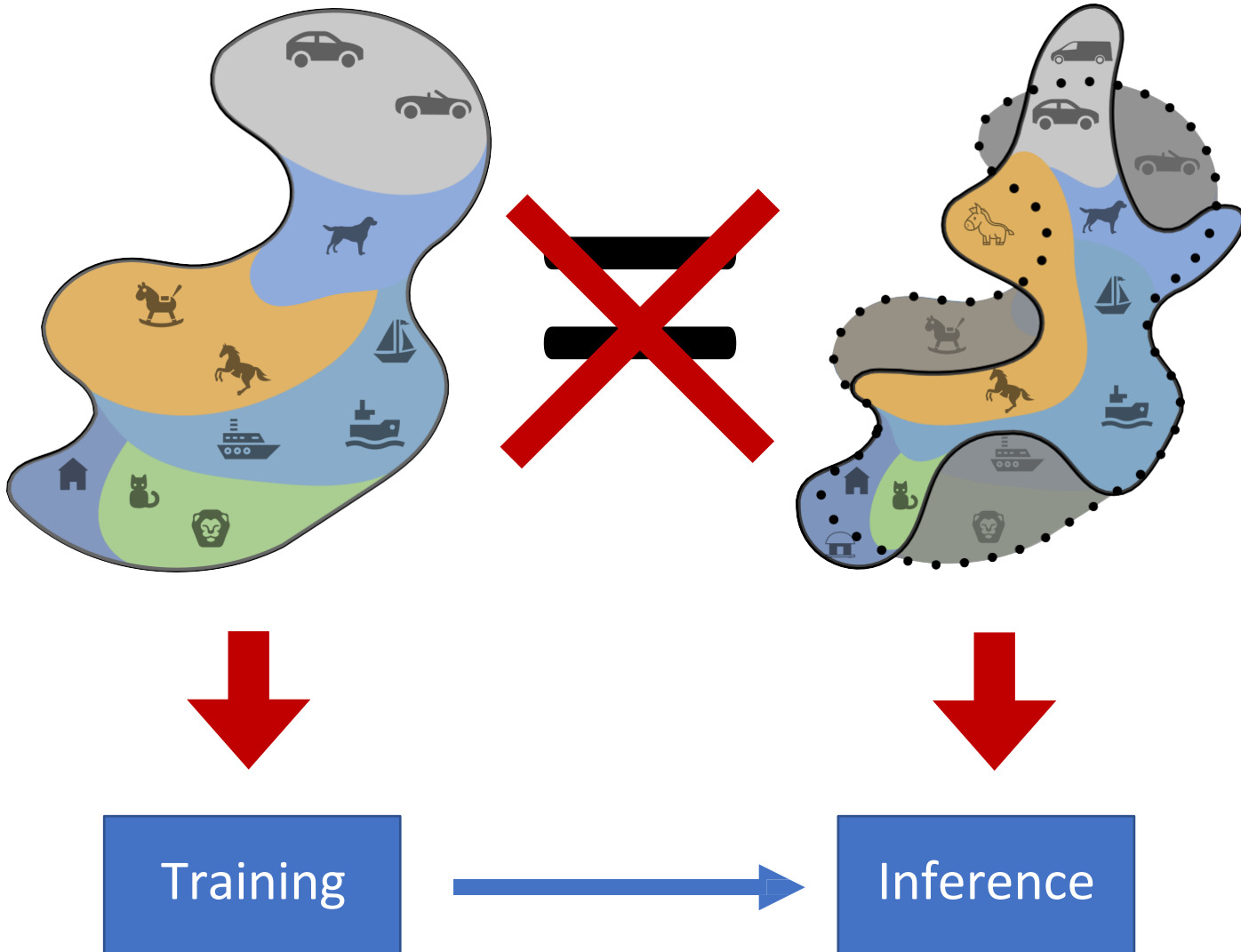
Measure of performance:
Fraction of mistakes during testing

But: In reality,
the distributions we **use** ML on
are NOT the ones we **train** it on

Training

Inference

A Limitation of the (Supervised) ML Framework

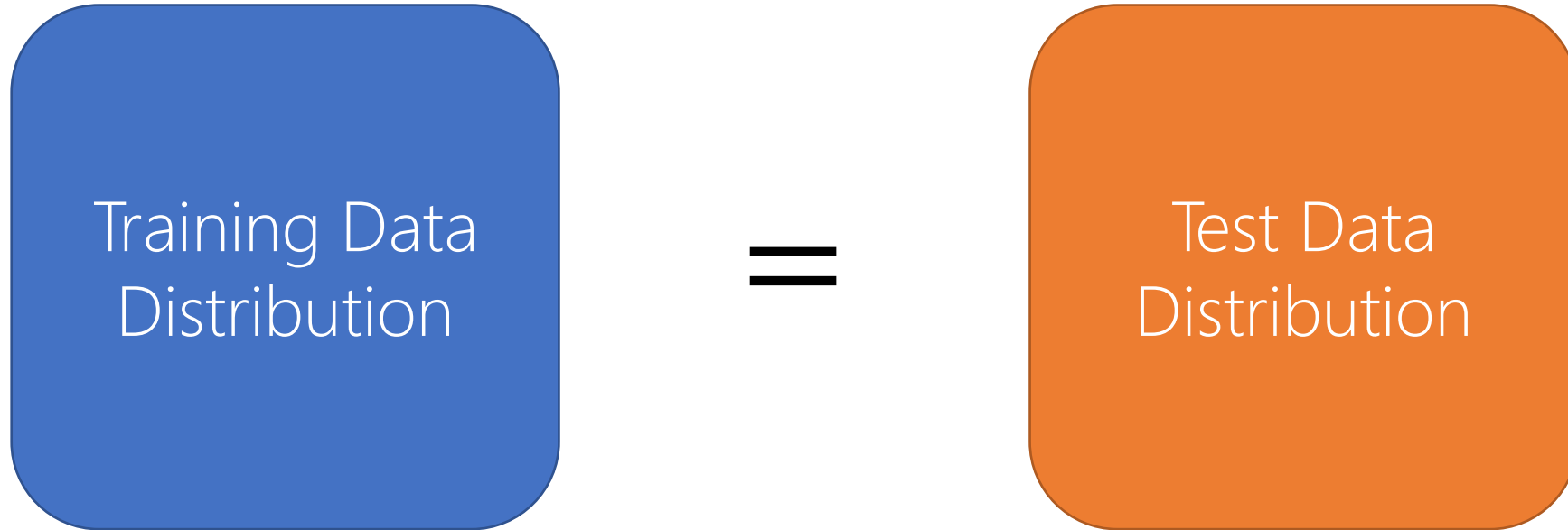


Measure of performance:
Fraction of mistakes during testing

But: In reality,
the distributions we **use** ML on
are **NOT** the ones we **train** it on

What can go wrong?

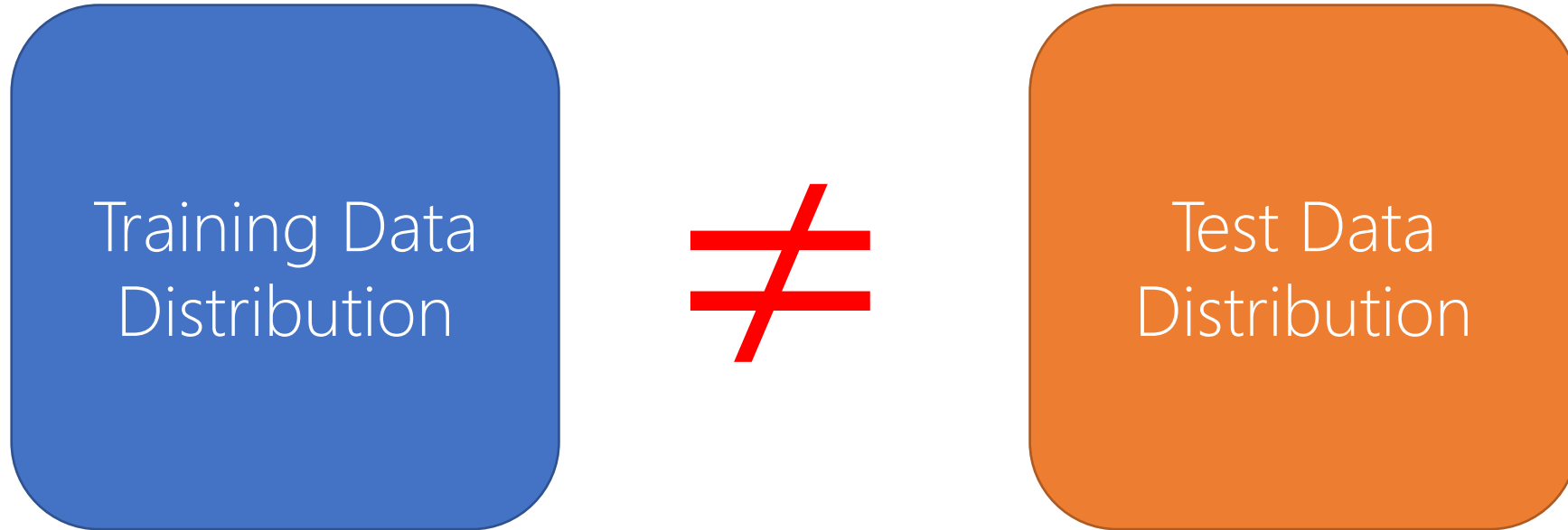
Standard *i.i.d.* Assumption in Machine Learning



"Independent and Identically Distributed"

Models learn useful patterns

Standard *i.i.d.* Assumption in Machine Learning



IID Assumption collapses in real-world "in-the-wild" settings
Model performance deteriorates

Example Scenarios



What your net is trained on

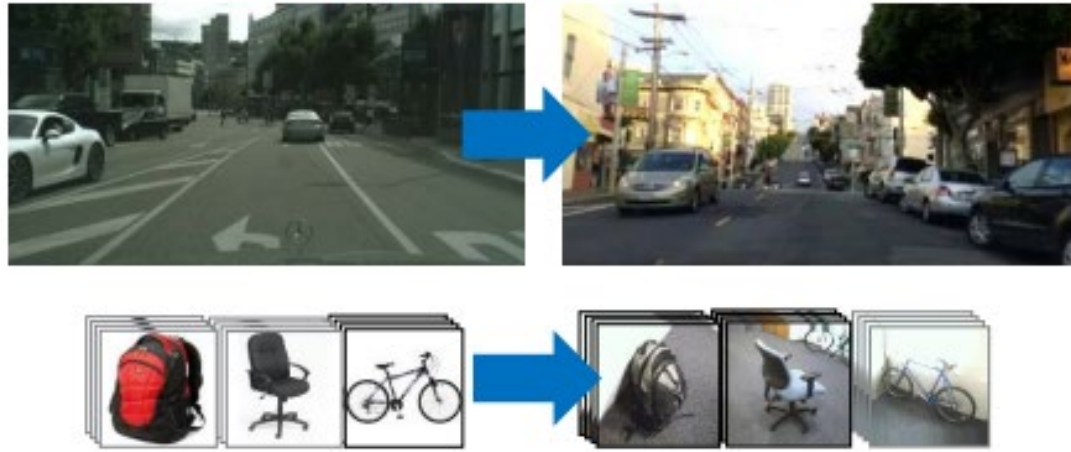


What it's asked to label

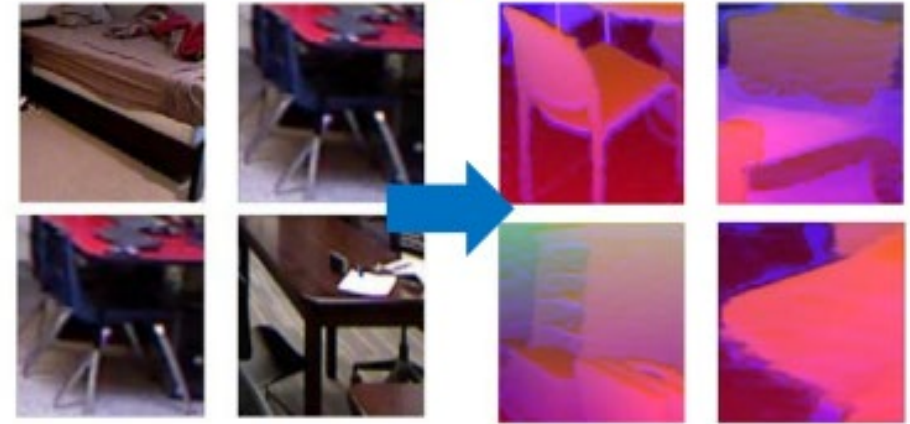
“Dataset Bias”
“Domain Shift”
“Domain Adaptation”
“Domain Transfer”

Example Scenarios

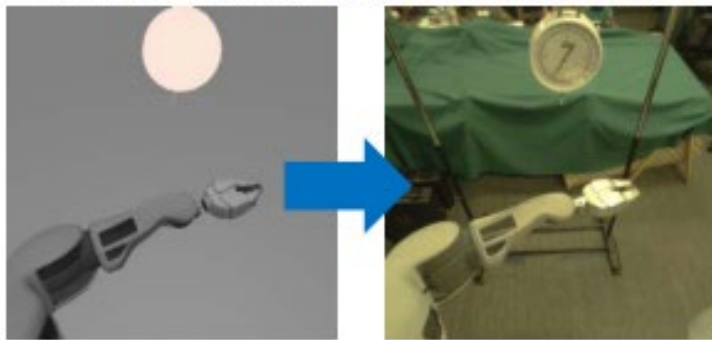
From dataset to dataset



From RGB to depth



From simulated to real control



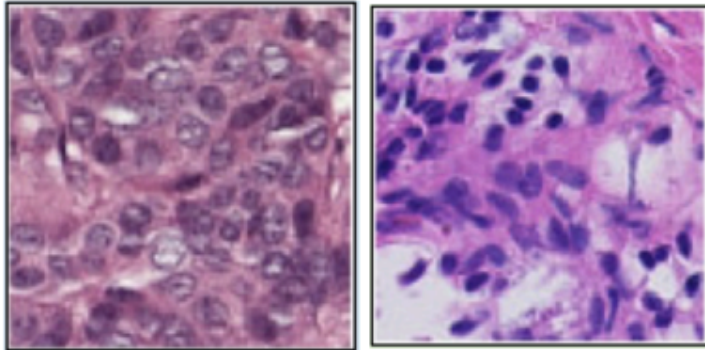
From CAD models to real images



Example Scenarios

Tumor detection & classification

Source hospital Target hospital



varying imaging techniques,
different demographics

Land use classification

Source region Target region



appearance of buildings, plants;
weather conditions, pollution

Text classification, generation

Source corpus Target corpus



Simple English
WIKIPEDIA

differing sentence structure,
vocabulary, word use



A vibrant, colorful market scene, likely a flower market, with stalls displaying various goods and people walking through the aisles. The scene is filled with bright colors and festive decorations, including colorful umbrellas and lanterns. The market is covered by a large, striped awning, and the ground is paved with stone tiles. The overall atmosphere is lively and bustling.
































Distribution shift is unavoidable for models that learn from data

A vibrant outdoor market scene with numerous stalls displaying colorful goods, likely flowers or produce. People are seen walking through the aisles, and the market is covered by a large, dark canopy. The overall atmosphere is busy and colorful.

Distribution shift is unavoidable for models that learn from data

Distribution shift causes failures of ML models

Benchmarks / Challenge Datasets


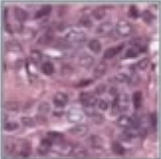
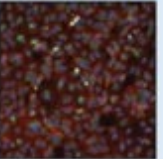
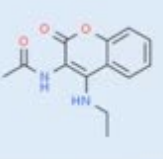
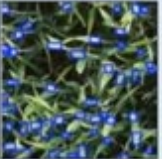



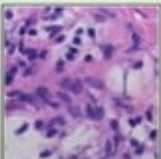
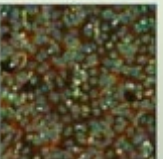
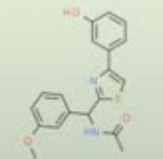



Dataset	Domains
Colored MNIST	<div style="display: flex; justify-content: space-around;"> <div style="text-align: center;">+90% </div> <div style="text-align: center;">+80% </div> <div style="text-align: center;">-90% </div> </div> <p><i>(degree of correlation between color and label)</i></p>
Rotated MNIST	<div style="display: flex; justify-content: space-around;"> <div style="text-align: center;">0° </div> <div style="text-align: center;">15° </div> <div style="text-align: center;">30° </div> <div style="text-align: center;">45° </div> <div style="text-align: center;">60° </div> <div style="text-align: center;">75° </div> </div>
VLCS	<div style="display: flex; justify-content: space-around;"> <div style="text-align: center;">Caltech101 </div> <div style="text-align: center;">LabelMe </div> <div style="text-align: center;">SUN09 </div> <div style="text-align: center;">VOC2007 </div> </div>
PACS	<div style="display: flex; justify-content: space-around;"> <div style="text-align: center;">Art </div> <div style="text-align: center;">Cartoon </div> <div style="text-align: center;">Photo </div> <div style="text-align: center;">Sketch </div> </div>
Office-Home	<div style="display: flex; justify-content: space-around;"> <div style="text-align: center;">Art </div> <div style="text-align: center;">Clipart </div> <div style="text-align: center;">Product </div> <div style="text-align: center;">Photo </div> </div>
Terra Incognita	<div style="display: flex; justify-content: space-around;"> <div style="text-align: center;">L100 </div> <div style="text-align: center;">L38 </div> <div style="text-align: center;">L43 </div> <div style="text-align: center;">L46 </div> </div> <p><i>(camera trap location)</i></p>
DomainNet	<div style="display: flex; justify-content: space-around;"> <div style="text-align: center;">Clipart </div> <div style="text-align: center;">Infographic </div> <div style="text-align: center;">Painting </div> <div style="text-align: center;">QuickDraw </div> <div style="text-align: center;">Photo </div> <div style="text-align: center;">Sketch </div> </div>

Algorithm	CMNIST	RMNIST	VLCS	PACS	OfficeHome	TerraInc	DomainNet	Average
ERM	51.5 ± 0.1	98.0 ± 0.0	77.5 ± 0.4	85.5 ± 0.2	66.5 ± 0.3	46.1 ± 1.8	40.9 ± 0.1	66.6
IRM	52.0 ± 0.1	97.7 ± 0.1	78.5 ± 0.5	83.5 ± 0.8	64.3 ± 2.2	47.6 ± 0.8	33.9 ± 2.8	65.4
GroupDRO	52.1 ± 0.0	98.0 ± 0.0	76.7 ± 0.6	84.4 ± 0.8	66.0 ± 0.7	43.2 ± 1.1	33.3 ± 0.2	64.8
Mixup	52.1 ± 0.2	98.0 ± 0.1	77.4 ± 0.6	84.6 ± 0.6	68.1 ± 0.3	47.9 ± 0.8	39.2 ± 0.1	66.7
MLDG	51.5 ± 0.1	97.9 ± 0.0	77.2 ± 0.4	84.9 ± 1.0	66.8 ± 0.6	47.7 ± 0.9	41.2 ± 0.1	66.7
CORAL	51.5 ± 0.1	98.0 ± 0.1	78.8 ± 0.6	86.2 ± 0.3	68.7 ± 0.3	47.6 ± 1.0	41.5 ± 0.1	67.5
MMD	51.5 ± 0.2	97.9 ± 0.0	77.5 ± 0.9	84.6 ± 0.5	66.3 ± 0.1	42.2 ± 1.6	23.4 ± 9.5	63.3
DANN	51.5 ± 0.3	97.8 ± 0.1	78.6 ± 0.4	83.6 ± 0.4	65.9 ± 0.6	46.7 ± 0.5	38.3 ± 0.1	66.1
CDANN	51.7 ± 0.1	97.9 ± 0.1	77.5 ± 0.1	82.6 ± 0.9	65.8 ± 1.3	45.8 ± 1.6	38.3 ± 0.3	65.6
MTL	51.4 ± 0.1	97.9 ± 0.0	77.2 ± 0.4	84.6 ± 0.5	66.4 ± 0.5	45.6 ± 1.2	40.6 ± 0.1	66.2
SagNet	51.7 ± 0.0	98.0 ± 0.0	77.8 ± 0.5	86.3 ± 0.2	68.1 ± 0.1	48.6 ± 1.0	40.3 ± 0.1	67.2
ARM	56.2 ± 0.2	98.2 ± 0.1	77.6 ± 0.3	85.1 ± 0.4	64.8 ± 0.3	45.5 ± 0.3	35.5 ± 0.2	66.1
VREx	51.8 ± 0.1	97.9 ± 0.1	78.3 ± 0.2	84.9 ± 0.6	66.4 ± 0.6	46.4 ± 0.6	33.6 ± 2.9	65.6
RSC	51.7 ± 0.2	97.6 ± 0.1	77.1 ± 0.5	85.2 ± 0.9	65.5 ± 0.9	46.6 ± 1.0	38.9 ± 0.5	66.1

Model selection: training-domain validation set

Benchmarks / Challenge Datasets

WILDS

	Domain shift					Subpopulation shift	Domain shift + subpopulation shift			
Dataset	iWildCam	Camelyon17	RxRx1	OGB-MolPCBA	GlobalWheat	CivilComments	FMoW	PovertyMap	Amazon	Py150
Input (x)	photo	tissue slide	cell image	molecular graph	wheat image	online comment	satellite image	satellite image	product review	code
Prediction (y)	animal species	tumor	perturbed gene	bioassays	wheat head bbox	toxicity	land use	asset wealth	sentiment	autocomplete
Domain (d)	camera	hospital	batch	scaffold	location, time	demographic	time, region	location	user	git repository
Train example						What do Black and LGBT people have to do with bicycle licensing?			Overall a solid package that has a good quality of construction for the price.	<pre>import numpy as np ... norm=np.____</pre>
Test example						As a Christian, I will not be patronizing any of those businesses.			I "loved" my French press, it's so perfect and came with all this fun stuff!	<pre>import subprocess as sp p=sp.Popen() stdout=p.____</pre>
Adapted from	Beery et al. 2020	Bandi et al. 2018	Taylor et al. 2019	Hu et al. 2020	David et al. 2021	Borkan et al. 2019	Christie et al. 2018	Yeh et al. 2020	Ni et al. 2019	Raychev et al. 2016

Solution?

Domain Adaptation

Domain Adaptation

- Problem Setup (Handwritten Notes)

- Theory
 - A theory of learning from different domains (Ben-David et al. MLJ 2010)
<https://link.springer.com/content/pdf/10.1007/s10994-009-5152-4.pdf>
 - Learning from multiple sources (Crammer et al. JMLR 2008)
<https://www.jmlr.org/papers/volume9/crammer08a/crammer08a.pdf>

Domain Adaptation Scenarios

(adapted from Mathieu Salzmann)

Standard Visual Recognition

Training data



Test data



Train a classifier on the training data and directly apply it to the test data

Domain Shift

Training data



Source domain

Test data



Target domain

A classifier trained on one domain may perform poorly on another domain

Semi-supervised vs Unsupervised

- Semi-supervised: Some labeled target data, but not enough to train from scratch

Source data



Fully-labeled

Target data



A few labels

Semi-supervised vs Unsupervised

- Unsupervised: No labels for the target data

Source data



Fully-labeled

Target data



Single vs Multiple Source Domains

Source domain 1



Source domain 2



Target domain



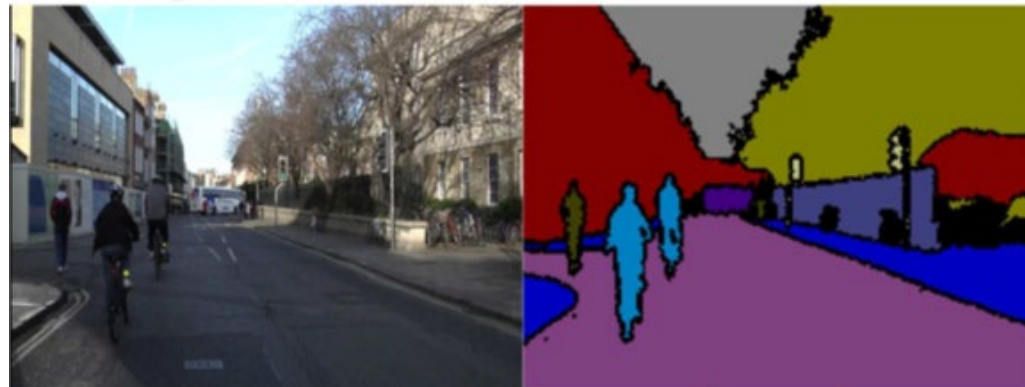
- Moving towards domain generalization

Domain Adaptation: Other Scenarios

Synthetic (source domain)



Real (target domain)



Domain Adaptation: Other Scenarios

Synthetic (source domain)



with facial landmarks



Real (target domain)

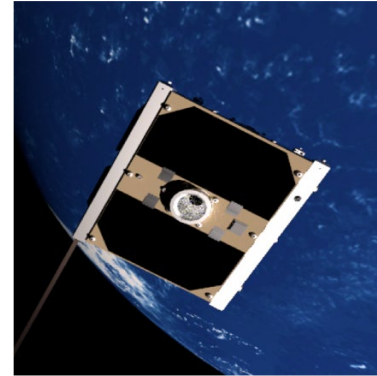
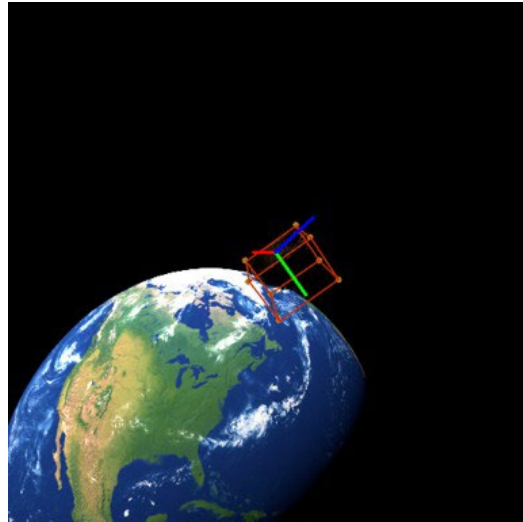


with facial landmarks

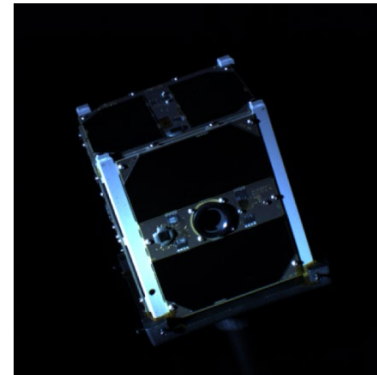


Domain Adaptation: Other Scenarios

Satellite 6D pose estimation



Synthetic (source)



Real (target)

Setup

- Each sample is represented by a feature vector:
 - In the traditional methods, e.g., bag of SURF features
 - More recently, features extracted by a deep backbone network



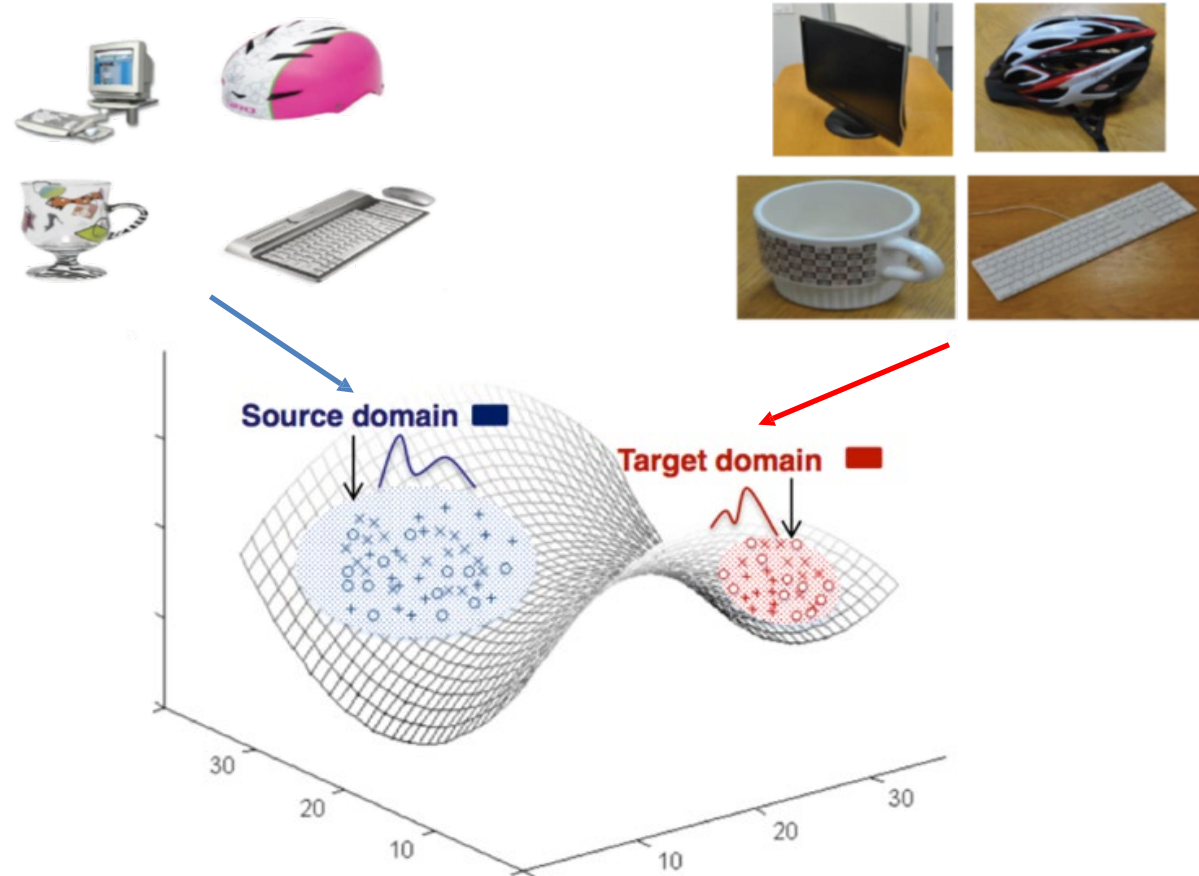
$$\mathbf{X}_s = \{\mathbf{x}_s^i\}_{i=1}^n$$

$$\mathbf{X}_t = \{\mathbf{x}_t^j\}_{j=1}^m$$

$$\text{Label: } \{y_s^i\}_{i=1}^n$$

Domain Shift

- The domain shift is defined as a difference in the distribution of the source and target samples



Domain Shift

- Typically, the literature focuses on the covariate shift case, where

$$p_t(x_t) \neq p_s(x_s)$$

- But

$$p_t(y|x_t) = p_s(y|x_s)$$

- The goal of domain adaptation is then often expressed as that of finding a transformation $T(\cdot)$, such that

$$p_t(T(x_t)) = p_s(T(x_s))$$