

Introduction Transfer Learning

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Motivation



Name this country



ChatGPT

Motivation



Name this country



ChatGPT

The arrow is pointing to a country in **northwestern Africa**, just south of Spain across the Strait of Gibraltar, and bordering both the **Atlantic Ocean** and the **Mediterranean Sea**.

👉 That country is Morocco.

Let me know if you'd like more geographic context or want to quiz me again!

Motivation



Name this country

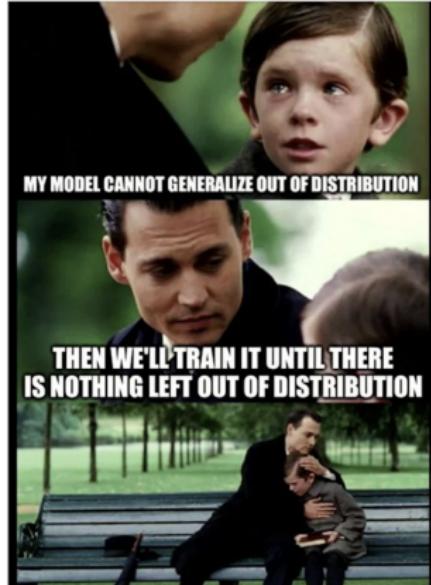


ChatGPT

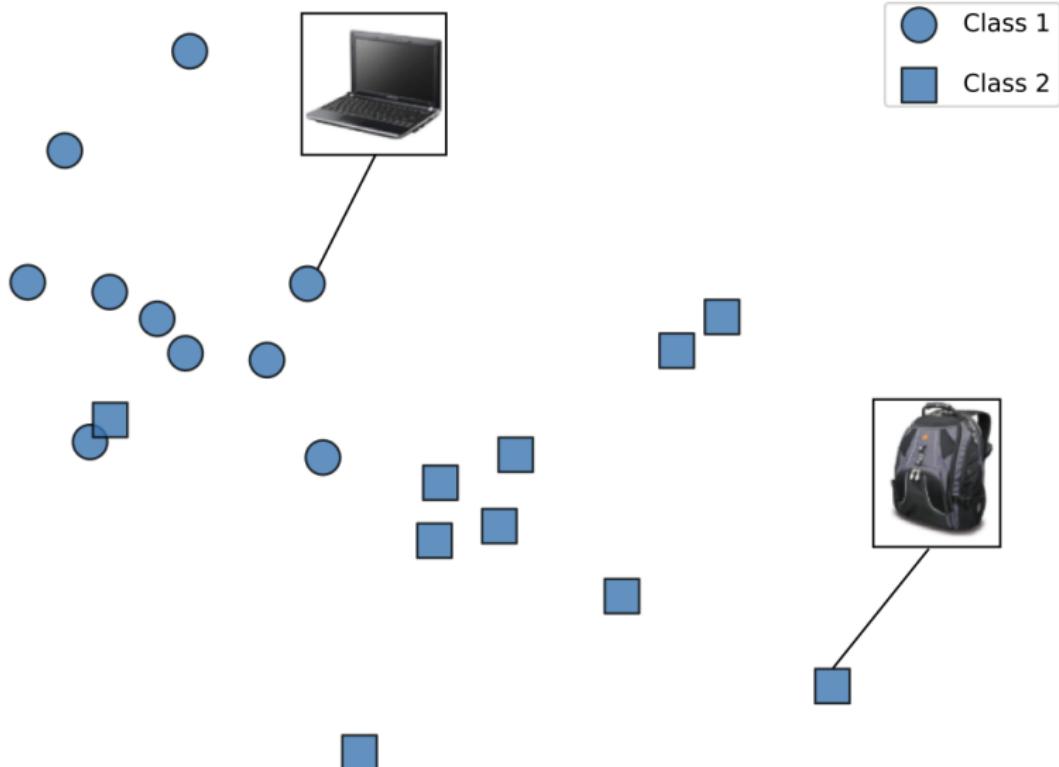
The arrow is pointing to a country in northwestern Africa, just south of Spain across the Strait of Gibraltar, and bordering both the Atlantic Ocean and the Mediterranean Sea.

👉 That country is Morocco.

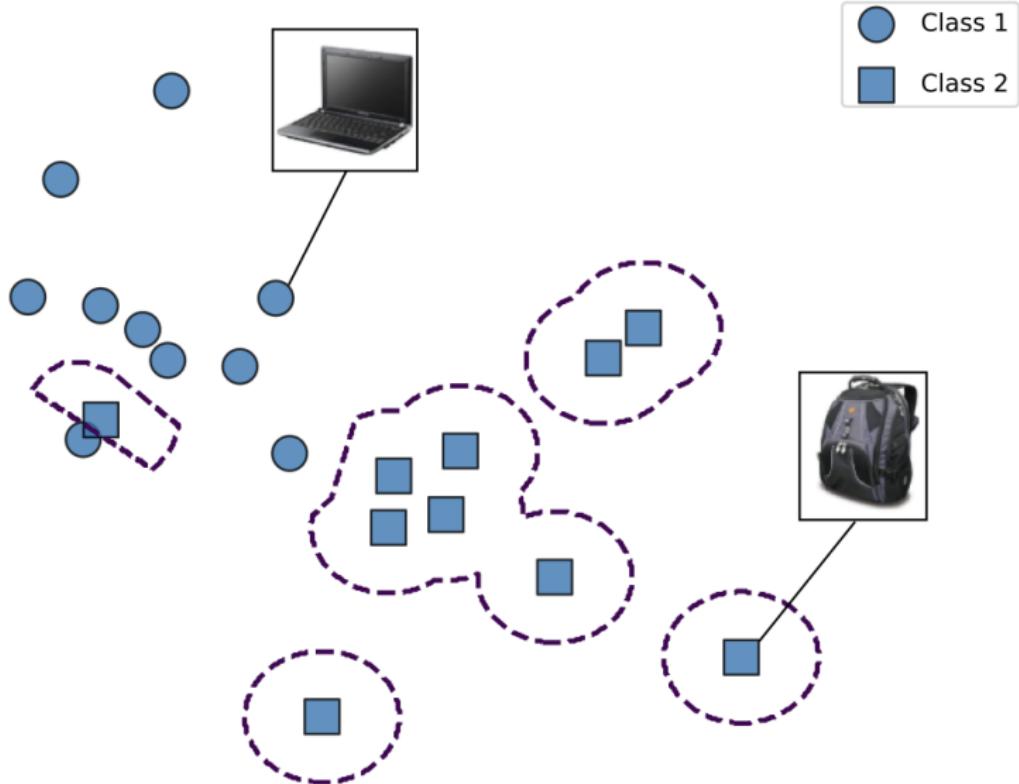
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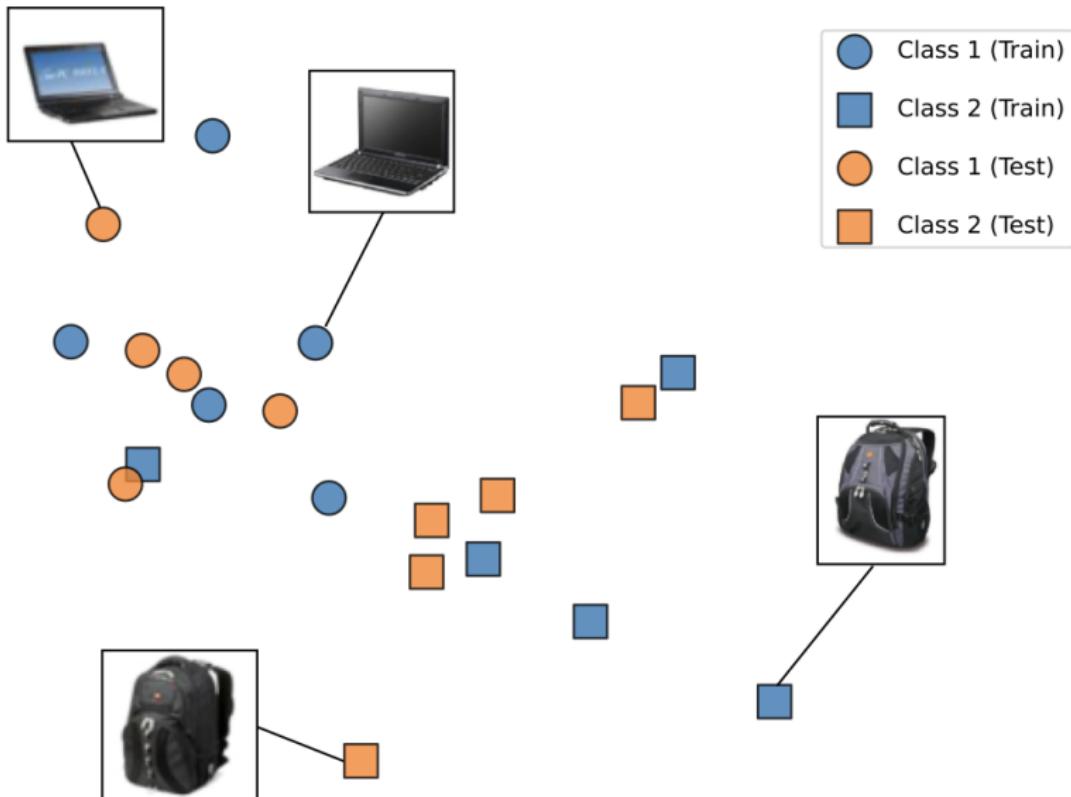
Motivation



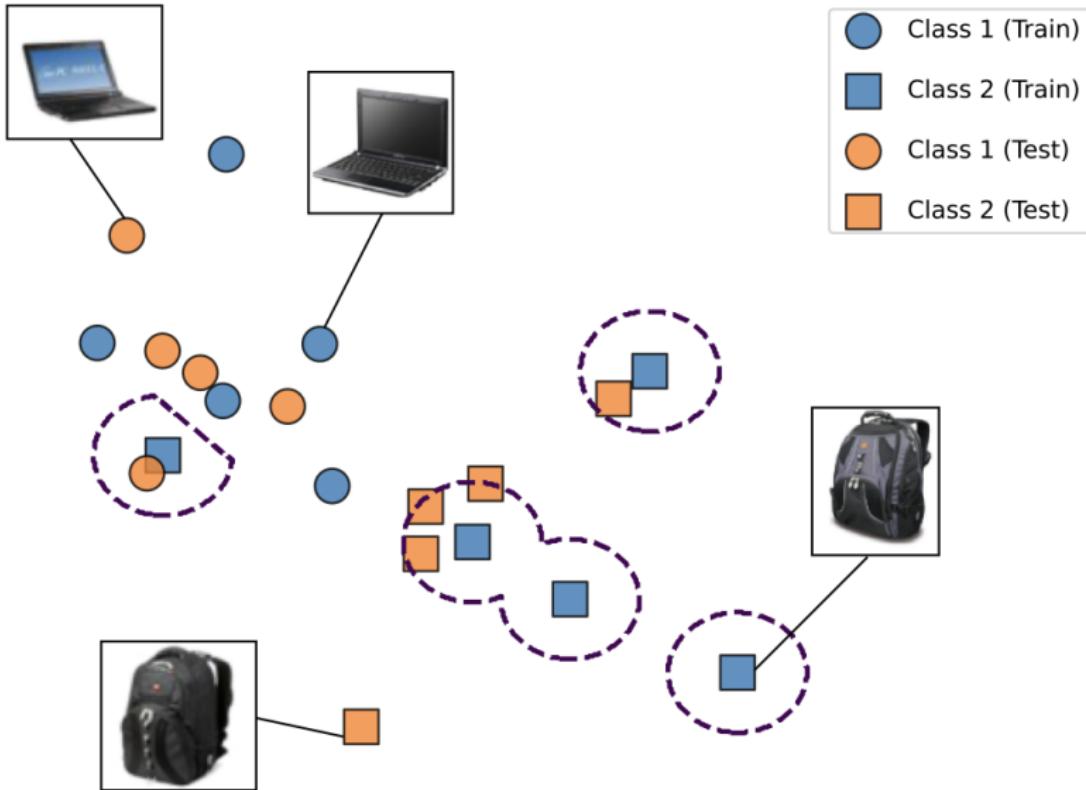
Motivation



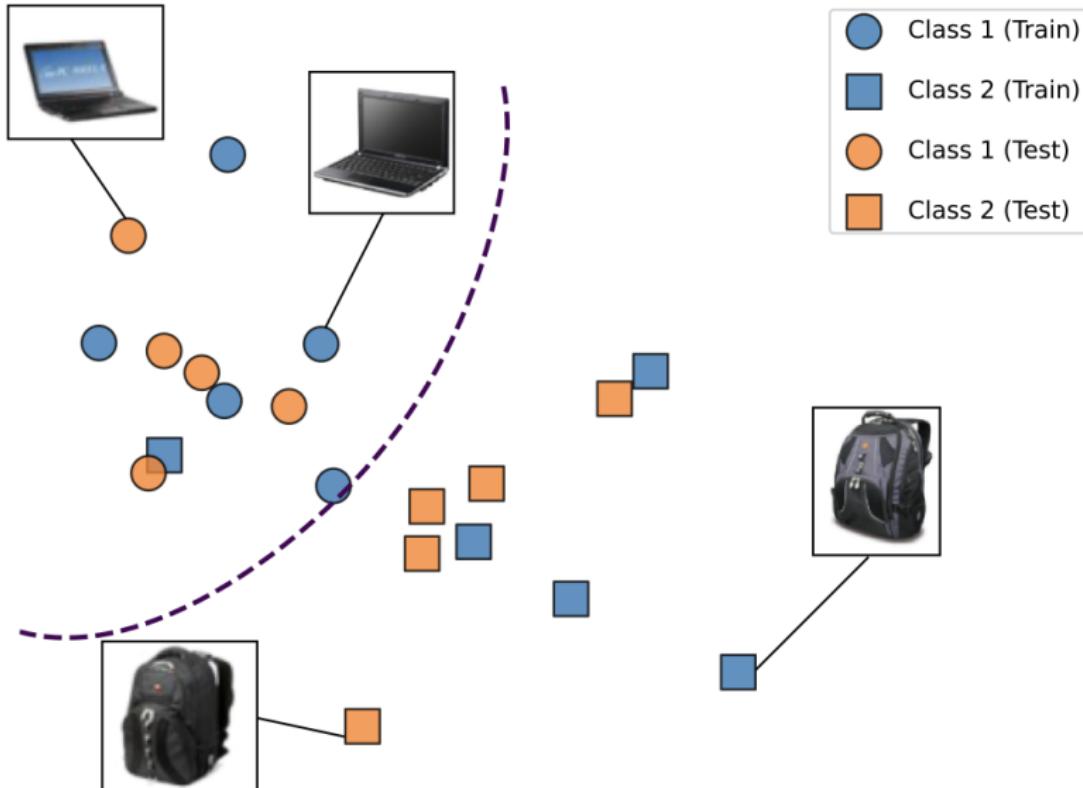
Motivation



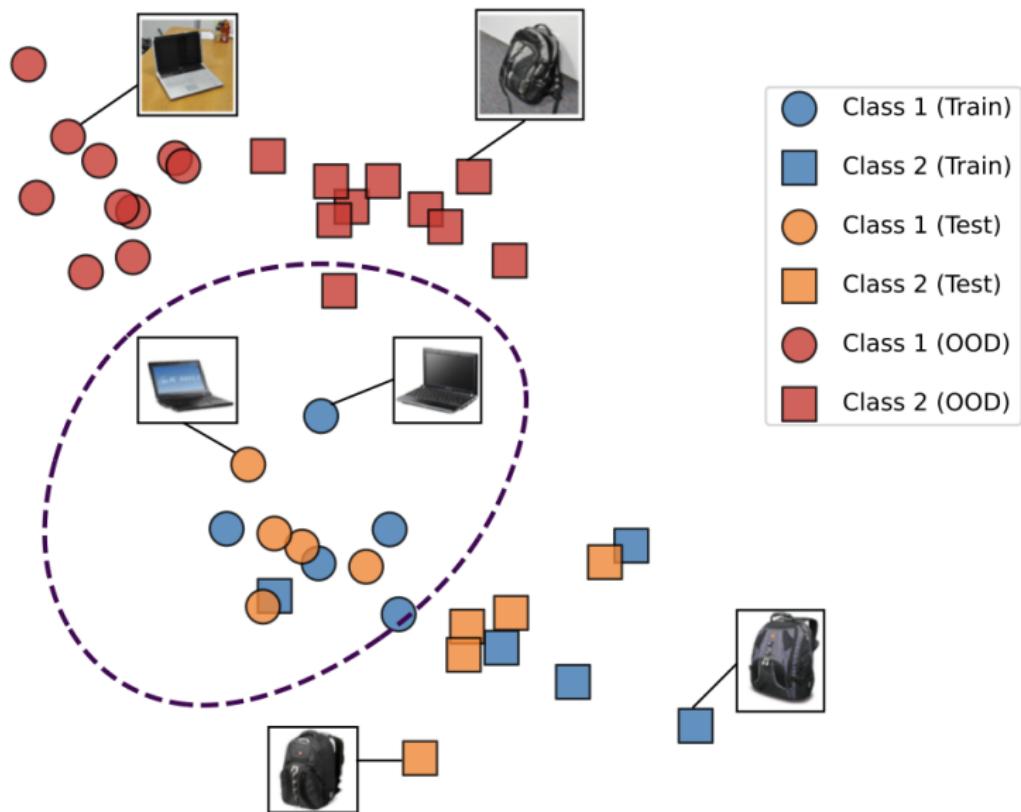
Motivation



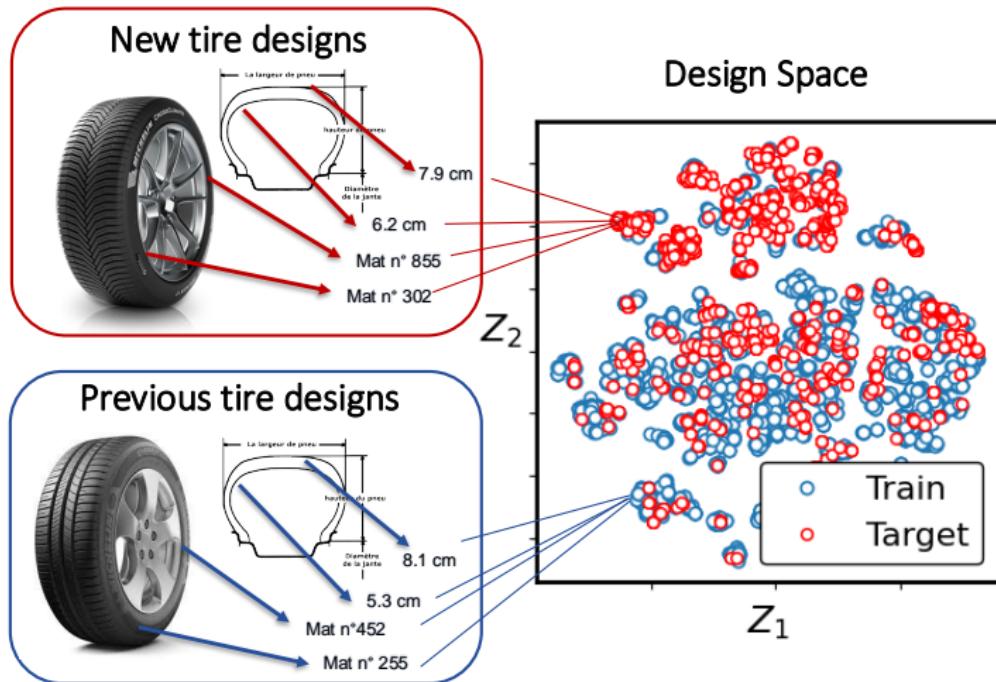
Motivation

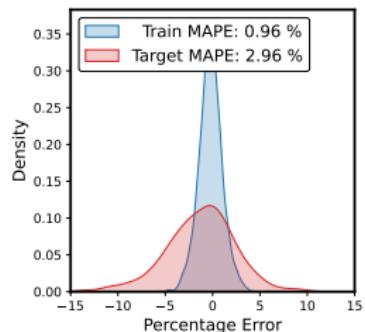
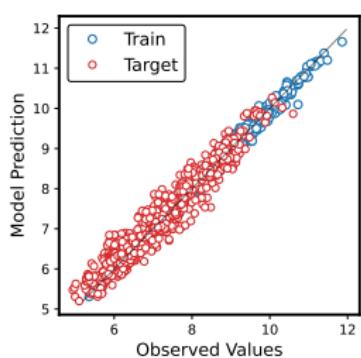
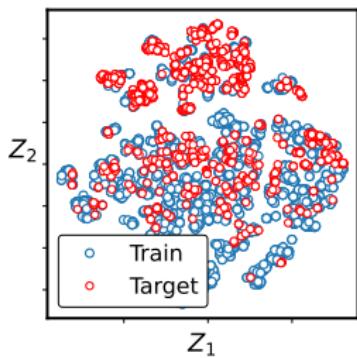
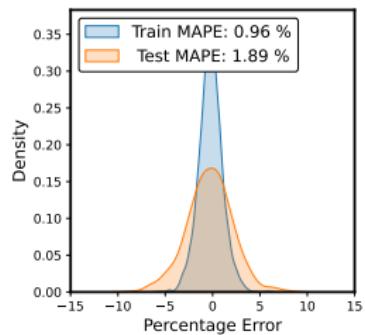
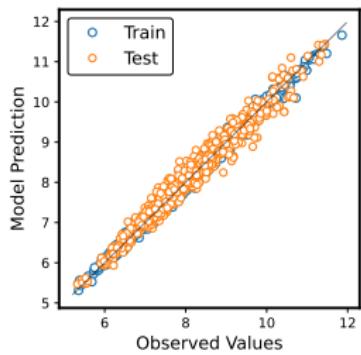
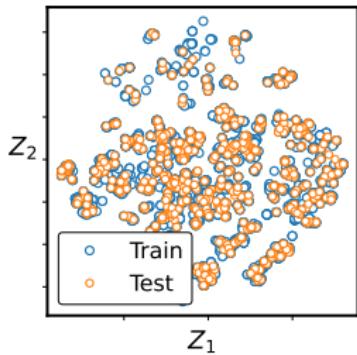


Motivation



Motivation



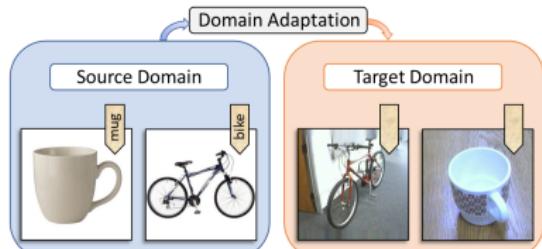
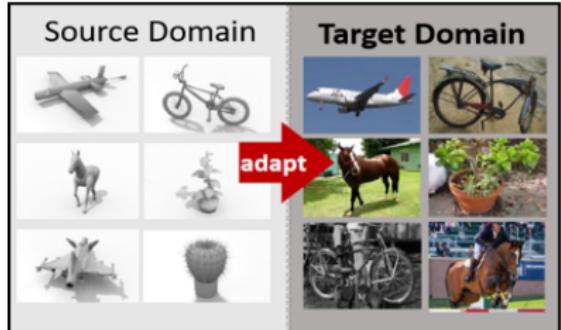
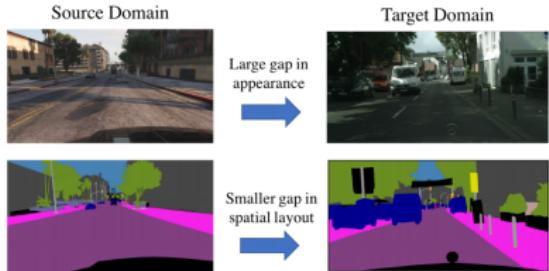


Design Space

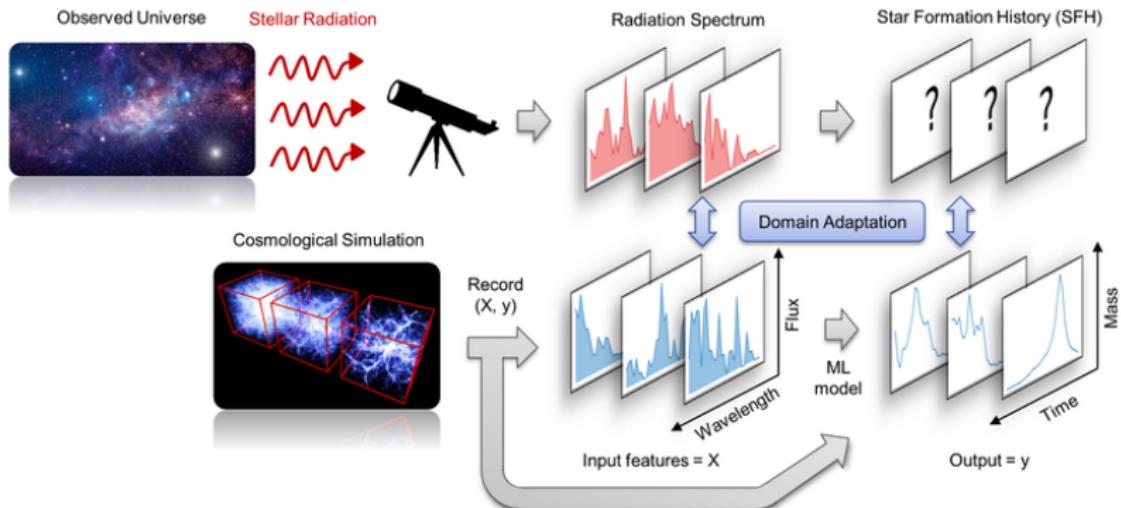
Validation

Residuals

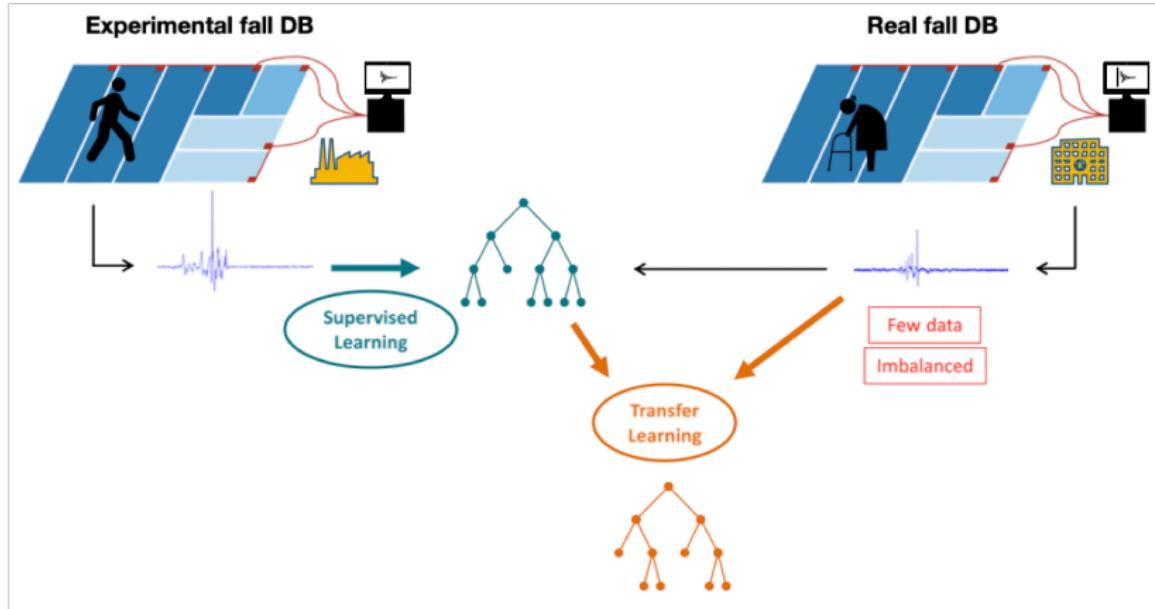
Motivation : From simulated to real data



Motivation : From simulated to real data



Motivation : From lab to real data



Motivation : Multisources / Batch Effect

Object recognition



Motivation : Multisources / Batch Effect

Sentiment analysis

★★★★★ Very high quality power supply.

Reviewed in the United States on November 9, 2022

I purchased this as an outboard power supply for an SMSL digital to analog converter. It works very well and provides stable power while not giving off QRM like the cheap little USB power supplies.



★★★★★ Raspberry Pi showing low power symbol

Reviewed in the United States on April 18, 2022

My Raspberry Pi 4 showing lightning ⚡ low power symbol after connect this unit. Unit feels pretty warm to the touch. Switched back to standard power cable and no issue. Looks like quality issue.



★★★★★ All good now

Reviewed in the United States on July 14, 2022

Originally this was a rushed game but in the 9 or so months it's been out there have been a ton of QOL changes and there is a large patch in the coming weeks with tons of content. With an expansion planned in the fall things are looking up and there is lots to do now.

4 people found this helpful



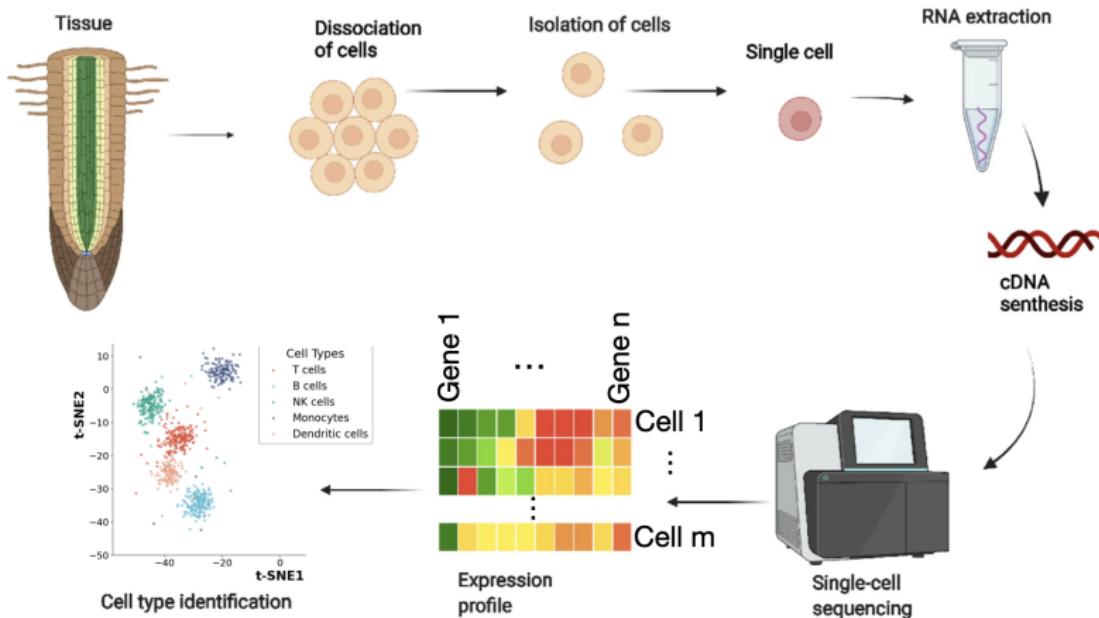
★★★★★ If I could give zero stars I would.

Reviewed in the United States on December 2, 2021

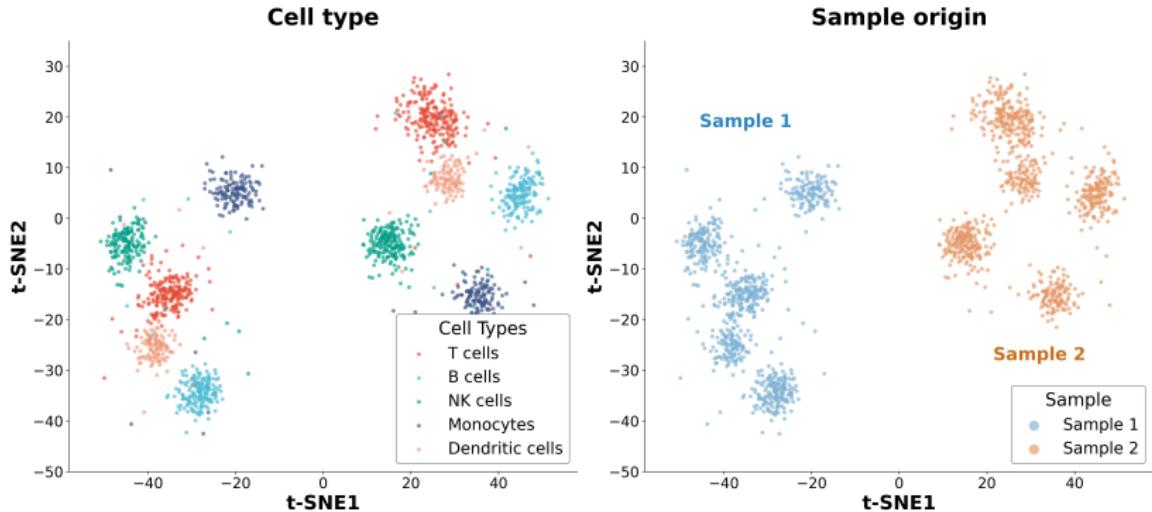
This is a company that cares more about selling new copies of the game instead of nurturing their creation.

There is potential for the game, yes. However, it has a long way to go before it gets there, and the company that owns this IP is driving it further away from that point - week over week.

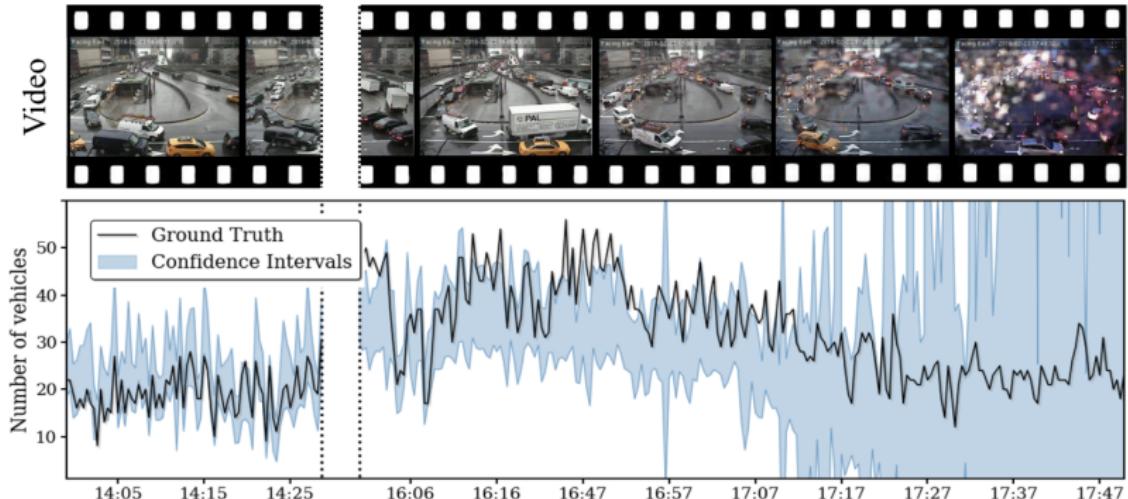
Motivation : Multisources / Batch Effect



Motivation : Multisources / Batch Effect

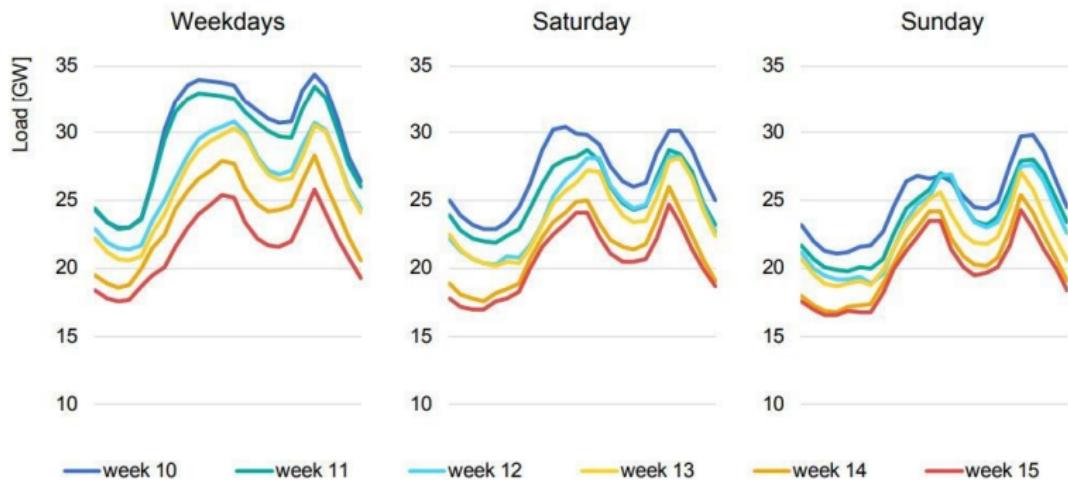


Motivation : Change in Experimental Conditions



Motivation : Change in Experimental Conditions

Impact of Covid 19 on hourly profile of electricity demand in Spain in 2020



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Motivation : Change in Experimental Conditions

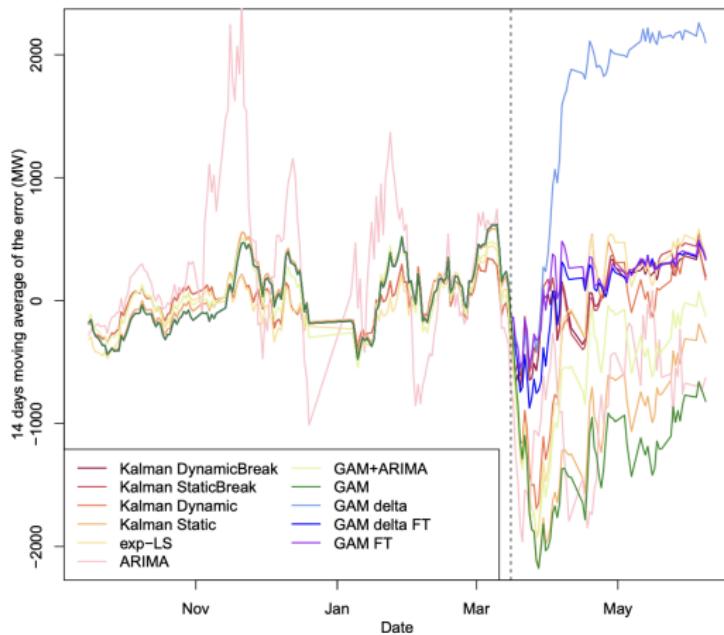
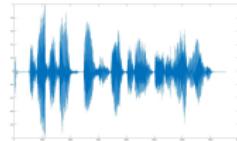


Figure 7.4 – Moving average of the error of the different models at 8-8:30 PM.

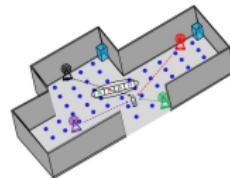
Various kinds of data :

- Time series
- Image and videos
- Audio and speech
- Natural language processing



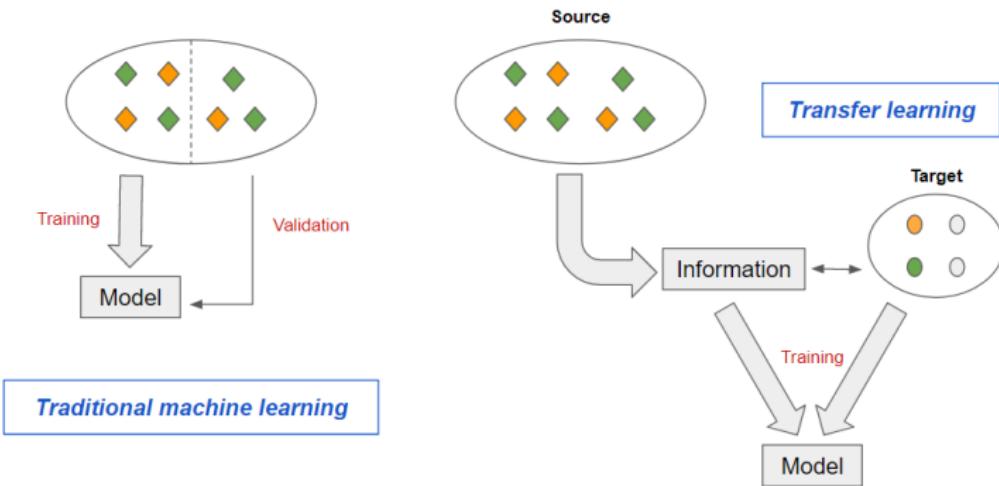
Various fields of application :

- Anomaly detection
- Biology
- Medicine
- Video games
- Indoor localization
- Computer vision



Transfer learning specificity

How is it different from classic ML ?



Why is re-training only on target domain/task not sufficient ?

- Few target data
- Unlabeled target data
- Partially representative data
- Missing features

Where should I start when solving TL problems ?

- Are **Source** data / model available ?
- Are **Source** / **Target** data labeled ?
- Do we consider the same feature/label spaces ?
- What kind of **Source** / **Target** relations do we observe / assume ?

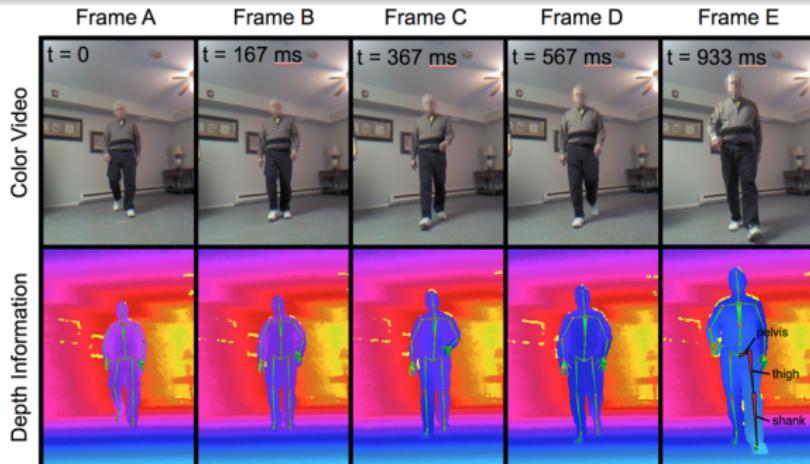
TL can be organized depending on :

- ① Applications : homogeneous/heterogeneous, supervised / unsupervised, inductive / transductive
- ② Assumptions : covariate shift, target shift, conditional shift
- ③ Methods : instance-based, feature-based, model-based

Homogeneous / Heterogeneous transfer

Heterogeneous transfer

While feature space or label space differs from **source** to **target** :
 $\mathcal{X}_S \neq \mathcal{X}_T$ or $\mathcal{Y}_S \neq \mathcal{Y}_T$.

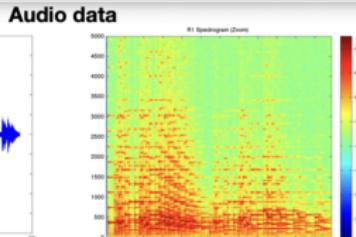
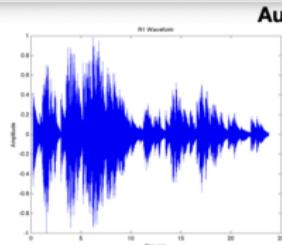


Example 1 : Motion tracking tasks from depth-camera images to normal images ($\mathcal{X}_S \neq \mathcal{X}_T$).

Homogeneous / Heterogeneous transfer

Heterogeneous transfer

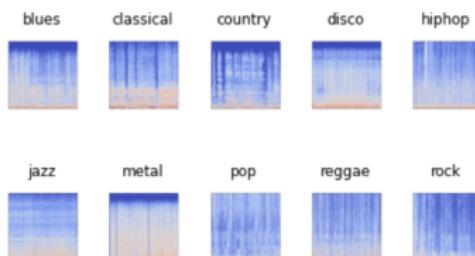
While feature space or label space differs from **source** to **target** :
 $\mathcal{X}_S \neq \mathcal{X}_T$ or $\mathcal{Y}_S \neq \mathcal{Y}_T$.



Source : Instrument detection



Target : Music style classification



Example 2 : Transfer from music instrument detection task to music style recognition task ($\mathcal{Y}_S \neq \mathcal{Y}_T$). 27/42

Categories of transfer depending on labels availability

- **Inductive** transfer : Labels are available both in **source** and **target**.
- **Transductive** transfer : Labels are available in **source** but not in **target**.
- Fully **unsupervised** transfer : No labels are available both on **source** and **target**.

Transfer learning definition

Domain/Task

\mathcal{X} a feature space and \mathcal{Y} a label space, a couple of random variables $(X, Y) \sim P$.

- **Domain** : $\mathcal{D} = \{X \in \mathcal{X}, P(X)\}$
- **Task** : $\mathcal{T} = \{Y \in \mathcal{Y}, P(Y|X=x)\}$

Transfer learning

Exploit information acquired from learning on **source** domain/task $(\mathcal{D}_S, \mathcal{T}_S)$ to benefit to new learning on *different* but *related* **target** domain/task $(\mathcal{D}_T, \mathcal{T}_T)$.

- Domain shift : $\mathcal{X}_S \neq \mathcal{X}_T$ or $P_S(X_S) \neq P_T(X_T)$
- Task shift : $\mathcal{Y}_S \neq \mathcal{Y}_T$ or $P_S(Y_S|X_S=x) \neq P_T(Y_T|X_T=x)$

How is it different from classic ML ?

Risk of a classifier

Risk $R(h)$ of a *classifier* $h : \mathcal{X} \rightarrow \mathcal{Y}$, according to a *loss function* ℓ , under a *probability distribution* P :

$$R(h) = \mathbb{E}_{(X,Y) \sim P} [\ell(h(X), Y)]$$

In transfer learning, risks on **Source** and **Target** differ :

$$P_S \neq P_T \rightarrow R_S(h) \neq R_T(h)$$

Main goal : good performance on **Target** domain/task but because of too few data or labels :

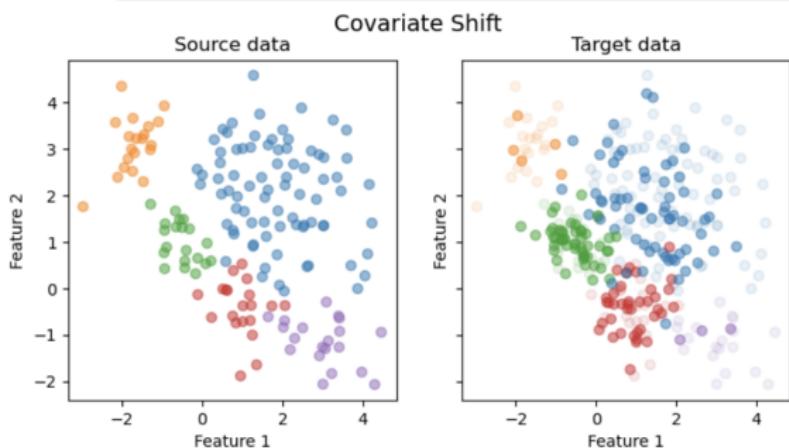
- Training only on **Target** is not sufficient.
- True performance on **Target** may be not assessable

Taxonomy of transfer learning [Assumption oriented]

Covariate shift

Marginal distribution changes between source and target but predictive dependency stays the same.

- $\mathcal{D}_T \neq \mathcal{D}_S, \quad (P_T(X) \neq P_S(X))$
- $\mathcal{T}_T = \mathcal{T}_S, \quad (P_T(Y|X) = P_S(Y|X))$



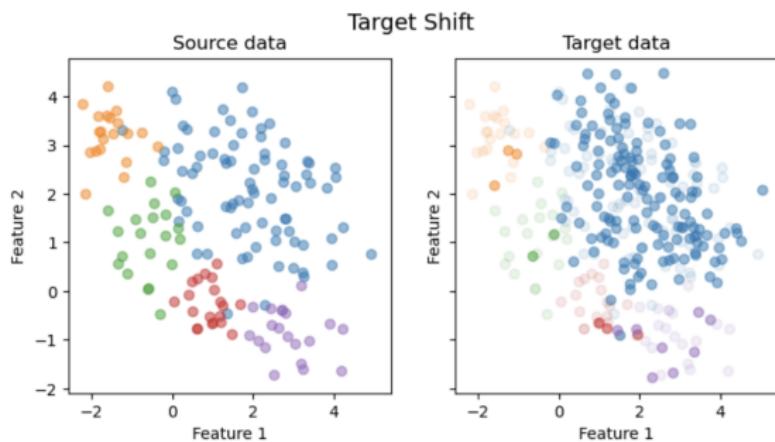
- Example : industrial machine downtime prediction, from normal to extreme conditions
- Challenges : support of source / target may not overlap, high-dimensions

Taxonomy of transfer learning [Assumption oriented]

Target shift

Conditional distribution for a given label y stays the same but the overall proportion of each label changes between source and target. $\forall y \in \mathcal{Y}$,

- $P_T(Y = y) \neq P_S(Y = y)$
- $P_T(X|Y = y) = P_S(X|Y = y)$



- Example : medical applications, studied population may not be representative
- Challenges : unsupervised learning, lack of data or labels

Sample-selection bias

Same underlying distribution P both on source and target. But hidden selection variable ξ that tends to exclude some observations from source data.

- $P_S(X, Y) = P(\xi = 1|X, Y)P(Y|X)P(X)$
 - $P_T(X, Y) = P(X, Y) = P(Y|X)P(X)$
- $$\implies P_S(X, Y) = P(\xi = 1|X, Y)P_T(X, Y)$$

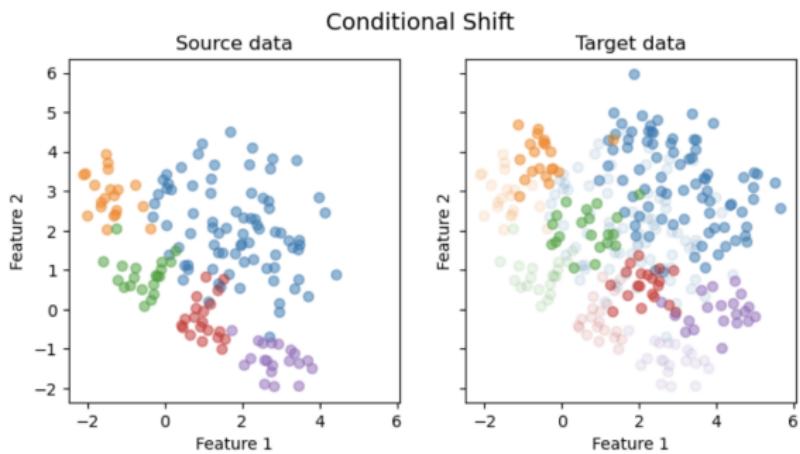
Taxonomy of transfer learning [Assumption oriented]

Concept shift

Both conditional distribution change between source and target.

- $P_T(Y|X) \neq P_S(Y|X)$
- $P_T(X|Y) \neq P_S(X|Y)$

Usually, a certain type of transformation is assumed (e.g.
 $P_T(X, Y) = P_S(\phi(X, Y))$).

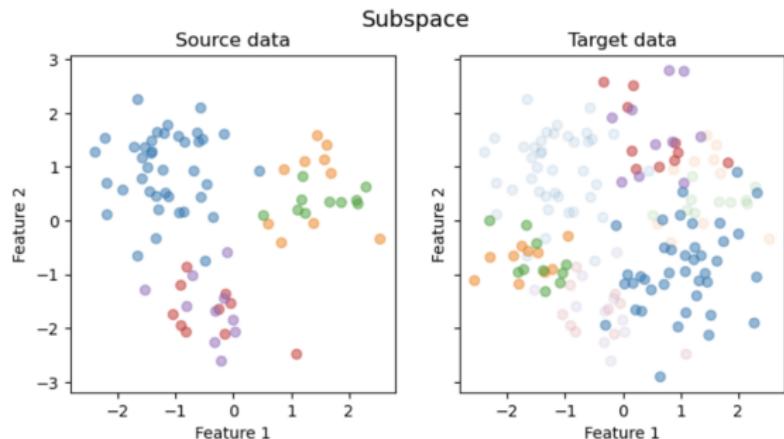


- Example : industrial sensor drifts
NLP from one language / usage context to another
- Challenges : prior information about the type of transformation between source / target (translations, rotations, scaling, etc...)

Subspace shift

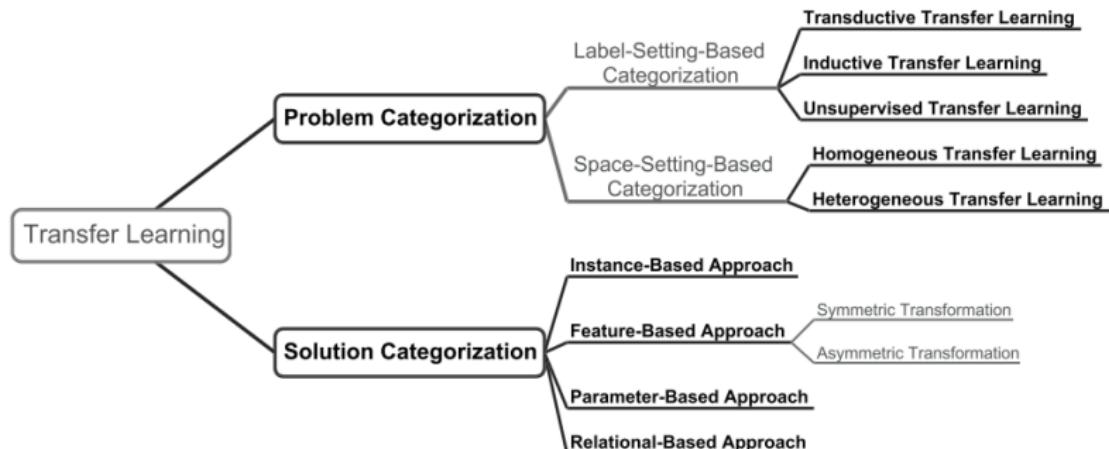
There exists a projection ϕ_d of dimension d such that :

- $P_T(Y/\phi_d(X)) = P_S(Y/\phi_d(X))$



- Example : different acquisition conditions in image processing
- Challenges : choosing the right dimension for the subspace, trade-off with some information loss

Taxonomy of transfer learning



A Comprehensive Survey on Transfer Learning (F. Zhuang et al., IEE 2021)

Transfer learning approaches

Transfer learning implies :

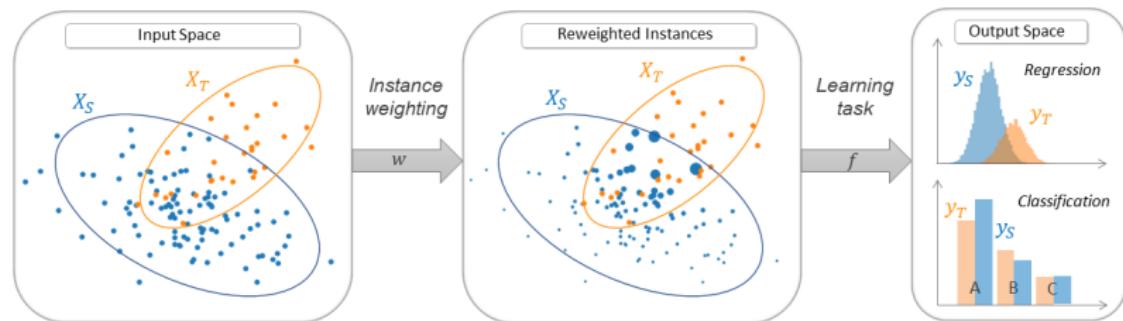
- ① Starting from a classical ML problem with \mathcal{X} a **feature** space and \mathcal{Y} a **label** space, (X, Y) random variables over these spaces.
- ② Two different distributions : $(X_S, Y_S) \sim P_S$ and $(X_T, Y_T) \sim P_T$.
- ③ Training only on **Target** data is not sufficient.
- ④ Move from a **Source** problem to a different but related **Target** problem.

Transfer learning approaches can rely on :

- Both **Source** and **Target** data
- Feature transformations into a **Source** / **Target** "common space"
- Assumptions about relations between **Source** and **Target** distributions
- **Similarity measures** between distributions or models

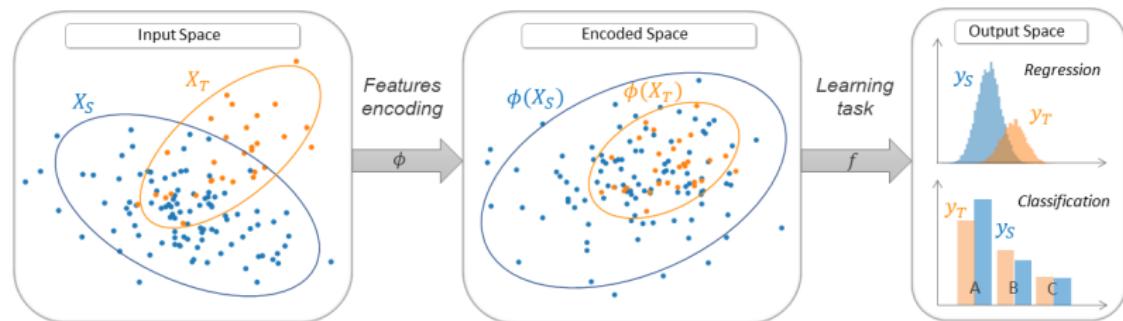
Transfer learning approaches : instance-based

Source and Target data used in training by **reweighting** strategies.



Transfer learning approaches : feature-based

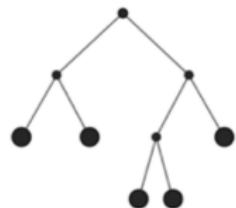
Source and **Target** features encoded into an intermediate feature space.



Transfer learning approaches : model-based

Pre-trained **Source** model, updated by **Target** data.

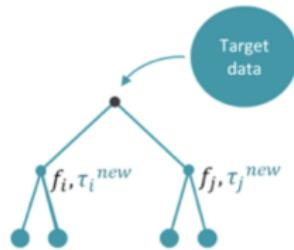
Initial source model



Updated by target data



Constraint on parameter Deviation



Transfer learning borders/limits

Negative transfer

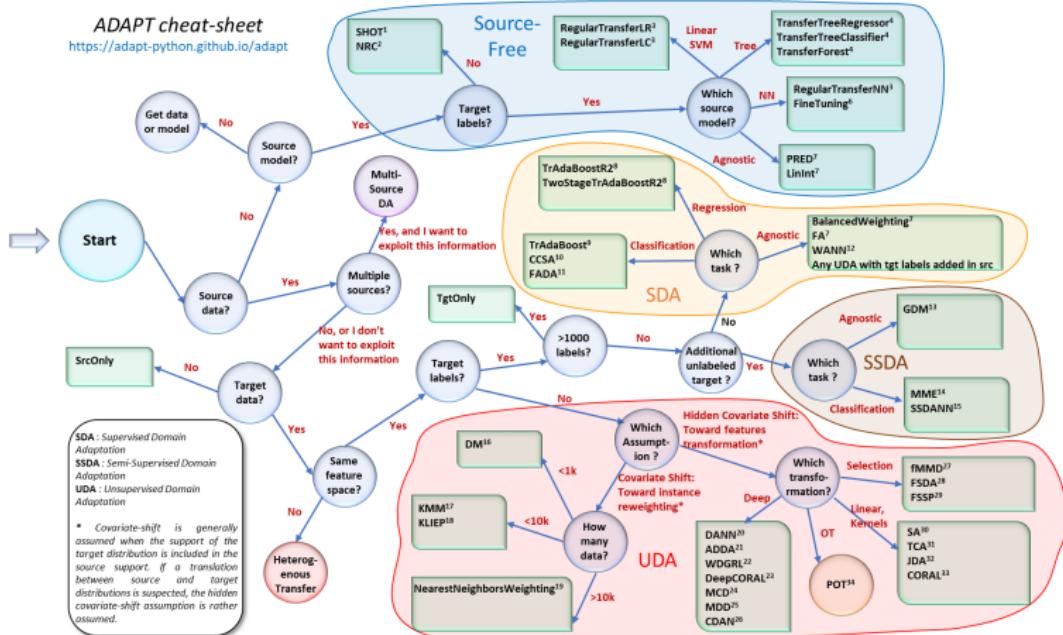
Negative transfer occurs while source knowledge is worst than training on target domain only.

- Dissimilarity between source and target domains is too important
- Source and target tasks are not enough related
- Transfer learning strategy is not well-suited for the problem

Related fields

- Multi-source learning / Multi-task learning
- Few-shot learning
- Reinforcement learning, online learning, lifelong learning
- Optimal transport

Taxonomy of ADAPT transfer learning methods



<https://adapt-python.github.io/adapt/map.html>