Domain Adaptation for Predictive Maintenance

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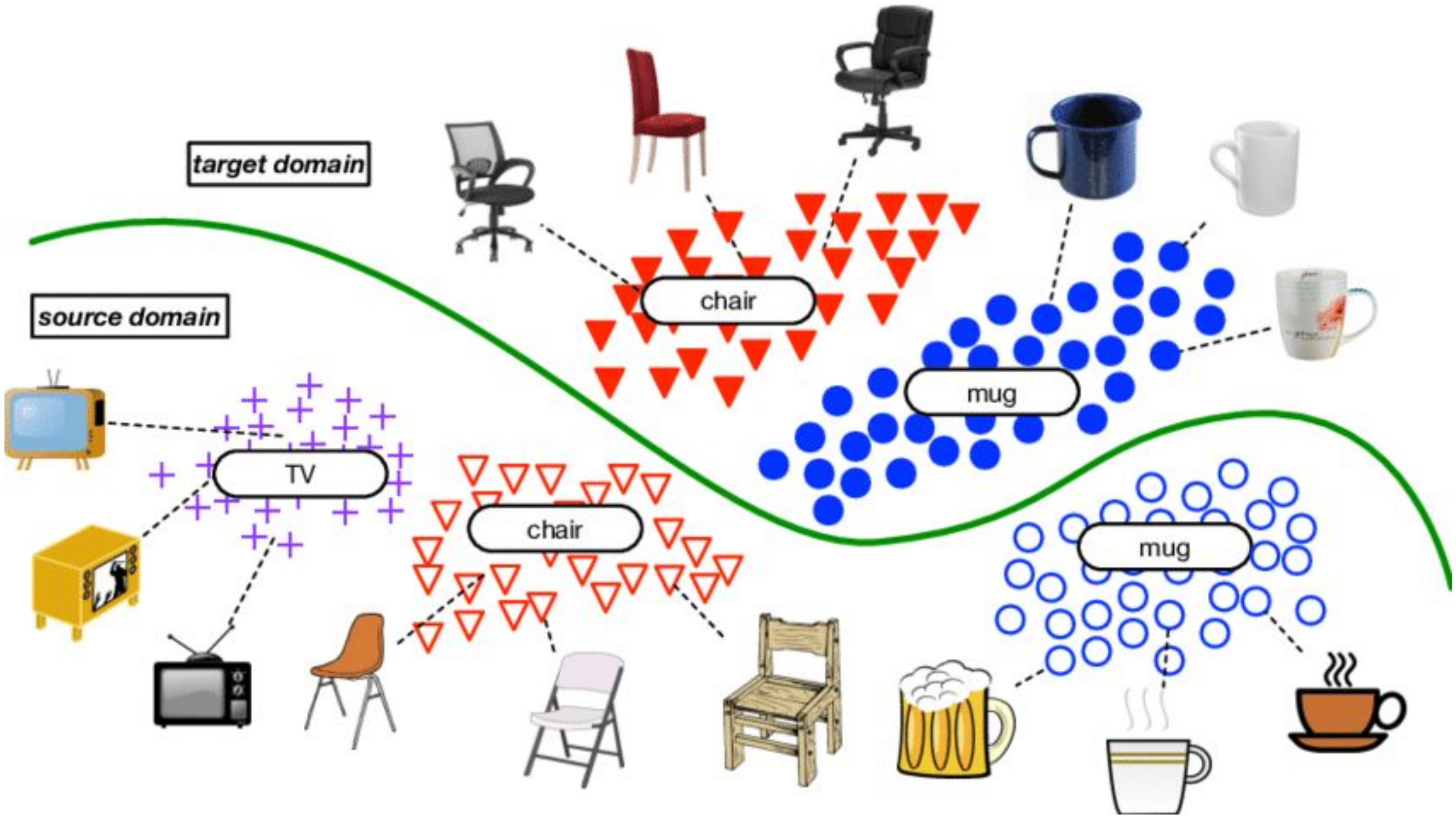
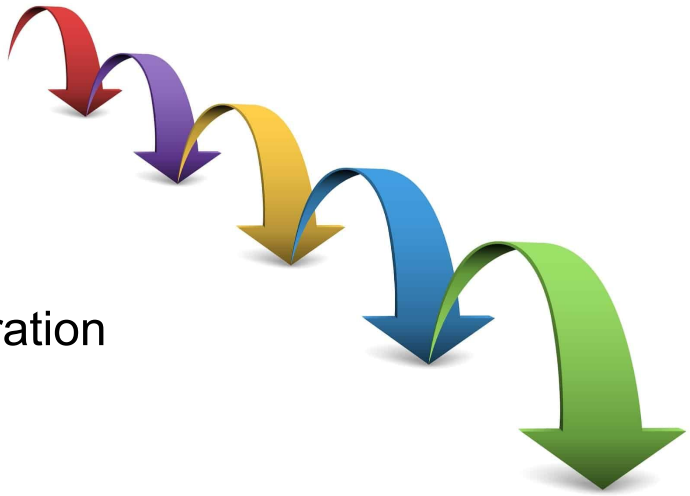

target domain
source domain
chair
mug
TV
chair
mug

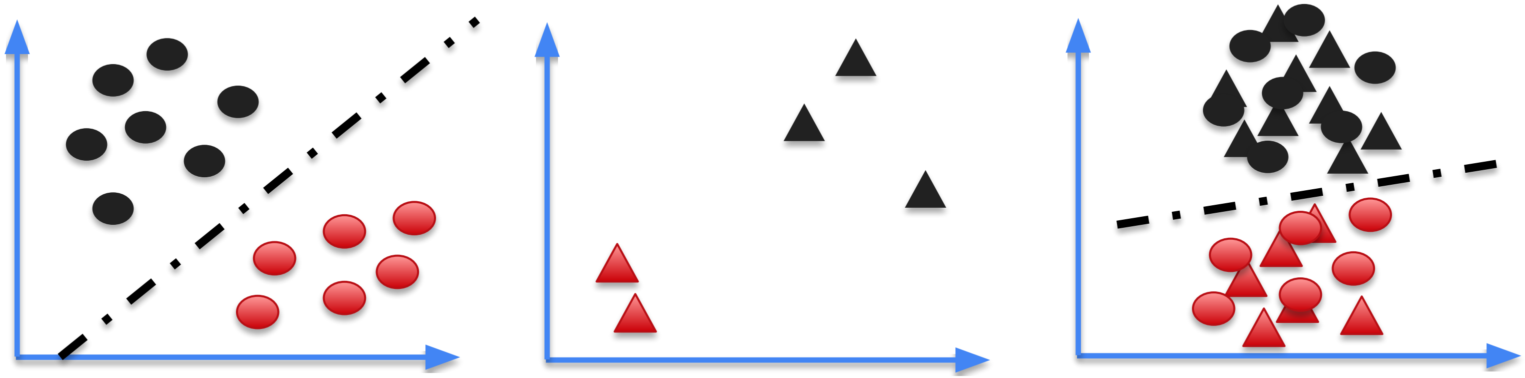
Why Transfer?

- To avoid building a model from scratch
  - Time consuming to train a model
- To reuse existing knowledge
  - Not to develop a model for each conditions
- To deal with a new system or a new configuration
  - Avoid collecting a lot of new data
- To preserve privacy
  - Share models rather than the data



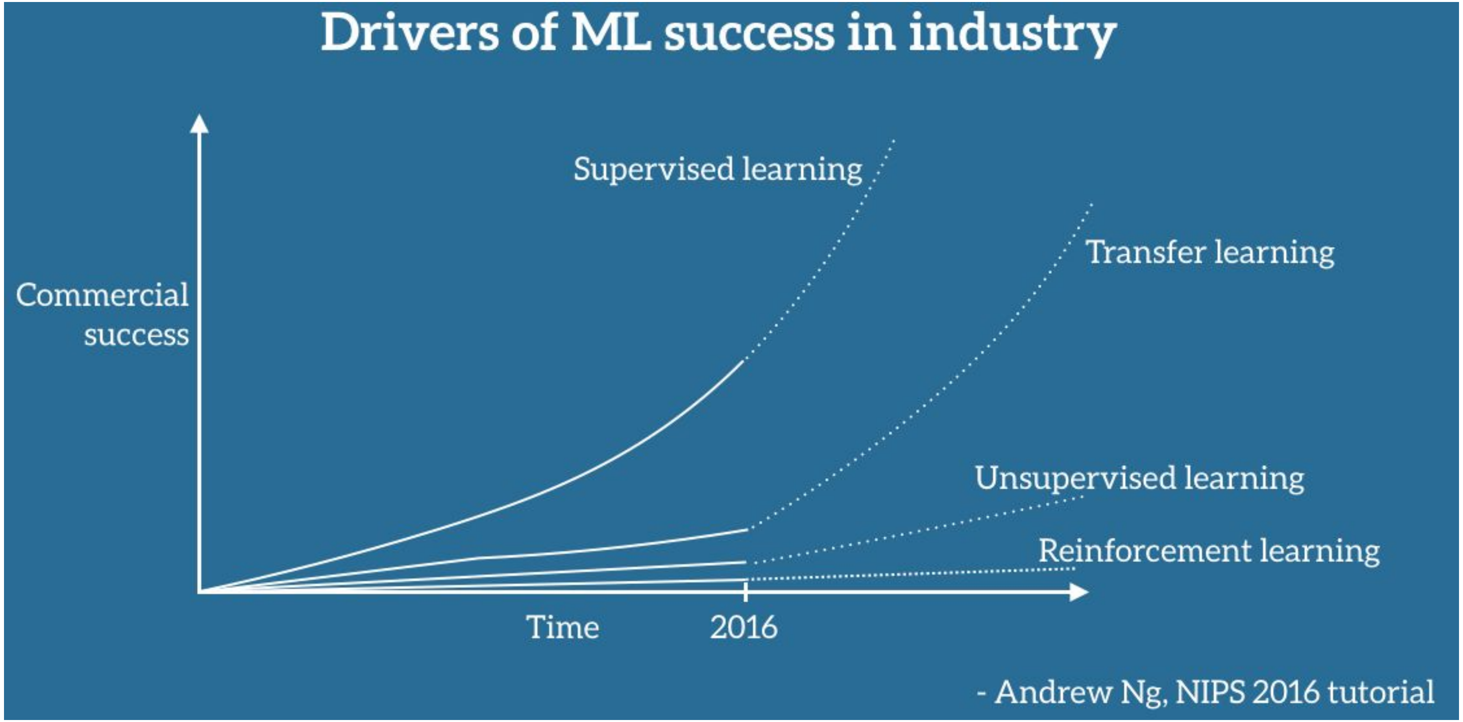
Transfer Learning

The ability of a system to recognise and apply knowledge and skills learned in **previous** domains/tasks to **novel** domains/tasks, which **share some commonality**.



Source domain | Target domain | Transfer Learning

Is transfer learning considers as ML's next frontier?



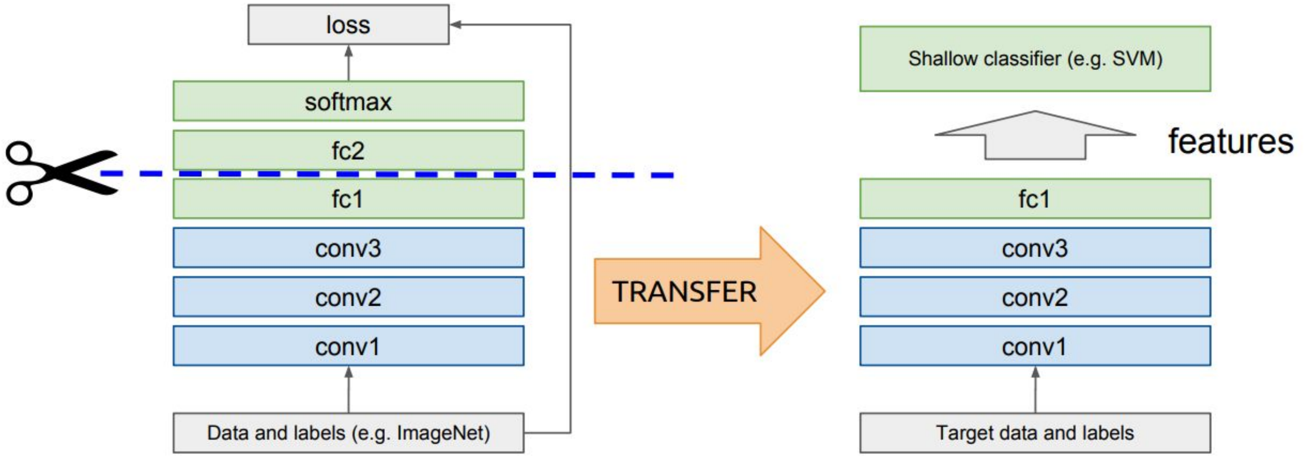
https://ruder.io/transfer-learning/index.html

Domain adaptation

“Off-the-shelf” strategy

Idea: use outputs of one or more layers of a network trained on a different task as generic feature detectors. Train a new shallow model on these features.

Assume: $\mathbf{D_S = D_T}$



Fine-tuning: supervised domain adaptation

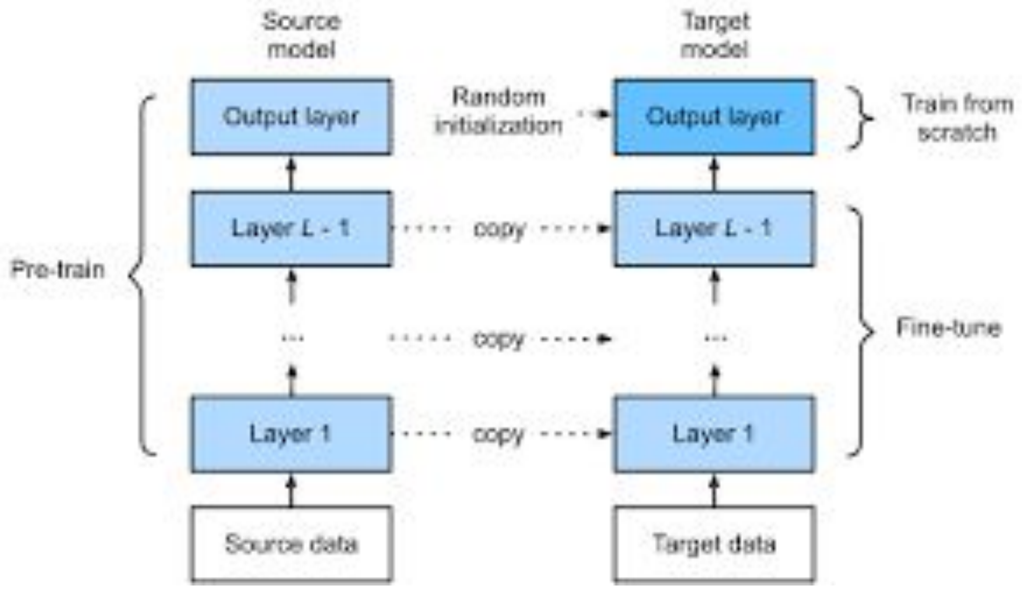
Pretrain a network which it is easy to get labels or select a pretrained network

- E.g. ImageNet classification
- Pseudo classes from augmented data
- Slow feature learning, ego-motion

Replace the last layer with supervised objective for target domain

Fine-tune network with labels for target domain

Aligns D_S with D_T



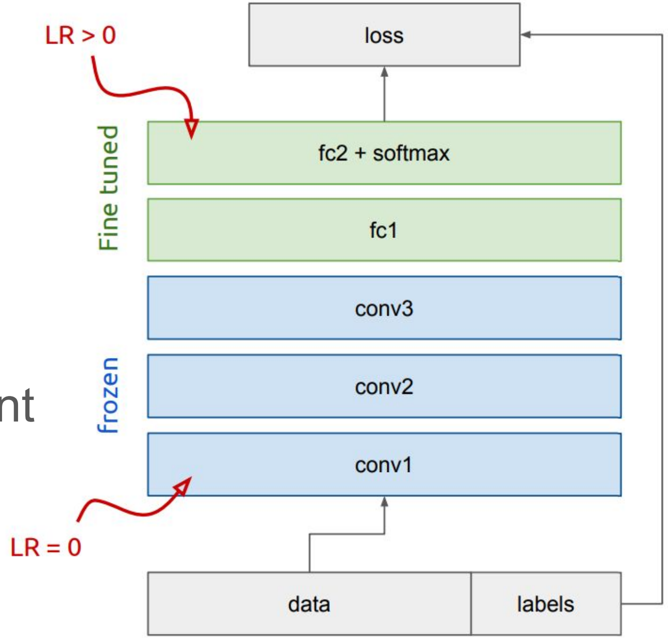
Freeze or fine-tune?

Bottom n layers can be frozen or fine tuned.

- **Frozen:** not updated during backprop
- **Fine-tuned:** updated during backprop

Which to do depends on target task:

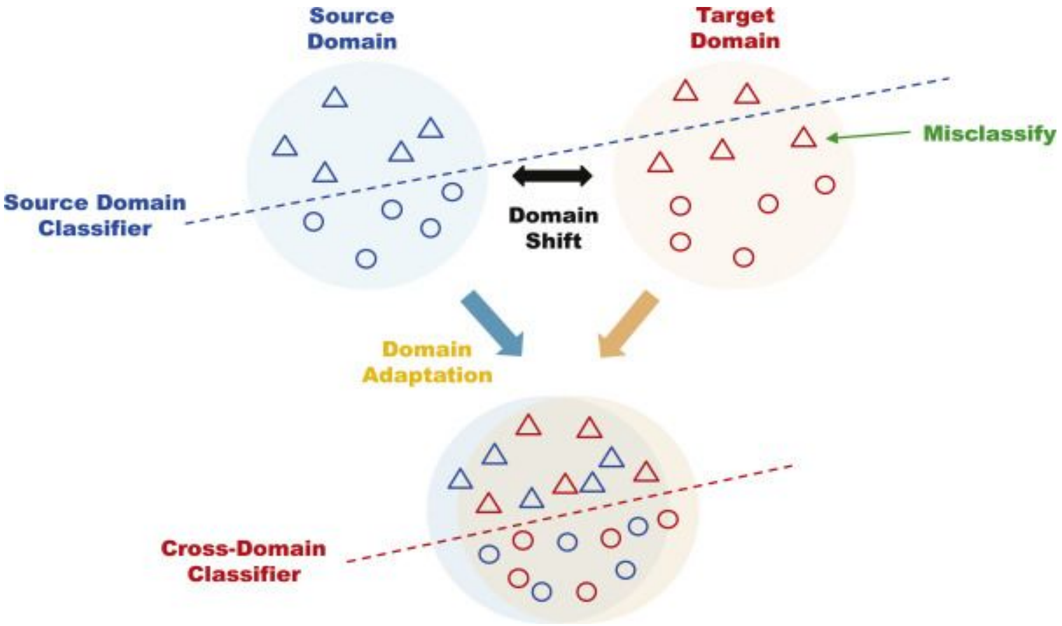
- **Freeze:** target task labels are scarce, and we want to avoid overfitting
- **Fine-tune:** target task labels are more plentiful In general



Learning with domain adaptation

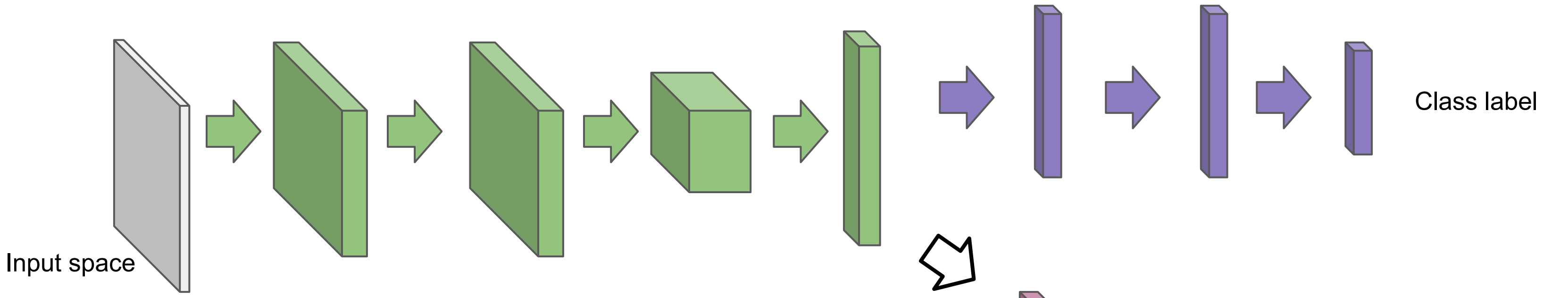
When data at source and target domains come from similar but different distributions

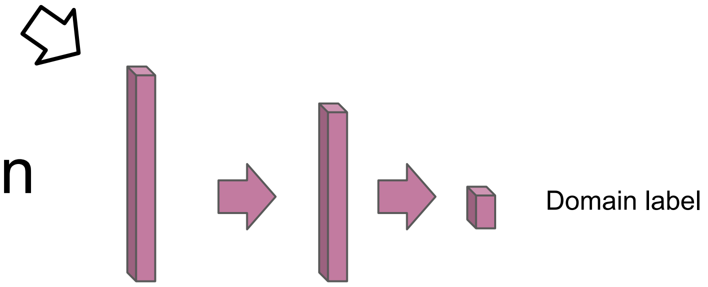
Create a new feature space that **cannot discriminate between the source and target domains** and **classify correctly in both domains**



https://arxiv.org/pdf/2010.03978.pdf

Domain Adversarial Neural Network (DANN)





Build a network for domain adaptation

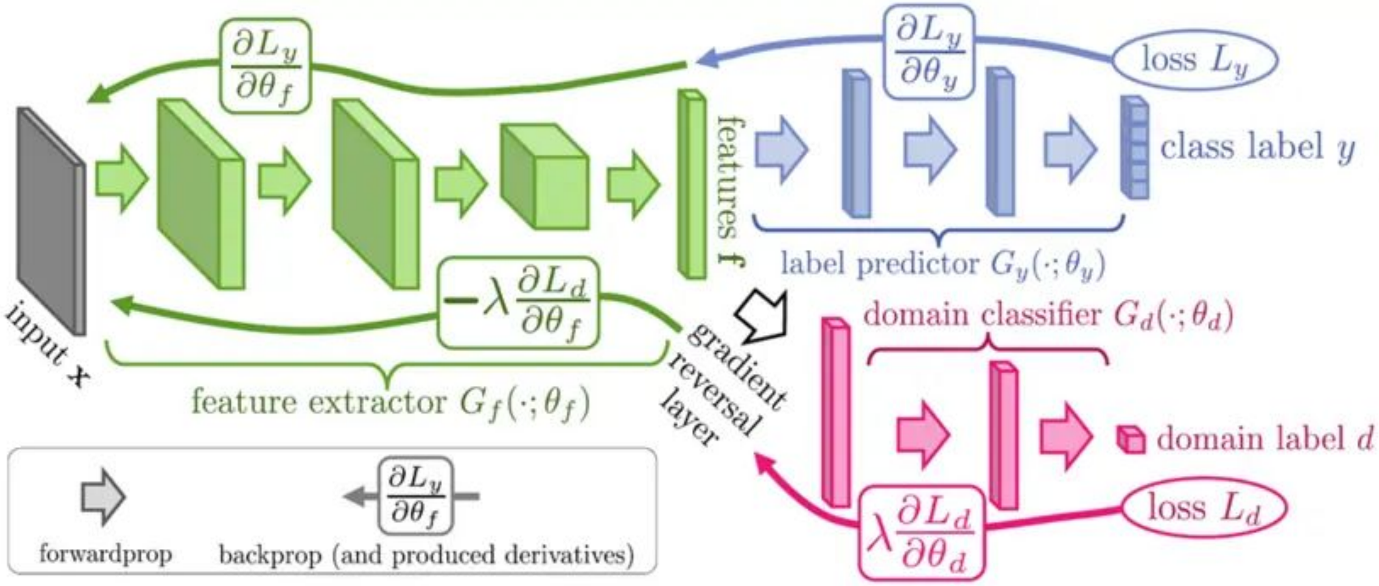
- Train a feature extractor and class predictor on **source data**
- Train a feature extractor and domain adaptor on **source and target data**
- Use a feature extractor and class predictor at the **test time**

DANN, https://arxiv.org/pdf/1505.07818.pdf

Backpropagation during training

Design the loss function in a way that we have

- Good class predictor
- Bad domain classifier



Minimising domain shift during backprop.

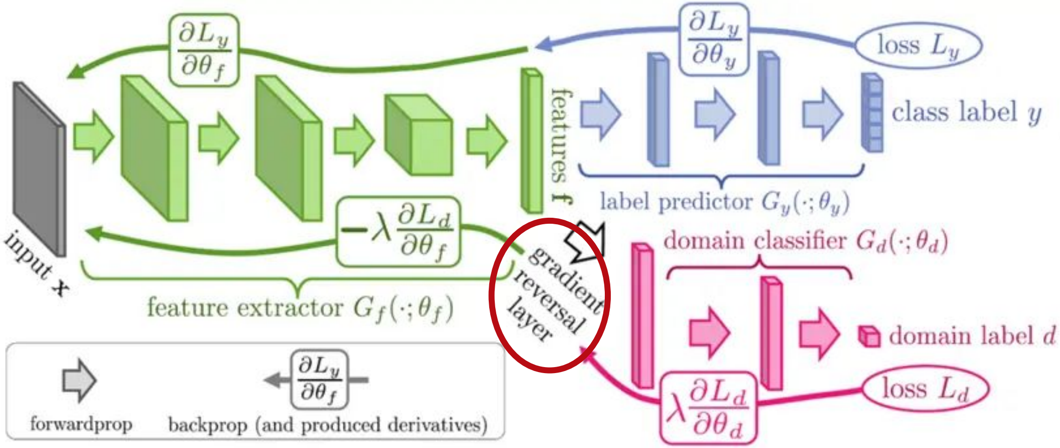
gradient reversal layer

- leaves the input unchanged during forward propagation
- reverses the gradient by multiplying it by a negative scalar during the backpropagation

$$\theta_f \longleftarrow \theta_f - \mu\left(\frac{\partial \mathcal{L}_y^i}{\partial \theta_f} - \lambda \frac{\partial \mathcal{L}_d^i}{\partial \theta_f}\right),$$

$$\theta_y \longleftarrow \theta_y - \mu \frac{\partial \mathcal{L}_y^i}{\partial \theta_y},$$

$$\theta_d \longleftarrow \theta_d - \mu\lambda \frac{\partial \mathcal{L}_d^i}{\partial \theta_d},$$

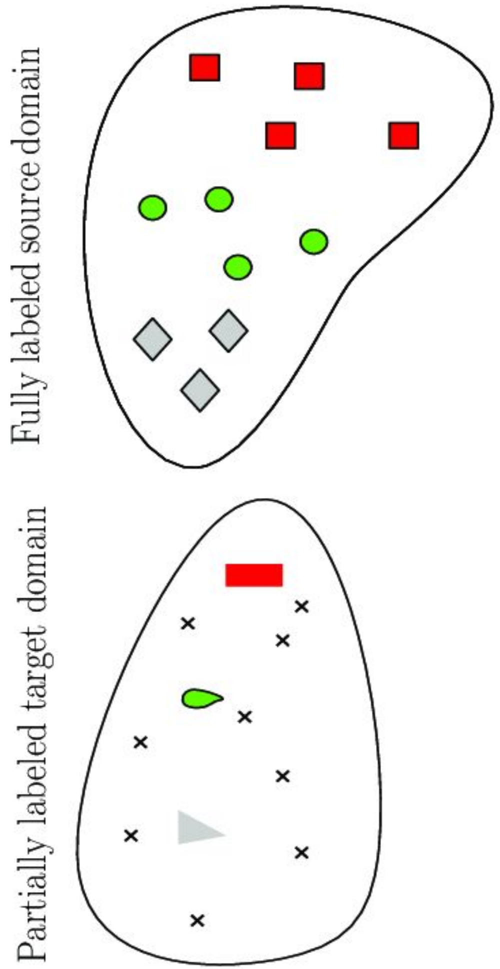


Semi-supervised domain adaptation

When some labels are available in the target domain, then we can use these when doing domain adaptation.

Simultaneously optimizing different criteria:

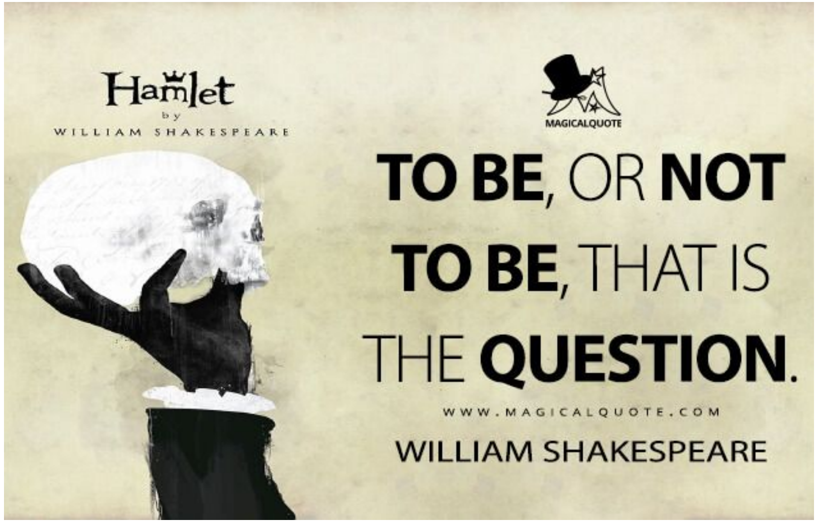
- Classification accuracy on both source and target datasets
- Goodness of mapping different domains



To transfer or not to transfer

Use transfer learning when

- Source and target domains are similar enough!
- Target data set is relatively small
- Source model has been trained on a quite big data set
- Source domain contain diverse set of the data, and not from a domain-specific task



VOLVO
Volvo Buses
Volvo Connected Solutions

EVE - Extending life of Vehicles within Electromobility era

HALMSTAD UNIVERSITY

VINNOVA

2019 - 2023

Goals

- Predicting lifetime of each individual battery
- Suggesting actions to extend battery lifetime
- Monitoring of other components in electric driveline,
  e.g. battery contactor
- Estimating energy consumption and proposing services for different behaviour groups

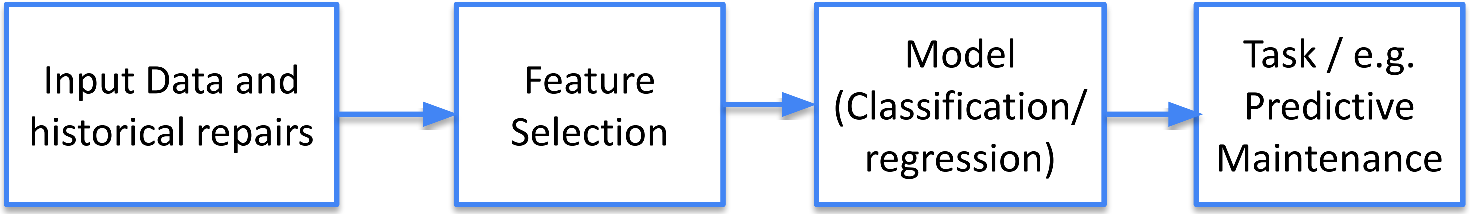
Monitoring drive batteries

Challenges

Real data is complex

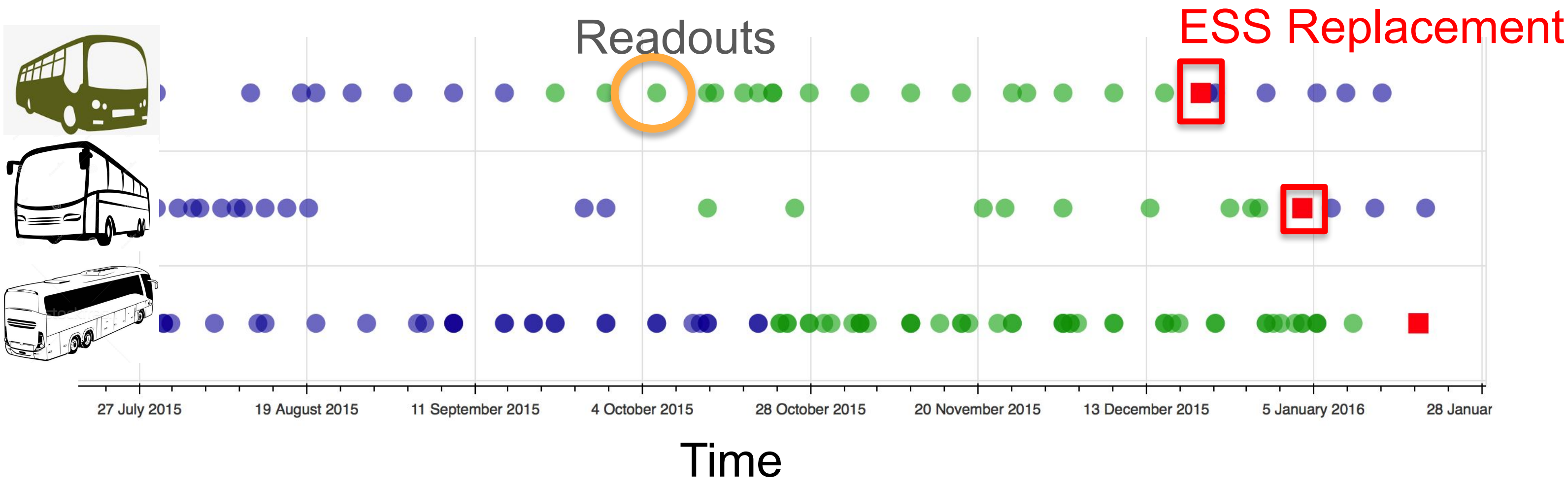
- Relevant information is seldomly directly measured
  - Labels (repair vs actual fault)
  - Sensor measurements (limited number of sensors)
- Data is heavily imbalanced
- Normal operation is difficult to characterise
  - Concept drift due to usage & external conditions
- Missing data
- Low data frequency

Typical Approach - Classical supervised machine learning



Analysing the current replacement strategy

- Can we create a model that predicts the current strategy?
- How can we improve the current strategy?



Results of ESS replacement model

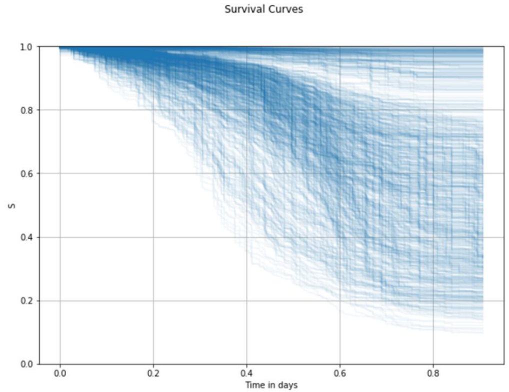
- A ML model to estimate if a bus is approaching an ESS replacement due date, based on operating parameters.
- Trained with 360 buses data and tested on 90 buses.

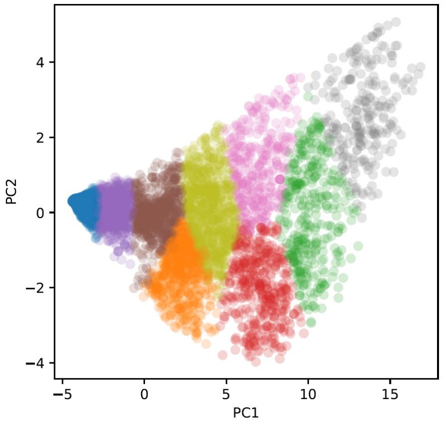
All - 180 Days	Predicted: **No**	Predicted: **Yes**
Actual: **No**	7,441	1,427
Actual: **Yes**	1,041	1,834

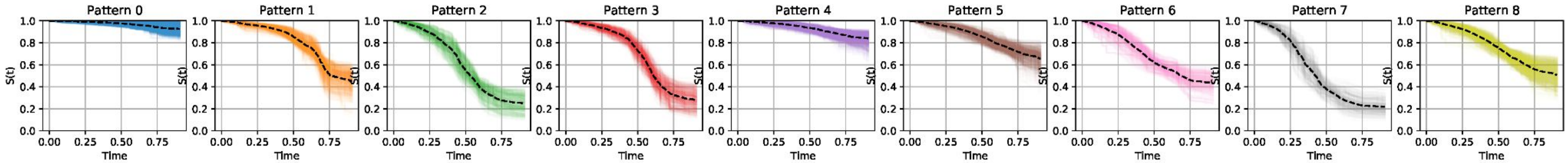
B5LH – 180 Days	Predicted: **No**	Predicted: **Yes**
Actual: **No**	3,516	933
Actual: **Yes**	654	2,540

Survival of batteries for hybrid buses

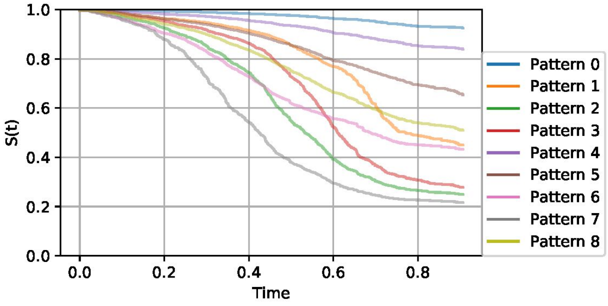
Different survival patterns



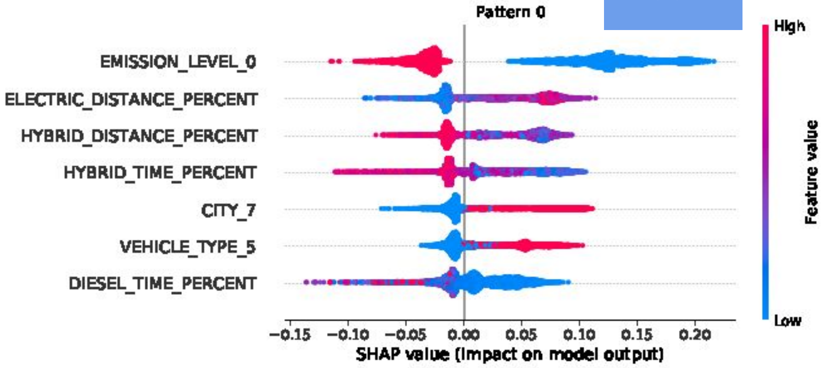




Explanation for pattern



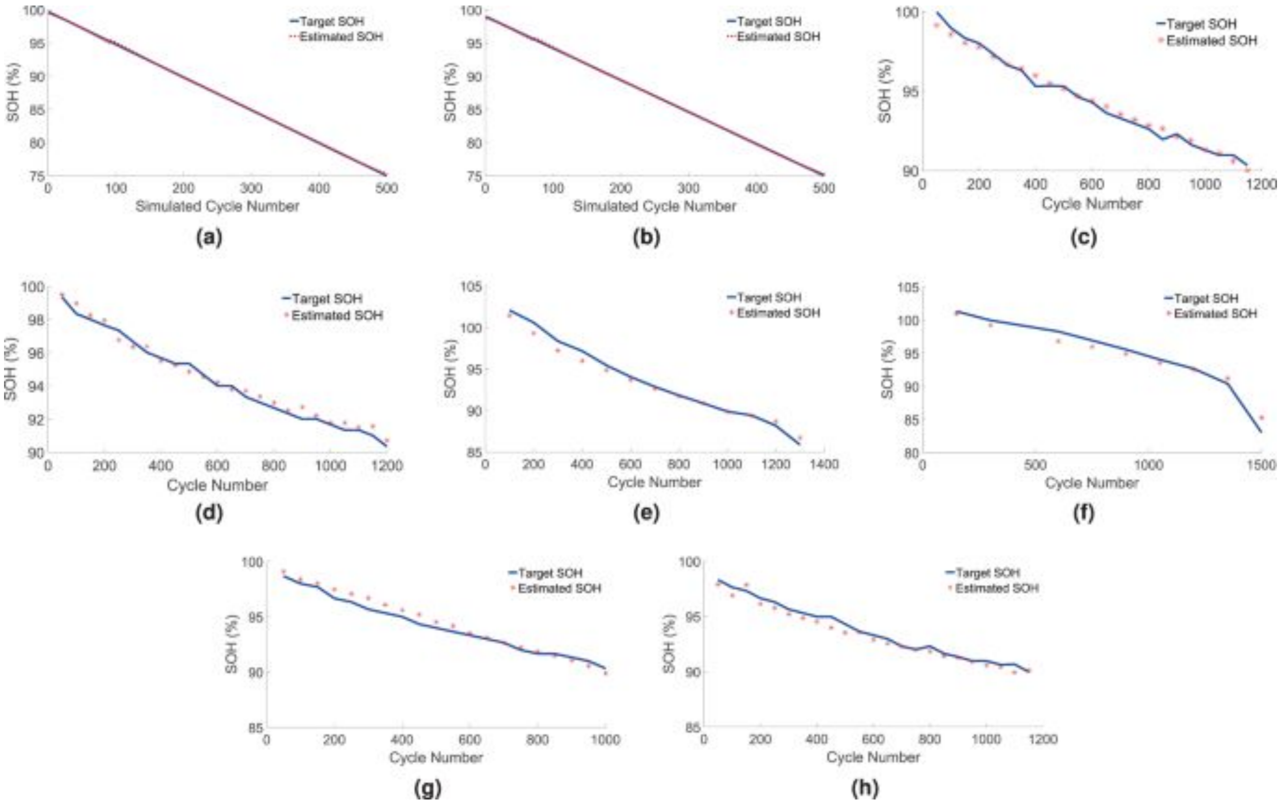
Best



Best Pattern:

- Not Emission Level 0
- High usage of the electric mode and low usage of hybrid mode (healthy battery)

Estimating and predicting the State of Health (SOH) for batteries for hybrid buses



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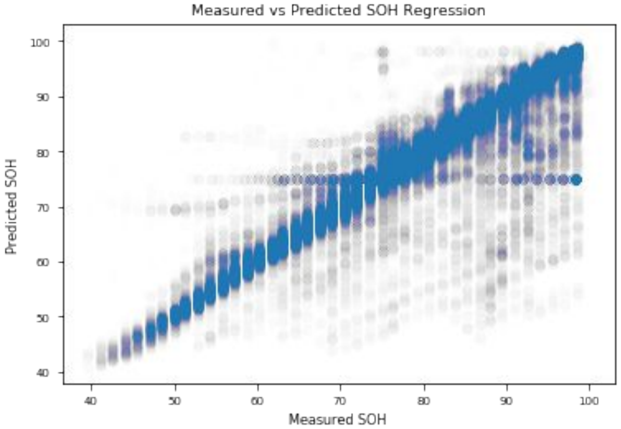
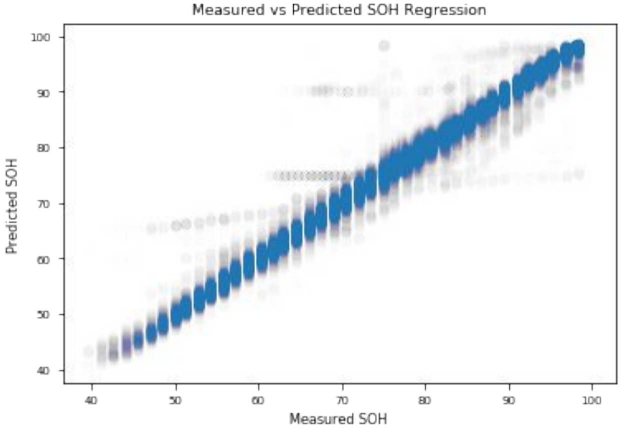




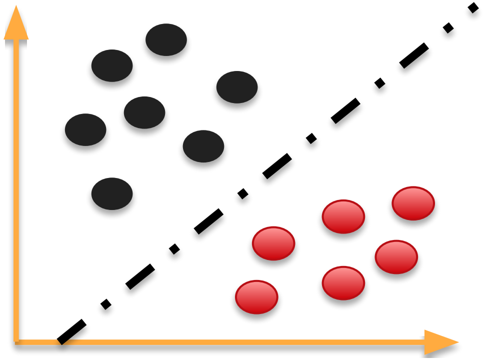
Metric	All (3212 Buses)	Monotonic-decreasing Function (2049 Buses)
MAE	2.60	1.04
R^2	0.81	0.98
Correlation	0.90	0.99

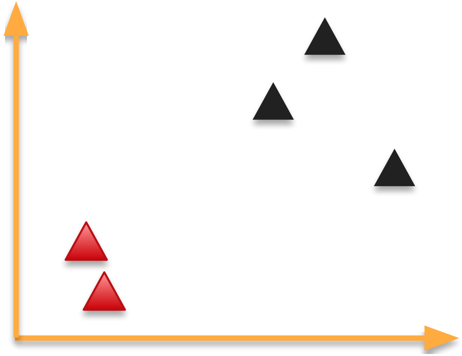
M. G. Altarabichi, Y. Fan, S. Pashami, S. Nowaczyk, and T. Rögnvaldsson. **Predicting State of Health and End of Life for Batteries in Hybrid Energy Buses**. ESREL-PSAM 2020 Conference, Italy, 1 - 6 November 2020.

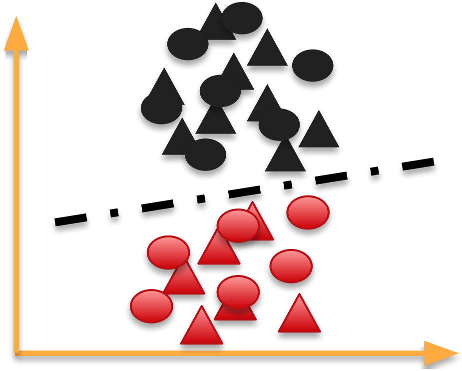
There are more challenges ...

- How to deal with a new system or a new configuration?
  - Can we avoid collecting a lot of new data?
  - E.g. Hybrid vs. full-electric, single vs. double deck
- How to deal with a different usage pattern?
  - E.g. deployment in a new country, long haul vs delivery vehicles
- How about diversity in operating conditions?
  - Do we need a new model for every possible operating condition?

Domain adaptation







Source domain

Target domain

Domain adaptation

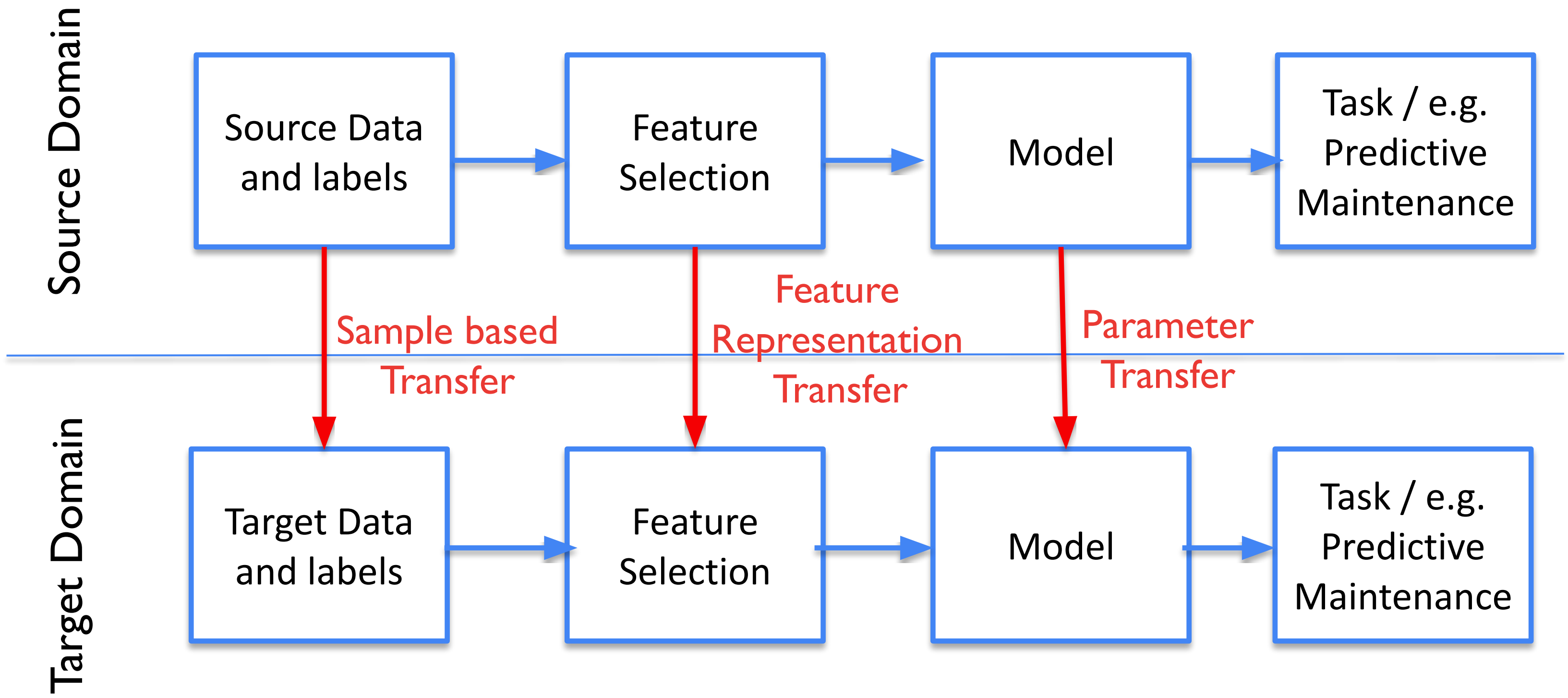
Where did we use transfer learning?

Hybrid buses

Modelling State of Health of Li-Ion Batteries

- Vehicle type
  - single decker, double decker, articulated
- Battery generation
  - Akasol, Samsung, …
- Countries
  - Sweden, UK, …
- Data driven grouping

Practical Approach - Domain adaptation



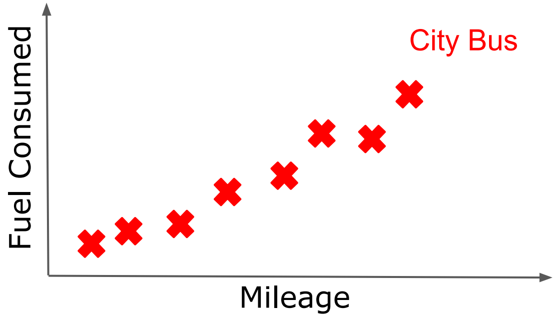
Sample Based Transfer Learning for Predictive Maintenance

- Selecting the right sample population for modelling
    - Physical configurations
    - Deployment areas
    - Operating conditions
    - Usage patterns
    - …
- Finding homogeneous sub-fleets based on similarity
    - Learning the representation to capture the characteristics of the equipment
    - Grouping peers with clustering and a similarity metric



Sample Based TL for Predictive Maintenance

- A data-driven approach for finding the sub-fleet cluster from the whole population
    - Learning the representation of different equipment from sensor data



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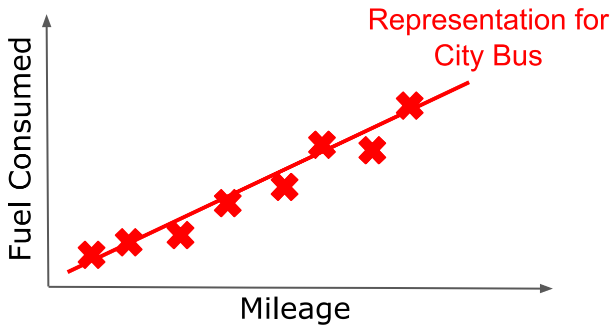

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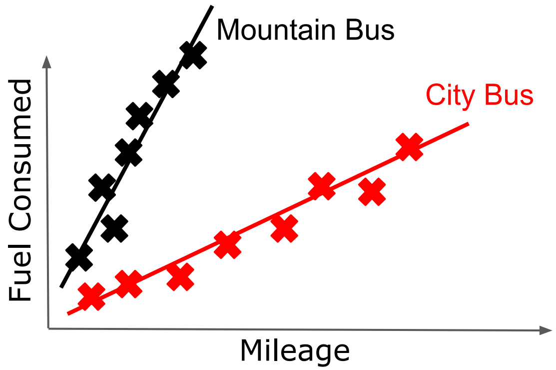
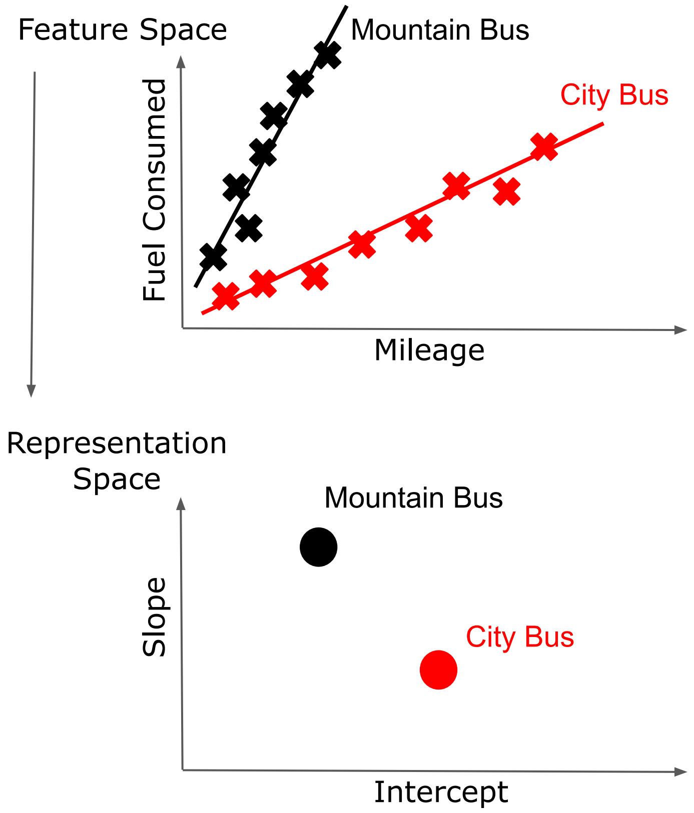


Sample Based TL for Predictive Maintenance

- A data-driven approach for finding the sub-fleet cluster from the whole population
  - Learning the representation of different equipment from sensor data
  - Finding clusters of peers in the representation space



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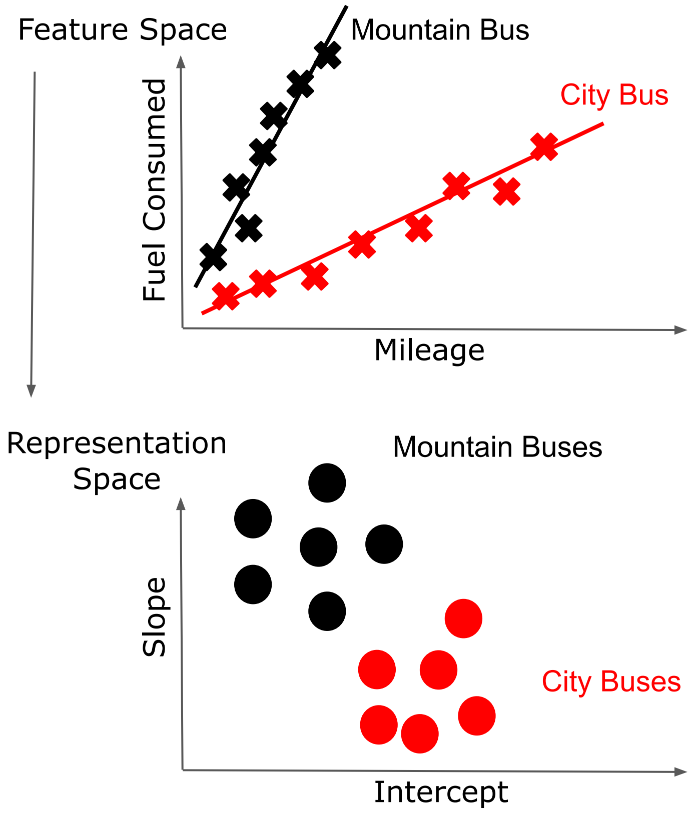

Sample Based TL for Predictive Maintenance

- A data-driven approach for finding the sub-fleet cluster from the whole population
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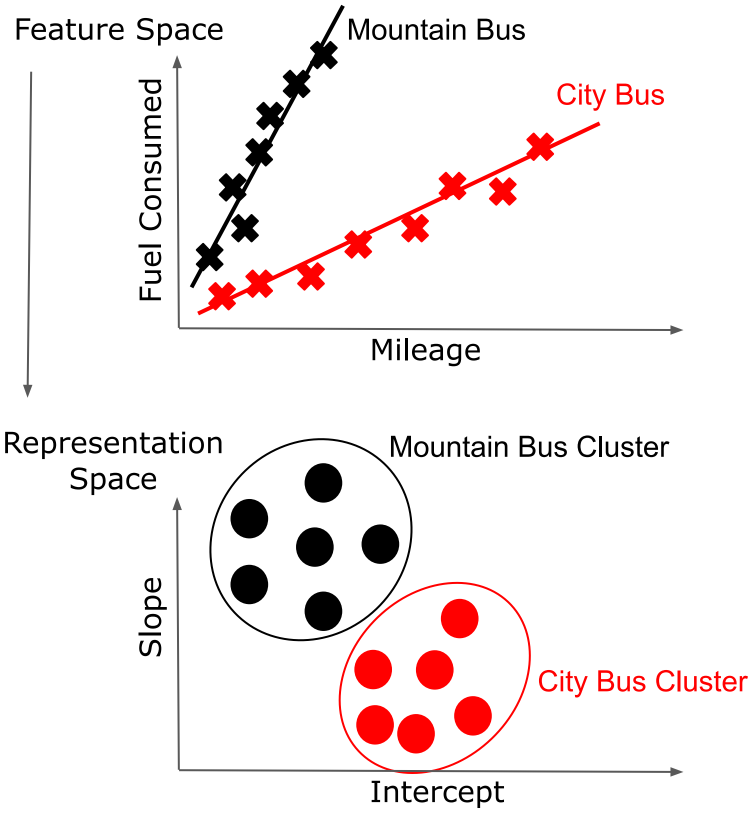
  - Finding clusters of peers in the representation space
  - Modelling the health indicator for each cluster



Sample Based TL for Predictive Maintenance

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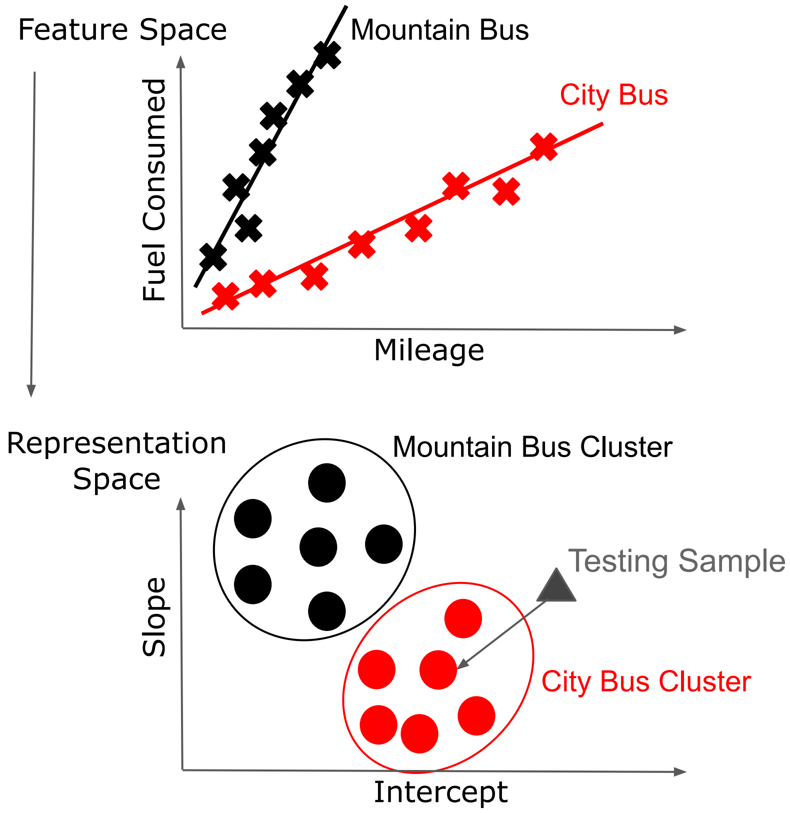

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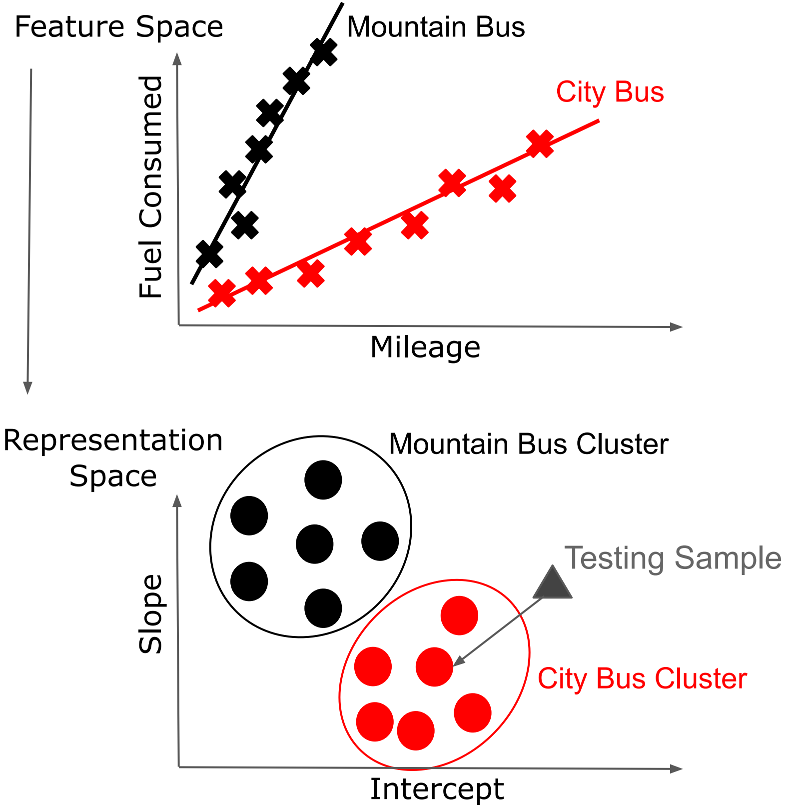
  - Finding clusters of peers in the representation space
  - Modelling the health indicator for each cluster
  - Matching the testing unit to a cluster and cast predictions on the health indicator
- Configuring the method based on the context information
  - Selecting the representation based on the characteristics of the features (linear or piecewise linear for accumulative variables)
  - The characteristics of battery deterioration varies between different generations



Results of Forecasting SOH

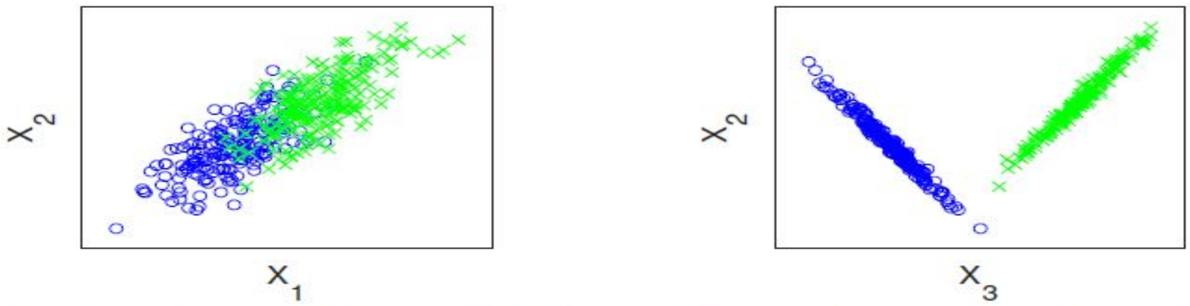
- Given five years of historical data
  - Predict SOH value at the end of the fifth year, given four and a half year of data for training

Methods	Training set vehicles (four years and half data included in the training process)	Leave-out set vehicles (completely excluded from the training process)
Random Forest (conventional approach)	3.2258 ± 0.1168	3.6935 ± 0.3017
FP linear model, k-means clustering, Random Forest	2.2137 ± 0.0826	2.5629 ± 0.322

Feature Based Transfer Learning for Predictive Maintenance

The Problem with Identifying Invariant Features

- ML faces a significant challenge in dynamically evolving environments, where the training conditions (domain) are different from the testing conditions.
- Aim is to identify features that are invariant across different domains.



Magliacane et al, 2018. Domain adaptation by using causal inference to predict invariant conditional distributions. In *Advances in Neural Information Processing Systems* (pp. 10846-10856)

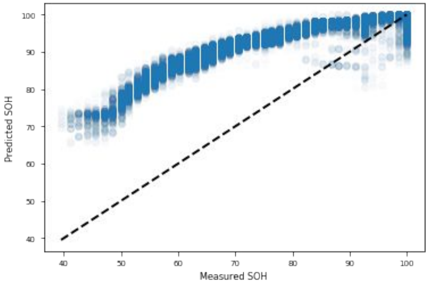
Identification of Invariant Features using GA

- We propose to use a Genetic Algorithm (GA) to select invariant features to transfer across multiple source domains D_S.
- We make a similar assumption to (Magliacane et al, 2018): if a feature subset is invariant across all source domains, then this holds in the target domain.
- The GA is initiated with a population of individuals encoding feature subsets as chromosomes of binary strings.
- The GA evaluates feature subsets according to their performance across all available source domains.

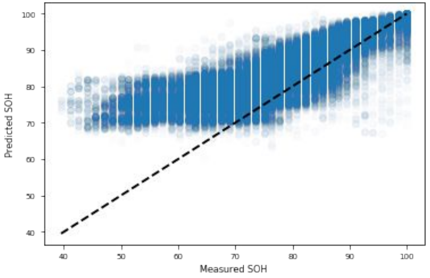
An Application to Li-Ion Batteries

- Our modeling of Li-Ion batteries showed that the hybrid bus battery deterioration processes vary significantly across different bus configuration and operating conditions.
- The GA is used to select invariant features to SoH (State of Health) that can be transferred from source to target domain.
- Our preliminary results identified invariant features under change of:
    - Battery Generation.
    - Chassis Type.
    - Operating Country.

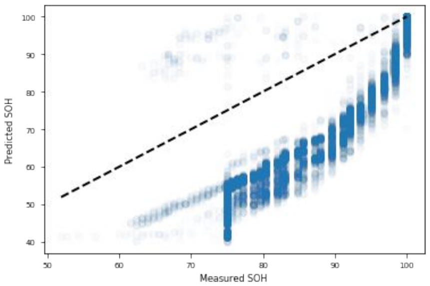
Invariant Feature Selection (Battery Generation)



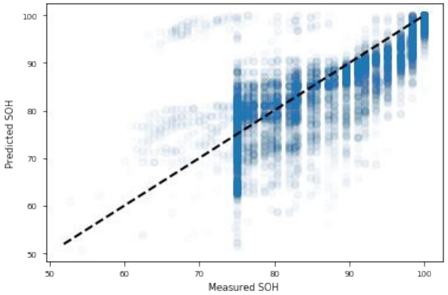
Before Invariant Feature Selection, MAE: **17.04%**



After Invariant Feature Selection, MAE**: 8.78%**



Before Invariant Feature Selection, MAE: **19.63%**



After Invariant Feature Selection, MAE**: 4.84%**

Altarabishi, M.G., et al. Extracting feature selection for predicting State of health of batteries in hybrid buses. DSAA 2021.

Experimental setting

- 1500 hybrid buses
- Different physical configurations
  - Double-Decker, Single-Decker, Articulated
- D
  - C

Scenario #	Source Domain D_S	Target Domain D_T
1	Moderate, Fast	Slow
2	Slow, Fast	Moderate
3	Slow, Moderate	Fast
4	Double-decker, Articulated	Single-decker
5	Single-decker, Articulated	Double-decker
6	Single-decker, Double-decker	Articulated

Performance comparison on all six scenarios

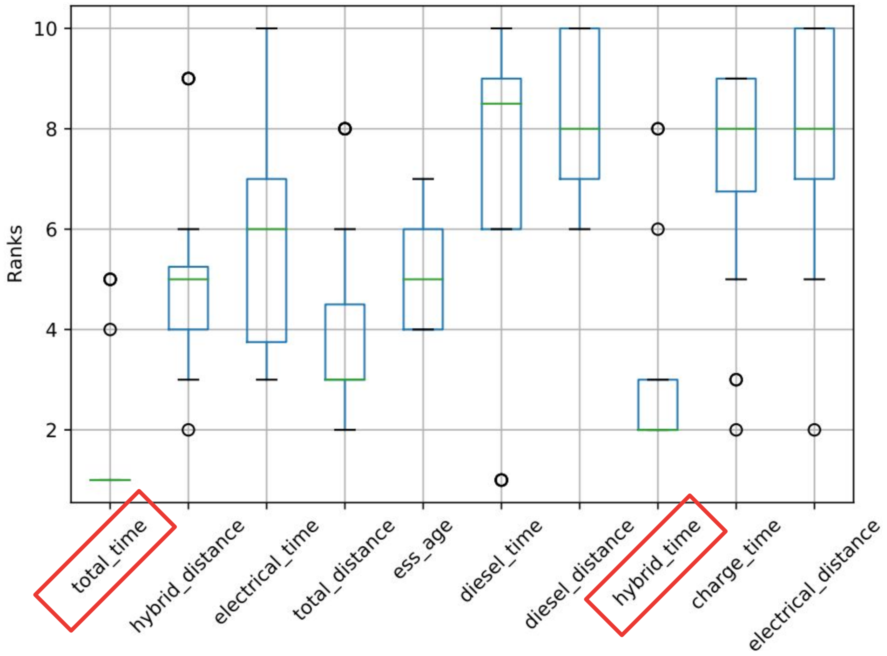
	Slow	Moderate	Fast
GA*	1.50 ± 0.01	1.59 ± 0.01	1.88 ± 0.01
GADIF	1.54 ± 0.02	**1.65 ± 0.01**	**1.96 ± 0.02**
Pearson	1.54 ± 0.06	1.74 ± 0.05	2.02 ± 0.01
RF	1.62 ± 0.07	1.72 ± 0.07	1.99 ± 0.04
LR	1.75 ± 0.06	1.81 ± 0.07	2.12 ± 0.02
SFS	1.54 ± 0.07	1.73 ± 0.07	2.03 ± 0.09
XGB	1.54 ± 0.07	1.74 ± 0.05	1.99 ± 0.11
All Features	**1.53 ± 0.07**	1.72 ± 0.09	2.06 ± 0.14

	Single-decker	Double-decker	Articulated
GA*	2.05 ± 0.00	1.53 ± 0.01	1.48 ± 0.01
GADIF	2.27 ± 0.03	**1.53 ± 0.01**	**1.67 ± 0.03**
Pearson	**2.16 ± 0.12**	1.54 ± 0.03	2.08 ± 0.16
RF	2.19 ± 0.14	1.54 ± 0.03	1.78 ± 0.10
LR	2.29 ± 0.09	1.67 ± 0.01	2.07 ± 0.41
SFS	2.19 ± 0.12	1.60 ± 0.03	2.10 ± 0.15
XGB	2.16 ± 0.12	1.57 ± 0.02	2.08 ± 0.16
All Features	2.19 ± 0.21	1.68 ± 0.05	2.07 ± 0.18

Ranking of features

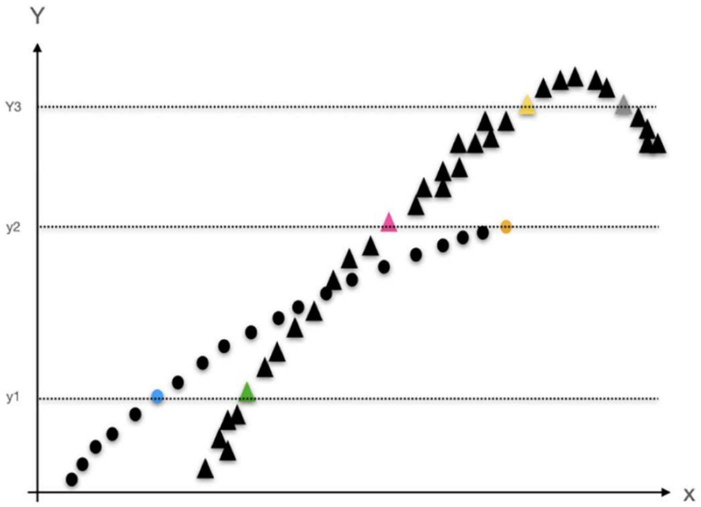
”**total time**” and ”**hybrid time**” are of the highest ranked two features

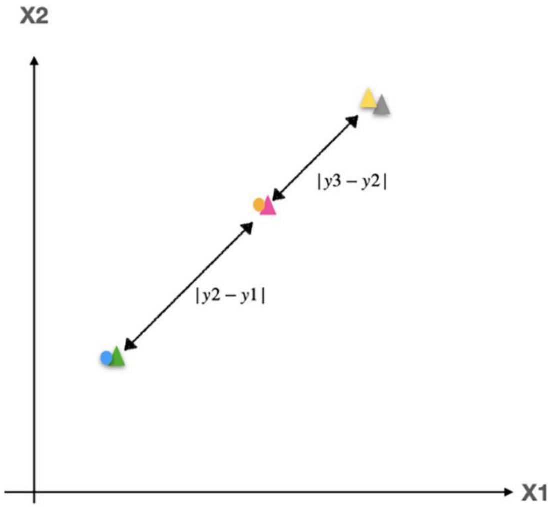
- followed by ”**hybrid distance**”, ”**electrical time**”,”**total distance**” and ”**ESS age**”



Domain Adaptation for Predictive Maintenance

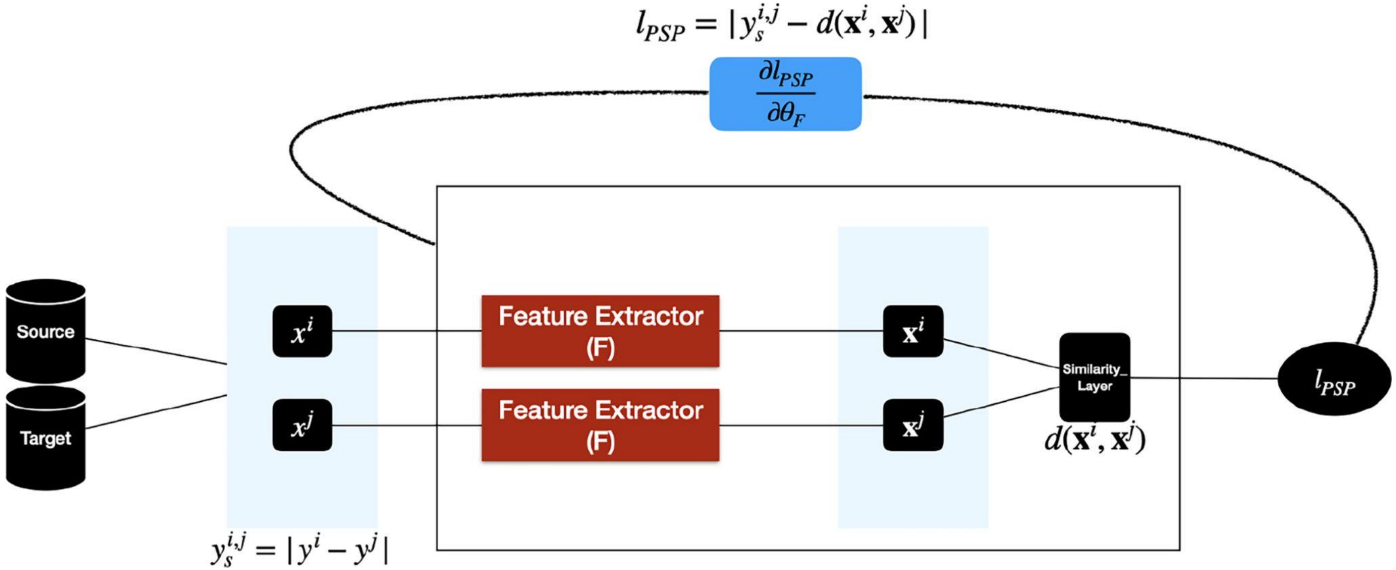
Multi-domain adaptation for regression under conditional distribution shift





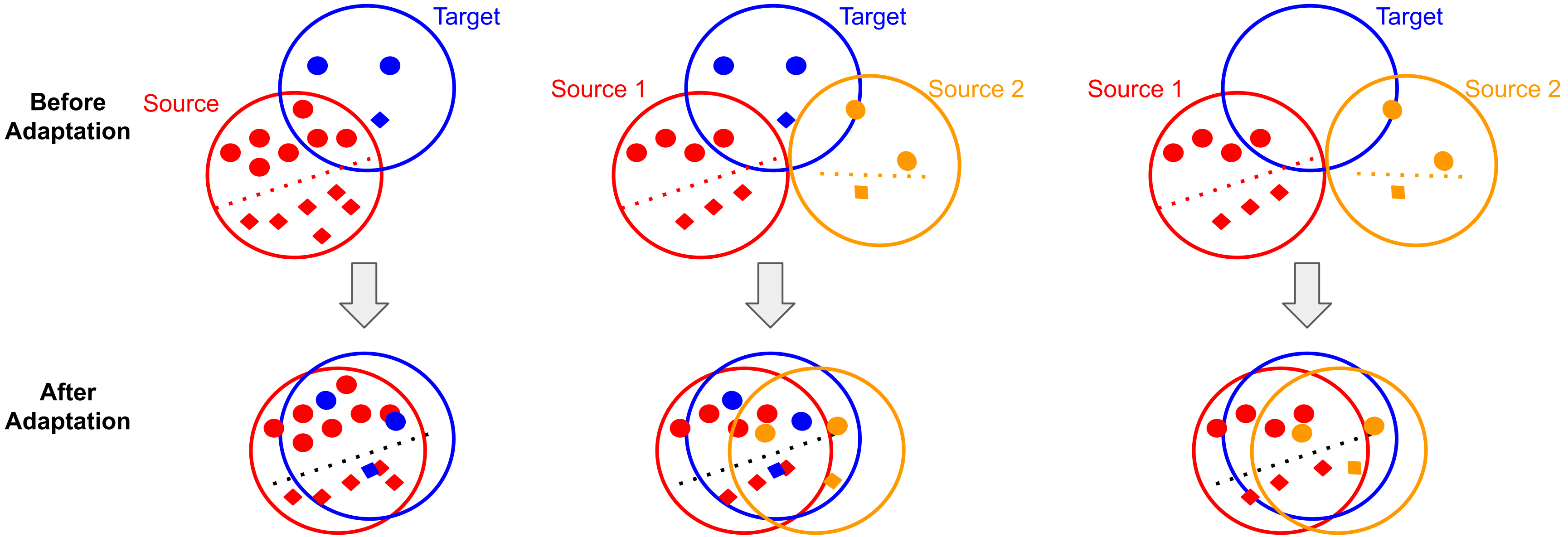
Taghiyarrenani et al. Expert system with application. 2023

Multi-domain adaptation for regression under conditional distribution shift



Taghiyarrenani et al. Expert system with application. 2023

Problem Formulation

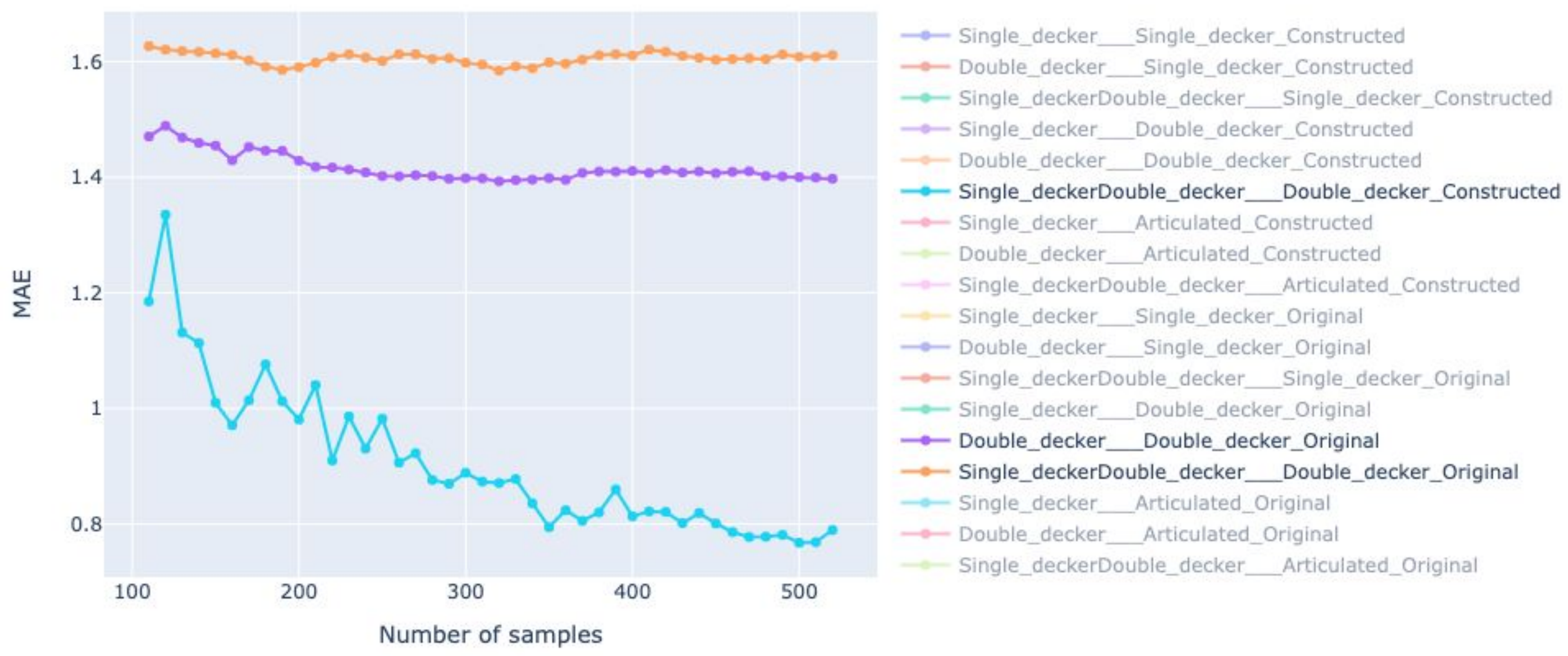


Two domains
- semi-supervised
- enough data in source
- little data in target

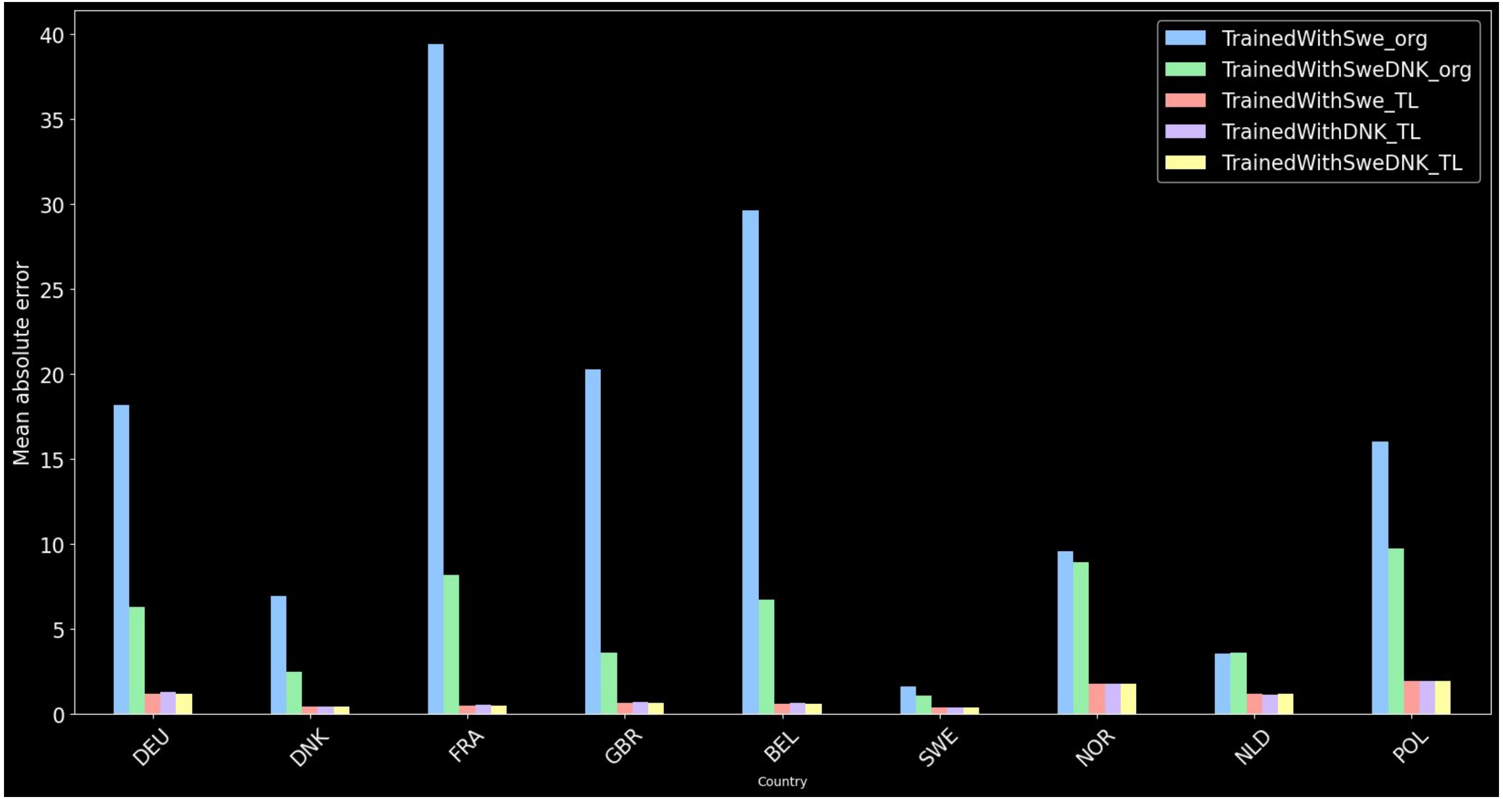
Multiple domains
- Supervised
- Little data in all

Domain Generalisation
- No data in target

Transfer learning from single decker to double decker



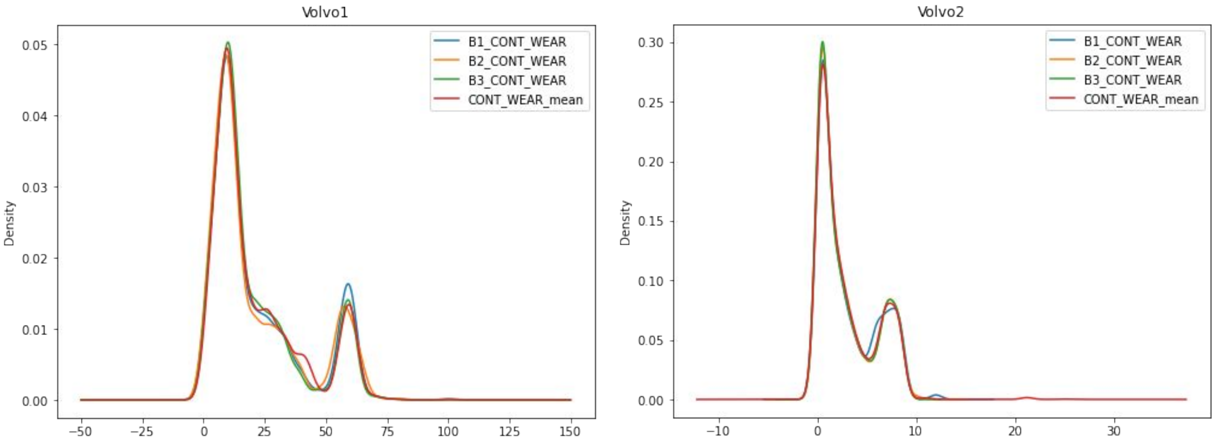
SOH Models trained on Sweden & Norway transfer well to other countries.

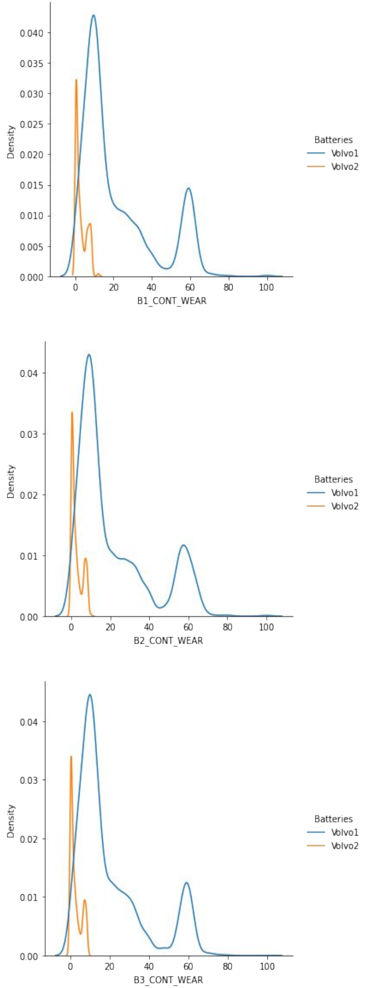


DA doesn't always make sense!

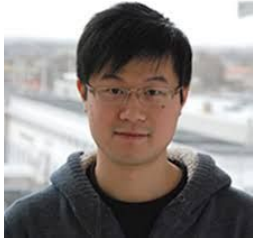
Comparison between Cotactor Types: 1 and 2

Comparison between on-board cotactors





Thank you :)



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