Predictive maintenance for heavy duty vehicles

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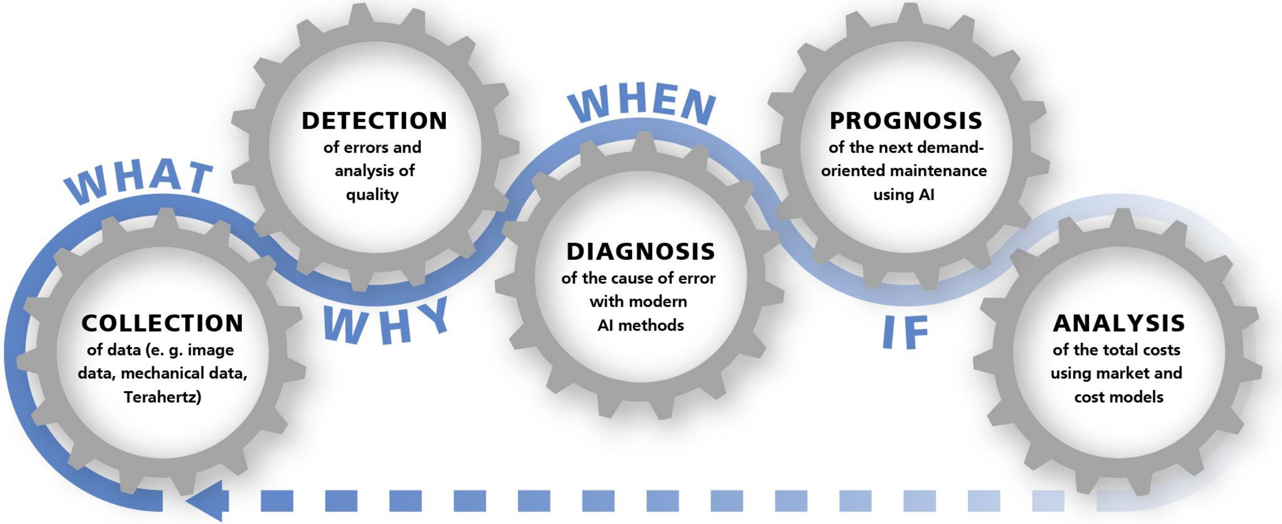
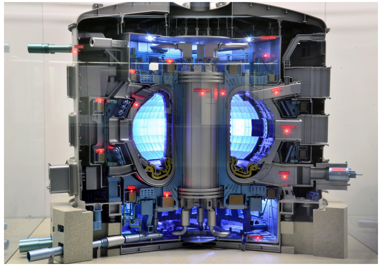
Predictive maintenance

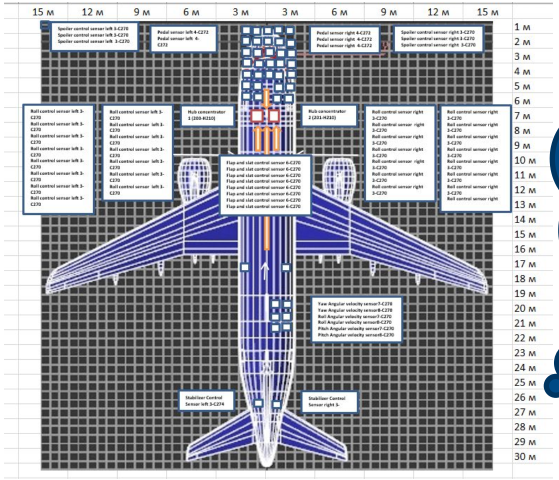
Identifying imminent failures and intervening sufficiently early to prevent them from happening.



https://www.itwm.fraunhofer.de/en/fields-of-application/predictive-maintenance.html

Success stories



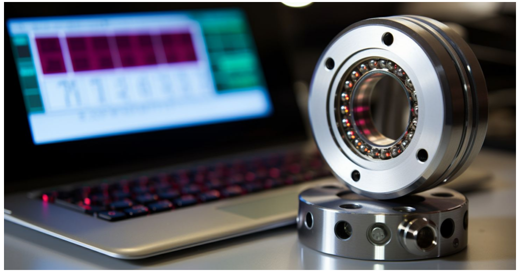


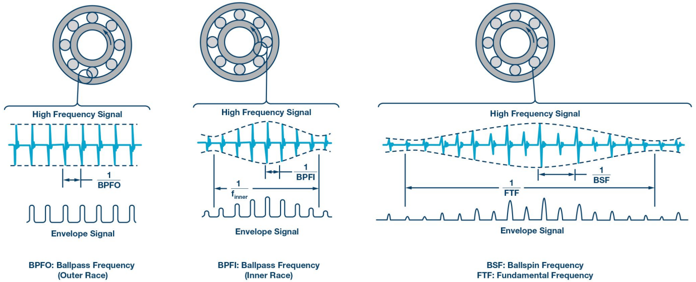
An airplane generates over 20TB of data per flight!

Critical & expensive equipment

e.g., nuclear power plants & aircrafts

the trick is lots of high-quality data



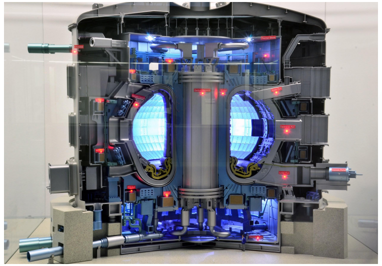


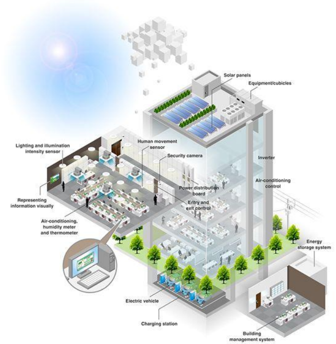
Simple equipment (physics-based)

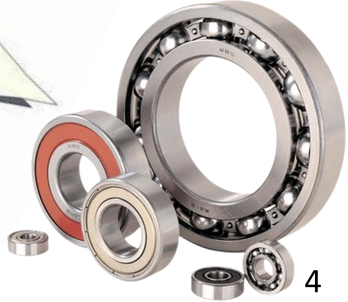
e.g., wheel bearings with vibrations sensors

the trick is well-understood failures

Complexity spectrum

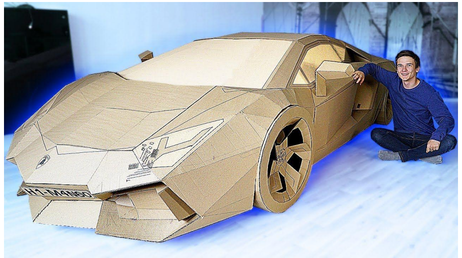






Two main challenges

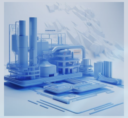
- Make predictions from low-quality data
  - tangential to the relevant processes
  - low measurement accuracy & frequency



- Equipment context is unknown
  - external conditions & usage
  - mixed with fault symptoms

Goal: Self-Aware Systems

- Build models describing reality
  - from available data
- Which ones are “interesting”?
  - based on unsupervised heuristics
- Discern abnormal from unusual
  - the real world is full of changes



- Open-ended PdM for vehicles
  - not limited to anticipated faults
  - resilient to context changes
- Not knowing what can go wrong
  - FMEA analysis showed only a 23% overlap between anticipated and really encountered faults

Self-monitoring for maintenance of vehicle fleets
T Rögnvaldsson, S Nowaczyk, S Byttner, R Prytz, M Svensson
Data Mining and Knowledge Discovery 32 (2), 344-384, 2018

COSMO: Consensus Self-organizing Models

1

2

3

4

A system that understands its own operation

One framework for different faults:

- jammed cylinder
- runaway engine fan
- weak air compressor
- …

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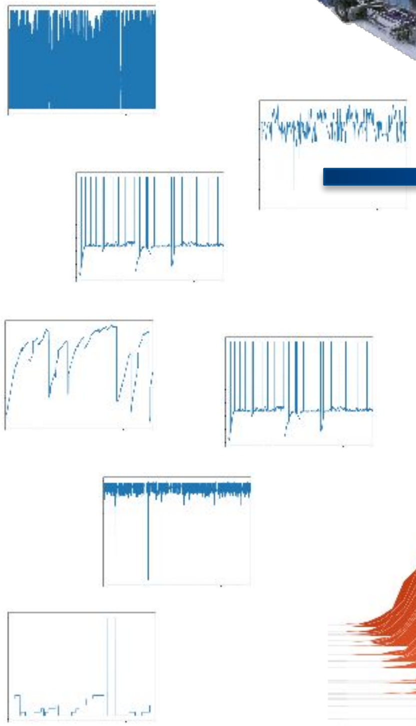
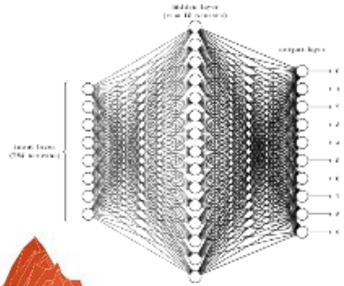
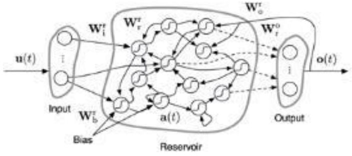
COSMO: Consensus Self-organizing Models

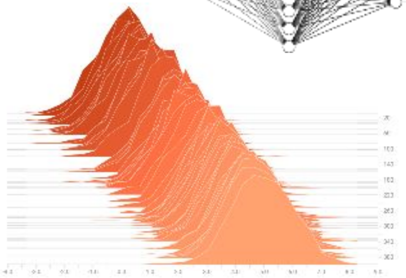
Reference Group

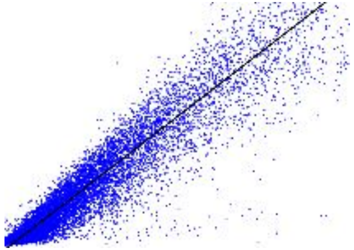


Models of Typical Behaviour

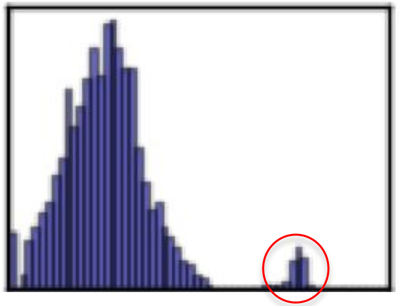








Expected Variability of Model Parameters within a Peer Group



Deviation Level over Time

Self-monitoring for maintenance of vehicle fleets
T Rögnvaldsson, S Nowaczyk, S Byttner, R Prytz, M Svensson
Data Mining and Knowledge Discovery 32 (2), 344-384, 2018

Likely a mistake!

Coolant system leak (Dec 5)

Tampering with EBS system (”sabotage”) Volvo Action Service (Feb 10)

Complaints that engine „runs strangely” Probable cause: CAC leak (Apr 12)

Problems with alternator belt tension (Jul 30)

Service (Oct 8)

Sep 2011 | Jan 2012 | Jul | Jan 2013

Gearbox problems (Nov 28)

Problems with Strocco heater (Dec 9 & Jan 30)

Oil pressure problems (Mar 2)

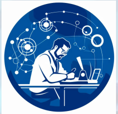
Service before annual inspection (Apr 24)

Also, not a good sign...

Engine ”knocks”. Cylinder 1 jams during annual inspection (Repair May 4)

Gear box not working, replaced or repaired (Nov 26)

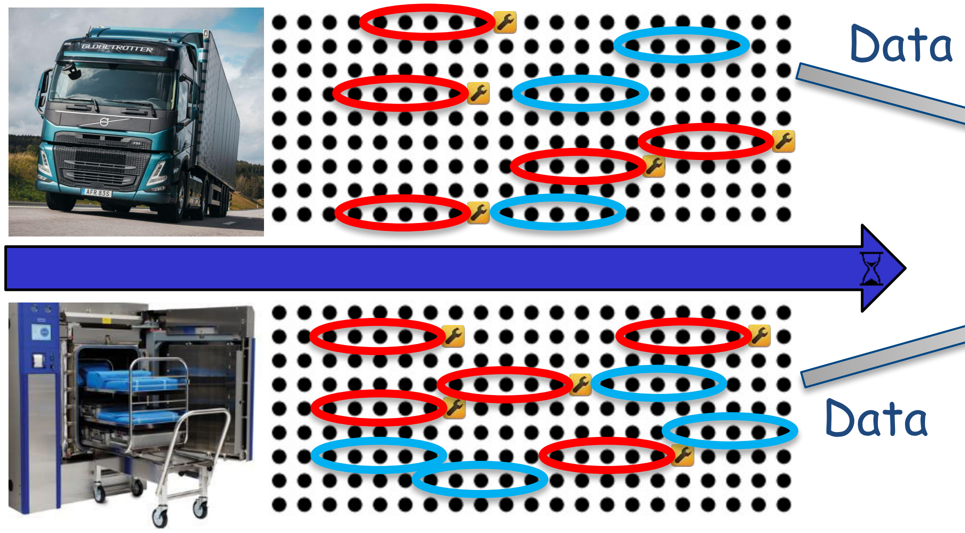
Goal: Production-Ready PdM System



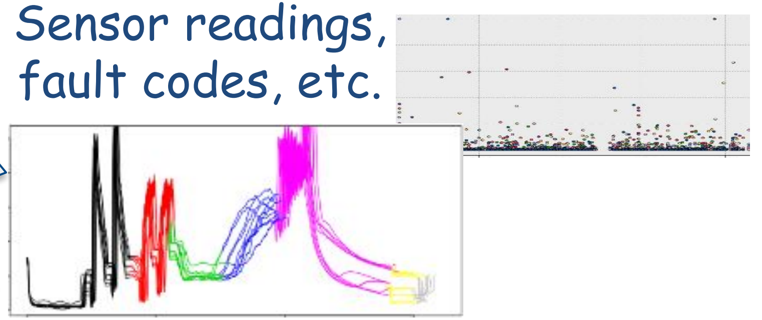
- Problem formulation
  - RUL regression vs binary classification
- Evaluation criteria
  - beyond accuracy & f-score
  - estimate financial gains
- A ready-to-deploy system
  - limited number of components
  - automated decision making
- Work within current limitations
  - low quality & frequency of data
  - unreliable & noisy label

Predicting the need for vehicle compressor repairs using maintenance records and logged vehicle data
R Prytz, S Nowaczyk, T Rögnvaldsson, S Byttner
Engineering Applications of Artificial Intelligence 41, 139-150, 2015

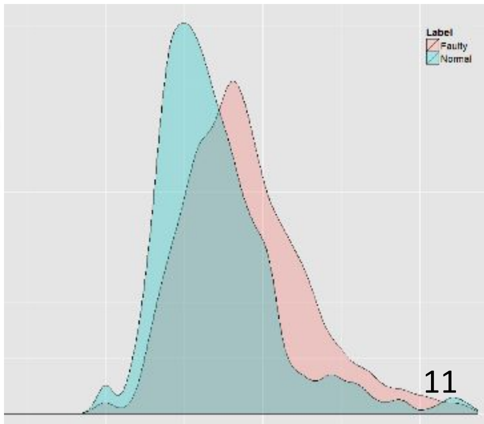
Automate Today’s Decisions



Sensor readings, fault codes, etc.



Find differences



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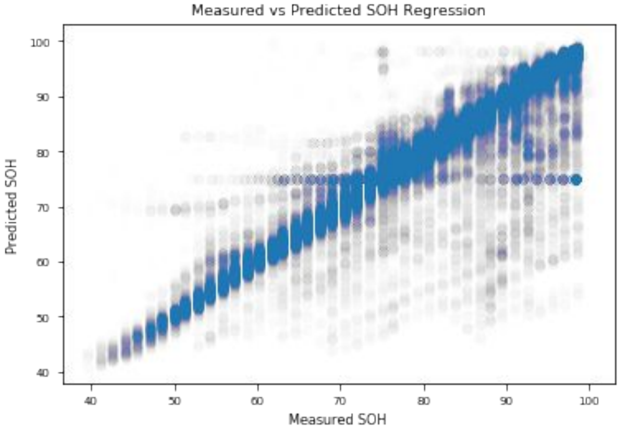
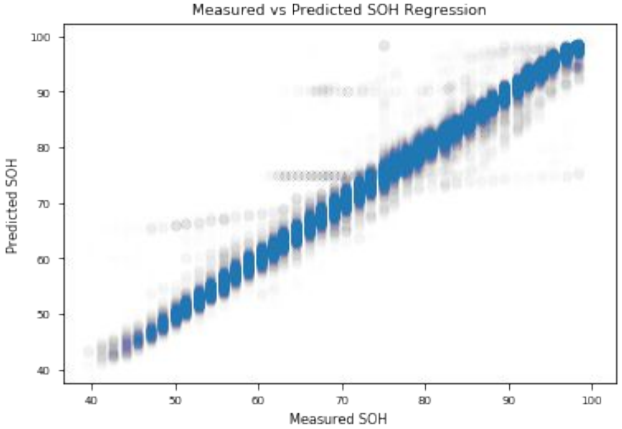
Estimating and predicting the State of Health (SOH) for batteries for hybrid buses

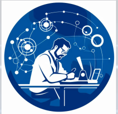




Metric	All (3212 Buses)	Monotonic-decreasing Function (2049 Buses)
MAE	2.60	1.04
R^2	0.81	0.98
Correlation	0.90	0.99

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

Goal: Real-World Generalisations



- Find sets of invariant features
  - those invariant across all source domains are likely to remain invariant also in unseen targets

- Estimate battery State of Health
  - different ML models
  - for different vehicles

- Simple and easy to understand
  - many TL methods are too complex

Extracting Invariant Features for Predicting State of Health of Batteries in Hybrid Energy Buses
MG Altarabichi, Y Fan, S Pashami, PS Mashhadi, S Nowaczyk
IEEE 8th International Conference on Data Science and Advanced Analytics (DSAA), pp. 1-6, 2021

Genetic Algorithm

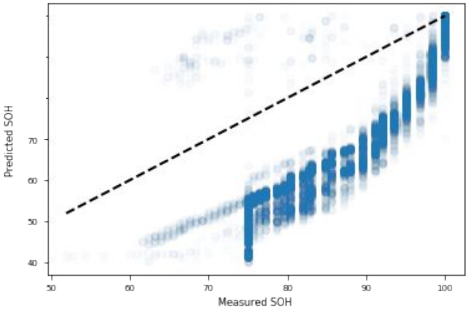


	Slow	Moderate	Fast
GA*	1.50 ± 0.01	1.59 ± 0.01	1.88 ± 0.01
GADIF	1.54 ± 0.02	**1.65 ± 0.01**	**1.96 ± 0.02**
Pearson	1.54 ± 0.06	1.74 ± 0.05	2.02 ± 0.01
RF	1.62 ± 0.07	1.72 ± 0.07	1.99 ± 0.04
LR	1.75 ± 0.06	1.81 ± 0.07	2.12 ± 0.02
SFS	1.54 ± 0.07	1.73 ± 0.07	2.03 ± 0.09
XGB	1.54 ± 0.07	1.74 ± 0.05	1.99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

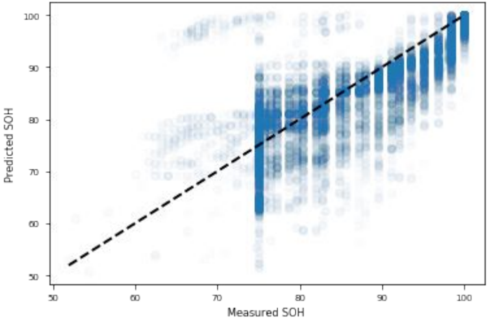


	Single-decker	Double-decker	Articulated
GA*	2.05 ± 0.00	1.53 ± 0.01	1.48 ± 0.01
GADIF	2.27 ± 0.03	**1.53 ± 0.01**	**1.67 ± 0.03**
Pearson	**2.16 ± 0.12**	1.54 ± 0.03	2.08 ± 0.16
RF	2.19 ± 0.14	1.54 ± 0.03	1.78 ± 0.10
LR	2.29 ± 0.09	1.67 ± 0.01	2.07 ± 0.41
SFS	2.19 ± 0.12	1.60 ± 0.03	2.10 ± 0.15
XGB	2.16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

Battery Generation:



Non-invariant, MAE 19%



Invariant, MAE 5%

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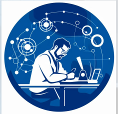
Goal: Domain Adaptation Regression

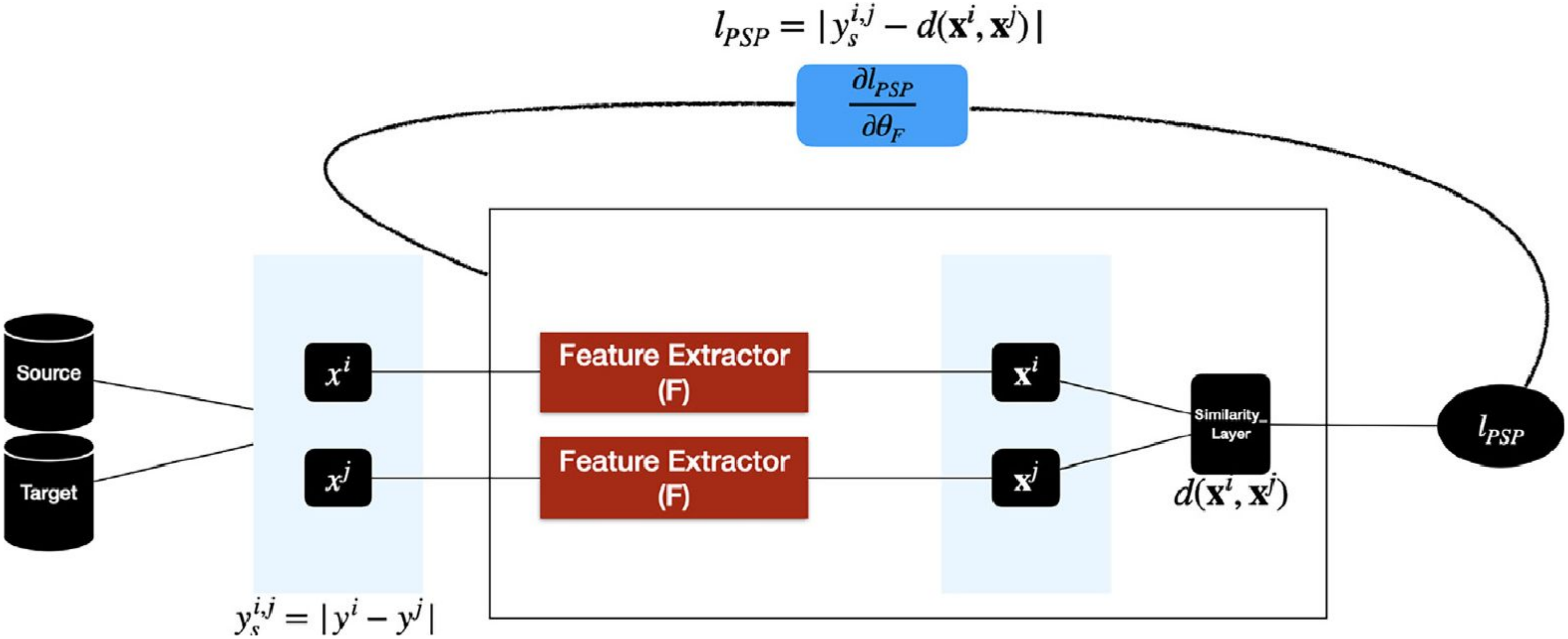


- Concept shift for regression
  - Pairwise Similarity Preserver loss
- Two-domain setting
  - source with sufficient data size
- Multi-domain setting
  - several equivalent domains
  - neither contains sufficient data

- Predict battery State of Health
  - a single model is not very good
- Country-specific seems to work
  - but some countries lack data

Multi-domain adaptation for regression under conditional distribution shift
Z Taghiyarrenani, S Nowaczyk, S Pashami, MR Bouguelia
Expert Systems with Applications 224, 119907, 2023

Pairwise Similarity Preserver



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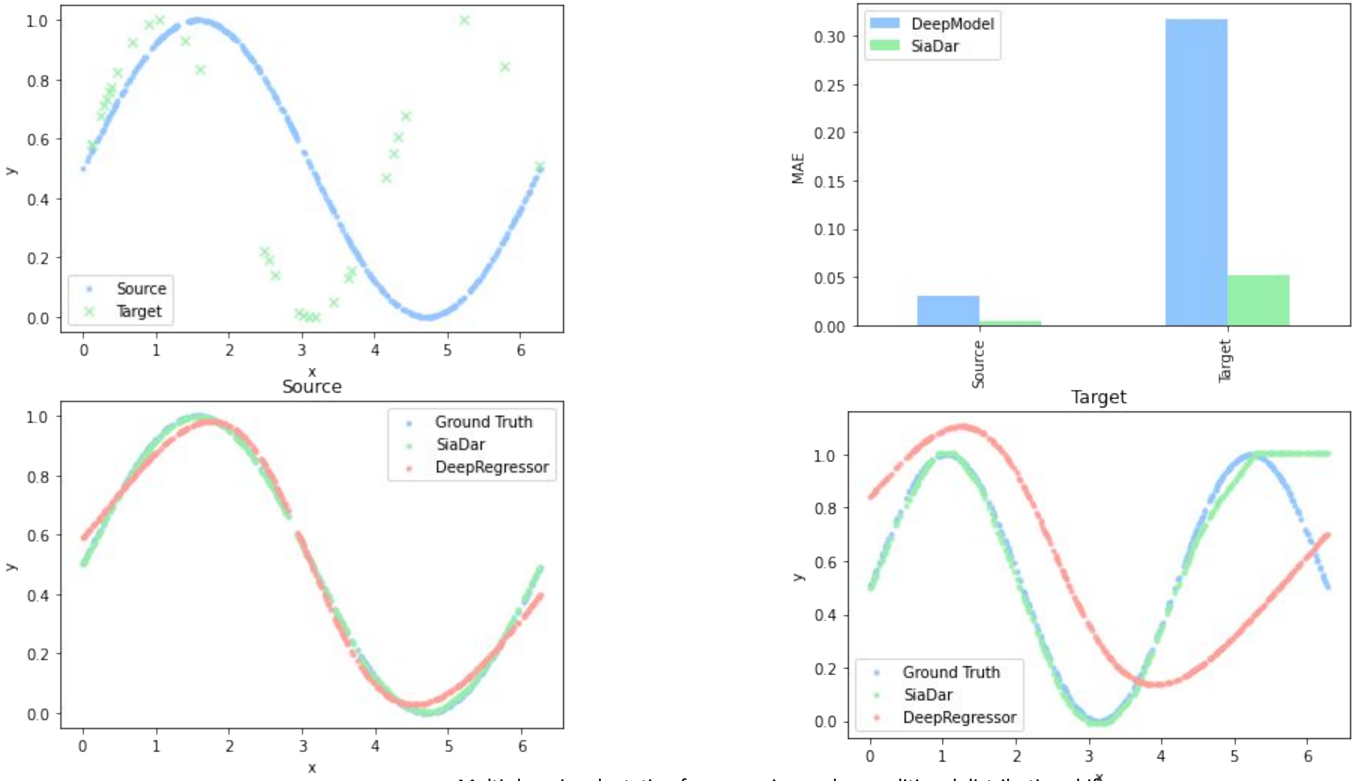
Domain Adaptation for Regression



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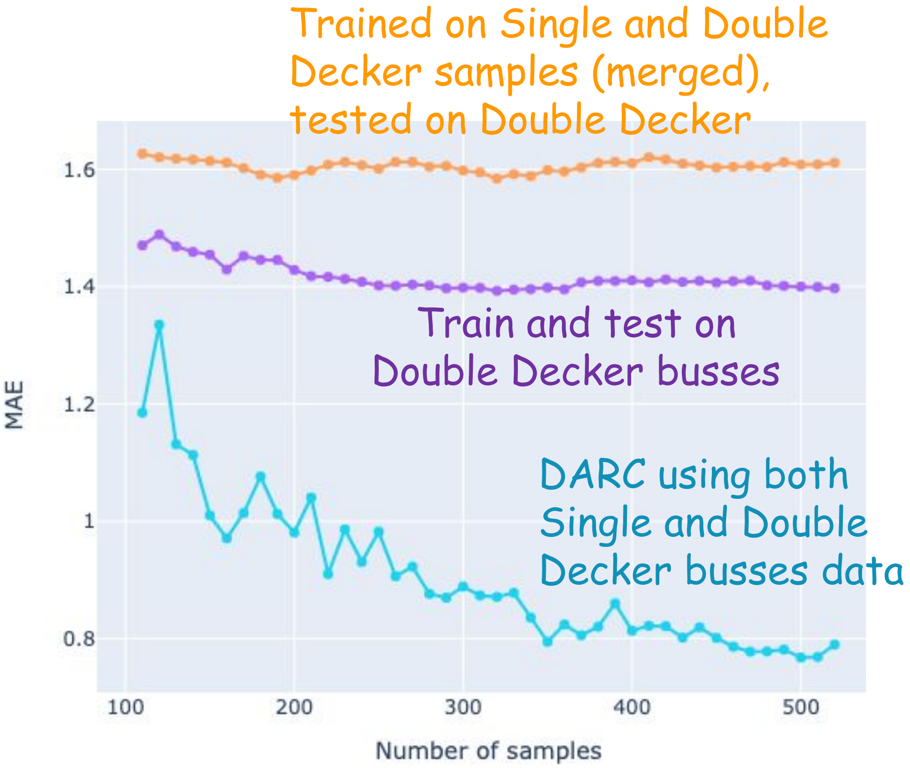
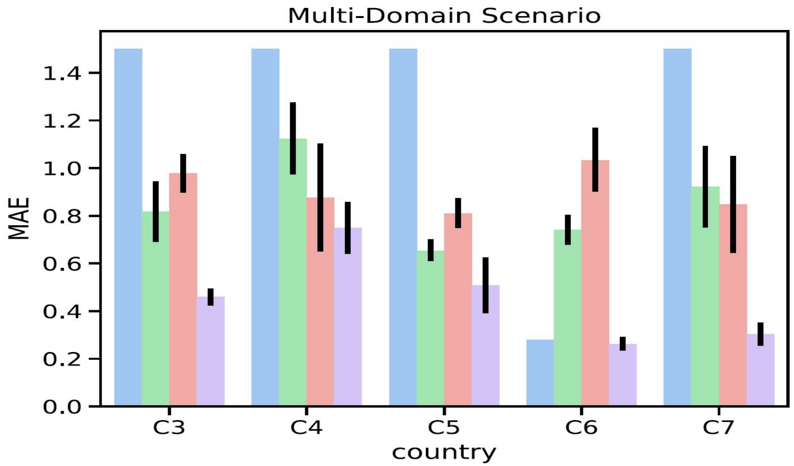
Real-World Data





Multi-domain adaptation for regression under conditional distribution shift
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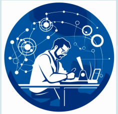
Goal: Explaining Survival Patterns

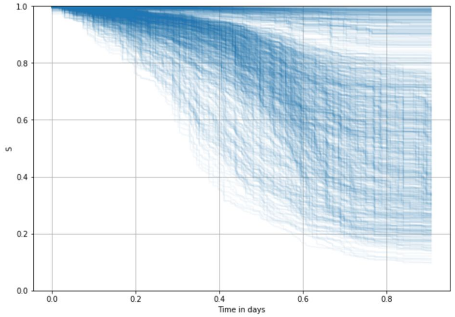


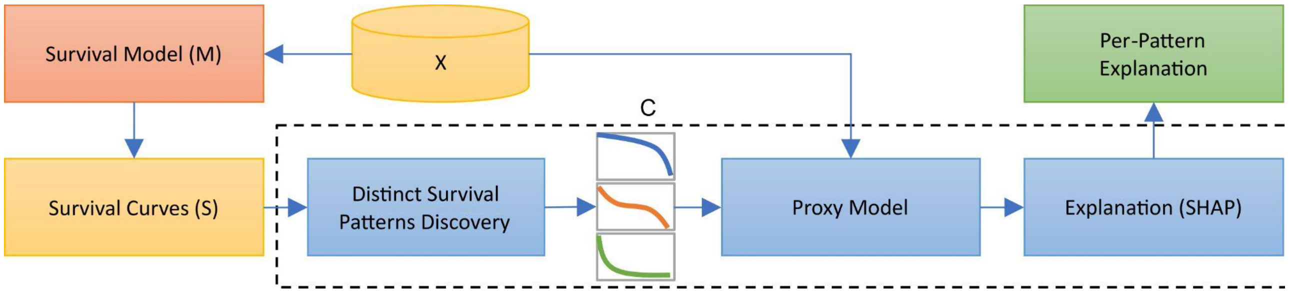
- Survival analysis is promising
  - able to exploit censored data
- Outputs are functions
  - typically, survival curves
  - XAI assumes point predictions

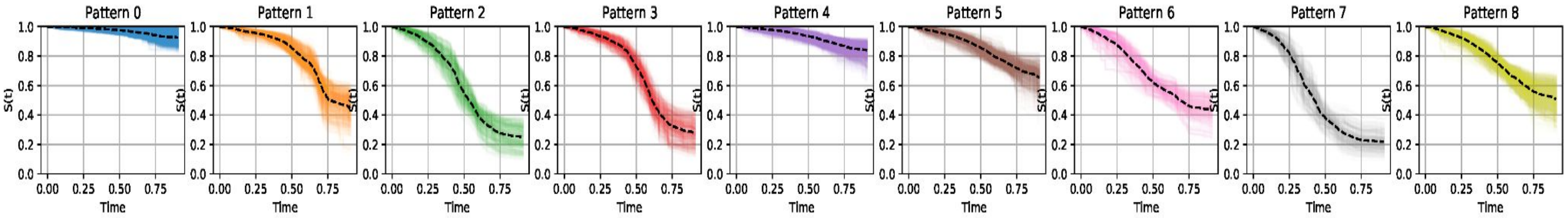
- Figure out battery replacements
  - in hybrid buses
- Characterise the differences
  - affecting the survival rate
- Provide actionable insights
  - describe diverse sub-groups

SurvSHAP: A Proxy-Based Algorithm for Explaining Survival Models with SHAP
A Alabdallah, S Pashami, T Rögnvaldsson, M Ohlsson
IEEE 9th International Conference on Data Science and Advanced Analytics (DSAA), pp. 1-10, 2022

Diverse Survival Patterns







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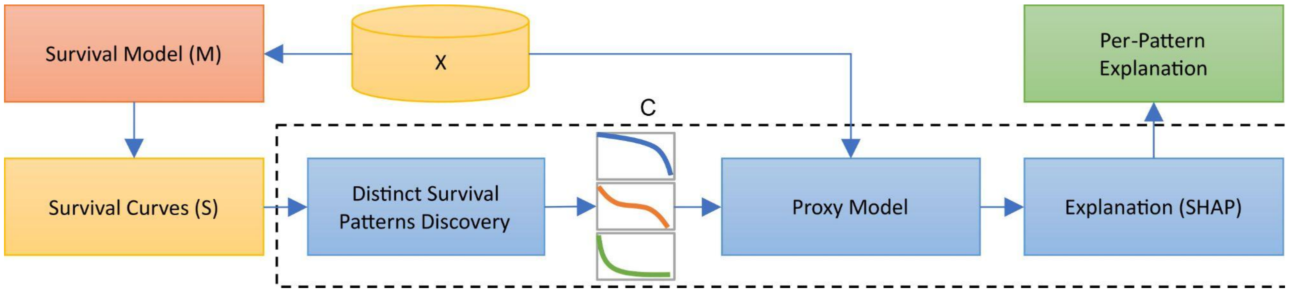
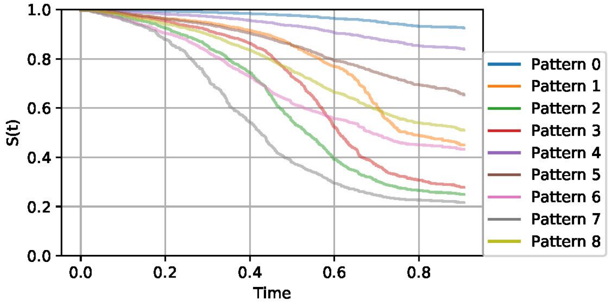
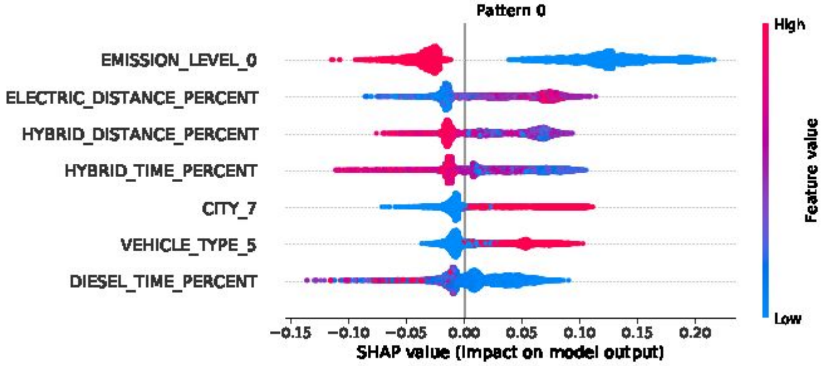
Explaining Survival Patterns (SurvSHAP)







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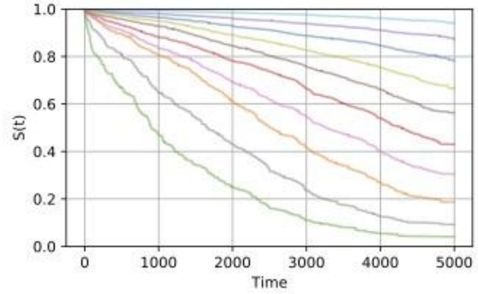
Counterfactual Explanation of Survival Patterns

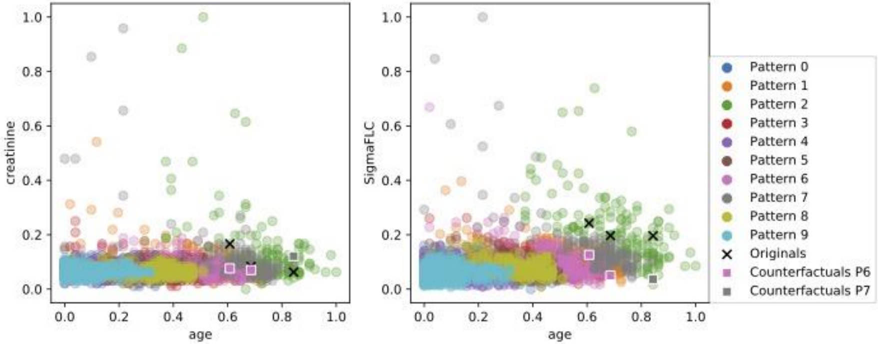
Particle Swarm Optimization (PSO) algorithm to optimize the following objectives:

- Achieve the desired change in the target output
- Minimal change to the input
- Plausibility of the counterfactual example
- Actionability of the counterfactual example

Actionability of Counterfactual Explanations

- Flchain dataset
- RSF
- Survival pattern
- Pattern 2 to 9
- When Age is masked or not





Predictive Maintenance

Dream Solution: **When a system can explain**

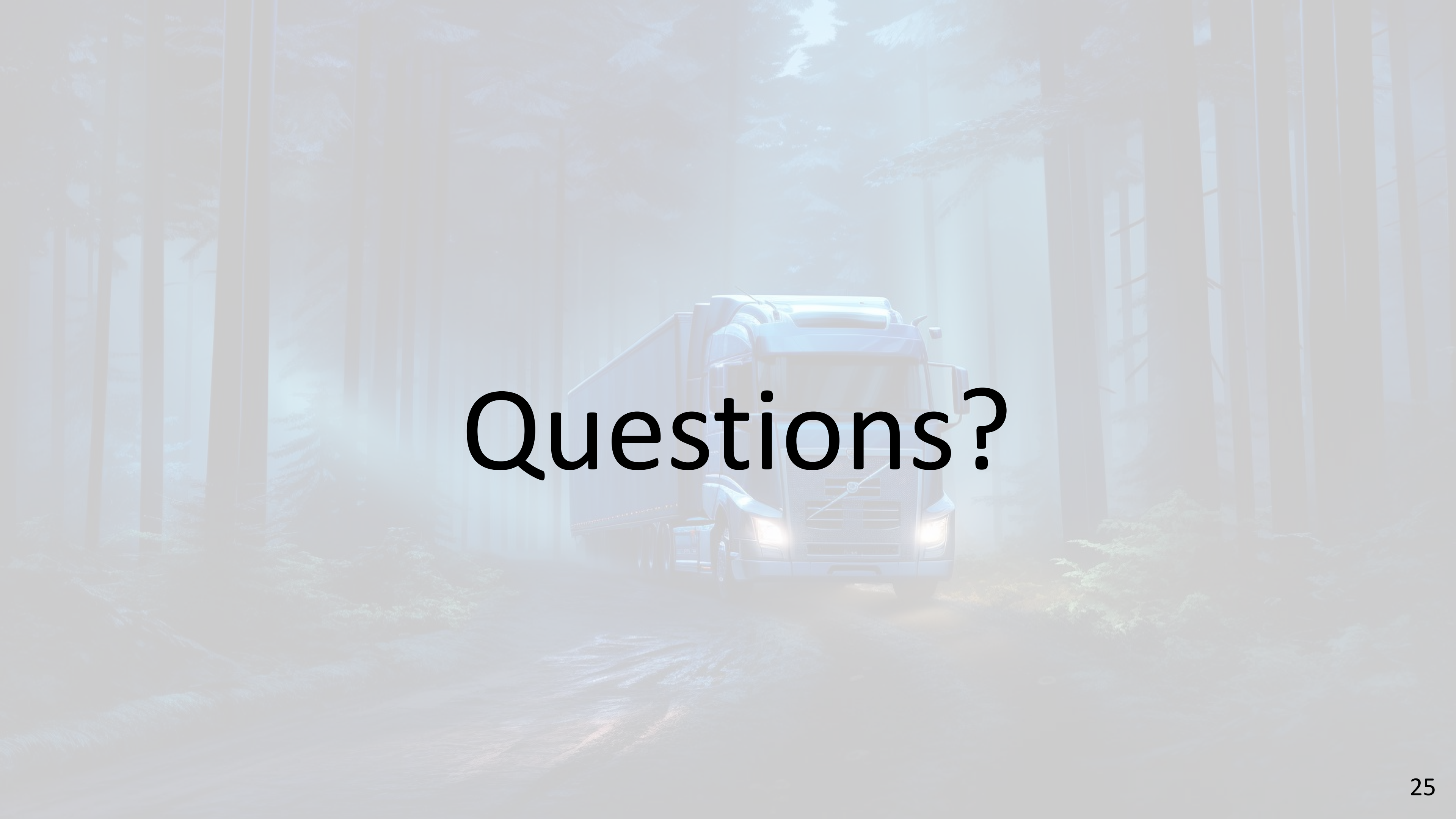
Almost Perfect Solution: **Wisdom of the Crowd**

Today’s Practical Solution: **Supervised Learning**

Generalizable Solution: **Domain Adaptation**

Understandable Solution: **Explainability methods**

"Does your car have any idea why my car pulled it over?"



Questions?