### CAN YOU ACTUALLY PREDICT A FUTURE FAILURE OF A VEHICLE?

RUNE PRYTZ – HEAD OF R&D STRATIO AUTOMOTIVE



### history of connected vehicles

- 1991 On board diagnostic (OBD)
- 1996 GM OnStar
- 2000 GM OnStar + GPS
- 2001 Remote OBD scan
- 2003 Vehicle Health reports
- 2014 CarPlay, Android Auto, Apps, WIFI...

Add pictures of vehicles and data aqusition devices





# 2014 - CarPlay, Android Auto, Apps, WIFI, Predictive maintenance...



# Who drives the predictive maintenance efforts today?

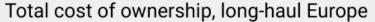
Any guesses?

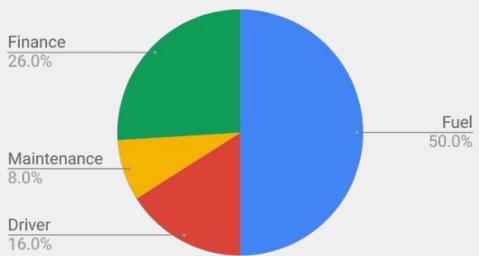


### **DRIVERS**

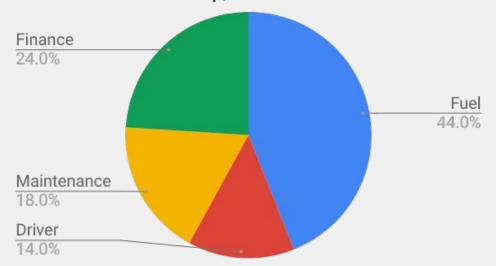
- The Operational costs
  - Downtime cost money
- Sales of spare parts at workshops
- Road system efficiency
  - congestions

### Downtime cost money





#### Total cost of ownership, one breakdown



### TURBO BREAKDOWN IN NUMBERS

PREVENTIVE REP	LACEMENT
----------------	----------

SPARE PART (TURBO) €1500 LABOR €250 **CORRECTIVE REPAIR** 

TOWING €500 SPARE PARTS €5000 ENGINE CLEANING €500

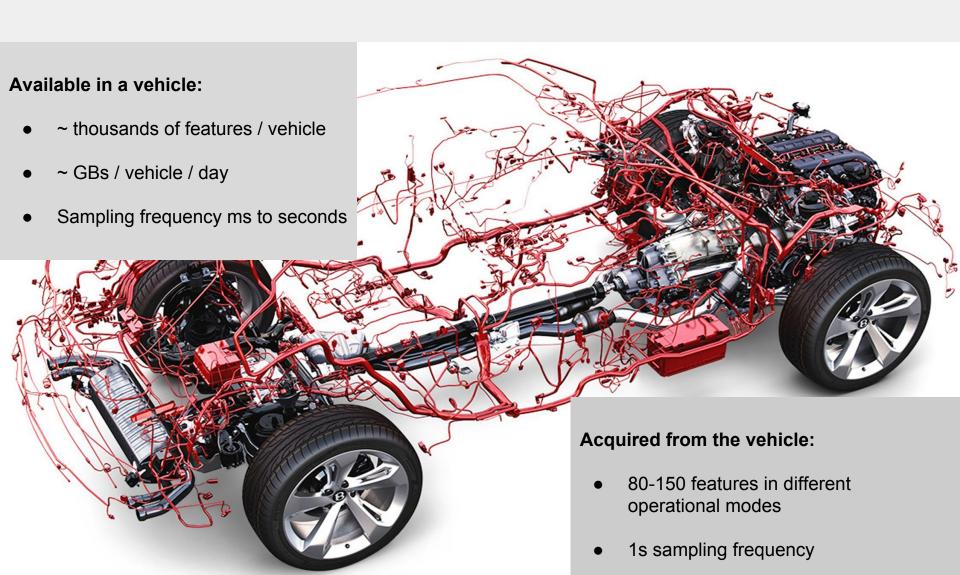
LABOR €1000

LOST REVENUE N/A

TOTAL: >€7000

TOTAL: €1750

### DATA ACQUISITION



### TWO WAYS OF ACHIEVING P.M.

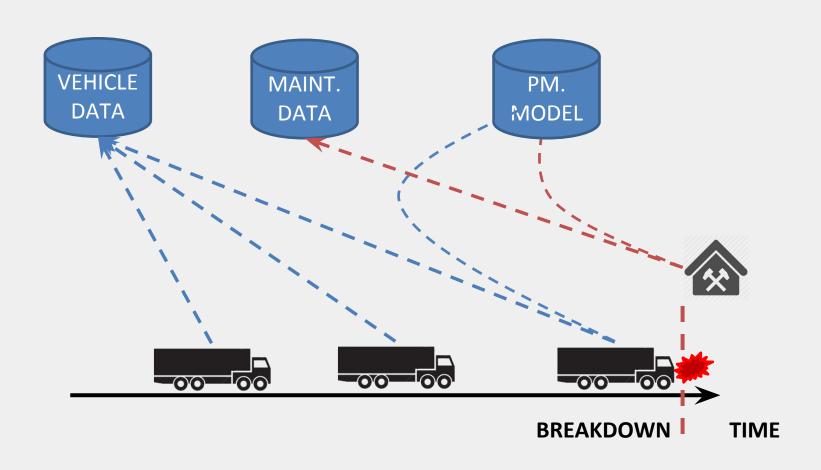
Classic supervised machine learning



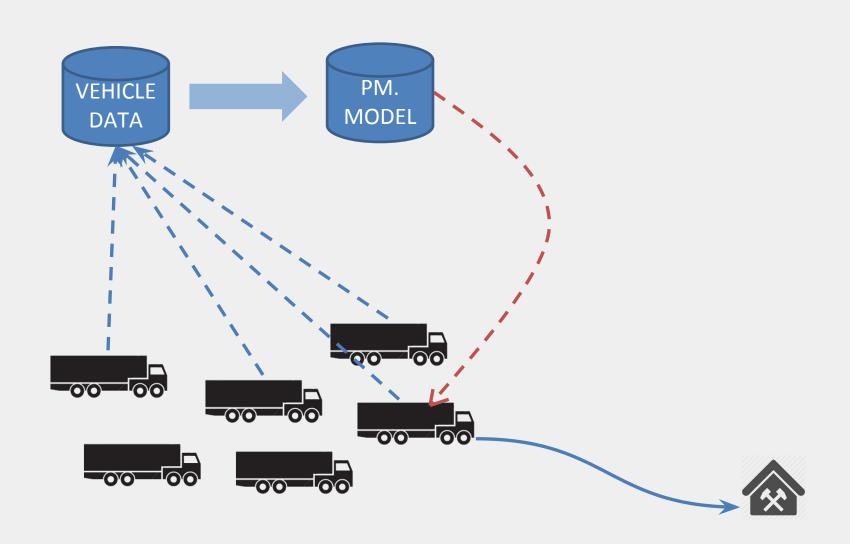
Unsupervised knowledge discovery



### SUPERVISED LEARNING



### SUPERVISED LEARNING



#### THE DATASET

- The source of data is not Independent and Identically Distributed
  - Selecting train and test dataset is difficult

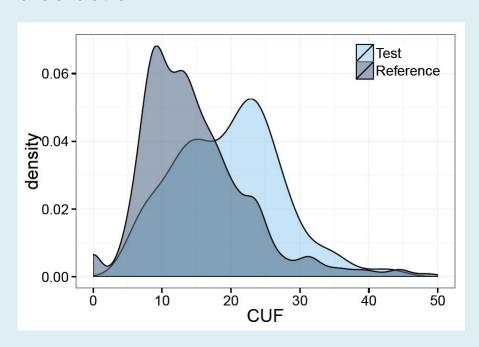
Date	Chassis ID	LVD CUF	LVD BIY	LVD OO	VDA IHF	TTF	Label
130101	A-12345	10	1240	10002	12	200	Faulty
130525	A-12345	15	3450	15200	12	75	Faulty
130430	A-23456	8	800	34423	13	Inf	Normal
131101	A-23456	6	1600	34555	14	Inf	Normal

- Labelling data is hard
  - Prediction Horizon

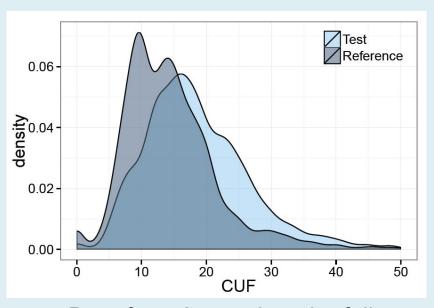
### **FEATURE SELECTION**

- Heterogeneous dataset across vehicles
  - No traditional method for feature selection

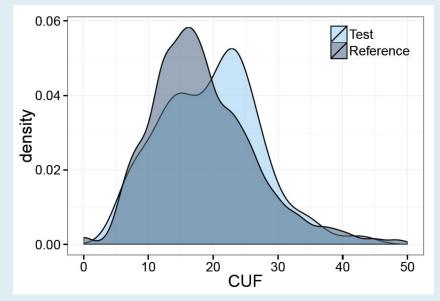
Differences in distribution based on usage and wear



## FEATURE SELECTION WEAR

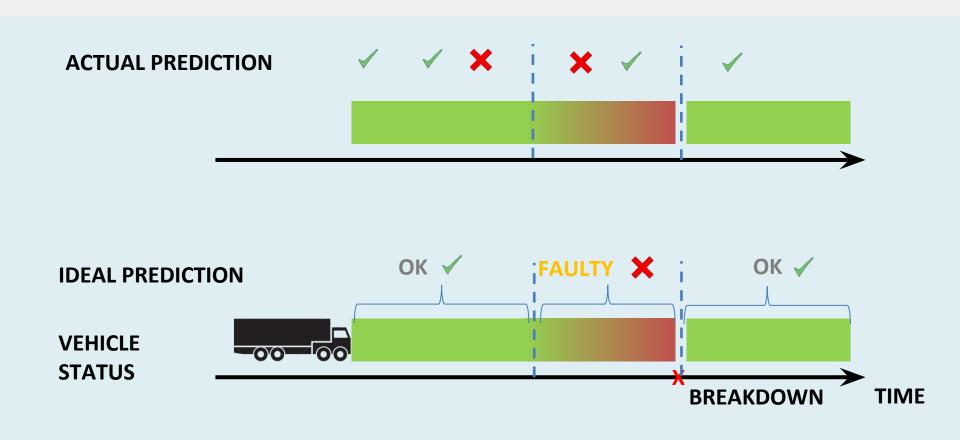


Data from 25 weeks prior failure



Data from 5 weeks prior failure

### PREDICTING A SINGLE VEHICLE



### **EVALUATING RESULT**

	Predicted Faulty	Predicted Normal
Observed Faulty	True positive	False Negative
Observed Normal	False Positive	True Negative

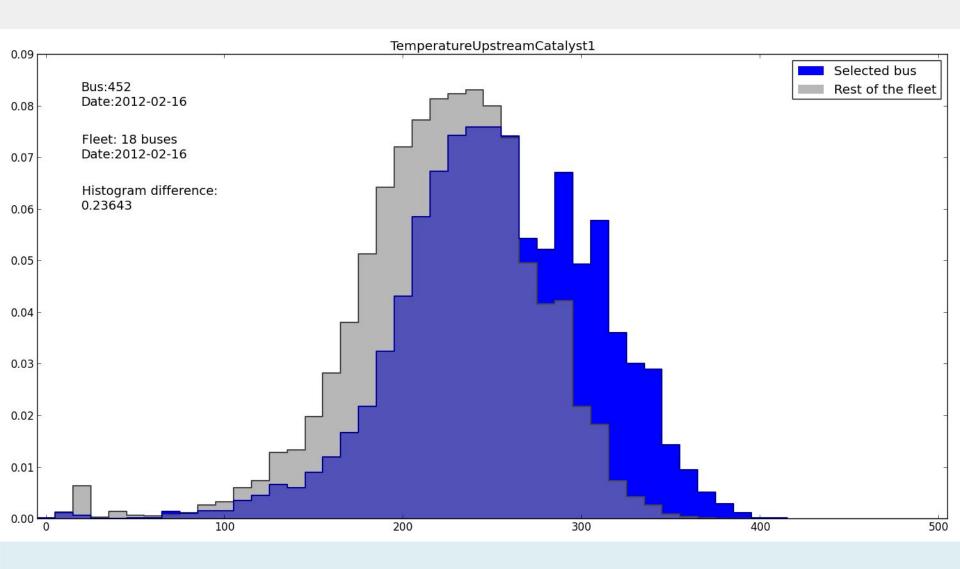
### **EVALUATING RESULT**

	Predicted Faulty	Predicted Normal
Observed Faulty	True positive Warned in advanced	False Negative  No warning / vehicle failure
Observed Normal	False Positive Unnecessary warning / repair shop visit.	True Negative No action

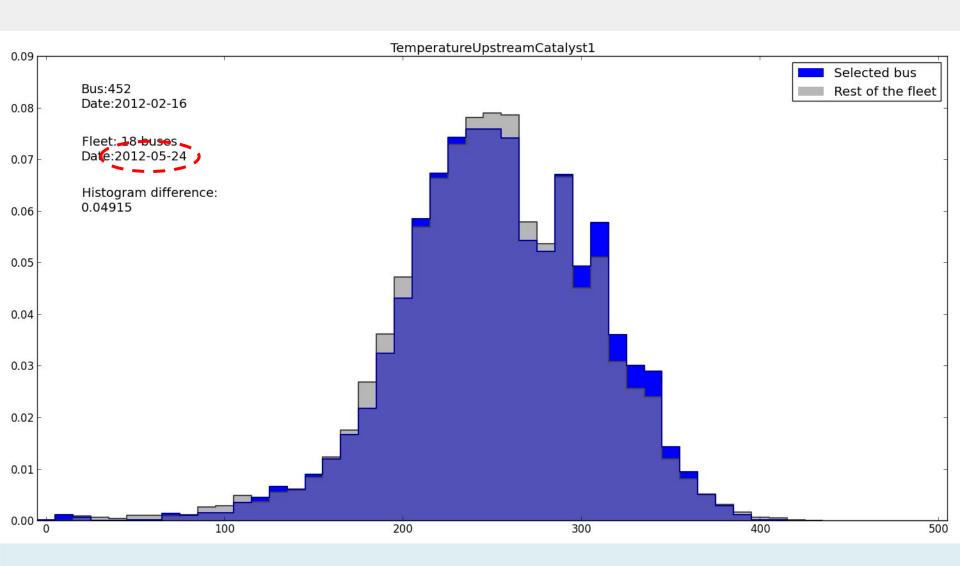
### UNSUPERVISED FLEET BASED APPROACH



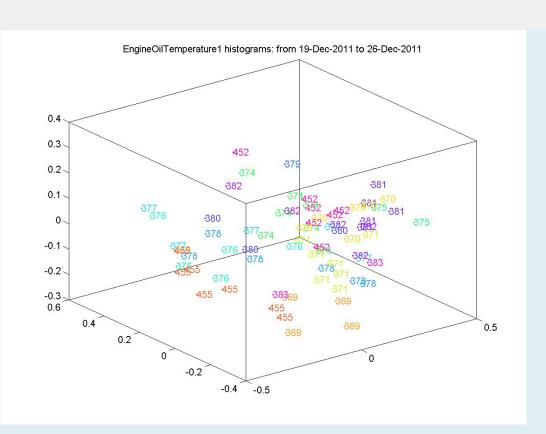
### FLEET BASED APPROACH



### FLEET BASED APPROACH



### HISTOGRAMS OF VEHICLES

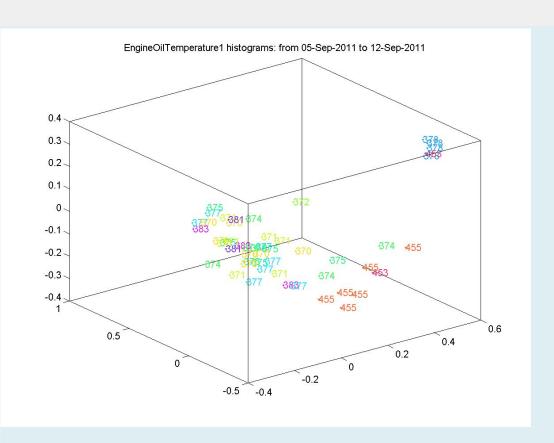


Each point corresponds to a bus observation (illustrated using multidimensional scaling)

- Distance between histograms
- 19 vehicles
- One week data

Evenly distributed - No significant pattern

### WHEN SOMETHING IS ODD...



We are looking for a vehicle that is different from rest of the group

Short circuit in ECU lead to coolant fan ran at 100% all the time

#### WHY THIS IS IMPORTANT TO ME

A strong business case with a clear objective

 Easy to relate to cars and busses. You see your product every day in Lisbon for instance.

 A tough problem with a potential to change people's life



### notes

#### Outline:

- 1. History
- 2. Why Predictive Maintenance
- 3. How Predictive Maintenance
  - a. Supervised
  - b. Unsupervised
- 4. Feature engineering & feature selection
- 5. Problems & result
  - a. Question about
- 6. Why this is important to me:
  - a. Clear link between data >model -> prediction business implication
  - b. Vehicles you see in every day life (Carris, Lisbon trash trucks)
  - c. Tough ML problems, get to work with great minds.