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Managing Streamed Sensor Data for Mobile Equipment Prognostics

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Intelligent Maintenance Conference, 8 & 9th September, Zurich

Project Motivation



- 125M connected cars on our roads by 2022¹
- Streamed sensor data on mining trucks and excavators now
- Equipment manufacturers' predictive maintenance solutions immature
- Asset operators
 - Raw data difficult to access and process
 - Are not getting **data-driven** insights for maintenance actions



Data Sources



Dataset of 13 excavators measured over 9 months totalling ~300M rows in 19.9GB



58 numeric sensors and 40 binary indicators (per excavator)



Fleet management database
Operator entered machine status codes



CMMS work orders describing maintenance events



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Raw Data State – normal transformation

Long form sensor data

Time	Sensor	Value
0:33:24	57	4.176
0:33:24	1	24
0:33:24	58	30537.4
0:33:24	3	59
0:33:54	1	24
0:33:54	58	30537.4
0:33:55	3	59
0:33:55	57	4.128
0:34:24	1	23
0:34:24	58	30537.4
0:34:24	57	3.792
0:34:25	3	60

Pivoted sensor data

Time	Sensor	Value
T	1	X
T+0.5	1	Y
T+0.3	2	A
T+1.3	2	B

Fleet management data

Start Time	End Time	Status
T	T+1.3	Loading
T+1.3	T+2.7	Hydraulic fault

CMMS data

Start Time	Work order short text
T +12.2	Repair hydraulic system

Wide form data (for data analysis)

Time	Sensor 1	Sensor 2	Loading	Hydraulic fault	CMMS
T	X	NA	1	0	0
T+0.3	NA	A	1	0	0
T+0.5	Y	NA	1	0	0
T+1.3	NA	B	0	1	0
...
T+12.2	Z	C	NA	0	1

3.1 GB

17 GB



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Size of the Data

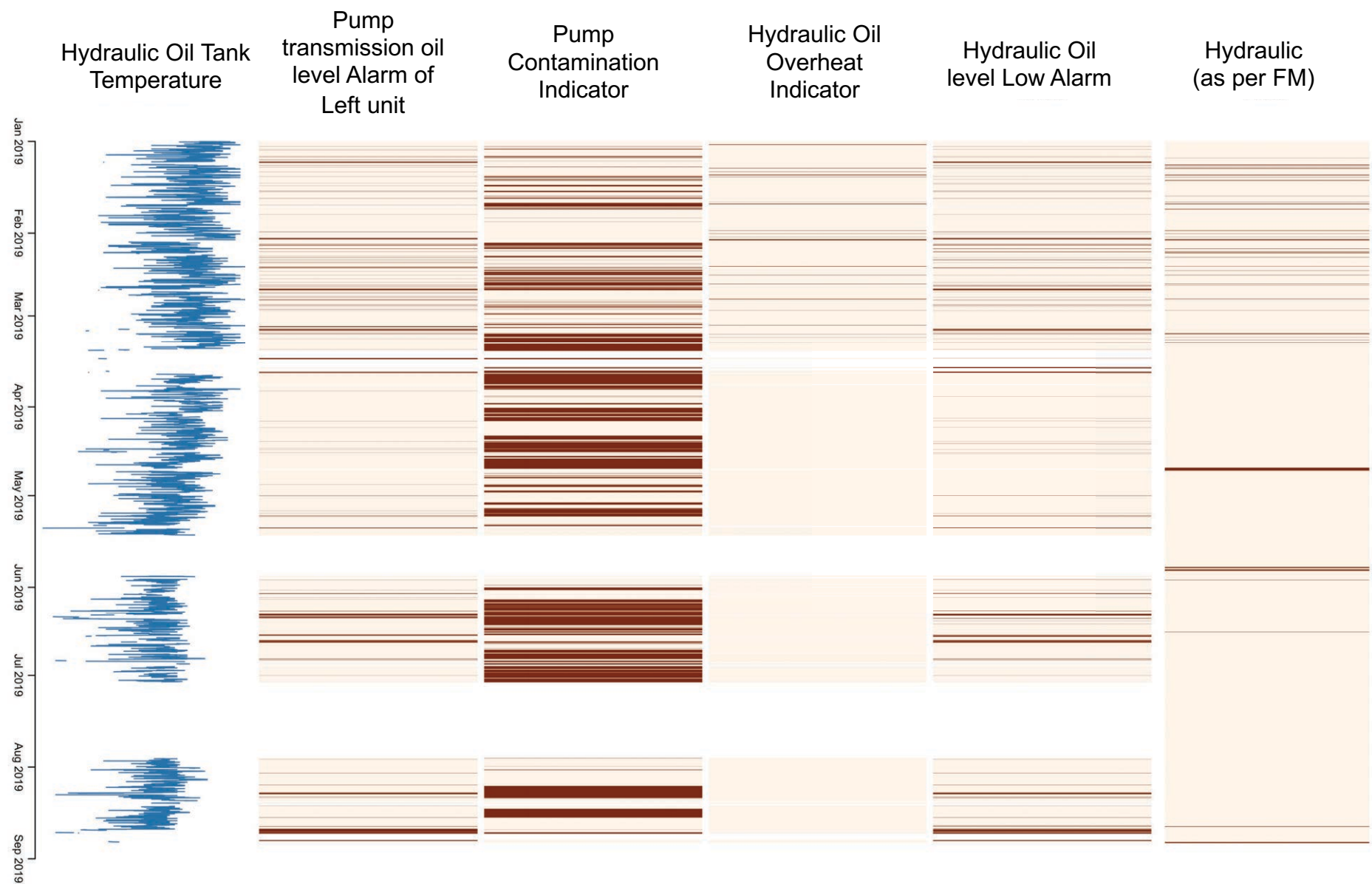


Hydraulic Oil Tank Temperature

- This example spans **four days**, showing data for one sensor on one excavator
- The complete dataset encompasses 58 numeric sensors and 40 binary indicators across 272 days for 13 excavators
- This extract can be considered **0.001%** of the data
- Impossible for engineers to monitor this volume of data visually



Failure signature?



Question



How can streamed sensor data be efficiently transformed and compressed and then used to inform maintenance on mobile equipment?



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Data Cleaning Pipeline

Transform

- Extract timestamps and values to separate files
- Pivot each separately

Compress

- OHLC (Open High Low Close) data representation

Model

- Engineering based dimension reduction
- Log-linear mean regression model



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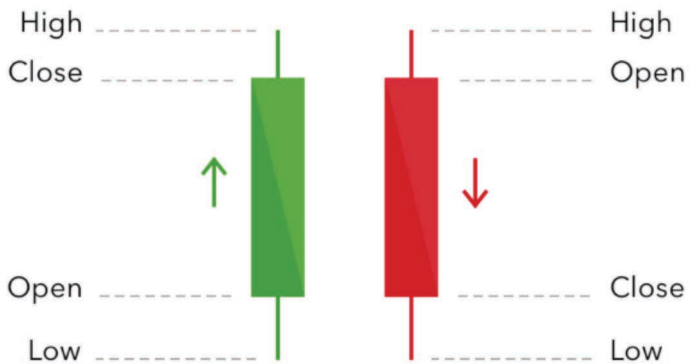
Data per sensor + CMMS data
+ Fleet Management data



Clean and separate into 146 files,
one for each sensor, alarm, fleet
management status and CMMS data

30 MB as opposed to 17GB

OHLC Data Transformation



- Original data has **14402** entries.
- OHLC data has **600** entries.
- Retains key trends of the original data.



Hydraulic Oil Tank Temperature



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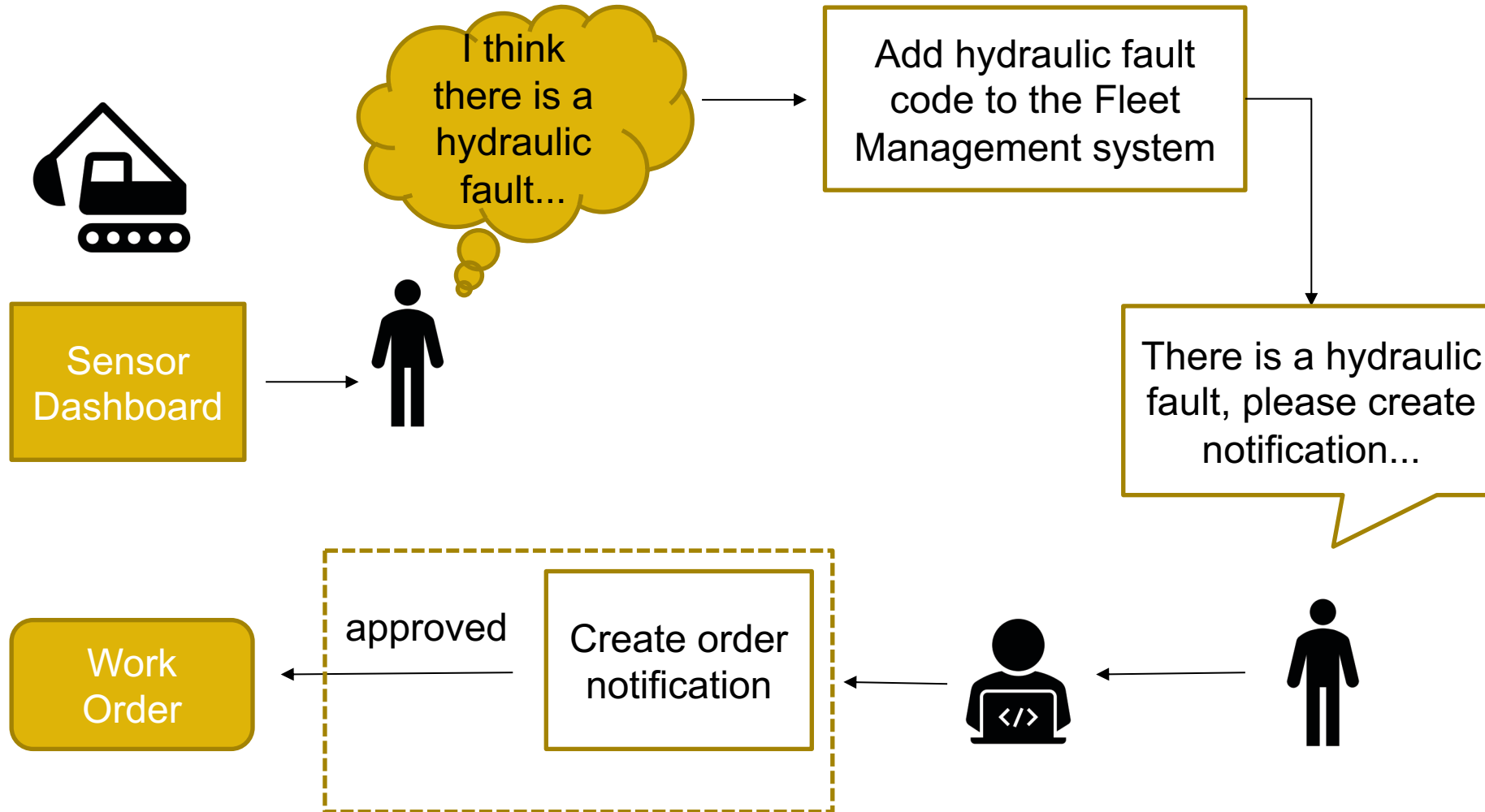


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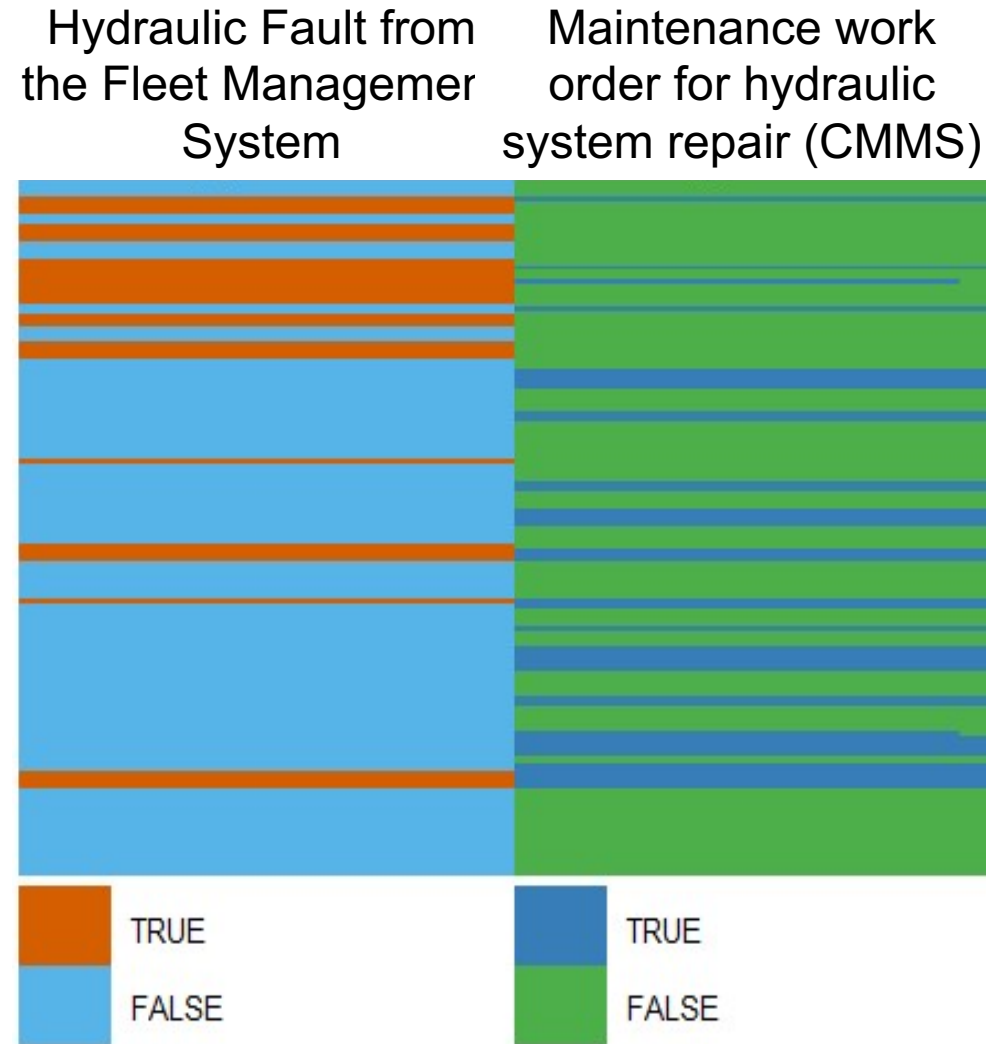
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Human in the loop



Response Variable

Both response variables are generated by an operator



Comparison of two response variables

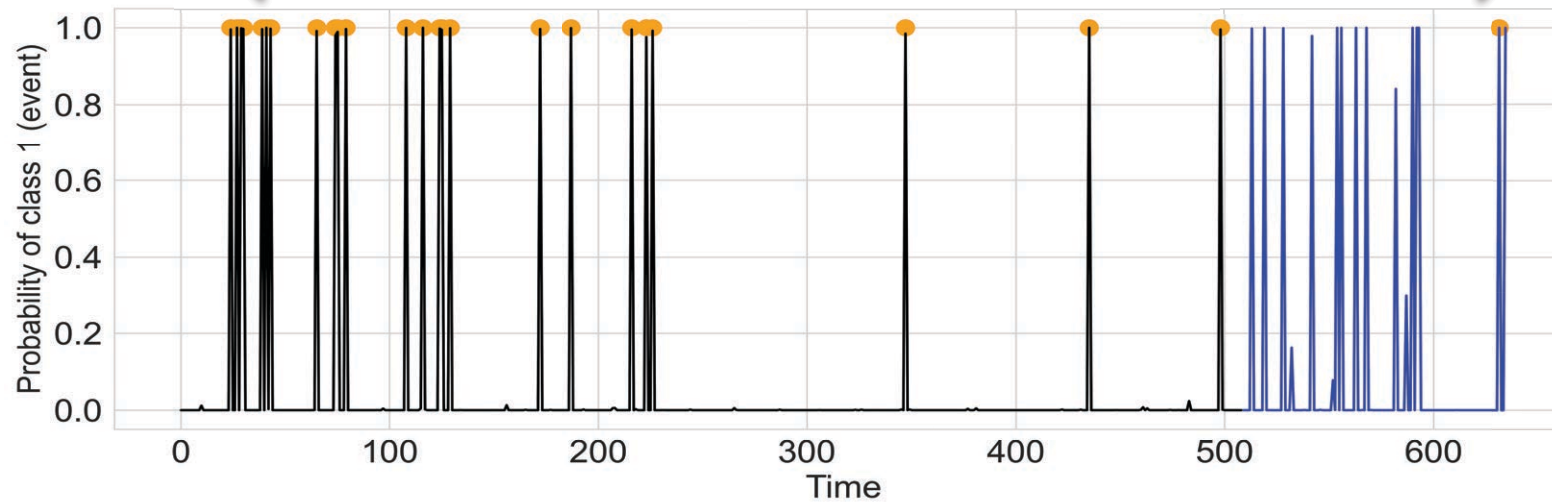


Modelling event occurrence

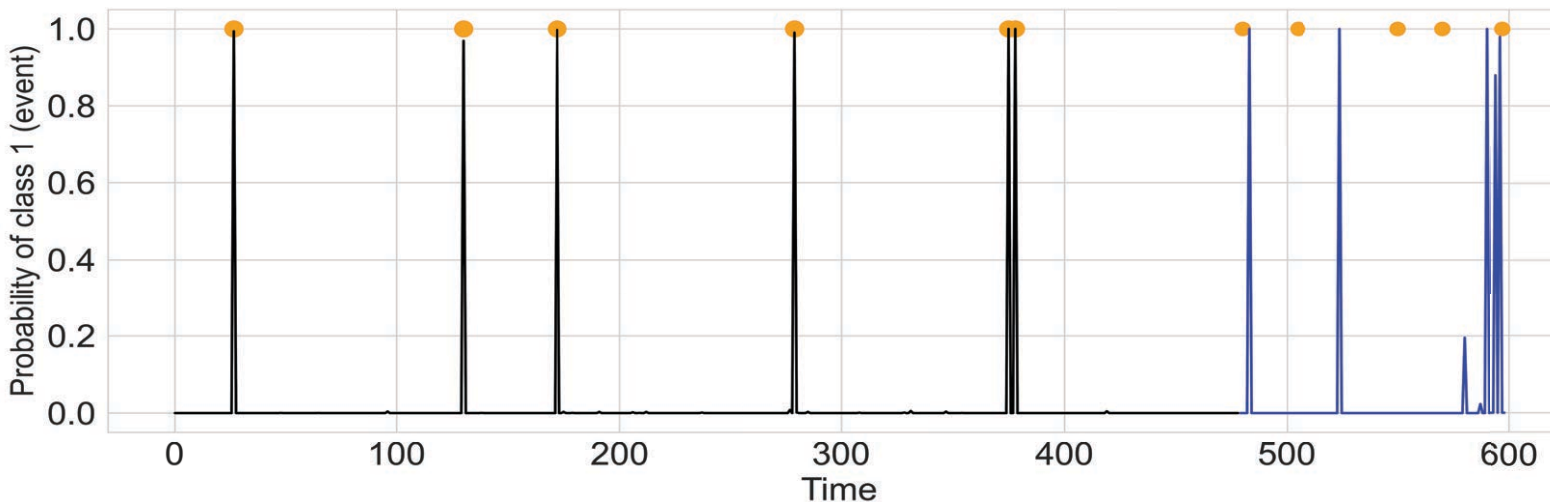
● event



Fleet Management



CMMS



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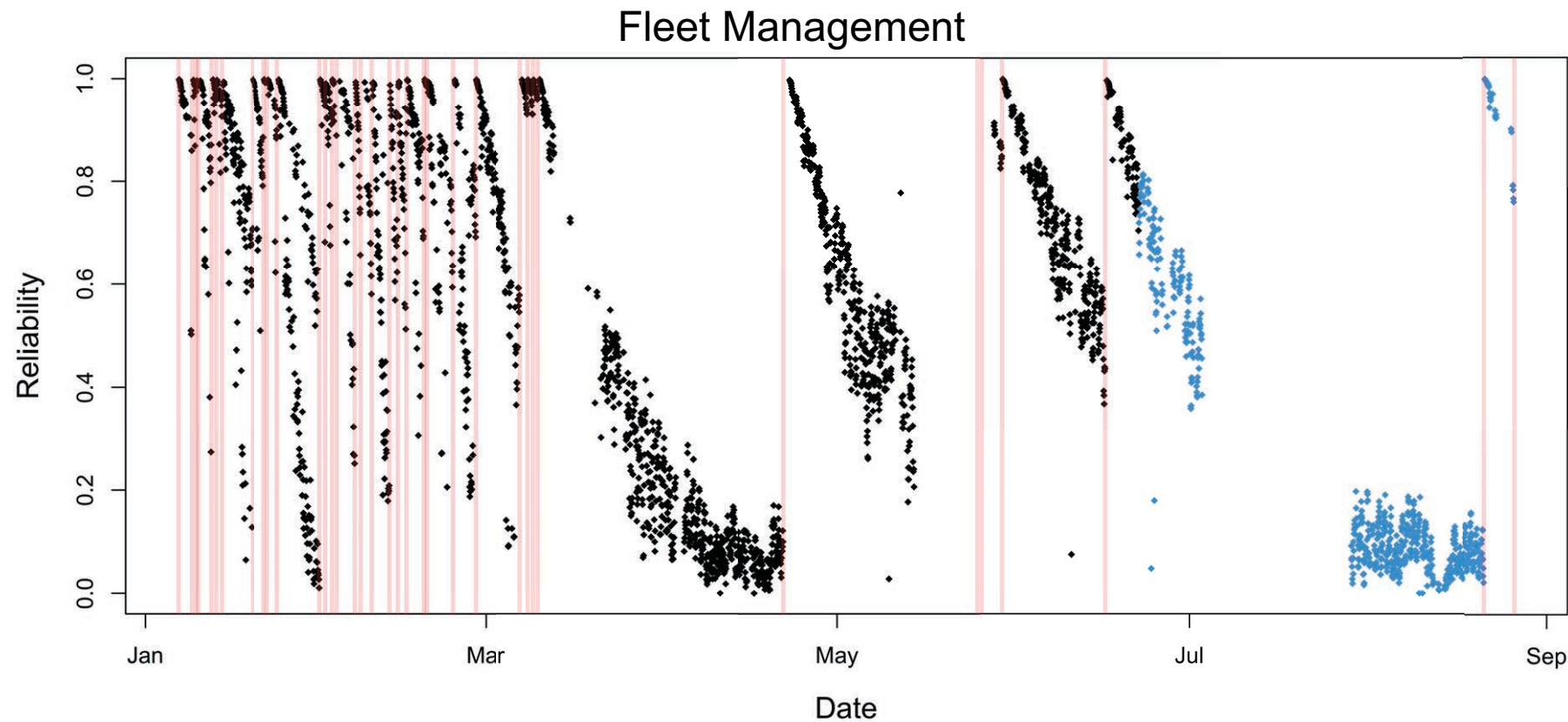


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Time to event modelling

- Developed a predictive survival model using time varying covariates
- Log linear regression model



What did we learn from the modelling?

- Traditional models for event prediction were overfitted and had poor predictive power
- For our log linear regression model the most influential covariates for predicting hydraulic faults based on response variables from a) fleet management and b) CMMS data are **not**
 - Hydraulic Oil Tank Temperatures
 - Pilot Pump Pressure
 - Hydraulic Oil Level Low Alarm
 - Hydraulic Oil Overheat Indicator
 - Pump Contamination Indicator
- This is less surprising than you might first think. There is no pattern in the data as the response variable is about a human (the operator) perception about an event that has not happened yet.



Conclusions

- Messy data – most of our time was devoted to transforming and compressing the dataset
- If you don't have an actual failure, what are you using as your response variable? Is a human involved?
- Both fleet management and CMMS data are based on operators:
 - perceptions (what they consider *potential* failures), and
 - actions (when they report them)
- Human data are not consistent for prediction purpose
- Data analysts may not realise that the fleet management entry is human generated
- Lots of time is being wasted in trying to build predictive models on asset data sets with poorly defined response variables
- Asset owners should consider having Data Engineers to ensure consistent pre-processing of their data and selection of 'good' response variables



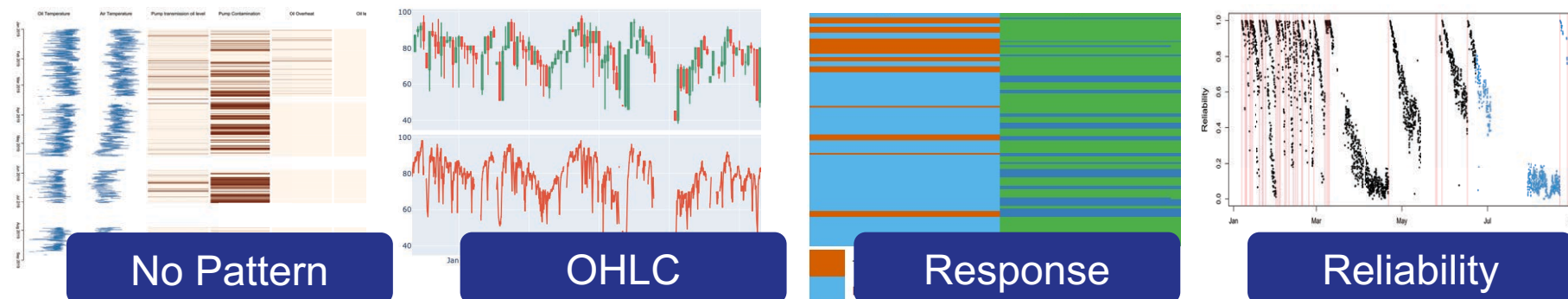
Thank you!

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Acknowledgements:

Our industry partner and the CTMTDS
BHP Fellowship for Engineering for Remote Operations





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