Americas' SAP Users' Group

FLEET INTELLIGENCE: RE-IMAGINED

Session ID #83625

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Agenda

01 Business Background

02 Solution Review

03 Technology Blueprint

04 ***Appendix of SAP Co-Innovation Examples***

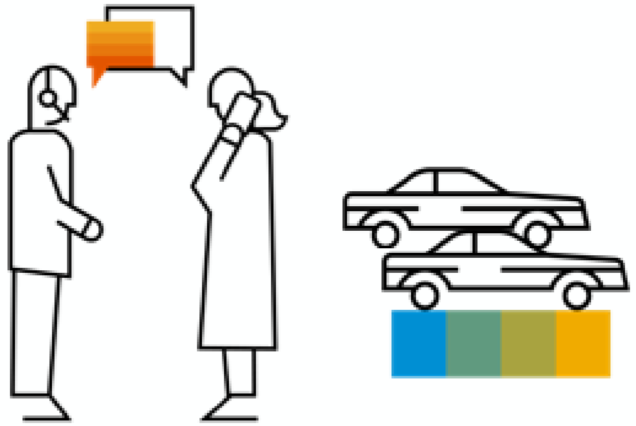
Key Outcomes/Objectives

01 Improve ***uptime*** and ***productivity*** of fleet operations

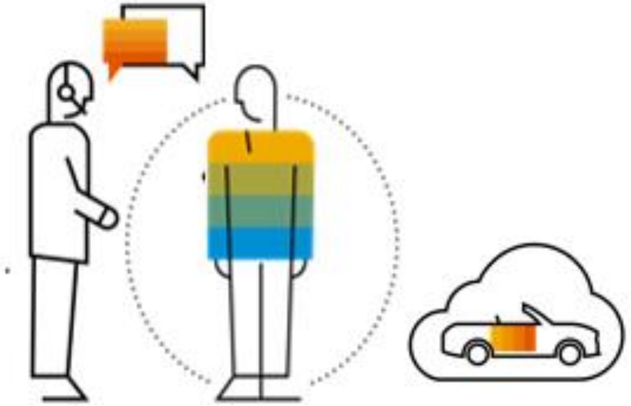
02 Identify ***top drivers*** for high spend vehicles

03 Optimize ***asset maintenance spend*** for ARI's customers with ***data driven insights***

Business Scenario

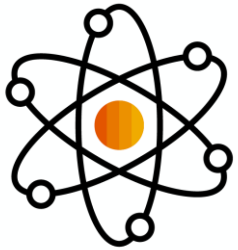


Existing customer fleets



New customer fleets

Trend
Analysis



Correlation
Analysis

Benchmarking
across fleets

Approach

Key Driver Analysis

Identify features or aspects that have the biggest impact on the cost for maintaining/ servicing vehicles

Service Expenditure Forecasting

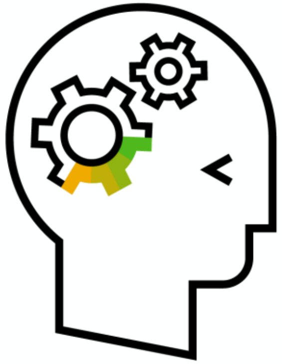
Based on the characteristics of each vehicle and the historical service costs predict the expenditure for servicing that vehicle next year

Objectives Overview

Key Driver Analysis

Process Speedup

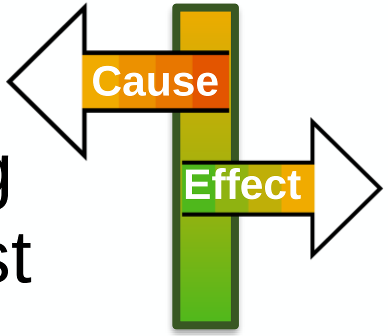
Insights Extraction



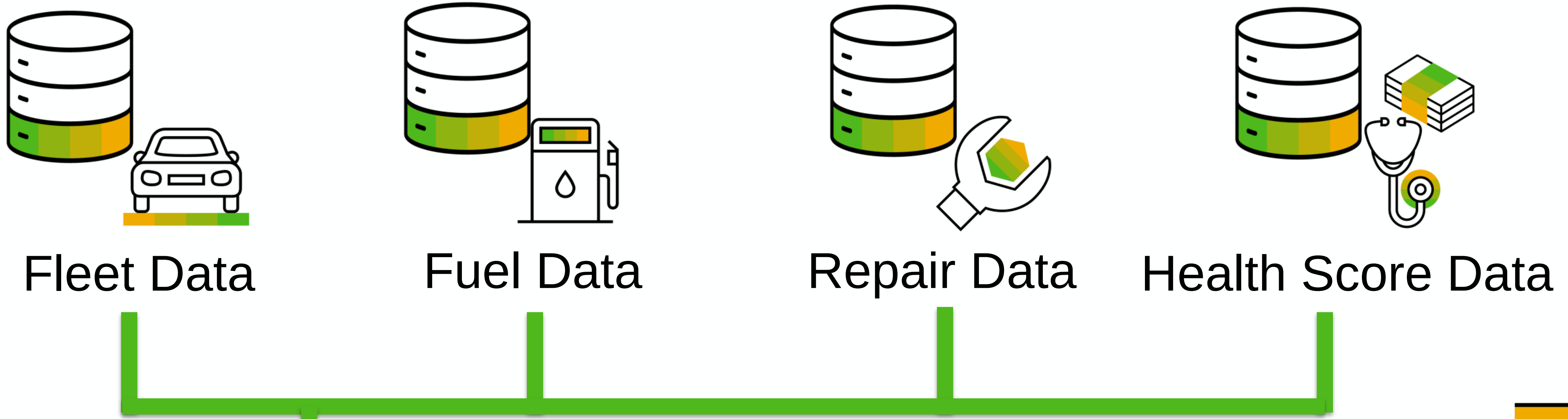
Service Expenditure Forecasting

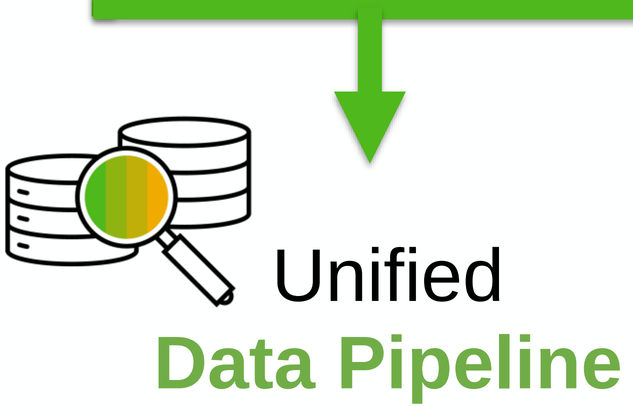
Accurate service cost prediction

Factors influencing service cost



Data sources



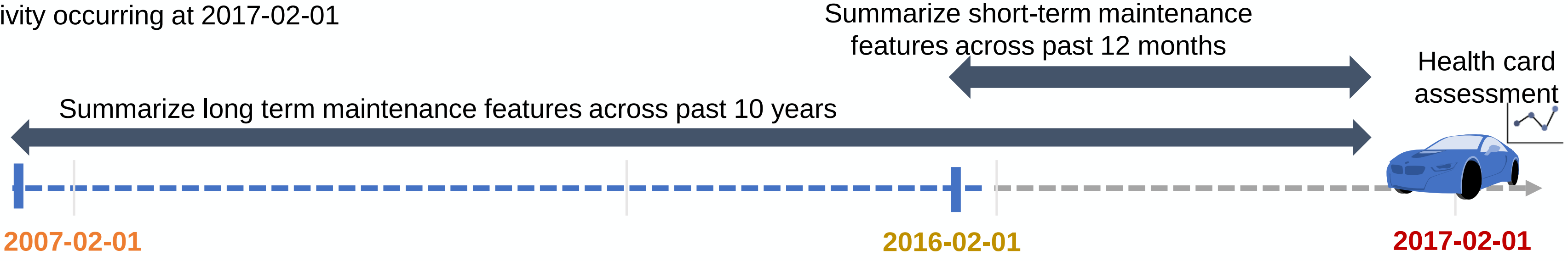


- >12M records ⇔ 47,268 vehicles
- >670 vehicle characteristics processed
- Features engineered encapsulate long and short-term servicing patterns

Data Modeling: Key Drivers Analysis

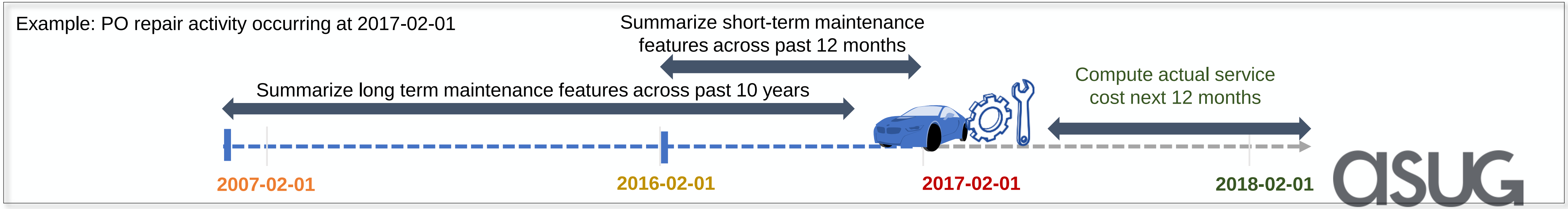
IDs		Explanatory Variables / Potential Key Drivers						Target
Vehicle	**PO Date/Time**	**Months in Service (MIS)**	**Make**	**….**	**Maintenance Adherence**	**Total Cost for Breaks past 12 months**	**Number of Lifetime Tires Replacements**	**Total Cost Label**
18112	2017-02-01	12	Ford F-350	…….	10%	$0	1	**Middle Spend**
18112	2017-06-07	16	Ford F-350	…….	12%	$157	2	**High Spend**
18112	2018-05-01	27	Ford F-350	…….	12%	$100	2	**High Spend**
16355	2017-12-26	1	Chevrolet	…….	60%	$0	0	**Middle Spend**
16355	2018-03-05	4	Chevrolet	…….	65%	$0	0	**Middle Spend**
34222	2018-04-17	18	Chevrolets	…….	90%	$987	4	**High Spend**
…	…	…	…	…	…	…	…	…

Example: PO repair activity occurring at 2017-02-01

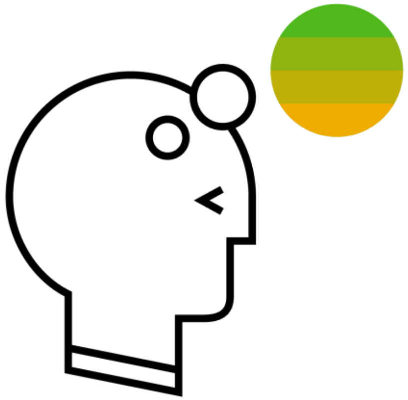


Data Modeling: Service Expenditure Forecasting

IDs		Explanatory Variables / Potential Key Drivers						Target
Vehicle	**PO Date/Time**	**Months in Service (MIS)**	**Make**	**….**	**Maintenance Adherence**	**Total Cost for Breaks past 12 months**	**Number of Lifetime Tires Replacements**	**Service cost next 12 months**
18112	2017-02-01	12	Ford F-350	…….	10%	$0	1	**$1,544**
18112	2017-06-07	16	Ford F-350	…….	12%	$157	2	**$1,698**
18112	2018-05-01	27	Ford F-350	…….	12%	$100	2	**$3,898**
16355	2017-12-26	1	Chevrolet	…….	60%	$0	0	**$157**
16355	2018-03-05	4	Chevrolet	…….	65%	$0	0	**$217**
34222	2018-04-17	18	Chevrolets	…….	90%	$987	4	**$12,000**
…	…	…	…	…	…	…	…	…



Predictive Modeling: Root-Cause Analysis

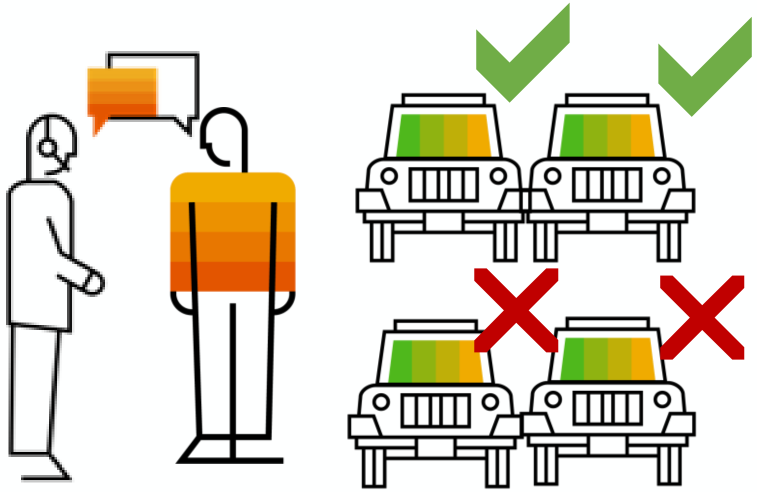


Idea:

1. Train a **classification** model that aims at learning how to correctly label a vehicle as high/ low spending based on the training data
2. Focus on the regression coefficients (i.e. the key drivers that influence the model's decision w.r.t labeling a vehicle as high/low spending)
3. Sort and review the value ranges of each key driver

Predictive Modeling: Root-Cause Analysis

Example:

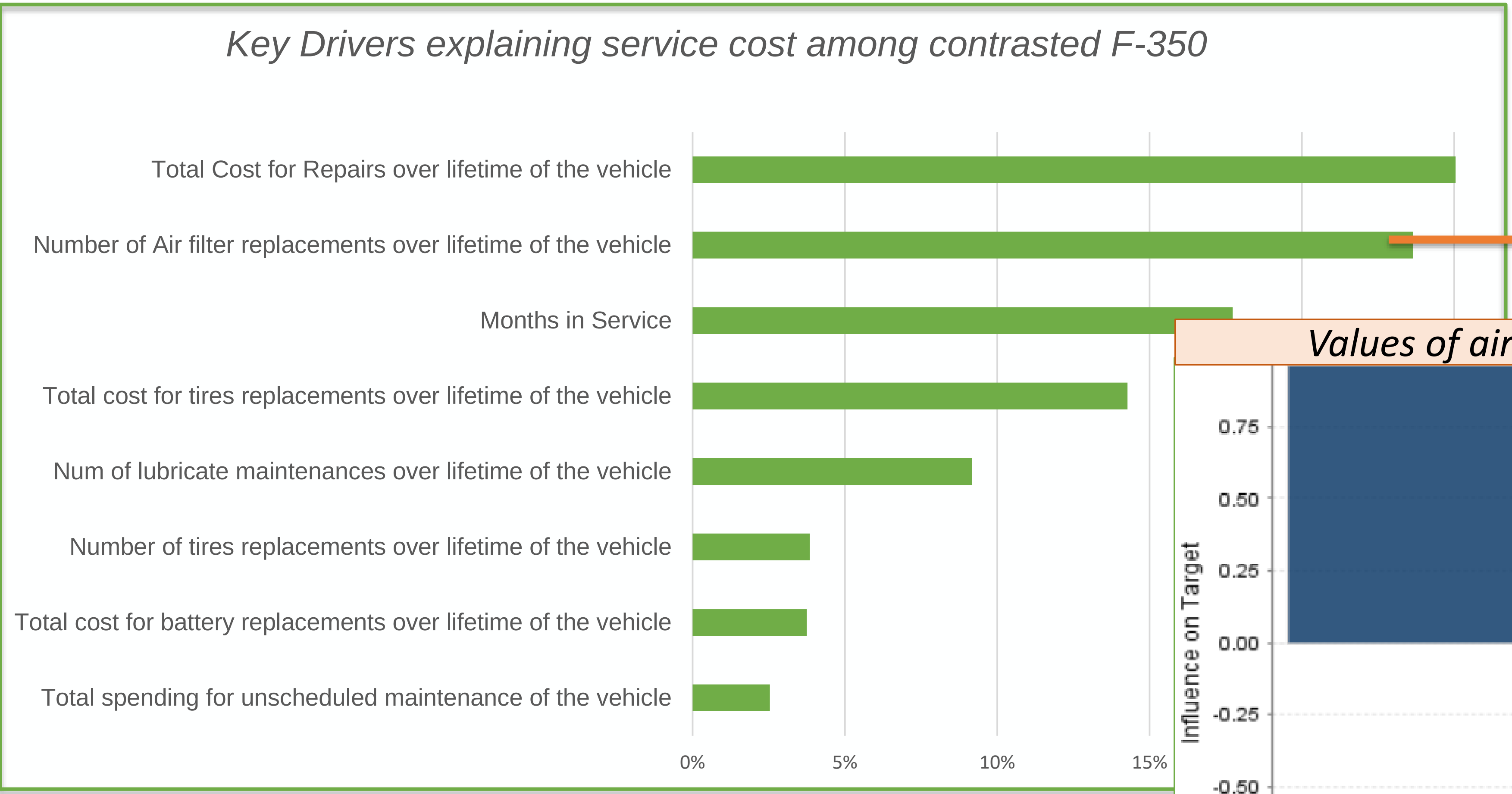


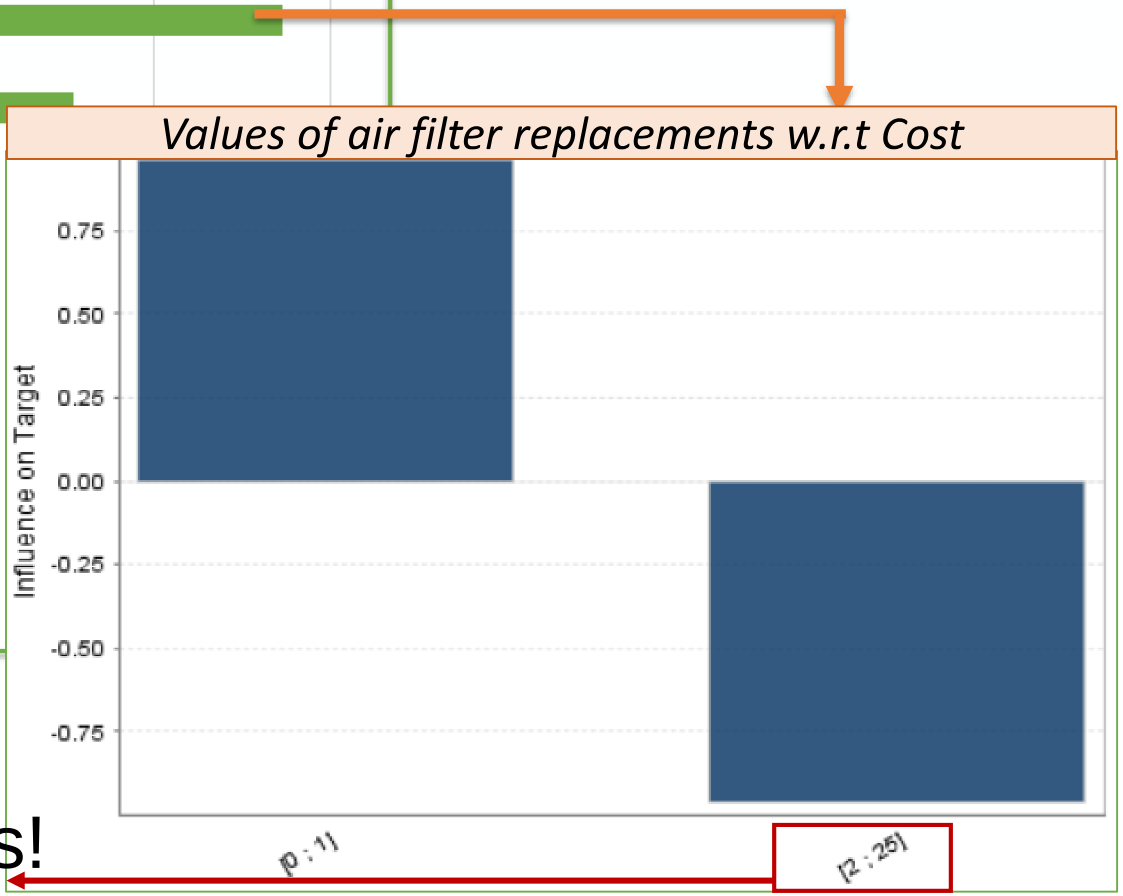
Existing customer fleets

- Customer has 804 Ford F-350 vehicles
  - 64 are labeled as High Spenders
  - 740 are labeled as Low Spenders
- Some high spending vehicles are relatively new (<12 Months in Service)

- Identify top influencers that can help explain the variance in the prices of the contrasted vehicles

Interpretable AI

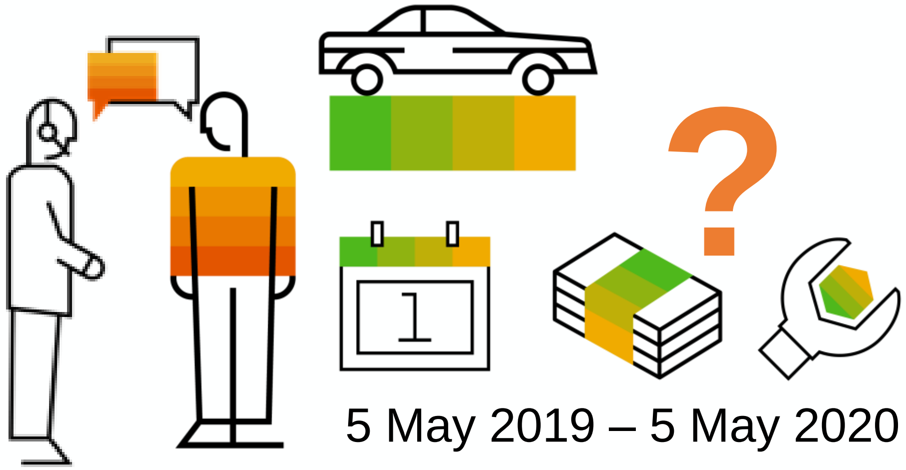




For some of the high cost vehicles the air filter has been replaced up to 25 times!

Predictive Modeling: Service Cost Forecasting

Example:



5 May 2019 – 5 May 2020

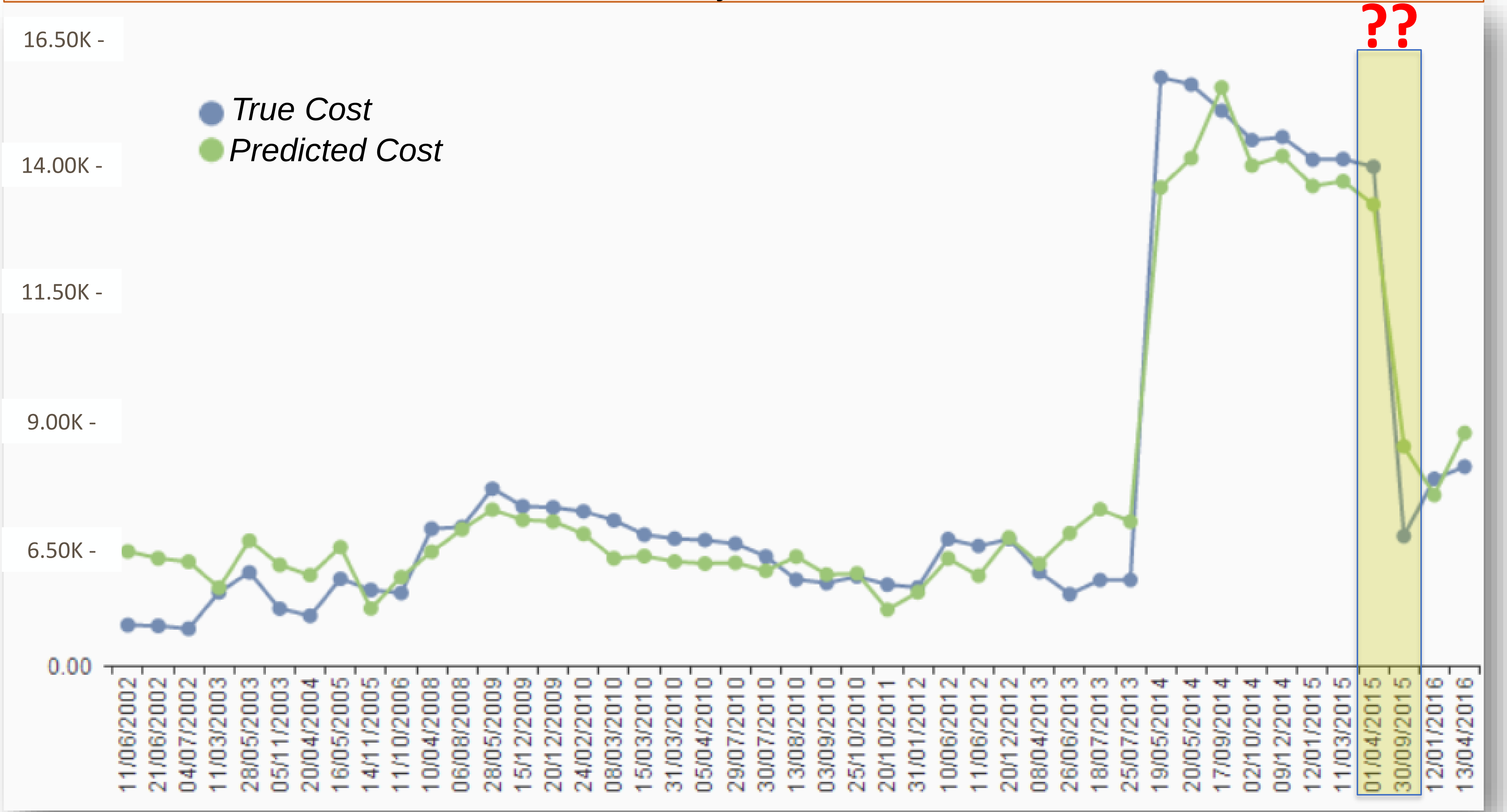
New fleet addition

- Customer wants to know at any given date, the servicing expenditure of a vehicle across the next 12 months
- A model is trained for each [Make – Model] combination (e.g. International 4700)

- Predict service cost for next 12 months
- Provide insights explaining the predicted cost

Predictive Modeling: Service Cost Forecasting

Prediction Evaluation Results for an International 4700 vehicle



Each tick on the x axis corresponds to a date the model is asked to provide with a prediction

Predictive Modeling: Service Cost Forecasting

Prediction Model insights:

International 4700

01 Apr 2015

Actual Cost	Predicted Cost	Top Reason supporting prediction
14,574 $	12,863 $	Amount spent for tire replacements over the past 12 months being equal to 0

- *The model has learned that tire replacements can be costly for International 4700 vehicles*
- *This vehicle has never had a tire change service so far, hence a higher service cost is expected in the next 12 months*

Actual vehicle service history

Date	Repair Action
18 April 2015	Tires Change
29 August 2015	Tires Change

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Predictive Modeling: Service Cost Forecasting

Prediction Model insights:

- *5 months later*

International 4700

30 Sep 2015

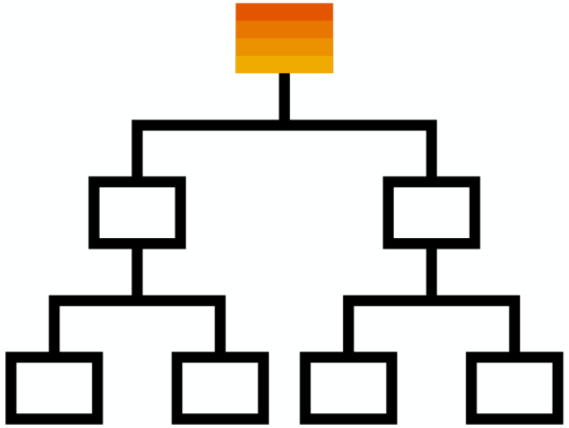
Actual Cost	Predicted Cost	Top Reason supporting prediction
7,283 $	7,343 $	Amount spent for tire replacements over past 12 months (2,259 $)

- *The model has captured that tires have been recently replaced (short-term maintenance feature)*
- *Predicts that no further tire maintenance cost will necessitate in the next 12 months and hence service cost will be reduced*

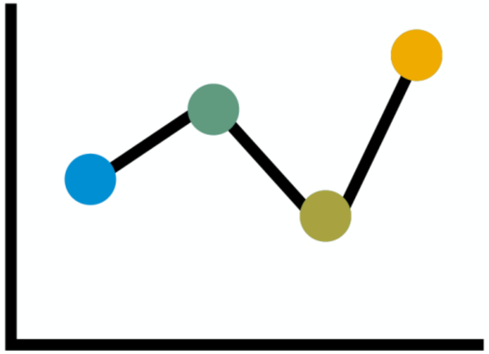
Actual vehicle service history

Date	Repair Action
18 April 2015	Tires Change
29 August 2015	Tires Change
19 January 2017	Tires Change

Predictive Modeling: Algorithms used



Decision Trees



Linear and Logistic Regression

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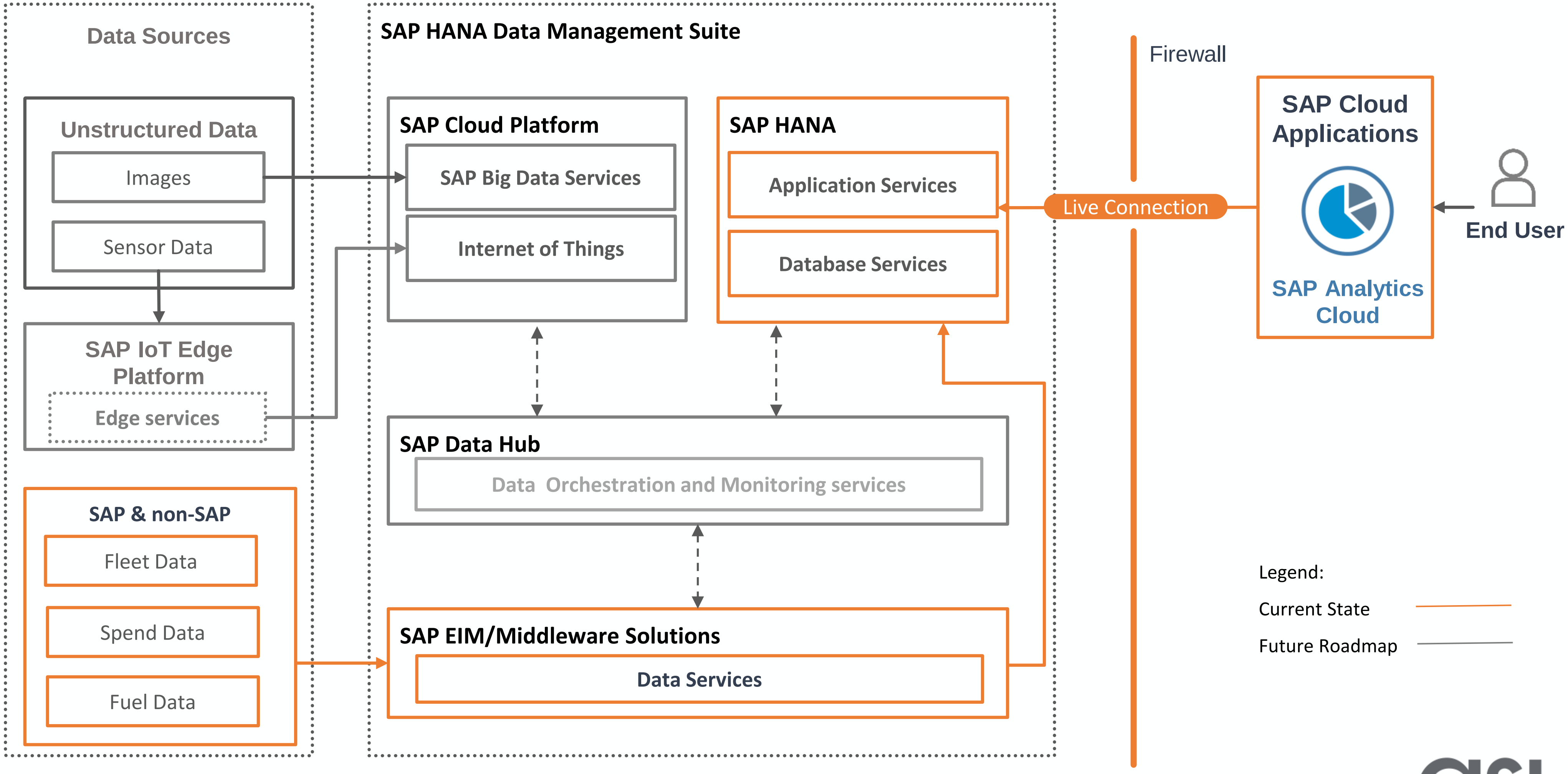
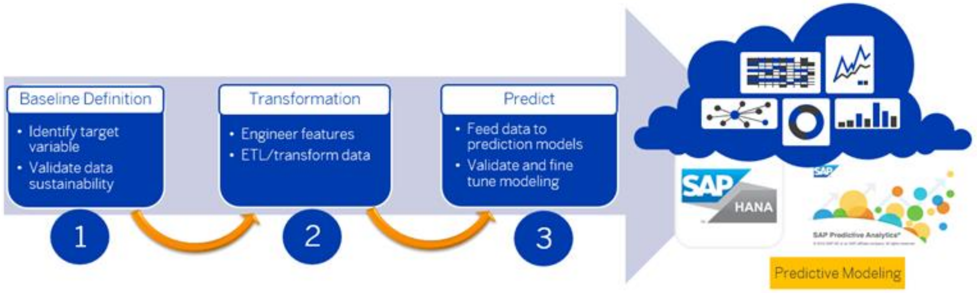
Technology Blueprint



Improve Overall Equipment Effectiveness

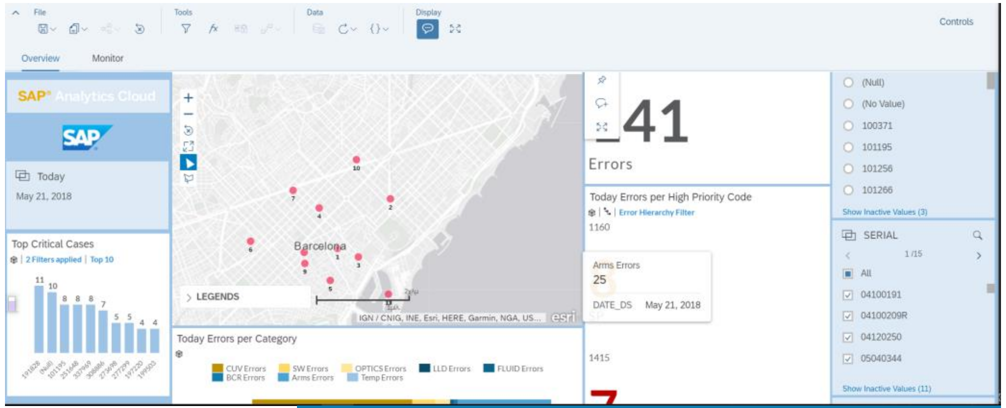
Business Challenge

- Real-time analysis of machine data to resolve issues remotely, and understand machine usage and prevent errors



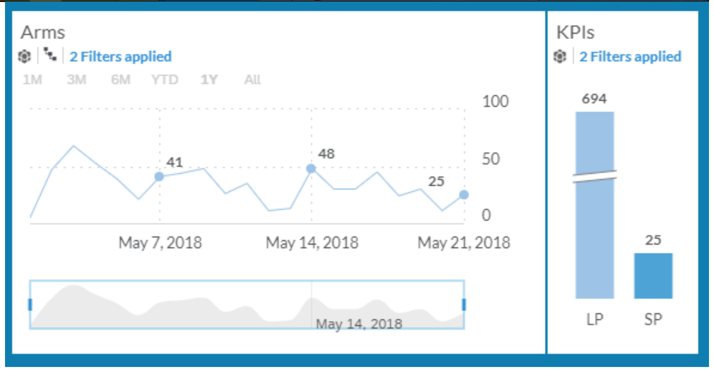
Solution

- Data model unification
- Expert rules validation
- Data-driven rules and insights



Benefits

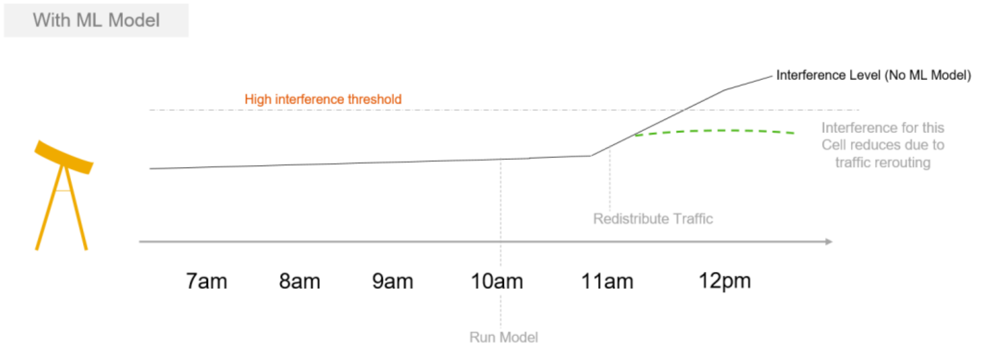
- Real-time overview of machines
- Identification of rapidly degrading machines
- Improved maintenance
- Increased first-visit fix rate



Predict Network Interference and Throughput

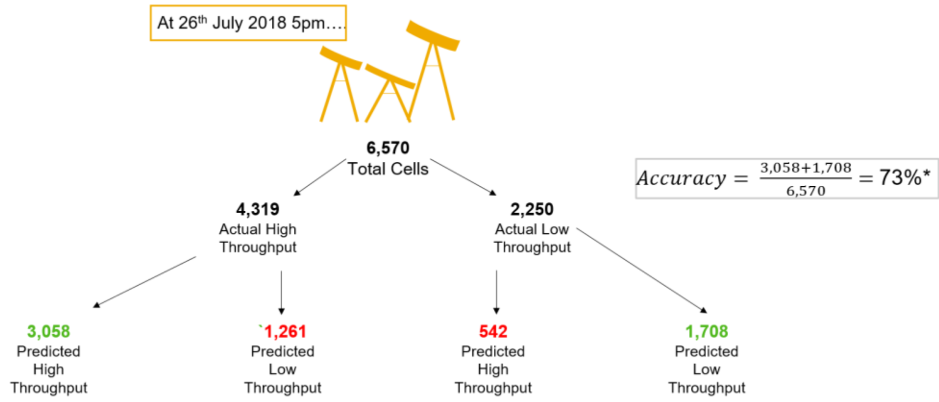
Business Challenge

- Optimize traffic re-routing to reduce interference and increase throughput without quality loss for Telco customers



Solution

- Predict interference and throughput
- Enrich model with weather and spatial data
- Cluster cells based on operational similarity



Benefits

- Promote self-healing automation
- Improved customer experience

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Q&A

For questions after this session, contact us at rellsworth@arifleet.ca, dimitrios.lyras@sap.com and lester.lobo@sap.com.

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