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Data mining for aircraft maintenance repair and overhaul (MRO) process optimization

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SLF
SERVICE LOGISTICS FORUM

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CREATING TOMORROW

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Aircraft Maintenance and Unpredictability

Source: blog.klm.com

MRO benchmarks: TAT, reliability, cost

Challenges:

- Large variation in maintenance duration (and TAT)
- Uncertainty in inspection findings / spare parts needed
- Components replaced (long) before end of life

Opportunity:

- Data growth and powerful algorithms

TAT: Short and reliable MRO lead times

Costs: Reduction of MRO idle time and overprocessing

Costs: Optimal use of components remaining life

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Research project Data Mining in MRO

HvA initiated applied research project, 2016 - 2018

25 case studies at 10+ companies

RAAK MKB program funded by SIA, Ministry of Economic Affairs

SiA Nationaal Regieorgaan Praktijkgericht Onderzoek

Research objective:
How can SME MRO's use fragmented historical maintenance data to decrease maintenance costs and aircraft downtime?

ABS JETS · EXSYN Digitizing Aviation · Tec4Jets · JetSupport Amsterdam · JetNetherlands · NEDAERO components · KVE Composites Group · Netherlands Aerospace Group · mro-air · Koninklijke Luchtmacht · CHC · FLYINGGROUP · TU Delft Delft University of Technology · KLM Engineering & Maintenance · NAYAK Aircraft Services · Lufthansa Technik

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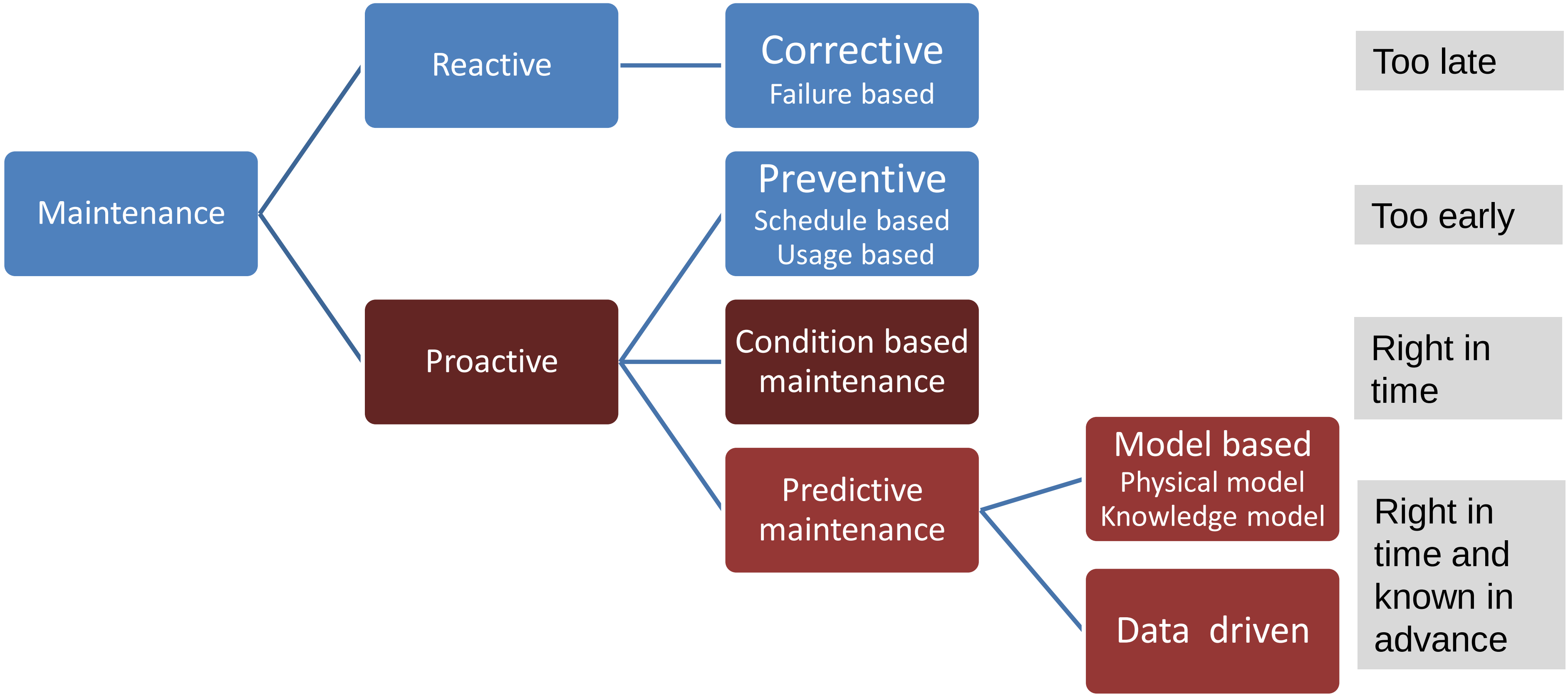
Maintenance taxonomy



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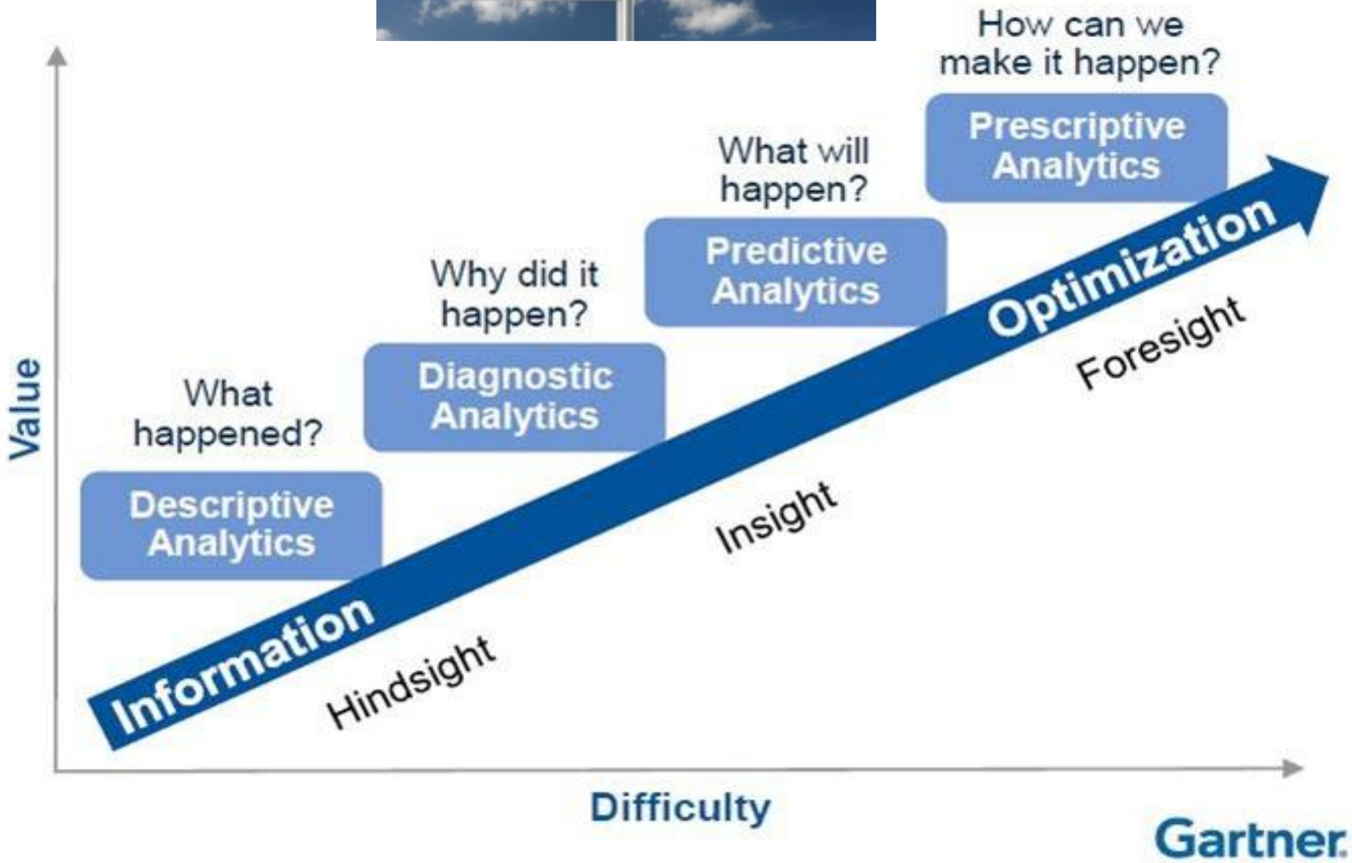
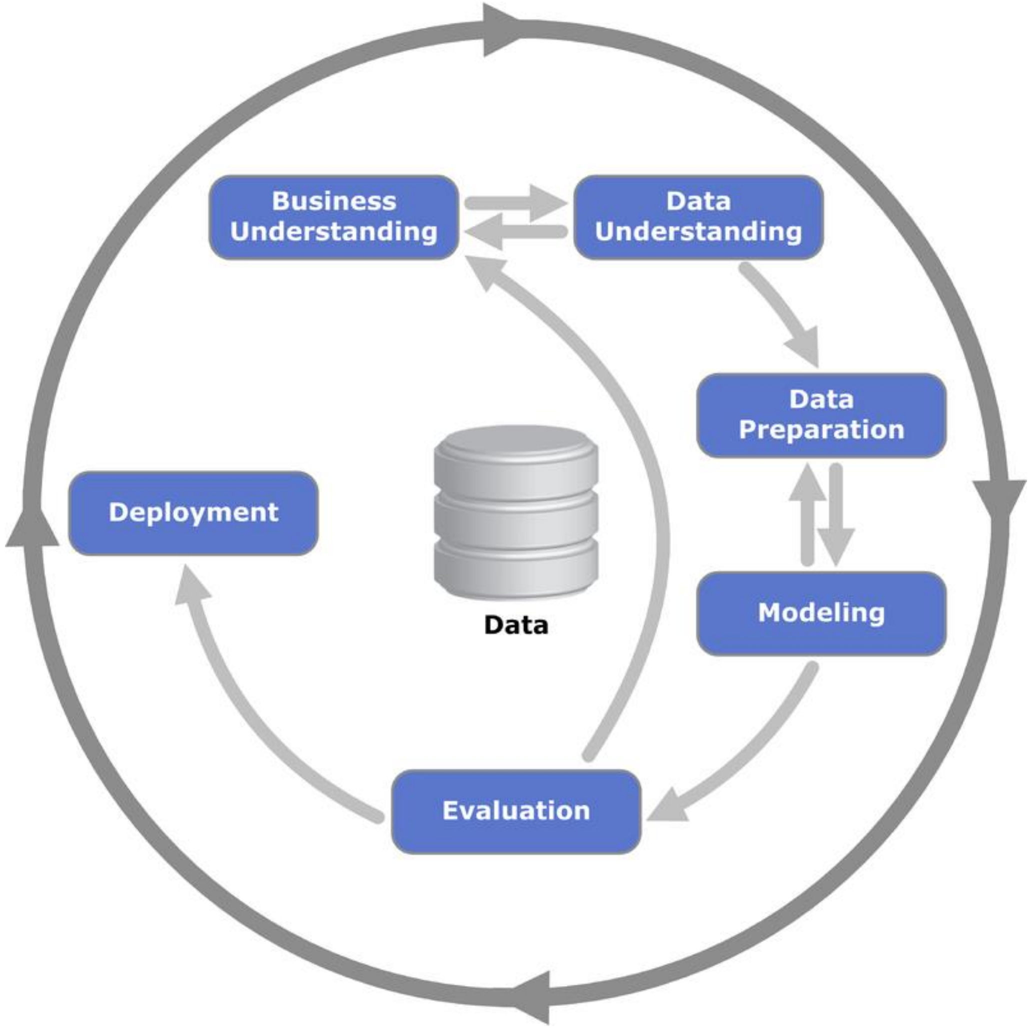
First describe and analyse the past, then predict the future and prescribe actions to be taken



CRISP-DM methodology for Data Mining in MRO

- Data mining: A sequence of steps
- Cross Industry Standard Process for Data Mining methodology: CRISP-DM
- Standard for data mining projects based on practical, real-world experience
- CRISP-DM is the most used data mining method (Piatetsky, 2014)



Source: Chapman, et al. (2000)

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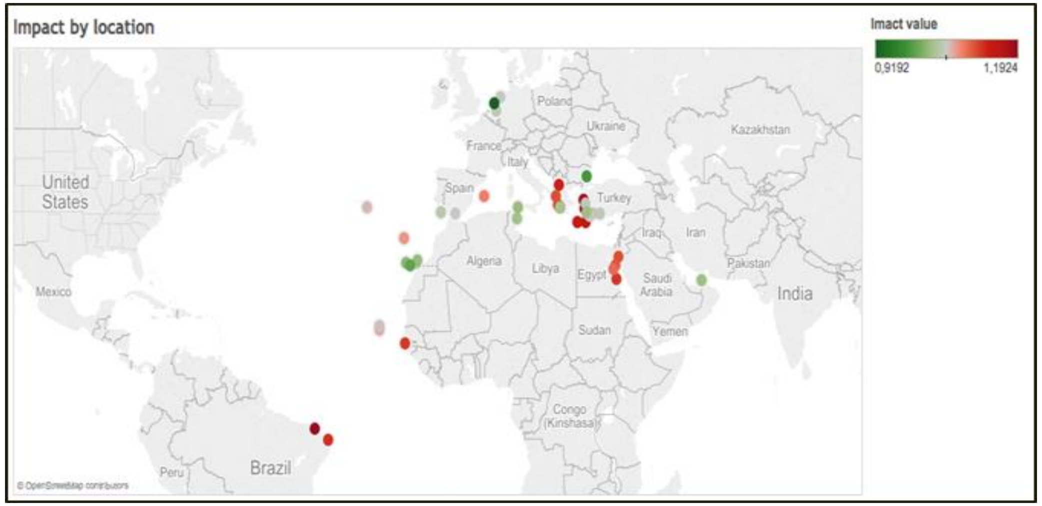
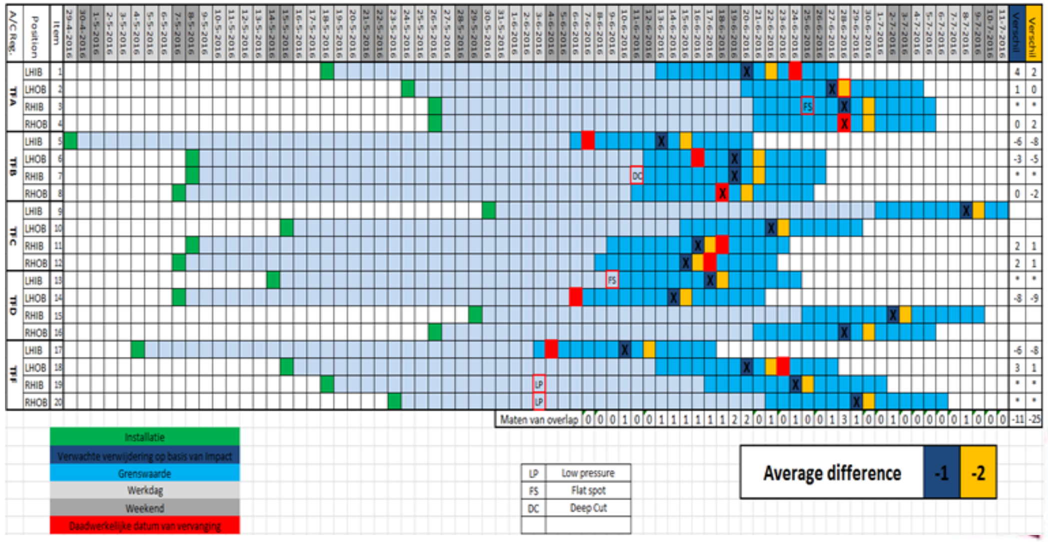
Case: Optimal aircraft tires replacement

Company: Line maintenance and A checks

→ Increase availability and lower maintenance costs

CRISP methodology	
Business understanding	Prediction of the remaining useful life time Optimal schedule for tire replacement
Data understanding	AMOS, FDM cycles, weight, braking action, location, runway length and temperature
Data preparation	Cleaning, integration into single dataset
Modelling	Linear regression
Evaluation Deployment	Highest correlation found: tire wear and airport Proof of concept: Prediction of optimal replacement moment





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- Aircraft maintenance and unpredictability
- Methodology
- Data sources and preparation
- Modelling
- Concluding remarks

Data Mining models extract condition / degradation information from data

Condition	Sensors, inspection	→ degradation monitoring
Load	Forces, temperature, etc	→ degradation rate
Usage	Hours, cycles, kilometers	→ indication of degradation
External data	Environment	→ influences degradation
	Benchmarks	→ learn from others

Strong growth in sensors, monitoring data

Massively growing amount of available data

Who has access to data and/or the rights to use?
Many formats, creators, users, owners of data were found in the case studies

- Flight data
- Maintenance data
- External data

- Manuals, forms digital or on paper
- Structured tables in relational databases (e.g. ERP)
- Free text reports of findings and repair action
- External data sources in various formats
- Sensor data
- Pictures, samples

Available data

Stakeholder	Operations data	Aircraft Health Monit	ERP	MPD	Jobcard	Form 1	OEM maintenance documentation	External sources
Airline	C U O	U?	C U O					U?
Aircraft owner	U O		U?				U?	U?
Airworthiness manager (CAMO)	U?		C U O	C U O			U	U?
OEM of aircraft, engine or other		U O					C O	U?
MRO company (Part-145)	U?	U?	C U O	U O	C U O	C U O	U	U?
MRO Support /tooling		U?	C U O	U O	C U O	C U O	U	U?

C: Creator
U: User
O: Owner

Example of a data distribution in Aviation MRO

Data preparation to clean and construct the final datasets from the initial raw data

- Deal with imperfect and incomplete data
- Clean, integrate, format and verify
- Often tedious, time consuming

Missing values
Outliers
Datasets not accessible, not available
Datasets incomplete
Data interpretation variability
Errors in values

	Cleaning steps	Construct data	Integrate data	Transform data	Reduce data
Software developer	Remove duplicates; Remove false malfunctions	Yes	Yes	Yes	No
MRO company 1 a	Remove errors; Fill empty cells; Remove empty cells; Outliner removal; Remove irrelevant data	Yes	Yes	Yes	Yes
MRO company 1 b	Remove irrelevant data	Yes	Yes	Yes	No
MRO company 1 c	Correct errors; Fill empty cells; Remove empty cells	Yes	No	Yes	No
Airline MRO 2	-	Yes	No	Yes	Yes
MRO company 2	Correct errors; Fill empty cells; Outliner removal	Yes	Yes	Yes	No
In house MRO	Remove errors; Fill empty cells; Remove irrelevant data	Yes	Yes	Yes	No
MRO company 3	Remove errors; Fill empty cells; Remove empty cells	Yes	Yes	Yes	Yes

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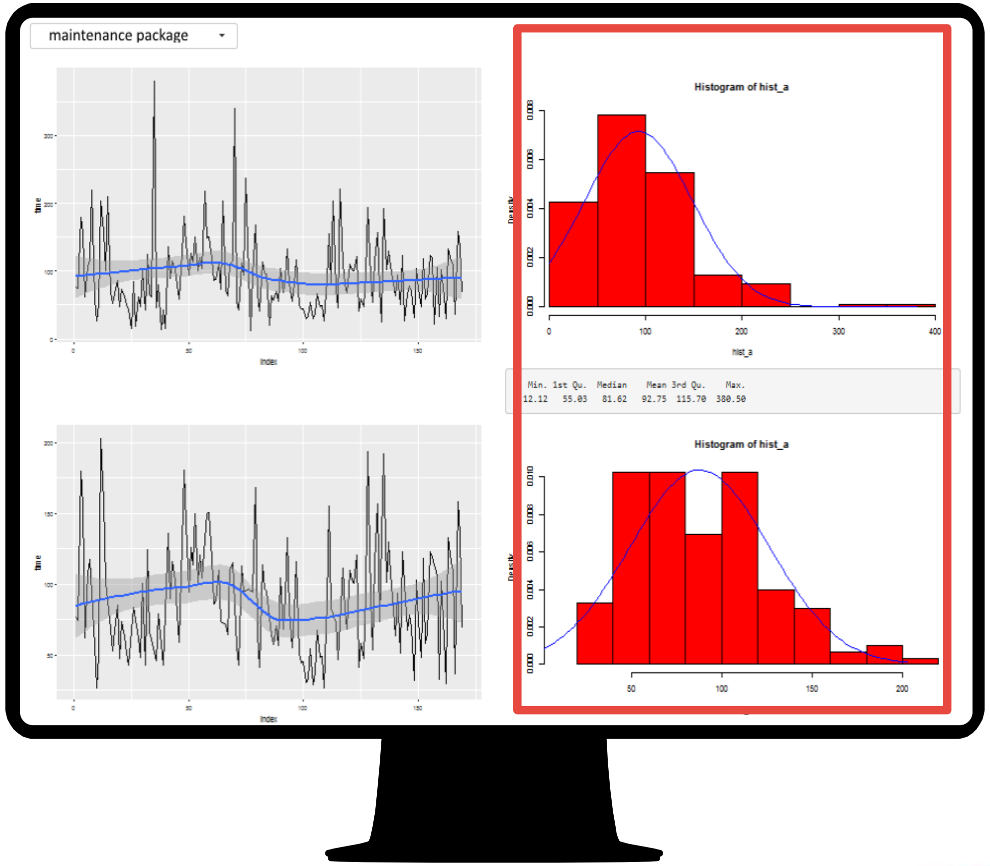
Case: Maintenance duration prediction

A predictive maintenance tool with reasonable accurate predicted maintenance tasks duration with automated selection of the:

1. Best fitting statistical distribution
2. Best performing time series forecasting model

For every maintenance package and/or job card of any aircraft type



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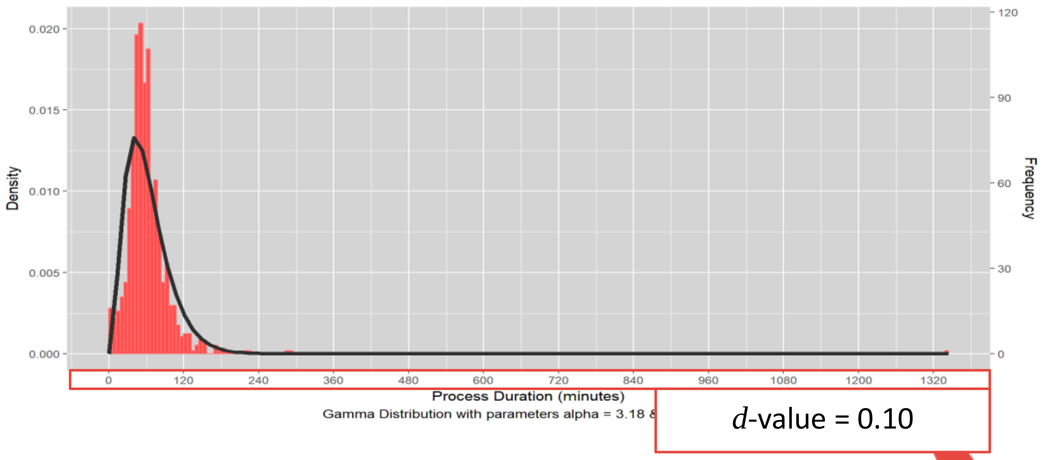
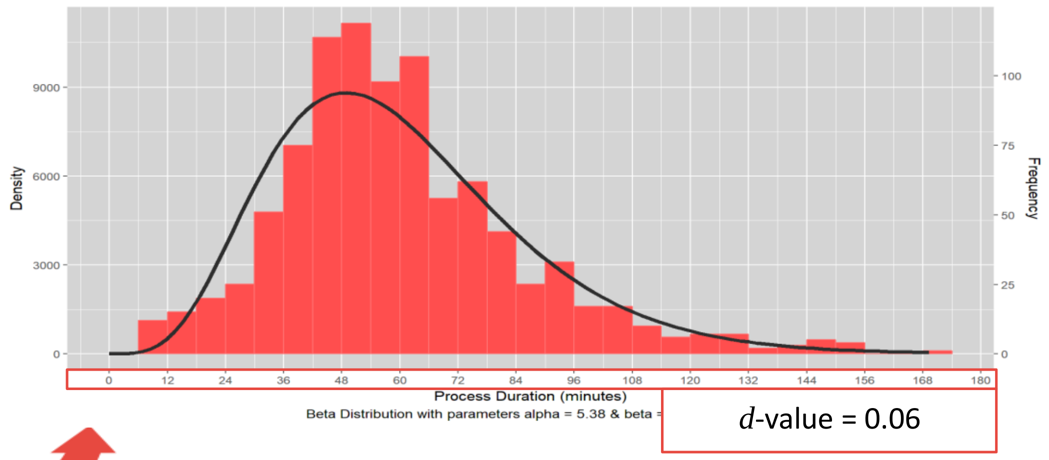
Data Preparation to make data processable





- Missing values
- Outliers
- Datasets incomplete
- Errors in values

sAircraft Type	idResourceTask	sDescriptionJobCard	dtCRSDate	time	sTitlePackage	sDescriptionPackage
Cessna 525A	10715	Clean the power plant - water rinse (Desalination)	1/2/2015 16:35:53	100	71-00-03-170-801	Desalination Wash
Cessna 525A	10715	Clean the power plant - water rinse (Desalination)	1/2/2015 16:35:53	90	71-00-03-170-801	Desalination Wash
Falcon 900C	10699	Departure - Meet & greet departure instructions	1/30/2015 19:07:00	50	M&G PH-EDM	Meet & Greet PH-EDM

(Fictional Values)

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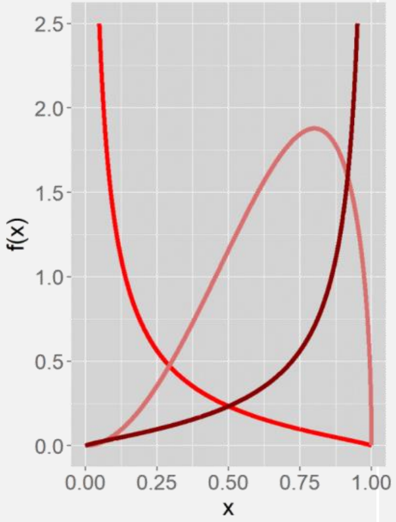
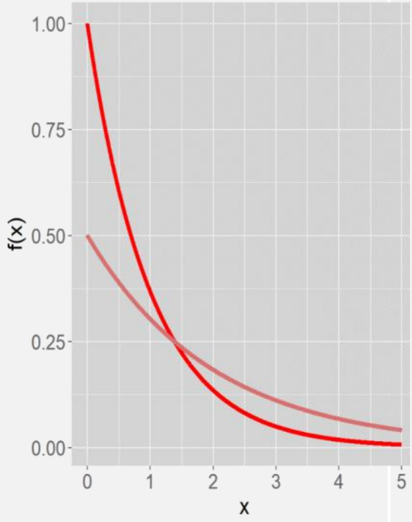
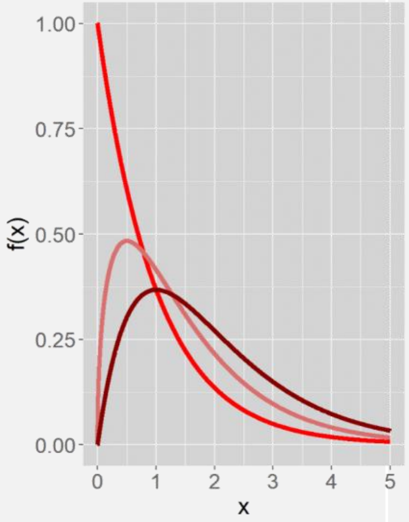
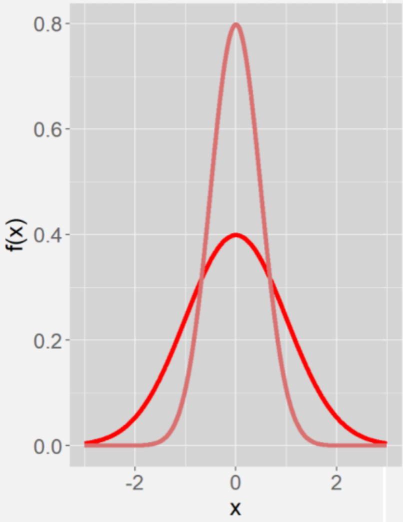
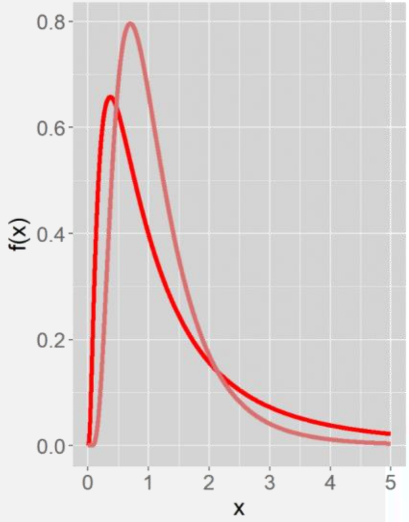
Selected Statistical Distributions based on literature

Distribution	Beta	Exponential	Gamma	Normal	Lognormal
Parameters	α & β	λ	α & λ	μ & σ	μ & σ
PDF					

(O'Connor & Kleyner, 2012)

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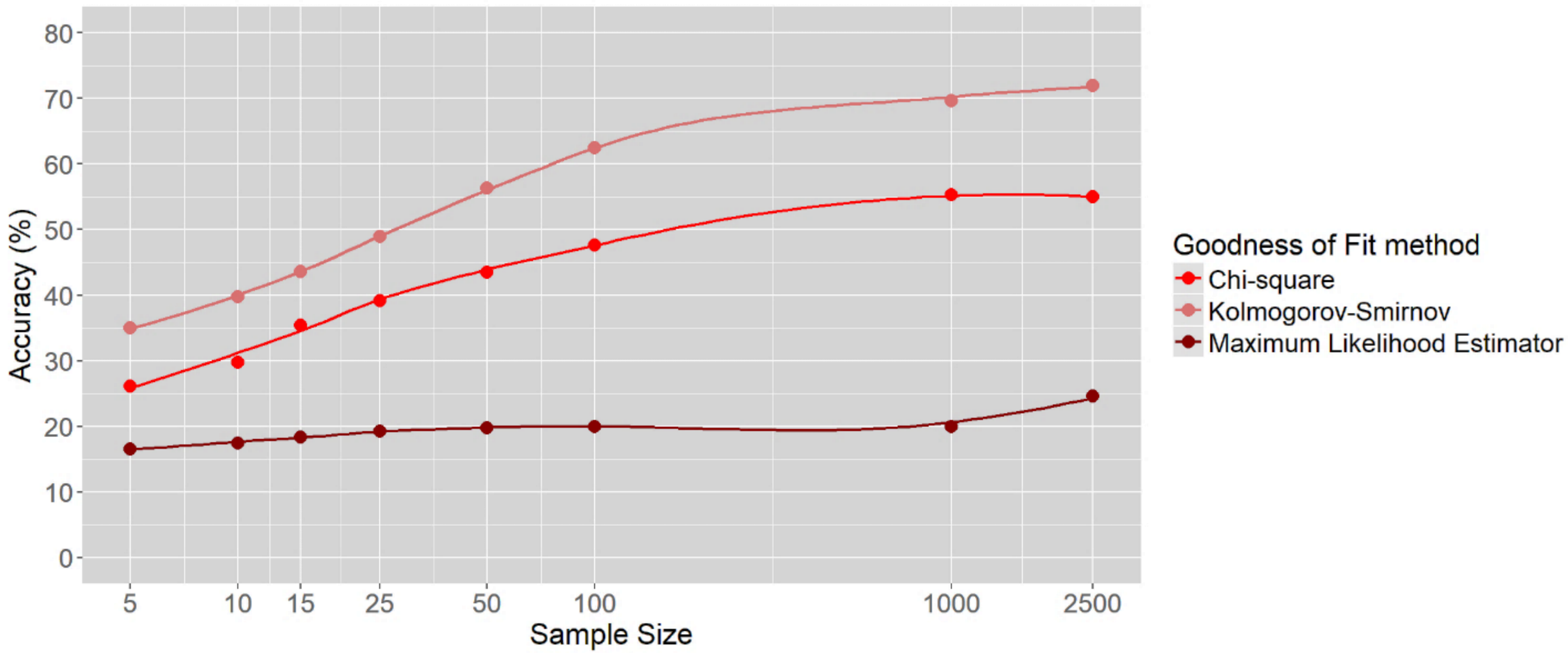
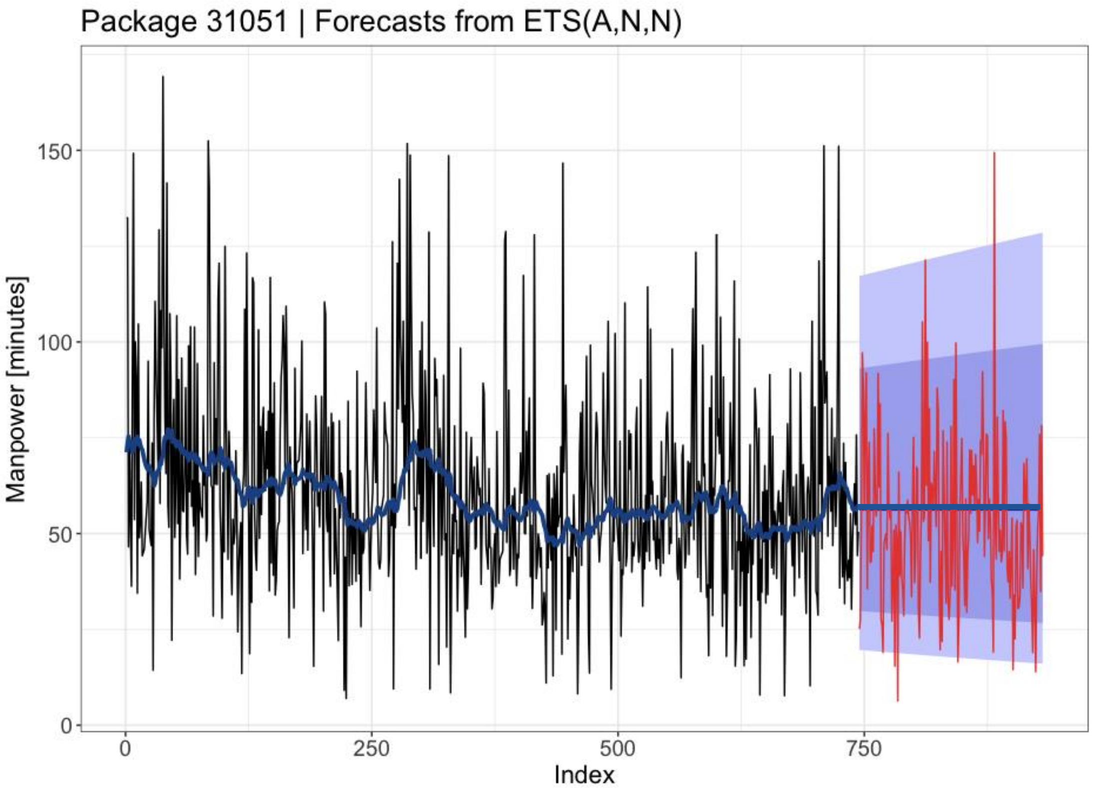
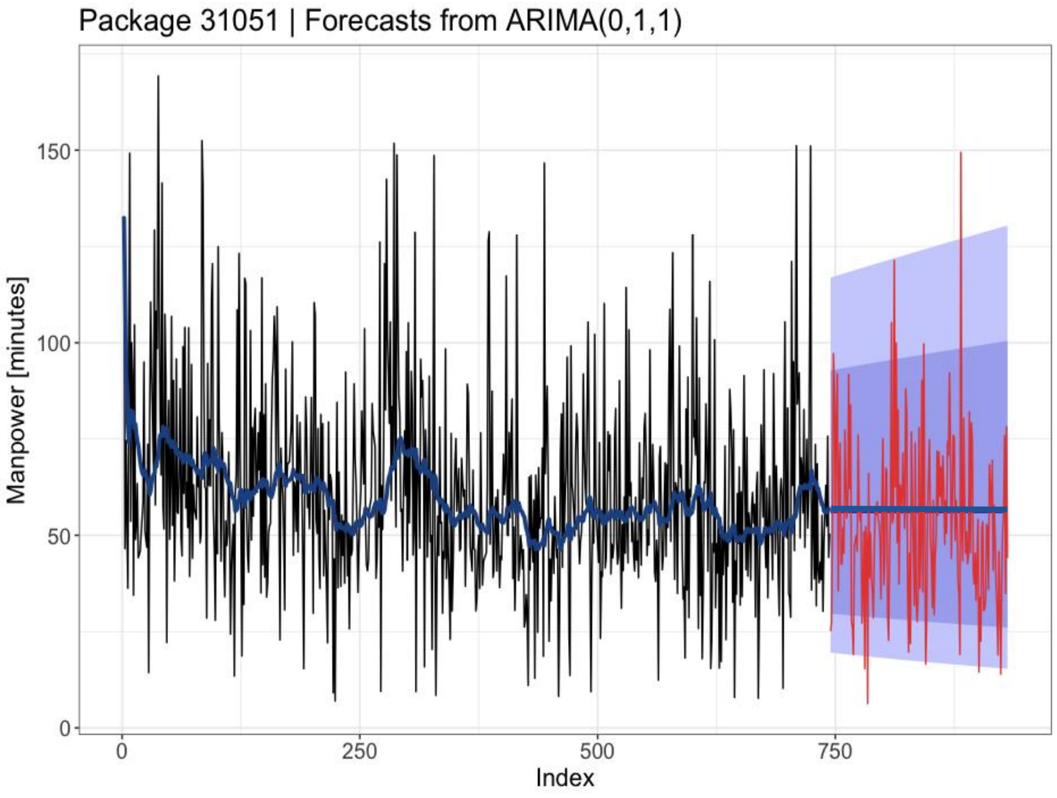
Results: Goodness of Fit accuracy comparison based on simulation



Minimum Sample Size	K-S Accuracy	Available Maintenance Packages	Available Job Cards
20	46%	27	209
30	50%	19	120
40	53%	12	82

Comparing the forecast performance of ETS and ARIMA





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Predictive Maintenance Tool dashboard

The probability of maintenance package 31051 requiring manpower for a duration between 26 and 84 minutes is 77.7 %

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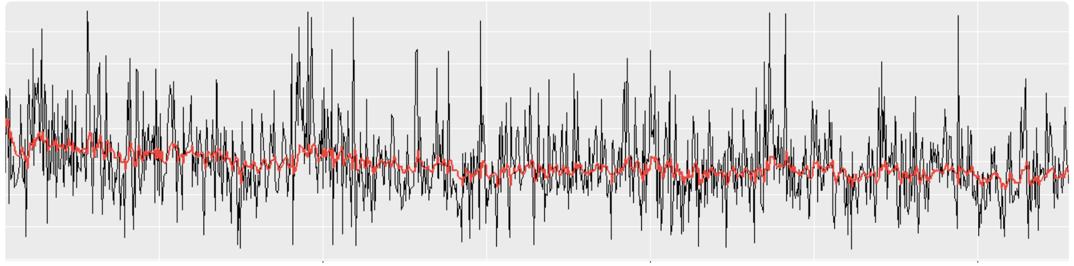
Statistics and time series forecasting require often relative large sample sizes



Univariate independent variable

Time series forecasting → Prediction / decision → Maintenance action

Challenge:

- In (SME) MRO the sample sizes are in many cases small because specific maintenance tasks or failures occur rarely

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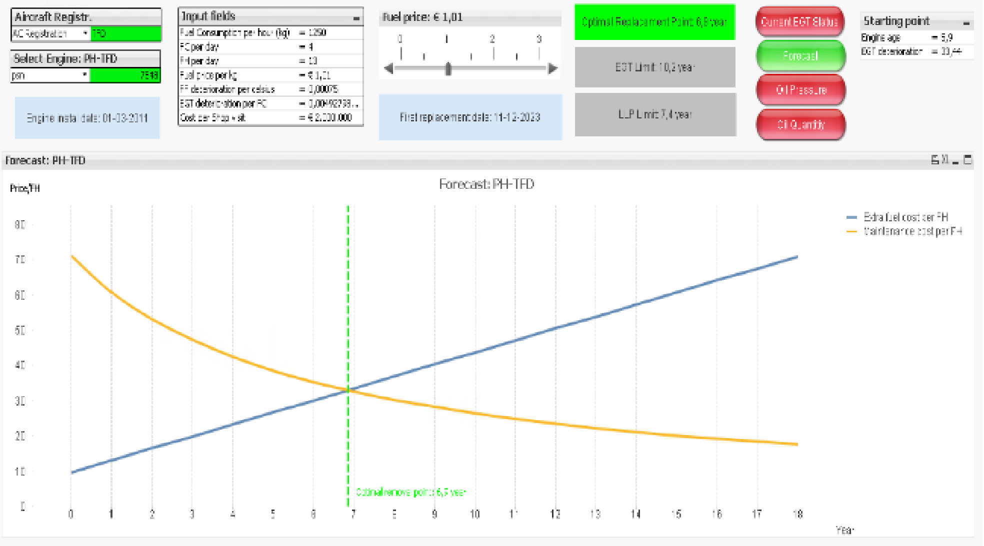
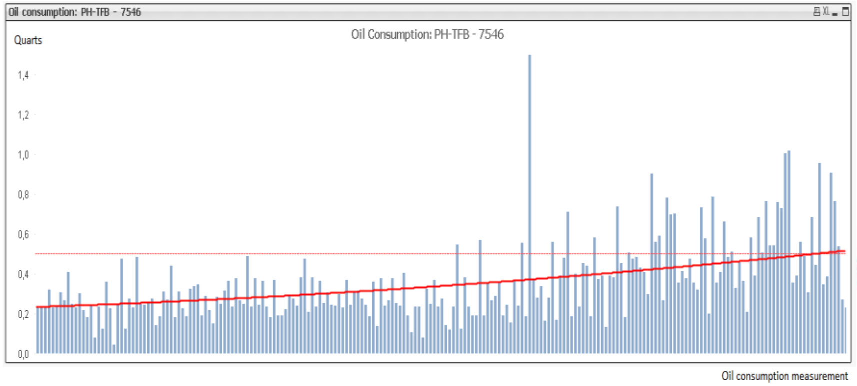
Case: Engine Health Monitoring with data that are available for Airlines

Inflight data from aircraft engines are sent to the manufacturer only

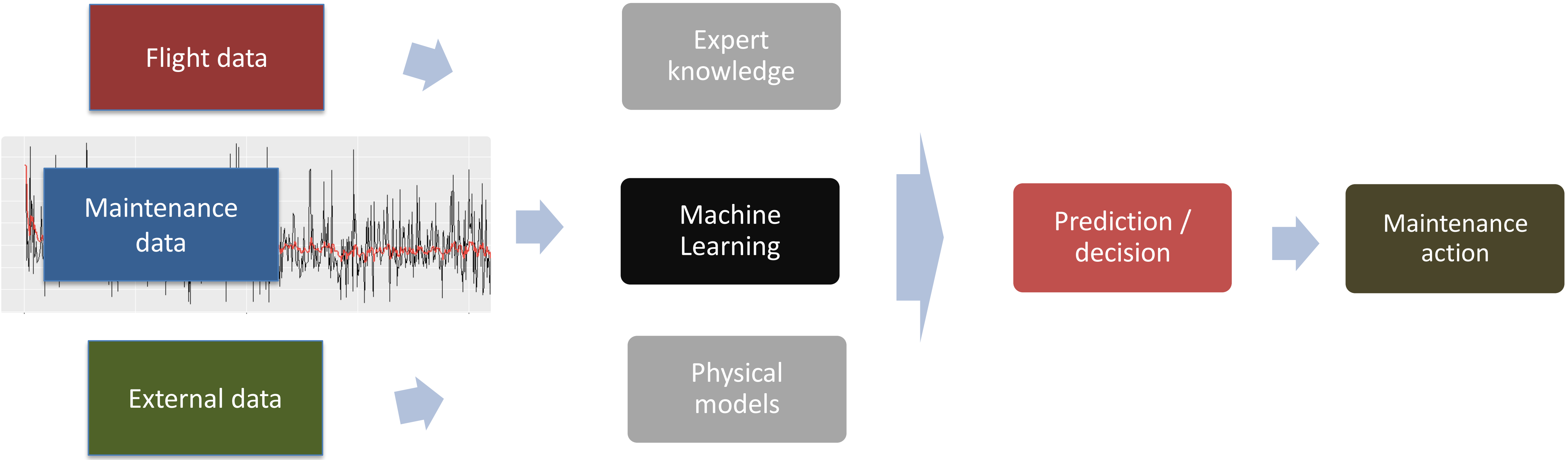
→ Improve maintenance efficiency using free available data



CRISP methodology	
Business understanding	Economic Replacement Point (ERP), Life Limiting Parts (LLP) and Exhaust Gas Temperature (EGT) define the optimal replacement time of engines
Data understanding	Available data: EGT, fuel consumption, oil pressure and oil consumption
Data preparation	Select engine type Clean and check data
Modelling	Develop Engine Health Monitoring model Forecast optimal engine replacement point
Evaluation Deployment	Aircraft uptime ↑, Part costs↓ EGT & LLP limits reached sooner than ERP



In this research other data sources and machine learning were added to overcome the prediction limitations of statistics on MRO datasets



Machine learning methods process many parameters and data types
Determine the parameters that strongly influence the output
Include the data of healthy systems

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Case: Text mining to analyze maintenance reports

Use historical work order summary reports to trigger alerts if a failure or repair occurs more often than usual

Show similar failures or repairs from the past to support investigations

CRISP methodology	
Business understanding	Improve TAT and reduce maintenance costs if failures and solutions are known in an earlier stage
Data understanding	AMOS database: Work order summary reports and additional aircraft data
Data preparation	Retrieved and checked
Modelling	Chi Squared Distance Function and K-Nearest Neighbours method to classify report text Present results in Reliability Dashboard
Evaluation Deployment	Accuracy score 75,5%. With human control (reinforcement): 77,5%

1. DATA INPUT PROCESS → 2. DATA PRE-PROCESSING MODEL → 3. AIRCRAFT RELIABILITY DASHBOARD

DATA MINING | *DATA MINING, TEXT MINING* | *STATISTICAL PROCESS CONTROL*

python

The 25 case studies can be divided in 3 groups of data mining approaches

Visualization

- Descriptive analytics using established math and graphical methods, resulting in for example KPI's control charts, management dashboards

Statistical data mining

- Descriptive and predictive analytics using established statistical methods, for example probability calculation, correlation and time series forcasting

Machine Learning

- Predictive analytics using machine learning methods for example regression, classification and clustering

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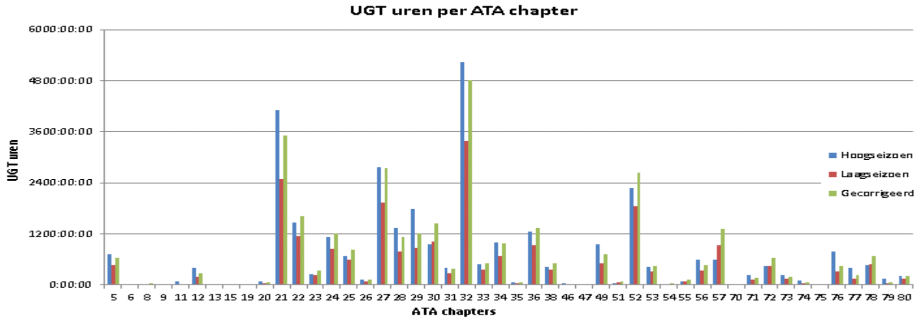
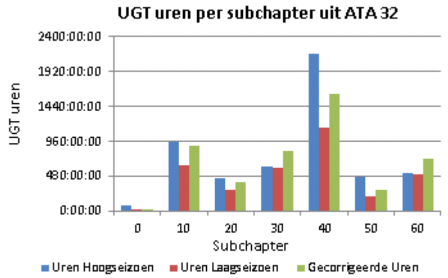
Case: Causes of low fleet availability in high season

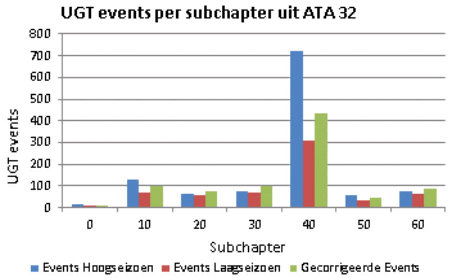
A/B-checks and line maintenance for Airline fleet

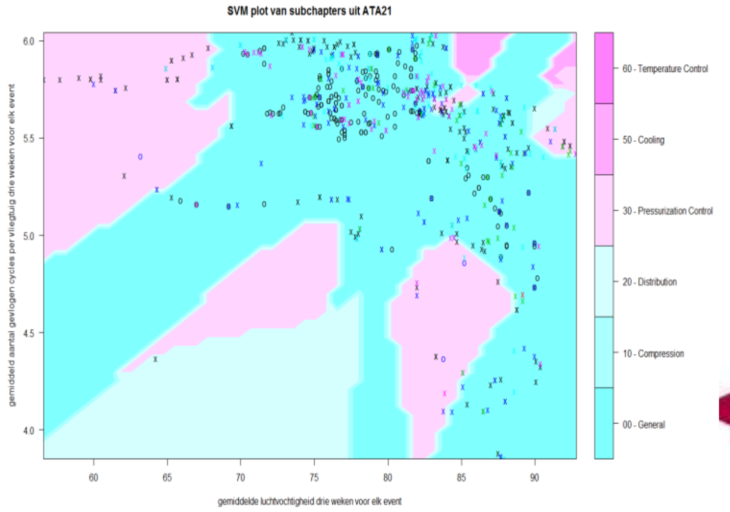
→ Causes of drop in Fleet Availability during high season

CRISP methodology	
Business understanding	Performance contract: aircraft uptime Correlate ATA (sub)chapter to problems
Data understanding	AMOS, weather data, flight data, unscheduled ground time events
Data preparation	Cleaned and integrated
Modelling	Descriptive analysis: highest unplanned ground time Support Vector Machine to predict problems related to weather
Evaluation Deployment	Aircraft uptime ↑, part costs↓ Performance drop correlated to ATA subchapter, e.g. tyres, brakes and cabin air quality









Software applied in Data Mining in MRO

Open source software

Large user community, need to employ a data scientist

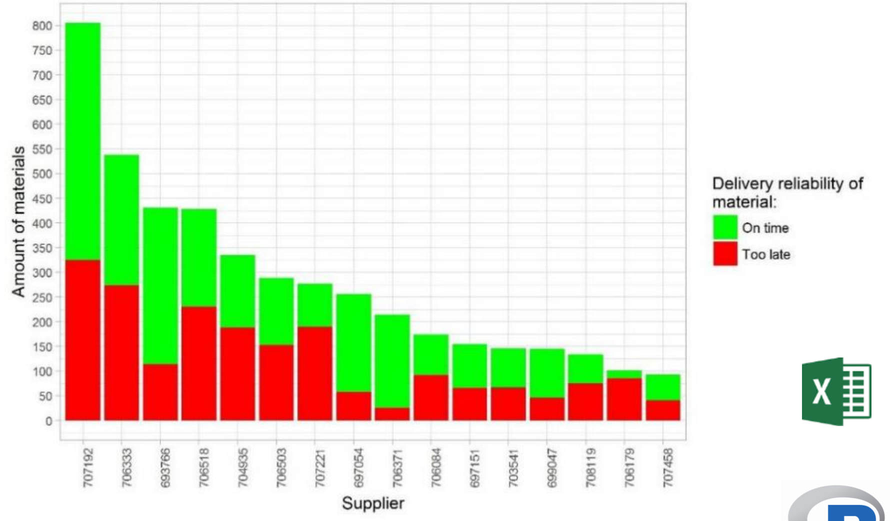
- R
- Python

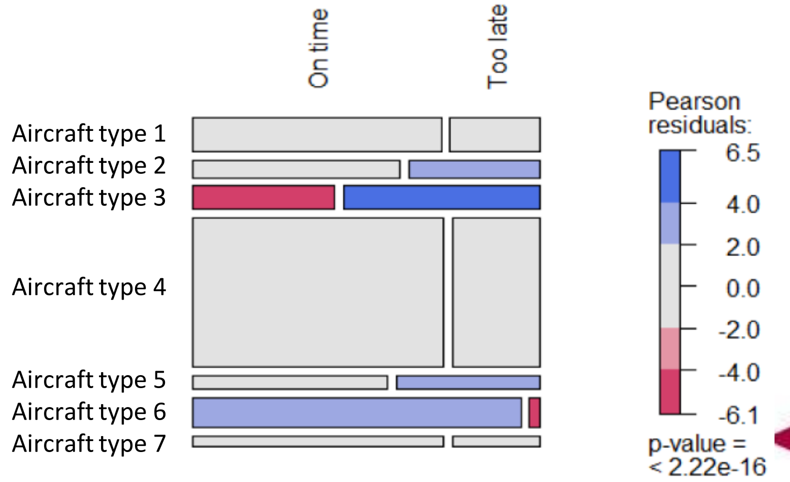
Commercial software

- Matlab
- IBM - SPSS
- Tableau
- Microsoft - Azure
- Exsyn: Aviation Analytics

Case : Causes of a reduced delivery reliability in aircraft component maintenance

CRISP methodology	
Business understanding	Explain the causes of the low delivery reliability of component maintenance (between 49% and 97%)
Data understanding	Maintenance database, parameters: Delivery reliability, group, priority, maintenance type, order type, work centers, supplier and materials, execution status, actual costs, added value, planned and actual worked hours, planned and actual TAT
Data preparation	Retrieved and checked on year of data from SAP maintenance management system
Modelling	Examined the relationship between delivery reliability and 13 selected parameters. Data visualization e.g. mosaic plot. Statistics e.g. chi-squared. Machine learning (Decision tree) to predict delivery performance of parts.
Evaluation Deployment	Pilot project proved to successful. Main causes identified.





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Conclusions

Case studies proved the value of statistical and machine learning methods (proof of concept)

- Aircraft uptime: optimal and accurate planning
- MRO costs: efficiency, part costs

CRISP-DM methodology useful

Confidentiality and data ownership issues

Visualization already proved to be very useful for companies

Databases designed for compliance not analysis

Data preparation much work

Selection of appropriate algorithms need expert knowledge

Recommendations

Introduce data scientists

Organize close interaction between (academic) data scientists and shop floor mechanics

Combine data driven models with expert- and failure models

Start with focussed applications targeting real problems

Set data mining performance goals

Modernize ICT to support data driven approach

Negotiate with OEMs and asset owners about access to data

Increase data volume with (automated) maintenance reporting and sensors

Investigate methods that deal with small datasets and open source data

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Links with Service Logistics

Spare parts

- demand forecast
- visibility
- stock location
- safety stocks levels
- logistic flows
- optimal assignment

After market

- repair, refurbish
- optimal capacity allocation
- make or buy or local digital production
- answer to OEMs who use data to tighten their grip on the aftermarket
- from service to solution

Relevant cases studies in our research

- MRO delivery performance dedicated MRO
- monitoring performance of outsourced MRO
- component maintenance
- and many others

Thank you for your attention

¿Questions?

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