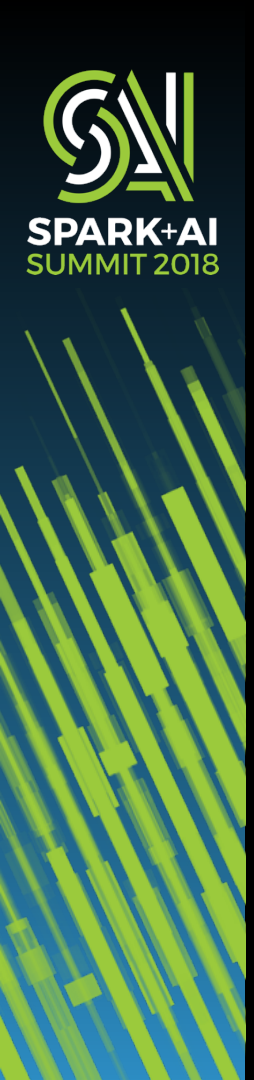

Predictive Maintenance at the Dutch Railways

Air leakage detection in train breaking pipes

Ivo Everts, GoDataDriven (Amsterdam, NL)

#DSSAIS16

GoDataDriven

proudly part of Xebia Group

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Janelle Zoutkamp

Consulting data scientist @ GoDataDriven
MSc in AI; PhD in Computer Vision
Did lot of scientific programming
Now mostly Python, Hadoop, Spark, Keras

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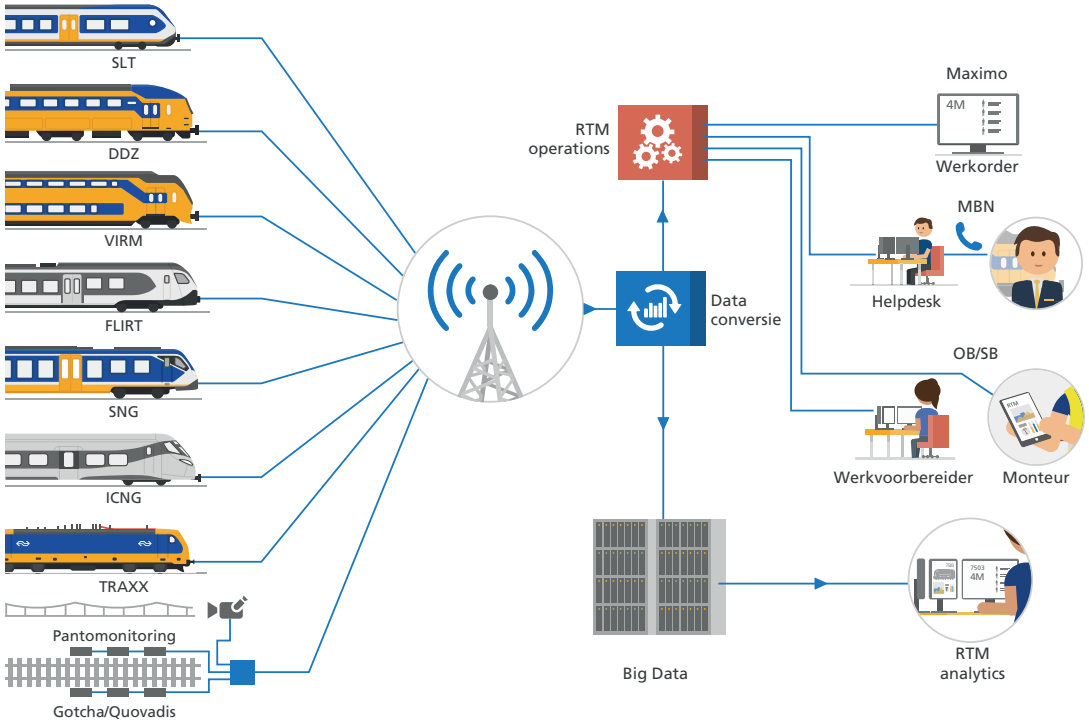
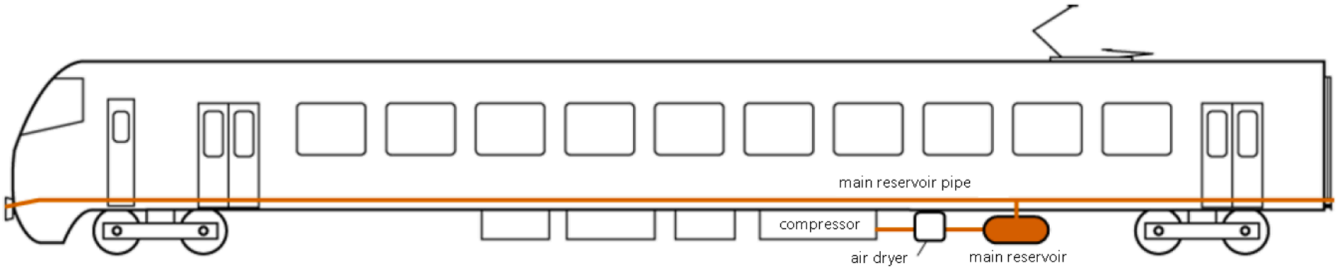
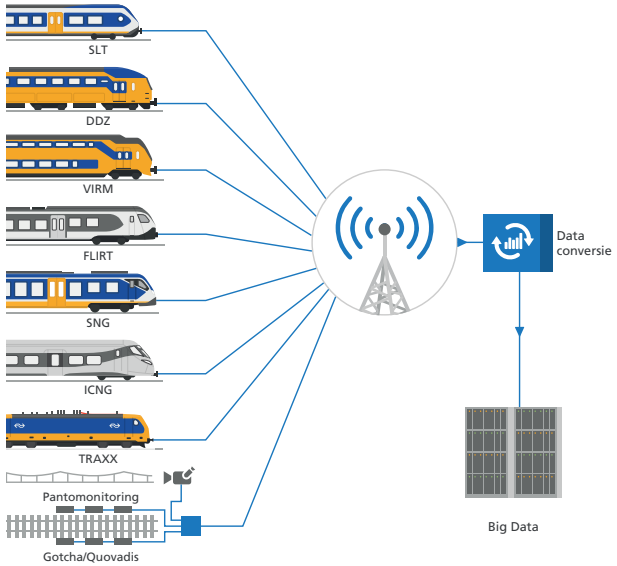
Big Data @ NS (Dutch Railways)



Outline

- Data ingestion
- Air leakage detection
- Other use cases





Collecting data for ***R**eal **T**ime **M**onitoring*

Data ingestion

Data ingestion

Real time data

~20GB per day; 22B records

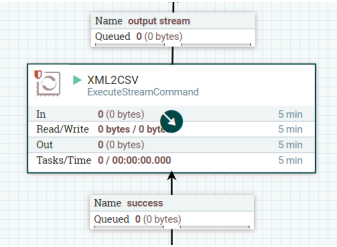
Historic data

22B records

Data ingestion

Real time data

~20GB per day; 22B records



Historic data

22B records

Data ingestion

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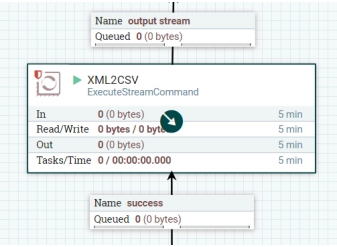

Property	Value
Command Arguments	rewrite-xml.py;${hiveTable};${origin}
Command Path	**python**
Ignore STDIN	false

Historic data

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Data ingestion

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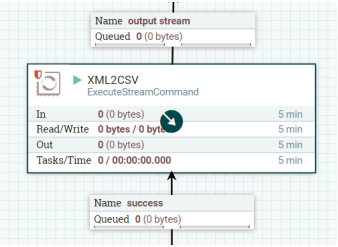

Property	Value
Command Arguments	rewrite-xml.py;${hiveTable};${origin}
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```
# fetch args
table_name = sys.argv[1]
origin = sys.argv[2]

# read xml string from stdin
xml_string = ''.join(sys.stdin.readlines())

# parse 'm and print to stdout
data = xml2table(xml_string, table_name, origin, start_dt, end_dt)
print(data.to_csv(encoding='utf-8', header=False, index=False,
```

Historic data

22B records

Data ingestion

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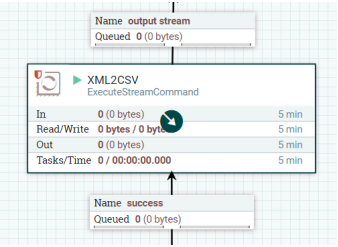

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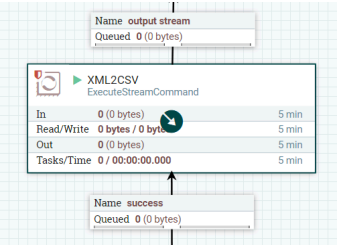

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```

Historic data

22B records

```
def get_history_df(hdfs_binary_files, output_table_name):
    rdd = (hdfs_binary_files
           .map(unzip_xml)
           .flatMap(lambda x: xml2rows(x, output_table_name)))
    return None if rdd.isEmpty() else rdd.toDF()

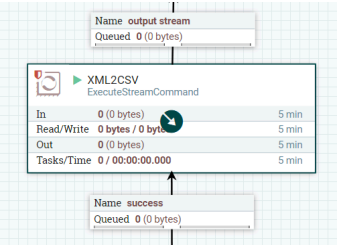
...
...

# read binary files and parse 'm
hdfs_binary_files = (sc.binaryFiles('{}*'.format(file_group))
                     .persist(StorageLevel.MEMORY_AND_DISK_SER)
                     .repartition(num_executors))
sdf = get_history_df(hdfs_binary_files, args.output_table_name)
```

Data ingestion

Real time data

~20GB per day; 22B records



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```
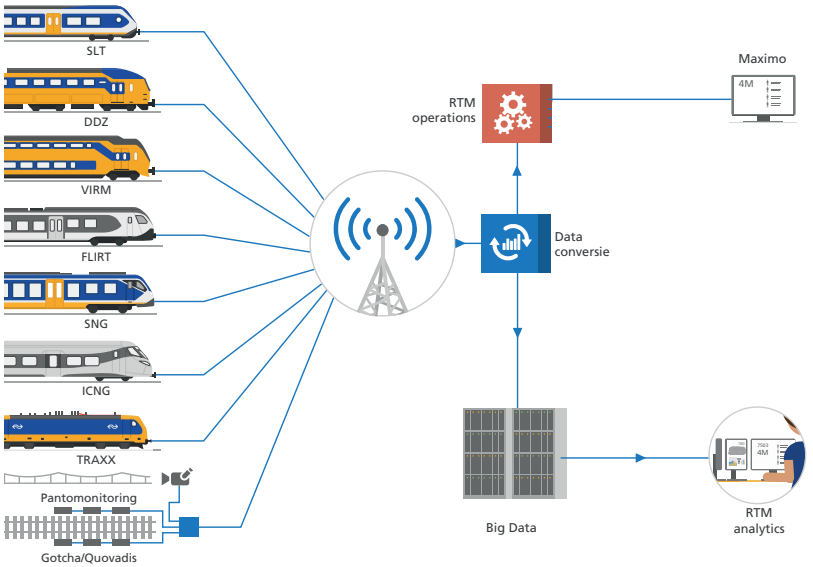
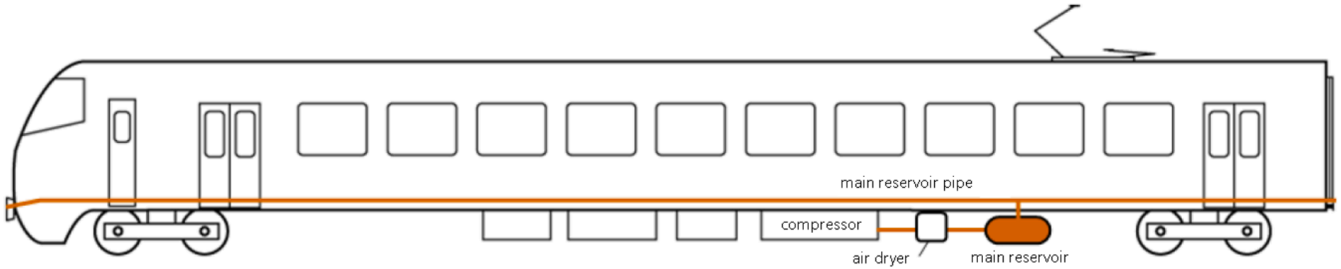

>> Better suited for large datasets
>> Easier to (re)partition and append
>> Preference for a unified approach



One of the cases using RTM data

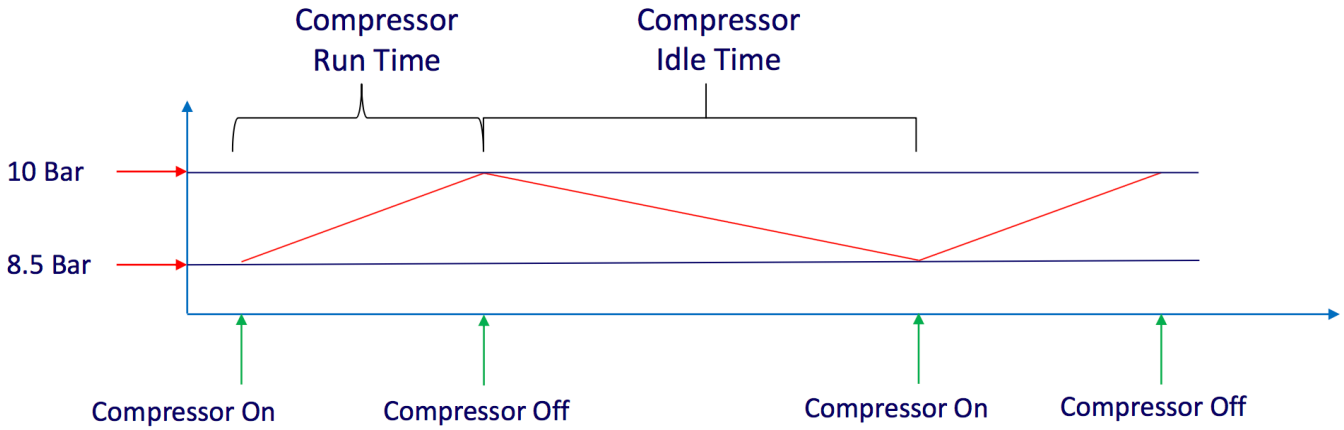
Air leakage detection

Air leakage detection



- **Data** compressor logs
- **Detection** classification
- **Diagnosis** clustering
- **Prognosis** regression
- **Operation** humans

Air leakage detection



We extract median compressor run- and idle- times per hour

- Data
  compressor logs
- Detection
  classification
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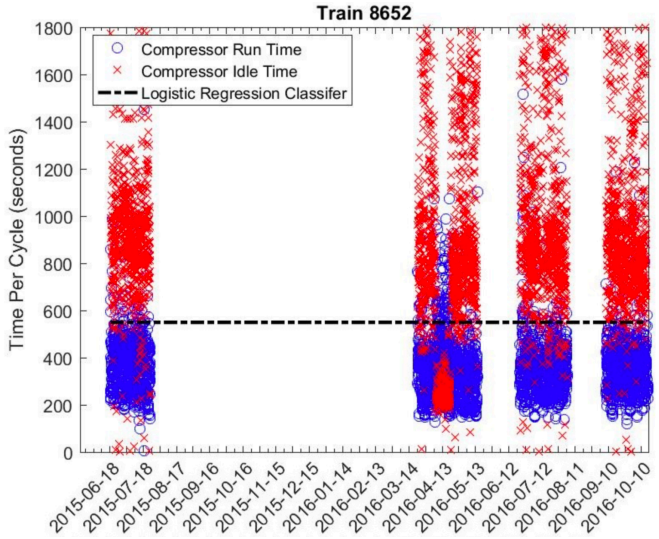
- Prognosis
  regression
- Operation
  humans

Air leakage detection



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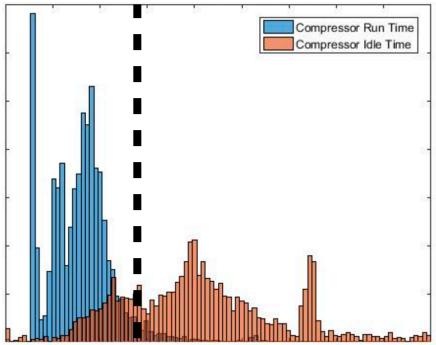
Air leakage detection

One model per train =>
compressor durations collected with a `groupBy()`
and modelled in a UDF using scikit-learn
to obtain the per-class probabilities:

$$P(Y = 0|X) = \frac{1}{1 + \exp(w_0 + \sum_{i=1}^{m} w_i x_i)}$$



Data
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classification

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Prognosis
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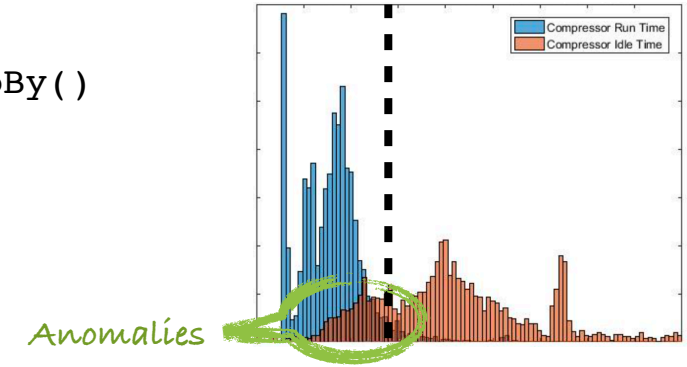

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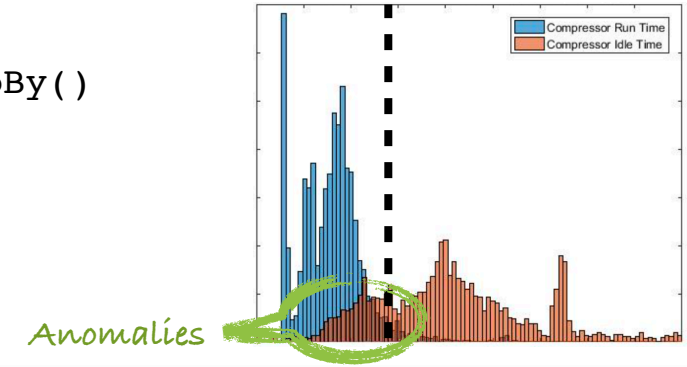


```
# group data per train and collect data LOL
train_data = (df.groupBy('rolling_stock_number')
                .agg(F.collect_list('median_duration').alias('median_duration'),
                     F.collect_list('label').alias('label')))

# define UDF and fit model
logistic_regression = F.udf(lambda X, y: sklearn_wrapper(X, y), ArrayType(FloatType()))
model_data = (train_data.withColumn('logistic_model_parameters',
                                    logistic_regression(train_data.median_duration,
                                                        train_data.label)))
```

- Data
  compressor logs
- Detection
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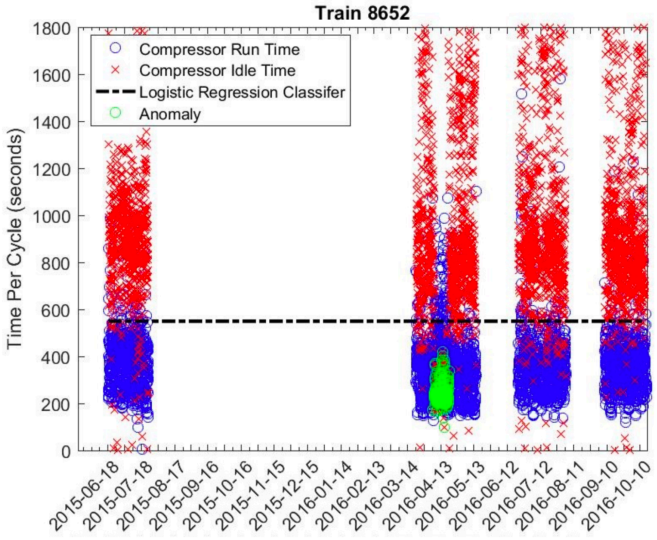
Air leakage detection

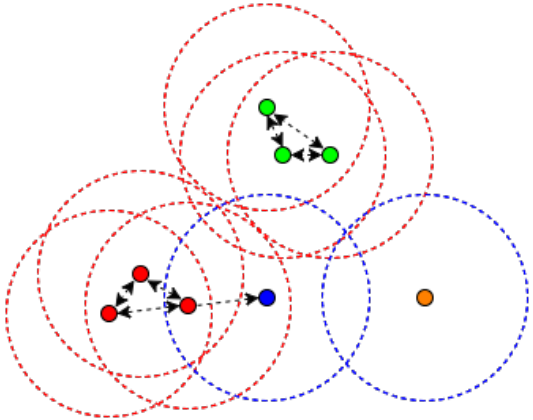


- **Data** — compressor logs
- **Detection** — classification
- **Diagnosis** — clustering
- **Prognosis** — regression
- **Operation** — humans

Air leakage detection

Air leakage is defined as a cluster of anomalies, robust against outliers. For this we use a 'dynamic' variation of dbscan clustering, in a UDF, where the minimal cluster size is dependent on the logistic function:

$$\beta = 2 * minPts * \frac{1}{1 + \exp(w_0 + \sum_{i=1}^{m} w_i x_i)}$$



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compressor logs

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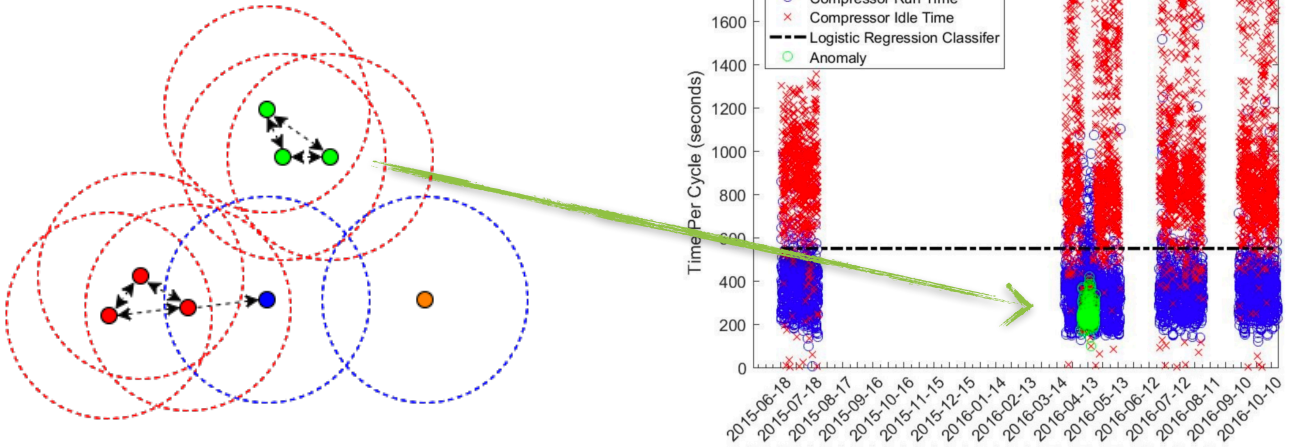
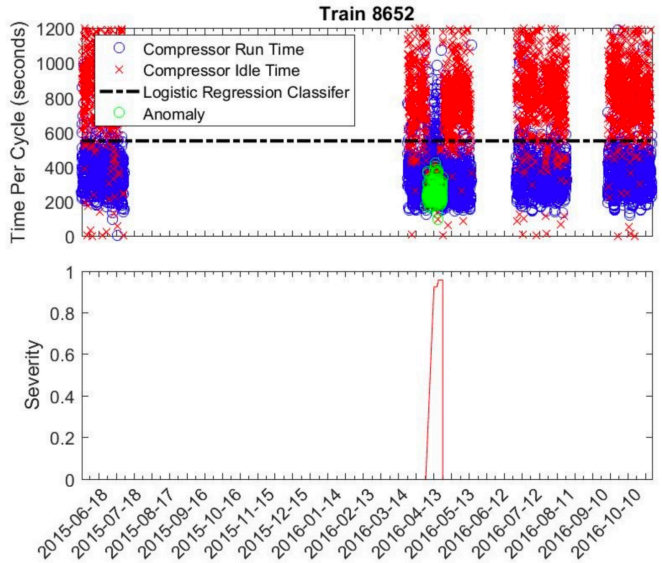


- Data: compressor logs
- Detection: classification
- Diagnosis: clustering
- Prognosis: regression
- Operation: humans

Air leakage detection



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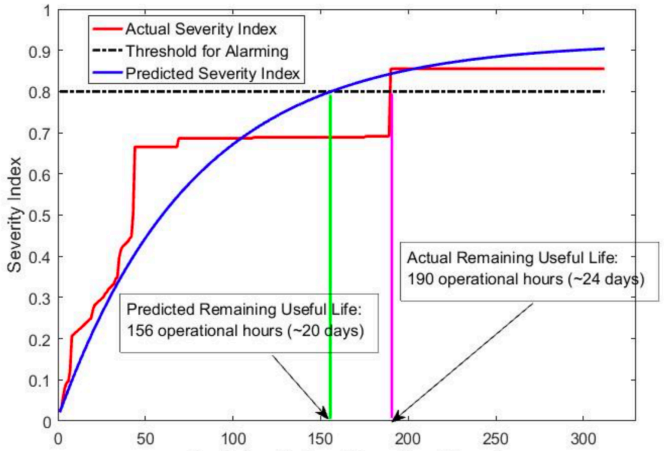

- **Data** compressor logs
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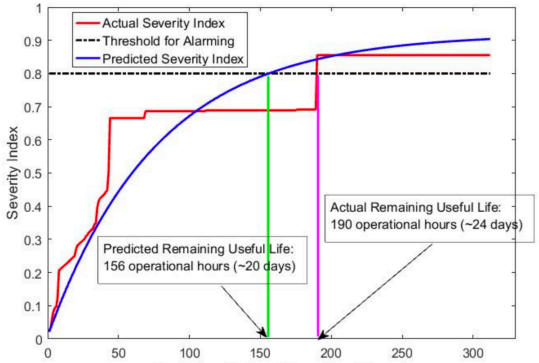
Air leakage detection

In the current implementation
we train one regressor for all trains,
so a pure Spark implementation is possible




```
# import relevant classes from sparkml
from pyspark.ml.feature import VectorAssembler
from pyspark.ml.regression import LinearRegression
...
# prepare and run linear regression
assembler = VectorAssembler(inputCols=x_cols, outputCol='features')
input = assembler.transform(train_data).select(['label', 'features'])
output = LinearRegression().setSolver('l-bfgs').fit(input)
```

- Data
  compressor logs
- Detection
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  regression
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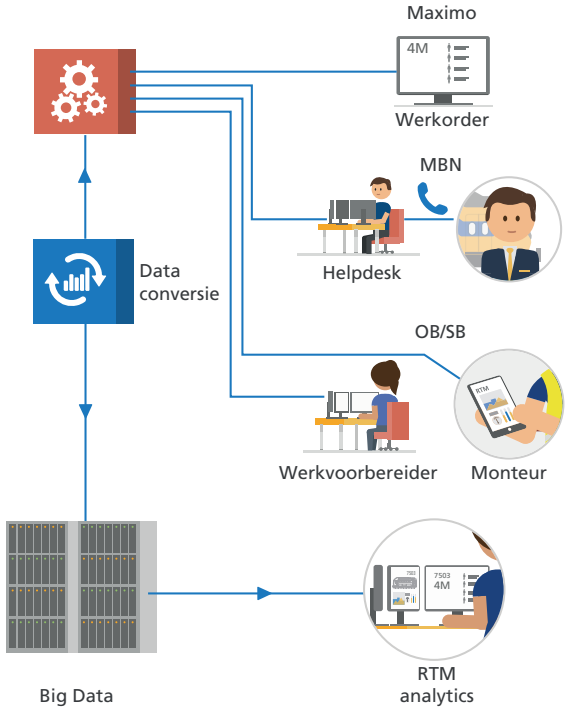
  humans

Air leakage detection

Oh no, humans in the loop!

- **>> Prognosis is difficult to explain and does not perform well enough**
- **>> Diagnosis does perform pretty good (~85% true positives; ~15% solved on time)**
- **>> Dedicated staff for bridging between algorithm and organisation**
- **>> We are observing recent air leakages that would have been prevented, so we're getting there**



Data
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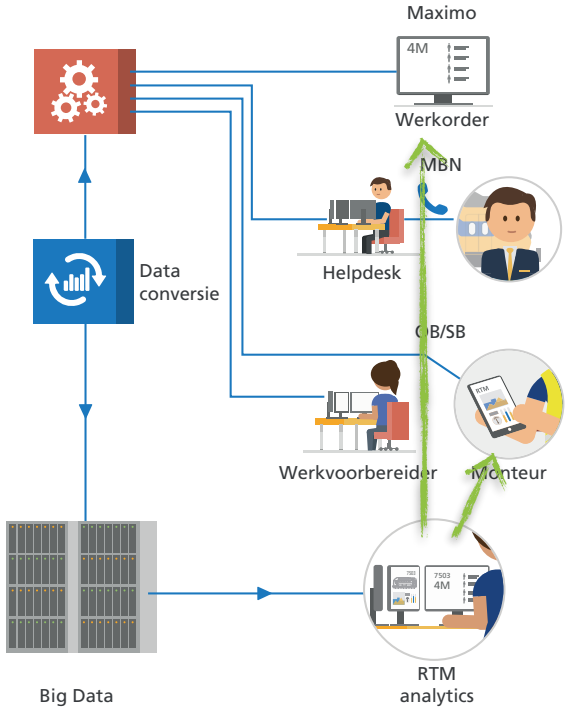

Data
compressor logs

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More use cases

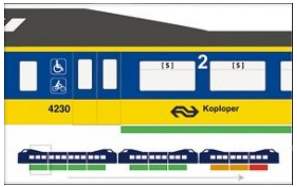
>> Hot wheels: failing axle bearings

>> Crowd control: passengers distribution

>> Slippery tracks: traction detection

>> Water usage: when you got to go you got to go

>> ...and many more to come



SPARK+AI SUMMIT 2018

Predictive Maintenance at the Dutch Railways

Air leakage detection in train breaking pipes

Ivo Everts | ivoeverts@godatadriven.com | @ivoeverts

#DSSAIS16