





# Time Series Analysis with Spark in the Automotive R&D Process

Til Piffl (tpf@norcom.de) Miha Pelko (@mpelko)

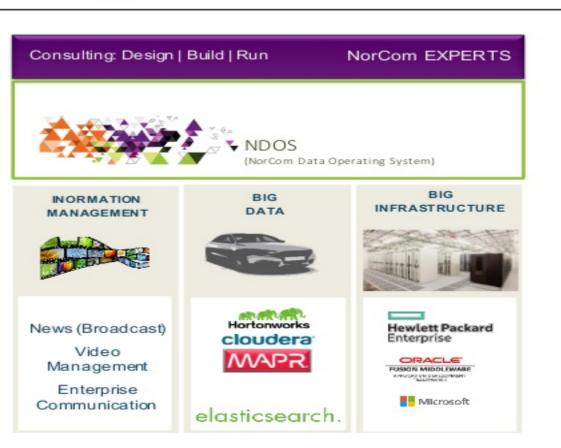
NorCom IT AG, Munich, Germany www.norcom.de



## NorCom IT AG - Facts & Figures



Numbers	<ul> <li>Established 1989</li> <li>IPO: 1999</li> <li>Turnover 16,5 Mio. €</li> <li>about 130 Employees</li> </ul>
Location	München     Nürnberg     San Jose
Customer	Automotive     Public (German)     Media     Finance





## Where is Big Data in Automotive?



- Development
  - Few development locations worldwide
  - Some test vehicles (<100)</li>
  - Raw sensor data (camera, radar, lidar, ...)
  - Algorithm development (Autonomous driving 60 TB per 8h shift
- Testing Phase
  - Many locations worldwide
  - Lots of test vehicles
  - Compressed Data (Video)
  - Verification
- Field
  - All around the world (with many regulators)
  - Hundreds of thousands of connected cars
  - Triggered Data
  - Predictive maintainanœ



Data Rate

2GB/s per vehicle

The State of State of

Current Generations

Data Rate

350MB/s per vehicle

~10 PB per Car type

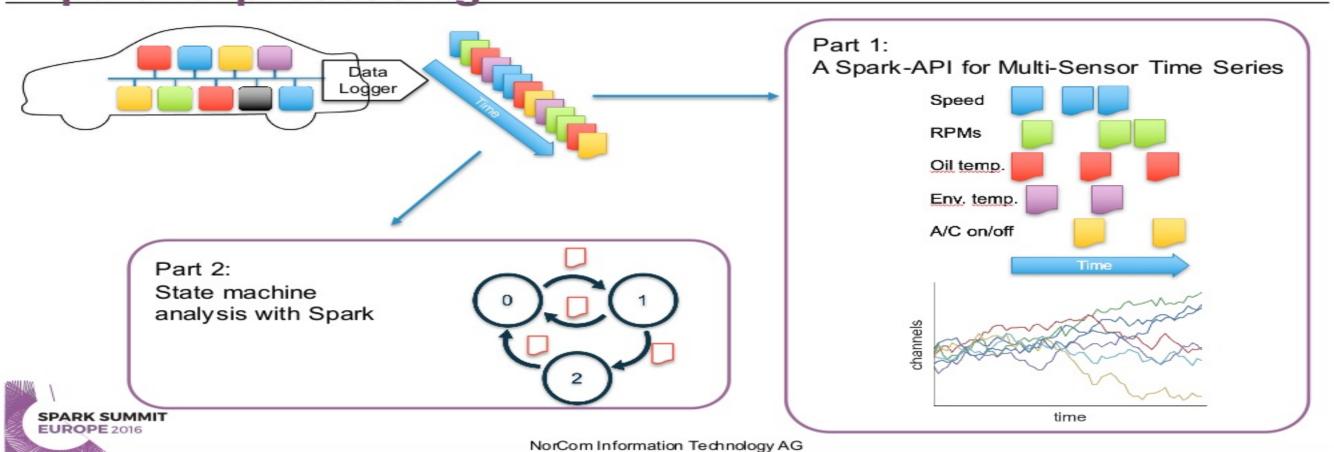
Connected Cars

Data Rate mainly mobile



# Automotive time series analysis requires parallel processing













# DaSense: A Spark-API for Multi-Sensor Time Series



NorCom Information Technology AG

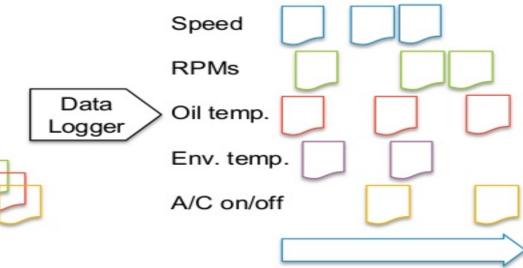
## **Multi-sensor time series**



- Bus communication is filtered and sorted
- Thousands of signal types
- Time series with millions of entries

SPARK SUMMIT

 Hundreds of measurement drives



## **Typical tasks**





## Time series API





Python-based



Reduces complexity by focusing on time series



Preserves lazy evaluation

## Important concepts:

Expressions

Data Extractors





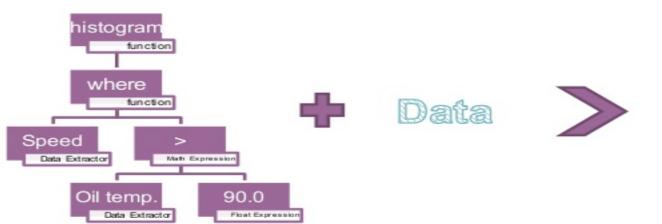


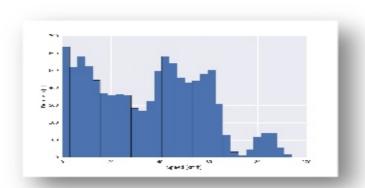
```
context = Context()
all_data = ChannelData("/mapr/norcom_cluster/test_data/test_drive.parquet", context)

OilTemp = ChannelExtractor('t_oil', unit='deg C')
Speed = ChannelExtractor('Speed', unit='km/h')

hist_expression = Speed.where(OilTemp > 90.0).histogram(bins=100)

result = all_data.evaluate({'Speed_histogram' : hist_expression})
```



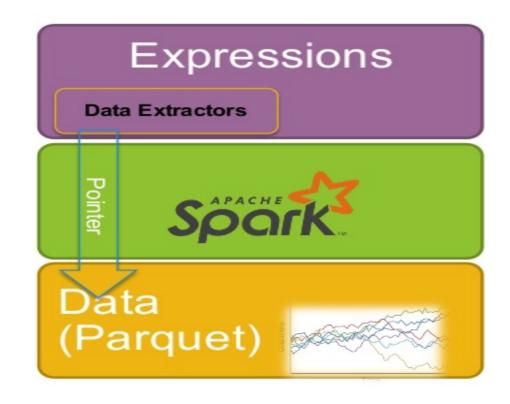


SPARK SUMMIT EUROPE 2016





- Basic time series expression
- Interface to actual data
- Handles
  - channel name aliases (Speed or VehV\_v?)
  - units and conversions (mph to km/h)
  - interpolation requirements (linear, zero-order,...)





## Workflow example



#### Ingest

- · Data quality gate
- Convert raw data to parquet

#### Filter

- Select relevant measurements
- Extract gear shift events

#### Processing

- Fourier transform
- Frequency filter
- · Feature extraction

Classification

#### DaSense Time series API

e.g. SparkML









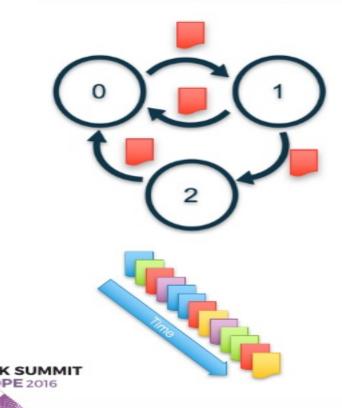
## Parallelization of a State Machine







#### States and transitions



#### Examples of states:

- Engine on / off / ready to start
- Current Gear
- States on the communication bus

#### Example of analytical use-case:

Analyze / Validate the communication protocol from the logs.

NorCom Information Technology AG

## Need for parallel Big Data solutions



#### Current approach – sequential:

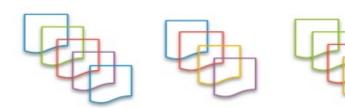
- Sequential replay of messages used for analysis
- No way of scaling within the single log

#### Desired approach – parallel:

- Split the log in partitions and analyze in parallel
- Enables scaling within the single log



EUROPE 2016



What is the status at the beginning of the partition?

## Various encodings of state machine transitions

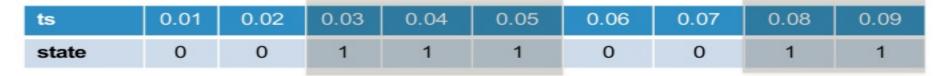


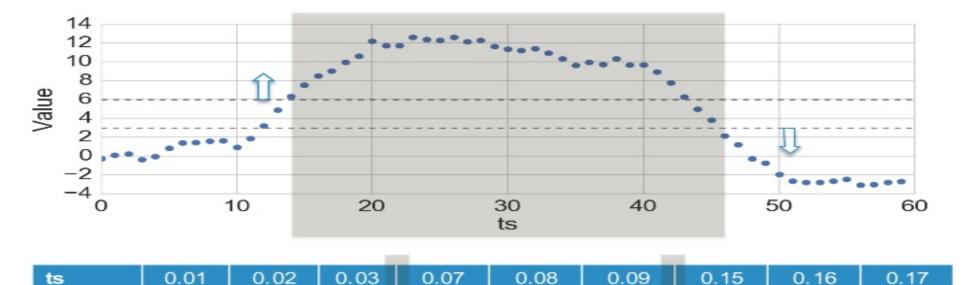
Explicitly in a message

Implicitly via message value

Implicitly via message timing

SPARK SUMMIT EUROPE 2016









Original log

ts	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09
state	0	0	1	1	1	0	0	1	1



1





Original log

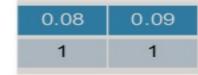
 ts
 0.01
 0.02
 0.03
 0.04
 0.05
 0.06
 0.07
 0.08
 0.09

 state
 0
 0
 1
 1
 1
 0
 0
 1
 1

Parallelized processing (mapPartitions)

ts	0.01	0.02	0.03
state	0	0	1

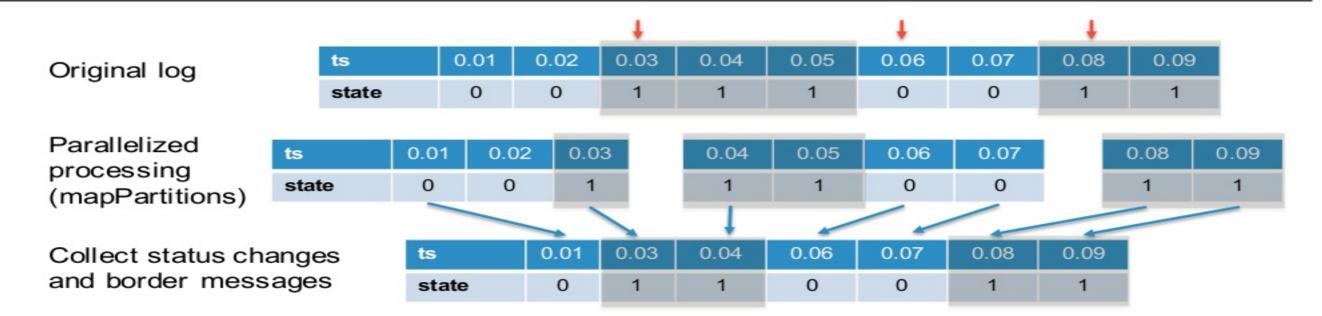
0.04	0.05	0.06	0.07
1	1	0	0



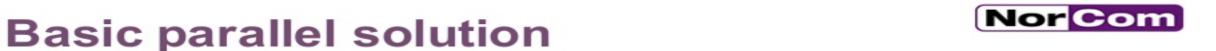












0.02 0.03 0.07 0.01 0.04 0.05 0.06 0.08 0.09 ts Original log state 0 0 0 0 Parallelized 0.01 0.02 0.03 0.04 0.05 0.06 0.07 0.09 ts 0.08 processing 0 state 0 0 (mapPartitions) 0.01 0.03 ts 0.04 0.06 0.07 0.08 0.09 Collect status changes and border messages 0 state 0 0 0.03 0.06 0.08 ts Final clean-up (locally, serial) state 0 1

SPARK SUMMIT EUROPE 2016

### **Alternatives**



- Use windowing functions
  - Window size unknown, could span the full time series
- "Broadcast" the borders from neighboring partitions (mapPartition → groupByKey)
  - groupByKey expensive, does not generalize well
- mapPartitionWithIndex → reduceByKey
  - Needs complex data structure to handle associativity and commutativity requirement



### In our experience







#### Sample code available at:

http://github.com/dasense/state\_machine\_analysis\_with\_spark









## Summary



## Summary





Automotive Industry is a major data producer



Data & problems are somewhat specific, but fun!



We are bringing Spark into production in Automotive R&D







## THANK YOU.

Til Piffl (tpf@norcom.de) Miha Pelko (@mpelko)

NorCom IT AG, Munich, Germany www.norcom.de



