Structured Streaming on Azure Databricks for Predictive Maintenance of Coordinate Measuring Machines

Jan-Philipp Simen
Data Scientist
Carl Zeiss AG

Spark + AI Summit Europe, London, 2018-10-03

#SAISEnt1

Agenda

1 About ZEISS

2 Motivation for Predictive Maintenance

3 Processing Live Data Streams

4 Processing Historical Data Batches

5 Bringing It Together

6 Summary

ZEISS Camera Lenses

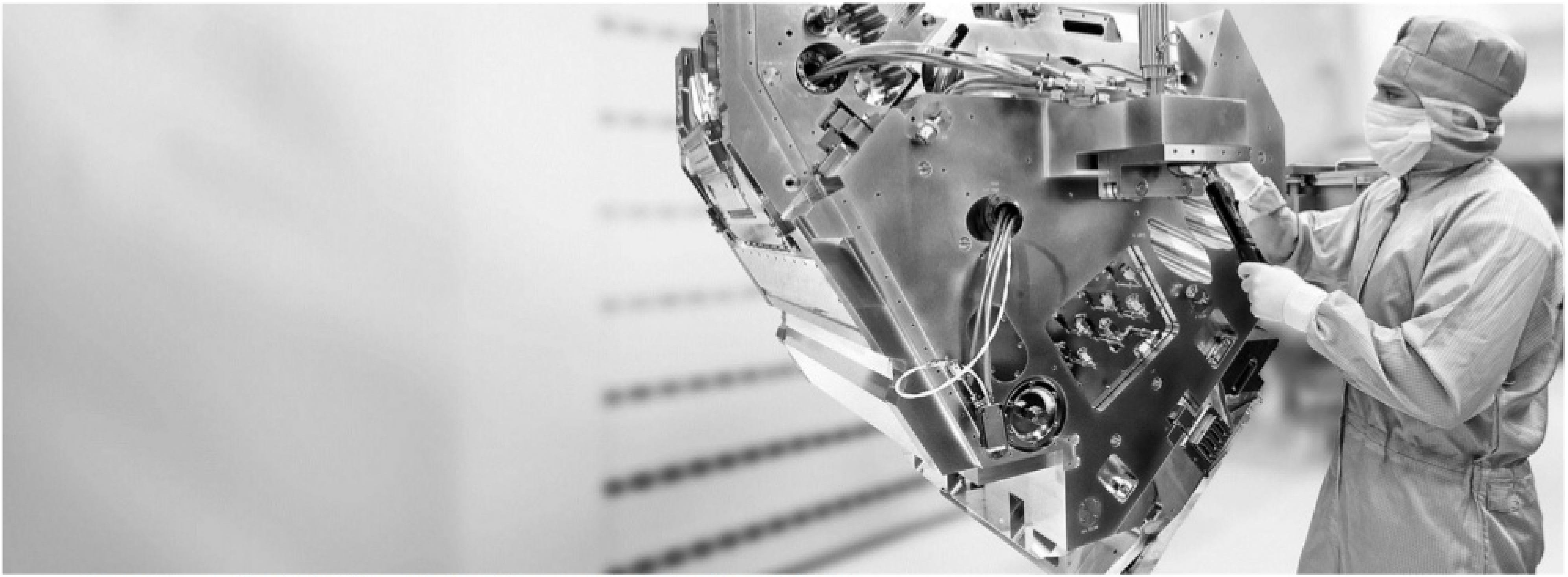
Three Technical Oscars

ZEISS Research & Quality Technology

More Than 20 Nobel Prizes Enabled by ZEISS Microscopes

https://www.zeiss.com/microscopy/int/about-us/nobel-prize-winners.html

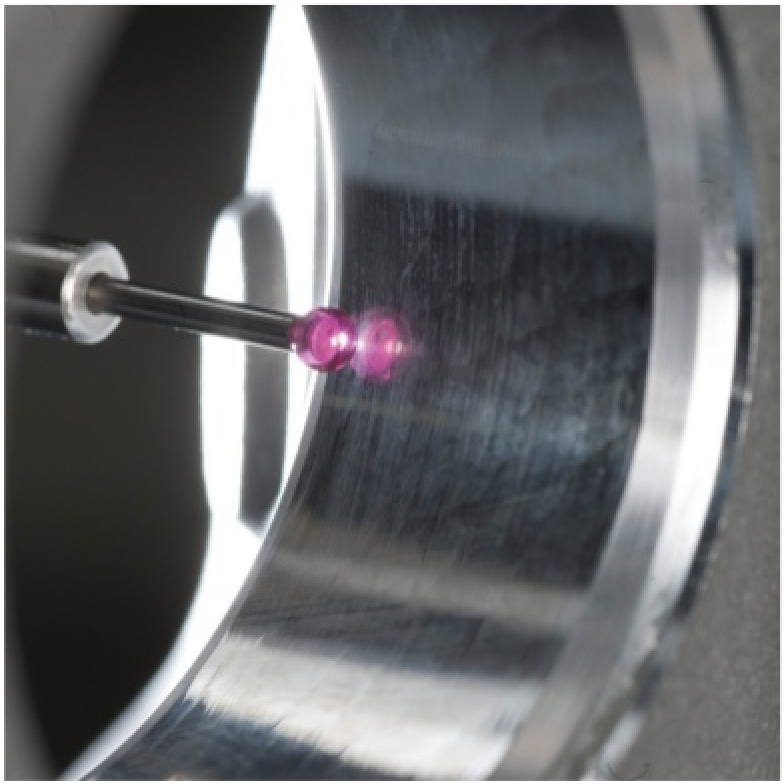
ZEISS Semiconductor Manufacturing Technology With Lithography at 13.5 Nanometers Wavelength, ZEISS Is Enabling the Digital World



More on Extreme Ultra Violet Lithography: https://www.youtube.com/watch?v=Hfsp2jljDpI

ZEISS Industrial Metrology

Precision up to 0.3 µm



Quality Assurance

Metrology

Coordinate Measuring Machines

Usually comparing CAD model to produced workpiece

tactile	optical
x-ray	laser

Agenda

1 About ZEISS

2 **Motivation for Predictive Maintenance**

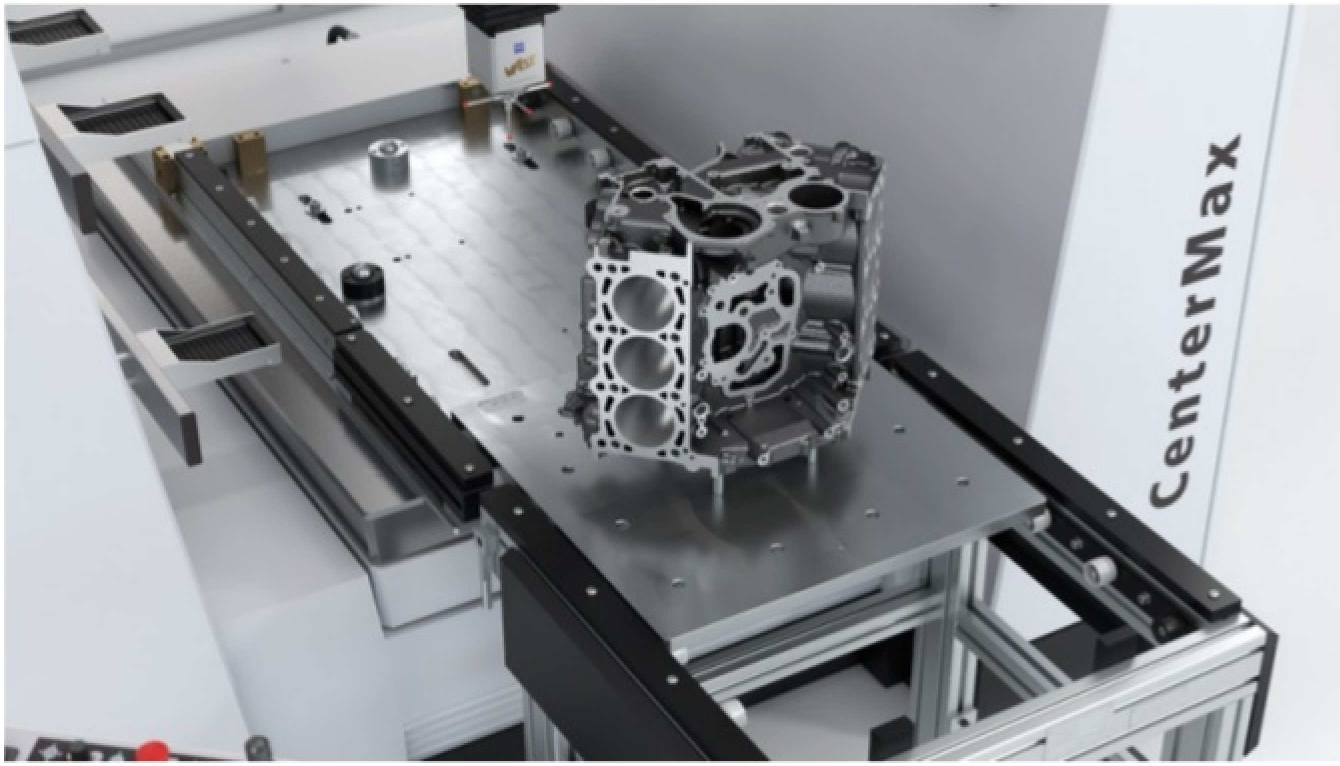
3 Processing Live Data Streams

4 Processing Historical Data Batches

5 Bringing It Together

6 Summary

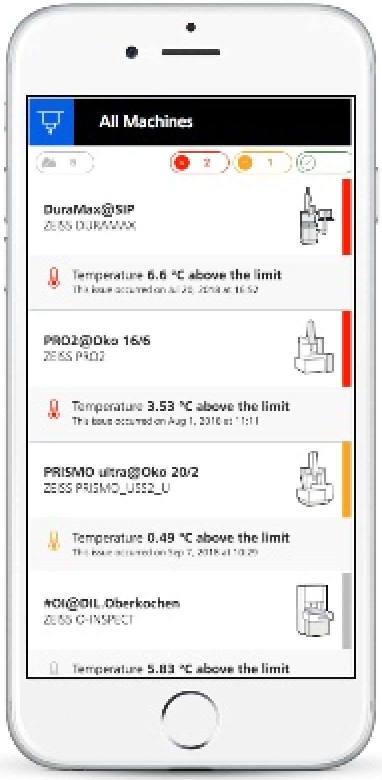
How Will Predictive Maintenance Benefit Our Customers?



Main goals:

1. avoid downtime
2. ensure reliable measurements

Delivering Customer Value from the Start



Start small, learn from data and develop first value-adding services

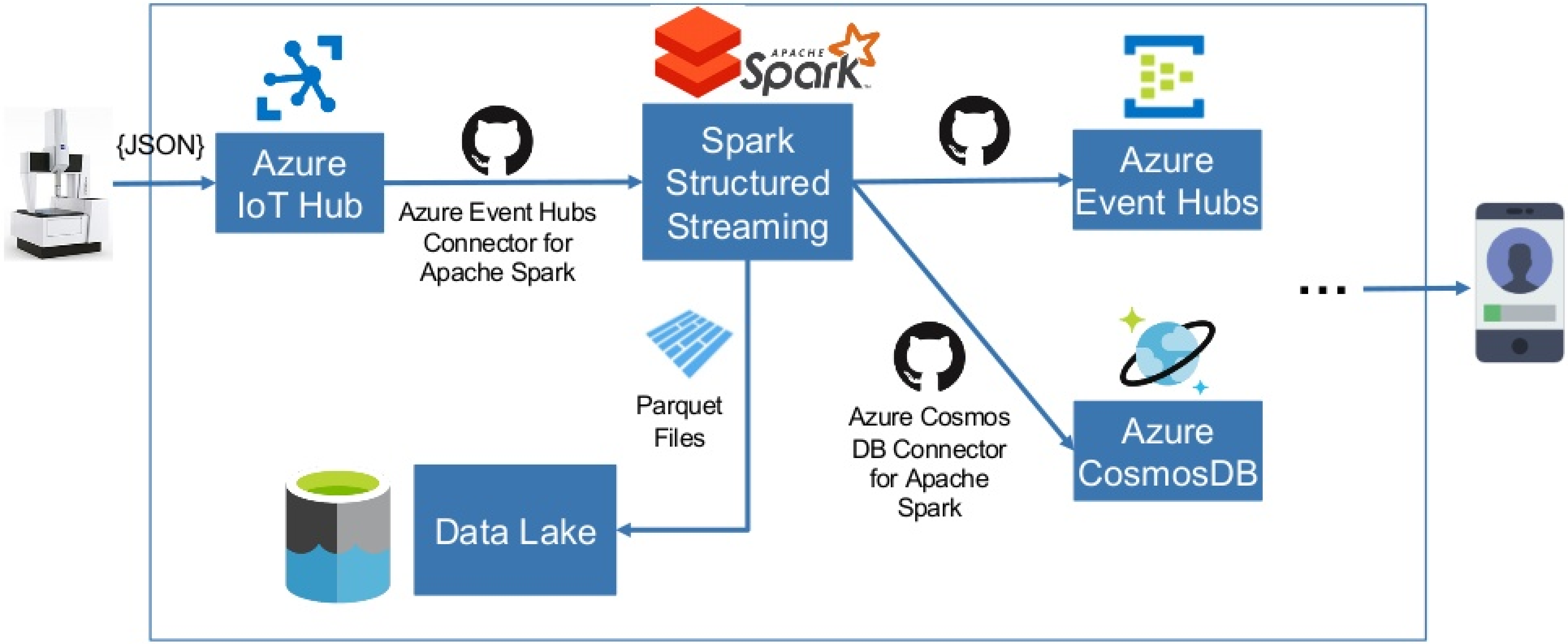
1. Condition monitoring app ✔
2. One-click support request ✔
3. Predictive models for internal use at ZEISS ✔
4. Predictive maintenance notifications in app

Agenda

ZEISS

1. About ZEISS
2. Motivation for Predictive Maintenance
3. **Processing Live Data Streams**
4. Processing Historical Data Batches
5. Bringing It Together
6. Summary

Streaming Architecture on Azure



In a Streaming Pipeline the Drawbacks of Untyped SQL Operations Are Even More Apparent

ZEISS

What is in there, again?

Don't forget to document the schema!

Did I spell this right?

```scala
def readSensor9Untyped(streamingDF: DataFrame): DataFrame =
  streamingDF.select(
    $"machineID",
    $"dateTime",
    udfParseDouble("sensor9")($"jsonString"))

def udfParseDouble(key: String) = ???
```

Our solution: Spark Datasets and Scala Case Classes

Spark Datasets + Scala Case Classes = Typesafe Data Processing

```scala
case class Event(machineID: String,
                 dateTime: Timestamp
                 jsonString: String)
```

```scala
case class Record[T](machineID: String,
                     timestamp: Timestamp,
                     value: T)
```

```scala
def jsonToRecord(sensorID: Int)(event: Event): Record[Option[Double]] =
  Record[Option[Double]](event.machineID,
                         event.dateTime,
                         parseSensorValue(sensorID, event.jsonString))

def parseSensorValue = ???
```

Leveraging the full potential of a good IDE:
- Auto completion
- Compile checks
- Quick fixes
- Refactoring

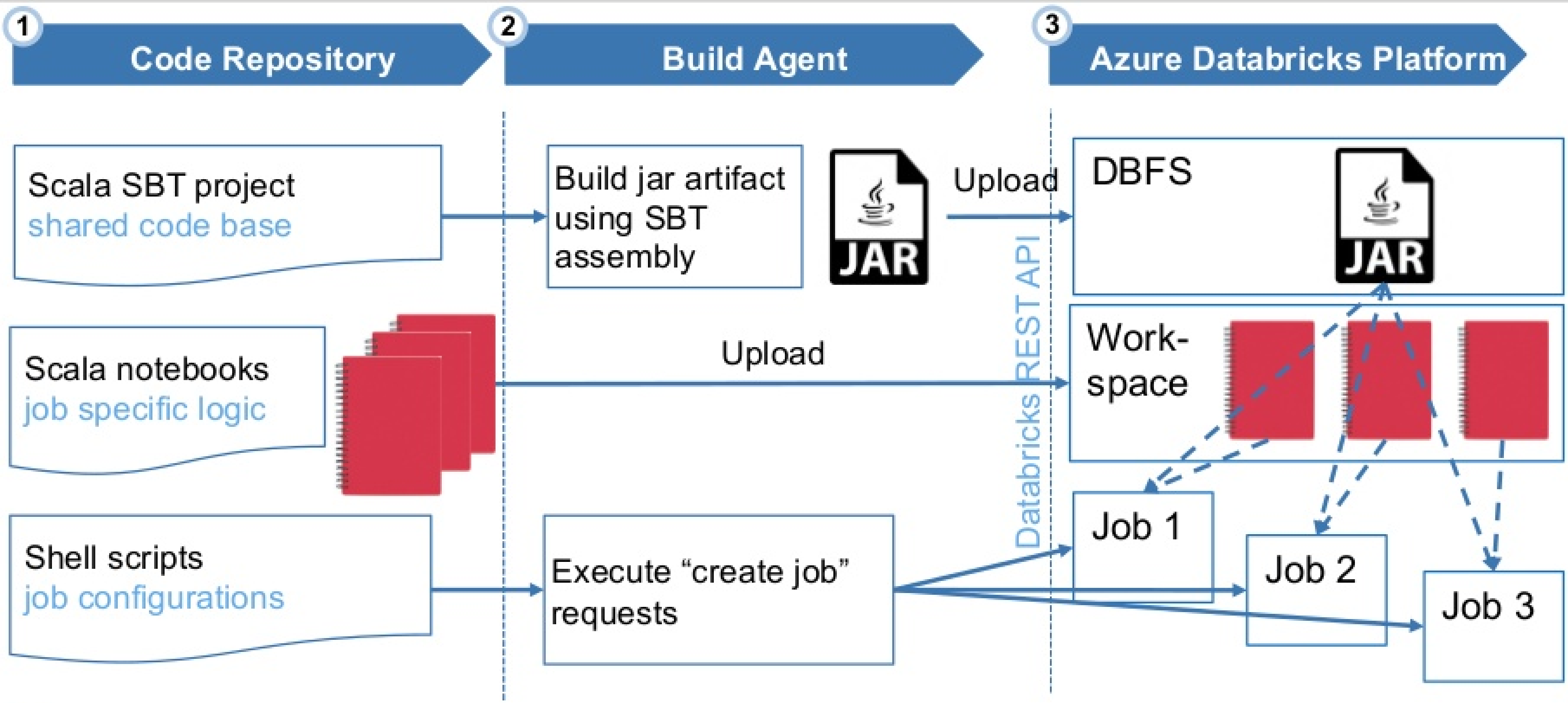
```scala
def readSensor9(streamingDS: Dataset[Event]): Dataset[Record[Option[Double]]] =
  streamingDS.map(jsonToRecord(9))
```

Spark features wish list
- Typesafe joins for Datasets
- Import / export case classes from / to JSON Schema would allow centralized schema repository

Implementing Alert Logic with Stateful Streaming

```scala
/** Checks a stream of JSON messages for threshold violations.
  *
  * @param jsonStream Dataset containing JSON messages as received from IoT Hub
  * @param cmms Dataset with thresholds and other specifications for each machine
  * @return Dataset with alert events as expected by the Eventhub
  */
def createAlerts(jsonStream: Dataset[JsonMessage],
                 cmms: Dataset[CmmSpecs]): Dataset[AlertEvent] = {

  val joined: Dataset[JsonPlusCmmSpecs] = joinStaticOnStream(jsonStream, cmms)

  // Group by serial number
  val grouped = joined.groupByKey(_.machineID)

  // Evaluate incoming messages in each group (that is for each individual machine)
  grouped.flatMapGroupsWithState[AlertState, AlertEvent](...)(evaluateTemperatureState)
}

def evaluateTemperatureState = ???
```

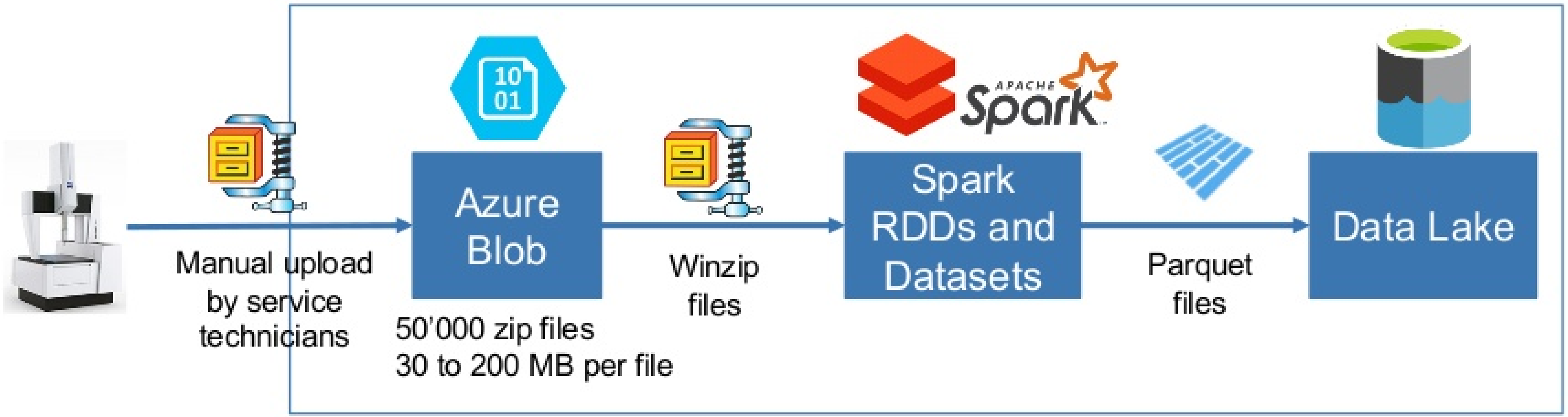
Automated Build and Deployment



Agenda

1. About ZEISS
2. Motivation for Predictive Maintenance
3. Processing Live Data Streams
4. **Processing Historical Data Batches**
5. Bringing It Together
6. Summary

Batch ETL Architecture



Unzipping Lessons Learned

In Theory

```
val allFilesOnBlob: RDD[(String, PortableDataStream)] = sc.binaryFiles(path)
def unzip(zipFile: PortableDataStream): Map[String, String] = easyUnzipFunction(zipFile)
val unzippedFiles: RDD[(String, Map[String, String])] = allFilesOnBlob.mapValues(unzip)
```

In Practice

- 250 lines of code only for the unzipping (Winzip format)!
- A lot of exception handling during unzipping.
- Many debugging iterations.
- Size of zip files ranging from 30 MB to 200 MB (compressed) ➡️ Had to reserve a lot of memory overhead for big zip files ➡️ Split RDD into three buckets, depending on file size

Next time:
Use gzip compression on file level instead of putting varying amounts of files into a Winzip archive.

Agenda

1 About ZEISS

2 Motivation for Predictive Maintenance

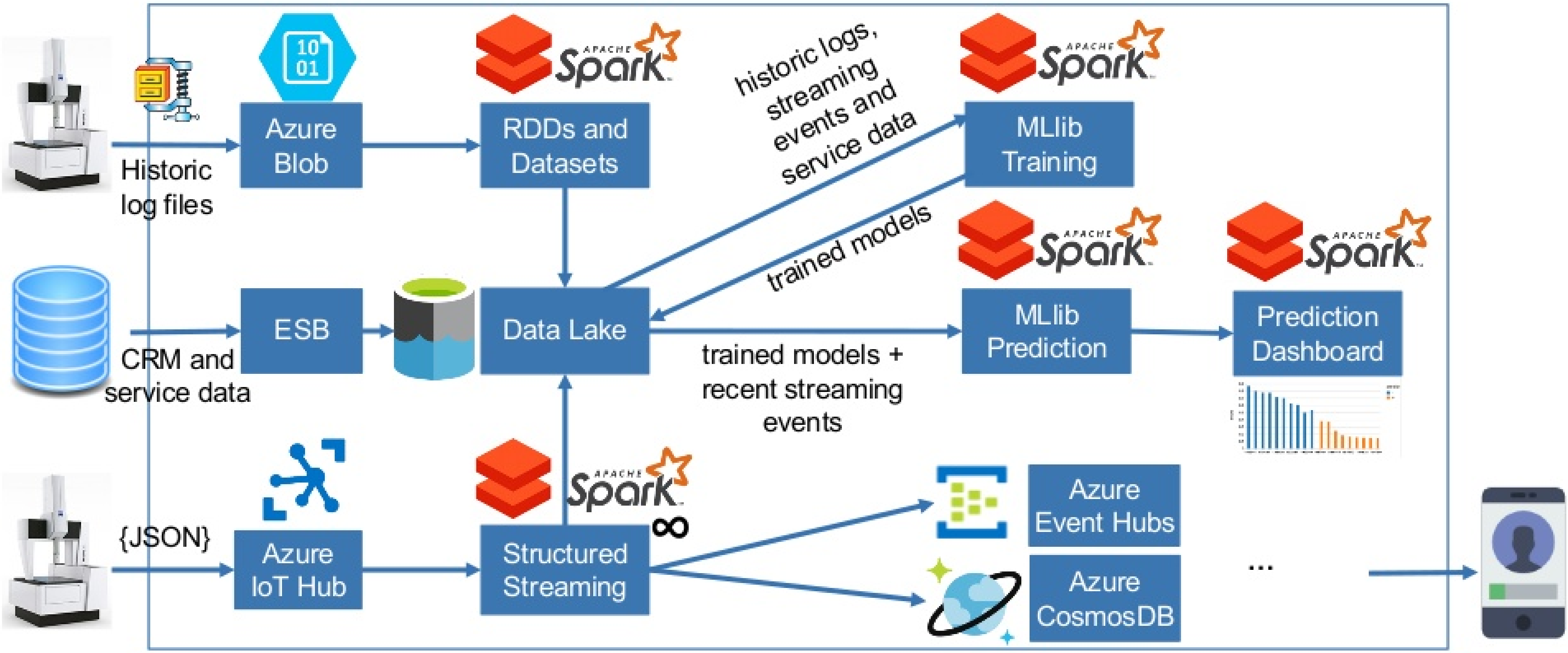
3 Processing Live Data Streams

4 Processing Historical Data Batches

5 **Bringing It Together**

6 Summary

Combining Batch and Streaming Data Sources and Adding Scheduled Machine Learning Notebooks



Agenda

1. About ZEISS
2. Motivation for Predictive Maintenance
3. Processing Live Data Streams
4. Processing Historical Data Batches
5. Bringing It Together
6. **Summary**

Things We Like

Things we like about Spark

- Datasets: Typesafe data processing
- Stateful Streaming: Powerful transformations of streaming datasets
- MLlib: State-of-the-art distributed algorithms
- All the other great things: Scalability, performance, …

Things we like about Azure Databricks

- Cluster management: Convenient setup, auto-scaling, auto-shutdown
- Job management: Convenient creation and scheduling of Spark jobs
- REST API: Enables automated deployment

Wish List

Features we would love to see in the future

- Datasets: Typesafe joins
- Central schema repository with export to different formats (Scala case class, JSON schema)
- Better monitoring for multiple, long-running jobs: Integration with external log aggregators or customizable log metrics in Databricks

Contact

Dr. Jan-Philipp Simen

Data Scientist
Digital Innovation Partners

Carl Zeiss AG
Kistlerhofstraße 70
81379 Munich

jan-philipp.simen@zeiss.com

https://www.linkedin.com/in/jpsimen

ZEISS