tenova

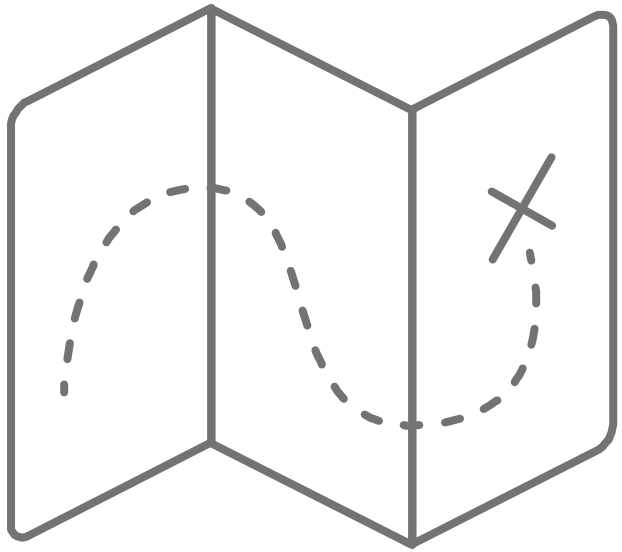
From telemetry data to CSVs with Python, Spark and Azure Databricks

EUROPYTHON 2021

Nicolò Giso

Agenda

- Background
- Data Applications
- Architecture
- Code
  - Some lines of codes
  - Other lines
  - And another bunch of them
- Orchestration
- Conclusion



Background

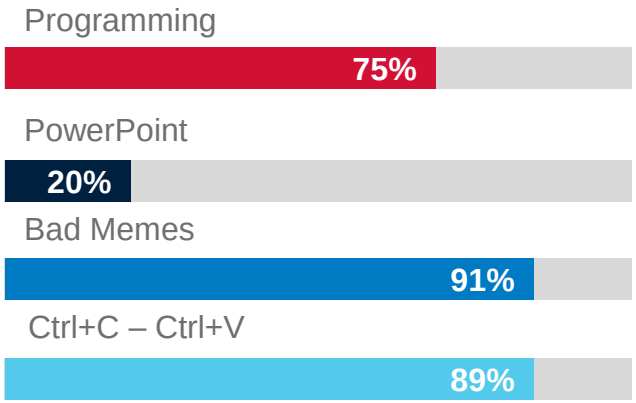
Let me introduce myself

Nicolò Giso

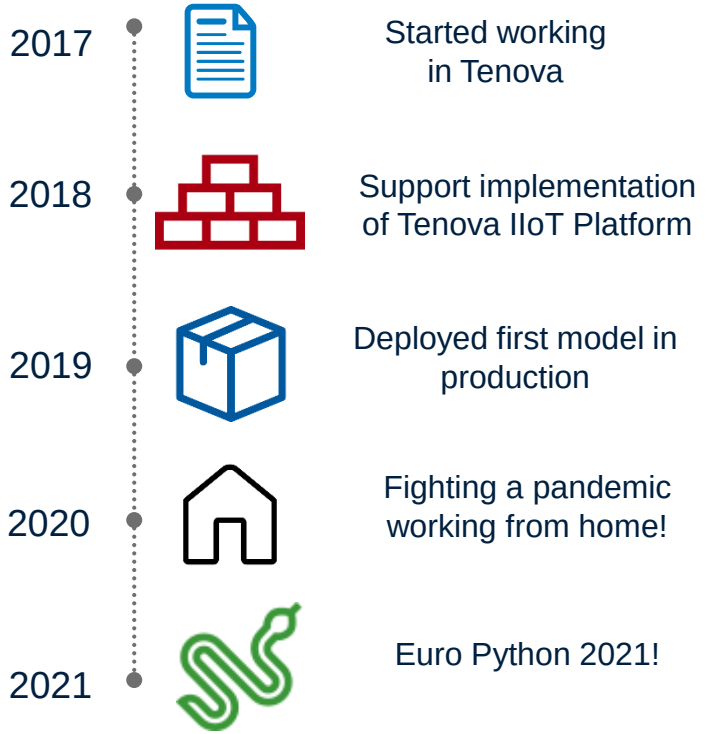
About Me

Role: Data Scientist
Company: Tenova
Interests: books, tv series, data

Professional Skills



My History



TENOVA, A TECHINT GROUP COMPANY, IS YOUR WORLDWIDE PARTNER
FOR **SUSTAINABLE, INNOVATIVE AND RELIABLE SOLUTIONS**
IN THE METALS AND –THROUGH THE WELL-KNOWN TAKRAF AND DELKOR BRANDS
– IN **THE MINING** INDUSTRIES.

WE DESIGN AND DEVELOP SOLUTIONS THAT HELP COMPANIES TO:

REDUCE COSTS

SAVE ENERGY

LIMIT ENVIRONMENTAL IMPACT

IMPROVE WORKING CONDITIONS

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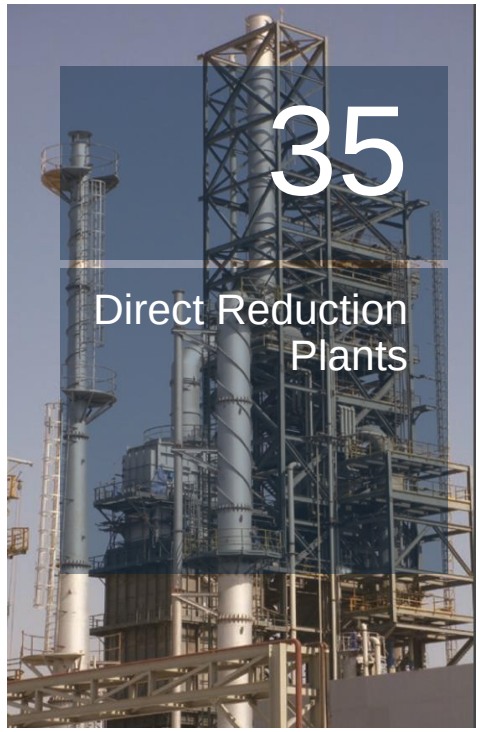
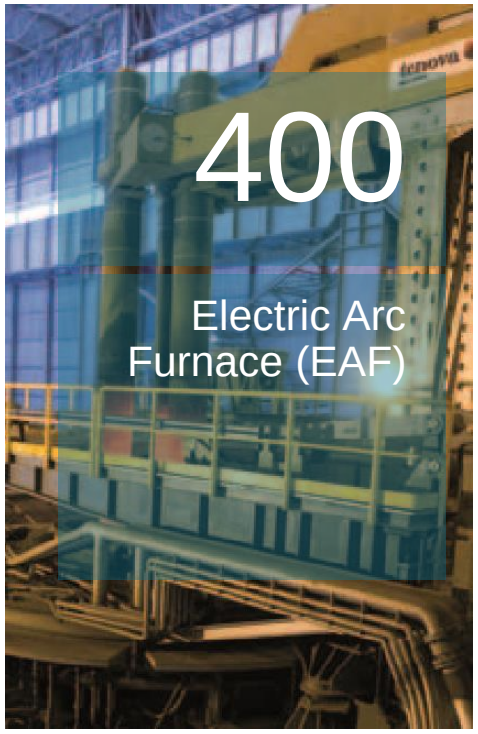
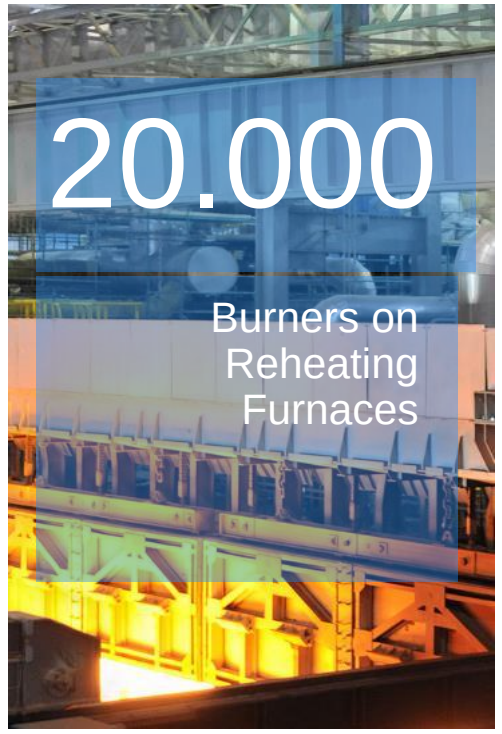
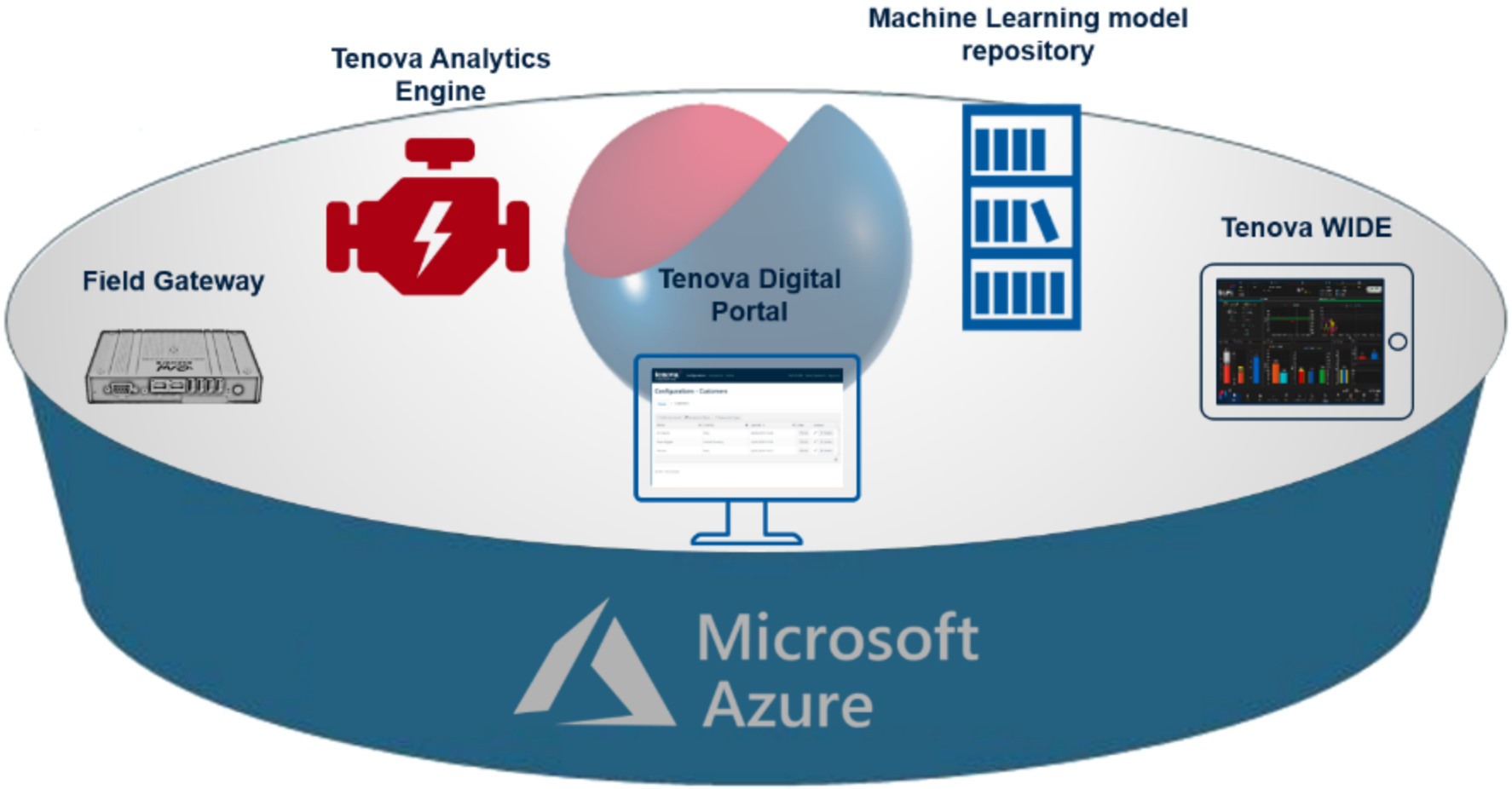
INSTALLED BASE





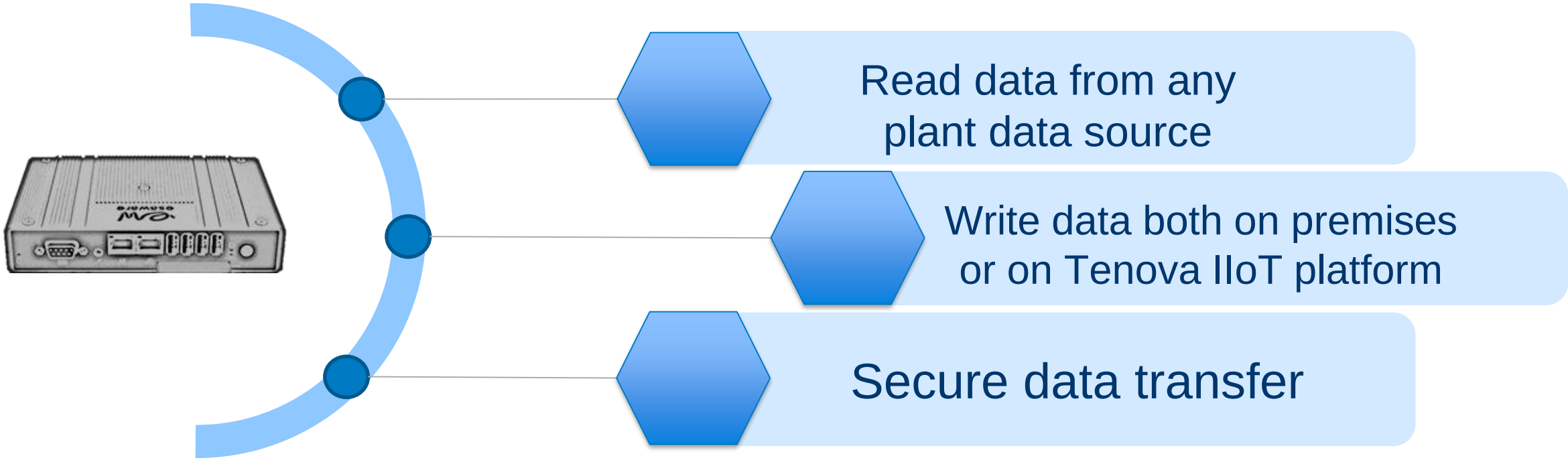


Tenova IIoT platform



Tenova IIoT platform

TENOVA EDGE

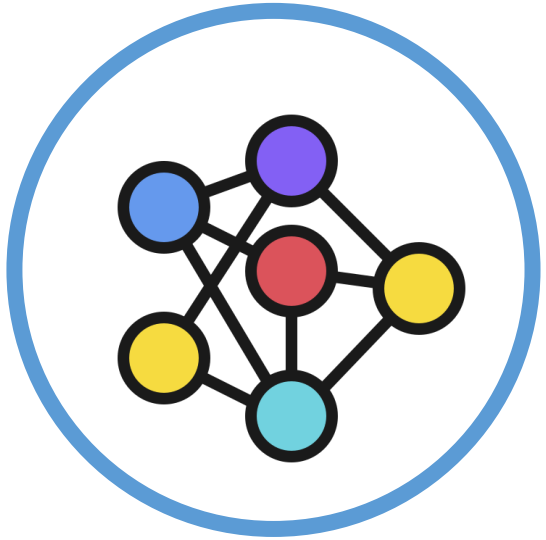


Data Applications

Data Applications

Monitoring

Data Analysis



ML Models

Raw Data


```
{"itemName": "SPEED","value": "{\"value\":46.1}","itemId": 1111,"utcTimestamp": "2021-07-07T18:09:05.2871434+00:00"}
{"itemName": "SPEED","value": "{\"value\":45.7}","itemId": 1111,"utcTimestamp": "2021-07-07T18:09:05.6376127+00:00"}
{"itemName": "TEMPERATURE","value": "{\"value\":104.9}","itemId": 1000,"utcTimestamp": "2021-07-07T18:09:05.8876127+00:00"}
{"itemName": "SPEED","value": "{\"value\":45.3}","itemId": 1111,"utcTimestamp": "2021-07-07T18:09:06.1349456+00:00"}
{"itemName": "SCRAP_IMAGE","value": "{\"ENTER_ID\":1010,\"CATEGORY\":\"A\"}","itemId": 1234,"utcTimestamp": "2021-07-07T18:09:06.5487926+00:00"}
{"itemName": "TEMPERATURE","value": "{\"value\":106.3}","itemId": 1000,"utcTimestamp": "2021-07-07T18:09:06.7259397+00:00"}
{"itemName": "TEMPERATURE","value": "{\"value\":107.4}","itemId": 1000,"utcTimestamp": "2021-07-07T18:09:07.3638633+00:00"}
{"itemName": "SPEED","value": "{\"value\":45.2}","itemId": 1111,"utcTimestamp": "2021-07-07T18:09:07.5824351+00:00"}
{"itemName": "SPEED","value": "{\"value\":44.8}","itemId": 1111,"utcTimestamp": "2021-07-07T18:09:07.6341427+00:00"}
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{"itemName": "TEMPERATURE","value": "{\"value\":107.4}","itemId": 1000,"utcTimestamp": "2021-07-07T18:09:09.1856561+00:00"}
{"itemName": "SCRAP_IMAGE","value": "{\"ENTER_ID\":1011,\"CATEGORY\":\"C\"}","itemId": 1234,"utcTimestamp": "2021-07-07T18:09:09.6186127+00:00"}
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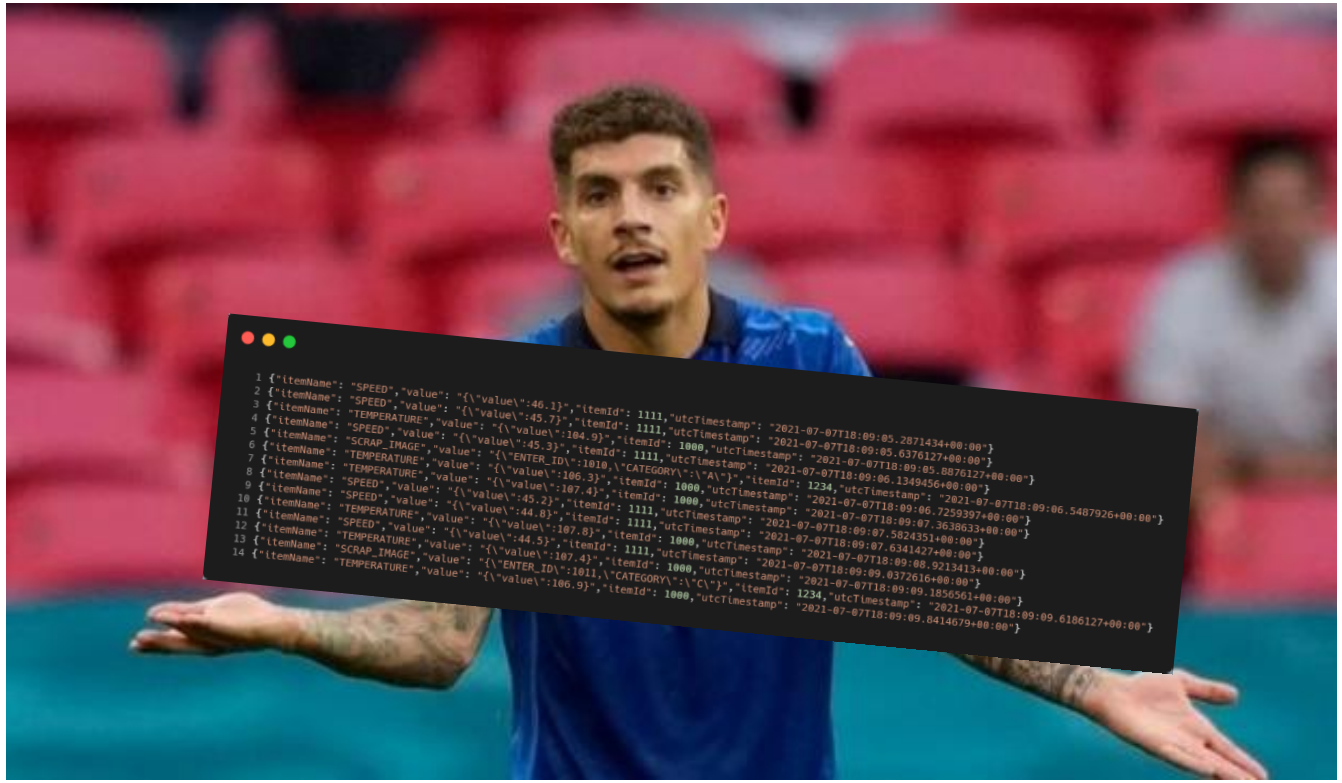
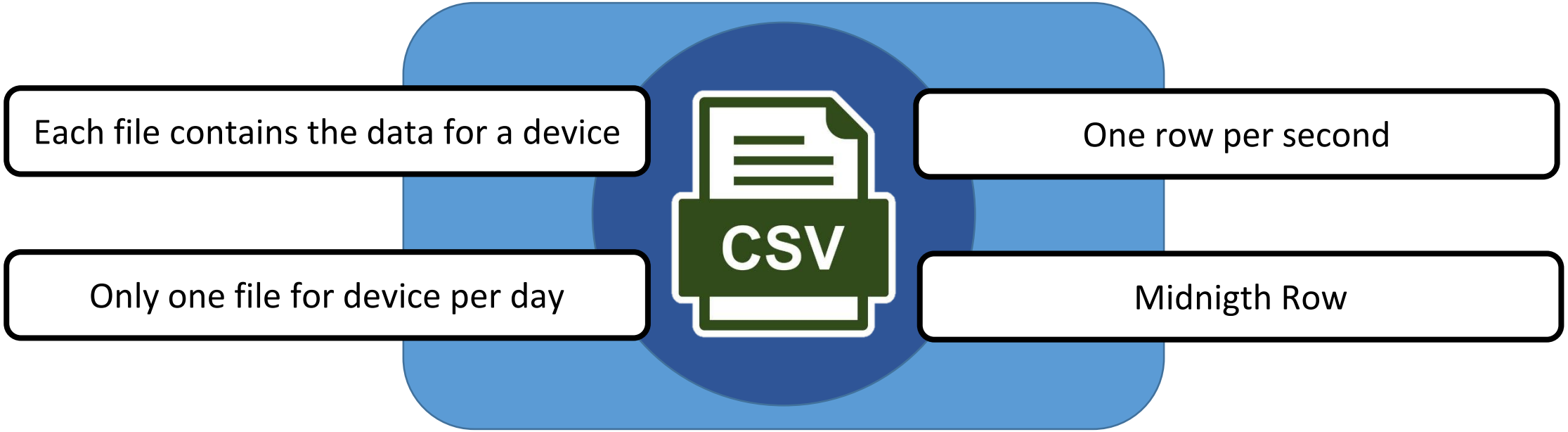
```

Our engineers looking at raw data

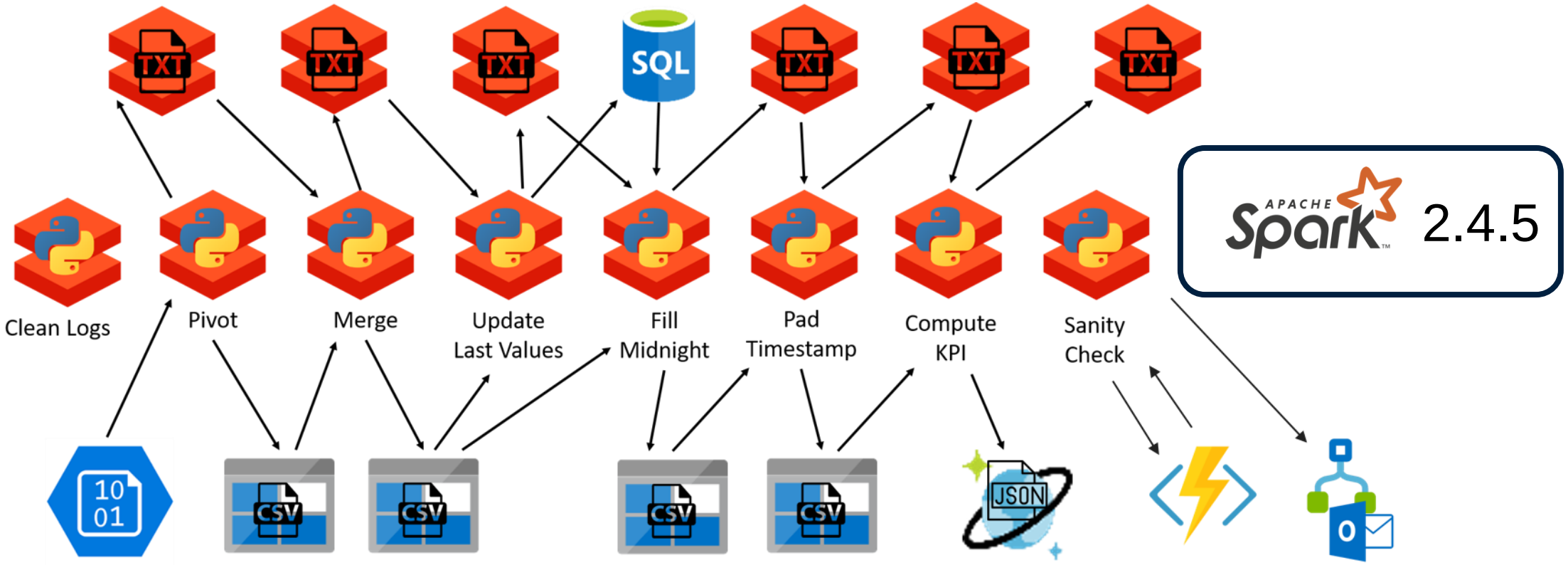


Requirements



Architecture

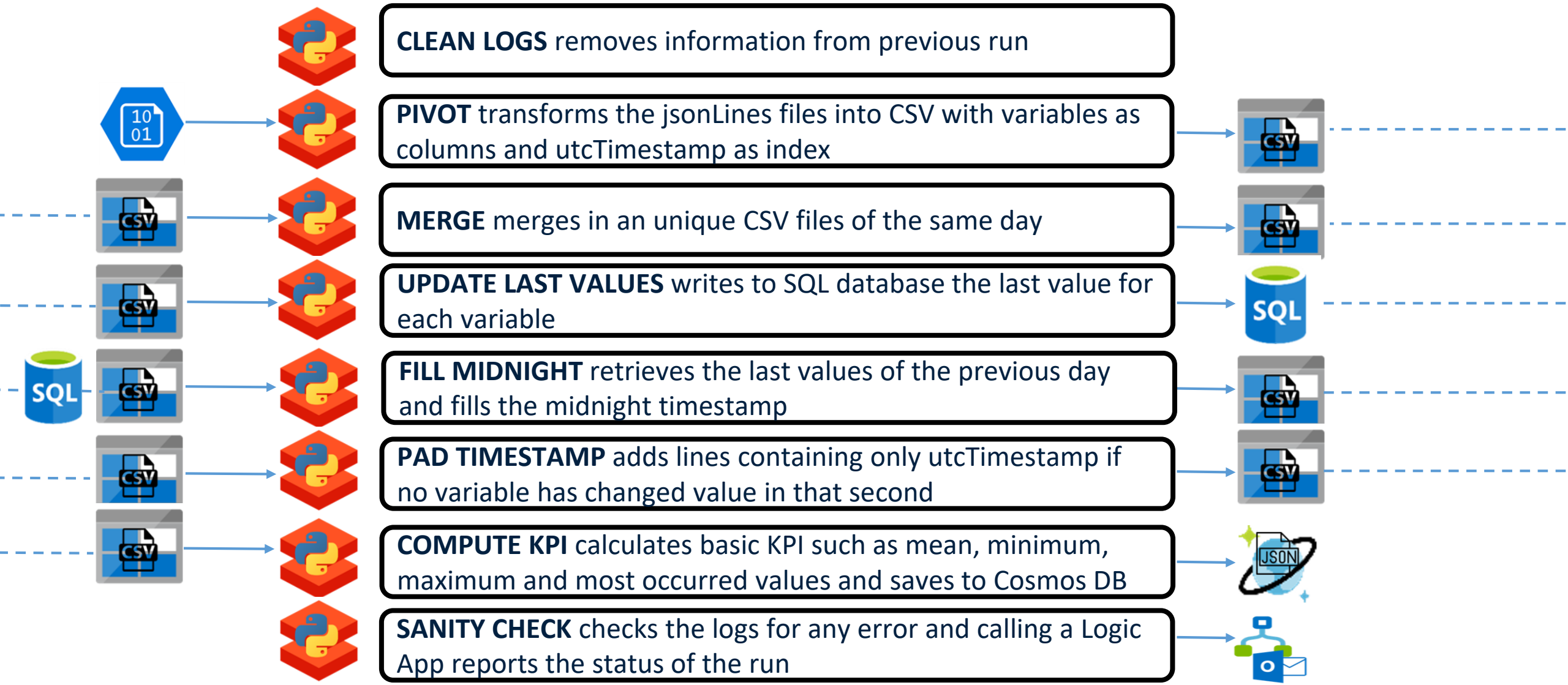
Architecture



Our intern looking at the architecture

Architecture

I HOPE IT'S A LITTLE CLEARER



Code

Raw data

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```

Pivot

CODE

PIVOT transforms the jsonLines files into CSV with variables as columns and utcTimestamp as index


```python
from pyspark.sql.functions import to_timestamp, explode, col, desc, last, date_trunc, row_number
from pyspark.sql.window import Window


def transform_dataframe(raw_df):
    df = raw_df.select(
        to_timestamp(raw_df.utcTimestamp).alias("utcTimestamp"),
        raw_df.itemName,
        explode(parse(raw_df.value)).alias("key", "value"),
        raw_df.itemId,
    )
    df = df.withColumn("variable", merge_columns("key", "itemName", "itemId"))
    df = df.select(df.utcTimestamp, df.variable, df.value)

    # truncatedUtc is introduced to select just the last value (desc) for each pair of [utcTimestamp, variable]
    df = df.withColumn("truncatedUtc", date_trunc("second", "utcTimestamp"))
    w = Window.partitionBy("variable", "truncatedUtc").orderBy(desc("utcTimestamp"))
    # for each variable at a given truncatedUtc the first row is selected.
    # Since the window is in descending order the last value is selected.
    df = df.withColumn("row_number", row_number().over(w)).where(col("row_number") == 1).drop("rownumber")

    # there is just one value per timestamp, per variable. last is used just to take the unique value.
    df = df.groupby("truncatedUtc").pivot("variable").agg(last("value"))
    df = df.drop("utcTimestamp").withColumnRenamed("truncatedUtc", "utcTimestamp").orderBy("utcTimestamp")

    return df
```

Pivot

OUTPUT

utcTimestamp	1000|TEMPERATURE	1111|SPEED	1234|SCRAP_IMAGE_ENTER_ID	1234|SCRAP_IMAGE_CATEGORY
2021-07-07T18:09:05	104.9	45.7		
2021-07-07T18:09:06	106.3	45.3	1010	A
2021-07-07T18:09:07	107.4	44.8		
2021-07-07T18:09:08	107.8			
2021-07-07T18:09:09	106.9	44.5	1011	C

Merge

CODE


MERGE merges in an unique CSV files of the same day

```python
def merge(day_files, conf):
    dfs = [spark.read.csv(_, header=True, multiLine=True) for _ in day_files]
    df_raw = reduce(
        lambda df1, df2: df1.join(
            df2, list(set(df1.columns).intersection(df2.columns)), "outer"
        ),
        dfs,
    )
    df_raw = sort_columns(df_raw)
    schema = df_raw.schema
    df_no_duplicates = df_raw.dropDuplicates(subset=["utcTimestamp"])
    if df_no_duplicates.count() == df_raw.count():
        return df_raw.sort(asc("utcTimestamp"))
    else:
        df_raw = df_raw.toPandas()
        df_duplicated = df_raw[df_raw.duplicated(subset="utcTimestamp", keep=False)]
        df_no_duplicates = df_raw[~df_raw.duplicated(subset="utcTimestamp", keep=False)]

        resolved_duplicates = df_duplicated.groupby("utcTimestamp").agg(unique_udf)
        resolved_duplicates["utcTimestamp"] = resolved_duplicates.index
        resolved_duplicates.index = range(len(resolved_duplicates))

        result = pd.concat([df_no_duplicates, resolved_duplicates]).sort_values(
            "utcTimestamp"
        )
        result = result[schema.fieldNames()]
        result = spark.createDataFrame(result, schema)
        return result
```

Update Last Values

CODE

UPDATE LAST VALUES writes to SQL database the last value for each variable


```python
def find_last_value_column(obj):
    last_non_null = obj.dropna().tail(1)
    try:
        last_non_null_value = last_non_null[0]
        last_non_null_timestamp = last_non_null.index[0]
        return {"value": last_non_null_value, "timestamp": last_non_null_timestamp}
    except:
        return None


def generate_last_values_dict(df):
    last_values_dict = {
        column: find_last_value_column(df[column])
        for column in df.columns
        if column != "utcTimestamp"
    }
    last_values_dict = {
        key: value for key, value in last_values_dict.items() if value is not None
    }
    return last_values_dict
```

Update Last Values

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QUERY

Timestamp	ItemId	Value	DeviceId	ItemName
2021-07-26 23:59:20	1000	103.5	1	TEMPERATURE
2021-07-26 23:59:56	1111	46.8	1	SPEED
2021-07-26 23:55:15	1234	1982	1	SCRAP_IMAGE_ENTER_ID
2021-07-26 23:55:15	1234	A	1	SCRAP_IMAGE_CATEGORY

```
1 /*get timestamp*/
2 SELECT Timestamp FROM lastValues  WHERE ItemId={itemId} AND CONVERT(DATE, Timestamp)=CONVERT(DATE, '{last_timestamp}') AND ItemName='{itemName}'
3
4 /*update last value*/
5 UPDATE lastValues SET ItemId = {itemId}, Timestamp = '{last_timestamp}', Value = '{value}', ItemName='{itemName}', DeviceId= {device} WHERE ItemId={itemId}
  AND ItemName='{itemName}' AND CONVERT(DATE, Timestamp)=CONVERT(DATE, '{last_timestamp}')
6
7 /*insert last value*/
8 INSERT INTO lastValues(ItemId, Timestamp, Value, DeviceId, ItemName) VALUES ('{itemId}', '{last_timestamp}', '{value}', {device}, '{itemName}')
```

Fill Midnight

RETRIEVE LAST VALUES


```python
from pandas import read_sql


def retrieve_last_values(device, day):
    data = read_sql(
        f"""SELECT itemid, itemname, value FROM LastValues
          WHERE DATEADD(DAY, +1, CONVERT(DATE, Timestamp))='{day}'
          and deviceid={device}""",
        cnxn,
    )
    yesterday_column_names = [
        f'{value}|{data["itemname"][key]}' for key, value in enumerate(data["itemid"])
    ]
    yesterday_last_values = dict(zip(yesterday_column_names, data["value"]))
    return yesterday_last_values
```

Fill Midnight

UPDATE DATAFRAME

```python
def midnight_exists(df):
    first_timestamp_string = df.select("utcTimestamp").first()["utcTimestamp"]
    # very bad trick
    hour_minute_seconds_string = first_timestamp_string.split("T")[1][:8]
    if hour_minute_seconds_string == "00:00:00":
        return True
    else:
        return False


def update_dataframe(df, info):
    variables_df = [_ for _ in df.columns if _ != "utcTimestamp"]
    if info == {}:
        return df
    for _ in variables_df:
        if _ not in info.keys():
            info[_] = ""
    if midnight_exists(df):
        df = fill_midnight_timestamp(df, info)
        print("fill midnight")
    else:
        print("insert midnight")
        df = insert_midnight_timestamp(df, info)
    return df
```

Pad Timestamp


PAD TIMESTAMP adds lines containing only utcTimestamp if no variable has changed value in that second

```python
from pyspark.sql.functions import col, min as min_, max as max_


def pad_timestamp(df, step=1):
    minp, maxp = df.select(
        min_("utcTimestamp").cast("timestamp").cast("int"),
        max_("utcTimestamp").cast("timestamp").cast("int"),
    ).first()
    reference = spark.range(
        (minp / step) * step, ((maxp / step) + 1) * step, step
    ).select(col("id").cast("timestamp").alias("utcTimestamp"))
    result = reference.join(df, ["utcTimestamp"], "leftouter")
    return result
```

Compute KPI

COMPUTE KPI calculates basic KPI such as mean, minimum, maximum and most occurred values and saves to Cosmos DB

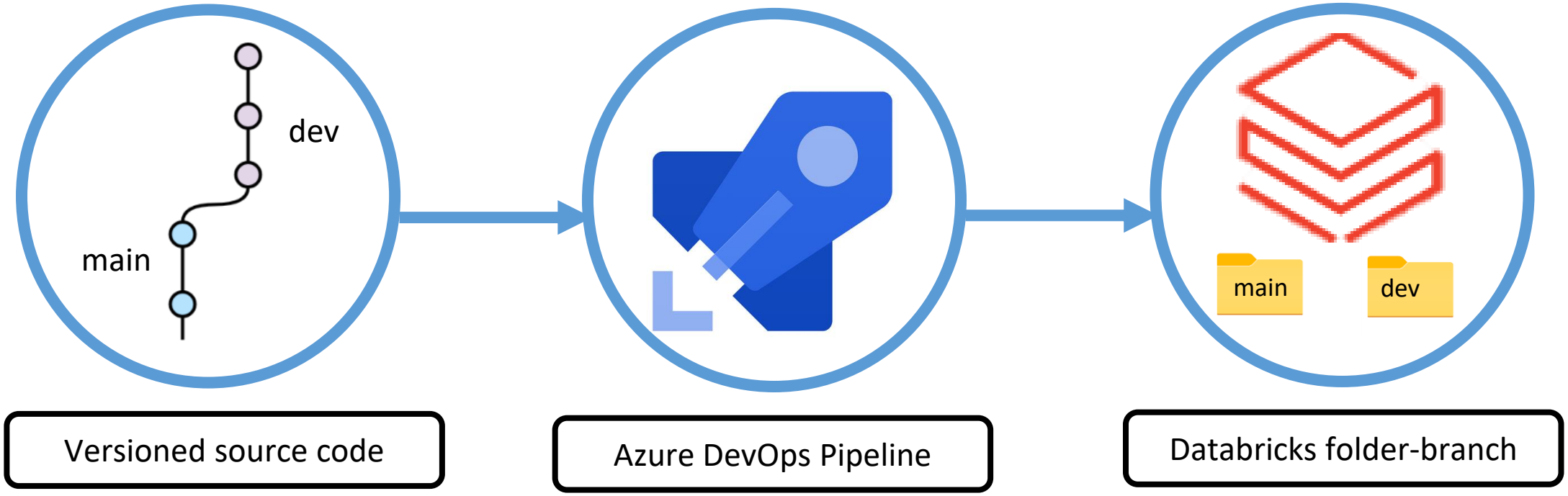

```python
import pandas as pd


def compute_basic_KPIs(df):
    df = df.apply(pd.to_numeric, errors="ignore")
    summary = df.describe(include="all")
    summary_pd = summary.drop(["utcTimestamp"], axis=1)
    df_filled = df.ffill()
    summary_filled = df_filled.describe(include="all")
    summary_filled_pd = summary_filled.drop(["utcTimestamp"], axis=1)

    result_pd = []
    for column in summary_pd.columns:
        item = {}
        tag_id, tag_name = column.split("|")
        item["TagId"] = tag_id
        item["KPI"] = build_KPI_dict_for_column(
            summary_not_filled=summary_pd,
            summary_filled=summary_filled_pd,
            column=column,
        )
        time_occ = df_filled[column].value_counts()
        item["TimeOccurencies"] = dict(time_occ[time_occ > 1])
        item["TagName"] = tag_name
        serialized_item = pd.Series(item).to_json()
        result_pd.append(item)
    return result_pd
```

Orchestration

Continuous Deployment



Orchestration

Azure Databricks

- Same environment as the notebooks
- Little flexibility for future developments

Azure Data Factory

- Easy to customize
- Flexibility in replacing some notebooks with other services

Conclusion

Next Steps

UPGRADE TO SPARK 3

COMPUTE AD HOC KPI

IMPROVE PERFORMANCE COMPUTE KPI

The End!