# Streaming processing of cosmic rays using Drift Tubes detectors

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# Introduction (1/2)



- The goal of our project is to simulate a live data processing network for a particle physics detector and show the results in a dashboard for continuous monitoring.
- The dataset is provided on a cloud storage bucket hosted on Cloud Veneto and is composed of multiple comma-separated values txt files.
- Our goal is to inject this data into a Kafka topic by emulating a continuous DAQ stream.

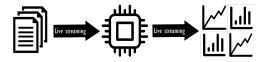


Figure: Very basic idea of live data streaming

# Introduction (2/2)



- We processed our data using batch intervals varying from 1 to 5 seconds.
- After an initial data cleansing process all information extracted was wrapped in one message per batch and injected into a new Kafka topic.

#### Tools



In order to implement our project different frameworks and python packages are used:

- Kafka 3.2.0: Distributed event streaming platform, used to manage the streaming of data, via confluent\_kafka as interface
- Spark 3.3.0: Cluster computing framework for data analytics, used to perform distributed computation.
- Bokeh 2.4.3: Useful python package for interactive plotting



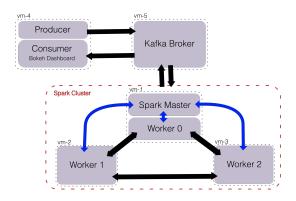




## Network Architecture



Our streaming-processing network architecture looks like the following:



# Producer (1/2)



#### Define parameter

```
from confluent_kafka import Producer
N_PARTITIONS = 12
BOOTSTRAP_SERVER = '10.67.22.61'
MSG_RATE = 1000 # number of messages per second
BATCH_FRACTION = 0.1 # can't be lower than 0.1
BATCH_SIZE = int(max(0.1*MSG_RATE, BATCH_FRACTION*MSG_RATE))
```

#### Create topic and producer

# Producer (2/2)



#### Connect to bucket

```
import boto3
url = 'https://cloud-areapd.pd.infn.it:5210'
s3_client = boto3.client('s3', endpoint_url=url, verify=False)
```

#### Write and send message

```
bucket name = 'mapd-minidt-stream'
batch count = 0 # counter for artificial delay
for key in s3 client.list objects(Bucket=bucket name)['Contents']:
    print('file:', key["Key"])
    # create line iterator
    line reader = s3 client.get object(Bucket=bucket name,
                                       Key=key['Key'])['Body'].iter_lines()
    next(line_reader) # skip header line for each file
    for line in line reader:
        producer.produce(topic_name, line) # produce message
        producer.poll(0) # pool producer
        batch count += 1 # update counter
        if batch count == BATCH SIZE: # add artificial rate control
            time.sleep(BATCH_SIZE/MSG_RATE)
            batch count = 0 # reset counter
producer.flush() # wait for last messages to be sent
```

# Spark Analysis (1/3)



#### Define spark session builder

```
spark = SparkSession.builder \
    .master("spark://10.67.22.29:7077")\
    .apnName("Test streaming")\
    .config('spark.executor.memory', '4g')\
    .config('spark.driver.memory', '1500m')\
    .config("spark.sql.execution.arrow.pyspark.enabled", "true")\
    .config("spark.sql.execution.arrow.pyspark.fallback.enabled", "false")\
    .config("spark.jars.packages", "org.apache.spark:spark-sql-kafka-0-10_2.12:3.3.0")\
    .config("spark.eventLog.enabled", 'true')\
    .getOrCreate()
spark.conf.set("spark.sql.shuffle.partitions", 12)
```

#### Read data from Kafka

```
inputDF = spark.readStream.format("kafka")\
    .option("kafka.bootstrap.servers", KAFKA_BOOTSTRAP_SERVERS)\
    .option("kafkaConsumer.pollTimeoutMs", 4000).option('subscribe', 'data')\
    .option("startingOffsets", "latest").load()
```

# Spark Analysis (2/3)



#### Message unpacking and pre-processing

```
# extract the value from the kafka message
csv df = inputDF.select(col("value").cast("string")).alias("csv").select("csv.*")
# split the csv line in the corresponding fields
df = csv_df.selectExpr("cast(split(value, ',')[0] as int) as HEAD",
                       "cast(split(value, ',')[1] as int) as FPGA",
                       "cast(split(value, ',')[2] as int) as TDC CHANNEL",
                       "cast(split(value, ',')[3] as long) as ORBIT_CNT",
                       "cast(split(value, ',')[4] as int) as BX_COUNTER",
                       "cast(split(value, ',')[5] as double) as TDC MEAS"
# remove unwanted rows
df = df.filter(df.HEAD==2)
# add CHAMBER column for easier grouping later
df = df.withColumn("CHAMBER", \
               when ((df.FPGA == 0)&(df.TDC CHANNEL>=0)&(df.TDC CHANNEL<64), 0)\
              .when((df.FPGA == 0)&(df.TDC CHANNEL>=64)&(df.TDC CHANNEL<128), 1)
              .when((df.FPGA == 1)&(df.TDC CHANNEL>=0)&(df.TDC CHANNEL<64), 2)
              .when((df.FPGA == 1)&(df.TDC CHANNEL>=64)&(df.TDC CHANNEL<128), 3)
# compute absolute time
df = df.withColumn("ABSOLUTE TIME", 25*(df.ORBIT CNT * 3564 +
                    + df.BX COUNTER + df.TDC MEAS/30))
```

# Spark Analysis (3/3)



#### Batch function

```
def batch func(df, epoch id):
 df.persist()
 hit count = df.count()
  hit count chamber = df.groupby('CHAMBER').agg(count('TDC CHANNEL'))
  .alias('HIT_COUNT')).sort("CHAMBER").select('HIT_COUNT')
  tdc counts = df.groupby(['CHAMBER', 'TDC CHANNEL']) \
  .agg(count('ORBIT CNT').alias('TDC COUNTS')).persist()
 ch0 tdc counts = tdc counts.filter(tdc counts.CHAMBER == 0).select('TDC COUNTS')
  # [... similar for 1,2,3]
  hit count chamber = hit count chamber.toPandas().values.reshape(-1)
  ch0 tdc counts hist, ch0 tdc counts be = np.histogram(ch0 tdc counts.toPandas()\
  .values.reshape(-1), bins = edges_list)
  # [... similar for 1,2,3]
 msq = { 'msq ID': ID,
          'hit count': hit count,
          'hit count chamber': hit count chamber.tolist(),
          'tdc counts chamber': {
            '0': {
                'bin_edges': edges_list_to_print,
                'hist counts': ch0 tdc counts hist.tolist() },
            # [... similar for 1,2,3] [...]
  producer.produce(TOPIC_NAME, json.dumps(msg).encode('utf-8'))
 producer.poll(0)
df.writeStream.outputMode("update").foreachBatch(batch_func) \
.trigger(processingTime='5 seconds').start().awaitTermination()
```

## Consumer and Dashboard (1/2)



#### Create a consumer

```
from confluent_kafka import Consumer
BOOTSTRAP_SERVER = '10.67.22.61'
consumer = Consumer({'bootstrap.servers': BOOTSTRAP_SERVER, 'group.id': 0})
consumer.subscribe(['results'])
```

## Consumer and Dashboard (1/2)



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```

#### Define an update function

## Consumer and Dashboard (2/2)



#### Define the plots

```
p = figure(plot_width=700, plot_height=250, title="Total number of hits", ...)
p.x_range.follow = "end"
p.x_range.follow_interval = 50
p.x_range.range_padding = 0
p_line = p.line([], [], color="firebrick", line_width=3)
# [...]
h0 = figure(width=350, height=250, title = "Chamber 0", ...)
h_tick = FixedTicker(ticks=[0,10,20,30,40,50,60,70], minor_ticks=[5,15,25, ...])
h_overrides = {70: '>70'}
h0.xaxis.ticker = h_tick
h0.xaxis.ticker = h_tick
h0.xaxis.major_label_overrides = h_overrides
hist0 = h0.quad(top=[], bottom=0, left=[], right=[], line_alpha=0, fill_color='blue')
# [...]
```

## Consumer and Dashboard (2/2)



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# [...]
```

#### Define the layout and create the callback

# Dashboard Result (1/3)

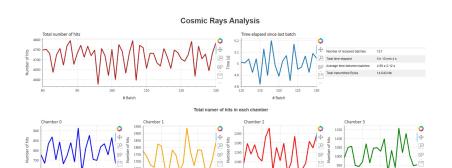
110

# Batch

110

# Batch





110

# Batch

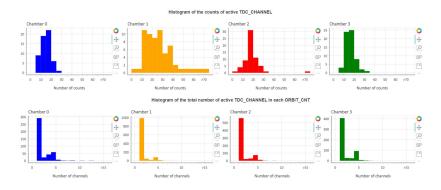
125 130

120

# Batch

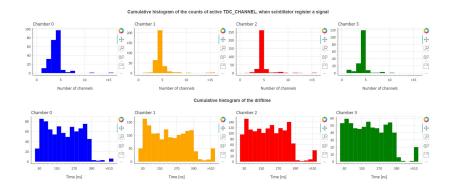
# Dashboard Result (2/3)





## Dashboard Result (3/3)







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- Number of workers (1-3)
- Number of partitions of data topic (1, number of cores,  $2 \times$  number of cores)
- Batch interval (1-5 seconds)

### Initial transient



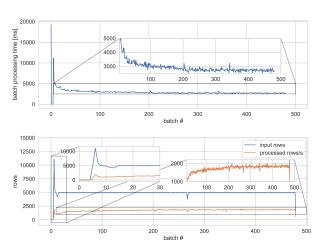


Figure: Processing time with 3 workers, 12 partitions and 1000 msg/s

# Scaling



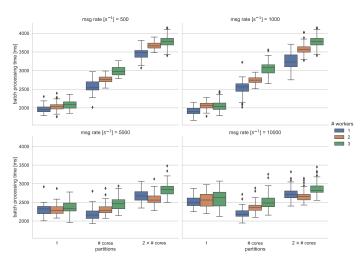


Figure: Processing time with batch interval of 5 seconds

#### Batch interval



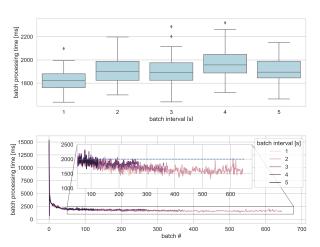


Figure: Processing time with 1 worker, 1 partition and 1000 msg/s



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- Try with a different implementation that better fits the task assigned:
  - Parallel execution of queries each on a single partition
  - Write each result in a different topic