BIGDATA TEAM

X5 Course: Big Data

Spark Structured Streaming

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X5

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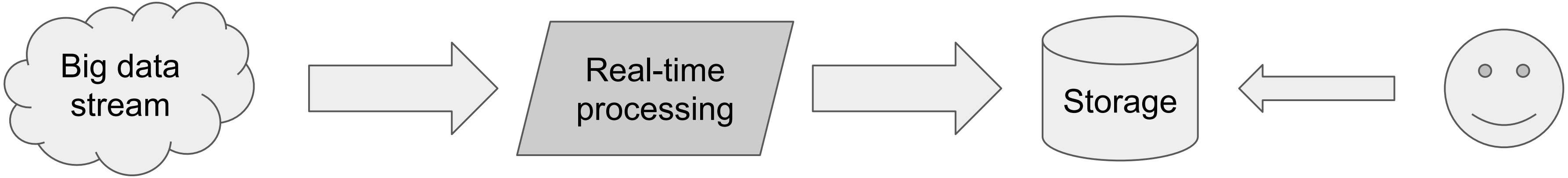
Spark Structured Streaming

- **Intro**
- Application example
- Hints

RT processing



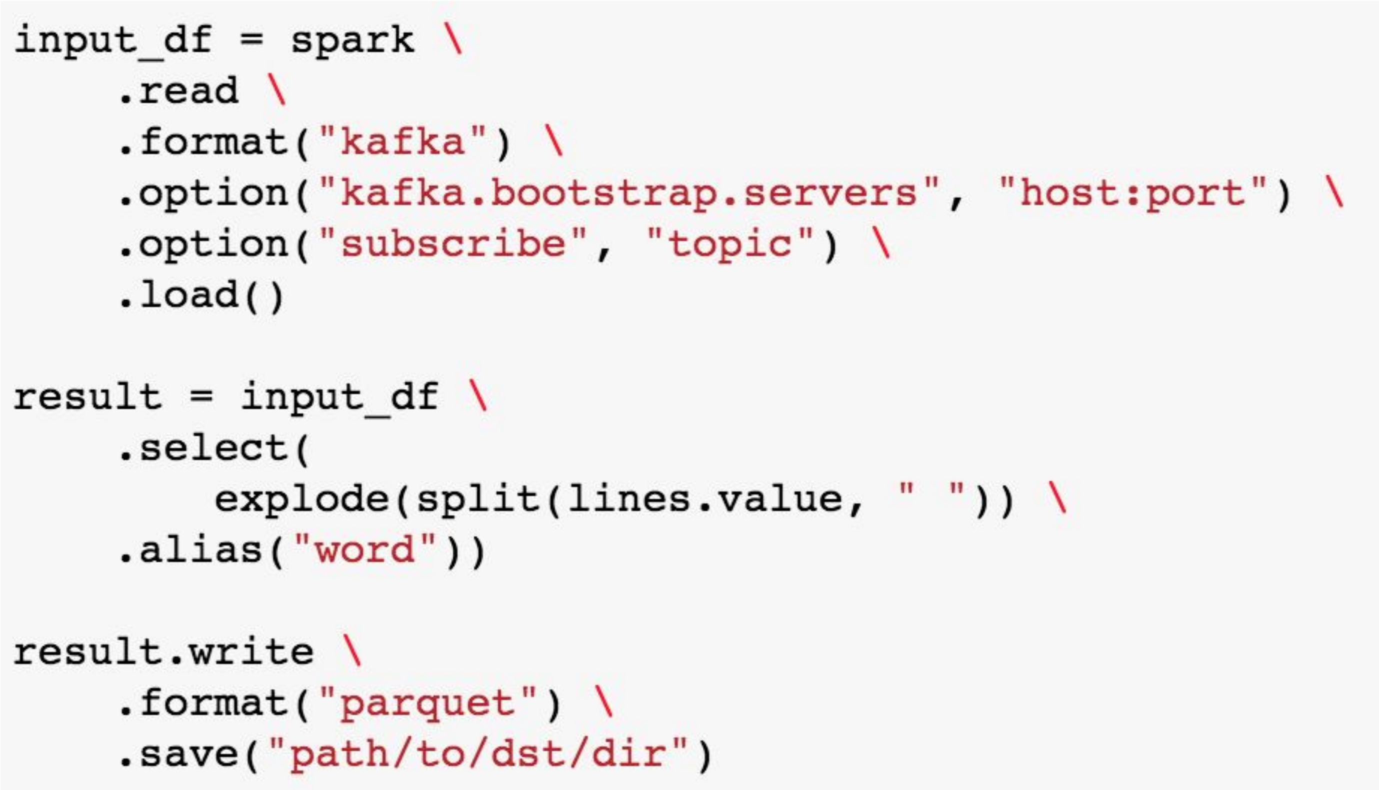
- ▶️ Apache Spark Streaming - classic
- ▶️ Apache Spark Structured Streaming - new wave (:

Apache Spark Structured Streaming

Spark Structured Streaming provides real-time stream processing letting the user leave its details unattended

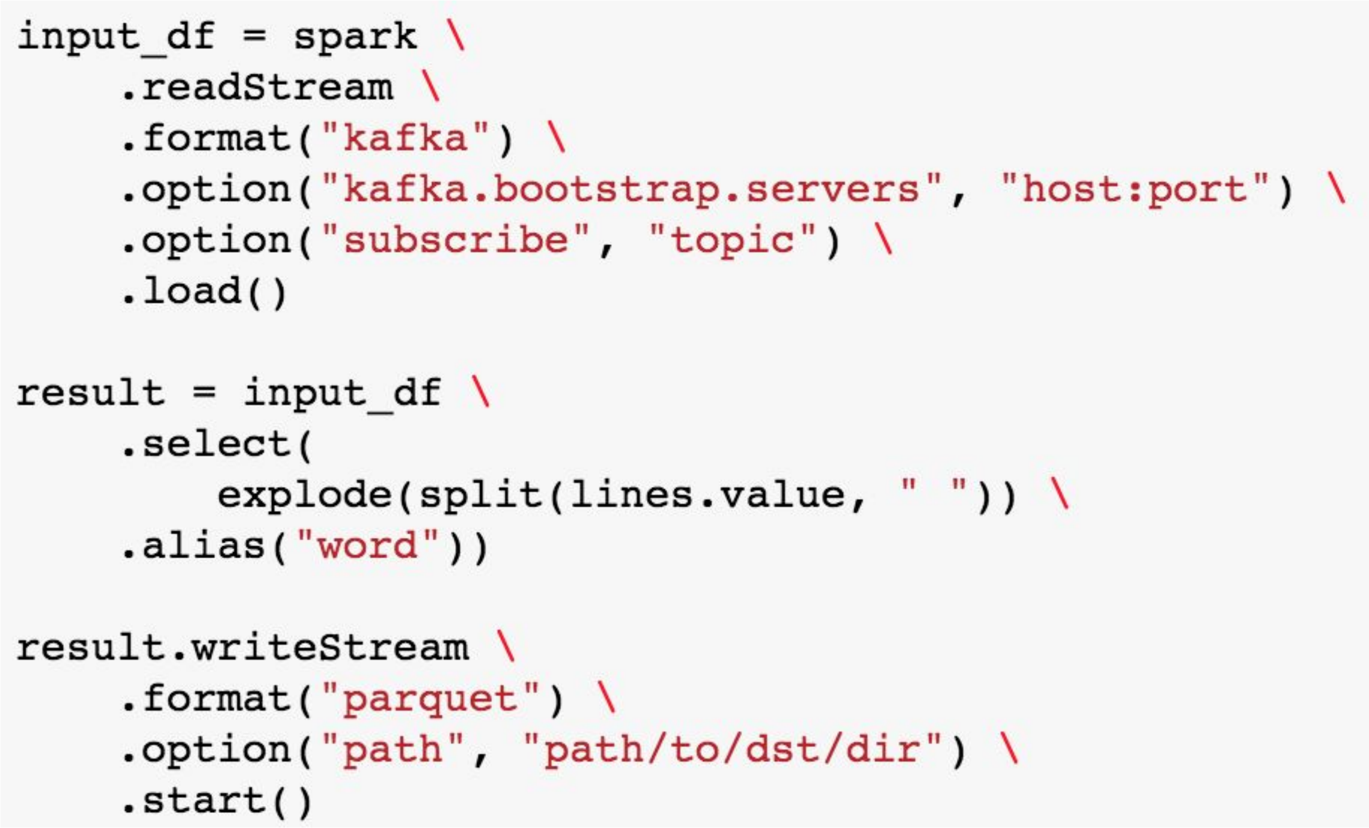
- ▶️ DataFrame -> DataFrame
- ▶️ Micro-batch approach
- ▶️ Event-based approach (2.3.0+)

Spark DataFrame



```
input_df = spark \
    .read \
    .format("kafka") \
    .option("kafka.bootstrap.servers", "host:port") \
    .option("subscribe", "topic") \
    .load()

result = input_df \
    .select(
        explode(split(lines.value, " ")) \
    .alias("word"))

result.write \
    .format("parquet") \
    .save("path/to/dst/dir")
```

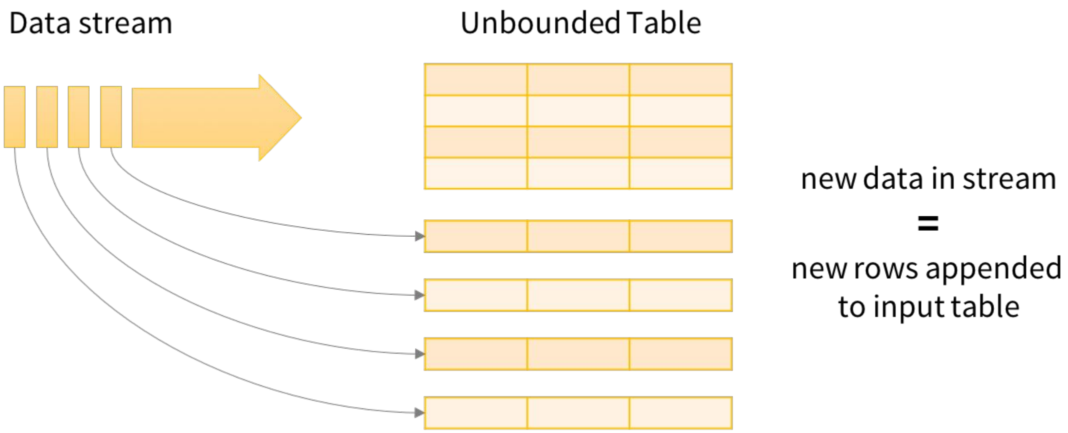
Spark Structured Streaming



```
input_df = spark \
     .readStream \
     .format("kafka") \
     .option("kafka.bootstrap.servers", "host:port") \
     .option("subscribe", "topic") \
     .load()

result = input_df \
     .select(
         explode(split(lines.value, " ")) \
     .alias("word"))

result.writeStream \
     .format("parquet") \
     .option("path", "path/to/dst/dir") \
     .start()
```

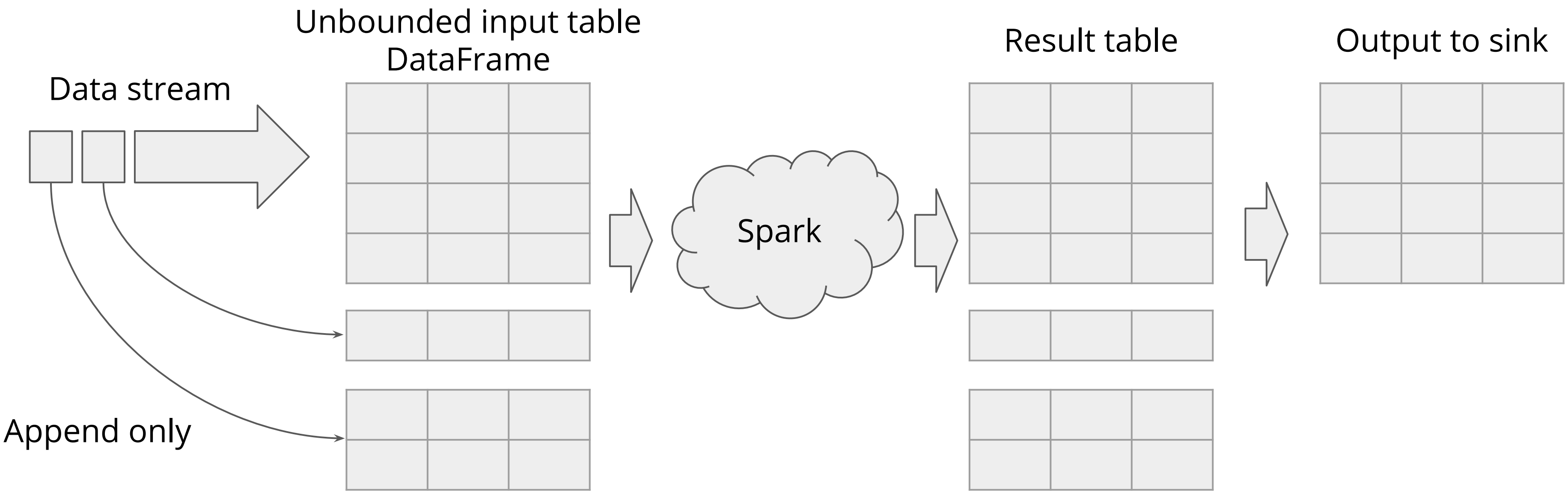
Unbounded table

- ▶ Each new item in the stream is like a row appended to the input table

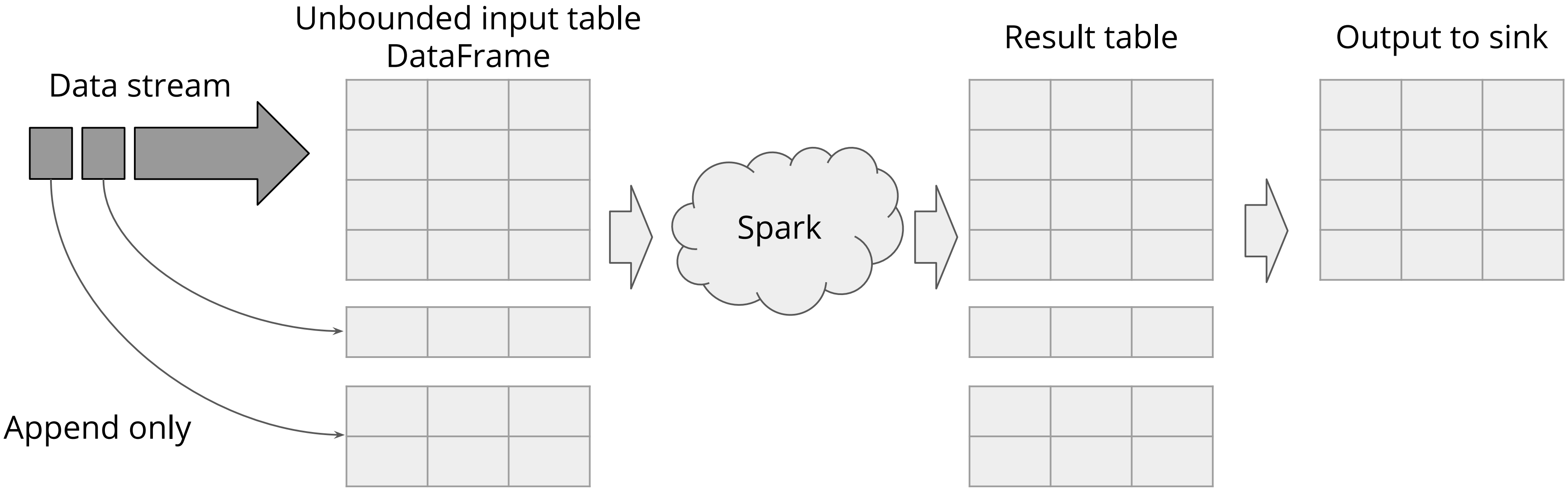


Data stream as an unbounded Input Table

Structured Streaming Base



Input sources

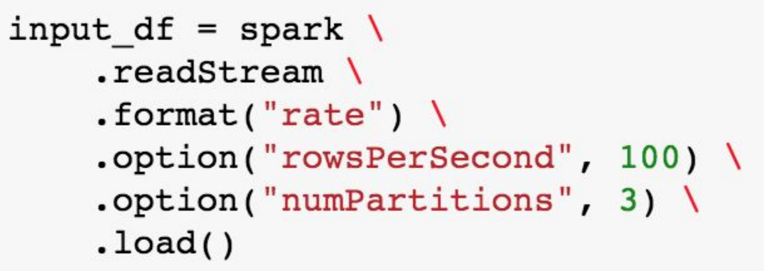


Input sources

- File source - reads files written in a directory as a stream of data
- Kafka source - reads data from Kafka
- Socket source - reads text data from a socket connection
- Rate source - generates data at the specified number of rows per second, each output row contains a timestamp and value
  - Useful for testing

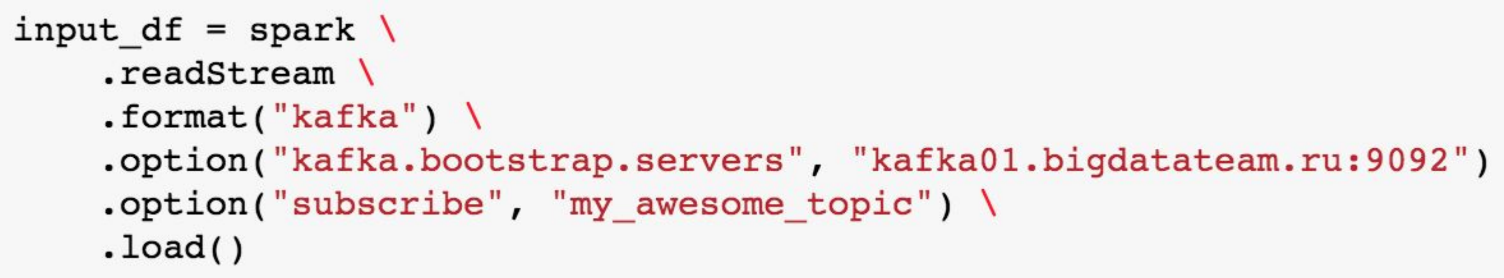
Input sources examples

- Rate source



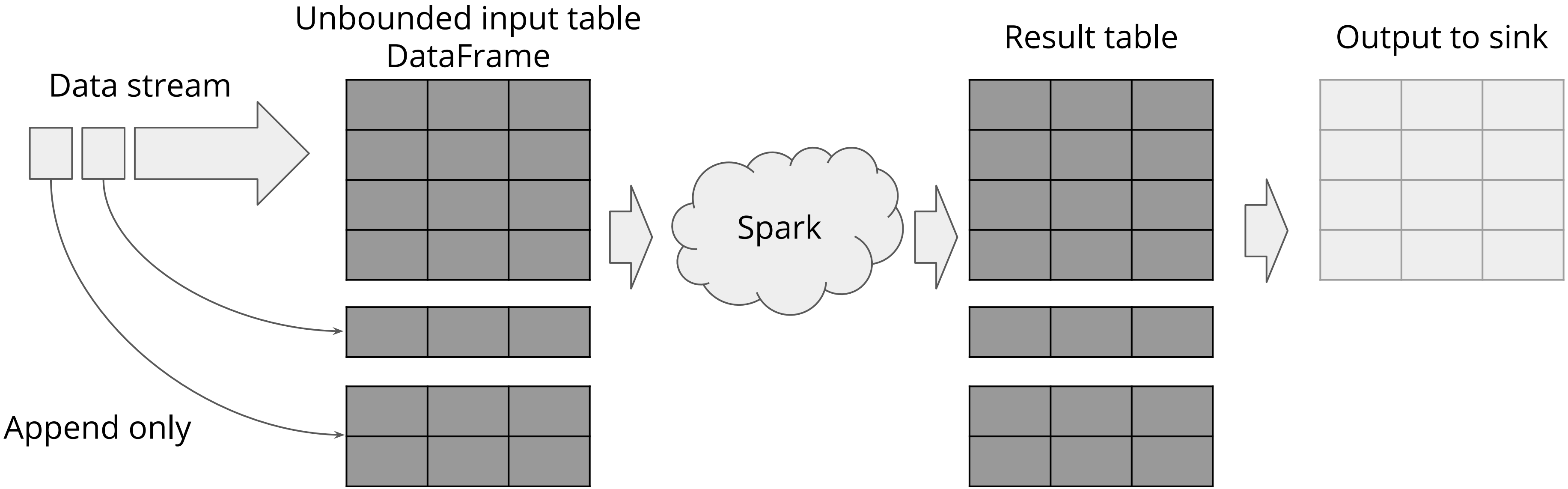
```
input_df = spark \
    .readStream \
    .format("rate") \
    .option("rowsPerSecond", 100) \
    .option("numPartitions", 3) \
    .load()
```

- Kafka Source

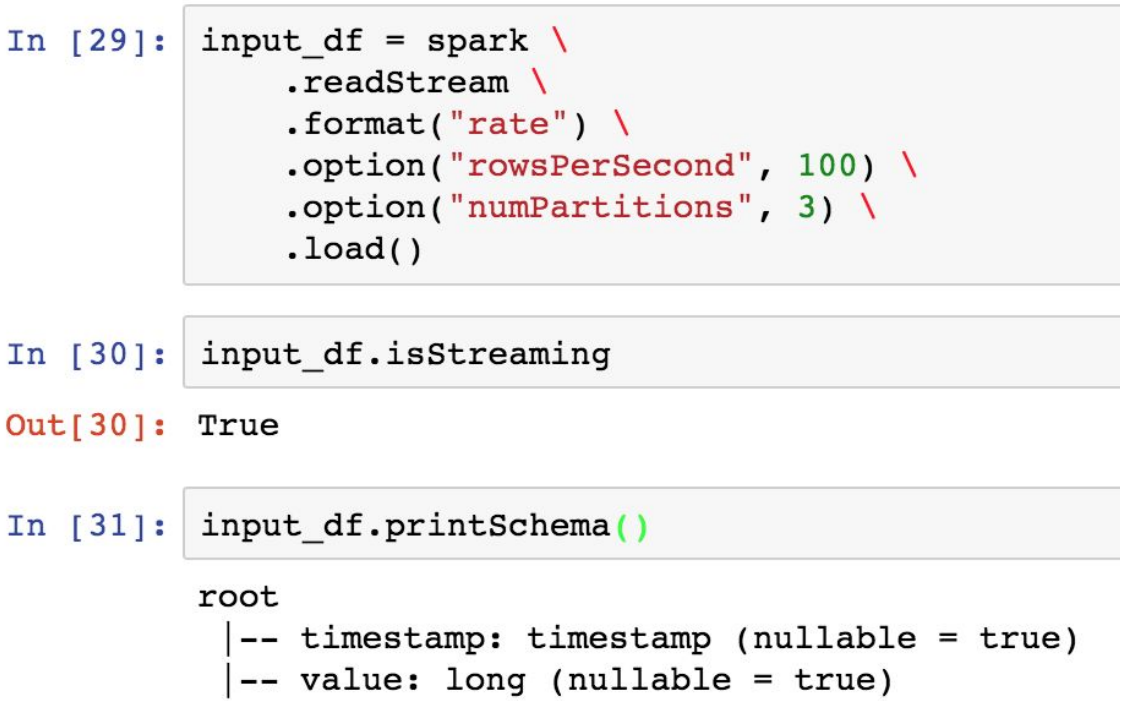


```
input_df = spark \
    .readStream \
    .format("kafka") \
    .option("kafka.bootstrap.servers", "kafka01.bigdatateam.ru:9092")
    .option("subscribe", "my_awesome_topic") \
    .load()
```

Unbounded dataframe



Unbounded dataframe



```
In [29]: input_df = spark \
             .readStream \
             .format("rate") \
             .option("rowsPerSecond", 100) \
             .option("numPartitions", 3) \
             .load()
```

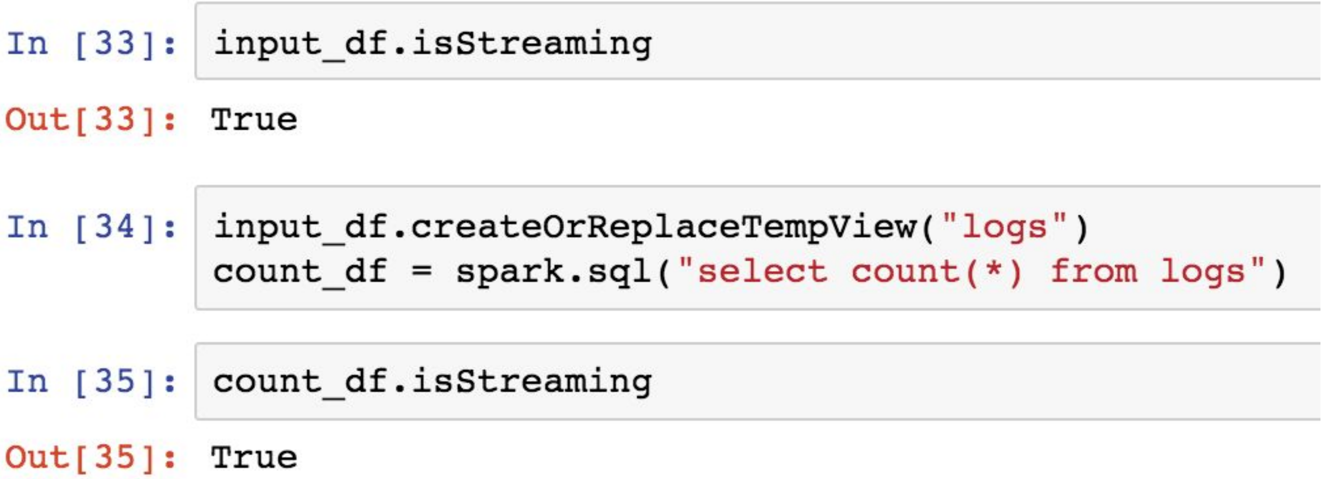
```
In [30]: input_df.isStreaming
```

```
Out[30]: True
```

```
In [31]: input_df.printSchema()
```

```
root
 |-- timestamp: timestamp (nullable = true)
 |-- value: long (nullable = true)
```

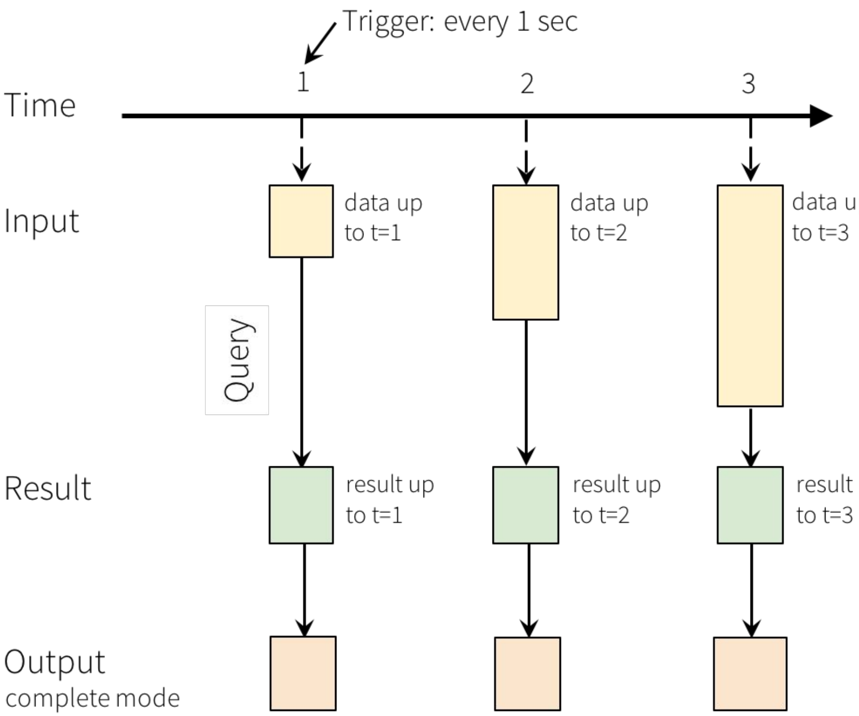
DF to SQL



```
In [33]: input_df.isStreaming

Out[33]: True

In [34]: input_df.createOrReplaceTempView("logs")
         count_df = spark.sql("select count(*) from logs")

In [35]: count_df.isStreaming

Out[35]: True
```

Structured Streaming Trigger

- Trigger determine when the processing on the accumulated data is started

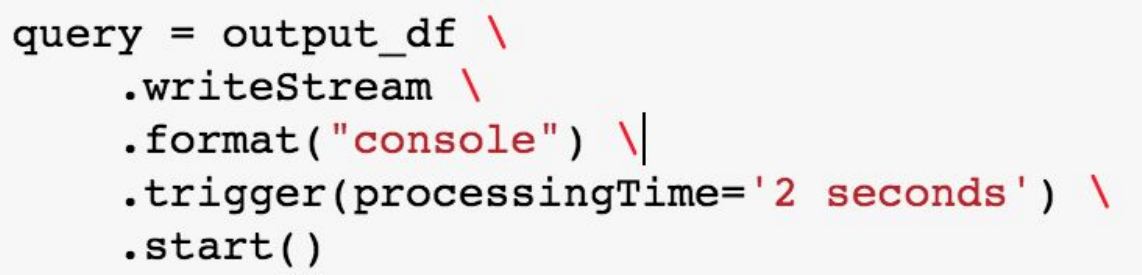


Triggers

- Default - micro-batches will be generated as soon as the previous micro-batch has completed processing
- Fixed interval micro-batches - micro-batches will be kicked off at the user-specified intervals (similar to spark streaming)
- One-time micro-batch - only one batch will be executed to process all the available data
  - Reprocessing of historical data
  - Testing purposes
- Continuous with fixed checkpoint interval (alpha) - continuous processing mode (similar event-based approach)

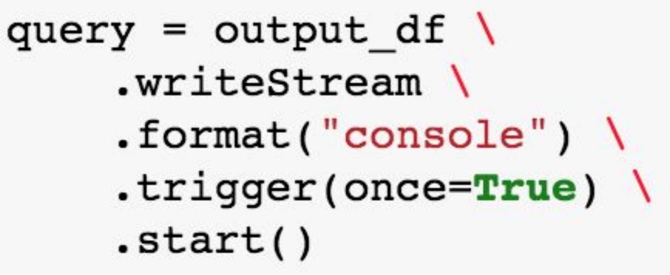
Triggers

- Fixed interval micro-batches



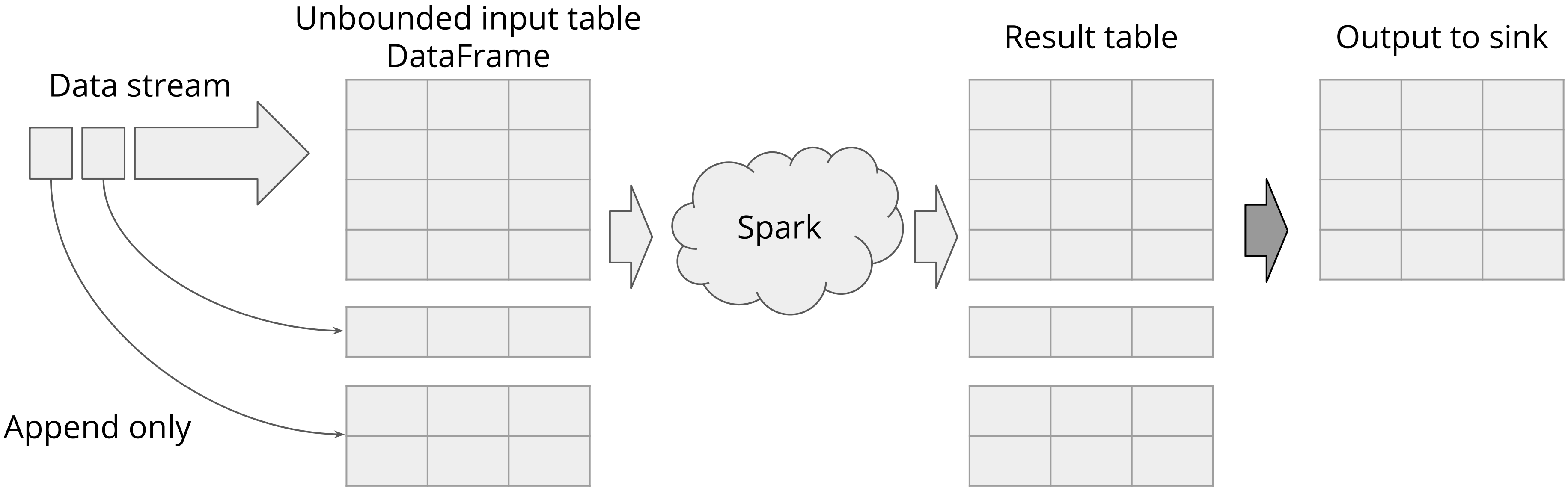
```
query = output_df \
      .writeStream \
      .format("console") \
      .trigger(processingTime='2 seconds') \
      .start()
```

- One-time micro-batch



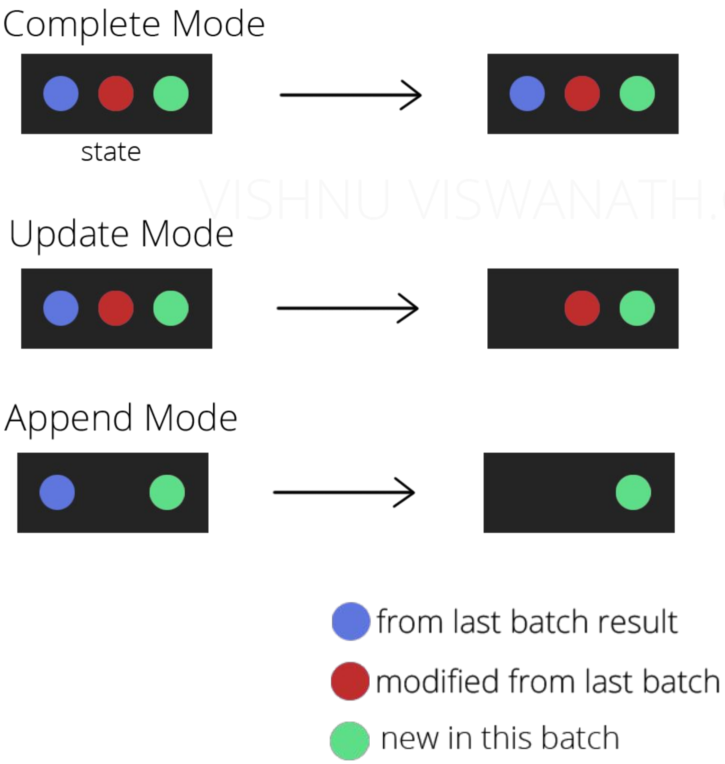
```
query = output_df \
      .writeStream \
      .format("console") \
      .trigger(once=True) \
      .start()
```

The output mode

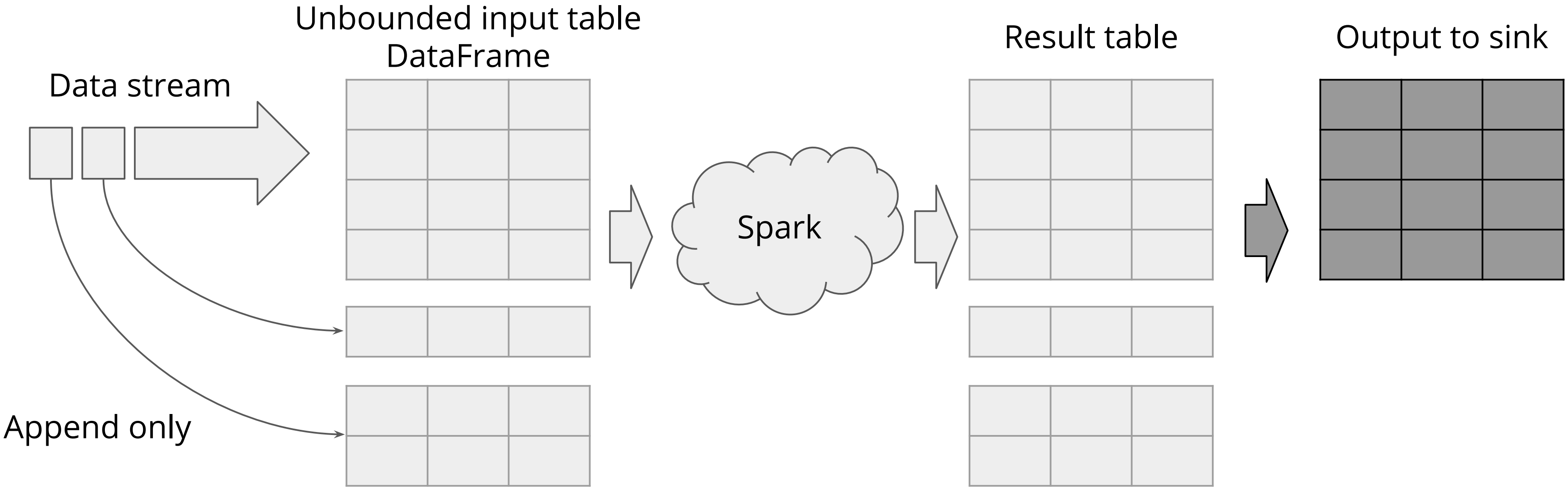


The output mode

- Result table => Output to sink
- **Complete Mode** - the whole result table will be outputted to the sink after every trigger
- **Update Mode** - only the rows in the result table that were updated since the last trigger will be outputted to the sink
- **Append Mode (default)** - only the new rows added to the result table since the last trigger will be outputted to the sink



Output sinks

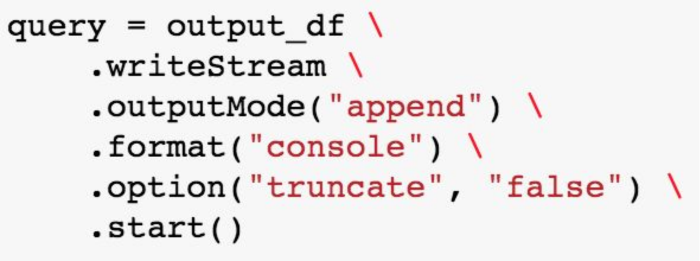


Output sinks

- File sink - stores the output to a directory
- Kafka sink - stores the output to one or more topics in Kafka
- Foreach sink - runs arbitrary computation on the records in the output (Python support in Spark 2.4.0+)
- Console sink - prints the output to the console/stdout every time there is a trigger
- Memory sink - the output is stored in memory as an in-memory table (for debugging)

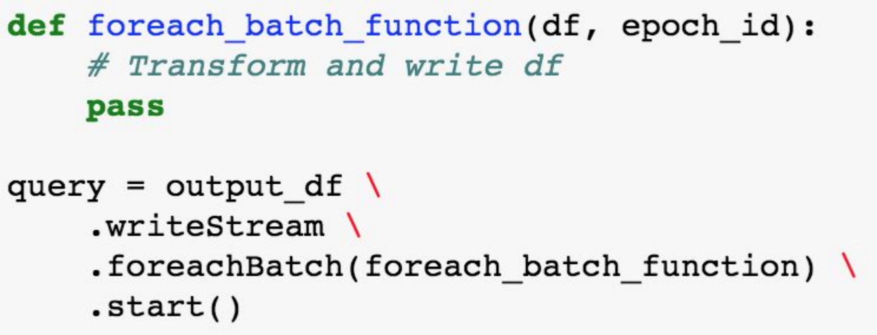
Output examples

- Console sink



```
query = output_df \
     .writeStream \
     .outputMode("append") \
     .format("console") \
     .option("truncate", "false") \
     .start()
```

- Foreach Sink



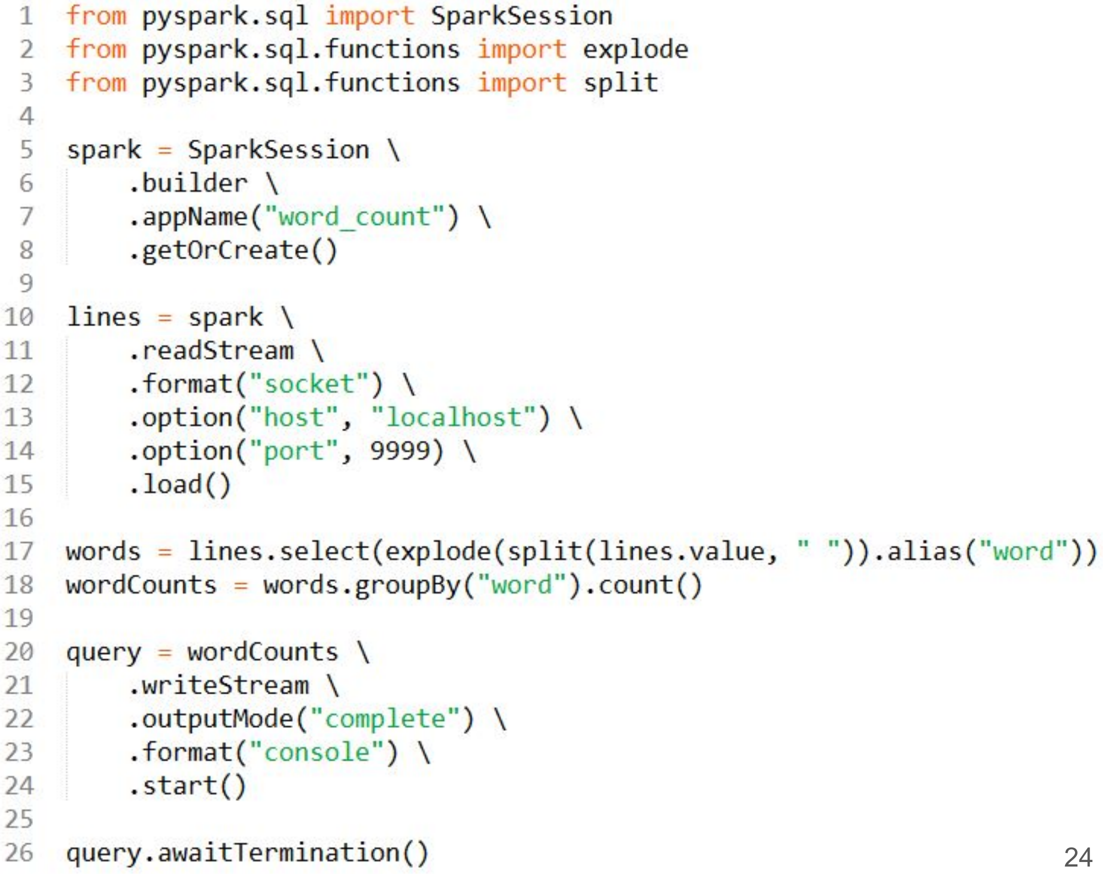
```
def foreach_batch_function(df, epoch_id):
    # Transform and write df
    pass

query = output_df \
     .writeStream \
     .foreachBatch(foreach_batch_function) \
     .start()
```

Spark Structured Streaming

- ▶ Intro
- ▶ **Application example**
- ▶ Hints

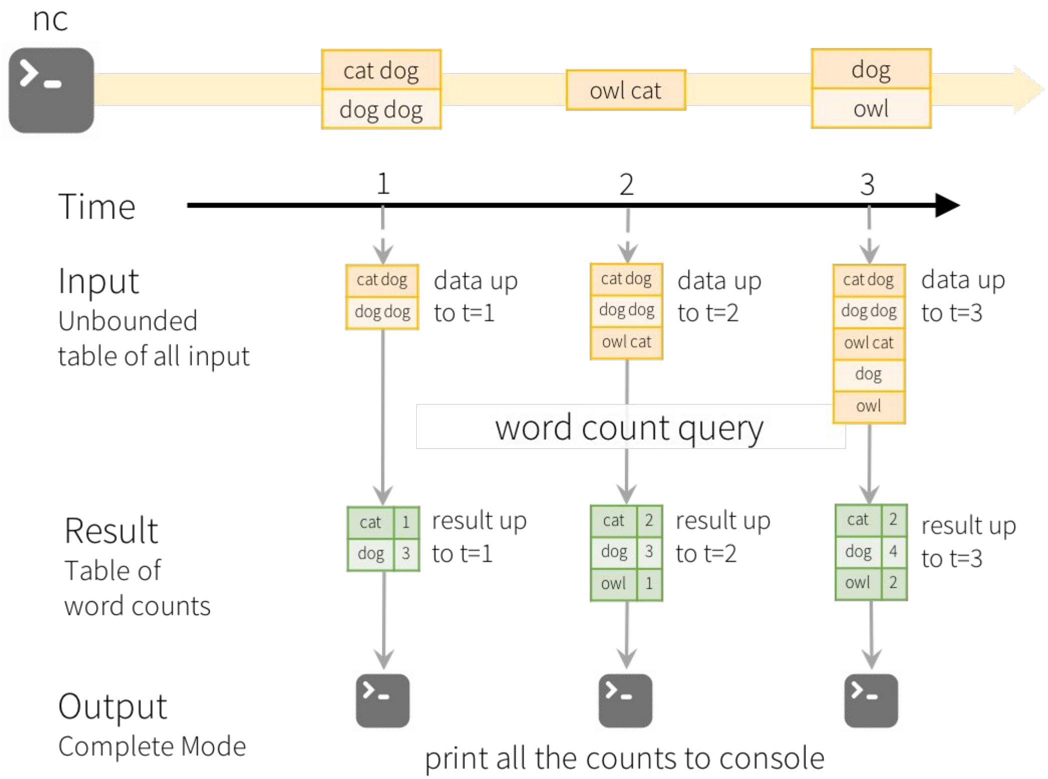
Example of App

- Create Spark Session
- Define input source
- Transform DataFrame
- Write result to output
- Start query
- Wait for exit (only for CLI)
- In Jupyter use query.stop()



```
from pyspark.sql import SparkSession
from pyspark.sql.functions import explode
from pyspark.sql.functions import split

spark = SparkSession \
    .builder \
    .appName("word_count") \
    .getOrCreate()

lines = spark \
    .readStream \
    .format("socket") \
    .option("host", "localhost") \
    .option("port", 9999) \
    .load()

words = lines.select(explode(split(lines.value, " ")).alias("word"))
wordCounts = words.groupBy("word").count()

query = wordCounts \
    .writeStream \
    .outputMode("complete") \
    .format("console") \
    .start()

query.awaitTermination()
```

Example of App



nc

cat dog
dog dog

owl cat

dog
owl

Time

1

2

3

Input
Unbounded
table of all input

cat dog
dog dog

data up
to t=1

cat dog
dog dog
owl cat

data up
to t=2

cat dog
dog dog
owl cat
dog
owl

data up
to t=3

word count query

Result
Table of
word counts

cat	1
dog	3

result up
to t=1

cat	2
dog	3
owl	1

result up
to t=2

cat	2
dog	4
owl	2

result up
to t=3

Output
Complete Mode

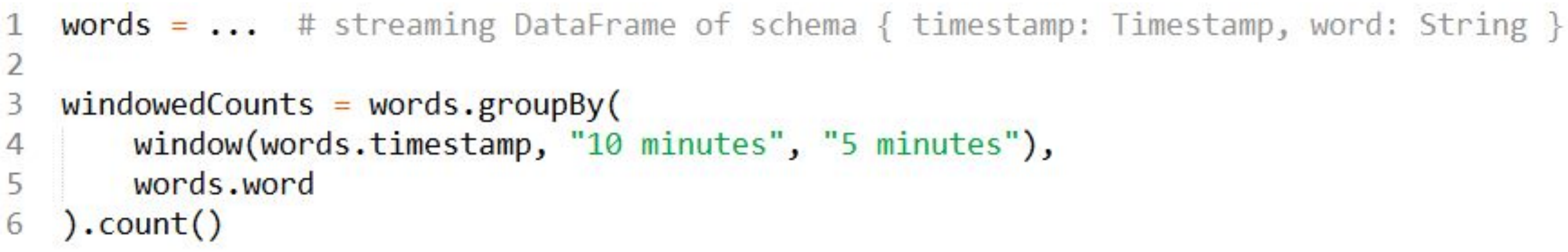
print all the counts to console

Spark Structured Streaming

- ▶️ Intro
- ▶️ Application example
- ▶️ **Hints**

Window operation

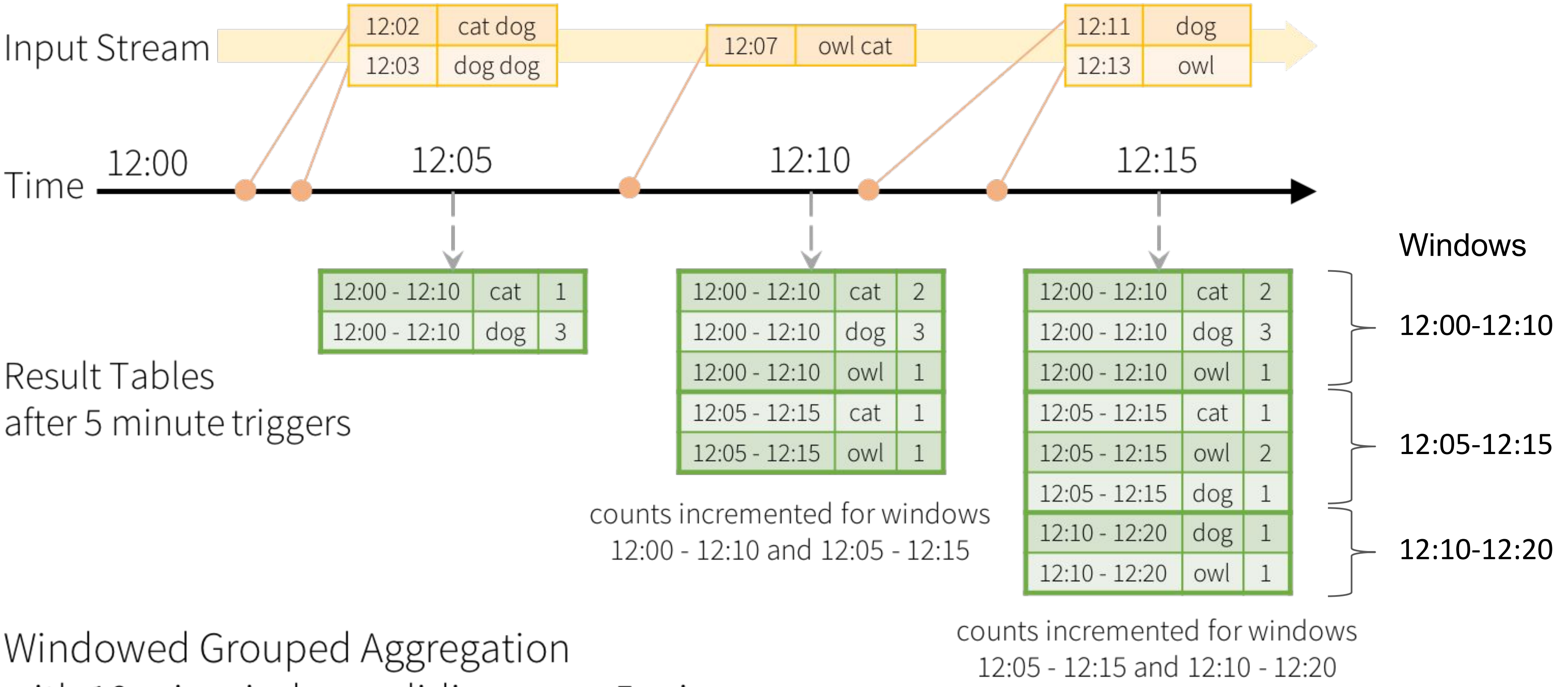
- Window operation provides a windowed approach, which allows you to apply transformations over a sliding window of data
- It is very similar to grouped aggregations



```
words = ...  # streaming DataFrame of schema { timestamp: Timestamp, word: String }

windowedCounts = words.groupBy(
    window(words.timestamp, "10 minutes", "5 minutes"),
    words.word
).count()
```

- Window size - 10 minutes
- Window slide - 5 minutes

Window operation



12:00 - 12:10	cat	1
12:00 - 12:10	dog	3

12:00 - 12:10	cat	2
12:00 - 12:10	dog	3
12:00 - 12:10	owl	1
12:05 - 12:15	cat	1
12:05 - 12:15	owl	1

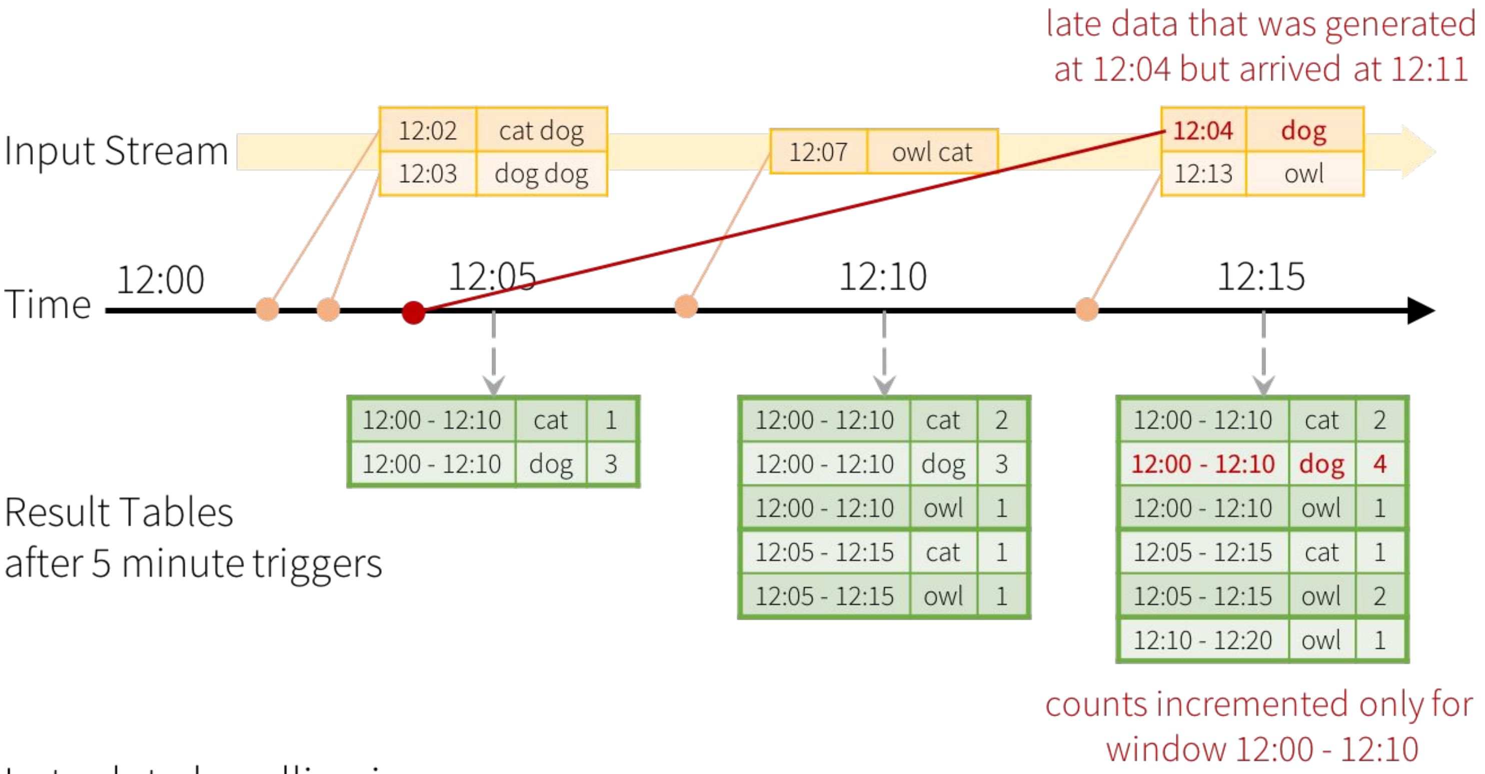
counts incremented for windows
12:00 - 12:10 and 12:05 - 12:15

12:00 - 12:10	cat	2
12:00 - 12:10	dog	3
12:00 - 12:10	owl	1
12:05 - 12:15	cat	1
12:05 - 12:15	owl	2
12:05 - 12:15	dog	1
12:10 - 12:20	dog	1
12:10 - 12:20	owl	1

counts incremented for windows
12:05 - 12:15 and 12:10 - 12:20

Windowed Grouped Aggregation
with 10 min windows, sliding every 5 mins

Window operation and late data



late data that was generated at 12:04 but arrived at 12:11
Input Stream
12:02
cat dog
12:03
dog dog
12:07
owl cat
12:04
dog
12:13
owl
Time
12:00
12:05
12:10
12:15
Result Tables after 5 minute triggers
counts incremented only for window 12:00 - 12:10

12:00 - 12:10	cat	1
12:00 - 12:10	dog	3

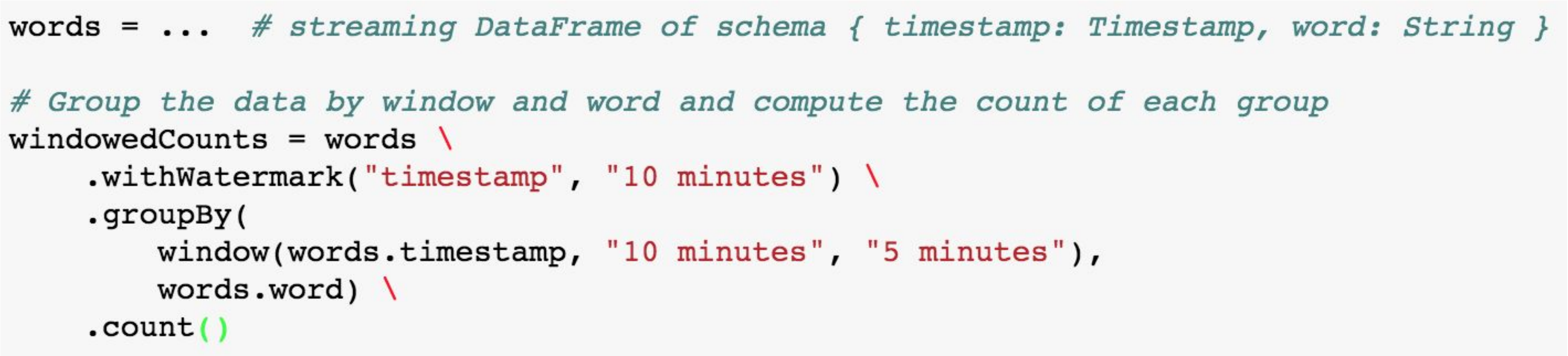
12:00 - 12:10	cat	2
12:00 - 12:10	dog	3
12:00 - 12:10	owl	1
12:05 - 12:15	cat	1
12:05 - 12:15	owl	1

12:00 - 12:10	cat	2
12:00 - 12:10	dog	4
12:00 - 12:10	owl	1
12:05 - 12:15	cat	1
12:05 - 12:15	owl	2
12:10 - 12:20	owl	1

Late data handling in
Windowed Grouped Aggregation

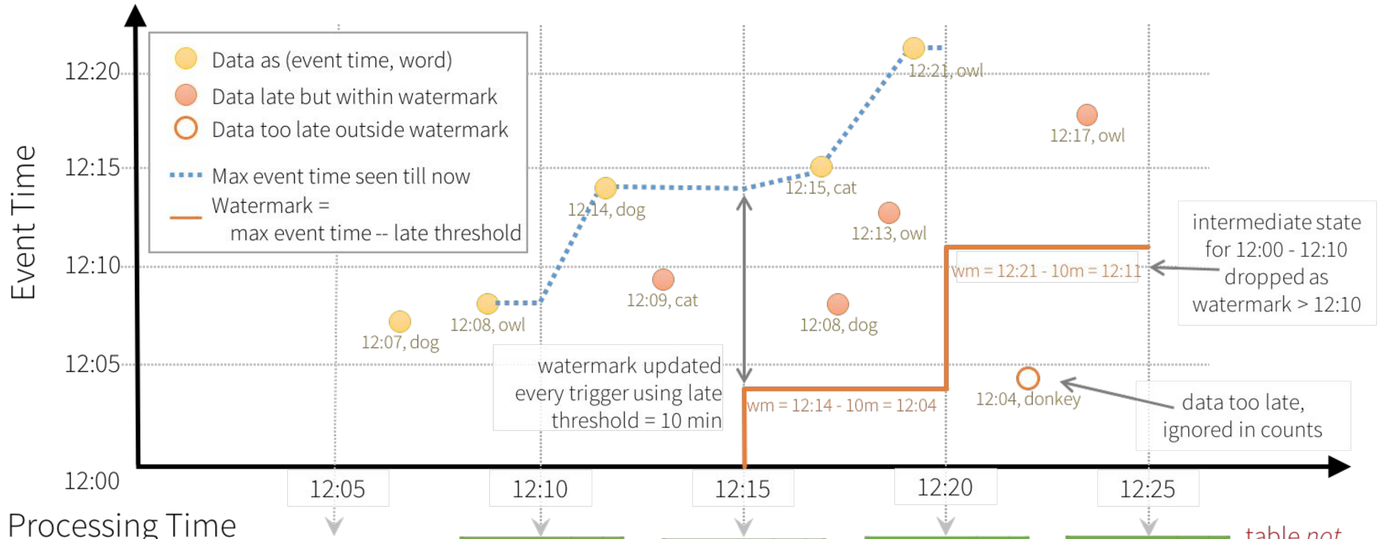
Watermarking

▶ Watermarking - lets the engine automatically track the current event time in the data and attempt to clean up old state accordingly.



```
words = ...  # streaming DataFrame of schema { timestamp: Timestamp, word: String }

# Group the data by window and word and compute the count of each group
windowedCounts = words \
    .withWatermark("timestamp", "10 minutes") \
    .groupBy(
        window(words.timestamp, "10 minutes", "5 minutes"),
        words.word) \
    .count()
```

Watermarking (window & update)



watermark updated every trigger using late threshold = 10 min

intermediate state for 12:00 - 12:10 dropped as watermark > 12:10

data too late, ignored in counts

Result Tables after each trigger

12:00 - 12:10	owl	1
12:00 - 12:10	dog	1
12:05 - 12:15	owl	1
12:05 - 12:15	dog	1

12:00 - 12:10	owl	1
12:00 - 12:10	dog	1
12:00 - 12:10	cat	1
12:05 - 12:15	owl	1
12:05 - 12:15	dog	2
12:05 - 12:15	cat	1
12:10 - 12:20	dog	1

12:00 - 12:10	owl	1
12:00 - 12:10	dog	2
12:00 - 12:10	cat	1
12:05 - 12:15	owl	2
12:05 - 12:15	dog	3
12:05 - 12:15	cat	2
12:10 - 12:20	dog	1
12:10 - 12:20	cat	1
12:10 - 12:20	owl	1
...		

12:00 - 12:10	owl	1
12:00 - 12:10	dog	2
12:00 - 12:10	cat	1
12:05 - 12:15	owl	2
12:05 - 12:15	dog	3
12:05 - 12:15	cat	2
12:10 - 12:20	dog	1
12:10 - 12:20	cat	1
12:10 - 12:20	owl	2
...		

table *not* updated with too late data (12:04, donkey)

table updated with late data (12:17, owl)

purple rows are updated rows that are written to the sink as output

Query Type VS Output Mode

Query type	Output modes
Without aggregations	Append, Update
With window aggregation and watermark	Append, Update, Complete
Other aggregation	Update, Complete

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Thank you! Questions?

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