# Потоковая обработка данных (Kafka, Spark Streaming, Flink)

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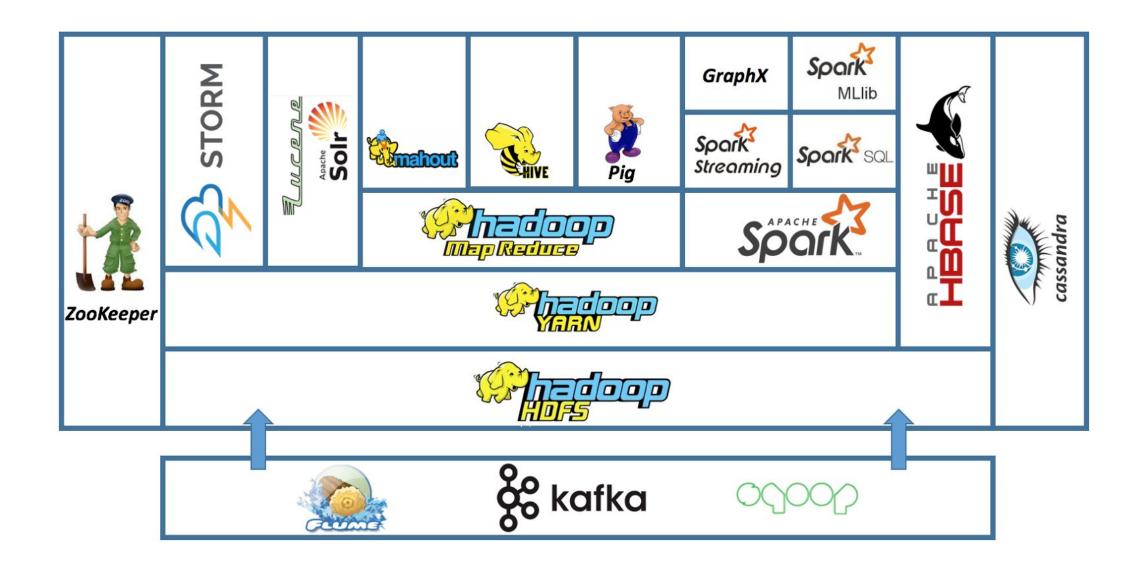
## Структура курса

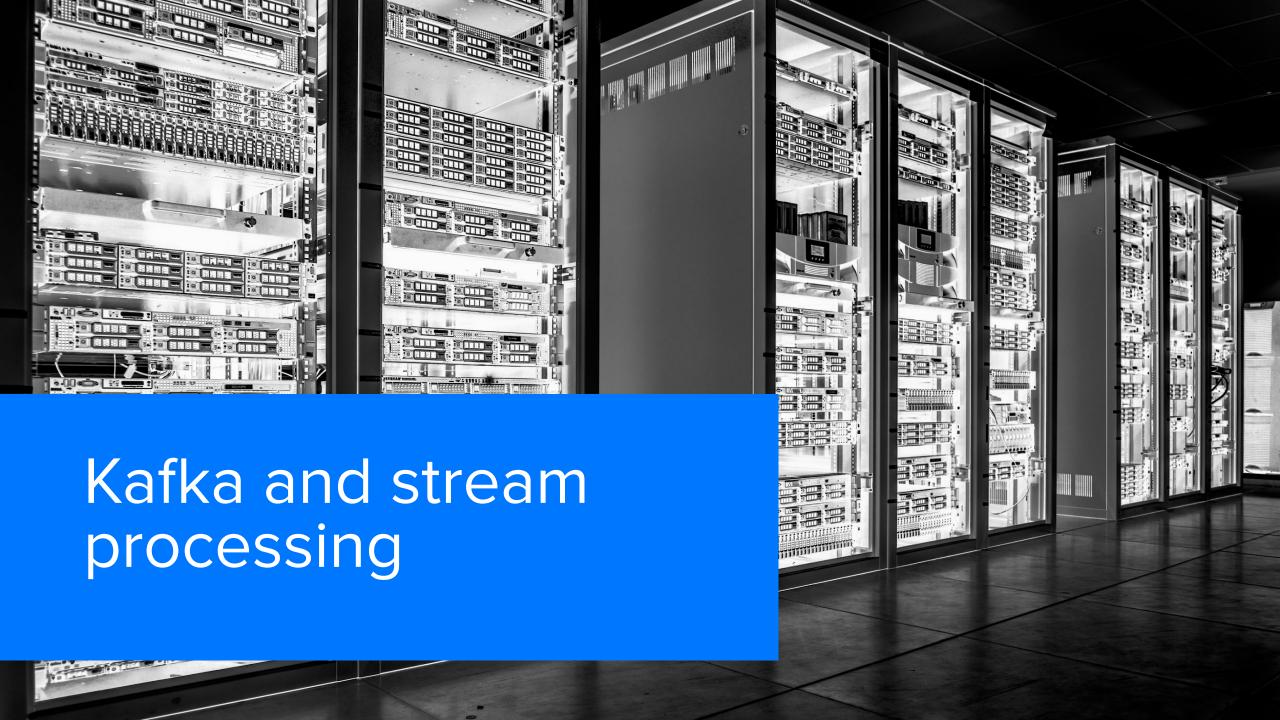
- 1. Введение в Большие Данные
- 2. Hadoop экосистема и MapReduce
- 3. SQL поверх больших данных
- 4. Инструменты визуализации при работе с Большими Данными
- 5. Введение в Scala
- 6. Устройство и API Spark
- 7. Approximate алгоритмы для больших данных
- 8. Потоковая обработка данных (Kafka, Spark Streaming, Flink) 🕒
- 9. Основы распределённой СУБД Apache Cassandra

### План занятия

- 1. Kafka and stream processing
- 2. Spark streaming
- 3. Workshop

# **Hadoop ecosystem**





# **Streaming**

Table 1.1 Classification of real-time systems

Classification	Examples	Latency measured in	Tolerance for delay
Hard	Pacemaker, anti-lock brakes	Microseconds-milliseconds	None—total system fail- ure, potential loss of life
Soft	Airline reservation sys- tem, online stock quotes, VoIP (Skype)	Milliseconds-seconds	Low—no system failure, no life at risk
Near	Skype video, home automation	Seconds-minutes	High—no system failure, no life at risk

#### **Event streams:**

- Event streams are ordered
- Immutable data records
- Event streams are replayable

#### **Event processing:**

- Request-response
- Batch processing
- Stream processing

# **Streaming applications**

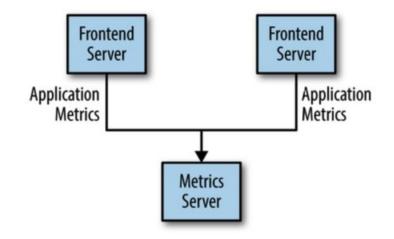
- 1. Device monitoring
- 2. Fault detection
- 3. Media recommendations
- 4. Faster loans
- 5. Fraud detection

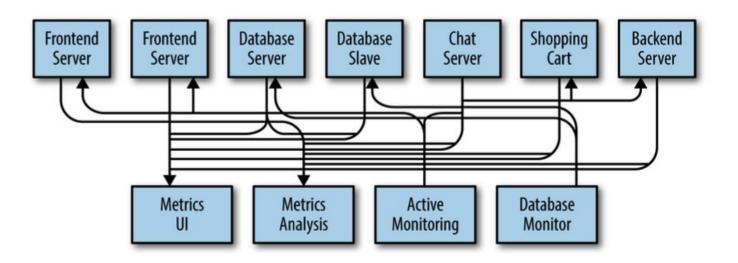
# Why streaming?

Streaming data processing is a big deal in big data these days, and for good reasons; among them are the following:

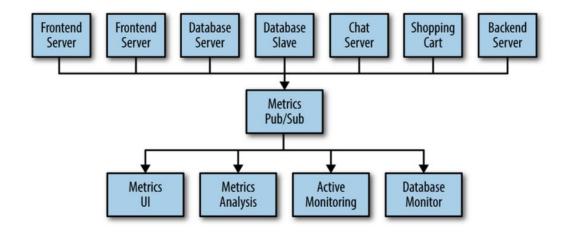
- Businesses crave ever-more timely insights into their data, and switching to streaming is a good way to achieve lower latency
- The massive, unbounded datasets that are increasingly common in modern business are more easily tamed using a system designed for such never-ending volumes of data.
- 3. Processing data as they arrive spreads workloads out more evenly over time, yielding more consistent and predictable consumption of resources.

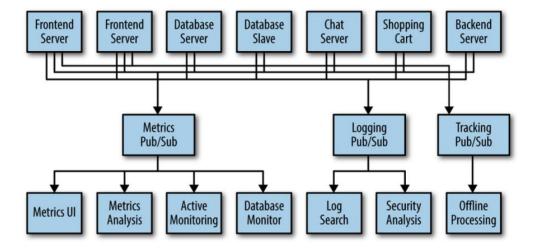
# **Real-time systems**



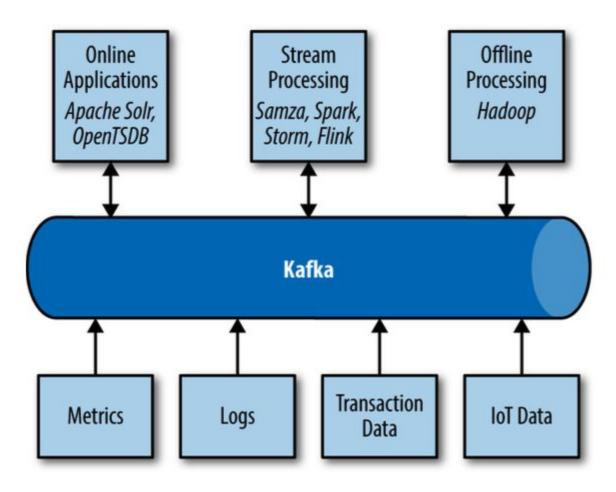


# **Real-time systems**

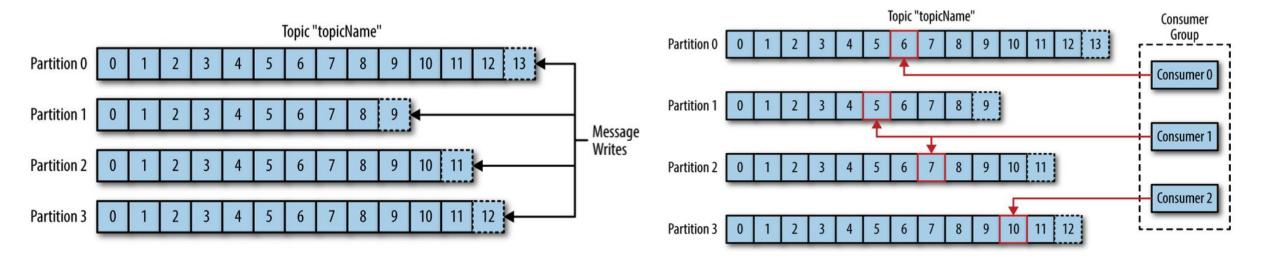




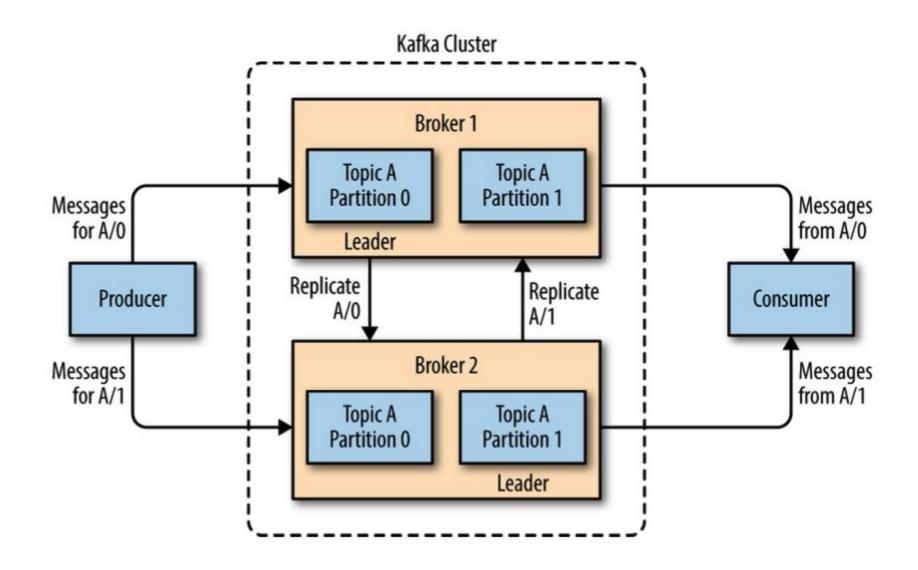
# Kafka



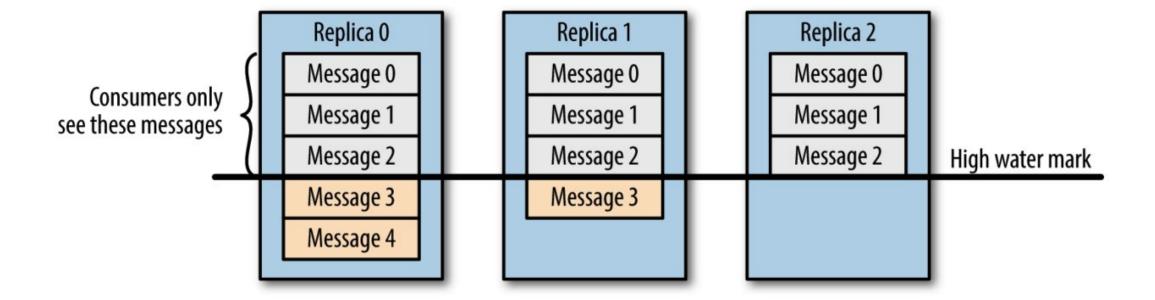
# Kafka topics



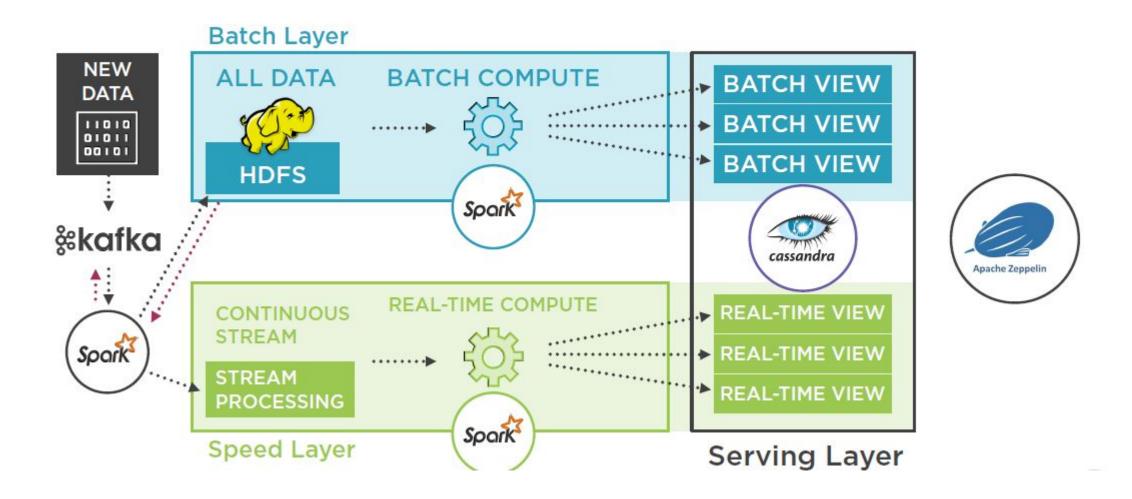
#### Kafka overview



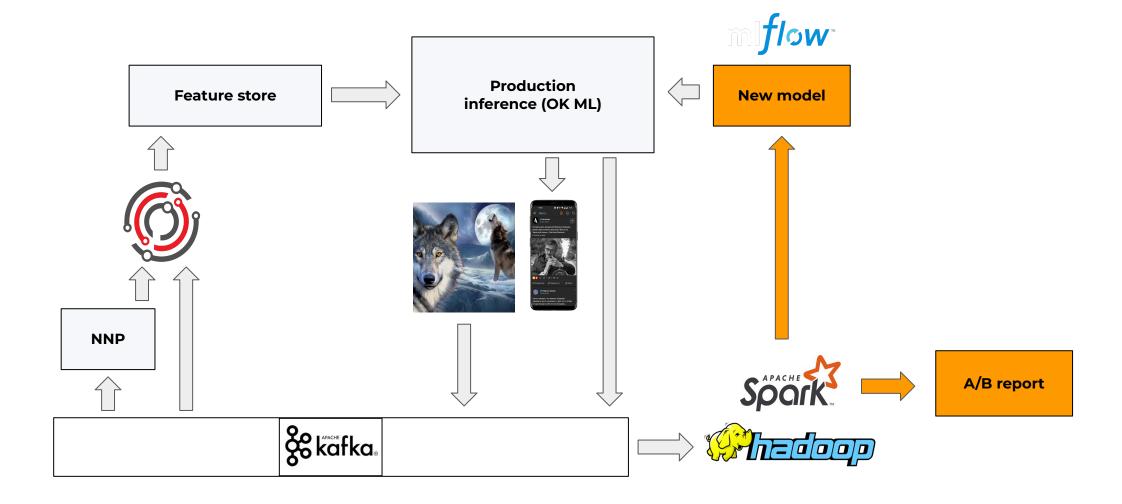
# Kafka replication



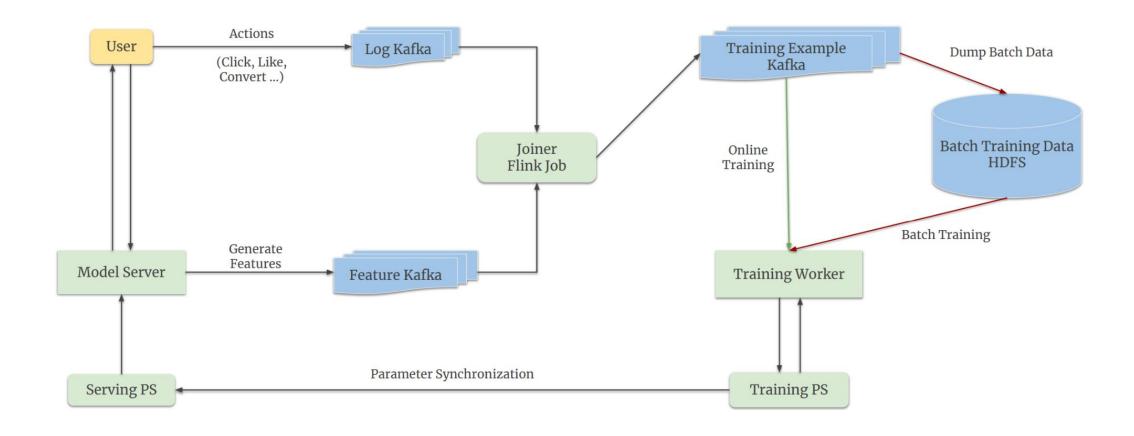
# **Processing layers. Lambda**



#### **OK Feed ML architecture**

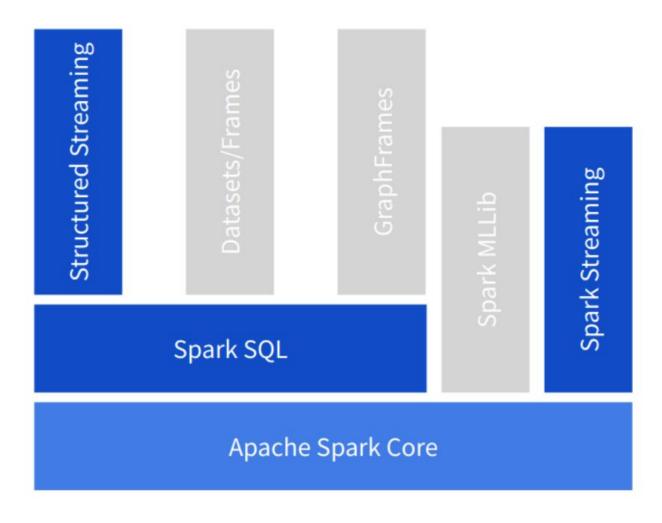


#### TikTok reco arch





# **Spark streaming**



# Streaming generic arch

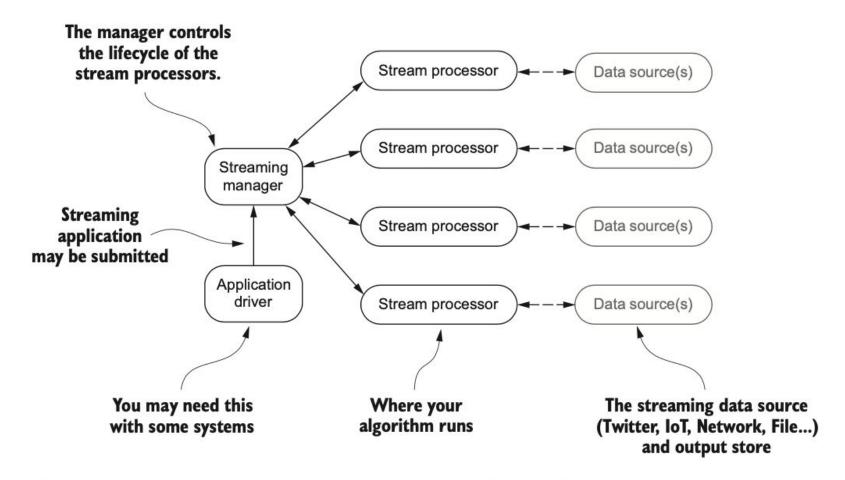


Figure 4.4 Generic streaming analysis architecture you will find with many products on the market

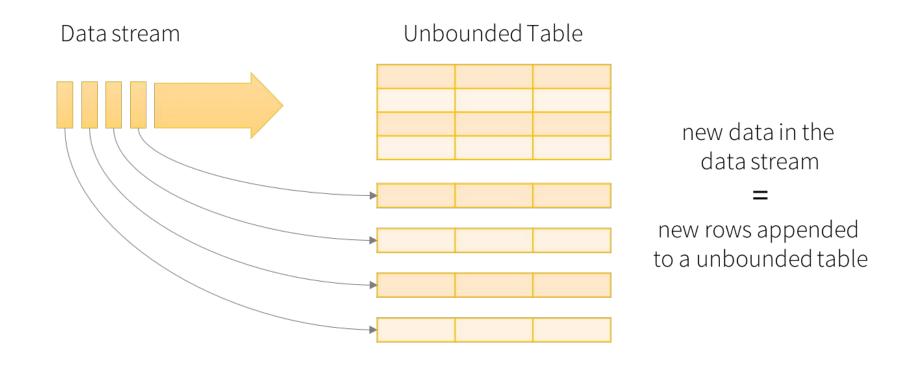
# **Streaming pipeline**



- File source
- Kafka source
- Socket source (for testing)
- Rate source (for testing)
- Transformations
- Aggregations

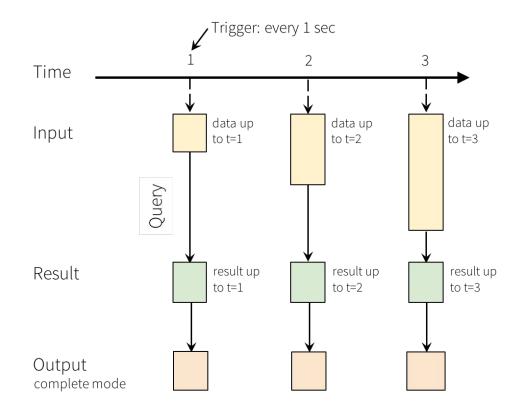
- File source
- Kafka source
- Socket source (for testing)
- Rate source (for testing)

# **Spark streaming abstract model**



Data stream as an unbounded table

# **Spark streaming modes**



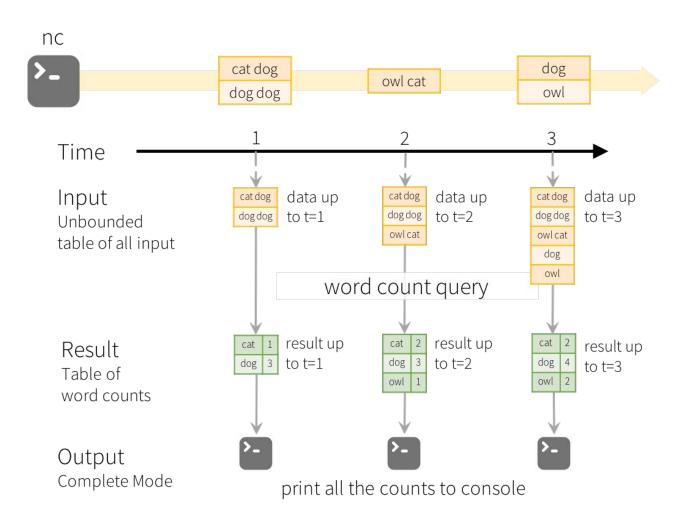
Programming Model for Structured Streaming

Complete Mode - The entire updated Result Table will be written to the external storage.

Append Mode - Only the new rows appended in the Result Table since the last trigger will be written to the external storage.

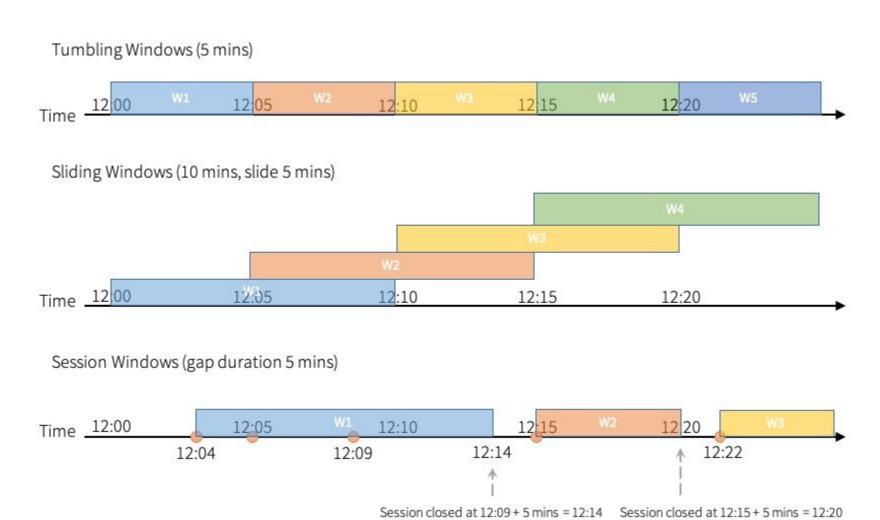
Update Mode - Only the rows that were updated in the Result Table since the last trigger will be written to the external storage.

# **Spark streaming example**



Model of the Quick Example

# **Spark streaming windows**

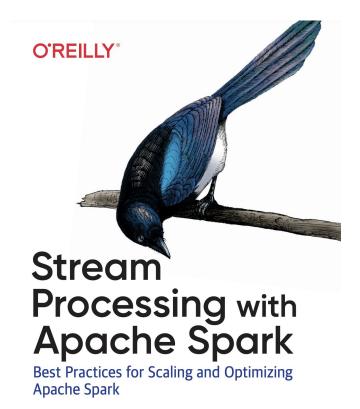


# **Alternative streaming frameworks**

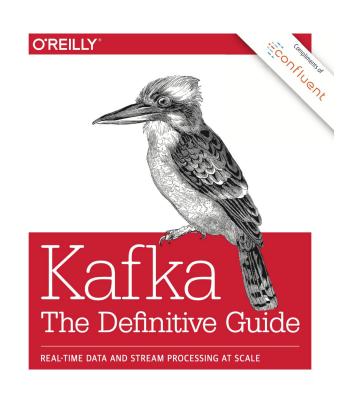
- Apache Storm
- Apache Samza
- Apache Flink
- Amazon Kinesis Streams
- Apache Apex
- Apache Flume



#### **Recommended literature**



Gerard Maas & François Garillot



Neha Narkhede, Gwen Shapira & Todd Palino

#### O'REILLY®

# Stream Processing with Apache Flink

Fundamentals, Implementation, and Operation of Streaming Applications



#### **Recommended literature**

O'REILLY°

