Introduction to Data Stream Processing

Amir H. Payberah
payberah@kth.se
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https://id2221kth.github.io
Where Are We?

**Data Processing**
- **Graph Data**
  - Pregel, GraphLab, PowerGraph
  - GraphX, X-Streem, Chaos
- **Structured Data**
  - Spark SQL
- **Machine Learning**
  - Mllib
  - Tensorflow
- **Batch Data**
  - MapReduce, Dryad
  - FlumeJava, Spark
- **Streaming Data**
  - Storm, SEEP, Naiad, Spark Streaming, Flink,
    Millwheel, Google Dataflow

**Data Storage**
- **Distributed File Systems**
  - GFS, Flat FS
- **NoSQL Databases**
  - Dynamo, BigTable, Cassandra
- **Distributed Messaging Systems**
  - Kafka

**Resource Management**
- Mesos, YARN
Stream processing is the act of continuously incorporating new data to compute a result.
The input data is unbounded.
  - A series of events, no predetermined beginning or end.
Stream Processing (2/4)

- The input data is **unbounded**.
  - A series of events, no predetermined **beginning or end**.
  - E.g., credit card transactions, clicks on a website, or sensor readings from IoT devices.
User applications can then compute various queries over this stream of events.

- E.g., tracking a running count of each type of event or aggregating them into hourly windows
Stream Processing (4/4)

- Database Management Systems (DBMS): data-at-rest analytics
  - Store and index data before processing it.
  - Process data only when explicitly asked by the users.

  - Processing information as it flows, without storing them persistently.
Stream Processing Systems Stack

- **Processing**
  - Spark Streaming, Flink, Storm, Google Dataflow

- **Storage**
  - Partitioned Logs
    - Apache Kafka, Amazon Kinesis, Twitter Distributed Log
  - Messaging Systems
    - Google Cloud Pub/Sub, RabbitMQ, ActiveMQ, Azure Service Bus
Data Stream Storage
We need *disseminate streams of events* from various *producers* to various *consumers*.
Example

- Suppose you have a website, and every time someone loads a page, you send a viewed page event to consumers.
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- Suppose you have a **website**, and every time someone **loads a page**, you send a **viewed page** event to consumers.

- The consumers may do any of the following:
  - **Store** the message in HDFS for future analysis
  - **Count page** views and update a dashboard
  - Trigger an **alert** if a page view fails
  - Send an **email** notification to another user
Possible Solutions

- Messaging systems
- Partitioned logs
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- Partitioned logs
What is Messaging System?

- **Messaging system** is an approach to notify consumers about new events.

- **Messaging systems**
  - Direct messaging
  - Message brokers
Direct Messaging (1/2)

- Necessary in **latency critical** applications (e.g., remote surgery).
- **Both consumers and producers** have to be **online at the same time**.
- A **producer** sends a message containing the event, which is **pushed** to **consumers**.
Direct Messaging (2/2)

- What happens if a consumer crashes or temporarily goes offline? (not durable)

- What happens if producers send messages faster than the consumers can process?
  - Dropping messages
  - Backpressure
Direct Messaging (2/2)

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Direct Messaging (2/2)

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- What happens if producers send messages faster than the consumers can process?
  - Dropping messages
  - Backpressure
- We need message brokers that can log events to process at a later time.
A message broker decouples the producer-consumer interaction. It runs as a server, with producers and consumers connecting to it as clients.
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Producers write messages to the broker, and consumers receive them by reading them from the broker.

Consumers are generally asynchronous.
Message Broker (2/2)

- When multiple consumers read messages in the same topic.
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- **Load balancing**: each message is delivered to one of the consumers.
Message Broker (2/2)

- When **multiple consumers** read messages in the **same topic**.
- **Load balancing**: each message is delivered to **one** of the consumers.

- **Fan-out**: each message is delivered to **all** of the consumers.
Possible Solutions

- Messaging systems
- Partitioned logs
Log-based message brokers combine the durable storage approach with the low-latency notification facilities.
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- A log is an append-only sequence of records on disk.

- A producer sends a message by appending it to the end of the log.

- A consumer receives messages by reading the log sequentially.
  - It waits for a notification, if it reaches the end of the log.
To scale up the system, logs can be partitioned hosted on different machines.

A topic is a group of partitions that all carry messages of the same type.
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A topic is a group of partitions that all carry messages of the same type.

Within each partition, the broker assigns a monotonically increasing sequence number (offset) to every message.
Kafka - A Log-Based Message Broker
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Kafka (5/5)

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Kafka is about logs.

Topics are queues: a stream of messages of a particular type.
Each message is assigned a sequential id called an offset.
Topics are logical collections of partitions (the physical files).

- Ordered
- Append only
- Immutable
Ordering is only guaranteed within a partition for a topic.

Messages sent by a producer to a particular topic partition will be appended in the order they are sent.

A consumer instance sees messages in the order they are stored in the log.
- Partitions of a topic are replicated: fault-tolerance

- A broker contains some of the partitions for a topic.

- One broker is the leader of a partition: all writes and reads must go to the leader.
Producers publish data to the topics of their choice.

Producers are responsible for choosing which message to assign to which partition within the topic.

- Round-robin
- Key-based
Consumers and Consumer Groups (1/2)

- Consumers pull a range of messages from brokers.
- Multiple consumers can read from the same topic on their own pace.
- Consumers maintain the message offset.
Consumers can be organized into consumer groups.

Each message is delivered to only one of the consumers within the group.

All messages from one partition are consumed only by a single consumer within each consumer group.
- The published messages are stored at a set of servers called brokers.
- Brokers are stateless.
- Messages are kept on log for predefined period of time.
Kafka uses Zookeeper for the following tasks:

- Detecting the addition and the removal of brokers and consumers.
- Triggering a rebalance process in each consumer.
- Keeping track of the consumed offset of each partition.
Kafka guarantees that messages from a single partition are delivered to a consumer in order.

There is no guarantee on the ordering of messages coming from different partitions.

Kafka only guarantees at-least-once delivery.

No exactly-once delivery: two-phase commits
# Start the ZooKeeper
zookeeper-server-start.sh config/zookeeper.properties

# Start the Kafka server
kafka-server-start.sh config/server.properties

# Create a topic, called "avg"
kafka-topics.sh --create --zookeeper localhost:2181 --replication-factor 1 --partitions 1 --topic avg

# Print the list of topics
kafka-topics.sh --list --zookeeper localhost:2181

# Produce messages and send them to the topic "avg"
kafka-console-producer.sh --broker-list localhost:9092 --topic avg

# Consume the messages sent to the topic "avg"
kafka-console-consumer.sh --bootstrap-server localhost:9092 --topic avg --from-beginning
object ScalaProducerExample extends App {
  def getRandomVal: String = { ... }
  val brokers = "localhost:9092"
  val topic = "avg"

  val props = new Properties()
  props.put(ProducerConfig.BOOTSTRAP_SERVERS_CONFIG, brokers)
  val producer = new KafkaProducer[String, String](props)

  while (true) {
    val data = new ProducerRecord[String, String](topic, null, getRandomVal)
    producer.send(data)
  }

  producer.close()
}
Programming Kafka in Scala - Consumer

```scala
object ScalaConsumerExample extends App {
  val brokers = "localhost:9092"
  val groupId = "group1"
  val topic = "avg"

  val props = new Properties()
  props.put(ConsumerConfig.BOOTSTRAP_SERVERS_CONFIG, brokers)
  props.put(ConsumerConfig.GROUP_ID_CONFIG, groupId)

  val consumer = new KafkaConsumer[String, String](props)
  consumer.subscribe(Collections.singletonList(topic))

  Executors.newSingleThreadExecutor.execute(new Runnable {
    override def run(): Unit = {
      while (true) {
        val records = consumer.poll(1000)
        for (record <- records) {
          System.out.println(record.key() + "", record.value() + ",", record.offset())
        }
      }
    }
  } }
```
Data Stream Processing
Streaming Data

- Data stream is **unbound data**, which is broken into a **sequence of individual tuples**.
- A data **tuple** is the **atomic** data item in a data stream.
- Can be **structured**, **semi-structured**, and **unstructured**.
Streaming Data Processing Design Points

- Event time vs. processing time
- Continuous vs. micro-batch processing
- Record-at-a-Time vs. declarative APIs
Streaming Data Processing Design Points

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Event Time vs. Processing Time (1/2)

- **Event time**: the time at which events *actually occurred*.
  - Timestamps inserted into each record *at the source*.

- **Processing time**: the time when the record is *received at the streaming application*. 
- Ideally, event time and processing time should be equal.
- Skew between event time and processing time.

[https://www.oreilly.com/ideas/the-world-beyond-batch-streaming-101]
Streaming Data Processing Design Points

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Windowing (1/3)

- **Window**: a buffer associated with an input port to retain previously received tuples.
- **Four** different windowing management policies.
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- **Four different windowing management policies.**
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  - Time-based policy: a wall-clock time period
  - Delta-based policy: a delta threshold in a tuple attribute
Windowing (1/3)

- **Window**: a buffer associated with an input port to retain previously received tuples.

- **Four** different windowing management policies.
  - **Count-based policy**: the maximum number of tuples a window buffer can hold
  - **Time-based policy**: a wall-clock time period
  - **Delta-based policy**: a delta threshold in a tuple attribute
  - **Punctuation-based policy**: a punctuation is received
Windowing (2/3)

- Two types of windows: **tumbling** and **sliding**
Two types of windows: tumbling and sliding

- **Tumbling window**: supports batch operations.
  - When the buffer fills up, all the tuples are evicted.

```
[ ] 1 2 3 4 5 6 7
```
Two types of windows: tumbling and sliding

Tumbling window: supports batch operations.
- When the buffer fills up, all the tuples are evicted.

Sliding window: supports incremental operations.
- When the buffer fills up, older tuples are evicted.
Windowing (3/3)

In summary:

- **Fixed windows**
- **Sliding windows**
- **Sessions**

[https://www.oreilly.com/ideas/the-world-beyond-batch-streaming-101]
Streaming Data Processing Patterns

- **Micro-batch systems**
  - **Batch engines**
  - Slicing up the unbounded data into a sets of bounded data, then process each batch.

![Diagram of streaming data processing]

- Microbatches of DataFrames
- Data
- File/Kafka
- Results
Streaming Data Processing Patterns

- **Micro-batch systems**
  - Batch engines
  - Slicing up the unbounded data into a set of bounded data, then process each batch.

- **Continuous processing-based systems**
  - Each node in the system continually listens to messages from other nodes and outputs new updates to its child nodes.
Processing Patterns - Micro-Batch Processing (1/2)

- **Fixed windows**

- Windowing input data into **fixed-sized windows**, then processing each of window as a **bounded data source**.

[https://www.oreilly.com/ideas/the-world-beyond-batch-streaming-101]
- Session

- Periods of activity (e.g., for a specific user) terminated by a gap of inactivity.

[https://www.oreilly.com/ideas/the-world-beyond-batch-streaming-101]
Processing Patterns - Continuous Processing (1/4)

- **Time-agnostic**
  - Time is essentially **irrelevant**, i.e., all relevant logic is **data driven**.
  - E.g., filtering, inner-join, ...

[https://www.oreilly.com/ideas/the-world-beyond-batch-streaming-101]
Approximation algorithms

These algorithms typically have some element of time in their design.

E.g., approximate Top-N, streaming K-means, ...

[https://www.oreilly.com/ideas/the-world-beyond-batch-streaming-101]
Processing Patterns - Continuous Processing (3/4)

- Windowing by processing time
- The system buffers up incoming data into windows until some amount of processing time has passed.
- E.g., five-minute fixed windows

[https://www.oreilly.com/ideas/the-world-beyond-batch-streaming-101]
- Windowing by **event time**
- This model is what we use when we need to **observe a data source in finite chunks that reflect the times at which those events actually happened.**

[https://www.oreilly.com/ideas/the-world-beyond-batch-streaming-101]
Streaming Data Processing Design Points

- Event time vs. processing time
- Continuous vs. micro-batch processing
- Record-at-a-Time vs. declarative APIs
Record-at-a-Time vs. Declarative APIs

▶ **Record-at-a-Time** API (e.g., Storm)
  - Low-level API
  - Passes each event to the application and let it react.
  - Useful when applications need full control over the processing of data.
  - Complicated factors, such as maintaining state, are governed by the application.

▶ **Declarative** API (e.g., Spark streaming, Flink, Google Dataflow)
  - Applications specify what to compute not how to compute it in response to each new event.
Streaming Data Processing Model
The tuples are processed by the application’s operators or processing element (PE).

A PE is the basic functional unit in an application.
- A PE processes input tuples, applies a function, and outputs tuples.
- A set of PEs and stream connections, organized into a data flow graph.
Streaming Data Processing (2/2)

- Data flow programming

- Flow composition: techniques for creating the topology associated with the flow graph for an application.

- Flow manipulation: the use of PEs to perform transformations on data flows.
Data Flow Composition

- Data flow composition patterns:
  - **Static** composition
  - **Dynamic** composition
Edge adaptation: converting data from external sources into tuples that can be consumed by downstream PEs.
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- **Aggregation**: collecting and summarizing a subset of tuples from one or more streams.
PEs Tasks (1/2)

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PEs Tasks (1/2)

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- **Merging**: combining multiple input streams.
▶ Logical and mathematical operations: applying different logical, relational and mathematical processing to tuple attributes.
PEs Tasks (2/2)

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- **Sequence manipulation**: reordering, delaying, or altering the temporal properties of a stream.
- **Logical and mathematical operations**: applying different logical, relational and mathematical processing to tuple attributes.

- **Sequence manipulation**: reordering, delaying, or altering the temporal properties of a stream.

- **Custom data manipulations**: applying data mining, machine learning, ...
A PE can either maintain internal state across tuples while processing them, or process tuples independently of each other.

- Stateful vs. stateless tasks
Stateless tasks: do not maintain state and process each tuple independently of prior history, or even from the order of arrival of tuples.
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- Easily parallelized.
- No synchronization.
- Restart upon failures without the need of any recovery procedure.
Stateful tasks: involves maintaining information across different tuples to detect complex patterns.
- **Stateful** tasks: involves maintaining information across different tuples to detect complex patterns.

- A **PE** is usually a **synopsis** of the tuples received so far.

- A subset of **recent tuples** kept in a **window buffer**.
Runtime Systems
Job and Job Management

- At runtime, an application is represented by one or more jobs.

- Jobs are deployed as a collection of PEs.

- Job management component must identify and track individual PEs, the jobs they belong to, and associate them with the user that instantiated them.
Logical Plan vs. Physical Plan (1/3)

- **Logical plan**: a data flow graph, where the vertices correspond to **PEs**, and the edges to **stream connections**.

- **Physical plan**: a data flow graph, where the vertices correspond to OS **processes**, and the edges to **transport connections**.
Logical Plan vs. Physical Plan (2/3)

Logical plan

Different physical plans
How to map a network of PEs onto the physical network of nodes?

- Parallelization
- Fault tolerance
- Optimization
Parallelization
Parallelization

- How to **scale** with increasing the **number queries** and the **rate of incoming events**?

- **Three** forms of parallelisms.
  - Pipelined parallelism
  - Task parallelism
  - Data parallelism
Pipelined Parallelism

- Sequential stages of a computation execute **concurrently** for different data items.
Independent processing stages of a larger computation are executed concurrently on the same or distinct data items.
The same computation takes place concurrently on different data items.
Data Parallelism (2/2)

- How to **allocate** data items to each **computation instance**?
Fault Tolerance
The recovery methods of streaming frameworks must take:

- **Correctness**, e.g., data loss and duplicates
- **Performance**, e.g., low latency
Recovery Methods (2/2)

- GAP recovery
- Rollback recovery
- Precise recovery
GAP Recovery (Cold Restart)

- The weakest recovery guarantee
- A new task takes over the operations of the failed task.
- The new task starts from an empty state.
- Tuples can be lost during the recovery phase.
Rollback Recovery

- The information loss is avoided, but the output may contain duplicate tuples.

- Three types of rollback recovery:
  - Active backup
  - Passive backup
  - Upstream backup
Rollback Recovery - Active Backup

- Each processing node has an associated backup node.
- Both primary and backup nodes are given the same input.
- The output tuples of the backup node are logged at the output queues and they are not sent downstream.
- If the primary fails, the backup takes over by sending the logged tuples to all downstream neighbors and then continuing its processing.
Rollback Recovery - Passive Backup

- Periodically check-points processing state to a shared storage.

- The backup node takes over from the latest checkpoint when the primary fails.

- The backup node is always equal or behind the primary.
Rollback Recovery - Upstream Backup

- **Upstream nodes** store the tuples until the downstream nodes acknowledge them.

- If a node fails, an empty node **rebuilds the latest state** of the failed primary from the logs kept at the upstream server.

- There is **no backup node** in this model.
Precise Recovery

- Post-failure output is exactly the same as the output without failure.

- Can be achieved by modifying the algorithms for rollback recovery.
  - For example, in passive backup, after a failure occurs the backup node can ask the downstream nodes for the latest tuples they received and trim the output queues accordingly to prevent the duplicates.
Optimization
Reduction of the **data volume** as early as possible.

- Sampling, filtering, quantization, projection, and aggregation.
Optimization - Reordering

- Operator reordering
  - Executing the *computationally cheaper* operator and/or the *more selective operator earlier* reduces the overall cost.
Removing the **redundant** segments from a data flow graph.
It changes only the physical layout.

- If two operators of the two ends of a stream connection are placed on different hosts: non-negligible network cost
Optimizer - Operator Fusion

- It changes only the physical layout.

- If two operators of the two ends of a stream connection are placed on different hosts: non-negligible network cost

- It is effective, if the per-tuple processing cost of the operators being fused is lower than the cost of transferring tuples across the stream connection.
Optimization - Tuple Batching

- Processing a group of tuples in every iteration of an operator’s internal algorithm.
- Can increase the throughput at the expense of higher latency.
Optimization - Load Balancing

- Flow partitioning to **distribute the workload**, e.g., **data or task parallelism**.
- Distributing the **load evenly** across the different subflows.
Optimization - Load Shedding

- Used by an operator to **reduce** the amount of **computational resources** it uses.
  - Decrease the operator **latency**, and **improve** the **throughput**.

- Different techniques: dropping incoming tuples, data reduction techniques (e.g., sampling), ...
Summary
Summary

- Messaging system and partitioned logs
- Decoupling producers and consumers
- Kafka: distributed, topic oriented, partitioned, replicated log service
- Logs, topics, partition
- Kafka architecture: producer, consumer (groups), broker, coordinator
Summary

- SPS vs. DBMS
- Data stream, unbounded data, tuples
- Event-time vs. processing time
- Micro-batch vs. continues processing (windowing)
- PEs and dataflow
- Stateless vs. Stateful PEs
- SPS runtime: parallelization, fault-tolerance, optimization
References

- J. Kreps et al., “Kafka: A distributed messaging system for log processing”, NetDB 2011
- J. Hwang et al., “High-availability algorithms for distributed stream processing”, ICDE 2005
Questions?