Introduction to Data Stream Processing

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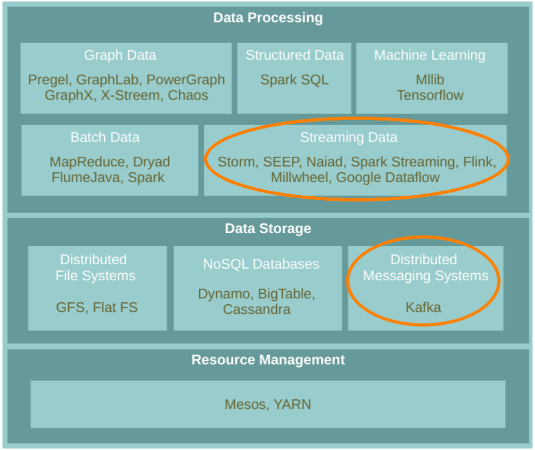
The Course Web Page

`https://id2221kth.github.io`

Where Are We?

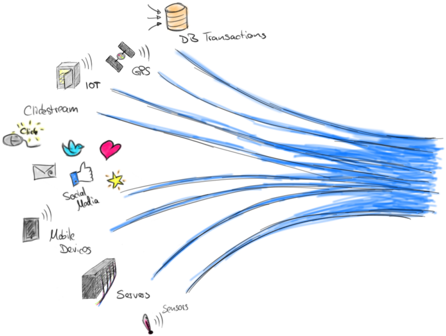

Data Processing
Graph Data
Pregel, GraphLab, PowerGraph
GraphX, X-Streem, Chaos
Structured Data
Spark SQL
Machine Learning
Mllib
Tensorflow
Batch Data
MapReduce, Dryad
FlumeJava, Spark
Streaming Data
Storm, SEEP, Naiad, Spark Streaming, Flink,
Millwheel, Google Dataflow
Data Storage
Distributed
File Systems
GFS, Flat FS
NoSQL Databases
Dynamo, BigTable,
Cassandra
Distributed
Messaging Systems
Kafka
Resource Management
Mesos, YARN

Stream Processing (1/4)

- Stream processing is the act of continuously incorporating new data to compute a result.

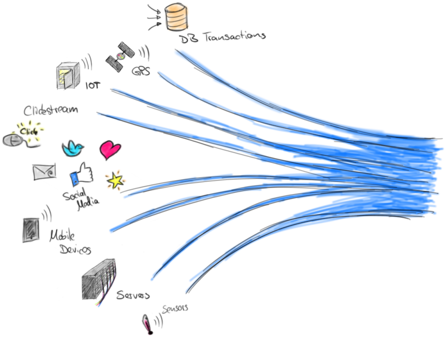
Stream Processing (2/4)

- The input data is unbounded.
  - A series of events, no predetermined beginning or end.



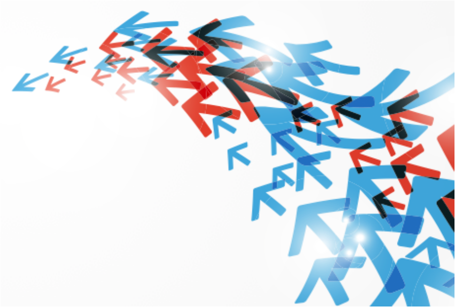
Stream Processing (2/4)

- 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.



Stream Processing (3/4)

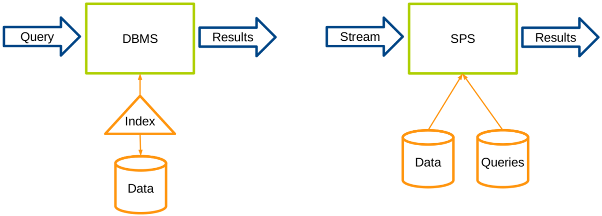
- User applications can then compute various queries over this stream of events.
  - E.g., tracking a running count of each type of event or aggregating them into hourly windows



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.

- Stream Processing Systems (SPS): data-in-motion analytics
  - 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

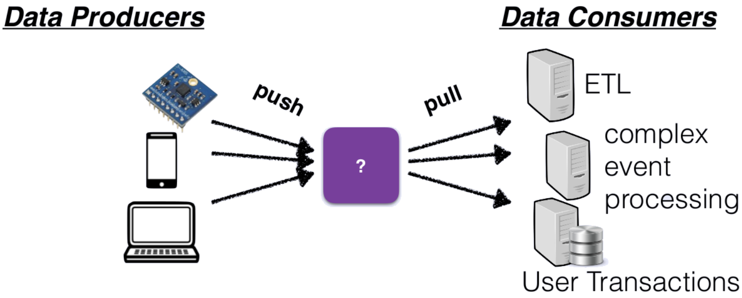
Messaging Systems

Google Cloud Pub/Sub, RabbitMQ
ActiveMQ, Azure Service Bus

Data Stream Storage

The Problem

- 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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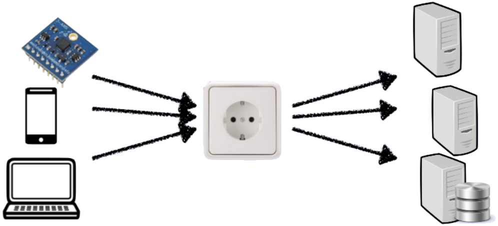
What is Messaging System?

- Messaging system is an approach to notify consumers about new events.
- Messaging systems
  - Direct messaging
  - Message brokers

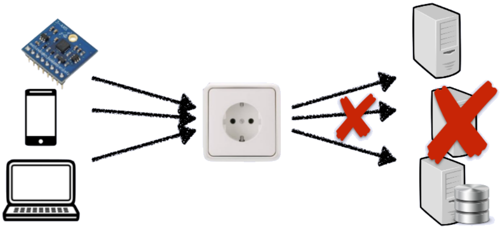
Direct Messaging (1/2)

- 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.



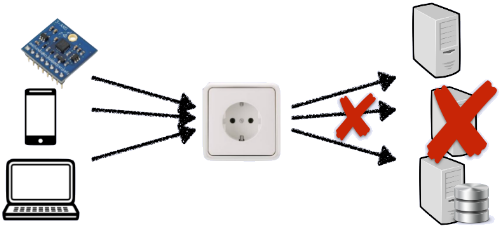
Direct Messaging (2/2)

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



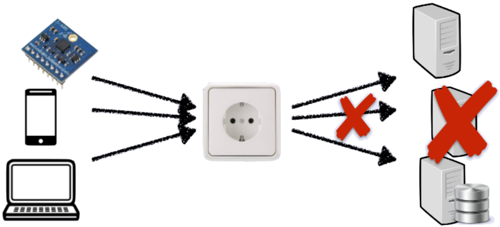
Direct Messaging (2/2)

- 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



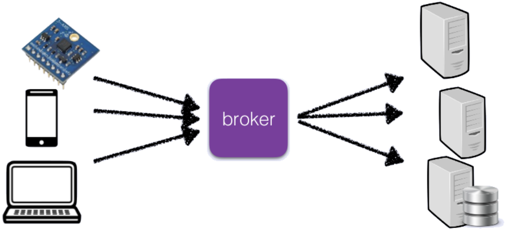
Direct Messaging (2/2)

- 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
- We need message brokers that can log events to process at a later time.



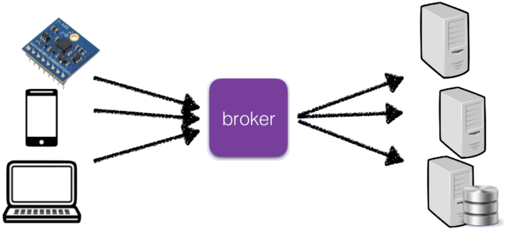
Message Broker (1/2)

- A message broker decouples the producer-consumer interaction.
- It runs as a server, with producers and consumers connecting to it as clients.



Message Broker (1/2)

- A message broker decouples the producer-consumer interaction.
- It runs as a server, with producers and consumers connecting to it as clients.
- Producers write messages to the broker, and consumers receive them by reading them from the broker.
- Consumers are generally asynchronous.



Message Broker (2/2)

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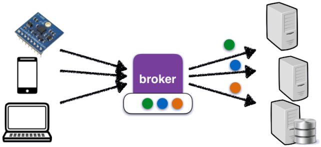
- Load balancing: each message is delivered to one of the consumers.



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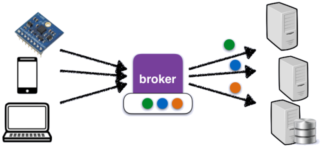
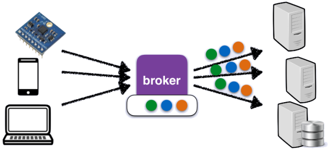


- Fan-out: each message is delivered to all of the consumers.



Possible Solutions

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- Partitioned logs

Partitioned Logs (1/2)

- Log-based message brokers combine the durable storage approach with the low-latency notification facilities.

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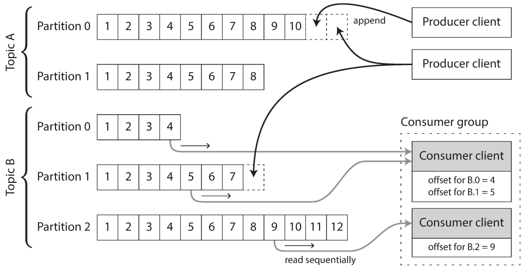
- A log is an append-only sequence of records on disk.
- A producer sends a message by appending it to the end of the log.
- A consumer receives messages by reading the log sequentially.
    - It waits for a notification, if it reaches the end of the log.

Partitioned Logs (2/2)

- 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.



Partitioned Logs (2/2)

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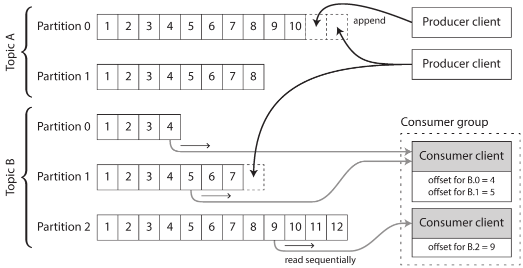
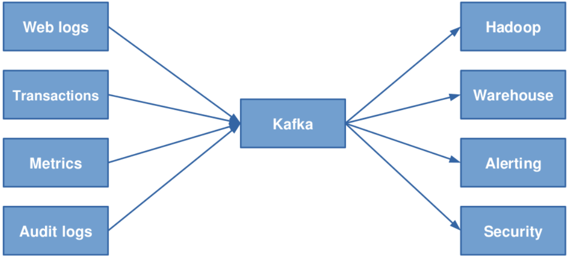
- Within each partition, the broker assigns a monotonically increasing sequence number (offset) to every message



Kafka - A Log-Based Message Broker

Kafka (1/5)

- Kafka is a distributed, topic oriented, partitioned, replicated commit log service.



Kafka (2/5)

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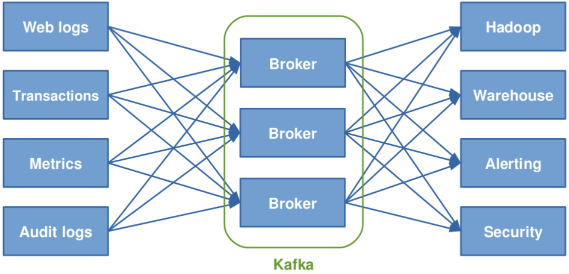

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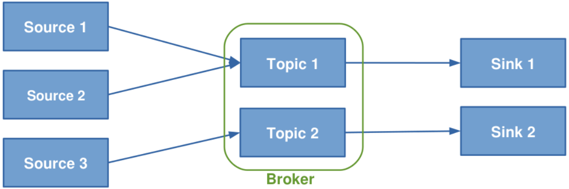

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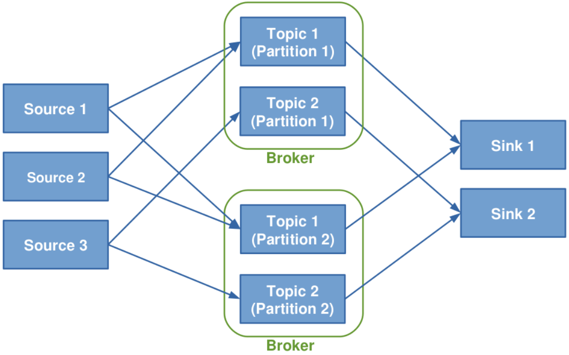

Kafka (5/5)

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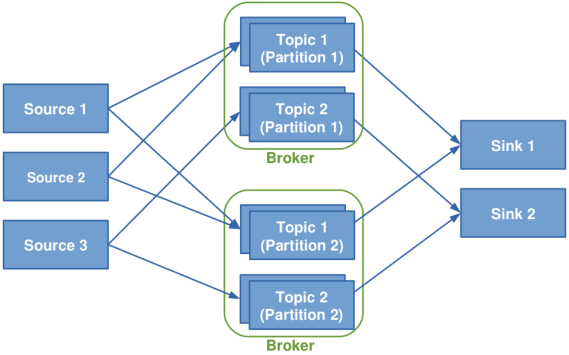

Logs, Topics and Partition (1/5)

- Kafka is about logs.
- Topics are queues: a stream of messages of a particular type

```
jkreps-mn:~ jkreps$ tail -f -n 20 /var/log/apache2/access_log
::1 - - [23/Mar/2014:15:07:00 -0700] "GET /images/apache_feather.gif HTTP/1.1" 200 4128
::1 - - [23/Mar/2014:15:07:04 -0700] "GET /images/producer_consumer.png HTTP/1.1" 200 86
::1 - - [23/Mar/2014:15:07:04 -0700] "GET /images/log_anatomy.png HTTP/1.1" 200 19579
::1 - - [23/Mar/2014:15:07:04 -0700] "GET /images/consumer-groups.png HTTP/1.1" 200 2682
::1 - - [23/Mar/2014:15:07:04 -0700] "GET /images/log_compaction.png HTTP/1.1" 200 41414
::1 - - [23/Mar/2014:15:07:04 -0700] "GET /documentation.html HTTP/1.1" 200 189893
::1 - - [23/Mar/2014:15:07:04 -0700] "GET /images/log_cleaner_anatomy.png HTTP/1.1" 200
::1 - - [23/Mar/2014:15:07:04 -0700] "GET /images/kafka_log.png HTTP/1.1" 200 134321
::1 - - [23/Mar/2014:15:07:04 -0700] "GET /images/mirror-maker.png HTTP/1.1" 200 17054
::1 - - [23/Mar/2014:15:08:07 -0700] "GET /documentation.html HTTP/1.1" 200 189937
::1 - - [23/Mar/2014:15:08:07 -0700] "GET /styles.css HTTP/1.1" 304 -
::1 - - [23/Mar/2014:15:08:07 -0700] "GET /images/kafka_logo.png HTTP/1.1" 304 -
::1 - - [23/Mar/2014:15:08:07 -0700] "GET /images/producer_consumer.png HTTP/1.1" 304 -
::1 - - [23/Mar/2014:15:08:07 -0700] "GET /images/log_anatomy.png HTTP/1.1" 304 -
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::1 - - [23/Mar/2014:15:09:55 -0700] "GET /documentation.html HTTP/1.1" 200 195264
```
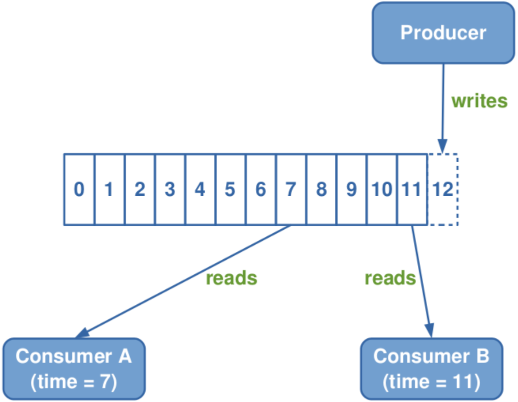
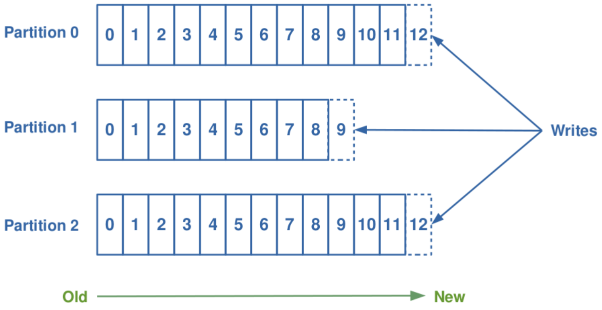

Logs, Topics and Partition (2/5)

- Each message is assigned a sequential id called an offset.



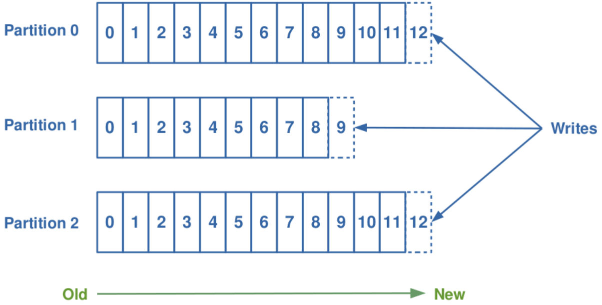
Logs, Topics and Partition (3/5)

- Topics are logical collections of partitions (the physical files).
  - Ordered
  - Append only
  - Immutable



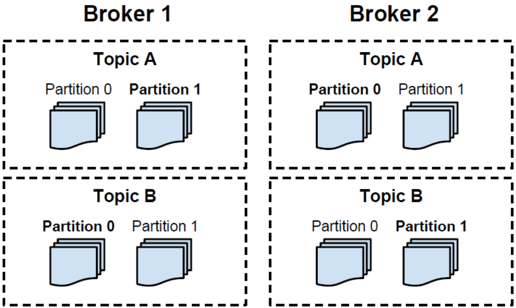
Logs, Topics and Partition (4/5)

- 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.

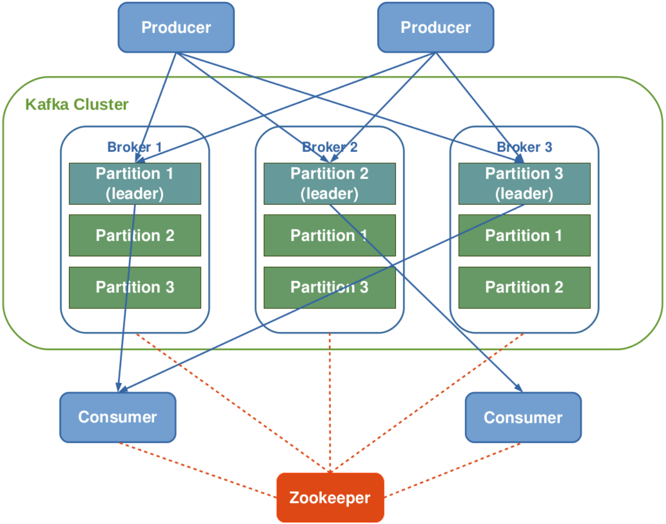


Logs, Topics and Partition (5/5)

- 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.



Kafka Architecture

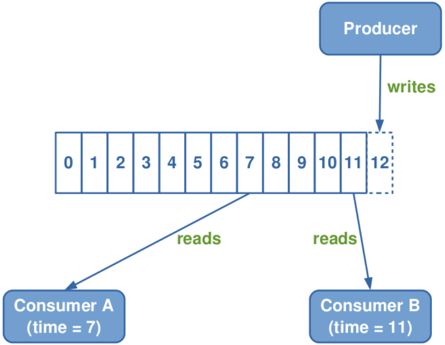


Producers

- 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

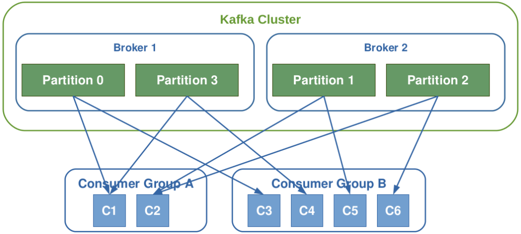
Consumers and Consumer Groups (1/2)

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



Consumers and Consumer Groups (2/2)

- 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.



Brokers

- The published messages are stored at a set of servers called brokers.
- Brokers are sateless.
- Messages are kept on log for predefined period of time.

Coordination

- 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.

Delivery Guarantees

- 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 and Work With Kafka

```
# 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
```

Programming Kafka in Scala - Producer

```scala
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

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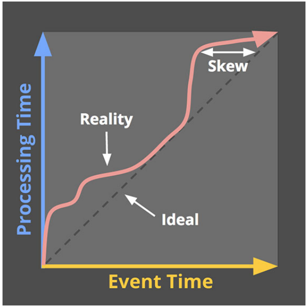
Event Time vs. Processing Time (1/2)

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

- Prcosseing time: the time when the record is received at the streaming application.

Event Time vs. Processing Time (2/2)

- 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

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

Windowing (1/3)

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- Four different windowing management policies.

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  - 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)

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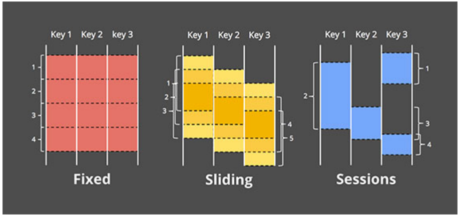
- Tumbling window: supports batch operations.
  - When the buffer fills up, all the tuples are evicted.

- Sliding window: supports incremental operations.
  - When the buffer fills up, older tuples are evicted.

Windowing (3/3)

- In summary:
  - Fixed windows
  - Sliding windows
  - Sessions



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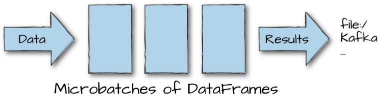
Streaming Data Processing Patterns

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



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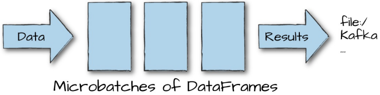
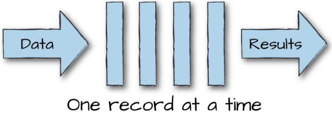
  - Slicing up the unbounded data into a sets of bounded data, then process each batch.

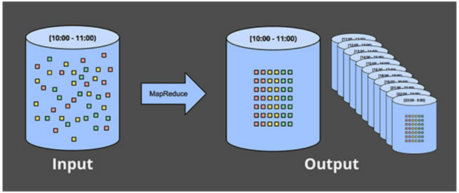


- Continuous processing-based systems
  - Each node in the system continually listens to messages from other nodes and outputs new updates to its child nodes.



Processing Patterns - Micro-Batch Processing (1/2)

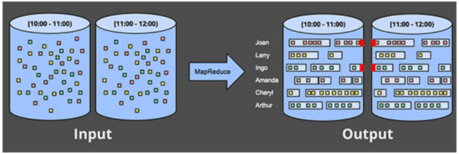
- Fixed windows
- Windowing input data into fixed-sized windows, then processing each of window as a bounded data source.



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

Processing Patterns - Micro-Batch Processing (2/2)

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



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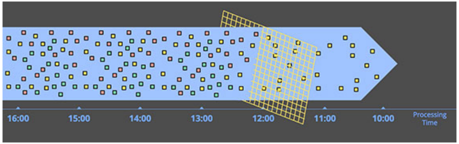
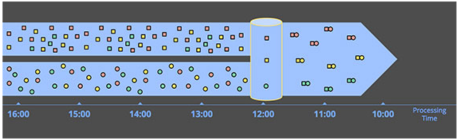
Processing Patterns - Continuous Processing (1/4)

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





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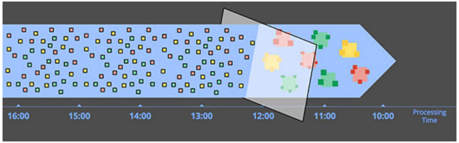
Processing Patterns - Continuous Processing (2/4)

- Approximation algorithms
- These algorithms typically have some element of time in their design.
- E.g., approximate Top-N, streaming K-means, ...



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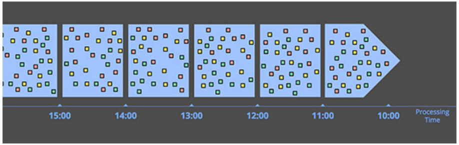
Processing Patterns - Continuous Processing (3/4)

- 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



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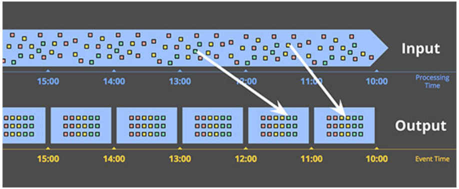
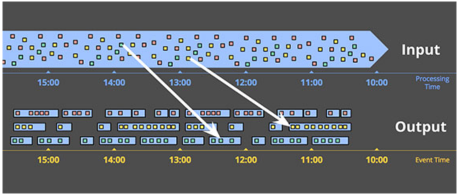
Processing Patterns - Continuous Processing (4/4)

- 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.





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Streaming Data Processing Design Points

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

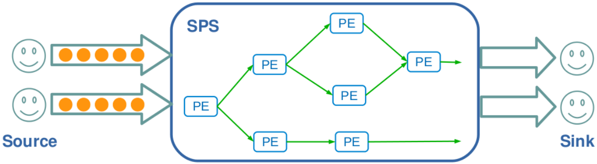
Record-at-a-Time vs. Declarative APIs

- 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)
  - Aapplications specify what to compute not how to compute it in response to each new event.

Streaming Data Processing Model

Streaming Data Processing (1/2)

- 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.

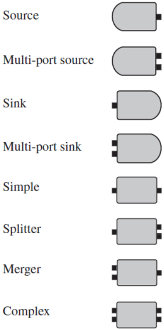


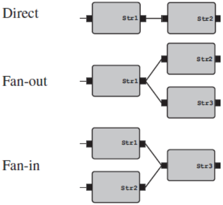
Streaming Data Processing (2/2)

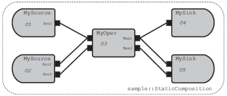
- Data flow programming
- Flow composition: techniques for creating the topology associated with the flow graph for an application.
- Flow manipulation: the use of PEs to perform transformations on data flows.

Data Flow Composition

- Data flow composition patterns:
  - Static composition
  - Dynamic composition







PEs Tasks (1/2)

- 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.
- Splitting: partitioning a stream into multiple streams.
- Merging: combining multiple input streams.

PEs Tasks (2/2)

- Logical and mathematical operations: applying different logical, relational and mathematical processing to tuple attributes.

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- 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, ...

PEs States (1/3)

- A PE can either maintain internal state across tuples while processing them, or process tuples independently of each other.
- Stateful vs. stateless tasks

PEs States (2/3)

- Stateless tasks: do not maintain state and process each tuple independently of prior history, or even from the order of arrival of tuples.

PEs States (2/3)

- Stateless tasks: do not maintain state and process each tuple independently of prior history, or even from the order of arrival of tuples.
- Easily parallelized.
- No synchronization.
- Restart upon failures without the need of any recovery procedure.

PEs States (3/3)

- Stateful tasks: involves maintaining information across different tuples to detect complex patterns.

PEs States (3/3)

- 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.

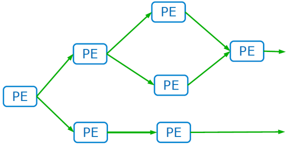
Runtime Systems

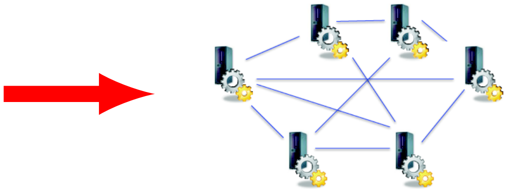
Job and Job Management

- 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.

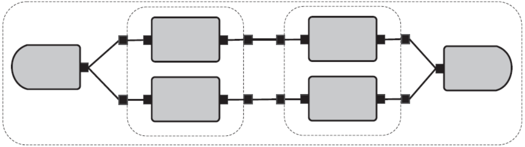
Logical Plan vs. Physical Plan (1/3)

- 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.

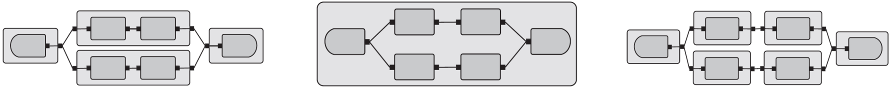




Logical Plan vs. Physical Plan (2/3)



Logical plan



Different physical plans

Logical Plan vs. Physical Plan (3/3)

- How to map a network of PEs onto the physical network of nodes?
  - Parallelization
  - Fault tolerance
  - Optimization

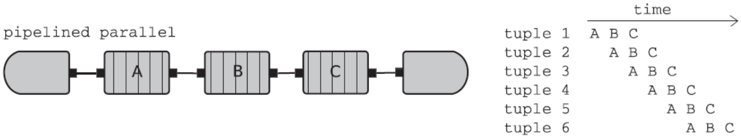
Parallelization

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

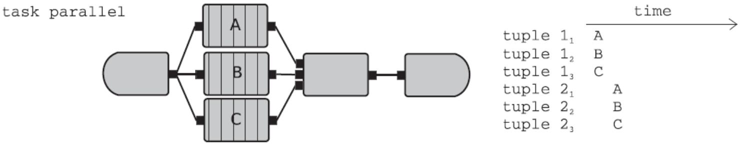
Pipelined Parallelism

- Sequential stages of a computation execute concurrently for different data items.



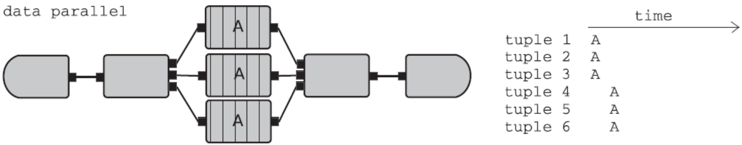
Task Parallelism

- Independent processing stages of a larger computation are executed concurrently on the same or distinct data items.



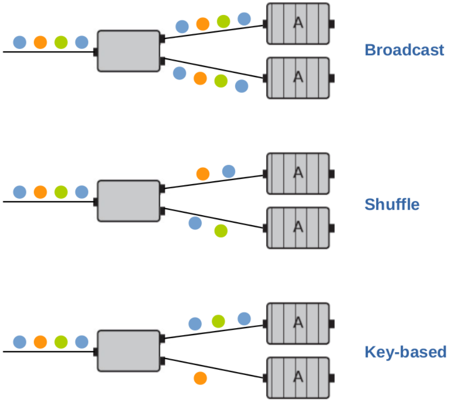
Data Parallelism (1/2)

- 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

Recovery Methods (1/2)

- 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)

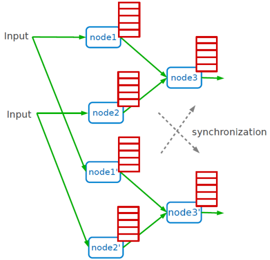
- The weakest recovery guarantee
- A new task takes over the operations of the failed task.
- The new task starts from an empty state.
- Tuples can be lost during the recovery phase.

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.

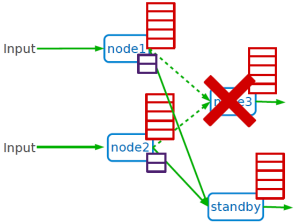


Rollback Recovery - Passive Backup

- 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

Optimization - Early Data Reduction

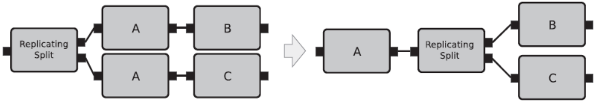
- Reducing the data volume as early as possible.
    - Sampling, filtering, quantization, projection, and aggregation.

Optimization - Reordering

- Operator reordering
  - Executing the computationally cheaper operator and/or the more selective operator earlier reduces the overall cost.

Optimization - Redundancy Elimination

- Removing the redundant segments from a data flow graph.



Optimization - 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

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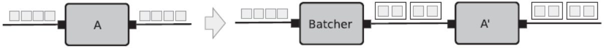
- It changes only the physical layout.
- If two operators of the two ends of a stream connection are placed on different hosts: non-negligible network cost
- It is effective, if the per-tuple processing cost of the operators being fused is lower than the cost of transferring tuples across the stream connection.

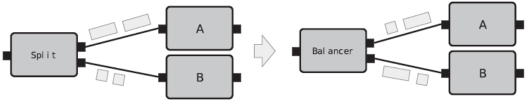
Optimization - Tuple Batching

- 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, topcs, 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

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Questions?