Chapter 6
PROCESSING OF REAL-TIME DATA AND STREAMING DATA

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Data Streaming

- **Data streaming** is the process of transmitting a continuous flow of data (also known as streams) typically fed into stream processing software to derive valuable insights.
- A data stream consists of a series of data elements ordered in time.
- The data represents an “event” or a change in state that has occurred in the business and is useful for the business to know about and analyze, often in real-time.
- Some examples of data streams include sensor data, activity logs from web browsers, and financial transaction logs.
- A data stream can be visualized as an endless conveyor belt, carrying data elements and continuously feeding them into a data processor.
- Personal health monitors and home security systems are two examples of data streaming sources.
- A home security system includes multiple motion sensors to monitor different areas of the house. These sensors generate a stream of data transmitted continuously to a processing infrastructure that monitors any unexpected activity either in real-time, or saves the data to analyze for harder to detect patterns later.
- Health monitors are another example of data streaming sources including heartbeat, blood pressure, or oxygen monitors. These devices continuously generate data. Timely analysis of this data is essential, as the safety of the person might depend on it.

General Characteristics of Data Streams

- Streaming data from sensors, web browsers, and other monitoring systems have certain characteristics that set them apart from traditional, historical data.
- The following are a few key characteristics of stream data:

1. Time Sensitive : Each element in a data stream carries a time stamp. The data streams are time sensitive and lose significance after a certain time. For example, the data from a home security system that indicates a suspicious movement should be analyzed and addressed within a short time period to remain relevant.
2. Continuous : There is no beginning or end to streaming data. Data streams are continuous and happen in real-time, but they aren't always acted upon in the moment, depending on system requirements.
3. Heterogeneous : The stream data often originates from thousands of different sources that can be geographically distant. Due to the disparity in the sources, the stream data might be a mix of different formats.
4. Imperfect : Due to the variety of their sources and different data transmission mechanisms, a data stream may have missing or damaged data elements. Also, the data elements in a stream might arrive out of order.
5. Volatile and Unrepeatable : As data streaming happens in real-time, repeated transmission of a stream is quite difficult. While there are provisions for retransmission, the new data may not be the same as the last one. This makes the data streams highly volatile. However, many modern systems keep a record of their data streams so even if you couldn't access it at the moment, you can still analyze it later.

Examples of Data Streaming

- Internet of Things: IoT includes a huge number of devices that collect data using sensors and transmit them in real-time to a data processor. IoT data generates stream data. Wearable health monitors like watches, home security systems, traffic monitoring systems, biometric scanners, connected home appliances, cybersecurity, and privacy systems generate and stream data in real-time.
- Real-time stock market monitors: Real-time finance data is often transmitted in a stream format. Processing and analyzing financial data (like stock prices and market trends) helps organizations make crucial decisions fast.
- Activity and transaction logs: The internet is also a major source of real-time stream data. When people visit websites or click on links, web browsers generate activity logs. Online financial transactions, like credit card purchases, also generate time-critical data that can be streamed and processed for real-time actions.
- Process monitors: Every company generates billions of data points from their internal systems. By streaming this data and processing in real-time, businesses are able to monitor the system health and act before things escalate. For example, manufacturing companies often have devices to monitor the health of the assembly line and to detect faults to assess risk in production. These devices can also stream time-critical data to monitor outages and even prevent them.

Data Ingestion

- In data ingestion, enterprises transport data from various sources to a target destination, often a storage medium.
- A similar concept to data integration, which combines data from internal systems, ingestion also extends to external data sources.

Types of Data Ingestion

1. Batch data ingestion

- The most commonly used model, *batch data ingestion,* collects data in large jobs, or batches, for transfer at periodic intervals. Data teams can set the task to run based on logical ordering or simple scheduling.
- Companies typically use batch ingestion for large datasets that don't require near-real-time analysis. For example, a business that wants to delve into the correlation between SaaS subscription renewals and customer support tickets could ingest the related data on a daily basis—it doesn't need to access and analyze data the instant a support ticket resolves.

2. Streaming data ingestion

- *Streaming data ingestion* collects data in real time for immediate loading into a target location.
- This is a more costly ingestion technique, requiring systems to continually monitor sources, but one that's necessary when instant information and insight are at premium.
- For example, online advertising scenarios that demand a split-second decision—which ad to serve—require streaming ingestion for data access and analysis.

3. Micro batch data ingestion

- *Micro batch data ingestion* takes in small batches of data at very short intervals—typically less than a minute. The technique makes data available in near-real-time, much like a streaming approach.
- In fact, the terms *micro-batching* and *streaming* are often used interchangeably in data architecture and software platform descriptions.

The data ingestion process

- To ingest data, a simple pipeline extracts data from where it was created or stored and loads it into a selected location or set of locations. When the paradigm includes steps to transform the data—such as aggregation, cleansing, or deduplication—it is considered an Extract, Transform, Load (ETL) or Extract, Load, Transform (ELT) procedure.
- The two core components comprising a data ingestion pipeline are:
- Sources: The process can extend well beyond a company's enterprise data center. In addition to internal systems and databases, sources for ingestion can include IoT applications, third-party platforms, and information gathered from the internet.
- Destinations: Data lakes, data warehouses, and document stores are often target locations for the data ingestion process. An ingestion pipeline may also simply send data to an app or messaging system.

Apache Kafka

- Apache Kafka (Kafka) is an open source, distributed streaming platform that enables the development of real-time, event-driven applications.
- Today, billions of data sources continuously generate streams of data records, including streams of *events*. An event is a digital record of an action that happened and the time that it happened. Typically, an event is an action that drives another action as part of a process.
- A customer placing an order, choosing a seat on a flight, or submitting a registration form are all examples of events.
- A streaming platform enables developers to build applications that continuously consume and process these streams at extremely high speeds, with a high level of fidelity and accuracy based on the correct order of their occurrence.
- LinkedIn developed Kafka in 2011 as a high-throughput message broker for its own use, then open-sourced and donated Kafka to the Apache Software Foundation.
- Fortune 500 organizations such as Target, Microsoft, AirBnB, and Netflix rely on Kafka to deliver real-time, data-driven experiences to their customers.

Components of Apache Kafka (1/4)

Components of Apache Kafka (2/4)

- **Topics :** A stream of messages that are a part of a specific category or feed name is referred to as a Kafka topic. In Kafka, data is stored in the form of topics. Producers write their data to topics, and consumers read the data from these topics.
- **Brokers :** A Kafka cluster comprises one or more servers that are known as brokers. In Kafka, a broker works as a container that can hold multiple topics with different partitions. A unique integer ID is used to identify brokers in the Kafka cluster. Connection with any one of the Kafka brokers in the cluster implies a connection with the whole cluster. If there is more than one broker in a cluster, the brokers need not contain the complete data associated with a particular topic.
- **Consumers and Consumer Groups :** Consumers read data from the Kafka cluster. The data to be read by the consumers has to be pulled from the broker when the consumer is ready to receive the message. A consumer group in Kafka refers to a number of consumers that pull data from the same topic or same set of topics.

Components of Apache Kafka (3/4)

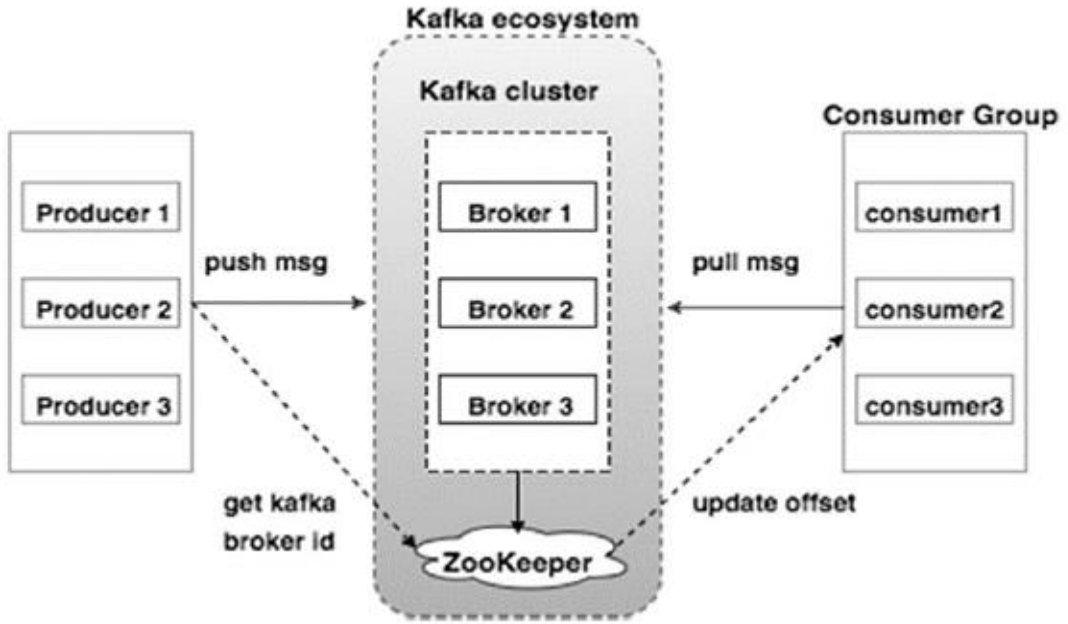
- **Producers :** Producers in Kafka publish messages to one or more topics. They send data to the Kafka cluster. Whenever a Kafka producer publishes a message to Kafka, the broker receives the message and appends it to a particular partition. Producers are given a choice to publish messages to a partition of their choice.
- **Partitions :** Topics in Kafka are divided into a configurable number of parts, which are known as partitions. Partitions allow several consumers to read data from a particular topic in parallel. Partitions are separated in order. The number of partitions is specified when configuring a topic, but this number can be changed later on. The partitions comprising a topic are distributed across servers in the Kafka cluster. Each server in the cluster handles the data and requests for its share of partitions. Messages are sent to the broker along with a key. The key can be used to determine which partition that particular message will go to. All messages which have the same key go to the same partition. If the key is not specified, then the partition will be decided in a round-robin fashion.
- **Partition Offset :** Messages or records in Kafka are assigned to a partition. To specify the position of the records within the partition, each record is provided with an offset. A record can be uniquely identified within its partition using the offset value associated with it. A partition offset carries meaning only within that particular partition. Older records will have lower offset values since records are added to the ends of partitions.

Components of Apache Kafka (4/4)

- **Replicas :** Replicas are like backups for partitions in Kafka. They are used to ensure that there is no data loss in the event of a failure or a planned shutdown. Partitions of a topic are published across multiple servers in a Kafka cluster. Copies of the partition are known as Replicas.
- **Leader and Follower :** Every partition in Kafka will have one server that plays the role of a leader for that particular partition. The leader is responsible for performing all the read and write tasks for the partition. Each partition can have zero or more followers. The duty of the follower is to replicate the data of the leader. In the event of a failure in the leader for a particular partition, one of the follower nodes can take on the role of the leader.

Apache Kafka - Cluster Architecture

1	Broker Kafka cluster typically consists of multiple brokers to maintain load balance. Kafka brokers are stateless, so they use ZooKeeper for maintaining their cluster state. One Kafka broker instance can handle hundreds of thousands of reads and writes per second and each broker can handle TB of messages without performance impact. Kafka broker leader election can be done by ZooKeeper.
2	ZooKeeper ZooKeeper is used for managing and coordinating Kafka broker. ZooKeeper service is mainly used to notify producer and consumer about the presence of any new broker in the Kafka system or failure of the broker in the Kafka system. As per the notification received by the Zookeeper regarding presence or failure of the broker then producer and consumer takes decision and starts coordinating their task with some other broker.
3	Producers Producers push data to brokers. When the new broker is started, all the producers search it and automatically sends a message to that new broker. Kafka producer doesn't wait for acknowledgements from the broker and sends messages as fast as the broker can handle.
4	Consumers Since Kafka brokers are stateless, which means that the consumer has to maintain how many messages have been consumed by using partition offset. If the consumer acknowledges a particular message offset, it implies that the consumer has consumed all prior messages. The consumer issues an asynchronous pull request to the broker to have a buffer of bytes ready to consume. The consumers can rewind or skip to any point in a partition simply by supplying an offset value. Consumer offset value is notified by ZooKeeper.



Apache Kafka – WorkFlow (1/2)

Following is the stepwise workflow of the Pub-Sub Messaging in Apache Kafka.

1. Producers send message to a topic at regular intervals.
2. Kafka broker stores all messages in the partitions configured for that particular topic. It ensures the messages are equally shared between partitions. If the producer sends two messages and there are two partitions, Kafka will store one message in the first partition and the second message in the second partition.
3. Consumer subscribes to a specific topic.
4. Once the consumer subscribes to a topic, Kafka will provide the current offset of the topic to the consumer and also saves the offset in the Zookeeper ensemble.
5. Consumer will request the Kafka in a regular interval (like 100 Ms) for new messages.
6. Once Kafka receives the messages from producers, it forwards these messages to the consumers.
7. Consumer will receive the message and process it.
8. Once the messages are processed, consumer will send an acknowledgement to the Kafka broker.
9. Once Kafka receives an acknowledgement, it changes the offset to the new value and updates it in the Zookeeper. Since offsets are maintained in the Zookeeper, the consumer can read next message correctly even during server outrages.
10. This above flow will repeat until the consumer stops the request.
11. Consumer has the option to rewind/skip to the desired offset of a topic at any time and read all the subsequent messages.

Apache Kafka – WorkFlow (2/2)

- **Kafka has three primary capabilities:**

1. It enables applications to publish or subscribe to data or event streams.
2. It stores records accurately (i.e., in the order in which they occurred) in a fault-tolerant and durable way.
3. It processes records in real-time (as they occur).

- **Developers can leverage these Kafka capabilities through four APIs:**

1. **Producer API:** This enables an application to publish a stream to a Kafka *topic*. A topic is a named log that stores the records in the order they occurred relative to one another. After a record is written to a topic, it can't be altered or deleted; instead, it remains in the topic for a preconfigured amount of time—for example, for two days—or until storage space runs out.
2. **Consumer API:** This enables an application to subscribe to one or more topics and to ingest and process the stream stored in the topic. It can work with records in the topic in real-time, or it can ingest and process past records.
3. **Streams API:** This builds on the Producer and Consumer APIs and adds complex processing capabilities that enable an application to perform continuous, front-to-back stream processing—specifically, to consume records from one or more topics, to analyze or aggregate or transform them as required, and to publish resulting streams to the same topics or other topics. While the Producer and Consumer APIs can be used for simple stream processing, it's the Streams API that enables development of more sophisticated data- and event-streaming applications.
4. **Connector API:** This lets developers build *connectors*, which are reusable producers or consumers that simplify and automate the integration of a data source into a Kafka cluster.

Applications of Apache Kafka

Kafka supports many of today's best industrial applications. We will provide a very brief overview of some of the most notable applications of Kafka here.

- **Twitter** : Twitter is an online social networking service that provides a platform to send and receive user tweets. Registered users can read and post tweets, but unregistered users can only read tweets. Twitter uses Storm-Kafka as a part of their stream processing infrastructure.
- **LinkedIn** : Apache Kafka is used at LinkedIn for activity stream data and operational metrics. Kafka mes-saging system helps LinkedIn with various products like LinkedIn Newsfeed, LinkedIn Today for online message consumption and in addition to offline analytics systems like Hadoop. Kafka's strong durability is also one of the key factors in connection with LinkedIn.
- **Netflix** : Netflix is an American multinational provider of on-demand Internet streaming media. Netflix uses Kafka for real-time monitoring and event processing.
- **Mozilla** : Mozilla is a free-software community, created in 1998 by members of Netscape. Kafka will soon be replacing a part of Mozilla current production system to collect performance and usage data from the end-user's browser for projects like Telemetry, Test Pilot, etc.
- **Oracle** : Oracle provides native connectivity to Kafka from its Enterprise Service Bus product called OSB (Oracle Service Bus) which allows developers to leverage OSB built-in mediation capabilities to implement staged data pipelines.

Comparison of Hadoop, Spark and Kafka

Parameters	Hadoop	Spark	Kafka
Brief Description	Apache Hadoop is an open-source, big data processing framework designed to handle large amounts of data (gigabytes to petabytes) in a distributed manner across a cluster of commodity servers.	General purpose distributed processing system used for big data workloads. It uses in-memory caching and optimized query execution to provide fast analytic queries against data of any size.	Distributed streaming platform that allows developers to create applications that continuously produces and consumes data streams.
Processing Model	Batch processing	Batch processing and streaming	Event streaming
Processing Features	Using local disk storage to process data across different clusters in batches.	Designed for in-memory processing	Stream processing solution to run complex operations on streams. Kafka Streams API need to be used.
Ecosystem Components	Hadoop HDFS, Hadoop YARN, Hadoop MapReduce, Hadoop Common Utilities	Spark Core, Spark SQL, MLlib, GraphX	Kafka Producers, Kafka Consumers, Kafka Topics, Kafka Brokers, Kafka Streams API
Throughput and Latency	High throughput, high latency	High throughput, low latency	High throughput, low latency
Language Support	Java	Java, Scala, Python, R	Java, Scala
Scalability	Hadoop is highly scalable with clusters and can be easily expanded to process more data by adding additional nodes.	Spark is horizontally scalable as a distributed system, though scaling is expensive due to RAM usage.	Kafka is horizontally scalable to support a growing number of users and use cases, meaning that it can handle an increasing amount of data by adding more nodes and partitions to the system.
Fault Tolerance	Hadoop is designed to handle failures gracefully by replicating information to prevent data loss and continue running even if the node in the cluster fail.	Fault tolerant because of RDDs. In case of node failure, it can automatically recalculate data.	Kafka is fault tolerant as it replicates data across multiple servers and can automatically recover from node failure.
General Applications	Performing big data analytics (not time-sensitive)	Performing interactive big data analytics, SQL, machine learning, graph operations.	Decoupling data dependencies by scalable pipelines for data ingestion and streaming.
Specific Use Cases	Web log analysis, clickstream analysis	Real-time processing, machine learning, graph processing	Messaging, Notifications, Stream Processing

Apache Storm

- Apache Storm is a distributed real-time big data-processing system.
- Storm is designed to process vast amount of data in a fault-tolerant and horizontal scalable method.
- It is a streaming data framework that has the capability of highest ingestion rates.
- Though Storm is stateless, it manages distributed environment and cluster state via Apache ZooKeeper.
- It is simple and you can execute all kinds of manipulations on real-time data in parallel.

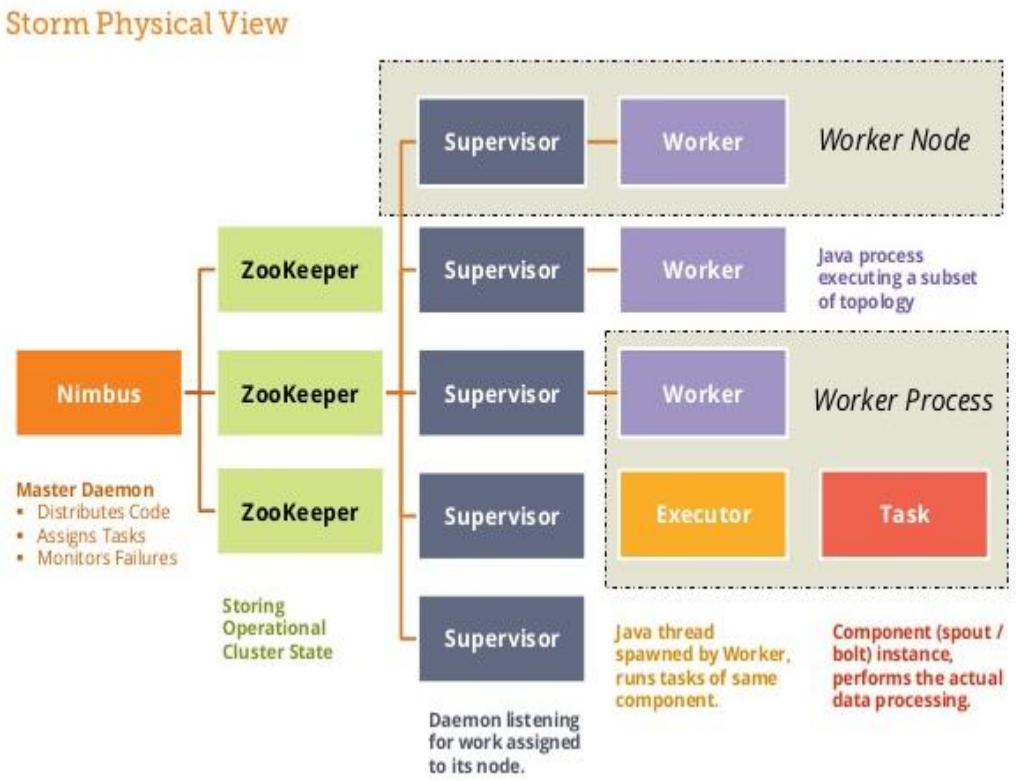
Apache Storm vs Hadoop

Storm	Hadoop
Real-time stream processing	Batch processing
Stateless	Stateful
Master/Slave architecture with ZooKeeper based coordination. The master node is called as **nimbus** and slaves are **supervisors**.	Master-slave architecture with/without ZooKeeper based coordination. Master node is **job tracker** and slave node is **task tracker**.
A Storm streaming process can access tens of thousands messages per second on cluster.	Hadoop Distributed File System (HDFS) uses MapReduce framework to process vast amount of data that takes minutes or hours.
Storm topology runs until shutdown by the user or an unexpected unrecoverable failure.	MapReduce jobs are executed in a sequential order and completed eventually.
Both are distributed and fault-tolerant	
If nimbus / supervisor dies, restarting makes it continue from where it stopped, hence nothing gets affected.	If the JobTracker dies, all the running jobs are lost.

Apache Storm Benefits

- Storm is open source, robust, and user friendly. It could be utilized in small companies as well as large corporations.
- Storm is fault tolerant, flexible, reliable, and supports any programming language.
- Allows real-time stream processing.
- Storm is unbelievably fast because it has enormous power of processing the data.
- Storm can keep up the performance even under increasing load by adding resources linearly. It is highly scalable.
- Storm performs data refresh and end-to-end delivery response in seconds or minutes depends upon the problem. It has very low latency.
- Storm has operational intelligence.
- Storm provides guaranteed data processing even if any of the connected nodes in the cluster die or messages are lost.

Components of Apache Storm



The storm comprises of 3 abstractions namely Spout, Bolt and Topologies.

Spout helps us to retrieve the data from the queueing systems. Spout implementations exist for most of the queueing systems.

Bolt used to process the input streams of data retrieved by spout from queueing systems. Most of the logical operations are performed in bolt such as filters, functions, talking to databases, streaming joins, streaming aggregations and so on.

Topology is a combination of both Spout and Bolt. Data transferred between spout and Bolt is called as Tuple. Tuple is a collection of values like messages and so on.

Nodes of Apache Storm

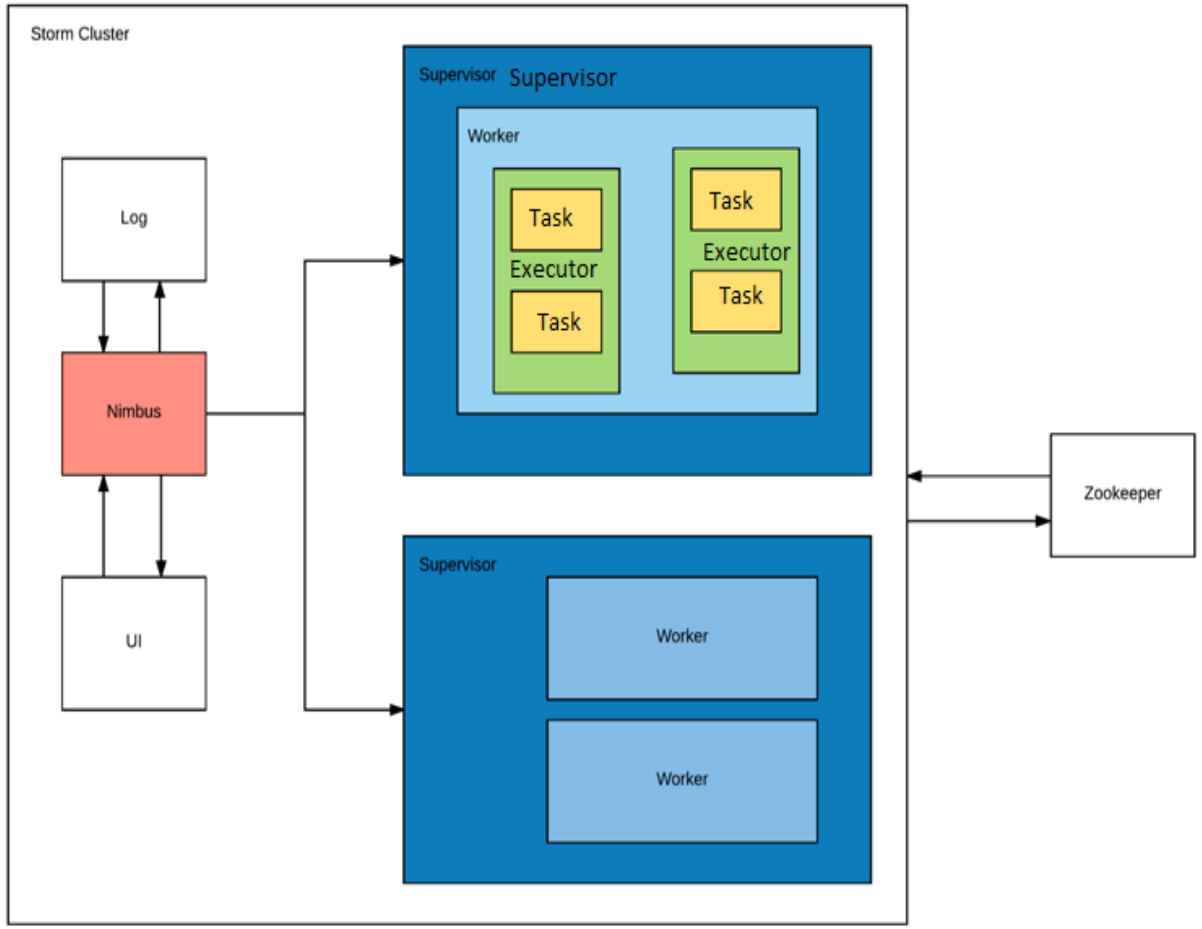
A Storm cluster has 3 sets of nodes namely Nimbus, Zookeeper and Supervisor nodes.

Nimbus node is also called as a master node and acts as a job tracker. It is responsible for distributing the code among supervisors, assigning input data sets to machines for processing and monitoring for failures. Nimbus node relies on zookeeper service to monitor the message processing tasks as all the supervisor nodes update their tasks status in zookeeper node.

Zookeeper node acts as an intermediate between nimbus and supervisor node. Communication and data exchange takes place with the help of zookeeper node. It helps to coordinate the entire cluster.

Supervisor node is also called as worker node and acts as task tracker. It receives the assigned work to a machine by nimbus service. It manages work processes to complete tasks assigned by Nimbus. It will start and stop the workers according to the signals from Nimbus. All supervisor nodes are interconnected with each other with the help of Zero MQ (Messaging Queue). The tasks from one supervisor node can be transferred to another by using Zero MQ.

Storm Cluster Architecture



Components	Description
Nimbus	Nimbus is a master node of Storm cluster. All other nodes in the cluster are called as **worker nodes**. Master node is responsible for distributing data among all the worker nodes, assign tasks to worker nodes and monitoring failures.
Supervisor	The nodes that follow instructions given by the nimbus are called as Supervisors. A **supervisor** has multiple worker processes and it governs worker processes to complete the tasks assigned by the nimbus.
Worker process	A worker process will execute tasks related to a specific topology. A worker process will not run a task by itself, instead it creates **executors** and asks them to perform a particular task. A worker process will have multiple executors.
Executor	An executor is nothing but a single thread spawn by a worker process. An executor runs one or more tasks but only for a specific spout or bolt.
Task	A task performs actual data processing. So, it is either a spout or a bolt.
ZooKeeper framework	Apache ZooKeeper is a service used by a cluster (group of nodes) to coordinate between themselves and maintaining shared data with robust synchronization techniques. Nimbus is stateless, so it depends on ZooKeeper to monitor the working node status. ZooKeeper helps the supervisor to interact with the nimbus. It is responsible to maintain the state of nimbus and supervisor.

Apache Storm Workflow

- Firstly, the nimbus will wait for the storm topology to be submitted to it.
- When the topology is submitted, it will process the topology and gather all the tasks that are to be carried out and the order in which the task is to execute.
- At a stipulated time interval, all supervisors will send status (alive or dead) to the nimbus to inform that they are still alive.
- If a supervisor dies and doesn’t address the status to the nimbus, then the nimbus assigns the tasks to another supervisor.
- When the Nimbus itself dies, the supervisor will work on an already assigned task without any interruption or issue.
- When all tasks are completed, the supervisor will wait for a new task to process.
- In a meanwhile, the dead nimbus will be restarted automatically by service monitoring tools.
- The restarted nimbus will continue from where it stopped working. The dead supervisor can restart automatically. Hence itis guaranteed that the entire task will be processed at least once.

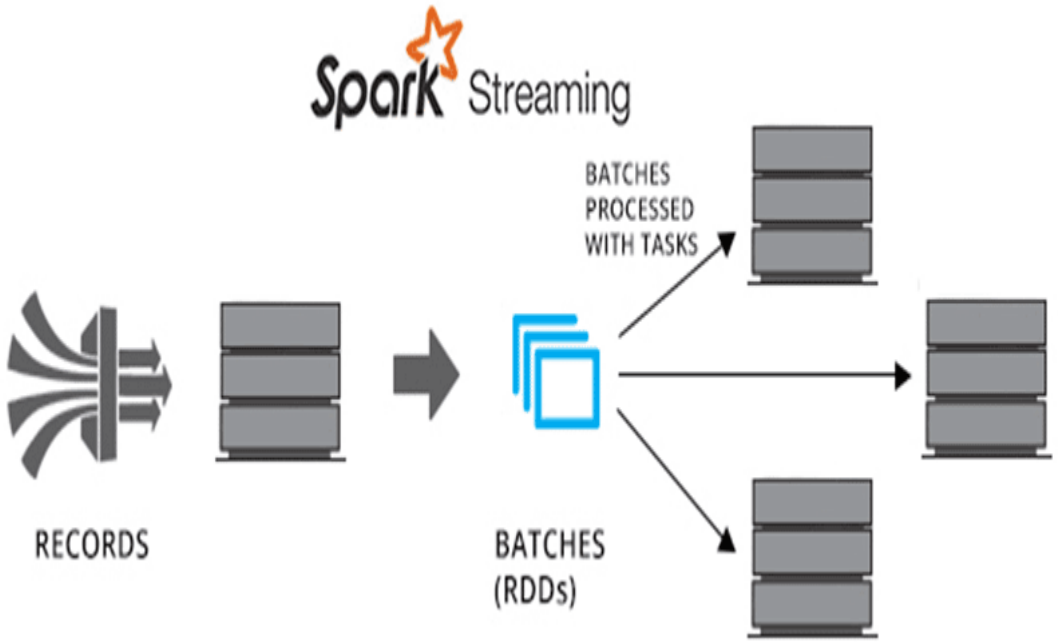
Applications of Apache Storm

- **Wego**-Wego is a travel metasearch engine. Travel related data fetch from many sources all over the world with different timing. Storm helps we go to search real-time data, resolve concurrency issue and find the best match for the end user.
- **NaviSite**-NaviSite is using Apache Storm for event log monitoring /auditing system. Each log generated in the system will go through the storm. The storm will check the content or message against the configured set of the regular expression, and if there is a match, then that particular message will be saved to the database.
- **Twitter**- It uses Storm for its range of publisher analytics products. Publisher analytics products process every tweet and click on the Twitter Platform. Apache Storm integrated with Twitter infrastructure.
- **Yahoo**- Yahoo is working on a next-generation platform that enables the convergence of big data and low latency processing. While Hadoop is primary technology for batch processing, storm empowers micro-batch processing of user event, feeds, and logs.

Spark Streaming

- Spark streaming is nothing but an extension of core Spark API that is responsible for fault-tolerant, high throughput, scalable processing of live streams.
- Spark streaming takes live data streams as input and provides as output batches by dividing them.
- These streams are then processed by the Spark engine and the final stream results in batches.
- **Some real-time examples of Apache Spark Streaming are:**
- Website and network monitoring
- Fraud detection
- Internet of Things sensors
- Advertising
- Web clicks

Spark Streaming Architecture



- Spark streaming discretizes into micro-batches of streaming data instead of processing the streaming data in steps of records per unit time.
- Data is accepted in parallel by the Spark streaming's receivers and in the worker nodes of Spark this data is held as buffer.
- To process batches the Spark engine which is typically latency optimized runs short tasks and outputs the results to other systems.
- Based on available resources and locality of data Spark tasks are dynamically assigned to the workers.
- Improved load balancing and rapid fault recovery are its obvious benefits.
- Resilient distributed dataset (RDD) constitutes each batch of data and for fault-tolerant dataset in Spark this is the basic abstraction. It is because of this feature that streaming data can be processed using any code snippet of Spark or library.