UMD DATA605 - Big Data Systems

12.1: Streaming and Real-time Analytics

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Motivation

- Big Data is generated as a **continuous, unbounded stream**
- Applications generate data at **high velocity**
  - Financial transactions and market feeds
  - Sensor instrumentation, RFID, IoT telemetry
  - Network and system monitoring
  - Continuous media (video, audio)
- A **data stream** is a time-ordered sequence of events
  - Stream processing treats streams as first-class computational objects
- **Requirements**
  - Ingest and handle high-throughput event streams
  - Low-latency, near-real-time operations (e.g., time-series analytics)
  - Efficient dissemination of relevant subsets to consumers
  - Distributed processing to scale beyond a single machine

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Examples of Data Stream Tasks

- Continuous queries
  - Any SQL query can be continuous
  - E.g., *"compute moving average over last hour every 10 mins"*
  - StreamSQL extends SQL to support windows over streams
- Pattern recognition
  - E.g., *"alert me when A occurs and then B within 10 mins"*
  - Correlate events from different streams
- Surveillance, anomaly detection
- Fraud detection and prevention
  - Anti-money laundering
  - RegNMS, MiFID
- Statistical tasks
  - E.g., de-noising measured readings
  - Build an online machine learning model
- Process multimedia data
  - E.g., online object detection, activity detection

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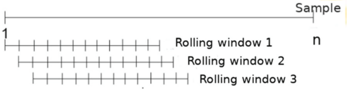
Why Not Using the Usual RDBM?

- Simple case: "*report moving average over last hour every 10 minutes*"
  - Insert items into DB table as they arrive
  - Execute query every 10 minutes
- One query: slow and inefficient
  - Doesn't reuse previous work
  - Can describe computation incrementally with recursion
- Computations
  - Can be complex (e.g., train LLM model with 1,000 GPUs)
  - Not always easily rewritten recursively
- Typically thousands of continuous queries



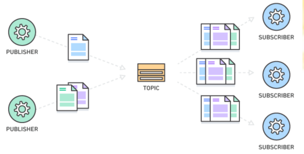
$$m_n = \frac{1}{n} \sum_{i=1}^{n} a_i$$

Computation

$$m_n = m_{n-1} + \frac{a_n - m_{n-1}}{n}$$

Pub-Sub Systems

- In modern architecture, complex distributed systems are built with **small and independent building blocks**
  - E.g., serverless, micro-services
  - E.g., Uber
  - Facilitate decoupling and allow systems to evolve independently
  - Allow scalability and flexibility
- **Publish-subscribe systems**
  - Aka pub-sub, message queues, message brokers
  - Provide communication and coordination between building blocks
  - Focus on data dissemination
    - Typically no complex queries
    - Topics categorize messages and events
  - E.g., AWS SQS, AWS Kinesis, Apache Kafka, RabbitMQ, Redis, Celery, JBoss



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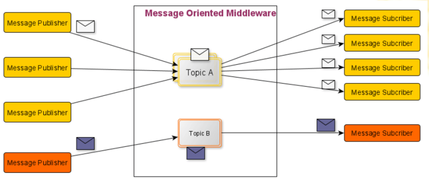
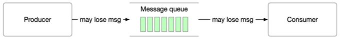
Pub-Sub Systems

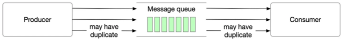
- **Publishers**
  - Send messages or events
- **Subscribers**
  - Consume messages
- **Message broker**
  - Manage message flow between publishers and subscribers
- **Design parameters**
  - Events distributed
    - Topics, by subscription
  - Event distribution method
    - Push, pull
  - Subscriber interest in topics
  - Delivery semantics
    - At-most once
    - At-least once
    - Exactly once

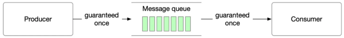


Delivery Semantics

- At-most once
  - Message may be lost, not redelivered
  - Pros
    - High-performance
    - Small implementation overhead
    - Easy to implement: “fire-and-forget”
  - E.g., monitoring metrics allow small data loss
- At-least once
  - Deliver message more than once, no message lost
  - Handle transport message loss
    - Keep state at sender
    - Acknowledge state at receiver
  - Works if
    - Data duplication is acceptable
    - Deduplication (e.g., storing key-value)
    - Idempotency
- Exactly once
  - Every message sent once
  - Friendly for downstream consumers
  - Difficult to implement
    - Two Generals’ Problem







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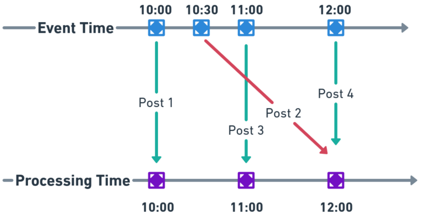
Event vs Processing Time

- In both streaming and pub-sub architectures
- Event time
  - Time when each record is generated
- Processing time
  - Time when each record is received
  - Ingestion vs processing time: when events are received vs processed
- Problems with events
  - Out of order
  - Tardiness
  - How long to wait for late data?
    - In an asynchronous system, never sure all data has arrived
    - Use bounds on delay
    - Assume data arrives every minute
  - Recompute once late data arrives? If not, drop late data?



Apache Streaming Zoo

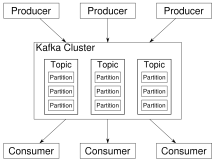
- Many different streaming frameworks
  - Apache Apex, Apache Beam, Apache Flink, Apache Kafka, Apache Spark, Apache Storm, Apache NiFi
- Use cases
  - Real-time analytics
  - Online machine learning
  - Continuous computation
  - ETL processes
  - Data pipeline processing
  - Messaging
  - Log aggregation
- Different solutions to the same problem
  - Batch vs streaming
  - Delivery semantic type
  - Computing vs messaging/pub-sub
  - Throughput vs fault-tolerance
  - Supported languages
- Built simultaneously at different companies, then open-sourced

Apache Storm

- Open-source distributed real-time computation system
  - Acquired and open-sourced by Twitter
- Horizontal scalability: add machines to handle increasing data
- Fault tolerance: **at-least-once** processing, automatic task restarts, workload redistribution
- Directed acyclic graph (DAG) with:
  - spouts (data sources)
  - bolts (processing units) as vertices
  - data streams as edges
- Suitable for complex data processing workflows with multiple stages and parallelism

Apache Kafka

- Open-source distributed streaming platform
    - Developed at LinkedIn, open-sourced in 2011
- Producers, brokers, consumers, topics, partitions
- Persistent storage, data replication across brokers
- High-throughput, low-latency messaging
- Fault tolerance: broker replication, automatic recovery
- Message delivery semantics:
    - **At-least-once, at-most-once, exactly-once**
- Kafka Connect: Integrate with data sources and sinks
- Kafka Streams: Stream processing library on Kafka

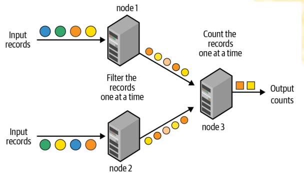


Apache Flink

- Open-source, distributed data processing framework
- Focus on stateful computations over data streams
- Scalability: Horizontal scaling across large clusters
- Fault tolerance:
  - **Exactly-once** processing semantics, checkpointing, state management
- Batch processing support: **unified API for stream and batch processing**
- Flexible windowing: time-based, count-based, session windows
- Deployment options: standalone, YARN, Mesos, Kubernetes, cloud environments

Record-at-a-time Processing

- Implemented in Apache Kafka
- Goal: handle endless data stream
- **Multiple-node distributed processing engine**
  - Map computation on DAG of nodes
  - Each node continuously
    - Receives one record
    - Processes it
    - Forwards to next node
- **Pros**
  - Very low latencies
    - E.g., less than msecs
- **Cons**
  - Inefficient node failure recovery
    - E.g., need failover resources/redundancy
  - Straggler nodes (slower than others)


node 1
Input records
Count the records one at a time
Filter the records one at a time
Output counts
node 3
Input records
node 2

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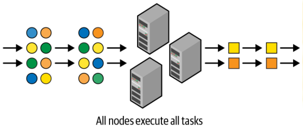
Micro-Batch Stream Processing

- Aka DStreams
- Implemented in Spark Streaming
- **Computation as a continuous series of batch jobs on small chunks of stream data**
    - E.g., 1 second
    - Process each batch in the Spark cluster in a distributed manner
- Pros
    - Recover from failures and stragglers using task scheduling
        - E.g., schedule same task multiple times
    - Deterministic tasks
        - Exactly-once processing guarantees
        - Consistent API: same functional semantics as RDDs
        - Fault-tolerance
- Cons
    - Higher latency
        - E.g., seconds



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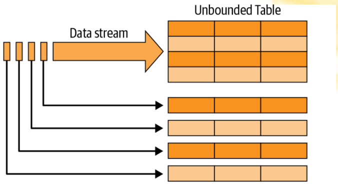
Spark Micro-Batch Processing: Cons

- Line between real-time and batch processing blurred
  - Application computing data hourly: stream or batch?
- No single API for batch and stream processing
  - Same abstractions (RDD) and operations
  - Rewrite code with different classes
- No support for event-time windows
  - Operations defined by processing time
  - No support for tardy data
- Spark replaced DStreams with Structured Streaming in v3
  - Supports micro-batch and continuous streaming
  - Closer batch vs streaming API

Spark Structured Streaming

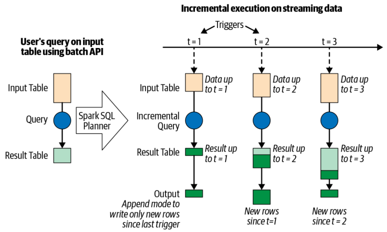
- New approach used by Spark
- Goal: write stream processing as easy as writing batch pipelines
  - Single unified programming model
  - Use SQL or DataFrames on stream
- Handle automatically
  - Fault tolerance
  - Optimizations
  - Incremental computation
  - Tardy data
- **Data abstraction**
  - Batch applications: table (DataFrame) is the abstraction
  - Structured Streaming: table is an unbounded, continuously appended table
    - New record becomes a new row appended
    - At time T, it's like a static dataframe with data until T



Data stream as an unbound input table

Incrementalization

- Automatically detect state to maintain
  - Build DAG of computation
  - Express output of graph at time T in terms of graph at time T-1
  - Cache results
- Developers specify triggers to update results
- Incrementally update result with each record arrival



Triggering Modes

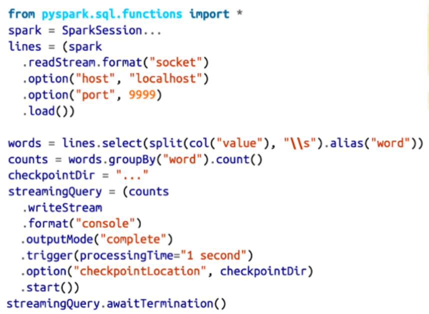
- Indicate when to process newly available streaming data
  - **Default**
    - Process micro-batch after previous completes
  - **Trigger interval**
    - Specify fixed interval for each micro-batch
    - E.g., “every 10 minutes”
  - **Once**
    - Wait for external trigger
    - E.g., “at end of day”
  - **Continuous (experimental)**
    - Process data continuously
    - Not all operations available
    - Lower latency

Saving Data

- Each time result table updates, write to external file system (e.g., HDFS, AWS S3) or DB (e.g., MySQL, Cassandra)
  - **Append mode**
    - Append new rows since last trigger
    - Use when existing rows don't change
  - **Update mode**
    - Write updated rows since last trigger
    - Update in place
  - **Complete mode**
    - Write entire updated result table
    - General but expensive

Spark Streaming “Hello world”

- `lines` looks like an RDD but it’s a `DataStreamReader`
  - Unbounded DataFrame
  - Set up reading but doesn’t start reading
- `words` split data in words
- `counts` is a streaming DataFrame
  - Running word count
- Stateless transformations don’t require maintaining state
  - E.g., `select()`, `filter()`
- Stateful transformations
  - E.g., `count()`
- Define how to write processed output
  - Where to write (e.g., `console`)
  - How to write (e.g., `complete` for updated word counts)
- When to trigger computation
  - E.g., every 1 second
- Where to save metadata for:



```python
from pyspark.sql.functions import *
spark = SparkSession...
lines = (spark
  .readStream.format("socket")
  .option("host", "localhost")
  .option("port", 9999)
  .load())

words = lines.select(split(col("value"), "\\s").alias("word"))
counts = words.groupBy("word").count()
checkpointDir = "..."
streamingQuery = (counts
  .writeStream
  .format("console")
  .outputMode("complete")
  .trigger(processingTime="1 second")
  .option("checkpointLocation", checkpointDir)
  .start())
streamingQuery.awaitTermination()
```