大数据
Big Data

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课程概要

- **Part 0: Overview**
  - Ch1: Introduction
- **Part 1 Relational Databases**
  - Ch2: Relational model
  - Ch3: Introduction to SQL
  - Ch4: Intermediate SQL
  - Ch5: Advanced SQL
- **Part 2 Database Design**
  - Ch6: Database design based on E-R model
  - Ch7: Relational database design
- **Part 3 Application Design & Development**
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  - Ch9: Application development
- **Part 4 Big data analytics**
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  - Ch11: Data analytics
- **Part 5 Data Storage & Indexing**
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  - Ch13: Data storage structure
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- **Part 6 Query Processing & Optimization**
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  - Ch16: Query optimization
- **Part 7 Transaction Management**
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  - Ch18: Concurrency control
  - Ch19: Recovery system
- **Part 8 Parallel & Distributed Database**
  - Ch20: Database system architecture
  - Ch21-23: Parallel & distributed storage, query processing & transaction processing
- **Part 9**
  - DB Platform: **OceanBase**, MongoDB, Neo4J

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Motivations

- **Very large volumes of data being collected**
  - Driven by growth of web, social media, and more recently internet-of-things
  - Web logs were an early source of data
    - Analytics on web logs has great value for advertisements, web site structuring, what posts to show to a user, etc.
- **Big Data: differentiated from data handled by earlier generation databases**
  - Volume: much larger amounts of data stored
  - Velocity: much higher rates of insertions
  - Variety: many types of data, beyond relational data

Querying Big Data

- Transaction processing systems that need very high scalability
  - Many applications willing to sacrifice ACID properties and other database features, if they can get very high scalability
- Query processing systems that
  - Need very high scalability, and
  - Need to support non-relation data

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Big Data Storage Systems

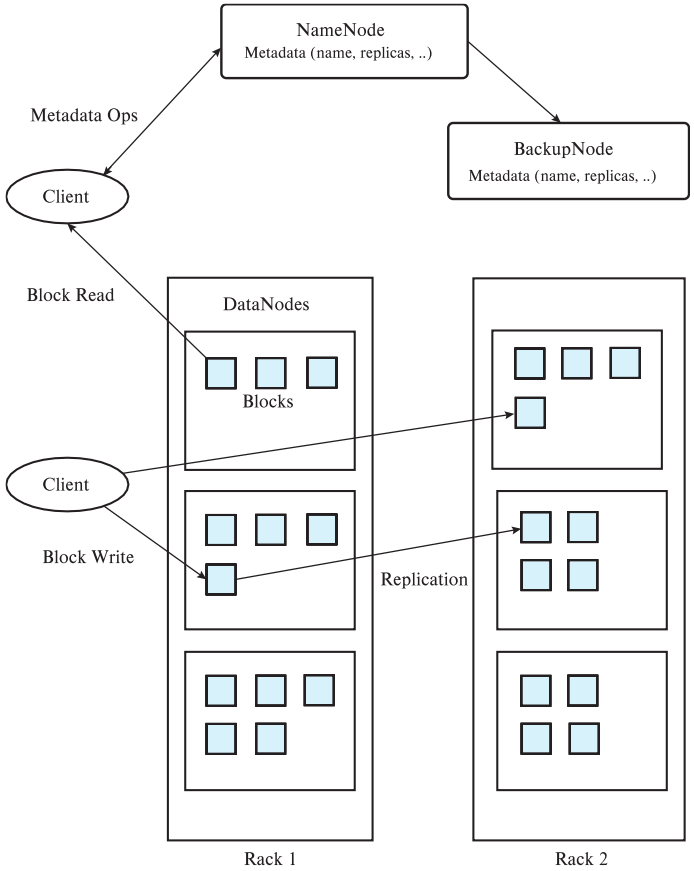
- Distributed file systems
- Shardring across multiple databases
- Key-value storage systems
- Parallel and distributed databases

Distributed File Systems

- A distributed file system stores data across a large collection of machines, but provides single file-system view
- Highly scalable distributed file system for large data-intensive applications.
  - E.g., 10K nodes, 100 million files, 10 PB
- Provides redundant storage of massive amounts of data on cheap and unreliable computers
  - Files are replicated to handle hardware failure
  - Detect failures and recovers from them
- Examples:
  - Google File System (GFS)
  - Hadoop File System (HDFS)

Hadoop File System Architecture

- Single Namespace for entire cluster
- Files are broken up into blocks
  - Typically 64 MB block size
  - Each block replicated on multiple DataNodes
- Client
  - Finds location of blocks from NameNode
  - Accesses data directly from DataNode



Hadoop Distributed File System (HDFS)

- **NameNode**
  - Maps a filename to list of Block IDs
  - Maps each Block ID to DataNodes containing a replica of the block
- **DataNode**: Maps a Block ID to a physical location on disk
- **Data Coherency**
  - Write-once-read-many access model
  - Client can only append to existing files
- **Distributed file systems good for millions of large files**
  - But have very high overheads and poor performance with billions of smaller tuples

Sharding

- **Sharding**: partition data across multiple databases
- Partitioning usually done on some ***partitioning attributes*** (also known as ***partitioning keys*** or ***shard keys*** e.g. user ID
  - E.g., records with key values from 1 to 100,000 on database 1, records with key values from 100,001 to 200,000 on database 2, etc.
- Application must track which records are on which database and send queries/updates to that database

Sharding

- Positives: scales well, easy to implement
- Drawbacks:
  - Not transparent: application has to deal with routing of queries, queries that span multiple databases
  - When a database is overloaded, moving part of its load out is not easy
  - Chance of failure more with more databases
    - need to keep replicas to ensure availability, which is more work for application

Parallel Databases and Data Stores

- Supporting scalable data access
  - Approach 1: memcache or other caching mechanisms at application servers, to reduce database access
    - Limited in scalability
  - Approach 2: Partition (“shard”) data across multiple separate database servers
  - Approach 3: Use existing parallel databases
    - Historically: parallel databases that can scale to large number of machines were designed for decision support not OLTP
  - Approach 4: Massively Parallel Key-Value Data Store
    - Partitioning, high availability etc. completely transparent to application
- Sharding systems and key-value stores don’t support many relational features, such as joins, integrity constraints, etc., across partitions.

Key Value Storage Systems

- Key-value storage systems store large numbers (billions or even more) of small (KB-MB) sized records
- Records are **partitioned** across multiple machines and
- Queries are routed by the system to appropriate machine
- Records are also **replicated** across multiple machines, to ensure availability even if a machine fails
  - Key-value stores ensure that updates are applied to all replicas, to ensure that their values are **consistent**

Key Value Storage Systems

- Key-value stores may store
  - **uninterpreted bytes**, with an associated key
    - E.g., Amazon S3, Amazon Dynamo
  - **Wide-table** (can have arbitrarily many attribute names) with associated key
    - Google BigTable, Apache Cassandra, Apache Hbase, Amazon DynamoDB
    - Allows some operations (e.g., filtering) to execute on storage node
  - JSON
    - MongoDB, CouchDB (document model)
- **Document stores** store semi-structured data, typically JSON
- Some key-value stores support multiple versions of data, with timestamps/version numbers

Data Representation

- An example of a JSON object:

```
{
    "ID": "22222",
    "name": {
        "firstname: "Albert",
        "lastname: "Einstein"
    },
    "deptname": "Physics",
    "children": [
        { "firstname": "Hans", "lastname": "Einstein" },
        { "firstname": "Eduard", "lastname": "Einstein" }
    ]
}
```

Key Value Storage Systems

- Key-value stores support
  - ***put***(key, value): used to store values with an associated key,
  - ***get***(key): which retrieves the stored value associated with the specified key
  - ***delete***(key) -- Remove the key and its associated value
- Some systems also support ***range queries*** on key values
- Document stores also support queries on non-key attributes
  - See book for MongoDB queries

Key Value Storage Systems

- Key value stores are not full database systems
  - Have no/limited support for transactional updates
  - Applications must manage query processing on their own
- Not supporting above features makes it easier to build scalable data storage systems
  - Also called **NoSQL** systems

Parallel and Distributed Databases

- Parallel databases run multiple machines (cluser)
  - Developed in 1980s, well before Big Data
- Parallel databases were designed for smaller scale (10s to 100s of machines)
  - Did not provide easy scalability
- **Replication** used to ensure data availability despite machine failure
  - But typically restart query in event of failure
    - Restarts may be frequent at very large scale
    - Map-reduce systems (coming up next) can continue query execution, working around failures

Replication and Consistency

- **Availability** (system can run even if parts have failed) is essential for parallel/distributed databases
  - Via replication, so even if a node has failed, another copy is available
- **Consistency** is important for replicated data
  - All live replicas have same value, and each read sees latest version
  - Often implemented using majority protocols
    - E.g., have 3 replicas, reads/writes must access 2 replicas
      - Details in chapter 23

Replication and Consistency

- **Network partitions** (network can break into two or more parts, each with active systems that can't talk to other parts)
- In presence of partitions, cannot guarantee both availability and consistency
  - Brewer's CAP "Theorem"

Replication and Consistency

- Very large systems will partition at some point
  - Choose one of consistency or availability
- Traditional database choose consistency
- Most Web applications choose availability
  - Except for specific parts such as order processing
- More details in Chapter 23

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- 流数据
- 图数据库

The MapReduce Paradigm

- Platform for reliable, scalable parallel computing
- Abstracts issues of distributed and parallel environment from programmer
  - Programmer provides core logic (via map() and reduce() functions)
  - System takes care of parallelization of computation, coordination, etc.
- Paradigm dates back many decades
  - But very large scale implementations running on clusters with 10^3 to 10^4 machines are more recent
  - Google Map Reduce, Hadoop, ..
- Data storage/access typically done using distributed file systems or key-value stores

MapReduce: Word Count Example

- Consider the problem of counting the number of occurrences of each word in a large collection of documents
- How would you do it in parallel?
- **Solution**:
  - Divide documents among workers
  - Each worker parses document to find all words, map function outputs (word, count) pairs
  - Partition (word, count) pairs across workers based on word
  - For each word at a worker, reduce function locally add up counts

MapReduce: Word Count Example

- Given input: “One a penny, two a penny, hot cross buns.”
  - Records output by the map() function would be
    - (“One” , 1), (“a” , 1), (“penny” , 1),(“two” , 1), (“a” , 1), (“penny” , 1), (“hot” , 1), (“cross” , 1), (“buns” , 1).
  - Records output by reduce function would be
    - (“One” , 1), (“a” , 2), (“penny” , 2), (“two” , 1), (“hot” , 1), (“cross” , 1), (“buns” , 1)

Pseudo-code of Word Count


```
map(String record):
    for each word in record
      emit(word, 1);

 // First attribute of emit above is called reduce key
 // In effect, group by is performed on reduce key to create a
 // list of values (all 1's in above code).  This requires shuffle step
 // across machines.
 // The reduce function is called on list of values in each group

reduce(String key, List value_list):
    String word = key
    int count = 0;
    for each value in value_list:
      count = count + value
    Output(word, count);
```

MapReduce Programming Model

- Inspired from map and reduce operations commonly used in functional programming languages like Lisp.
- Input: a set of key/value pairs
- User supplies two functions:
  - **map**(k,v) → list(k1,v1)
  - **reduce**(k1, list(v1)) → v2
- (k1,v1) is an intermediate key/value pair
- Output is the set of (k1,v2) pairs
- For our example, assume that system
  - Breaks up files into lines, and
  - Calls map function with value of each line
    - Key is the line number

MapReduce Example 2: Log Processing

- Given log file in following format:

  ...
  2013/02/21 10:31:22.00EST /slide-dir/11.ppt
  2013/02/21 10:43:12.00EST /slide-dir/12.ppt
  2013/02/22 18:26:45.00EST /slide-dir/13.ppt
  2013/02/22 20:53:29.00EST /slide-dir/12.ppt
  ...

- Goal: find how many times each of the files in the slide-dir directory was accessed between 2013/01/01 and 2013/01/31.
- Options:
  - Sequential program too slow on massive datasets
  - Load into database expensive, direct operation on log files cheaper
  - Custom built parallel program for this task possible, but very laborious
  - Map-reduce paradigm

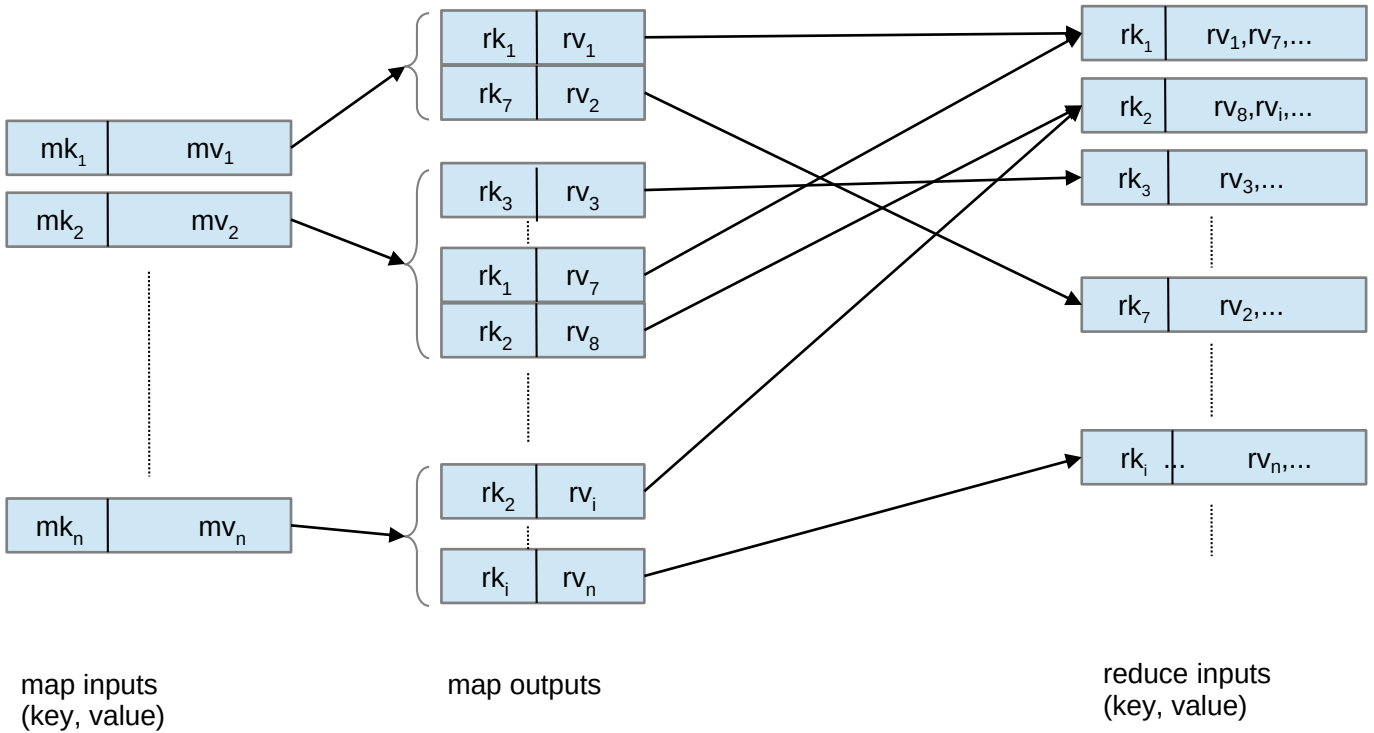
MapReduce: File Access Count Example


```
map(String key, String record) {
    String attribute[3];
    …. break up record into tokens (based on
      space character), and store the tokens in
      array attributes
    String date = attribute[0];
    String time = attribute[1];
    String filename = attribute[2];
    if (date between 2013/01/01 and
      2013/01/31
            and filename starts with "/slide-dir/")
       emit(filename, 1).
}
```

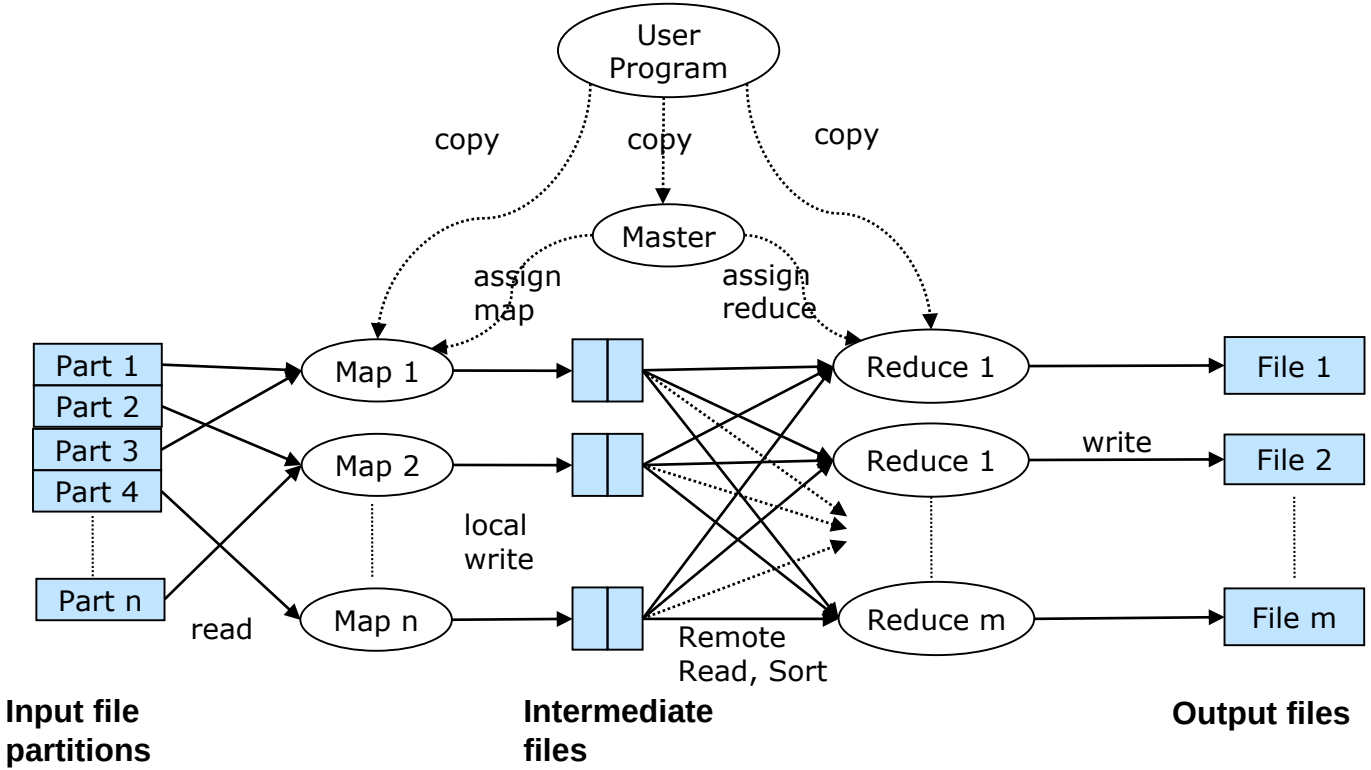
```
reduce(String key, List recordlist) {
    String filename = key;
    int count = 0;
    For each record in recordlist
       count = count + 1.
    output(filename, count)
}
```

Schematic Flow of Keys and Values

- Flow of keys and values in a map reduce task



Parallel Processing of MapReduce Job



Hadoop MapReduce

- Google pioneered map-reduce implementations that could run on thousands of machines (nodes), and transparently handle failures of machines
- Hadoop is a widely used open source implementation of Map Reduce written in Java
  - Map and reduce functions can be written in several different languages, we use Java.
- Input and output to map reduce systems such as Hadoop must be done in parallel
  - Google used GFS distributed file system
  - Hadoop uses Hadoop File System (HDFS),
  - Input files can be in several formats
    - Text/CSV
    - compressed representation such as Avro, ORC and Parquet
  - Hadoop also supports key-value stores such as Hbase, Cassandra, MongoDB, etc.

Types in Hadoop

- Generic Mapper and Reducer interfaces both take four type arguments, that specify the types of the
  - input key, input value, output key and output value
- Map class in next slide implements the Mapper interface
  - Map input key is of type LongWritable, i.e. a long integer
  - Map input value which is (all or part of) a document, is of type Text.
  - Map output key is of type Text, since the key is a word,
  - Map output value is of type IntWritable, which is an integer value.

Hadoop Code in Java: Map Function


```
public static class Map extends Mapper<LongWritable, Text, Text, IntWritable>
{
    private final static IntWritable one = new IntWritable(1);
    private Text word = new Text();
    public void map(LongWritable key, Text value, Context context)
            throws IOException, InterruptedException
    {
        String line = value.toString();
        StringTokenizer tokenizer = new StringTokenizer(line);
        while (tokenizer.hasMoreTokens()) {
            word.set(tokenizer.nextToken());
            context.write(word, one);
        }
    }
}
```

Hadoop Code in Java: Reduce Function


```
public static class Reduce extends Reducer<Text, IntWritable, Text, IntWritable> {
    public void reduce(Text key, Iterable<IntWritable> values,
            Context context)  throws IOException, InterruptedException
    {
        int sum = 0;
        for (IntWritable val : values) {
            sum += val.get();
        }
        context.write(key, new IntWritable(sum));
    }
}
```

Hadoop Job Parameters

- The classes that contain the map and reduce functions for the job
  - Set by methods setMapperClass() and setReducerClass()
- The types of the job's output key and values
  - Set by methods setOutputKeyClass() and setOutputValueClass()
- The input format of the job
  - Set by method job.setInputFormatClass()
    - Default input format in Hadoop is the TextInputFormat,
      - Map key whose value is a byte offset into the file, and
      - Map value is the contents of one line of the file
- The directories where the input files are stored, and where the output files must be created
  - Set by addInputPath() and addOutputPath()
- And many more parameters

Hadoop Code in Java: Overall Program


```
public class WordCount {
    public static void main(String[] args) throws Exception {
        Configuration conf = new Configuration();
        Job job = new Job(conf, "wordcount");
        job.setOutputKeyClass(Text.class);
        job.setOutputValueClass(IntWritable.class);
        job.setMapperClass(Map.class);
        job.setReducerClass(Reduce.class);
        job.setInputFormatClass(TextInputFormat.class);
        job.setOutputFormatClass(TextOutputFormat.class);
        FileInputFormat.addInputPath(job, new Path(args[0]));
        FileOutputFormat.setOutputPath(job, new Path(args[1]));
        job.waitForCompletion(true);
    }
}
```

Local Pre-Aggregation

- **Combiners**: perform partial aggregation to minimize network traffic
  - E.g., within machine
  - And/or at rack level
- In Hadoop, reduce function is used by default if combiners are enabled
  - But alternative implementation of combiner can be specified if input and output types of reducers are different

MapReduce vs. Databases

- MapReduce is widely used for parallel processing
  - Google, Yahoo, and 100′ s of other companies
  - Example uses: compute PageRank, build keyword indices, do data analysis of web click logs, ….
  - Allows procedural code in map and reduce functions
  - Allows data of any type
- Many real-world uses of MapReduce cannot be expressed in SQL
- But many computations are much easier to express in SQL
  - Map Reduce is cumbersome for writing simple queries

MapReduce vs. Databases (Cont.)

- Relational operations (select, project, join, aggregation, etc.) can be expressed using Map Reduce
- SQL queries can be translated into Map Reduce infrastructure for execution
  - Apache Hive SQL, Apache Pig Latin, Microsoft SCOPE
- Current generation execution engines support not only Map Reduce, but also other algebraic operations such as joins, aggregation, etc. natively.

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Algebraic Operations

- Current generation execution engines
  - natively support algebraic operations such as joins, aggregation, etc. natively.
  - Allow users to create their own algebraic operators
  - Support trees of algebraic operators that can be executed on multiple nodes in parallel
- E.g. Apache Tez, Spark
  - Tex provides low level API; Hive on Tez compiles SQL to Tez
  - Spark provides more user-friendly API

Algebraic Operations in Spark

- **Resilient Distributed Dataset (RDD)** abstraction
  - Collection of records that can be stored across multiple machines
- RDDs can be created by applying algebraic operations on other RDDs
- RDDs can be lazily computed when needed
- Spark programs can be written in Java/Scala/R
  - Our examples are in Java
- Spark makes use of Java 8 Lambda expressions; the code

  s - > Arrays.asList(s.split(" ")).iterator()

  defines unnamed function that takes argument s and executes the expression Arrays.asList(s.split(" ")).iterator() on the argument
- Lambda functions are particularly convenient as arguments to map, reduce and other functions

Algebraic Operations in Spark

- Algebraic operations in Spark are typically executed in parallel on multiple machines
  - With data partitioned across the machines
- Algebraic operations are executed lazily, not immediately
  - Our preceding program creates an operator tree
  - Tree is executed only on specific functions such as saveAsTextFile() or collect()
  - Query optimization can be performed on tree before it is executed

Spark DataFrames and DataSet

- RDDs in Spark can be typed in programs, but not dynamically
- The DataSet type allows types to be specified dynamically
- Row is a row type, with attribute names
  - In code below, attribute names/types of instructor and department are inferred from files read
- Operations filter, join, groupBy, agg, etc defined on DataSet, and can execute in parallel
  -
```
Dataset<Row> instructor = spark.read().parquet("...");
Dataset<Row> department = spark.read().parquet("...");
instructor.filter(instructor.col("salary").gt(100000))
.join(department, instructor.col("dept name")
.equalTo(department.col("dept name")))
.groupBy(department.col("building"))
.agg(count(instructor.col("ID")));
```

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Streaming Data and Applications

- **Streaming data** refers to data that arrives in a continuous fashion
  - Contrast to **data-at-rest**
- Applications include:
  - Stock market: stream of trades
  - e-commerce site: purchases, searches
  - Sensors: sensor readings
    - Internet of things
  - Network monitoring data
  - Social media: tweets and posts can be viewed as a stream
- Queries on streams can be very useful
  - Monitoring, alerts, automated triggering of actions

Querying Streaming Data

- Approaches to querying streams:
- **Windowing**: Break up stream into windows, and queries are run on windows
  - Stream query languages support window operations
  - Windows may be based on time or tuples
  - Must figure out when all tuples in a window have been seen
    - Easy if stream totally ordered by timestamp
    - **Punctuations** specify that all future tuples have timestamp greater that some value
- **Continuous Queries**: Queries written e.g. in SQL, output partial results based on stream seen so far; query results updated continuously
  - Have some applications, but can lead to flood of updates

Querying Streaming Data (Cont.)

- Approaches to querying streams (Cont.):
- **Algebraic operators on streams**:
  - Each operator consumes tuples from a stream and outputs tuples
  - Operators can be written e.g., in an imperative language
  - Operator may maintain state
- **Pattern matching**:
  - Queries specify patterns, system detects occurrences of patterns and triggers actions
  - **Complex Event Processing** (**CEP**) systems
  - E.g., Microsoft StreamInsight, Flink CEP, Oracle Event Processing

Stream Processing Architectures

- Many stream processing systems are purely in-memory, and do not persist data
- **Lambda architecture**: split stream into two, one output goes to stream processing system and the other to a database for storage
  - Easy to implement and widely used
  - But often leads to duplication of querying effort, once on streaming system and once in database

Stream Extensions to SQL

- SQL Window functions described in Section 5.5.2
- Streaming systems often support more window types
  - **Tumbling window**
    - E.g., hourly windows, windows don’t overlab
  - **Hopping window**
    - E.g., hourly window computed every 20 minutes
  - **Sliding window**
    - Window of specified size (based on timestamp interval or number of tuples) around each incoming tuple
  - **Session window**
    - Groups tuples based on user sessions

Window Syntax in SQL

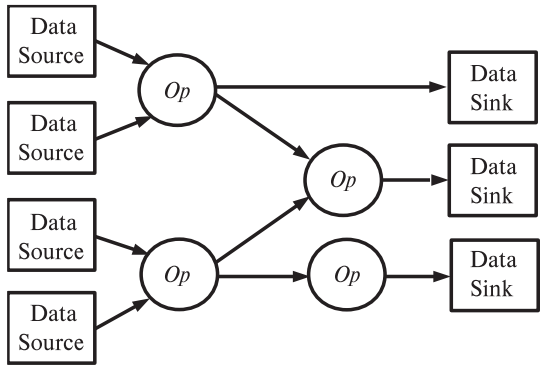
- Windowing syntax varies widely by system
- E.g., in Azure Stream Analytics SQL:

  select *item*, *System.Timestamp* **as** *window end*, **sum**(*amount*)
  from *order* **timestamp by** *datetime*
  group by *itemid*, **tumblingwindow**(*hour*, 1)

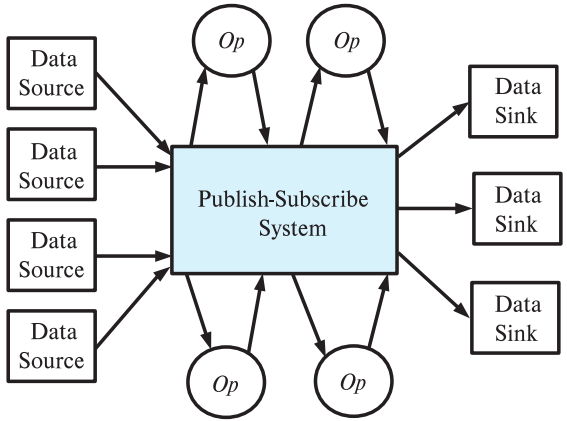
- Aggregates are applied on windows
- Result of windowing operation on a stream is a relation
- Many systems support stream-relation joins
- Stream-stream joins often require join conditions to specify bound on timestamp gap between matching tuples
  - E.g., tuples must be at most 30 minutes apart in timestamp

Algebraic Operations on Streams

- Tuples in streams need to be routed to operators
- Routing of streams using DAG and publish-subscribe representations
  - Used in Apache Storm and Apache Kafka respective



(a) DAG representation of streaming data flow



(b) Publish-subscribe representation of streaming data flow

Publish Subscribe Systems

- **Publish-subscribe** (**pub-sub**) systems provide convenient abstraction for processing streams
  - Tuples in a stream are published to a topic
  - Consumers subscribe to topic
- Parallel pub-sub systems allow tuples in a topic to be partitioned across multiple machines
- **Apache Kafka** is a popular parallel pub-sub system widely used to manage streaming data
- More details in book

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Graph Data Model

- Graphs are a very general data model
- ER model of an enterprise can be viewed as a graph
  - Every entity is a node
  - Every binary relationship is an edge
  - Ternary and higher degree relationships can be modelled as binary relationships

Graph Data Model (Cont.)

- Graphs can be modelled as relations
  - *node*(*ID, label, node_data*)
  - *edge*(*fromID, toID, label, edge_data*)
- Above representation too simplistic
- Graph databases like Neo4J can provide a **graph view of relational schema**
  - Relations can be identified as representing either nodes or edges
- Query languages for graph databases make it
  - easy to express queries requiring edge traversal
  - allow efficient algorithms to be used for evaluation

Graph Data Model (Cont.)

- Suppose
  - Relations *instructor* and *student* are nodes, and
  - Relation *advisor* represents edges between instructors and student
- Query in Neo4J:
  match (*i*:*instructor*)<-[:*advisor*]-(*s*:*student*)
  where *i*.*dept name*= 'Comp. Sci.'
  return *i*.ID **as** ID, *i*.*name* **as** *name*, **collect**(*s*.*name*) **as** *advisees*
- **match** clause matches nodes and edges in graphs
- Recursive traversal of edges is also possible
  - Suppose *prereq*(*course_id, prereq_id*) is modeled as an edge
  - Transitive closure can be done as follows:

    match (*c1*:*course*)-[:*prereq* *1..]->(*c2*:*course*)
    return *c*1.*course id*, *c*2.*course id*

Parallel Graph Processing

- Very large graphs (billions of nodes, trillions of edges)
  - Web graph: web pages are nodes, hyper links are edges
  - Social network graph: people are nodes, friend/follow links are edges
- Two popular approaches for parallel processing on such graphs
  - Map-reduce and algebraic frameworks
  - **Bulk synchronous processing (BSP)** framework
- Multiple iterations are required for any computations on graphs
  - Map-reduce/algebraic frameworks often have high overheads per iteration
  - BSP frameworks have much lower per-iteration overheads
- Google's Pregel system popularized the BSP framework
- Apache Giraph is an open-source version of Pregel
- Apache Spark's GraphX component provides a Pregel-like API

Bulk Synchronous Processing

- Each vertex (node) of a graph has data (state) associated with it
  - Vertices are partitioned across multiple machines, and state of node kept in-memory
- Analogous to map() and reduce() functions, programmers provide methods to be executed for each node
  - Node method can send messages to or receive messages from neighboring nodes
- Computation consists of multiple iterations, or supersteps
- In each **superstep**
  - Nodes process received messages
  - Update their state, and
  - Send further messages or vote to halt
  - Computation ends when all nodes vote to halt, and there are no pending messages