Chapter 10: Big Data

Database System Concepts, 7th Ed.

Motivation

- 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

Big Data Storage Systems

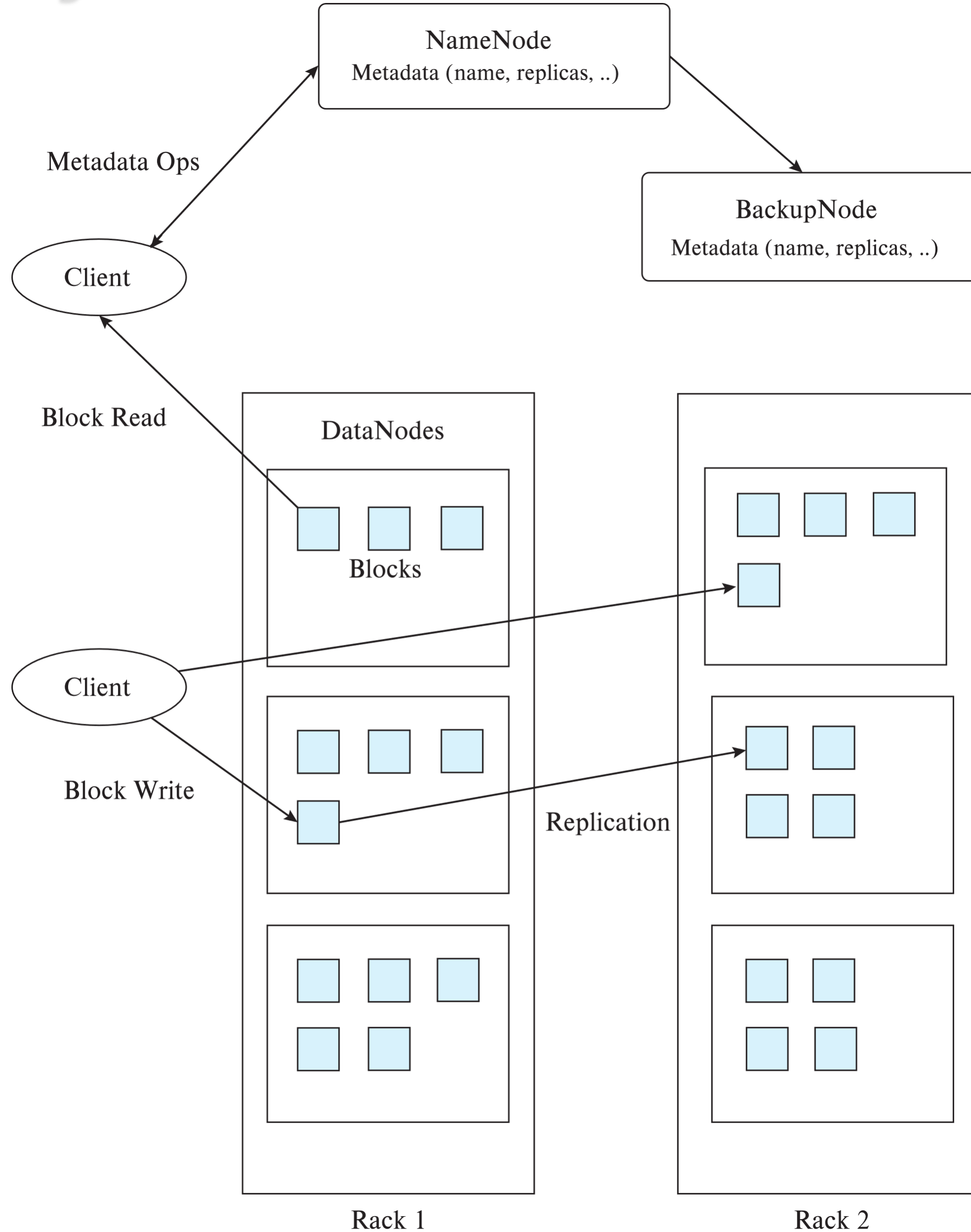
- Distributed file systems
- Sharding across multiple databases
- Key-value storage systems
- Parallel and distributed databases

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
- 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

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 is:

```
{
    "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 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
- **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 later, in Chapter 23

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
- 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
  ...

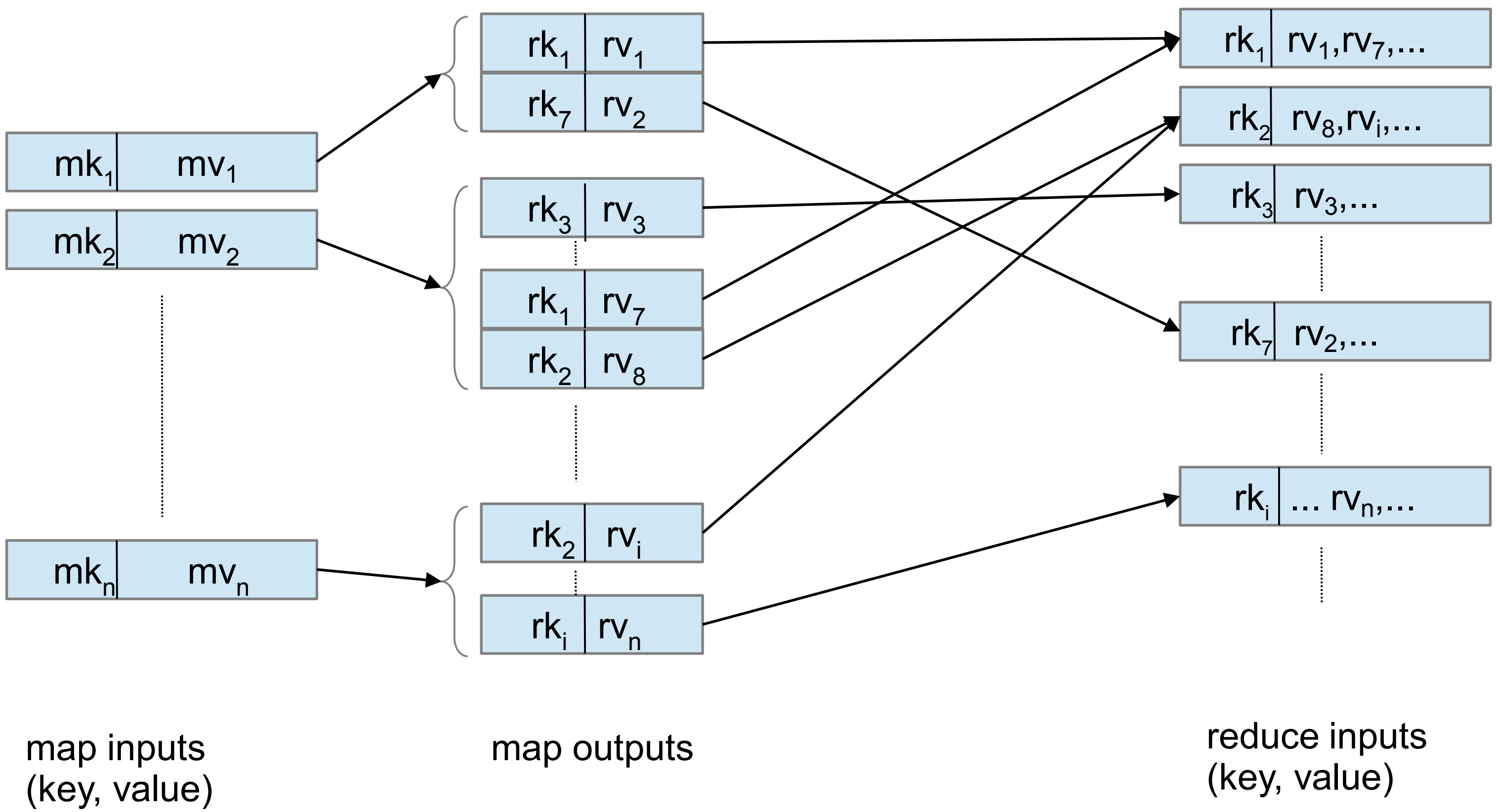
- Goal: find how many times each of the files in the slide-dir directory was accessed between 2013/01/01 and 2013/01/31.
- Options:
  - Sequential program too slow on massive datasets
  - Load into database expensive, direct operation on log files cheaper
  - Custom built parallel program for this task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

MapReduce: File Access Count Example

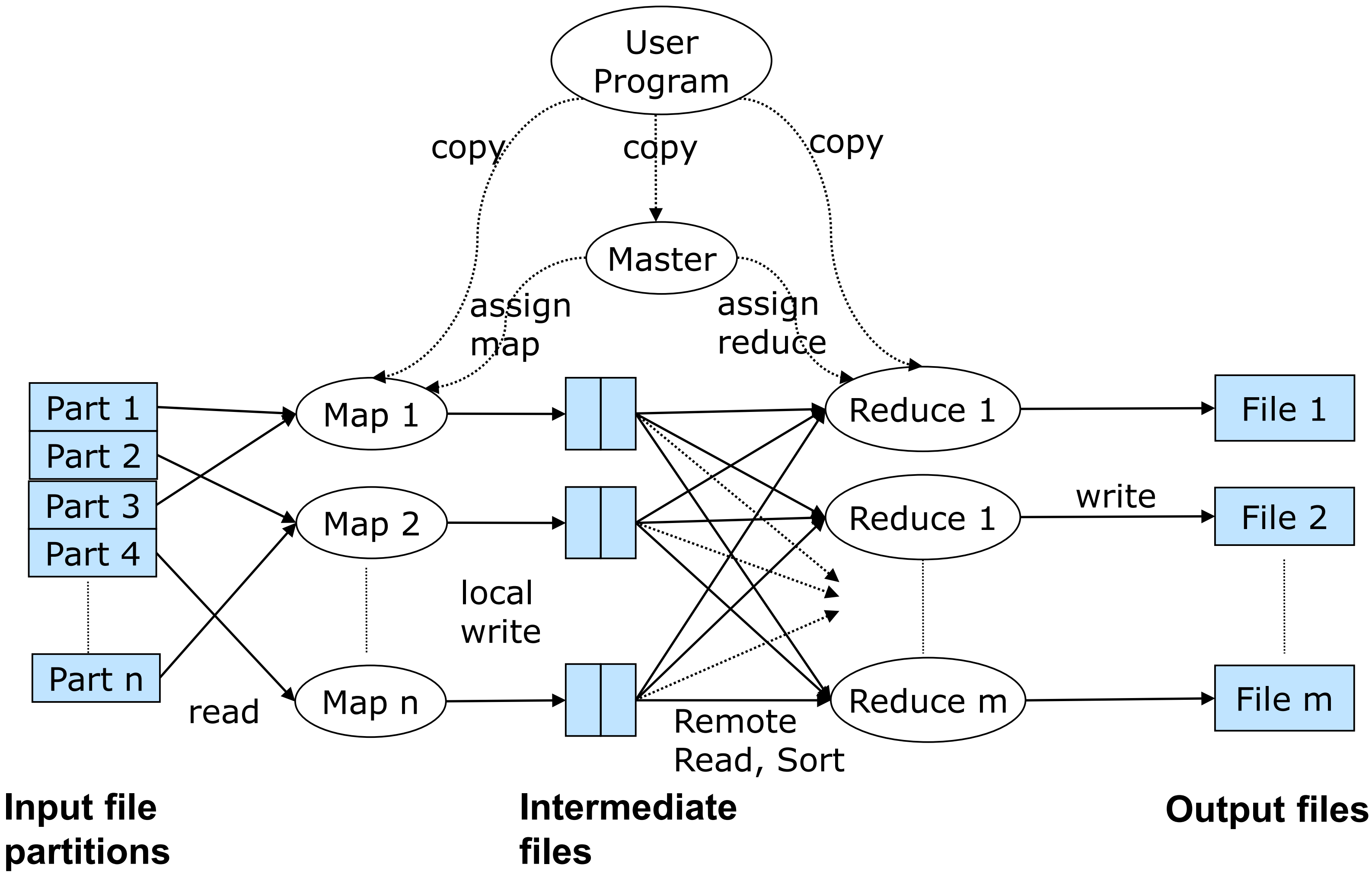
```
map(String key, String record) {
    String attribute[3];
    …. break up record into tokens (based on space character), and store the
         tokens in array attributes
    String date = attribute[0];
    String time = attribute[1];
    String filename = attribute[2];
    if (date between 2013/01/01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

Hadoop

- 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);
    }
}
```

Map Reduce vs. Databases

- Map Reduce 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

Map Reduce 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 exectuion
  - 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.

BEYOND MAPREDUCE: ALGEBRAIC OPERATIONS

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

Word Count in Spark

```
SparkSession spark =
        SparkSession.builder().appName(”WordCount”).getOrCreate();

JavaRDD<String> lines = spark.read().textFile(args[0]).javaRDD();
JavaRDD<String> words = lines.flatMap(s -> Arrays.asList(s.split(“ ”)).iterator());
JavaPairRDD<String, Integer> ones = words.mapToPair(s -> new Tuple2<>(s, 1));
JavaPairRDD<String, Integer> counts = ones.reduceByKey((i1, i2) -> i1 + i2);

counts.saveAsTextFile(”outputDir”); // Save output files in this directory

List<Tuple2<String, Integer>> output = counts.collect();
for (Tuple2<String,Integer> tuple : output) {
        System.out.println(tuple);
}
spark.stop();
```

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")));
```

STREAMING DATA

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

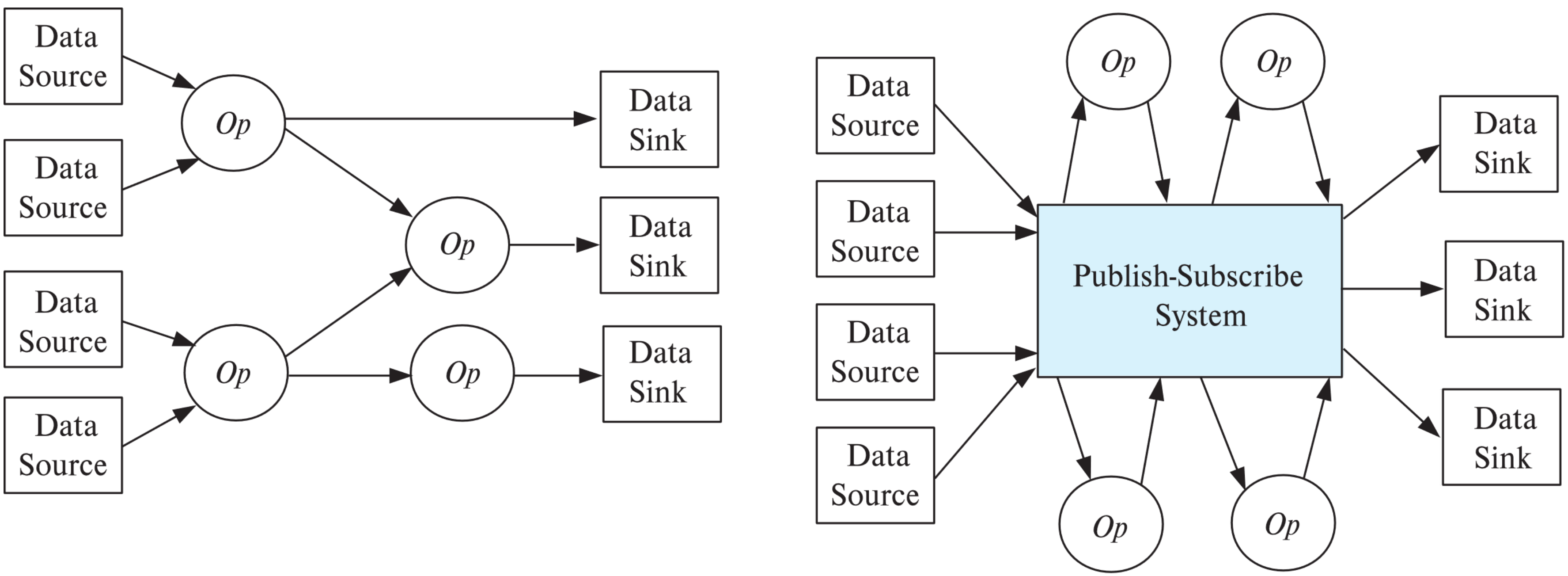
- SQL Window functions described in Section 5.5.2
- Streaming systems often support more window types
  - **Tumbling window**
    - E.g. hourly windows, windows don’t overlab
  - **Hopping window**
    - E.g. hourly window computed every 20 minutes
  - **Sliding window**
    - Window of specified size (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 e.g. 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

GRAPH DATABASES

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

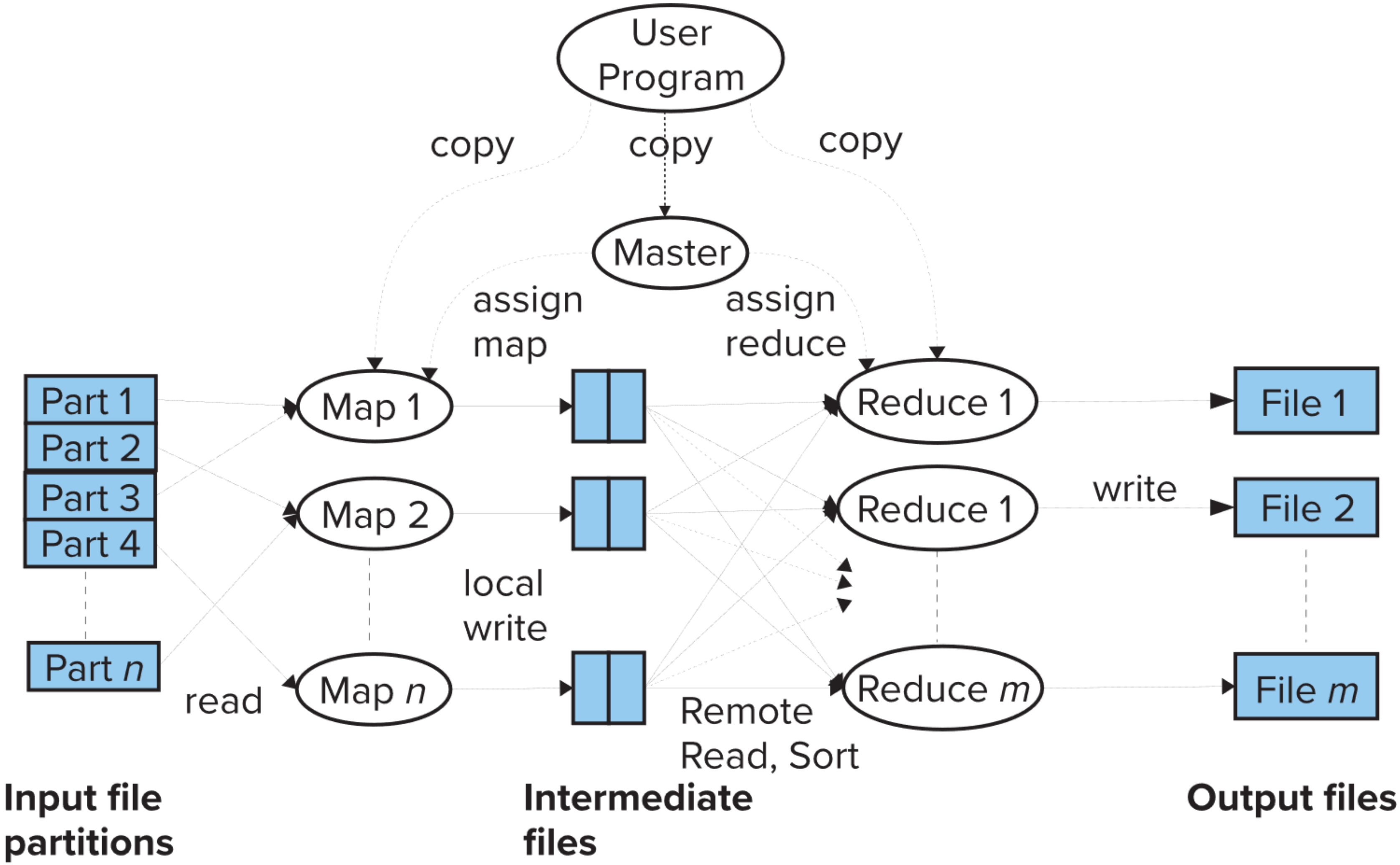
- Very large graphs (billions of nodes, trillions of edges)
  - Web graph: web pages are nodes, hyper links are edges
  - Social network graph: people are nodes, friend/follow links are edges
- Two popular approaches for parallel processing on such graphs
  - Map-reduce and algebraic frameworks
  - **Bulk 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

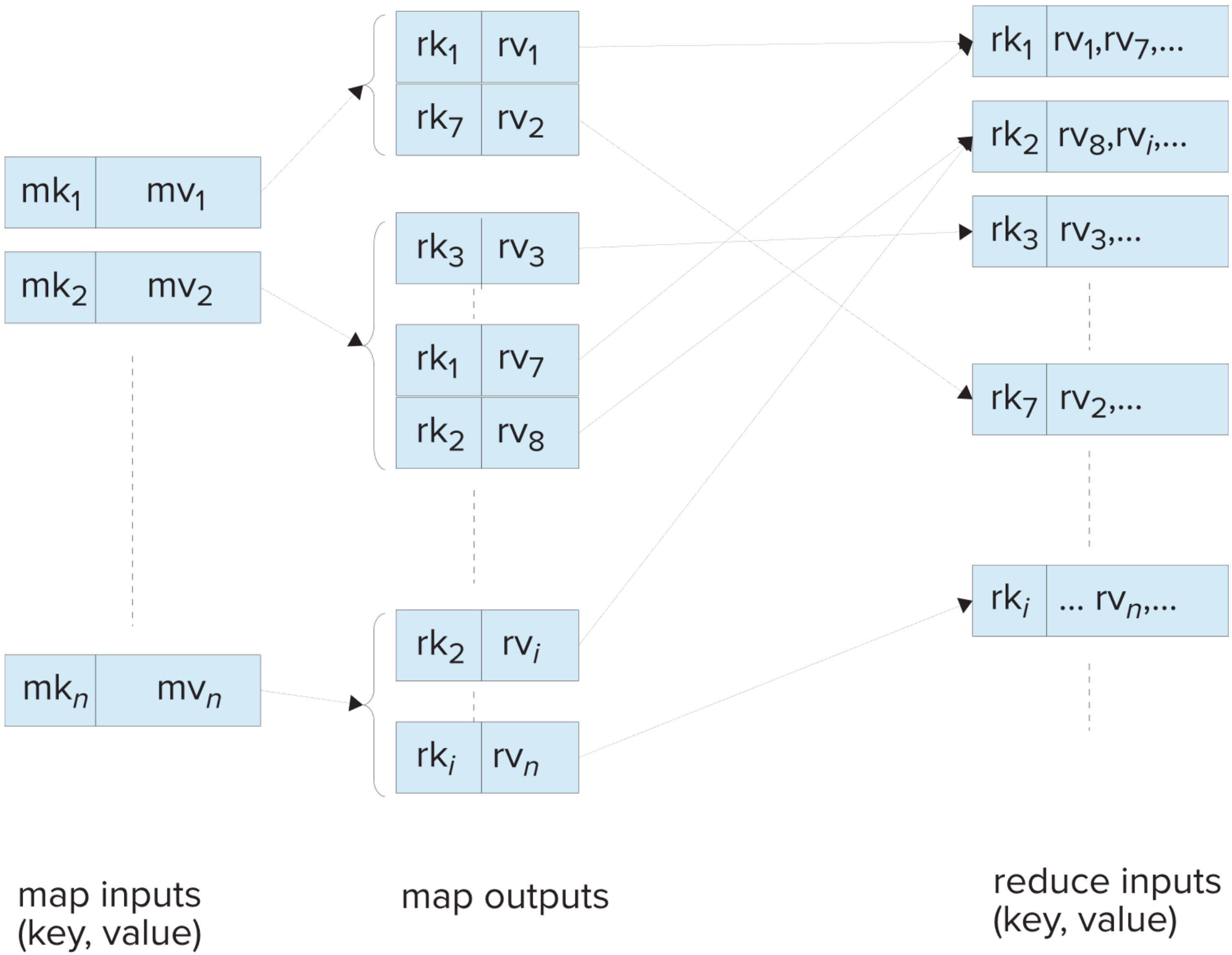
Bulk Synchronous Processing

Bulk synchronous processing framework

- 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;

END OF CHAPTER


User Program
copy
copy
copy
Master
assign map
assign reduce
Part 1
Part 2
Part 3
Part 4
Part n
read
Map 1
Map 2
Map n
local write
Reduce 1
Reduce 1
Reduce m
Remote Read, Sort
write
File 1
File 2
File m
Input file partitions
Intermediate files
Output files


mk1 mv1
mk2 mv2
mkn mvn
rk1 rv1
rk7 rv2
rk3 rv3
rk1 rv7
rk2 rv8
rk2 rvi
rki rvn
rk1 rv1,rv7,...
rk2 rv8,rvi,...
rk3 rv3,...
rk7 rv2,...
rki ... rvn,...
map inputs
(key, value)
map outputs
reduce inputs
(key, value)