HEIDELBERG LAUREATE FORUM

INDIAN INSTITUTE OF INFORMATION TECHNOLOGY
Dharwad
ज्ञानेन विकासः

acm India Council
Pingala Interactions In Computing

Big Data Analytics

Dr. Animesh Chaturvedi

Assistant Professor: IIIT Dharwad

Young Researcher: Pingala Interaction in Computing

Young Researcher: Heidelberg Laureate Forum

Postdoc: King's College London & The Alan Turing Institute

PhD: IIT Indore MTech: IIITDM Jabalpur

KING'S College LONDON

The Alan Turing Institute

Indian Institute of Technology Indore
भारतीय प्रौद्योगिकी संस्थान इंदौर

PDPM
Indian Institute of Information Technology, Design and Manufacturing, Jabalpur

Big Data Analytics

1. Big Data
2. Storm
3. Spark: Big Data Analytics
4. Resilient Distributed Datasets (RDD)
5. Spark libraries (SQL, DataFrames, MLlib for machine learning, GraphX, and Streaming)
6. PFP: Parallel FP-Growth

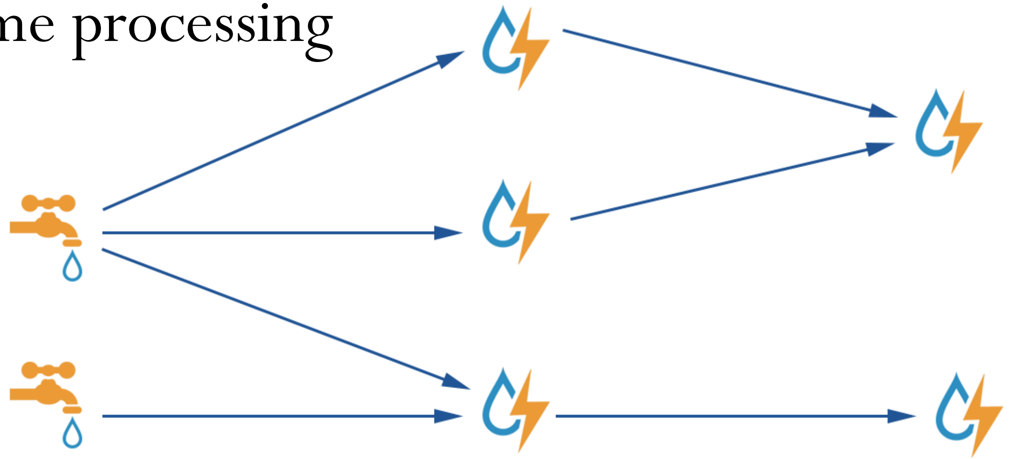
Big Data

- Big data can be described by the following characteristics:
  - Volume: size large than terabytes and petabytes
  - Variety: type and nature, structured, semi-structured or unstructured
  - Velocity: speed of generation and processing to meet the demands
  - Veracity: the data quality and the data value
  - Value: Useful or not useful
- The main components and ecosystem of Big Data
  - Data Analytics: data mining, machine learning and natural language processing
  - Technologies: Business Intelligence, Cloud computing & Databases
  - Visualization: Charts, Graphs etc.

Storm

Storm

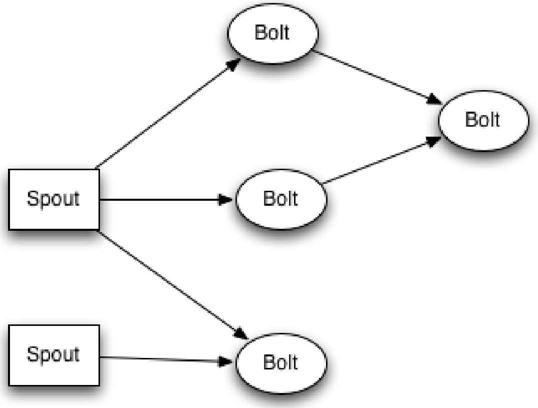
- Reliably for processing unbounded streams of data
- Hadoop for batch processing. Storm real-time processing
- Realtime analytics
- Online machine learning
- Continuous computation
- Distributed RPC.

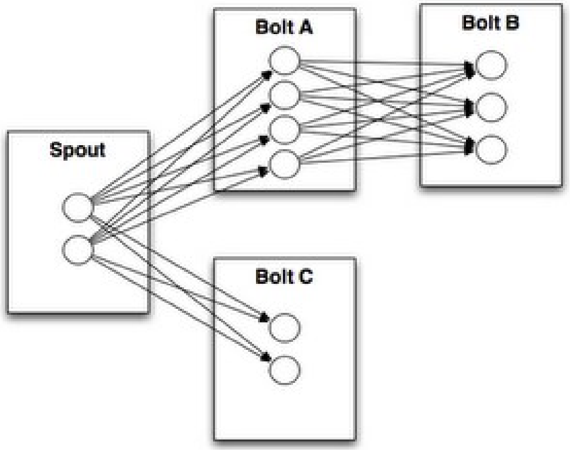


- A million tupples can be processed per second per node.
- It is scalable, fault-tolerant, guarantees your data will be processed, and is easy to set up and operate.

Storm

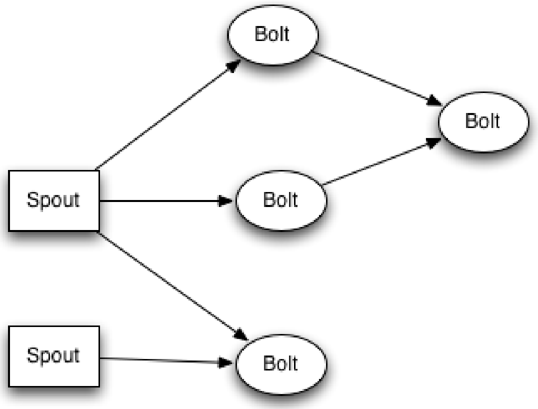
- Apache Storm is a free and open source distributed Realtime computation system.
- Apache Storm makes it easy to reliably process unbounded streams of data, doing for Realtime processing what Hadoop did for batch processing.
- Apache Storm integrates with the queueing and database technologies you already use.
- An Apache Storm topology consumes streams of data and processes those streams in arbitrarily complex ways, repartitioning the streams between each stage of the computation however needed.





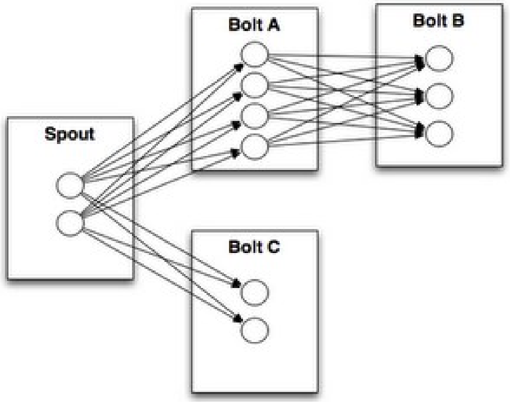
Storm

- Topologies: analogous to a MapReduce job. MapReduce job finishes, whereas a topology runs forever or until you kill it.
  - A topology is a graph of spouts and bolts that are connected with stream groupings.
- Streams: is an unbounded sequence of tuples that is processed and created in parallel in a distributed fashion.
  - Streams are defined with a schema that names the fields in the stream's tuples.
  - Schema are integers, longs, shorts, bytes, strings, doubles, floats, booleans, and byte arrays.
  - Every stream is given an id when declared.



Storm

- **Spouts:** A spout is a source of streams in a topology. Generally spouts will read tuples from an external source and emit them into the topology.
  - **Reliable Spouts:** Replaying a tuple if it failed to be processed.
  - **Unreliable Spouts:** Forgets about the tuple as soon as it is emitted.

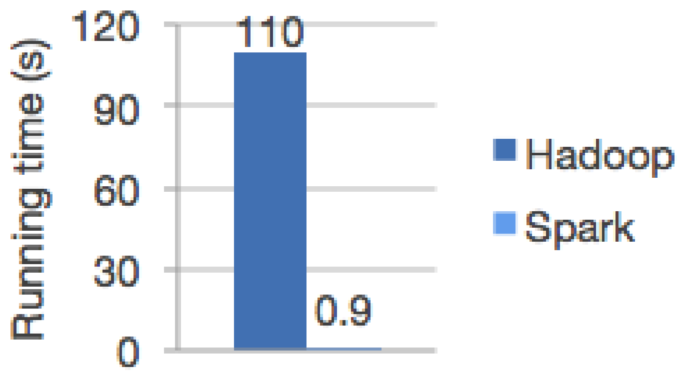


- **Bolts:** All processing in topologies is done in bolts.
  - Bolts can do filtering, functions, aggregations, joins, talking to databases, and more.
  - Bolts can do stream transformations into a new stream in a distributed and reliable way.
  - Complex stream transformations often requires multiple steps and thus multiple bolts.
  - For example, transform a stream of tweets into a stream of trending topics.

Spark

Apache Spark

- Unified analytics engine for large-scale data processing.
- Speed: Run workloads 100x faster.
- Both batch and streaming data, using Directed Acyclic Graph (DAG) scheduler, a query optimizer, and a physical execution engine.
- Ease of Use: Write applications quickly in Java, Scala, Python, R, and SQL.
- Spark offers 80+ high-level operators to build parallel apps.



https://spark.apache.org/

Spark: Unified Big Data Analytics

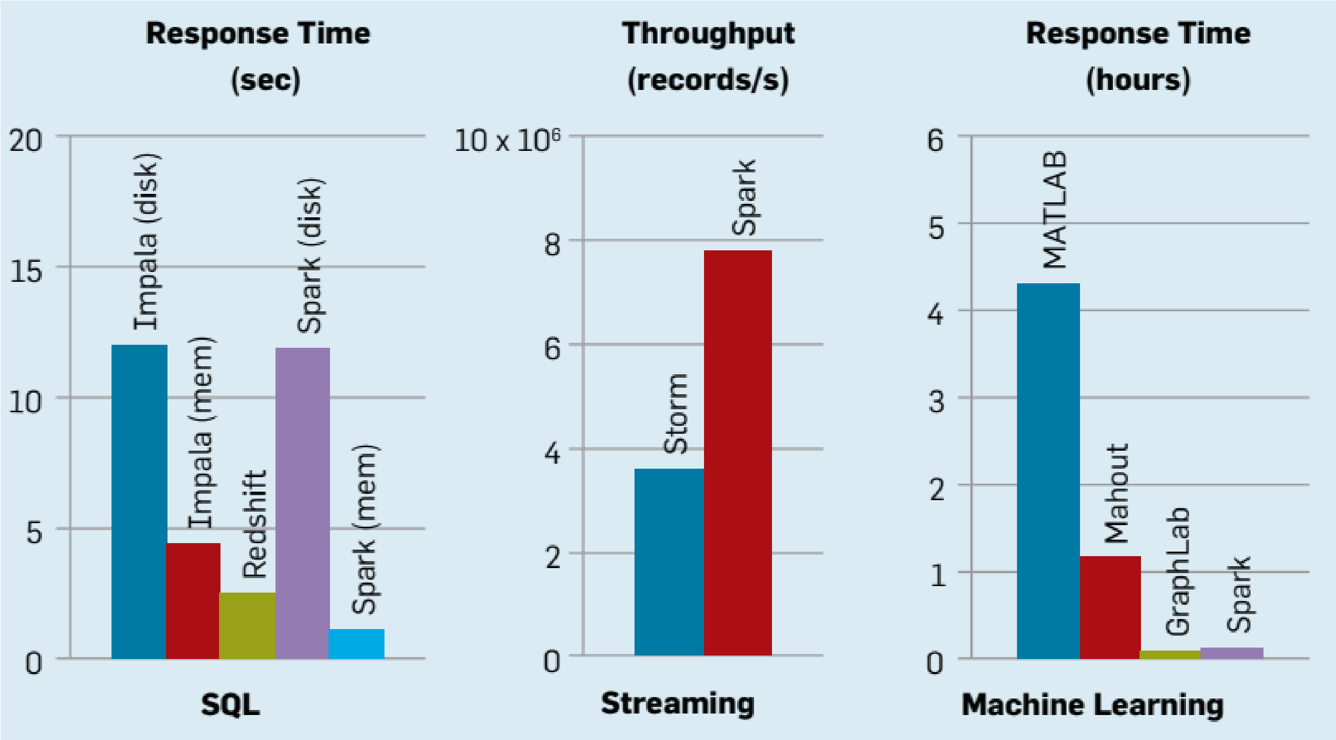
- New applications of Big data workloads on Unified Engine of
  - Streaming, Batch, and Interactive.
- Composability in programming libraries for big data and encourages development of interoperable libraries
- Combining the SQL, machine learning, and streaming libraries in Spark

```
// Load historical data as an RDD using Spark SQL
val trainingData = sql(
   "SELECT location, language FROM old_tweets")

// Train a K-means model using MLlib
val model = new KMeans()
   .setFeaturesCol("location")
   .setPredictionCol("language")
   .fit(trainingData)
// Apply the model to new tweets in a stream
TwitterUtils.createStream(...)
      .map(tweet => model.predict(tweet.location))
```

Zaharia, Matei, et al. "Apache spark: a unified engine for big data processing." *Communications of the ACM* 59.11 (2016): 56-65.

Spark: Unified Big Data Analytics

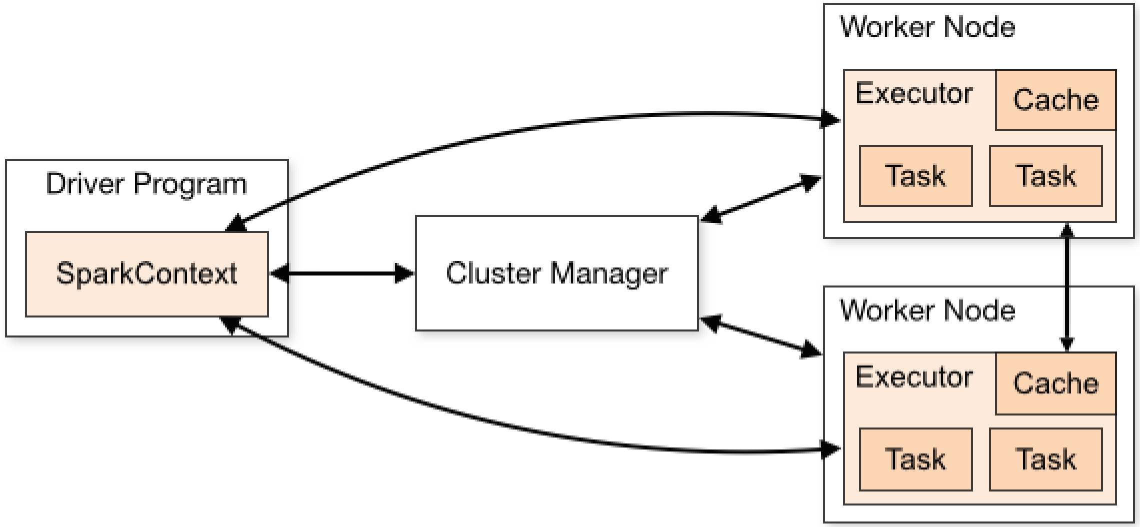
- Spark has MapReduce programming model with extended data-sharing abstraction called "Resilient Distributed Datasets," or RDDs.



Zaharia, Matei, et al. "Apache spark: a unified engine for big data processing." *Communications of the ACM* 59.11 (2016): 56-65.

Spark Architecture

- Spark works on the popular Master-Slave architecture.
- Cluster works with a single master and multiple slaves.
- The Spark architecture depends upon two abstractions:
  - Resilient Distributed Dataset (RDD)
  - Directed Acyclic Graph (DAG)

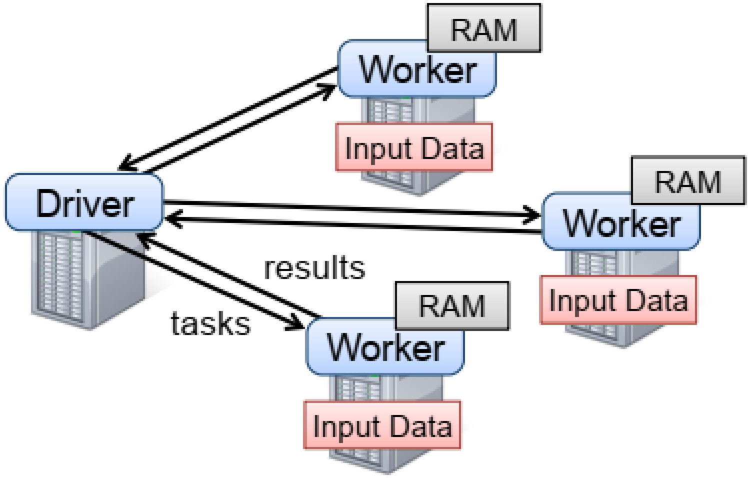


https://spark.apache.org/docs/latest/cluster-overview.html

Resilient Distributed Datasets (RDD)

Resilient Distributed Datasets (RDD)

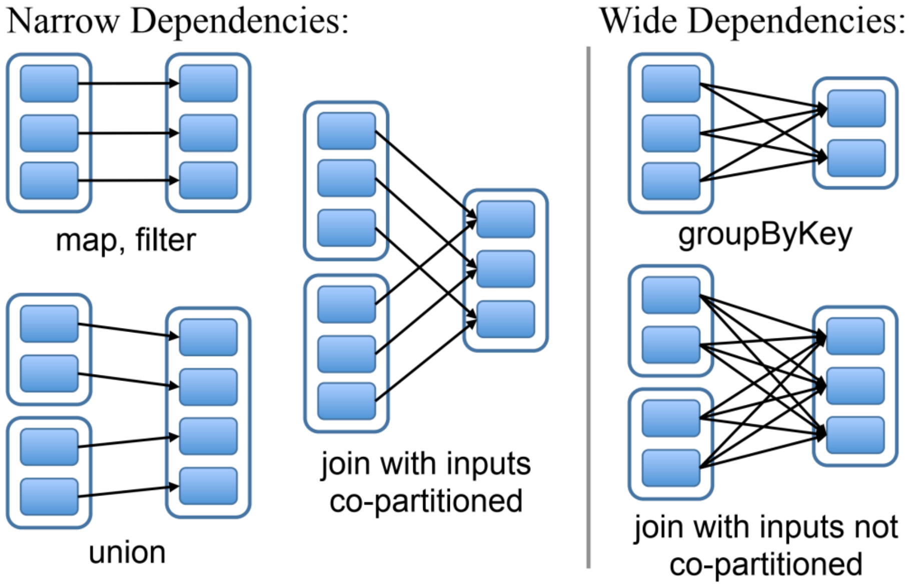
- A distributed memory abstraction: perform in-memory computations on large clusters
- Keeping data in memory can improve performance
- Spark runtime: Driver program launches multiple workers that read data blocks from a distributed file system and can persist computed RDD partitions in memory.



Zaharia, Matei, et al. "Resilient distributed datasets: A fault-tolerant abstraction for in-memory cluster computing." *Presented as part of the 9th {USENIX} Symposium on Networked Systems Design and Implementation ({NSDI} 12)*. 2012.

Resilient Distributed Datasets (RDD)

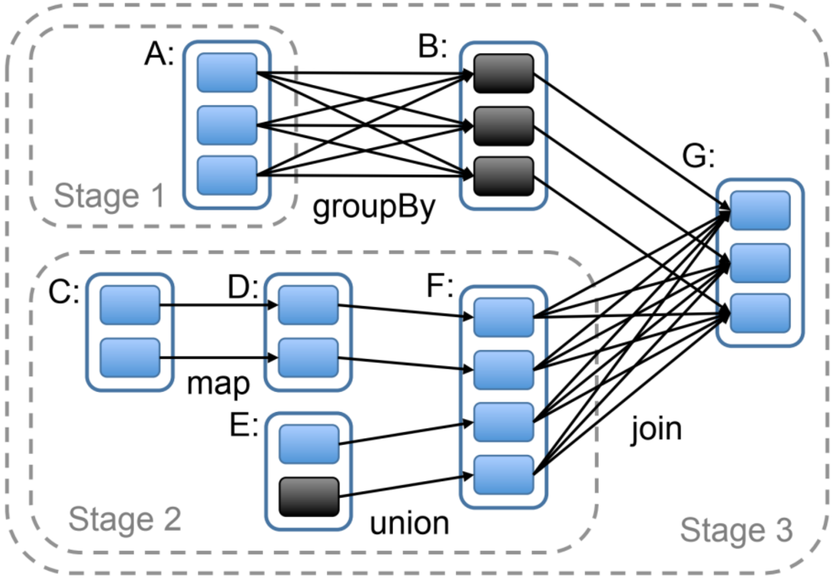
- Each box is an RDD, with partitions as shaded rectangles.
- *narrow* dependencies, where each partition of the parent RDD is used by at most one partition of the child RDD,
- *wide* dependencies, where multiple child partitions may depend on it.



Zaharia, Matei, et al. "Resilient distributed datasets: A fault-tolerant abstraction for in-memory cluster computing." *Presented as part of the 9th {USENIX} Symposium on Networked Systems Design and Implementation ({NSDI} 12)*. 2012.

Resilient Distributed Datasets (RDD)

- Direct Acyclic Graph (DAG) to perform a sequence of computations
- Each node is an RDD partition,
- Run an action (*e.g.*, *count* or *save*) on an RDD, the scheduler examines that RDD's lineage graph to build a DAG of *stages* to execute.
- Each stage contains with narrow dependencies
- The boundaries of the stages are the shuffle operations required for wide dependencies.
- Scheduler computes missing partitions until it computed RDD.



Zaharia, Matei, et al. "Resilient distributed datasets: A fault-tolerant abstraction for in-memory cluster computing." *Presented as part of the 9th {USENIX} Symposium on Networked Systems Design and Implementation ({NSDI} 12)*. 2012.

Apache Spark

- Combine SQL, streaming, and complex analytics. Spark libraries
  - SQL and DataFrames,
  - MLlib for machine learning,
  - GraphX, and
  - Spark Streaming.
- Spark runs on Hadoop, Apache Mesos, Kubernetes, standalone, or in the cloud.
- Run Spark using its standalone cluster mode, on EC2, on Hadoop YARN, on Mesos, or on Kubernetes.
- Access data in HDFS, Alluxio, Apache Cassandra, Apache HBase, Apache Hive, and hundreds of other data sources.

https://spark.apache.org/

Spark Code Example

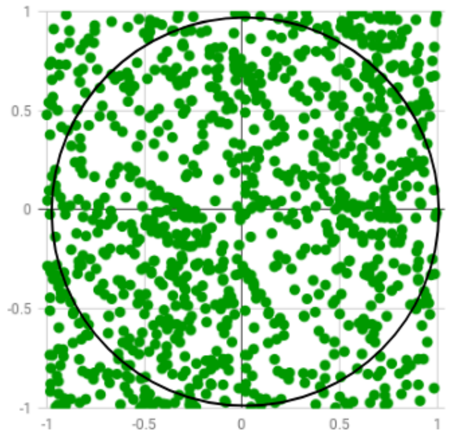
- Word Count

```
JavaRDD<String> textFile = sc.textFile("hdfs://...");
JavaPairRDD<String, Integer> counts = textFile
    .flatMap(s -> Arrays.asList(s.split(" ")).iterator())
    .mapToPair(word -> new Tuple2<>(word, 1))
    .reduceByKey((a, b) -> a + b);
counts.saveAsTextFile("hdfs://...");
```

- Pi Estimation

```
List<Integer> l = new ArrayList<>(NUM_SAMPLES);
for (int i = 0; i < NUM_SAMPLES; i++) {
  l.add(i);
}

long count = sc.parallelize(l).filter(i -> {
  double x = Math.random();
  double y = Math.random();
  return x*x + y*y < 1;
}).count();
System.out.println("Pi is roughly " + 4.0 * count / NUM_SAMPLES);
```

$$\mathrm{Pi} = 4 \times \frac{\textit{number of random point inside the circle}}{\textit{number of random point inside the square}}$$



Spark SQL

- Working with structured data.
- Integrated: SQL queries with Spark programs.

```
results = spark.sql("SELECT * FROM people")
names = results.map(lambda p: p.name)
```

Apply functions to results of SQL queries.

- Uniform Data Access: Connect to data sources, including Hive, Avro, Parquet, ORC, JSON, and JDBC.

```
spark.read.json("s3n://...").registerTempTable("json")
results = spark.sql("""SELECT * FROM people JOIN json ...""")
```

- Query and join different data sources
- Hive Integration Spark HiveQL
- Standard Connectivity: Connect through JDBC or ODBC.
- Business intelligence tools to query big data.

https://spark.apache.org/sql/

DataFrame API Examples

- Collection of data organized into named columns
- Use DataFrame API to perform various relational operations
- Automatically optimized by Spark's built-in optimizer

```
// Creates a DataFrame having a single column named "line"
JavaRDD<String> textFile = sc.textFile("hdfs://...");
JavaRDD<Row> rowRDD = textFile.map(RowFactory::create);
List<StructField> fields = Arrays.asList(
  DataTypes.createStructField("line", DataTypes.StringType, true));
StructType schema = DataTypes.createStructType(fields);
DataFrame df = sqlContext.createDataFrame(rowRDD, schema);

DataFrame errors = df.filter(col("line").like("%ERROR%"));
// Counts all the errors
errors.count();
// Counts errors mentioning MySQL
errors.filter(col("line").like("%MySQL%")).count();
// Fetches the MySQL errors as an array of strings
errors.filter(col("line").like("%MySQL%")).collect();
```

Spark Streaming

- Build scalable fault-tolerant streaming applications.
- Write streaming jobs -- Same Way -- Write batch jobs
  - Counting tweets on a sliding window

```
TwitterUtils.createStream(...)
.filter(_.getText.contains("Spark"))
.countByWindow(Seconds(5))
```

- Reuse the same code for batch processing
  - Find words with higher frequency than historic data:

```
stream.join(historicCounts).filter {
  case (word, (curCount, oldCount)) =>
    curCount > oldCount
}
```

Batch processing takes N unit time to process M unit of data

Batch processing **takes N+x unit time** to process **M+y unit of data**

Stream processing takes N unit time to process M unit of data

Stream processing **takes x unit time** to process **M+y unit of data**

https://spark.apache.org/streaming/

Spark GraphX

- Spark's API for graphs and graph-parallel computation

```
graph = Graph(vertices, edges)
messages = spark.textFile("hdfs://...")
graph2 = graph.joinVertices(messages) {
  (id, vertex, msg) => ...
}
```

- Fast Speed for graph algorithms
- GraphX graph algorithms
  - PageRank
  - Connected components
  - Label propagation
  - SVD++
  - Strongly connected components
  - Triangle count

https://spark.apache.org/graphx/

Spark MLlib

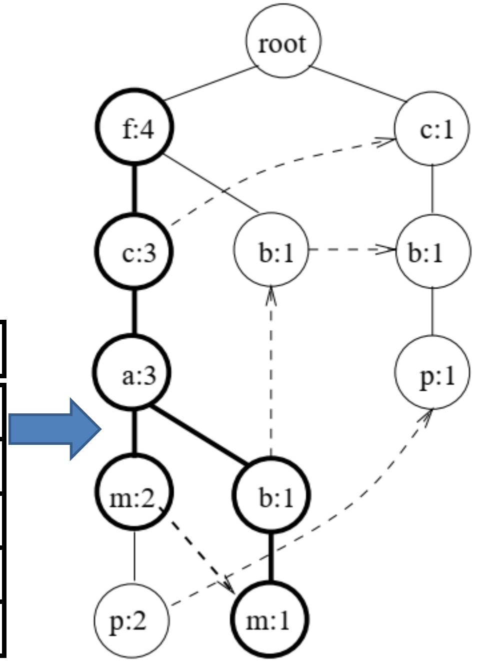
- Spark's scalable machine learning library
- Spark MLlib algorithms
  - Classification: logistic regression, naive Bayes,…
  - Regression: generalized linear regression, survival regression,…
  - Decision trees, Random forests, and Gradient-boosted trees
  - Recommendation: Alternating Least Squares (ALS)
  - Clustering: K-means, Gaussian mixtures (GMMs),…
  - Topic modeling: Latent Dirichlet Allocation (LDA)
  - **Frequent itemsets, Association rules, and Sequential pattern mining**

https://spark.apache.org/graphx/

FP-Growth for recommendation

- "FP" stands for Frequent Pattern in a Dataset of transactions
  1. calculate item frequencies and identify frequent items,
  2. a suffix tree (FP-tree) structure to encode transactions, and
  3. frequent itemsets can be extracted from the FP-tree.
- Input: Transaction database
- Intermediate Output: FP-Tree
- Output: {f, c, a → a, m p}, {f, c, a → b, m}

TID	Items Bought	(Ordered) Frequent Items
100	f, a, c, d, g, i, m, p	f, c, a, m, p
200	a, b, c, f, l, m, o	f, c, a, b, m
300	b, f, h, j, o	f, b
400	b, c, k, s, p	c, b, p
500	a, f, c, e, l, p, m, n	f, c, a, m, p



Han Jiawei, Jian Pei, and Yiwen Yin. "Mining frequent patterns without candidate generation." *ACM SIGMOD Record* 29.2 (2000): 1-12.

PFP: Parallel FP-Growth

- In Spark ML-Library (MLLib), a parallel version of FP-growth called PFP: Parallel FP-Growth
- PFP distributes the work of growing FP-trees based on the suffixes of transactions.
- More scalable than a single-machine implementation.
- PFP partitions computation, where each machine executes an independent group of mining tasks

Li, Haoyuan, et al. "PFP: Parallel FP-Growth for query recommendation." *Proceedings of the 2008 ACM Conference on Recommender systems*. 2008.

PFP: Parallel FP-Growth

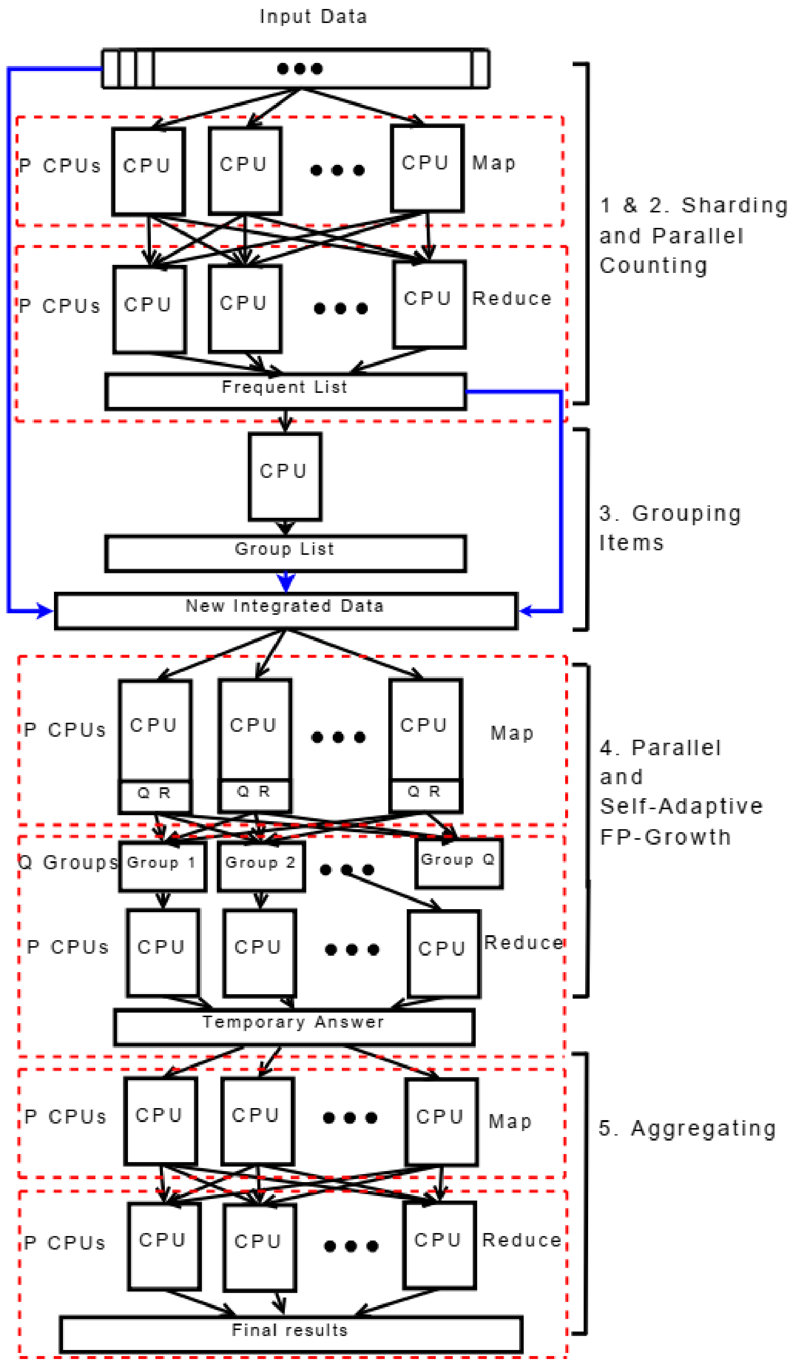
Example of MapReduce FP-Growth: Five transactions composed of lower-case alphabets representing items

Map inputs (transactions) key="": value	Sorted transactions (with infrequent items eliminated)	Map outputs (conditional transactions) key: value
f a c d g i m p	f c a m p	p: f c a m m: f c a a: fc c: f
a b c f l m o	f c a b m	m: f c a b b: f c a a: f c c: f
b f h j o	f b	b: f
b c k s p	c b p	p: c b b: c
a f c e l p m n	f c a m p	p: f c a m m: f c a a: f c c: f

Reduce inputs (conditional databases) key: value	Conditional FP–trees
p: { f c a m / f c a m / c b }	{(c:3)} | p
m: { f c a / f c a / f c a b }	{ (f:3, c:3, a:3) } | m
b: { f c a / f / c }	{} | b
a: { f c / f c / f c }	{ (f:3, c:3) } | a
c: { f / f / f }	{ (f:3) } | c

Li, Haoyuan, et al. "PFP: Parallel FP-Growth for query recommendation." *Proceedings of the 2008 ACM Conference on Recommender systems*. 2008.

- **Sharding:** Divide DB into successive parts and storing the parts (as a Shard) on P different computers.
- **Parallel Counting:** MapReduce counts the support of all items that appear in DB. Each mapper inputs one shard of DB. The result is stored in F-list.
- **Grouping Items:** Dividing all the items on F-List into Q groups of a list (G-list).
- **Parallel FP-Growth:** A MapReduce
  - **Mapper:** Each mapper uses a Shard. It reads a transaction in the G-list and outputs one or more key-value pairs, where each key is a *group-id* and value is a **group-dependent transaction**.
  - For each *group-id*, the MapReduce groups all group-dependent transactions into a shard.
  - **Reducer:** Each reducer processes one or more group-dependent Shard. For each shard, a reducer builds a local FP-Tree and discover patterns.
- **Aggregating:** Aggregate the results generated as final result.



Li, Haoyuan, et al. "PFP: Parallel FP-Growth for query recommendation." *ACM Conf. on Recommender systems*. 2008.

PFP: Parallel FP-Growth

- FP-Growth implementation takes the following (hyper-)parameters
  - minSupport: the minimum support for an itemset to be identified as frequent e.g., if an item appears 3 out of 5 transactions, it has a support of 3/5=0.6.
  - minConfidence: minimum confidence for generating Association Rule e.g., if in the transactions itemset X appears 4 times, X and Y co-occur only 2 times, the confidence for the rule X => Y is then 2/4 = 0.5.
  - numPartitions: the number of partitions used to distribute the work.
- FP-Growth model provides:
  - freqItemsets: frequent itemsets in the format of DataFrame("items"[Array], "freq"[Long])
  - associationRules: association rules generated with confidence above minConfidence, in the format of DataFrame("antecedent"[Array], "consequent"[Array], "confidence"[Double]).

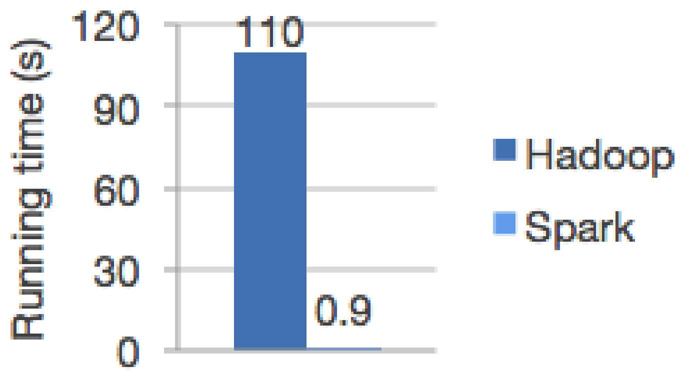
PFP: Parallel FP-Growth

```java
import java.util.Arrays;
import java.util.List;

import org.apache.spark.ml.fpm.FPGrowth;
import org.apache.spark.ml.fpm.FPGrowthModel;
import org.apache.spark.sql.Dataset;
import org.apache.spark.sql.Row;
import org.apache.spark.sql.RowFactory;
import org.apache.spark.sql.SparkSession;
import org.apache.spark.sql.types.*;

List<Row> data = Arrays.asList(
  RowFactory.create(Arrays.asList("1 2 5".split(" "))),
  RowFactory.create(Arrays.asList("1 2 3 5".split(" "))),
  RowFactory.create(Arrays.asList("1 2".split(" ")))
);
StructType schema = new StructType(new StructField[]{ new StructField(
  "items", new ArrayType(DataTypes.StringType, true), false, Metadata.empty())
});
Dataset<Row> itemsDF = spark.createDataFrame(data, schema);

FPGrowthModel model = new FPGrowth()
  .setItemsCol("items")
  .setMinSupport(0.5)
  .setMinConfidence(0.6)
  .fit(itemsDF);

// Display frequent itemsets.
model.freqItemsets().show();

// Display generated association rules.
model.associationRules().show();

// transform examines the input items against all the association rules and summarize the
// consequents as prediction
model.transform(itemsDF).show();
```

Spark

Apache Spark

- Unified analytics engine for large-scale data processing.
- Speed: Run workloads 100x faster.
- Both batch and streaming data, using Directed Acyclic Graph (DAG) scheduler, a query optimizer, and a physical execution engine.
- Ease of Use: Write applications quickly in Java, Scala, Python, R, and SQL.
- Spark offers 80+ high-level operators to build parallel apps.



https://spark.apache.org/

Apache Spark

- Combine SQL, streaming, and complex analytics. Spark libraries
  - SQL and DataFrames,
  - MLlib for machine learning,
  - GraphX, and
  - Spark Streaming.
- Spark runs on Hadoop, Apache Mesos, Kubernetes, standalone, or in the cloud.
- Run Spark using its standalone cluster mode, on EC2, on Hadoop YARN, on Mesos, or on Kubernetes.
- Access data in HDFS, Alluxio, Apache Cassandra, Apache HBase, Apache Hive, and hundreds of other data sources.

https://spark.apache.org/

Spark: Unified Big Data Analytics

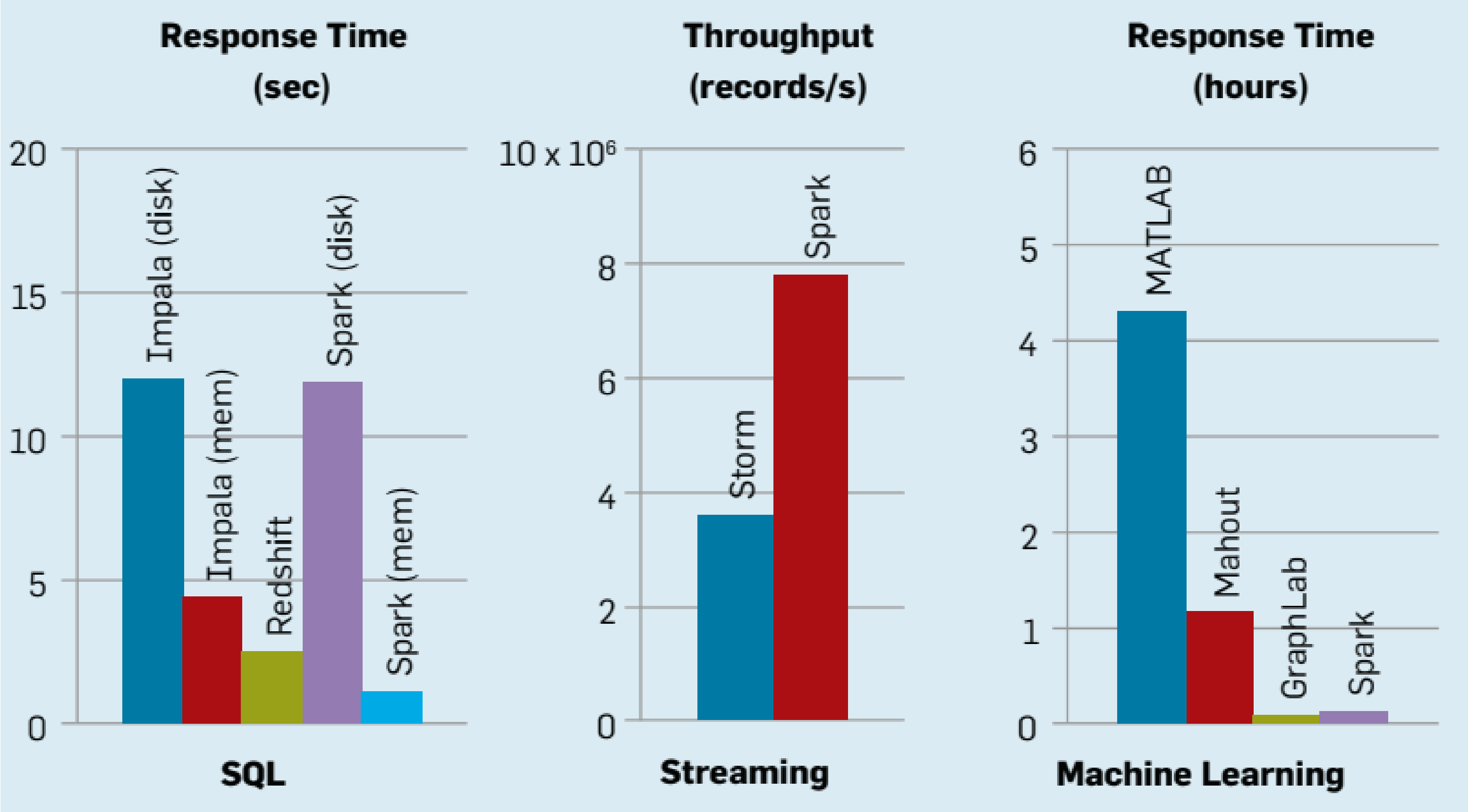
- New applications of Big data workloads on Unified Engine of
  - Streaming, Batch, and Interactive.
- Composability in programming libraries for big data and encourages development of interoperable libraries
- Combining the SQL, machine learning, and streaming libraries in Spark

```
// Load historical data as an RDD using Spark SQL
val trainingData = sql(
   "SELECT location, language FROM old_tweets")

// Train a K-means model using MLlib
val model = new KMeans()
   .setFeaturesCol("location")
   .setPredictionCol("language")
   .fit(trainingData)
// Apply the model to new tweets in a stream
TwitterUtils.createStream(...)
      .map(tweet => model.predict(tweet.location))
```

Matei Zaharia, et al. "Apache spark: a unified engine for big data processing." *Communications of the ACM* 59.11 (2016): 56-65.

Spark: Unified Big Data Analytics

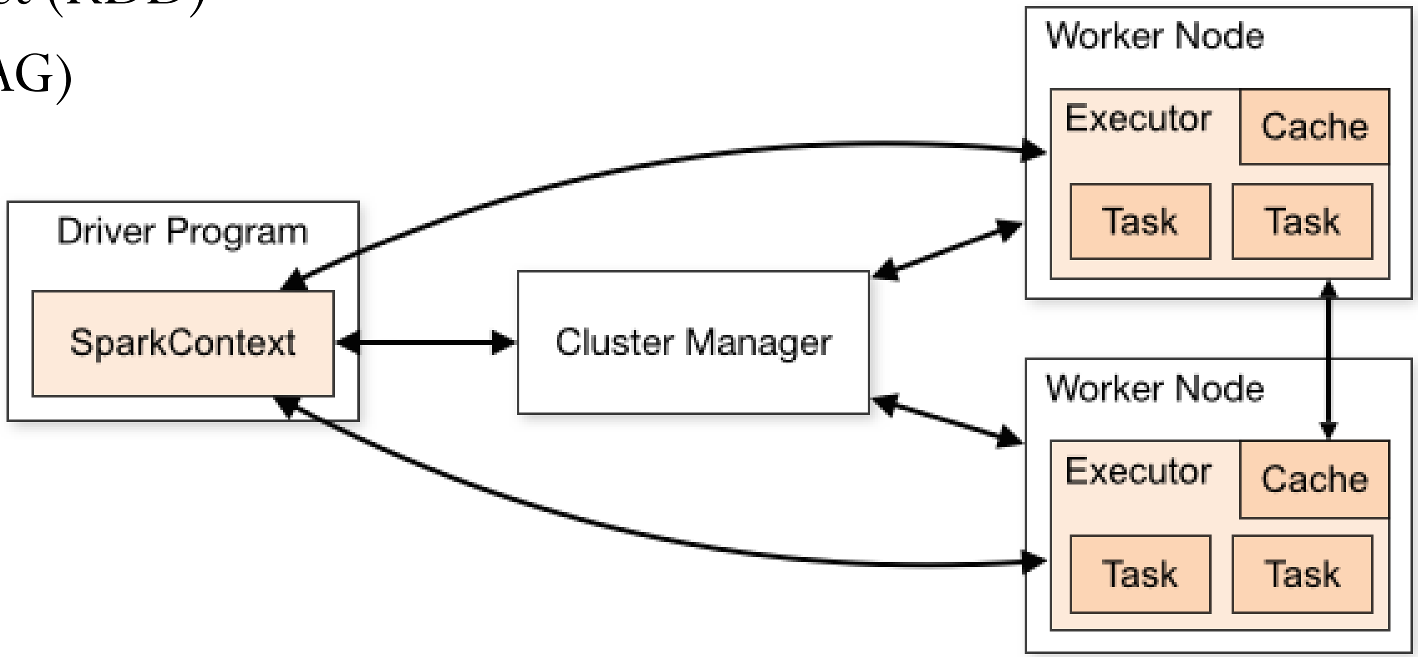
- Spark has MapReduce programming model with extended data-sharing abstraction called "Resilient Distributed Datasets," or RDDs.



Matei Zaharia, et al. "Apache spark: a unified engine for big data processing." *Communications of the ACM* 59.11 (2016): 56-65.

Spark Architecture

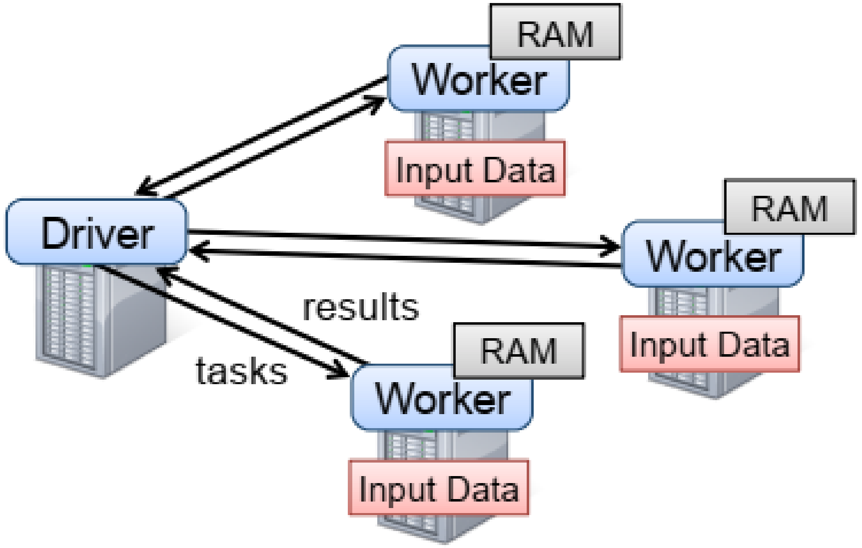
- Spark works on the popular Master-Slave architecture.
- Cluster works with a single master and multiple slaves.
- The Spark architecture depends upon two abstractions:
  - Resilient Distributed Dataset (RDD)
  - Directed Acyclic Graph (DAG)



https://spark.apache.org/docs/latest/cluster-overview.html

Resilient Distributed Datasets (RDD)

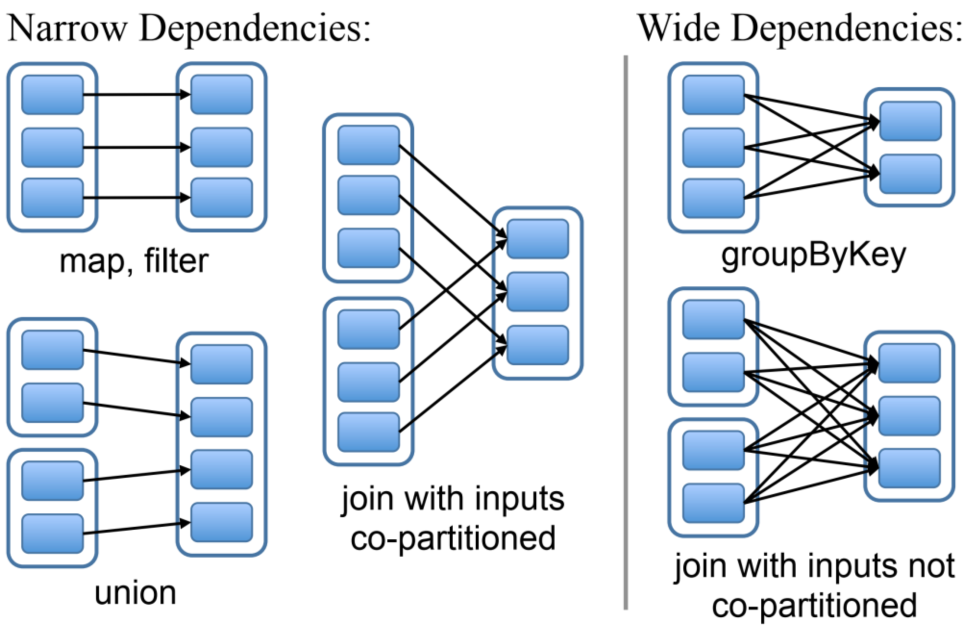
- A distributed memory abstraction: perform in-memory computations on large clusters
- Keeping data in memory can improve performance
- Spark runtime: Driver program launches multiple workers that read data blocks from a distributed file system and can persist computed RDD partitions in memory.



Matei Zaharia, et al. "Resilient distributed datasets: A fault-tolerant abstraction for in-memory cluster computing." *Presented as part of the 9th {USENIX} Symposium on Networked Systems Design and Implementation ({NSDI} 12)*. 2012.

Resilient Distributed Datasets (RDD)

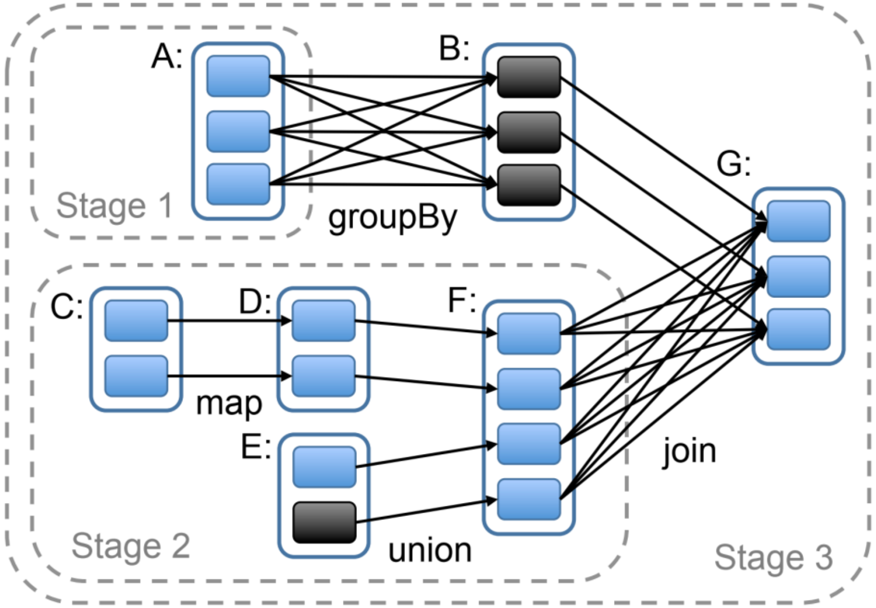
- Each box is an RDD, with partitions as shaded rectangles.
- *narrow* dependencies, where each partition of the parent RDD is used by at most one partition of the child RDD,
- *wide* dependencies, where multiple child partitions may depend on it.



Matei Zaharia, et al. "Resilient distributed datasets: A fault-tolerant abstraction for in-memory cluster computing." *Presented as part of the 9th {USENIX} Symposium on Networked Systems Design and Implementation ({NSDI} 12)*. 2012.

Resilient Distributed Datasets (RDD)

- Direct Acyclic Graph (DAG) to perform a sequence of computations
- Each node is an RDD partition,
- Run an action (*e.g.*, *count* or *save*) on an RDD, the scheduler examines that RDD's lineage graph to build a DAG of *stages* to execute.
- Each stage contains with narrow dependencies
- The boundaries of the stages are the shuffle operations required for wide dependencies.
- Scheduler computes missing partitions until it computed RDD.



Matei Zaharia, et al. "Resilient distributed datasets: A fault-tolerant abstraction for in-memory cluster computing." *Presented as part of the 9th {USENIX} Symposium on Networked Systems Design and Implementation ({NSDI} 12)*. 2012.

Spark libraries (SQL, DataFrames, MLlib for machine learning, GraphX, and Streaming)

Spark Code Example

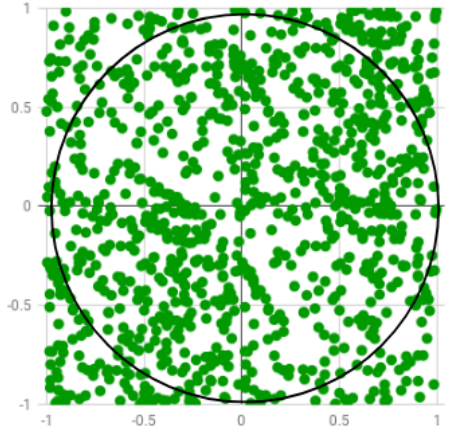
- Word Count

```
JavaRDD<String> textFile = sc.textFile("hdfs://...");
JavaPairRDD<String, Integer> counts = textFile
    .flatMap(s -> Arrays.asList(s.split(" ")).iterator())
    .mapToPair(word -> new Tuple2<>(word, 1))
    .reduceByKey((a, b) -> a + b);
counts.saveAsTextFile("hdfs://...");
```

- Pi Estimation

```
List<Integer> l = new ArrayList<>(NUM_SAMPLES);
for (int i = 0; i < NUM_SAMPLES; i++) {
  l.add(i);
}

long count = sc.parallelize(l).filter(i -> {
  double x = Math.random();
  double y = Math.random();
  return x*x + y*y < 1;
}).count();
System.out.println("Pi is roughly " + 4.0 * count / NUM_SAMPLES);
```

$$\text{Pi} = 4 \times \frac{\textit{number of random point inside the circle}}{\textit{number of random point inside the square}}$$



Spark SQL

- Working with structured data.
- Integrated: SQL queries with Spark programs.

```
results = spark.sql("SELECT * FROM people")
names = results.map(lambda p: p.name)
```

Apply functions to results of SQL queries.

- Uniform Data Access: Connect to data sources, including Hive, Avro, Parquet, ORC, JSON, and JDBC.

```
spark.read.json("s3n://...").registerTempTable("json")
results = spark.sql("""SELECT * FROM people JOIN json ...""")
```

- Query and join different data sources
- Hive Integration Spark HiveQL
- Standard Connectivity: Connect through JDBC or ODBC.
- Business intelligence tools to query big data.

https://spark.apache.org/sql/

DataFrame API Examples

- Collection of data organized into named columns
- Use DataFrame API to perform various relational operations
- Automatically optimized by Spark's built-in optimizer

```
// Creates a DataFrame having a single column named "line"
JavaRDD<String> textFile = sc.textFile("hdfs://...");
JavaRDD<Row> rowRDD = textFile.map(RowFactory::create);
List<StructField> fields = Arrays.asList(
  DataTypes.createStructField("line", DataTypes.StringType, true));
StructType schema = DataTypes.createStructType(fields);
DataFrame df = sqlContext.createDataFrame(rowRDD, schema);

DataFrame errors = df.filter(col("line").like("%ERROR%"));
// Counts all the errors
errors.count();
// Counts errors mentioning MySQL
errors.filter(col("line").like("%MySQL%")).count();
// Fetches the MySQL errors as an array of strings
errors.filter(col("line").like("%MySQL%")).collect();
```

Spark Streaming

- Build scalable fault-tolerant streaming applications.
- Write streaming jobs -- Same Way -- Write batch jobs
  - Counting tweets on a sliding window

```
TwitterUtils.createStream(...)
.filter(_.getText.contains("Spark"))
.countByWindow(Seconds(5))
```

- Reuse the same code for batch processing
  - Find words with higher frequency than historic data:

```
stream.join(historicCounts).filter {
  case (word, (curCount, oldCount)) =>
    curCount > oldCount
}
```

Batch processing takes N unit time to process M unit of data

Batch processing **takes N+x unit time** to process **M+y unit of data**

Stream processing takes N unit time to process M unit of data

Stream processing **takes x unit time** to process **M+y unit of data**

https://spark.apache.org/streaming/

Spark GraphX

- Spark's API for graphs and graph-parallel computation

```
graph = Graph(vertices, edges)
messages = spark.textFile("hdfs://...")
graph2 = graph.joinVertices(messages) {
  (id, vertex, msg) => ...
}
```

- Fast Speed for graph algorithms
- GraphX graph algorithms
  - PageRank
  - Connected components
  - Label propagation
  - SVD++
  - Strongly connected components
  - Triangle count

- The **joinVertices** operator joins the vertices with the input RDD and returns a new graph with the vertex properties obtained by applying the user defined map function to the result of the joined vertices.
- Vertices without a matching value in the RDD retain their original value.

https://spark.apache.org/graphx/

Spark MLlib

- Spark's scalable machine learning library
- Spark MLlib algorithms
  - Classification: logistic regression, naive Bayes,…
  - Regression: generalized linear regression, survival regression,…
  - Decision trees, Random forests, and Gradient-boosted trees
  - Recommendation: Alternating Least Squares (ALS)
  - Clustering: K-means, Gaussian mixtures (GMMs),…
  - Topic modeling: Latent Dirichlet Allocation (LDA)
  - **Frequent itemsets, Association rules, and Sequential pattern mining**

https://spark.apache.org/graphx/

Parallel Frequent Pattern Growth for Rule Mining

Apriori algorithm: Association Rule Mining

- Let I = $\{i_1, i_2, \ldots.\ i_m\}$ be a set of literals, called items.
- *Support* of a rule X →Y is the percentage of transactions that contain both X and Y.
- *Confidence* of a rule is percentage the if-then statements (X →Y) are found true
- Find all rules that satisfy a user-specified *minimum support* and *minimum confidence*

TID	Transaction Items
1	Bread, Jelly, PeanutButter
2	Bread, PeanutButter
3	Bread, Milk, PeanutButter
4	Beer, Bread
5	Beer, Milk

{Bread} → {PeanutButter} (Sup = 60%, Conf = 75%)

{PeanutButter} → {Bread} (Sup = 60%, Conf = 100%)

{Beer} → {Bread} (Sup = 20%, Conf = 50%)

{PeanutButter} → {Jelly} (Sup = 20%, Conf = 33.33%)

{Jelly} → {PeanutButter} (Sup = 20%, Conf = 100%)

{Jelly} → {Milk} (Sup = 0%, Conf = 0%)

Rakesh Agrawal, Tomasz Imieliński, and Arun Swami. "Mining association rules between sets of items in large databases." *SIG-MOD*. 1993.
Ramakrishnan Srikant, and Rakesh Agrawal. "Mining Generalized Association Rules.“ *VLDB* 1995.

Apriori algorithm: Association Rule Mining

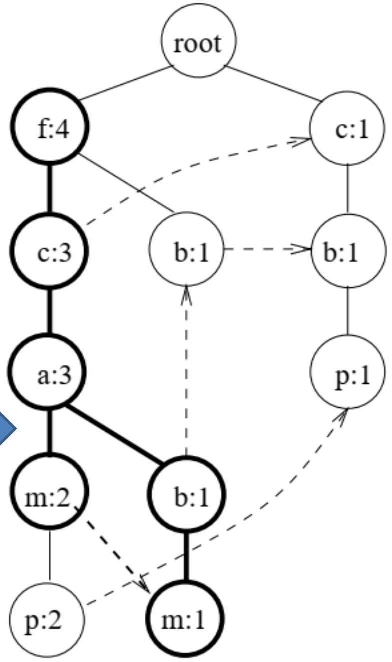
- Let I = $\{i_1, i_2, \ldots\ i_m\}$ be a set of literals, called items.
- *Support* of a rule X →Y is the percentage of transactions that contain both X and Y.
- *Confidence* of a rule is percentage the if-then statements (X →Y) are found true
- Find all rules that satisfy a user-specified *minimum support* and *minimum confidence*
  - 75% of transactions that purchase *Bread* (antecedent) also purchase *PeanutButter* (consequent). The number 75% is the confidence factor of the rule
    - {Bread} → {PeanutButter} (Sup = 60%, Conf = 75%) (3/5 , 3/4)
    - Similarly, {PeanutButter} → {Bread} (Sup = 60%, Conf = 100%) (3/5 , 3/3)
  - 98% of customers who purchase *Tires* and *Auto accessories* also buy some *Automotive services*; here 98% is called the confidence of the rule.
    - [*Auto Accessories*], [*Tires*] → [*Automotive Services*] 98%

Rakesh Agrawal, Tomasz Imieliński, and Arun Swami. "Mining association rules between sets of items in large databases." *SIG-MOD*. 1993.
Ramakrishnan Srikant, and Rakesh Agrawal. "Mining Generalized Association Rules." *VLDB* 1995.

FP-Growth for recommendation

- "FP" stands for Frequent Pattern in a Dataset of transactions
  1. calculate item frequencies and identify frequent items,
  2. a suffix tree (FP-tree) structure to encode transactions, and
  3. frequent itemsets can be extracted from the FP-tree.
- Input: Transaction database
- Intermediate Output: FP-Tree
- Output: {f, c, a → a, m p}, {f, c, a → b, m}

TID	Items Bought	(Ordered) Frequent Items
100	f, a, c, d, g, i, m, p	f, c, a, m, p
200	a, b, c, f, l, m, o	f, c, a, b, m
300	b, f, h, j, o	f, b
400	b, c, k, s, p	c, b, p
500	a, f, c, e, l, p, m, n	f, c, a, m, p



Han Jiawei, Jian Pei, and Yiwen Yin. "Mining frequent patterns without candidate generation." *ACM SIGMOD Record* 29.2 (2000): 1-12.

PFP: Parallel FP-Growth

- In Spark ML-Library (MLLib), a parallel version of FP-growth called
  - PFP: Parallel FP-Growth
- PFP distributes the work of growing FP-trees based on the suffixes of transactions.
- More scalable than a single-machine implementation.
- PFP partitions computation, where each machine executes an independent group of mining tasks

Haoyuan Li, et al. "PFP: Parallel FP-Growth for query recommendation."
Proceedings of the 2008 ACM Conference on Recommender systems. 2008.

PFP: Parallel FP-Growth

MapReduce FP-Growth: 5 transactions composed of lower-case alphabets as items

Map inputs (transactions) key="": value	Sorted transactions (with infrequent items eliminated)	Map outputs (conditional transactions) key: value
f a c d g i m p	f c a m p	p: f c a m m: f c a a: fc c: f
a b c f l m o	f c a b m	m: f c a b b: f c a a: f c c: f
b f h j o	f b	b: f
b c k s p	c b p	p: c b b: c
a f c e l p m n	f c a m p	p: f c a m m: f c a a: f c c: f

Reduce inputs (conditional databases) key: value	Conditional FP−trees
p: { f c a m / f c a m / c b }	{(c:3)} | p
m: { f c a / f c a / f c a b }	{ (f:3, c:3, a:3) } | m
b: { f c a / f / c }	{} | b
a: { f c / f c / f c }	{ (f:3, c:3) } | a
c: { f / f / f }	{ (f:3) } | c

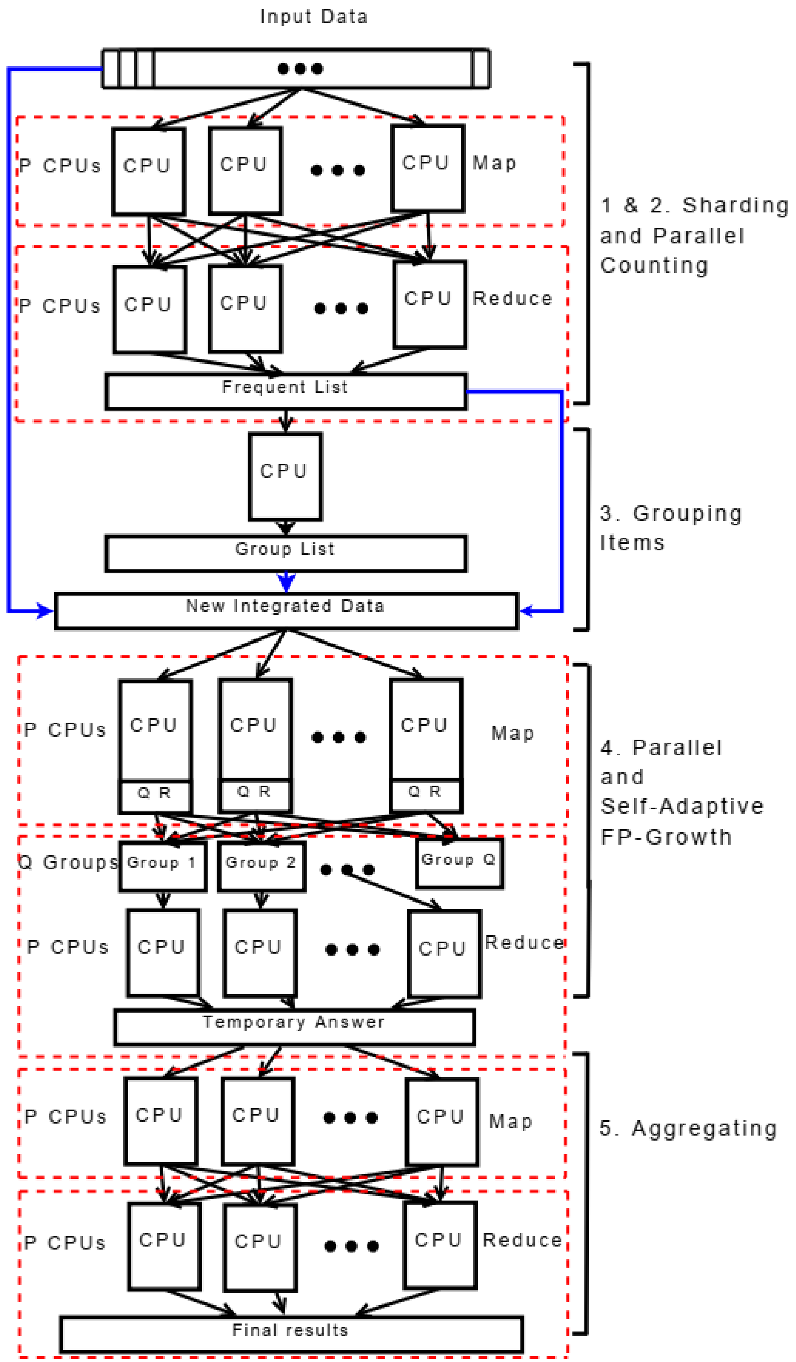
Haoyuan Li, et al. “PFP: Parallel FP-Growth for query recommendation”. *ACM Conference on Recommender systems*. 2008.

- **Sharding:** Divide DB into successive parts and storing the parts (as a Shard) on P different computers.
- **Parallel Counting:** MapReduce counts the support of all items that appear in DB. Each mapper inputs one shard of DB. The result is stored in F-list.
- **Grouping Items:** Dividing all the items on F-List into Q groups of a list (G-list).
- **Parallel FP-Growth:** A MapReduce

  - Mapper: Each mapper uses a Shard. It reads a transaction in the G-list and outputs one or more key-value pairs, where each key is a *group-id* and value is a **group-dependent transaction**.

  - For each *group-id*, the MapReduce groups all group-dependent transactions into a shard.

  - Reducer: Each reducer processes one or more group-dependent Shard. For each shard, a reducer builds a local FP-Tree and discover patterns.
- **Aggregating:** Aggregate the results generated as final result.



Haoyuan Li, et al. "PFP: Parallel FP-Growth for query recommendation." *Proceedings of the 2008 ACM Conference on Recommender systems*. 2008.

PFP: Parallel FP-Growth

```java
List<Row> data = Arrays.asList(
  RowFactory.create(Arrays.asList("1 2 5".split(" "))),
  RowFactory.create(Arrays.asList("1 2 3 5".split(" "))),
  RowFactory.create(Arrays.asList("1 2".split(" ")))
);
StructType schema = new StructType(new StructField[]{ new StructField(
  "items", new ArrayType(DataTypes.StringType, true), false, Metadata.empty())
});
Dataset<Row> itemsDF = spark.createDataFrame(data, schema);

FPGrowthModel model = new FPGrowth()
  .setItemsCol("items")
  .setMinSupport(0.5)
  .setMinConfidence(0.6)
  .fit(itemsDF);

// Display frequent itemsets.
model.freqItemsets().show();

// Display generated association rules.
model.associationRules().show();

// transform examines the input items against all the association rules and summarize the
// consequents as prediction
model.transform(itemsDF).show();
```

https://spark.apache.org/docs/3.3.1/ml-frequent-pattern-mining.html

PFP: Parallel FP-Growth

- FP-Growth implementation takes the following (hyper-)parameters
  - minSupport: the minimum support for an itemset to be identified as frequent e.g., if an item appears 3 out of 6 transactions, it has a support of 3/6=0.5.
  - minConfidence: minimum confidence for generating Association Rule e.g., if in the transactions itemset X appears 5 times, X and Y co-occur only 3 times, the confidence for the rule X => Y is then 3/5 = 0.6.
  - numPartitions: the number of partitions used to distribute the work.
- FP-Growth model provides:
  - freqItemsets: frequent itemsets in the format of DataFrame("items"[Array], "freq"[Long])
  - associationRules: association rules generated with confidence above minConfidence, in the format of DataFrame("antecedent"[Array], "consequent"[Array], "confidence"[Double]).

https://spark.apache.org/docs/3.3.1/ml-frequent-pattern-mining.html

References

- https://spark.apache.org/
- Zaharia, Matei, et al. "Apache spark: a unified engine for big data processing." Communications of the ACM 59.11 (2016): 56-65.
- Zaharia, Matei, et al. "Resilient distributed datasets: A fault-tolerant abstraction for in-memory cluster computing." Presented as part of the 9th USENIX Symposium on Networked Systems Design and Implementation (NSDI 12). 2012.
- https://spark.apache.org/docs/latest/cluster-overview.html
- https://spark.apache.org/docs/latest/cluster-overview.html
- https://spark.apache.org/
- https://spark.apache.org/sql/
- https://spark.apache.org/streaming/
- https://spark.apache.org/graphx/
- https://spark.apache.org/docs/3.3.1/ml-frequent-pattern-mining.html
- Han Jiawei, Jian Pei, and Yiwen Yin. "Mining frequent patterns without candidate generation." *ACM SIGMOD Record* 29.2 (2000): 1-12.
- Li, Haoyuan, et al. "PFP: Parallel FP-Growth for query recommendation." *Proceedings of the 2008 ACM Conference on Recommender systems*. 2008.

תודה רבה
Hebrew

Ευχαριστώ
Greek

Спасибо
Russian

Danke
German

धन्यवादः
Sanskrit

Merci
French

ধন্যবাদ
Bangla

நன்றி
Tamil

شكراً
Arabic

ಧನ್ಯವಾದಗಳು
Kannada

Thank You
English

നന്ദി
Malayalam

Grazie
Italian

多謝
Traditional Chinese

ధన్యవాదాలు
Telugu

આભાર
Gujarati

ਧੰਨਵਾਦ
Punjabi

धन्यवाद
Hindi & Marathi

Gracias
Spanish

多谢
Simplified Chinese

https://sites.google.com/site/animeshchaturvedi07

Obrigado
Portuguese

ありがとうございました
Japanese

ขอบคุณ
Thai

감사합니다
Korean