Aalto University
School of Science

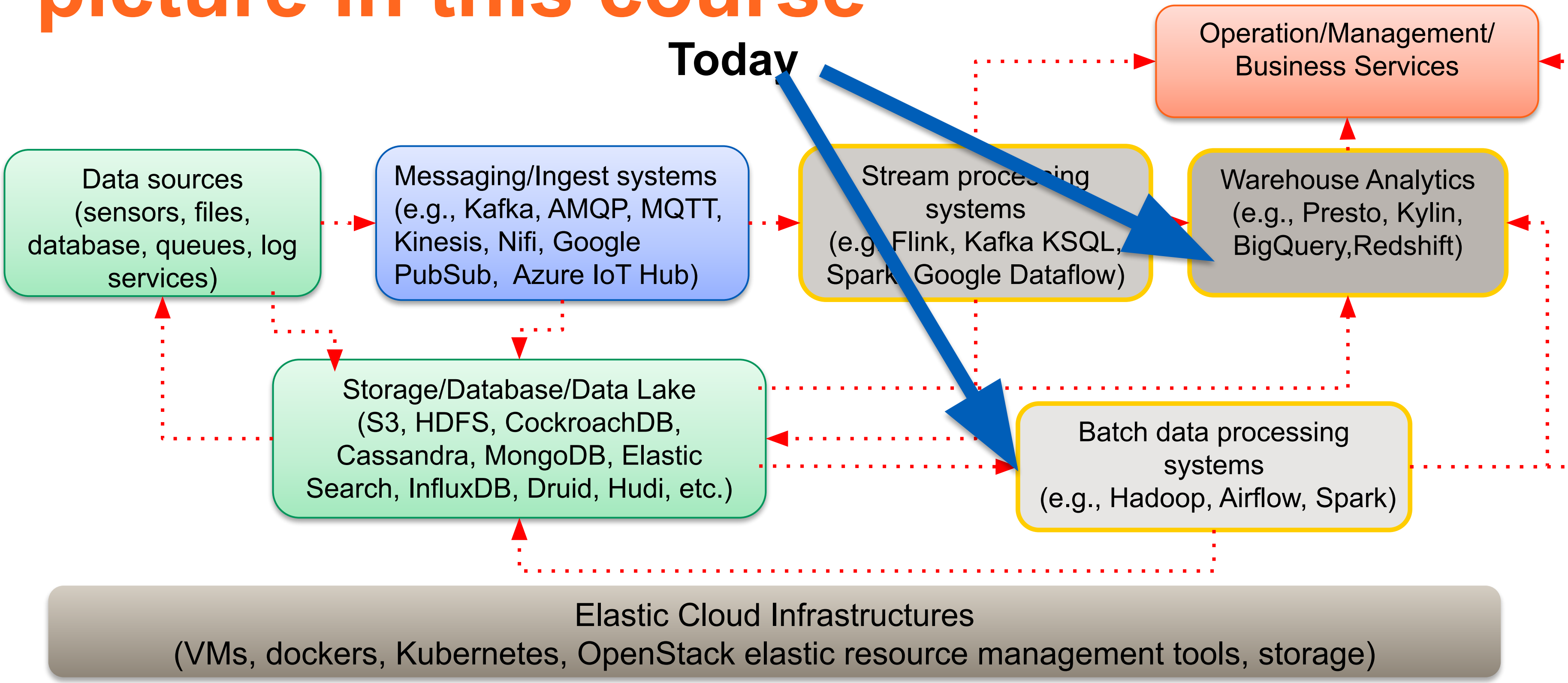
Big Data Processing with MapReduce/Spark Programming Models

Hong-Linh Truong
Department of Computer Science
linh.truong@aalto.fi, https://rdsea.github.io

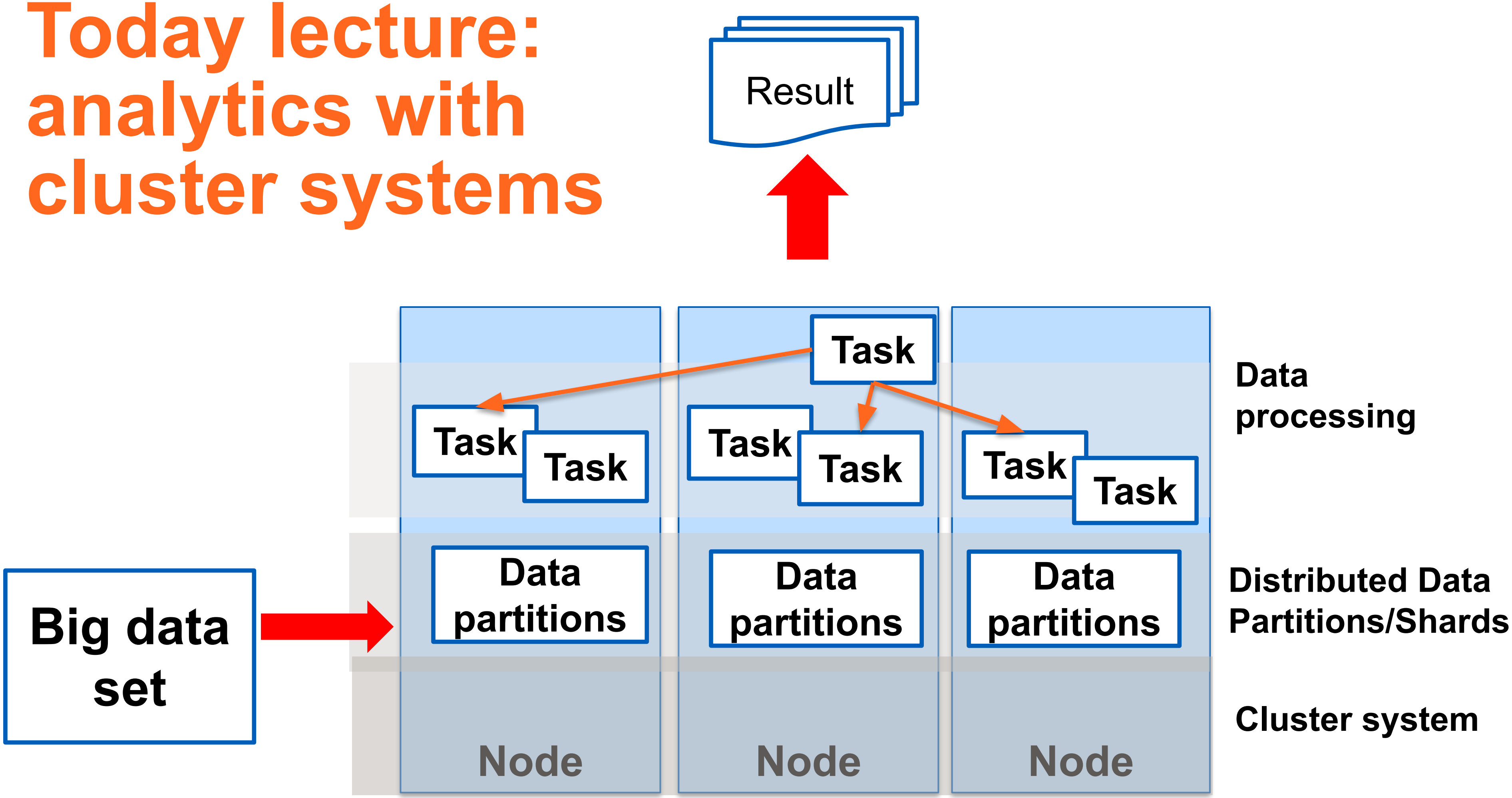
Learning objectives

- Be familiar with big data processing models using multiple nodes/clusters
- Understand MapReduce/Spark programming models for big data processing
- Able to perform practical programming features with MapReduce/Spark
- Able to design and apply MapReduce/Spark data processing with Hadoop and other frameworks

Big data at large-scale: the big picture in this course



Today lecture: analytics with cluster systems



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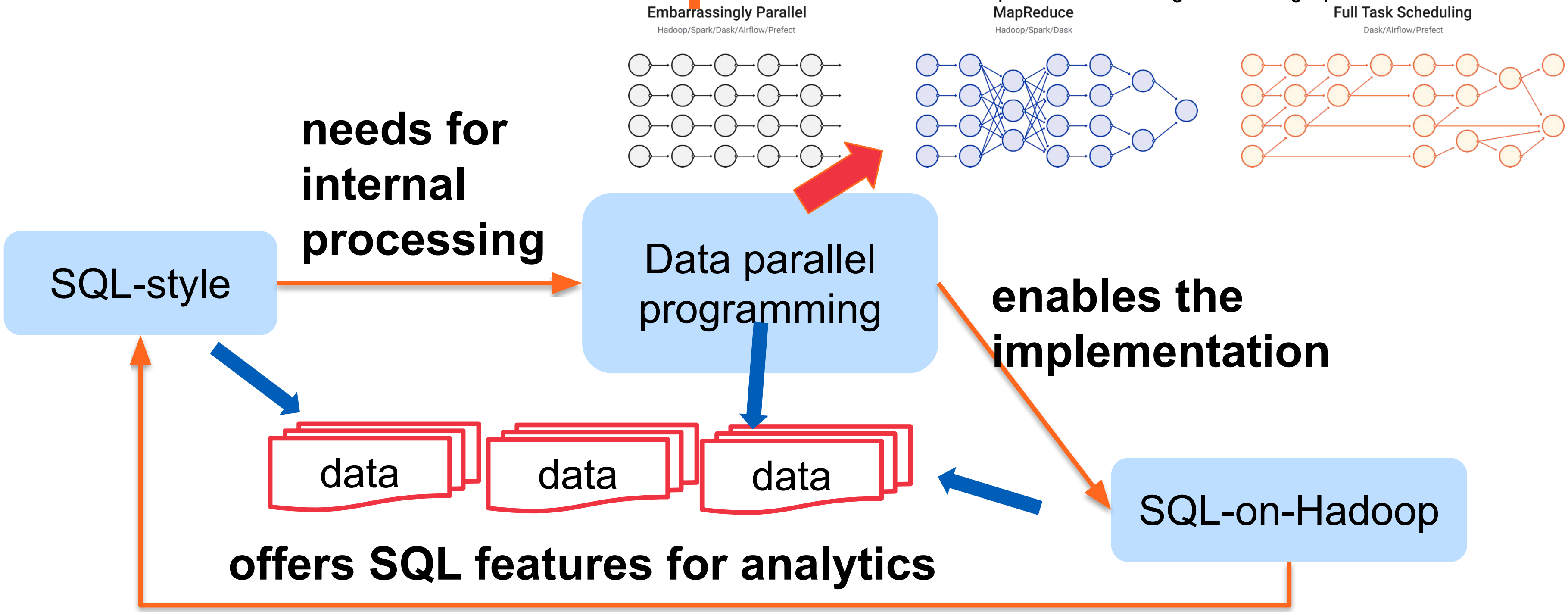
Our first focus: big data analytics for data at rest

Recall: Data at rest

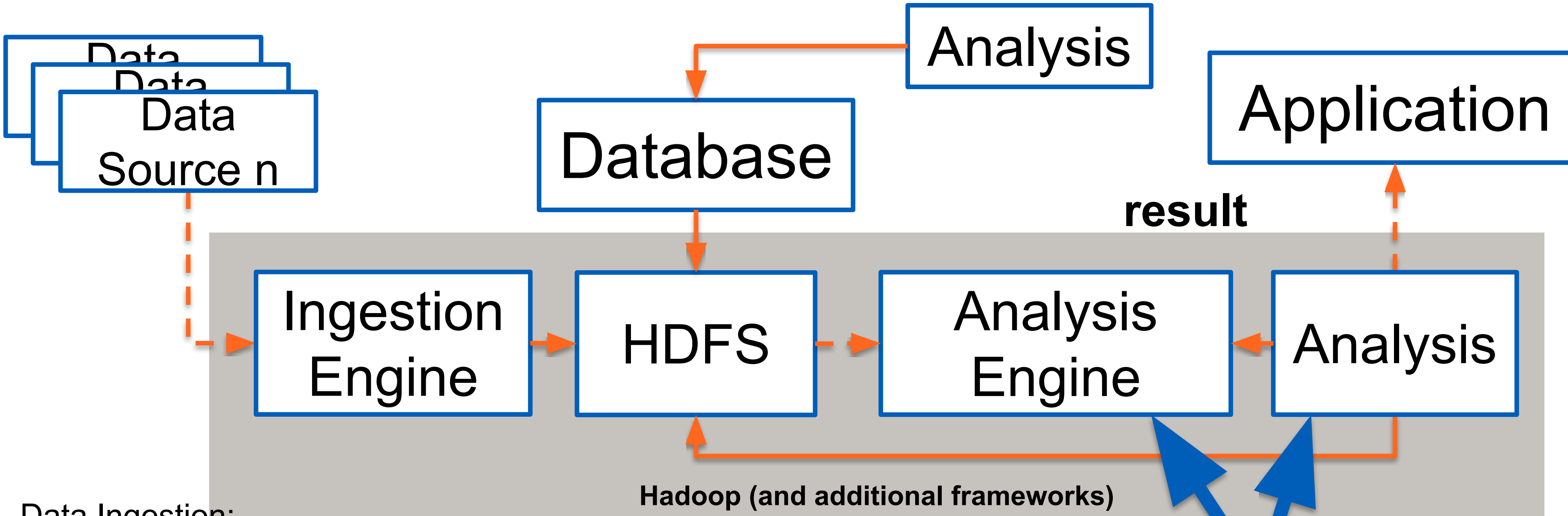
- **At rest**
  - distributed file systems/object storages
    - *in big data we have a lot of files with different data formats*
  - data in a set of databases
- **Multiple types of big data analytics with high concurrent/parallel data writes/reads**
- **Dealing with different data access/analytics frequencies:**
  - organize data into **hot, warm and cold data**

SQL-style/data parallel processing for data in Hadoop FS

Figure source:
https://docs.dask.org/en/stable/graphs.html



ETL and Analytics with Hadoop/HDFS



- Data Ingestion:
  - HDFS Client/Hadoop Streaming
  - Spark Streaming
  - Kafka Connect
  - Apache Nifi
- HDFS as storage for databases
  - Accumulo, Druid, etc.
- Computing/Data Processing Framework
  - Apache Spark
  - Hadoop MapReduce
  - Apache Tez

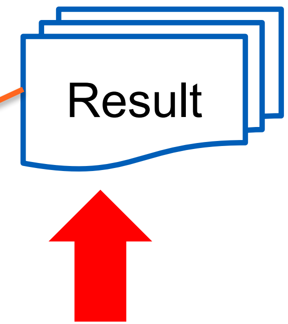
DataFrame/Table view of data

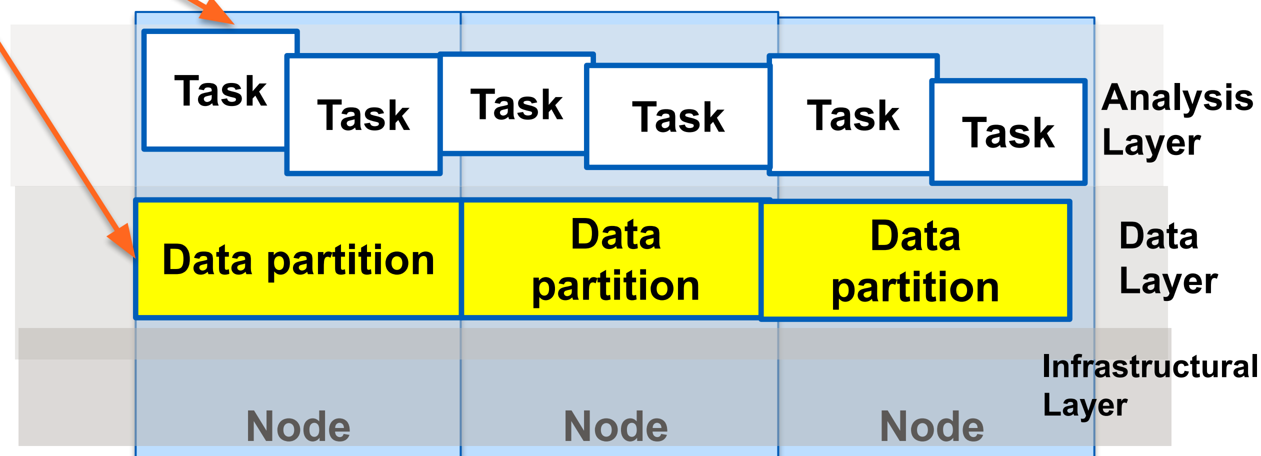
Example taxi records: named columns

passenger_count	trip_distance	RatecodeID	store_and_fwd_flag	PULocationID	DOLocationID	payment_type	fare_amount	extra	mta_tax	tip_amount	tolls_amount	improvement_surcharge	total_amount
1	1.34	1	N	238	236	2	10.0	0.0	0.5	0.0	0.0	0.3	10.8
1	1.34	1	N	238	236	2	10.0	0.0	0.5	0.0	0.0	0.3	10.8
1	0.32	1	N	238	238	2	4.0	0.0	0.5	0.0	0.0	0.3	4.8
1	0.32	1	N	238	238	2	4.0	0.0	0.5	0.0	0.0	0.3	4.8
1	1.85	1	N	236	238	2	10.0	0.0	0.5	0.0	0.0	0.3	10.8
1	1.85	1	N	236	238	2	10.0	0.0	0.5	0.0	0.0	0.3	10.8
1	1.65	1	N	68	237	2	12.5	0.0	0.5	0.0	0.0	0.3	13.3
1	1.65	1	N	68	237	2	12.5	0.0	0.5	0.0	0.0	0.3	13.3
1	1.07	1	N	170	68	2	9.0	0.0	0.5	0.0	0.0	0.3	9.8
1	1.07	1	N	170	68	2	9.0	0.0	0.5	0.0	0.0	0.3	9.8
1	1.3	1	N	107	170	2	7.5	0.0	0.5	0.0	0.0	0.3	8.3
1	1.3	1	N	107	170	2	7.5	0.0	0.5	0.0	0.0	0.3	8.3
1	1.85	1	N	113	137	2	10.0	0.0	0.5	0.0	0.0	0.3	10.8
1	1.85	1	N	113	137	2	10.0	0.0	0.5	0.0	0.0	0.3	10.8
1	0.62	1	N	231	231	2	4.5	0.0	0.5	0.0	0.0	0.3	5.3
1	0.62	1	N	231	231	2	4.5	0.0	0.5	0.0	0.0	0.3	5.3
1	0.0	1	N	264	264	2	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.29	1	N	162	162	2	4.0	0.0	0.5	0.0	0.0	0.3	4.8
1	0.29	1	N	162	162	2	4.0	0.0	0.5	0.0	0.0	0.3	4.8
1	1.34	1	N	239	151	2	7.0	0.5	0.5	0.0	0.0	0.3	8.3

- Very common we analyze **big data files** based on this view
- Streaming data can be also represented as **unbounded tables**

```python
inputFile =args.input_file
## hadoop inputFile="hdfs://"
df =spark.read.csv(inputFile,header=True,inferSchema=True)
#df.show()
print("Number of trips", df.count())
#number of passenger count per vendor and total amount of money
passenser_exprs = {"passenger_count":"sum","total_amount":"sum"}
df2 = df.groupBy('VendorID').agg(passenser_exprs)
# Where do you want to write the output
df2.repartition(1).write.csv(args.output_dir,header=True)
```





What we need when we develop analysis programs for big data

Big data processing techniques in our focus for data at rest

- **Programming models**
  - MapReduce/Spark
  - Workflows
- **Studied frameworks**
  - Apache Hadoop/Spark, Dask
  - Apache Airflow
- **Not in our focus:**
  - Bulk synchronous parallel (BSP)
  - HPC MPI (Message Passing Interface)

MapReduce Programming Model

MapReduce programming model

- **MapReduce is a programming model from Google**
  - Various implementations/frameworks support MapReduce
    - Apache Hadoop (**https://hadoop.apache.org)**
- **Support batch data processing for very large datasets**
- **Suitable for batch jobs in big data, e.g.,**
  - Web search, document processing, ecommerce information
  - Extract, transform, data wrangling, and data cleansing tasks

Common needs

- **Thinking if we have data that can be represented as record=(key,value)**
  - e.g., key="aalto", value="1000" (1000 likes in linkedin)
  - potentially millions of records, with millions of keys
- **Operations**
  - data analytics like summarization/aggregation/filtering
    - *count, min, max, average, etc.*
  - joining data from big data set
  - collecting data and shuffling the data to the right tasks

Map & Reduce

- **Map: map data into (key, value)**
  - Receives <key,value>
  - Outputs <key,value> - new set of <key,value>
- **Reduce: compute results from the same key**
  - Receives <key, Iterable[value]>
  - Outputs <key,value>

Example of a real data

Look at the network monitoring data

PROVINCECODE,DEVICEID,IFINDEX,FRAME,SLOT,PORT,ONUINDEX,ONUID,TIME,SPEEDIN,SPEEDOUT
XXN,10XXXXXX023,26XXXXXX8,1,2,7,39,100XXXXXX2310207039,01/08/2019 00:04:07,148163,49018
XXN,10XXXXXX023,26XXXXXX8,1,2,7,38,100XXXXXX2310207038,01/08/2019 00:04:07,1658,1362
XXN,10XXXXXX023,26XXXXXX8,1,2,7,9,100XXXXXX2310207009,01/08/2019 00:04:07,6693,5185

Sample: https://version.aalto.fi/gitlab/bigdataplatforms/cs-e4640/-/tree/master/data/onudata

Understand the MapReduce programming model

ONUID SPEEDIN

Key	Value
…	879656
…	65252
…	…
….	103831
…	1045755
…	

Map

Key	Value
7039	879656
7038	65252
…	

Key	Value
7039	103831
7038	1045755

Key	Value
7038	65252
7038	1045755
…	…
7039	103831
7039	879656
…	…

Reduce

Key	Value
7038	…
7039	…
…	…
…	…
…	…
…	

Big files (e.g. in HDFS)

Parallelizing data

Sort/Shuffle

Group/Aggregation

Key ideas of MapReduce

- **A kind of divide-and-conquer paradigm**
- **Data can be divided by "Map" operators**
  - data processing tasks extract "intermediate results"
- **Intermediate results can be aggregated through "Reduce" operators**
  - data processing tasks produce a result from "intermediate results"
- **We can glue "Map" and "Reduce" operators into a multi-stage data flow model**
- **Other possible operators:**
  - `Combiner:` performs "Reduce" at local nodes
  - `Partitioner:` decides key/value for Reduce

Key ideas of MapReduce

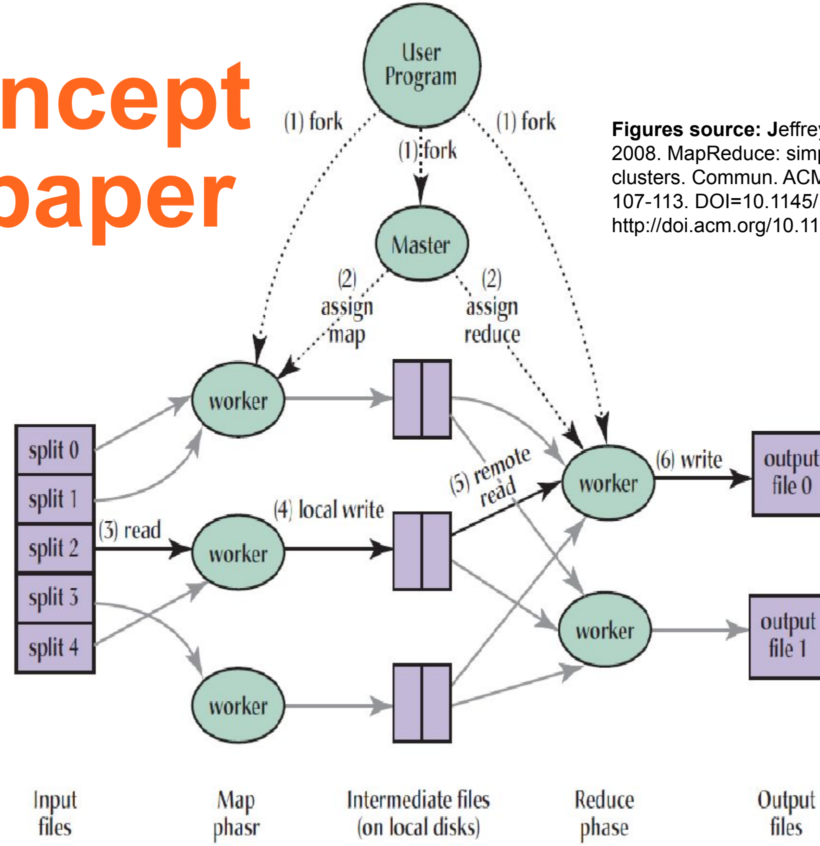
- **Key points for the developers**
  - should write only the main "logic": Map and Reduce operators
- **The runtime framework will**
  - handle data movement and input/output management for Map/Reduce tasks
  - parallelizing tasks in multiple nodes

MapReduce concept in the original paper

Figures source: Jeffrey Dean and Sanjay Ghemawat. 2008. MapReduce: simplified data processing on large clusters. Commun. ACM 51, 1 (January 2008), 107-113. DOI=10.1145/1327452.1327492 http://doi.acm.org/10.1145/1327452.1327492

```
map(String key, String value):
  // key: document name
  // value: document contents
  for each word w in value:
    EmitIntermediate(w, "1");

reduce(String key, Iterator values):
  // key: a word
  // values: a list of counts
  int result = 0;
  for each v in values:
    result += ParseInt(v);
  Emit(AsString(result));
```



Key point: parallelize workers to process a lot of input files and produce a lot of output files

Tasks and their dependencies

- **A task (Map or Reduce) is stateless**
  - executed as an individual process
- **Acyclic graph of tasks as a workflow**
  - can be executed using a batch job scheduler
  - files as the exchange medium among tasks

Hadoop MapReduce

- **Hadoop supports the MapReduce programming model**
  - Use cluster nodes for data processing tasks
  - Access data in HDFS files and partitions in different nodes
  - Hadoop runtime automatically creates parallel tasks
  - YARN is used to run jobs of MapReduce applications
- **Data management (HDFS) and data processing (MapReduce) are aligned nicely**
  - Run in the same nodes ⇒ data locality optimization

Map/Reduce tasks and data/node partitions

- **A Map task can handle a data partition in the same node**
  - e.g., a Map task handles a HDFS data block ⇒ local data optimization: no data movement - local processing
  - Results from a Map task are intermediate ⇒ to where a task will store them?
  - *what if a Map task fails?*
- **Reduce Task**
  - to deal with data produced from different Map tasks ⇒ *where to run the Reduce tasks?*

Examples - Map

Input

Output

```
public static class SpeedInMapper
      extends Mapper<Object, Text, LongWritable , AverageWritable>{
   private LongWritable id =new LongWritable();
   private AverageWritable averagecount = new AverageWritable();
   public void map(Object key, Text value, Context output)
         throws IOException, InterruptedException {

         String valueString = value.toString();
         String[] record = valueString.split(",");
         id.set(Long.parseLong(record[7]));
         averagecount.setAverage(Float.parseFloat(record[9]));
         averagecount.setCount(1);
         output.write(id,averagecount);
   }
}
```

Parse the data to get ONUID and SPEEDIN

Map (ONUID,(SPEEDIN, count))

Example - Reduce

Input

Output

```
public static class SpeedInAverageReducer
      extends Reducer<LongWritable,AverageWritable,LongWritable,FloatWritable> {
  private FloatWritable new_result = new FloatWritable();


  public void reduce(LongWritable key, Iterable<AverageWritable> values,
                     Context context
                     ) throws IOException, InterruptedException {
    float avg = 0;
    int count = 0;
    for (AverageWritable val : values) {
        float current_avg =val.getAverage();
        int current_count =val.getCount();
        avg = avg + (current_avg*current_count);
        count = count + current_count;
    }

   new_result.set(avg/count);
   context.write(key, new_result);
  }
}
```

Simple way to determine the average as "Reduce" operator

Reduce (ONUID,AVG)

Driver: connect Map and Reduce operators

```
public static void main(String[] args) throws Exception {
  Configuration conf = new Configuration();
  Job job = Job.getInstance(conf, "simpleonuaverage");
  job.setJarByClass(SimpleAverage.class);
  job.setMapperClass(SpeedInMapper.class);
  job.setCombinerClass(SpeedInAverageCombiner.class);
  job.setReducerClass(SpeedInAverageReducer.class);
  job.setMapOutputKeyClass(LongWritable.class);
  job.setMapOutputValueClass(AverageWritable.class);
  job.setOutputKeyClass(LongWritable.class);
  job.setOutputValueClass(FloatWritable.class);
  FileInputFormat.addInputPath(job, new Path(args[0]));
  FileOutputFormat.setOutputPath(job, new Path(args[1]));
  System.exit(job.waitForCompletion(true) ? 0 : 1);
}
```

Combiner

Example with Python using MRJob

```python
class ONUSpeedinAverage(MRJob):
    def mapper(self, _, entry):
        provincecode,deviceid,ifindex,frame,slot,port,onuindex,onuid,timestamp,speedin,speedout= entry.split(",")
        #average speed is speedin with count = 1
        yield (onuid, (float(speedin),1))

   ## recalculate the new speedin average through an array of speedin average values
    def _recalculate_avg(self, onuid, speedin_avg_values):
        current_speedin_total = 0
        new_avg_count = 0
        for speedin_avg, avg_count  in speedin_avg_values:
            current_speedin_total = current_speedin_total +(speedin_avg*avg_count)
            new_avg_count = new_avg_count + avg_count
        new_speedin_avg = current_speedin_total/new_avg_count
        return (onuid, (new_speedin_avg, new_avg_count))

    def combiner(self, onuid, speedin_avg_values):
        yield self._recalculate_avg(onuid, speedin_avg_values)

    def reducer(self, onuid,speedin_avg_values):
        onuid, (speedin_avg, avg_count) = self._recalculate_avg(onuid,speedin_avg_values)
        yield (onuid, speedin_avg)

if __name__ == '__main__':
    ONUSpeedinAverage.run()
```

Note: see code examples in our GIT

Scheduling and monitoring

- **A MapReduce program runs ⇒ MapReduce Job**
  - includes many tasks (Map and Reduce processes + others)
- **JobTracker**
  - monitors the whole job (all tasks of a MapReduce program)
- **TaskTracker**
  - performs a task of the MapReduce applications
  - informs JobTracker about the state of the tasks

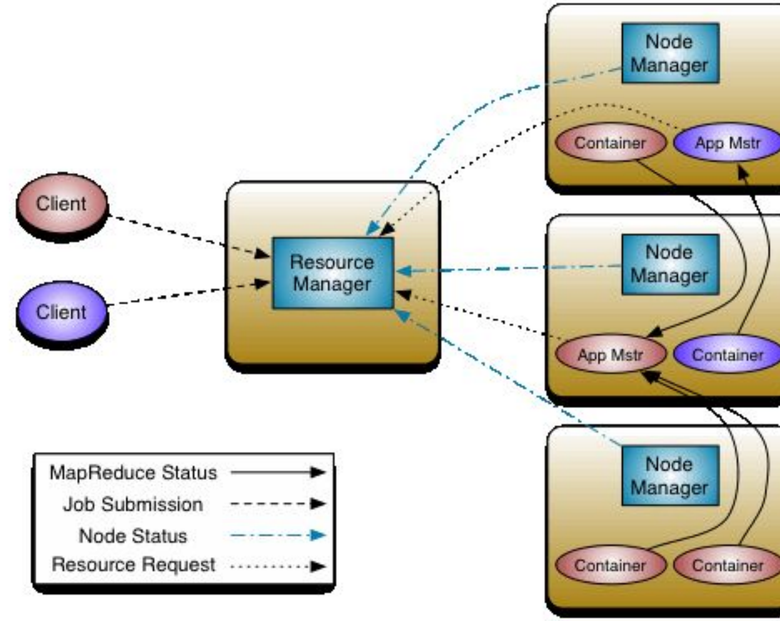
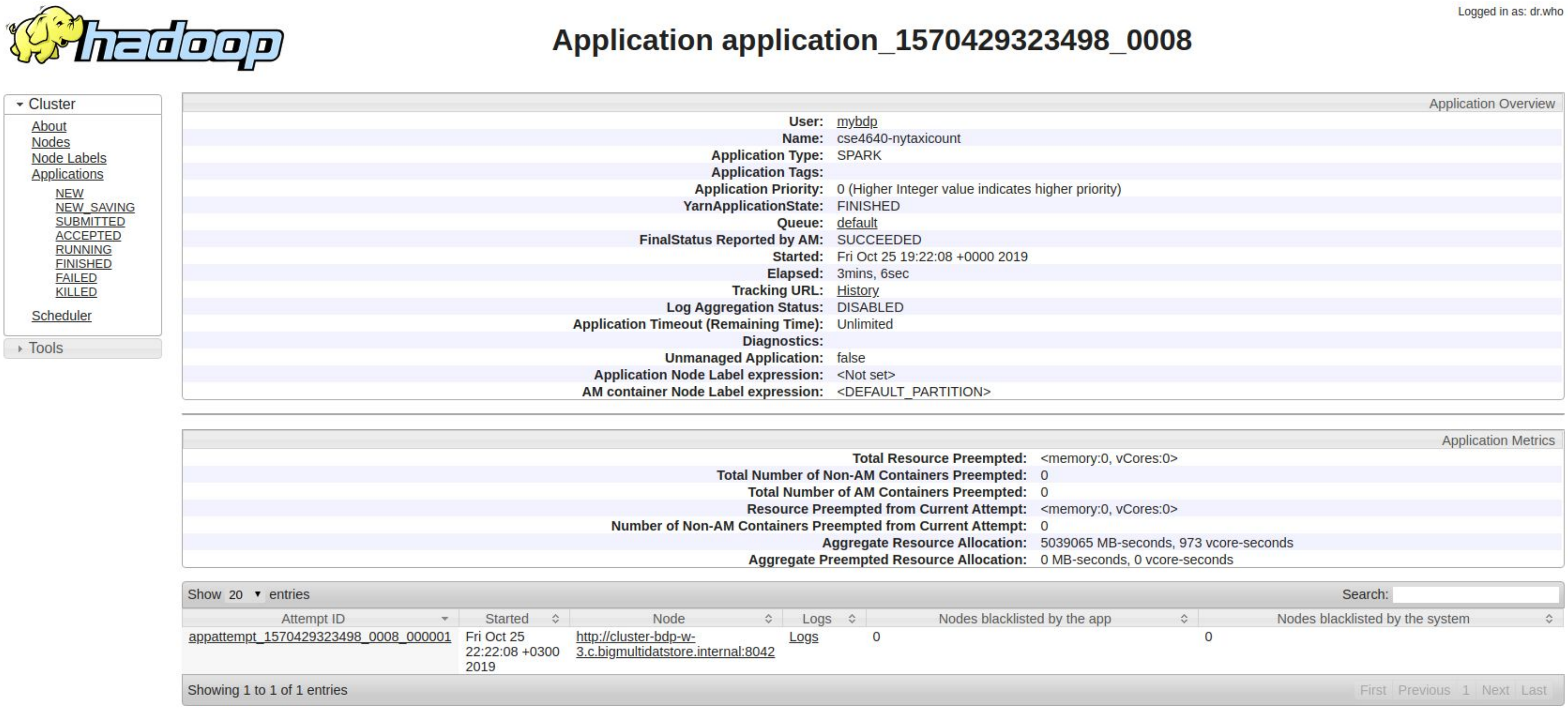


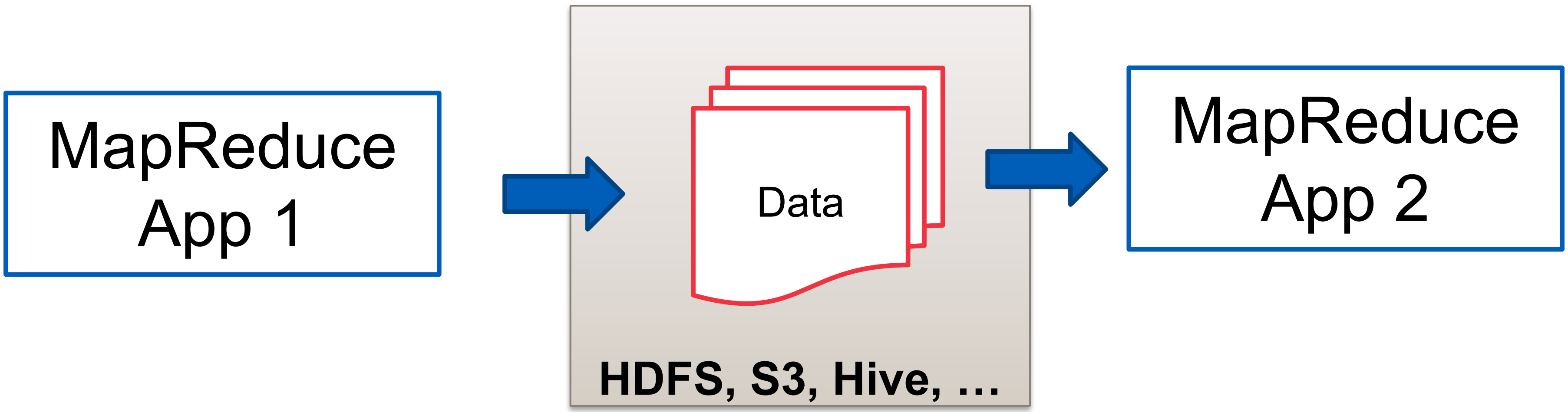
Figure source:
http://hadoop.apache.org/docs/current/hadoop-yarn/hadoop-yarn-site/YARN.html

Monitoring MapReduce Jobs



Connecting MapReduce applications

Build complex MapReduce pipelines



Using big data storage/database as data exchange

We can use workflows to coordinate different MapReduce apps

Problems with MapReduce

- **Strict Map & Reduce tasks connection ⇒ limitation**
- **Need more flexible in processing big data workloads**
  - batch data flows and streaming data flows
- **Programming diversity support**
  - software engineering productivity

Apache Spark

https://spark.apache.org/

Apache Spark

- **Cluster-based high-level computing framework**
- **“unified engine” for different types of big data processing**
  - SQL/structured data processing
  - Machine learning
  - Graph processing
  - Streaming processing
- **It is a powerful computing framework and system ⇒ an important service that a big data platform should support**
  - public cloud: Google DataProc, Azure HDInsight, Amazon EMR
  - data lake systems: e.g., Hudi and Delta Lake

Apache Spark

Can be run a top

- **Hadoop (using HDFS and YARN)**
- **Mesos cluster**
  - http://mesos.apache.org/
- **Kubernetes**
- **Standalone machines**

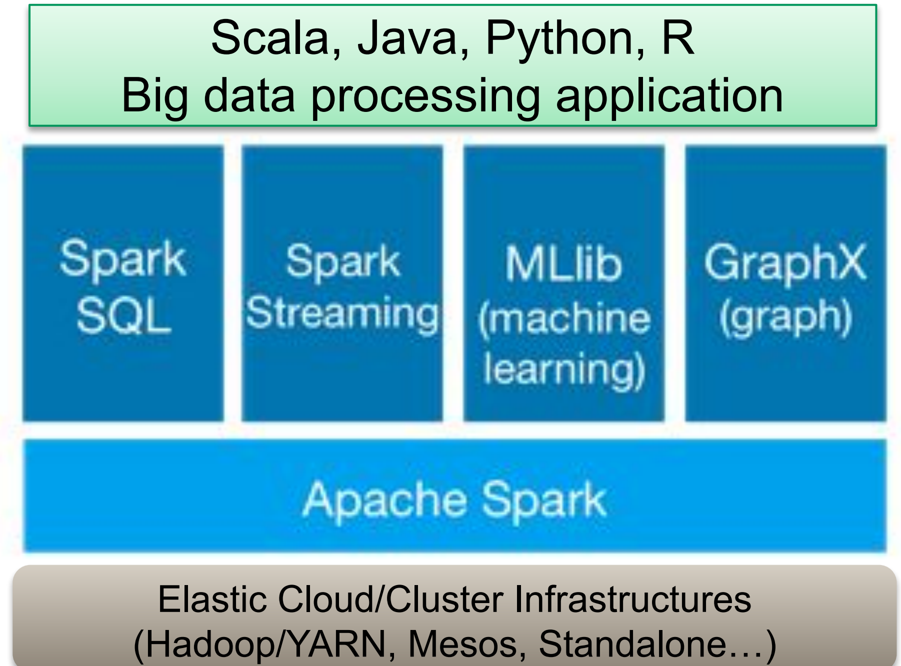
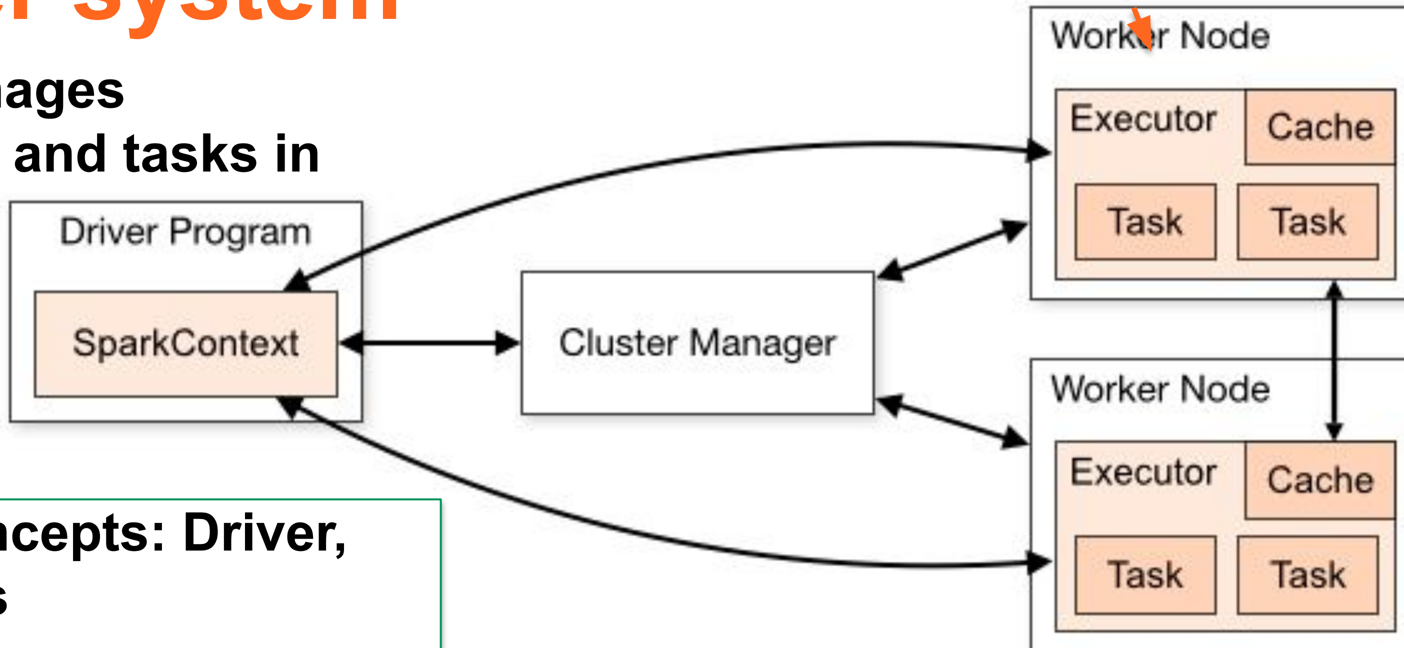


Figure source: http://spark.apache.org/

Execution model in a cluster system

Computing resources in a cluster node

Driver manages operations and tasks in nodes

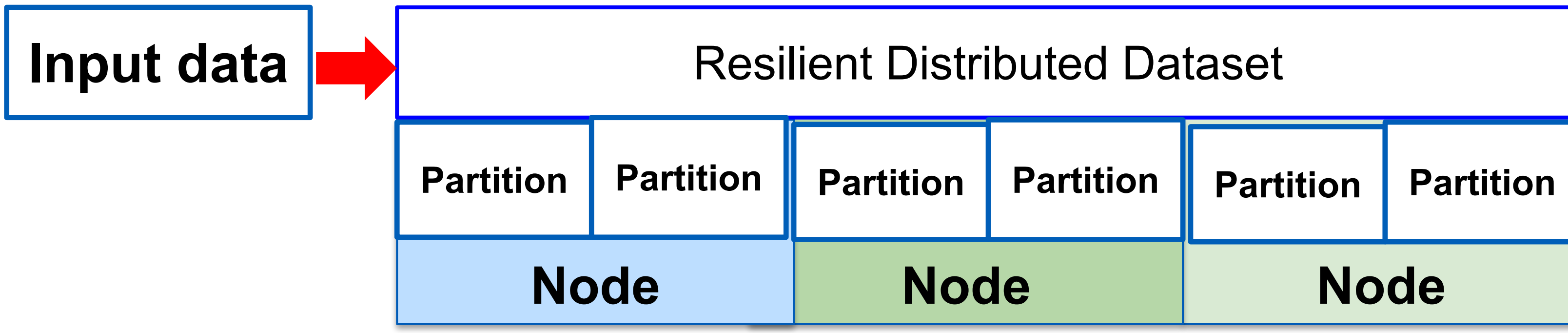


Common concepts: Driver, Nodes, Tasks

Workload styles: OLAP/batch jobs with a lot of data

Figure source:
http://spark.apache.org/docs/latest/cluster-overview.html

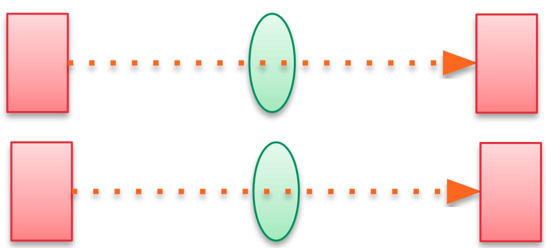
Key features



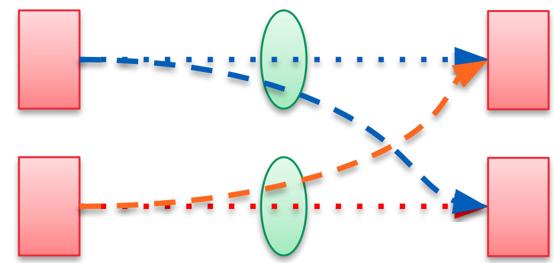
- **Input data is distributed in different nodes for processing**
  - Support partitions for data processing: a node keeps one or n partitions, a partition resides only in a node ⇒ for computing
- **Key operations: transformations and actions on data**
- **Leverage parallel computing concepts to run multiple tasks**
  - Operation -> task executed by executor
  - Parallel tasks, task pipeline, DAG of processing stages
- **Persistent data in memory/disk for operations**

Transformation operations

- **Transformation:**
  - Instructions about how to transform a data in a form to another form ☐ it will not change the original data (immutability)
- **Only tell what to do: to build a DAG (direct acyclic graph): a lineage of what to do**
- **lazy approach ⇒ real transformation will be done at action operators**



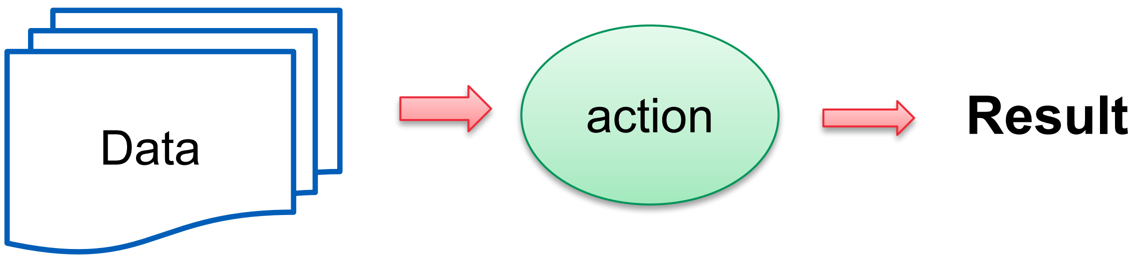
Narrow transformation, no data shuffle



Wide transformation, cross data partitions, requires a shuffle

Action operations

- **Compute the results for a set of transformations**
  - Examples: count or average
- **Actions: view, collect, write, calculation**



Lazy approach: an action triggers execution of transformation operations ⇒ enable various types of optimization

Spark program: programming elements

- **SparkSession**
  - Act as a program driver to manage the execution of tasks
  - SparkContext: manages connection to cluster, manage internal services
- **Data APIs**
  - Low-level Resilient Distributed Dataset (RDD)
  - High-level DataFrames/DataSets
  - Load and hold distributed data
  - Transformation and action functions
- **ML, graph and streaming functions and pipelines**

Spark application management: high-level view

- **Submission/Request**
  - submit the Spark application for running
  - resource is provided for running the Driver
- **Launch**
  - the Driver requests resources for executors (through SparkContext)
  - establish executors across worker nodes
- **Execution**
  - the Driver starts to execute code and move data
- **Finish/Completion:**
  - finish, release executors

Spark program logic: typical steps

- **Load data and distribute data**
  - data is immutable after created
  - data partition in Spark: a partition is allocated in a node
- **Perform transformations and actions operations**
  - *transformations:* build plans for transforming data models
  - *actions:* perform computation on data

Resilient distributed dataset (RDD)

- **Low-level data structure**
  - collection of data elements partitioned across nodes in the cluster
  - with data sharing, parallel operations, fault-tolerant features
- **Create RDD**
  - created by loading data from files (text, sequence file) including local file systems, HDFS, Cassandra, HBase, Amazon S3, etc.
- **Persist RDD**
  - in memory or to files

RDD transformations and actions

Transformations

- map
- filter
- sample
- intersection
- groupByKey

Actions

- reduce()
- collect()
- count()
- saveAs…File()

Example with RDD

```
VendorID,tpep_pickup_datetime,tpep_dropoff_datetime,passenger_count,trip_distance,RatecodeID,store_and_fwd_flag,PULocationID,DOLocationID,payment_type,fare_amount,extra,mta_tax,tip_amount,tolls_amount,improvement_surcharge,total_amount
2,11/04/2084 12:32:24 PM,11/04/2084 12:47:41 PM,1,1.34,1,N,238,236,2,10,0,0.5,0,0,0.3,10.8
2,11/04/2084 12:32:24 PM,11/04/2084 12:47:41 PM,1,1.34,1,N,238,236,2,10,0,0.5,0,0,0.3,10.8
2,11/04/2084 12:25:53 PM,11/04/2084 12:29:00 PM,1,0.32,1,N,238,238,2,4,0,0.5,0,0,0.3,4.8
```

as a text file

```python
conf = SparkConf().setAppName("cse4640-rddshow").setMaster(args.master)
sc = SparkContext(conf=conf)
##modify the input data
rdd=sc.textFile(args.input_file)
## if there is a header we can filter it otherwise comment two lines
csvheader = rdd.first()
rdd =  rdd.filter(lambda csventry: csventry != csvheader)
## using map to parse csv text entry
rdd=rdd.map(lambda csventry: csventry.split(","))
rdd.repartition(1)
rdd.saveAsTextFile(args.output_dir)
```

Shared variables

- **A function is executed a remote and various tasks running in parallel**
  - how do tasks share variables? common patterns in parallel computing: *broadcast and global counter*
- **Variables used in parallel operations**
  - variables are copied among parallel tasks
  - shared among tasks or between tasks and the driver
- **Types of variables**
  - broadcast variables: cache a value in all nodes
  - accumulators: a global counter shared across processes

Examples

```
conf = SparkConf().setAppName("cse4640-broadcast").setMaster(args.master)
sc = SparkContext(conf=conf)
bVar = sc.broadcast([5,10])
print("The value of the broadcast",bVar.value,sep=" ")
counter = sc.accumulator(0)
sc.parallelize([1, 2, 3, 4]).foreach(lambda x: counter.add(bVar.value[0]))
print("The value of the counter is ",counter.value,sep=" ")
```

Use cases:

- **Broadcast variables: lookup tables**
- **Accumulators: monitoring/checkpoint counters**

Spark SQL and DataFrames

- **High-level APIs**
  - design with common programming patterns in data analysis, multi-language support
- **SparkSQL: enable dealing with structured data**
  - SQL query execution, Hive, JDBC/ODBC
- **DataFrame**
  - distributed data organized into named columns, similar to a table in relational database
  - Pandas and Spark DataFrames have similar design concepts

DataFrame

```
inputFile =args.input_file
df =spark.read.csv(inputFile,header=True,inferSchema=True)
print("Number of partition",df.rdd.getNumPartitions())
df.show()
```

PROVINCECODE	DEVICEID	IFINDEX	FRAME	SLOT	PORT	ONUINDEX	ONUID	TIME	SPEEDIN	SPEEDOUT
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[redacted]YN	[redacted]3023	[redacted]528	1	2	7	20	10[redacted]07020	01/08/2019 00:04:07	330	184

Create DataFrame

DataFrames can be created from a Hive table, from Spark data sources, or another DataFrame

Load and save

- From Hive, JSON, CSV
- HDFS, local file, etc.

Formats and Sources supported by DataFrames

Figure source:
https://databricks.com/blog/2015/02/17/introducing-dataframes-in-spark-for-large-scale-data-science.html

DataFrame Transformations & Actions

- **Several transformations can be done**
  - *Think transformation for relational database or matrix*
- **Select**
  - *df.select*
- **Filter**
  - *df.filter*
- **Groupby**
  - *df.groupBy*
- **Handle missing data**
  - *Drop duplicate rows, drop rows with NA/null data*
  - *Fill NA/null data*

Actions

- Return values calculated from DataFrame

Examples

- reduce, max, min, sum, variance and stdev

⇒ Distributed and parallel processing but it is done by the framework

Example of a Spark

```
#!/usr/bin/env python2
#encoding: UTF-8
# CS-E4640
import csv
import sys
from datetime import datetime
from pyspark.sql import SparkSession
import numpy as np
from pyspark.sql import functions as F
import argparse
parser = argparse.ArgumentParser()
parser.add_argument('--input_file', help='input data file')
parser.add_argument('--output_dir',help='output dir')
args = parser.parse_args()

##define a context
spark = SparkSession.builder.appName("cse4640-onu").getOrCreate()
#NOTE: using hdfs:///..... for HDFS file or file:///
inputFile =args.input_file
df =spark.read.csv(inputFile,header=True,inferSchema=True)
#df.show()
print("Number of records", df.count())
exprs = {"SPEEDIN":"avg"}
df2 = df.groupBy('ONUID').agg(exprs)
df2.repartition(1).write.csv(args.output_file,header=True)
```

Session/Driver

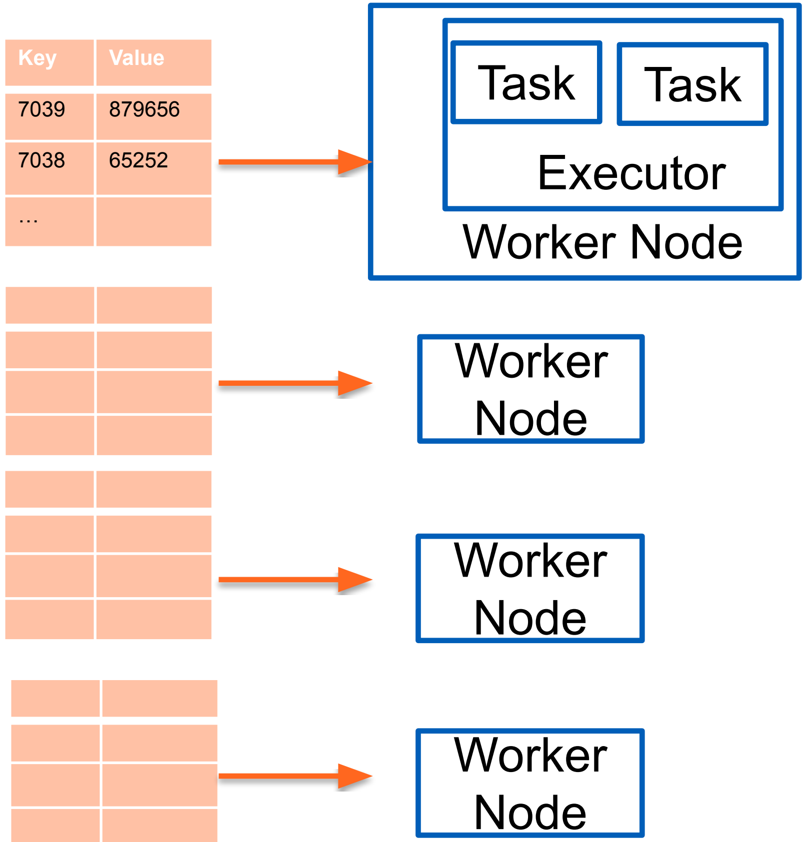
Read data

Apply operations

Spark application runtime view

- **Tasks:**
  - a unit of work executed in an executor: e.g., set of transformations for a data partition
- **Stage**
  - a set of tasks executed in many nodes for computing the same operation
  - move to a new stage: through shuffle operations
- **Job**
  - runtime view of an action operation (produce a result), includes many stages

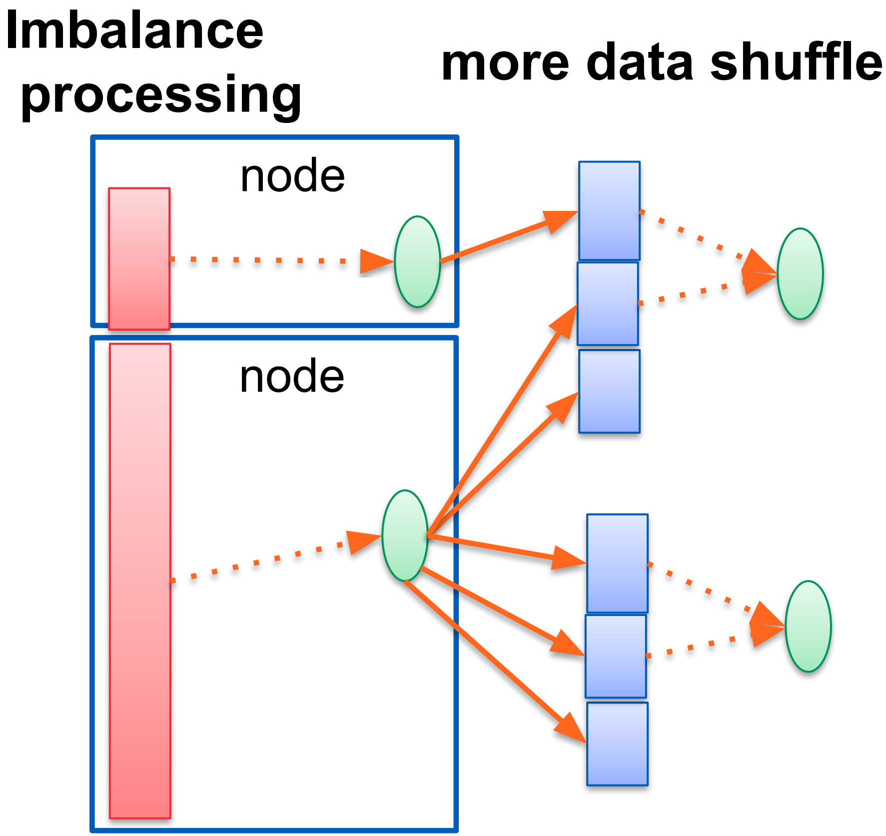
Data Distribution



One task works on a partition at a time

⇒ Parallelism and performance are strongly dependent on number of partitions, tasks, CPU cores

Data Distribution: Load balance



- **It is important to have well-balanced data distribution across nodes**
- **Detection:**
  - look at runtime execution time to see problems or check your data
- **Examples of solution:**
  - repartition
  - broadcast
  - change group keys

Pipelining, Shuffle and DAG

- **Operations work in a pipeline without moving data across nodes**
  - e.g., map->filter, select->filter
- **Shuffle persistent**
  - shuffle needs move data across nodes
  - source tasks save shuffle files into local disks for data shuffle, then the target tasks will read data from source nodes
    - *Save time, recovery, fault tolerance*

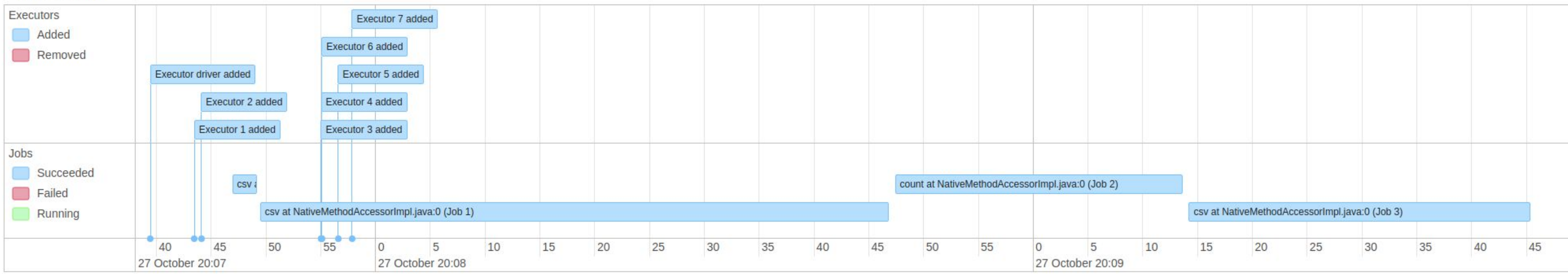
Monitoring Spark: Executors and tasks

Spark 2.3.3 | Jobs | Stages | Storage | Environment | Executors | SQL | **cse4640-nytaxicount** application UI

Spark Jobs (?)

User: truong
Total Uptime: 2.1 min
Scheduling Mode: FAIR
Completed Jobs: 4

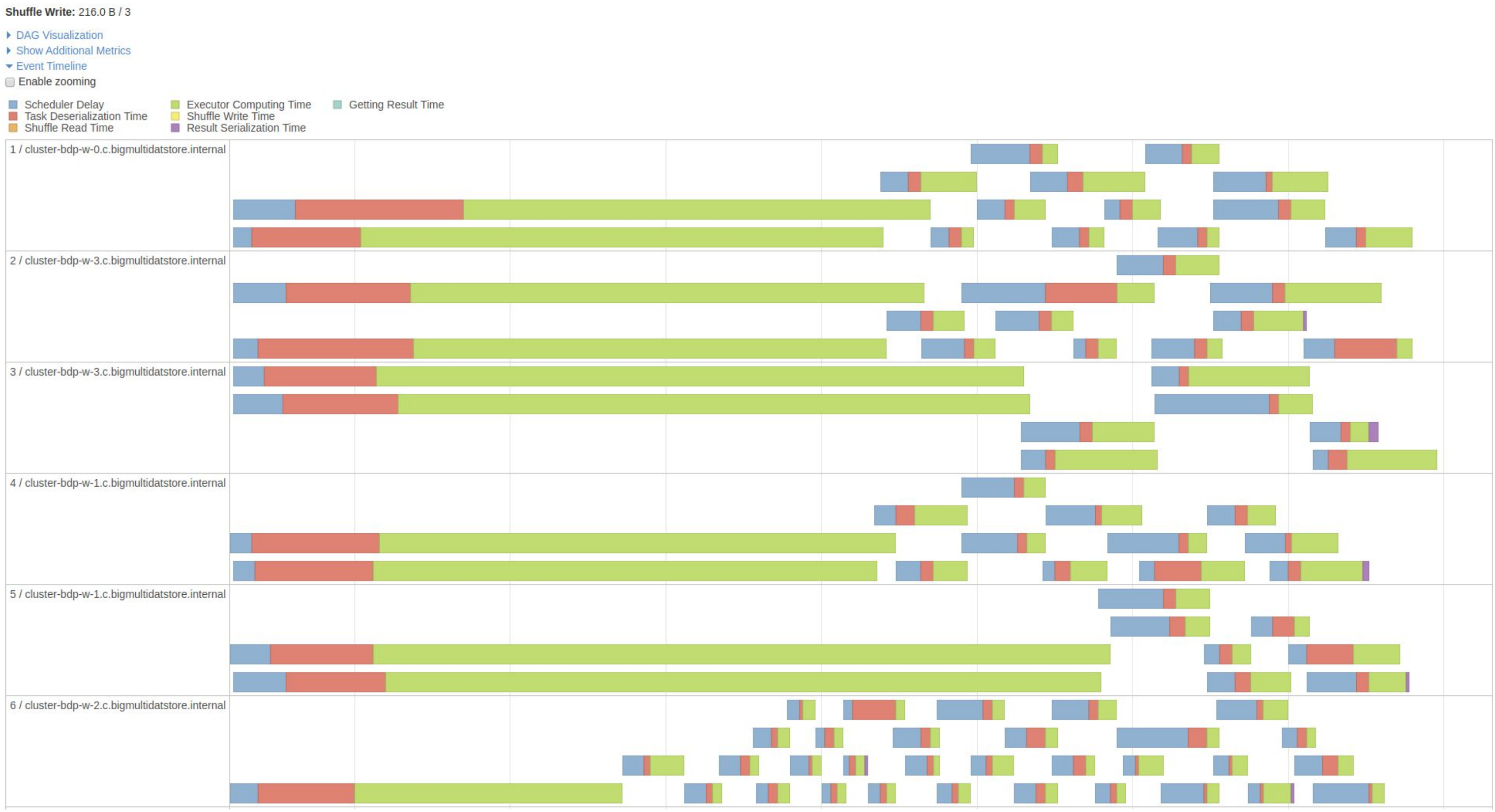
▾ Event Timeline
☐ Enable zooming



Completed Jobs (4)

Job Id ▾	Description	Submitted	Duration	Stages: Succeeded/Total	Tasks (for all stages): Succeeded/Total
3	csv at NativeMethodAccessorImpl.java:0 csv at NativeMethodAccessorImpl.java:0	2019/10/27 20:09:14	31 s	3/3	279/279
2	count at NativeMethodAccessorImpl.java:0 count at NativeMethodAccessorImpl.java:0	2019/10/27 20:08:47	26 s	2/2	79/79
1	csv at NativeMethodAccessorImpl.java:0 csv at NativeMethodAccessorImpl.java:0	2019/10/27 20:07:49	57 s	1/1	78/78
0	csv at NativeMethodAccessorImpl.java:0 csv at NativeMethodAccessorImpl.java:0	2019/10/27 20:07:46	2 s	1/1	1/1

Executors and tasks



Other important support of Spark

- **MLlib - Machine learning**
  - Distributed and parallel machine learning algorithms with big data and clusters
- **Streaming: data processing in near-realtime**
  - *Related to our topic: stream data processing*
- **Graph Processing: Spark GraphX**
  - Parallel computation for graphs
- **Many third-party frameworks, e.g.,**
  - SparkOCR (https://www.johnsnowlabs.com/spark-ocr/), SparkNLP (https://nlp.johnsnowlabs.com/)
  -

Summary

- **Facts:**
  - MapReduce and Spark are important frameworks
  - A user/developer needs to learn to develop MapReduce/Spark applications
  - A platform operator/provider offer services for managing resources, processing and monitoring
- **Thoughts:**
  - Think about the success of Apache Spark: rich ecosystems!
  - Think if you combine data, different distributed programming supports for your big data platform

Thanks!

Hong-Linh Truong
Department of Computer Science

rdsea.github.io