CS4225/CS5425 Big Data Systems for Data Science

Spark I: Basics

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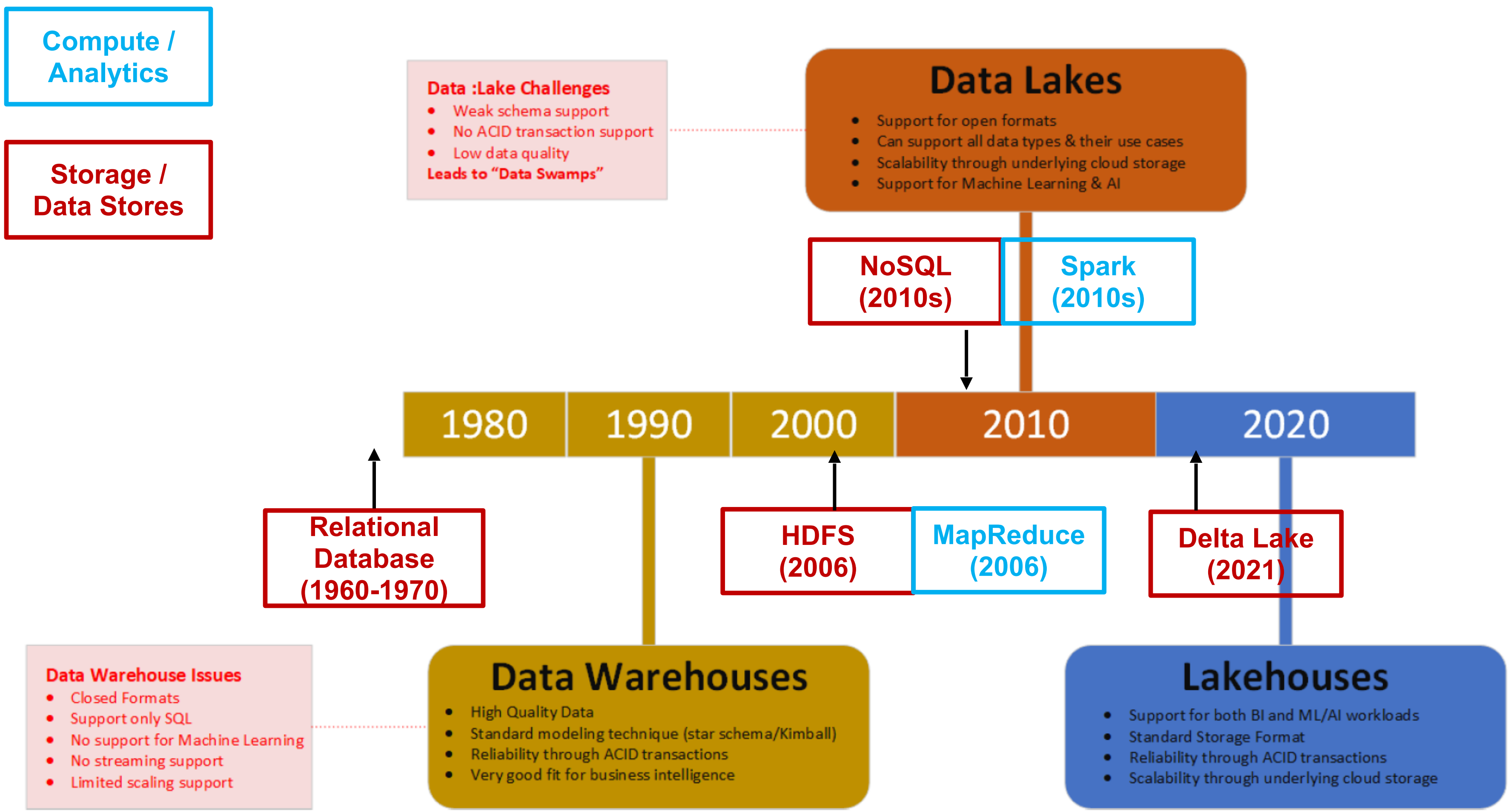
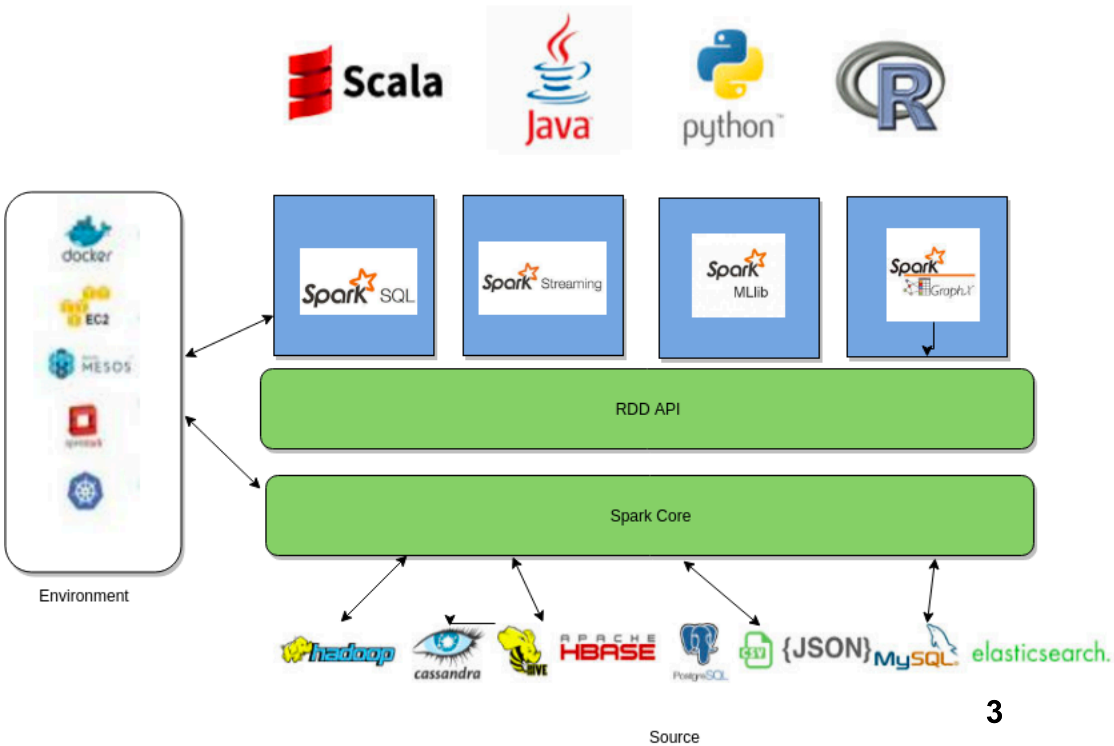
Evolution of Data Architectures

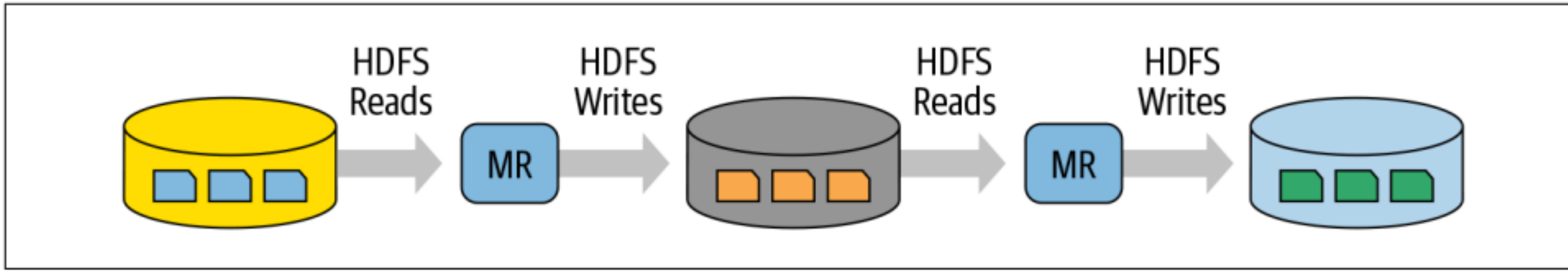


Today's Plan

- **Introduction and Basics**
- Working with RDDs
- Caching and DAGs
- DataFrames and Datasets

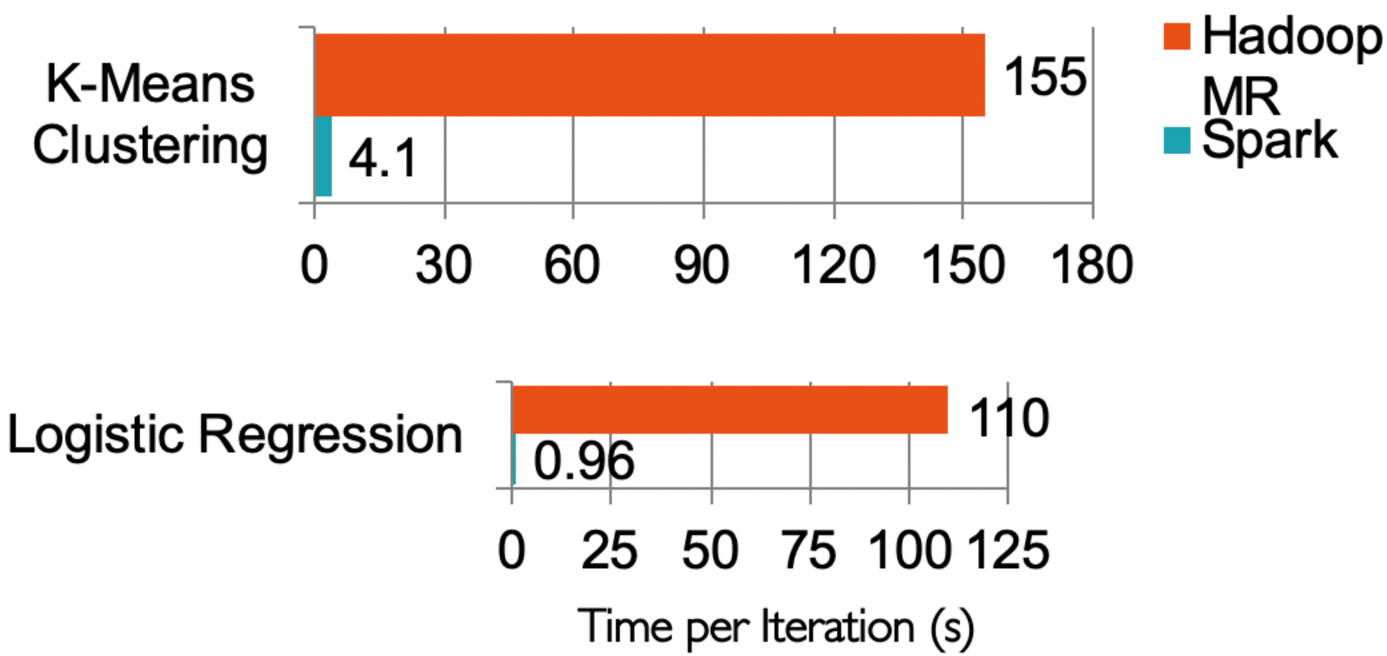


Motivation: Hadoop vs Spark



- Issues with Hadoop Mapreduce:
  - **Network and disk I/O costs**: intermediate data has to be written to local disks and shuffled across machines, which is slow
  - Not suitable for **iterative** (i.e. modifying small amounts of data repeatedly) processing, such as interactive workflows, as each individual step has to be modelled as a MapReduce job.
- Spark stores most of its intermediate results in memory, making it much faster, especially for iterative processing
  - When memory is insufficient, Spark **spills to disk** which requires disk I/O

Performance Comparison



Ease of Programmability

```java
import java.io.IOException;
import java.util.StringTokenizer;

import org.apache.hadoop.conf.Configuration;
import org.apache.hadoop.fs.Path;
import org.apache.hadoop.io.IntWritable;
import org.apache.hadoop.io.Text;
import org.apache.hadoop.mapreduce.Job;
import org.apache.hadoop.mapreduce.Mapper;
import org.apache.hadoop.mapreduce.Reducer;
import org.apache.hadoop.mapreduce.lib.input.FileInputFormat;
import org.apache.hadoop.mapreduce.lib.output.FileOutputFormat;

public class WordCount {

  public static class TokenizerMapper
       extends Mapper<Object, Text, Text, IntWritable>{

    private final static IntWritable one = new IntWritable(1);
    private Text word = new Text();

    public void map(Object key, Text value, Context context
                    ) throws IOException, InterruptedException {
      StringTokenizer itr = new StringTokenizer(value.toString());
      while (itr.hasMoreTokens()) {
        word.set(itr.nextToken());
        context.write(word, one);
      }
    }
  }

  public static class IntSumReducer
       extends Reducer<Text,IntWritable,Text,IntWritable> {
    private IntWritable result = new IntWritable();

    public void reduce(Text key, Iterable<IntWritable> values,
                       Context context
                       ) throws IOException, InterruptedException {
      int sum = 0;
      for (IntWritable val : values) {
        sum += val.get();
      }
      result.set(sum);
      context.write(key, result);
    }
  }

  public static void main(String[] args) throws Exception {
    Configuration conf = new Configuration();
    Job job = Job.getInstance(conf, "word count");
    job.setJarByClass(WordCount.class);
    job.setMapperClass(TokenizerMapper.class);
    job.setCombinerClass(IntSumReducer.class);
    job.setReducerClass(IntSumReducer.class);
    job.setOutputKeyClass(Text.class);
    job.setOutputValueClass(IntWritable.class);
    FileInputFormat.addInputPath(job, new Path(args[0]));
    FileOutputFormat.setOutputPath(job, new Path(args[1]));
    System.exit(job.waitForCompletion(true) ? 0 : 1);
  }
}
```

WordCount (Hadoop MapReduce)

Ease of Programmability

```
val file = sc.textFile("hdfs://...")
val counts = file.flatMap(line => line.split(" "))
                 .map(word => (word, 1))
                 .reduceByKey(_ + _)
counts.save("...")
```

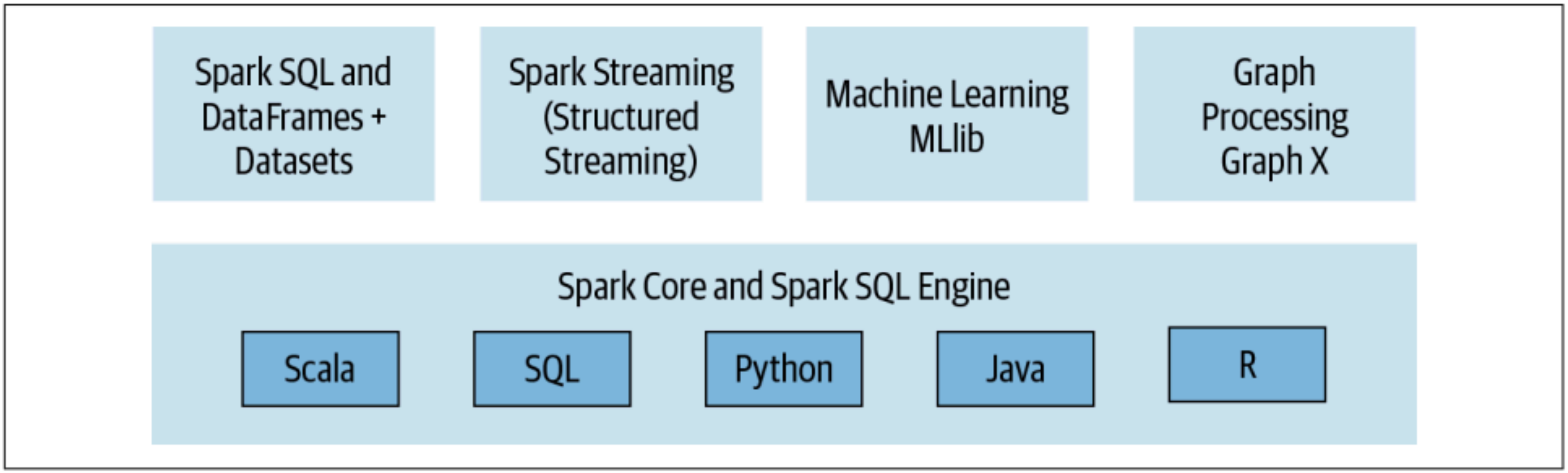
the cat sits on the mat

the 1
cat 1
sits 1
on 1
the 1
mat 1

the (1, 1)
cat (1)
sits (1)
on (1)
mat (!)

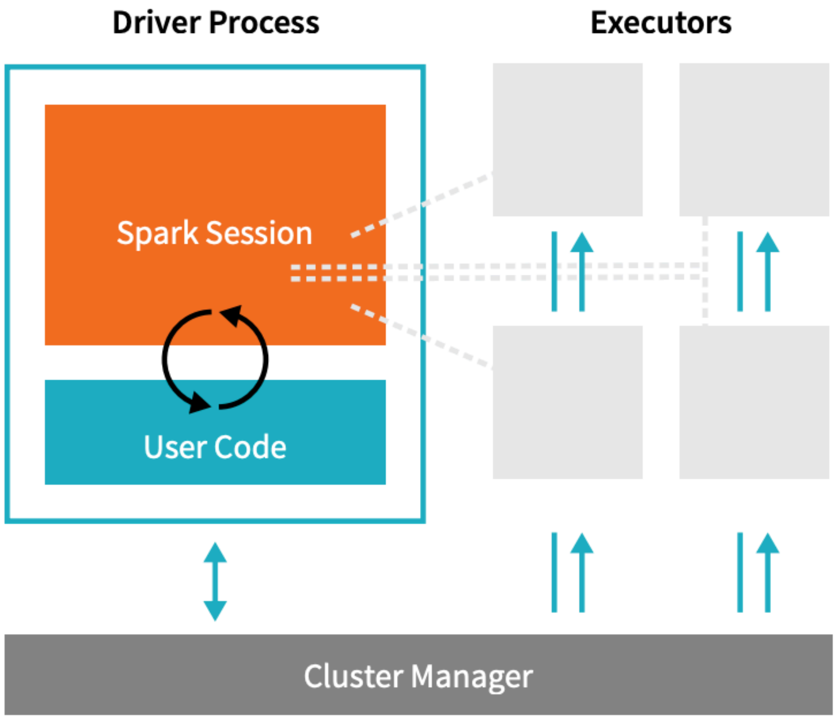
WordCount (Spark)

Spark Components and API Stack



Use any language. It later changes it to scala/java and processes it for faster efficiency.

Spark Architecture



- **Driver Process** responds to user input, manages the Spark application etc., and distributes work to **Executors**, which run the code assigned to them and send the results back to the driver
- **Cluster Manager** (can be Spark's standalone cluster manager, YARN, Mesos or Kubernetes) allocates resources when the application requests it
- In **local mode,** all these processes run on the same machine

Evolution of Spark APIs

Resilient Distributed Datasets (2011) → **DataFrame (2013)** → **DataSet (2013)**

Resilient Distributed Datasets (2011)

- A distributed collection of JVM objects
- Functional operation (map, filter, etc)

DataFrame (2013)

- A distributed collection of rows with the same schema
- Each row is a generic untyped JVM object (Row) which may hold different types of fields
- Expression-based relational operations (join, GroupBy)
- Logical plans and optimizer

DataSet (2013)

- Very Similar to DataFrame
- Each row is a strongly typed JVM object
  - Type-safety
  - Customized operations

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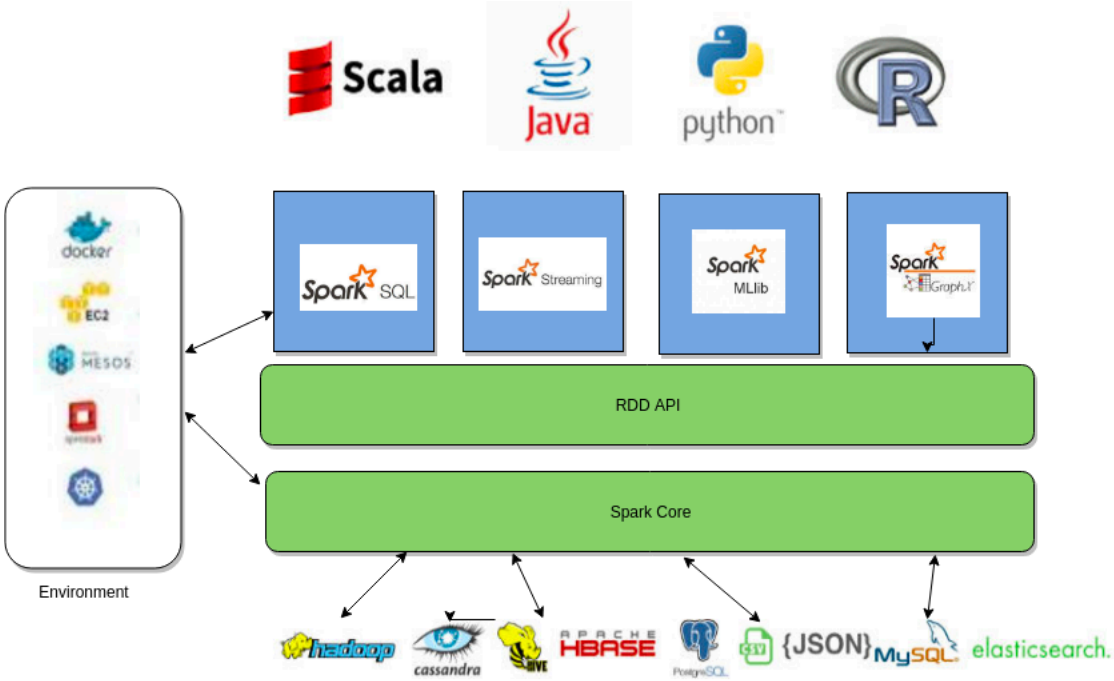


Source

Achieve fault tolerance through **lineages**

Instead of replicas like in map-reduce

Represent a collection of objects that is **distributed over machines**

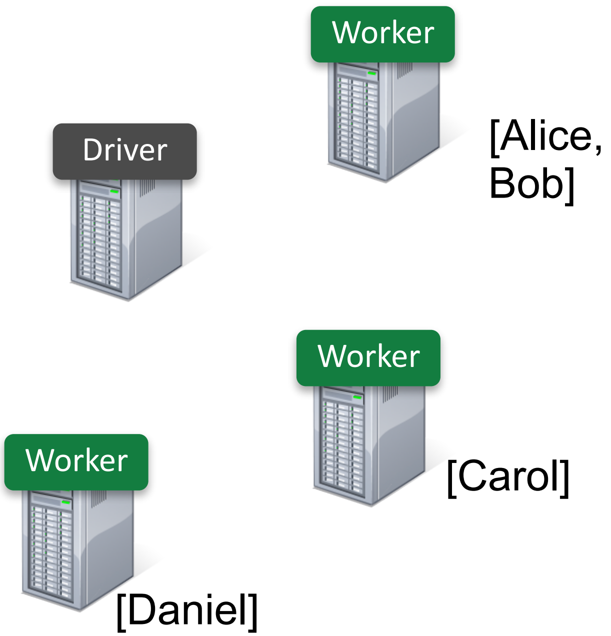
Resilient Distributed Datasets (RDDs)

RDD: Distributed Data

```
# Create an RDD of names, distributed over 3 partitions
dataRDD = sc.parallelize(["Alice", "Bob", "Carol",
"Daniel"], 3)
```

Partition data
into 3 parts

- RDDs are **immutable**, i.e. they cannot be changed once created.
- This is an RDD with 4 strings. In actual hardware, it will be partitioned into the 3 workers.

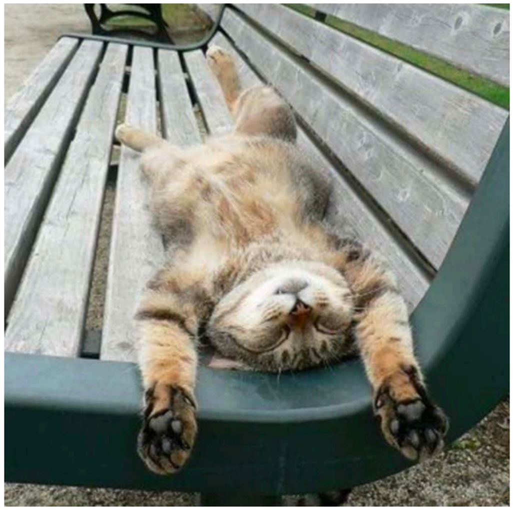


Transformations

- **Transformations** are a way of transforming RDDs into RDDs.

```
# Create an RDD of tuples (name, age)
dataRDD = sc.parallelize(["Alice", "Bob", "Carol",
"Daniel"], 3)
nameLen = dataRDD.map(lambda s: len(s))
```

- This represents the transformation that maps each string to its length, creating a new RDD.
- However, transformations are **lazy**. This means the transformation will not be executed yet, until an **action** is called on it
  - Q: what are the advantages of being lazy?
  - A: Spark can optimize the query plan to improve speed (e.g. removing unneeded operations)
- Examples of transformations: `map, order, groupBy, filter, join, select`



Actions

- **Actions** trigger Spark to compute a result from a series of transformations.

```
dataRDD = sc.parallelize(["Alice", "Bob", "Carol",
"Daniel"], 3)
nameLen = dataRDD.map(lambda s: len(s))
nameLen.collect()
```

```
[5, 3, 5, 6]
```

- collect() here is an action.
  - It is the action that asks Spark to retrieve all elements of the RDD to the driver node.
- Examples of actions: `show, count, save, collect`

Distributed Processing

```python
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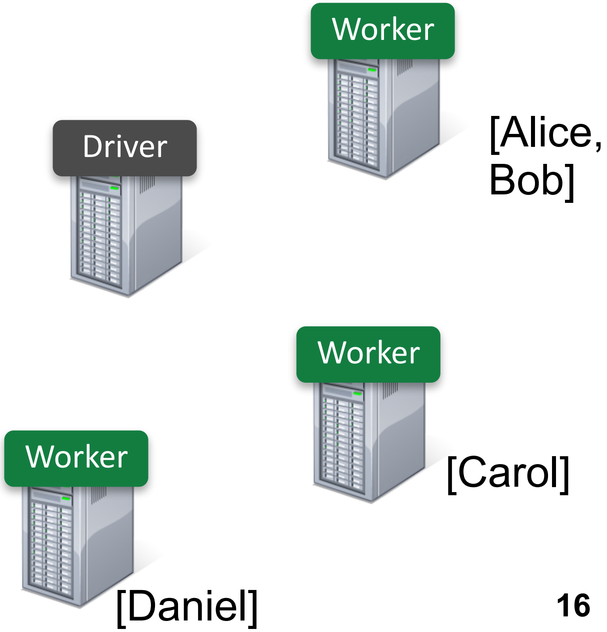
- As we previously said, RDDs are actually distributed across machines.
- Thus, the transformations and actions are executed in parallel. The results are only sent to the driver in the final step.



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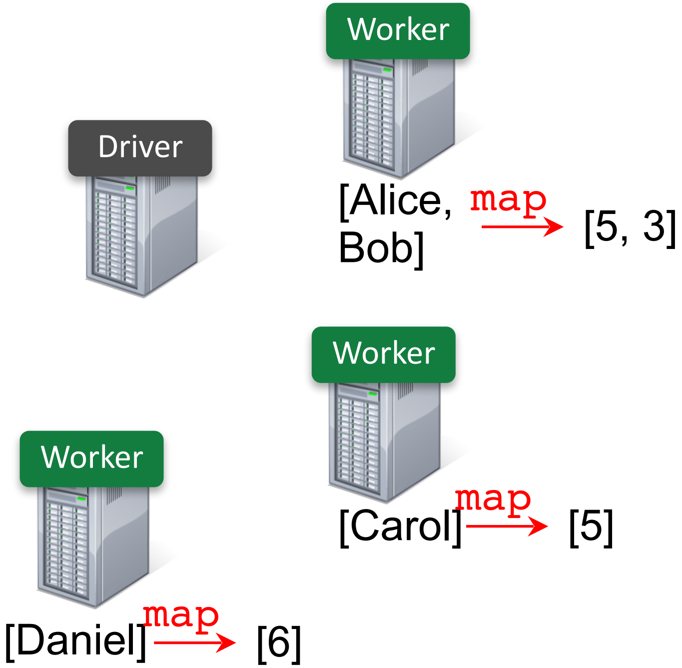

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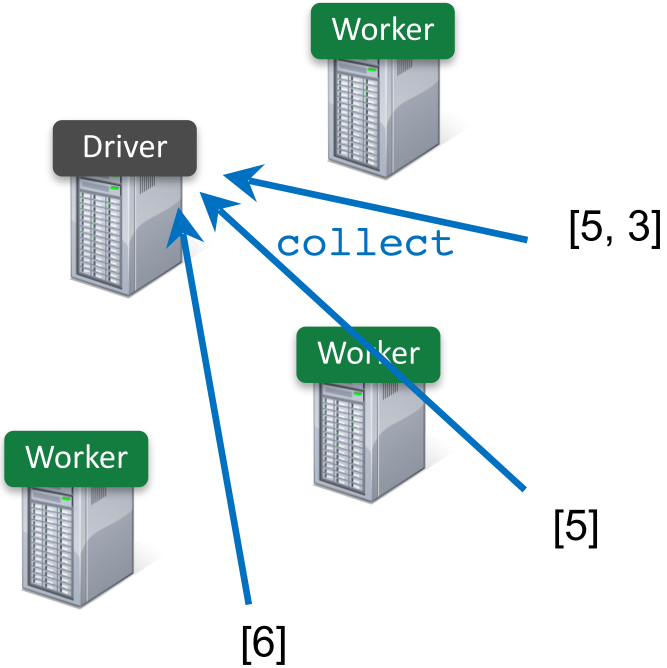

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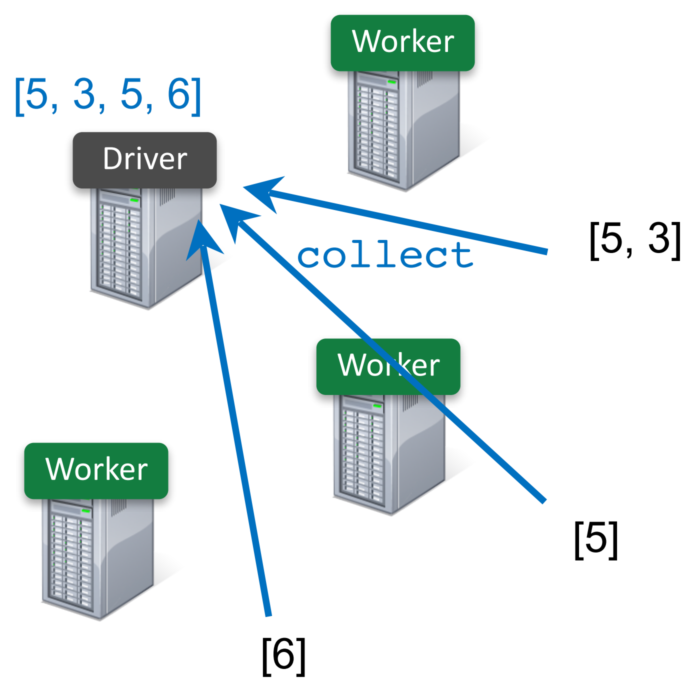
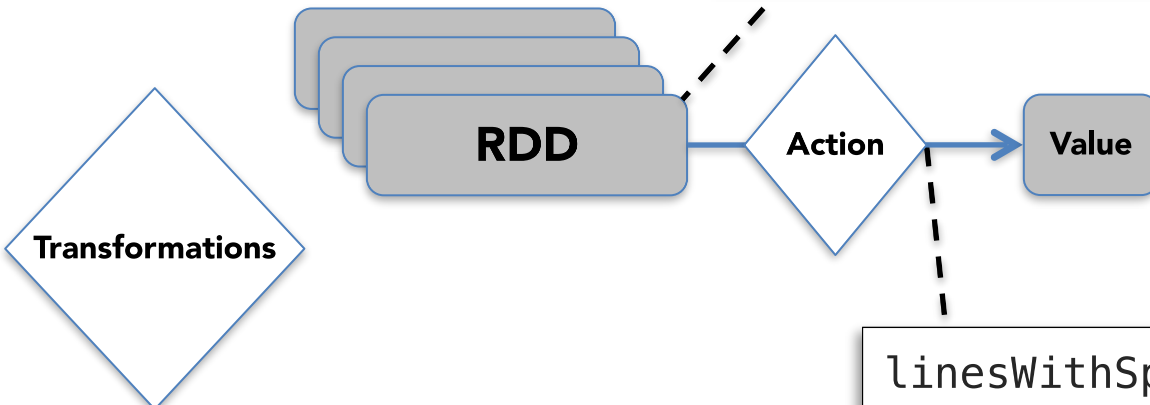


Working with RDDs

Note: this reads the file on each worker node in parallel, not on the driver node

```
textFile = sc.textFile("File.txt")
```




```
linesWithSpark.count()
74

linesWithSpark.first()
# Apache Spark
```

```
linesWithSpark = textFile.filter(lambda line: "Spark" in line)
```

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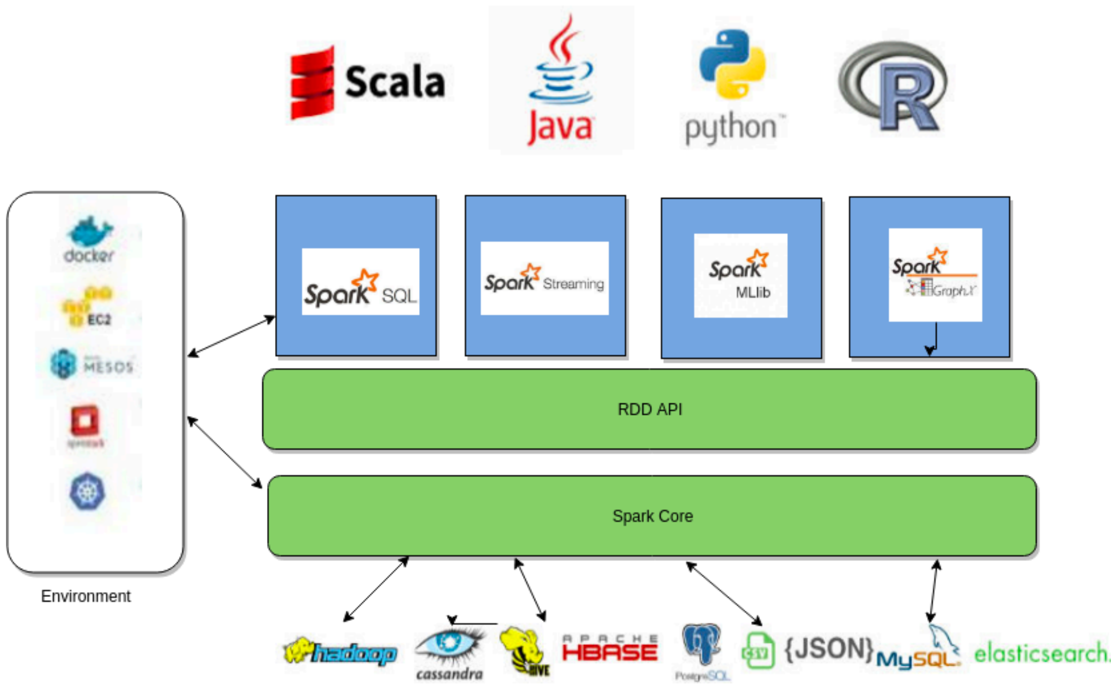


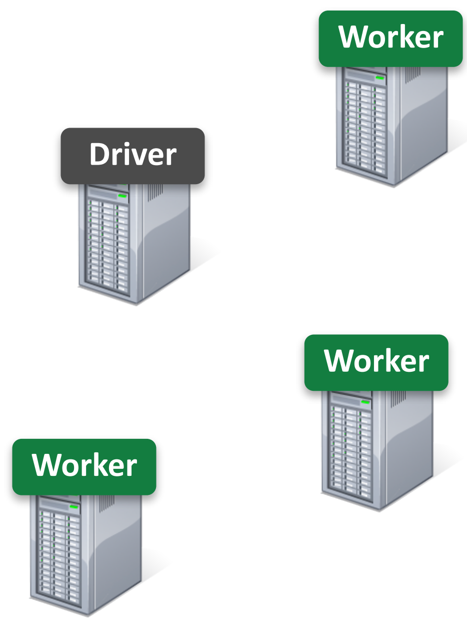
Source

Caching

Log Mining example: Load error messages from a log into memory, then interactively search for various patterns

```
lines = sc.textFile("hdfs://...")
errors = lines.filter(lambda s: s.startswith("ERROR"))
messages = errors.map(lambda s: s.split("\t")[2])
messages.cache()
```

```
messages.filter(lambda s: "mysql" in s).count()
```



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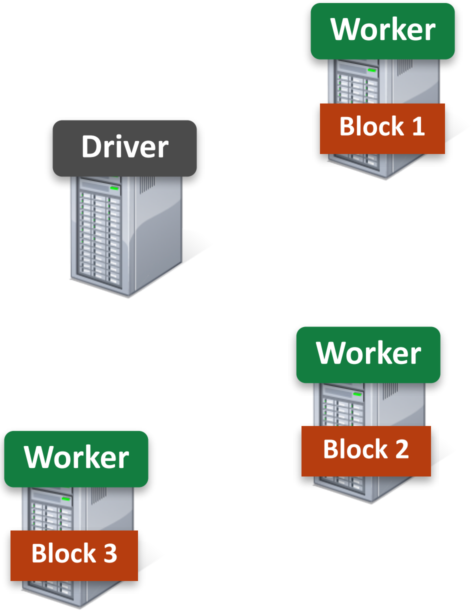

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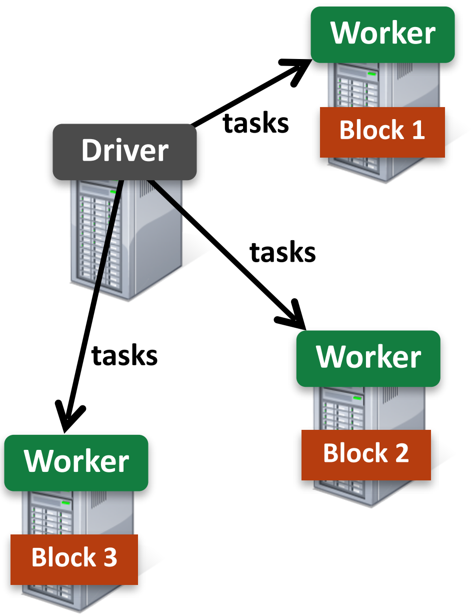

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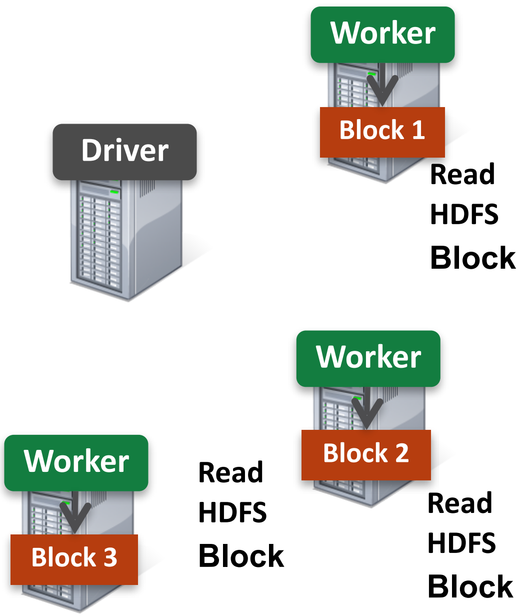

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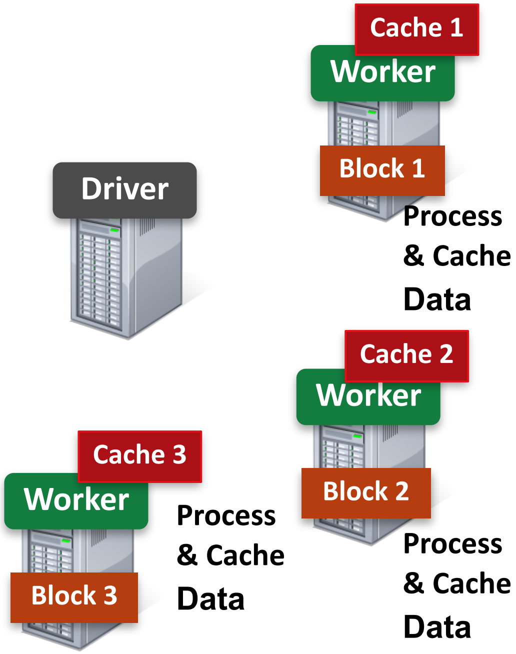

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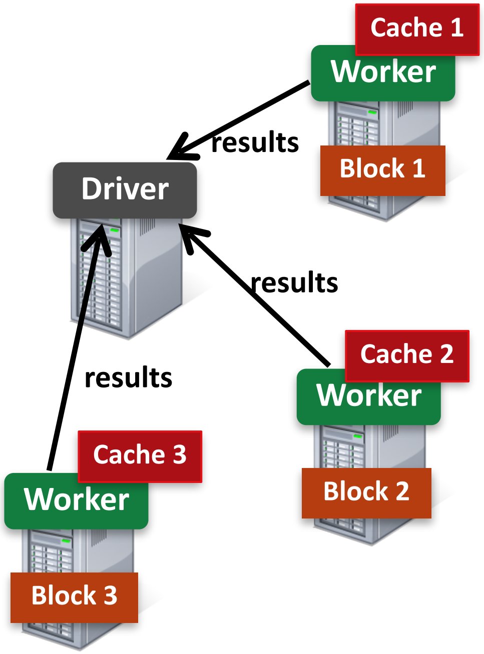

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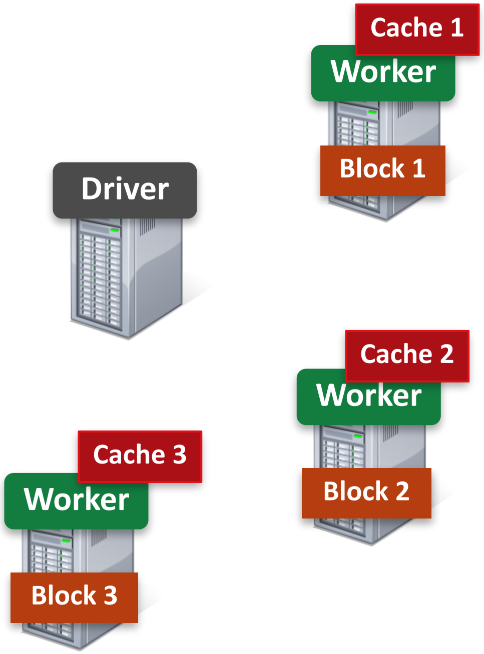

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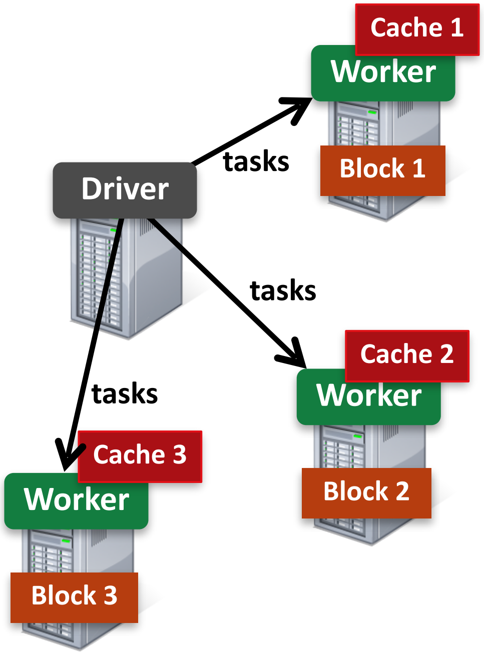

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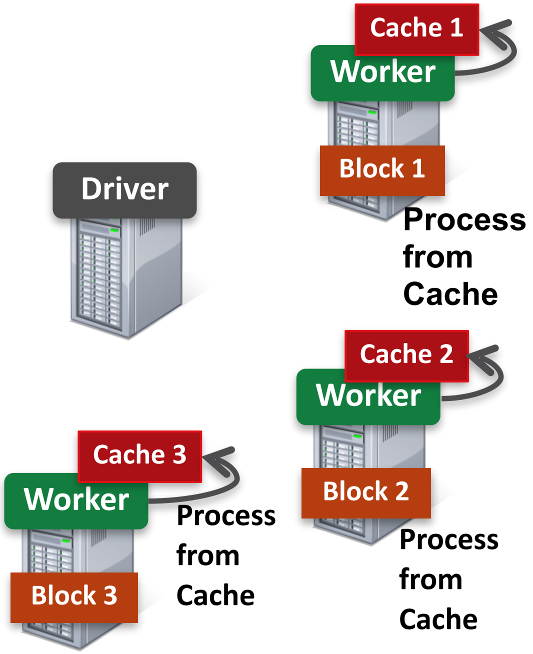

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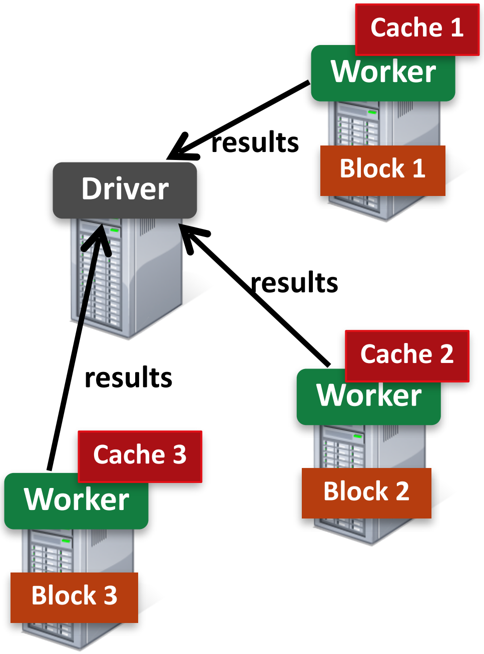

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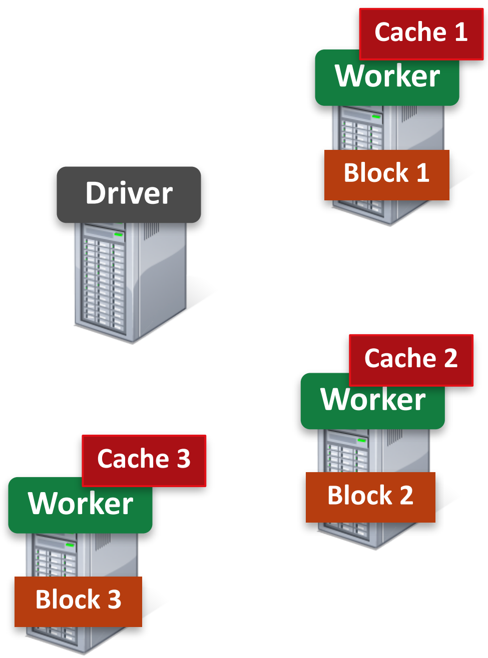
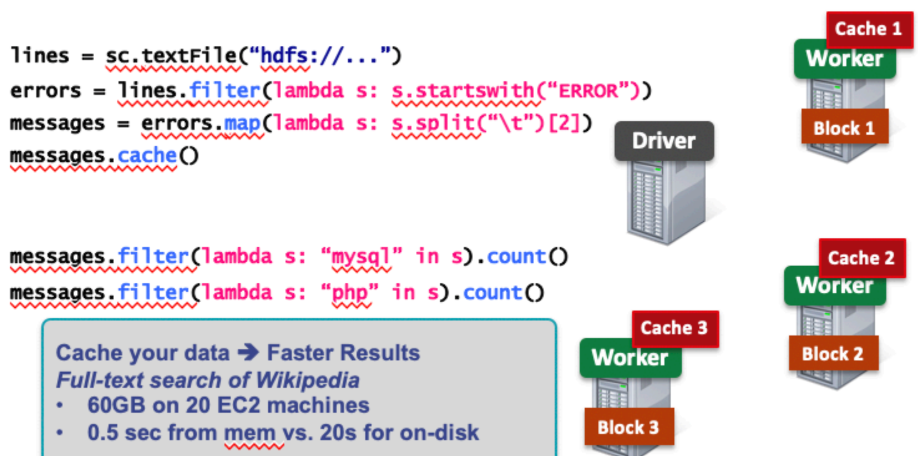


Cache your data → Faster Results
Full-text search of Wikipedia

- **60GB on 20 EC2 machines**
- **0.5 sec from mem vs. 20s for on-disk**

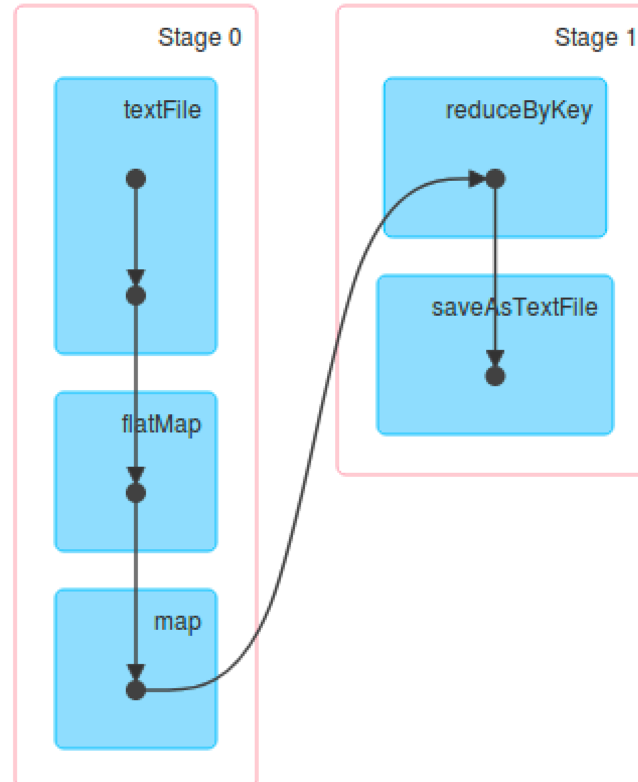
Caching

- `cache()`: saves an RDD to memory (of each worker node).
- `persist(options)`: can be used to save an RDD to memory, disk, or off-heap memory
- When should we cache or not cache an RDD?
  - When it is expensive to compute and needs to be re-used multiple times.
  - If worker nodes have not enough memory, they will evict the "least recently used" RDDs. So, be aware of memory limitations when caching.



Directed Acyclic Graph (DAG)

- Internally, Spark creates a graph ("directed acyclic graph") which represents all the RDD objects and how they will be transformed.
- Transformations construct this graph; actions trigger computations on it.

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                 .map(word => (word, 1))
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counts.save("...")
```
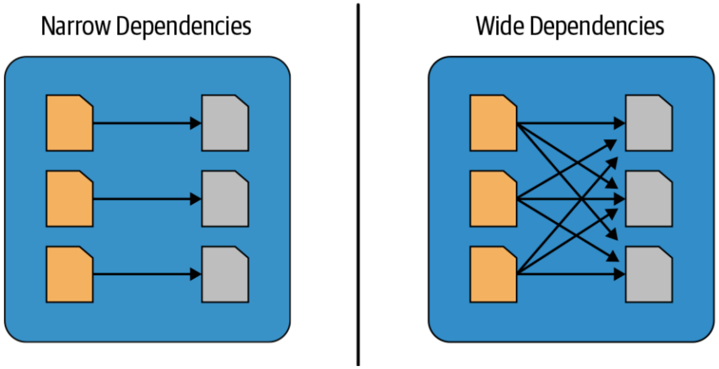
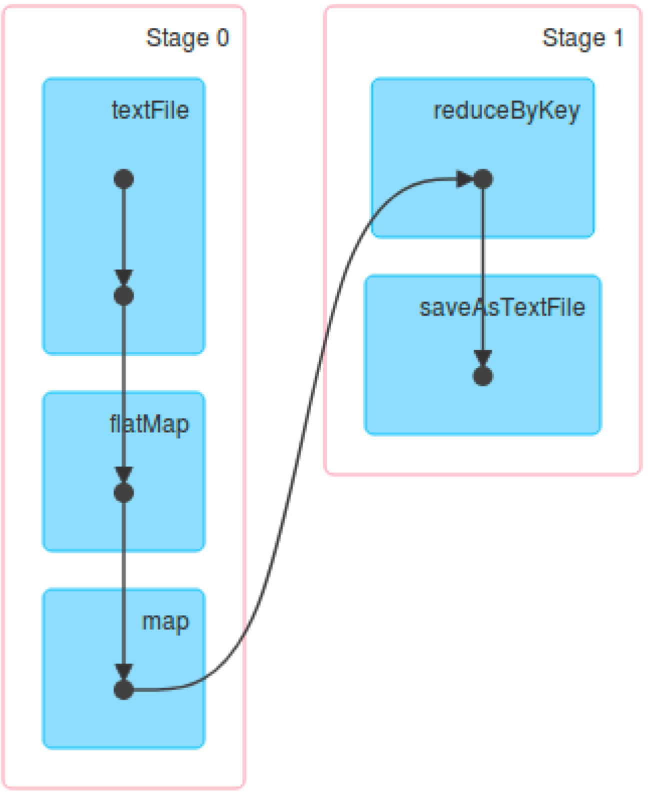

WordCount (Spark)

Narrow and Wide Dependencies

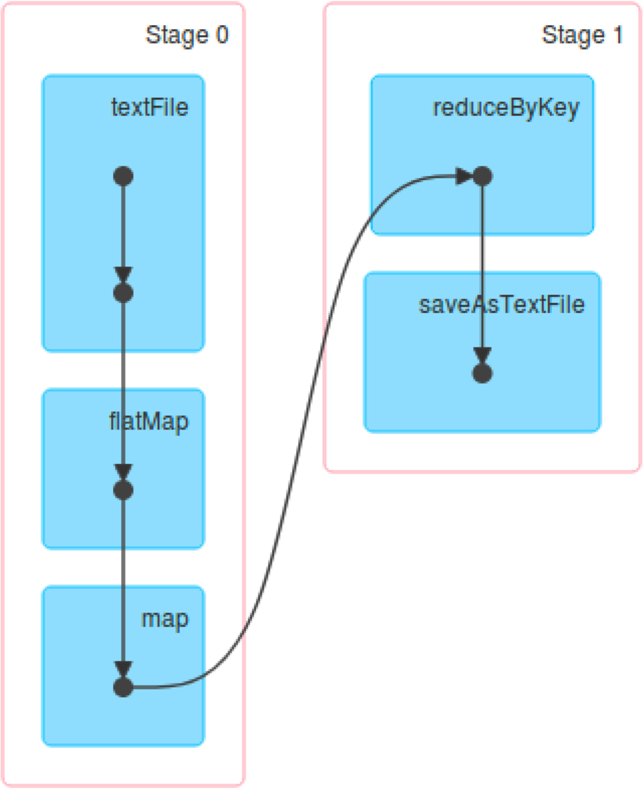
- **Narrow dependencies** are where each partition of the parent RDD is used by at most 1 partition of the child RDD
  - E.g. map, flatMap, filter, contains
- **Wide dependencies** are the opposite (each partition of parent RDD is used by multiple partitions of the child RDD)
  - E.g. reduceByKey, groupBy, orderBy
- In the DAG, consecutive narrow dependencies are grouped together as "**stages**".
- **Within stages**, Spark performs consecutive transformations on the same machines.
- **Across stages**, data needs to be **shuffled**, i.e. exchanged across partitions, in a process very similar to map-reduce, which involves writing intermediate results to disk
- Minimizing shuffling is good practice for improving performance.





Lineage and Fault Tolerance

- Unlike Hadoop, Spark does not use replication to allow fault tolerance. Why?
  - Spark tries to store all the data in memory, not disk. Memory capacity is much more limited than disk, so simply duplicating all data is expensive.
- **Lineage approach**: if a worker node goes down, we replace it by a new worker node, and use the graph (DAG) to recompute the data in the lost partition.
  - Note that we only need to recompute the RDDs from the lost partition.



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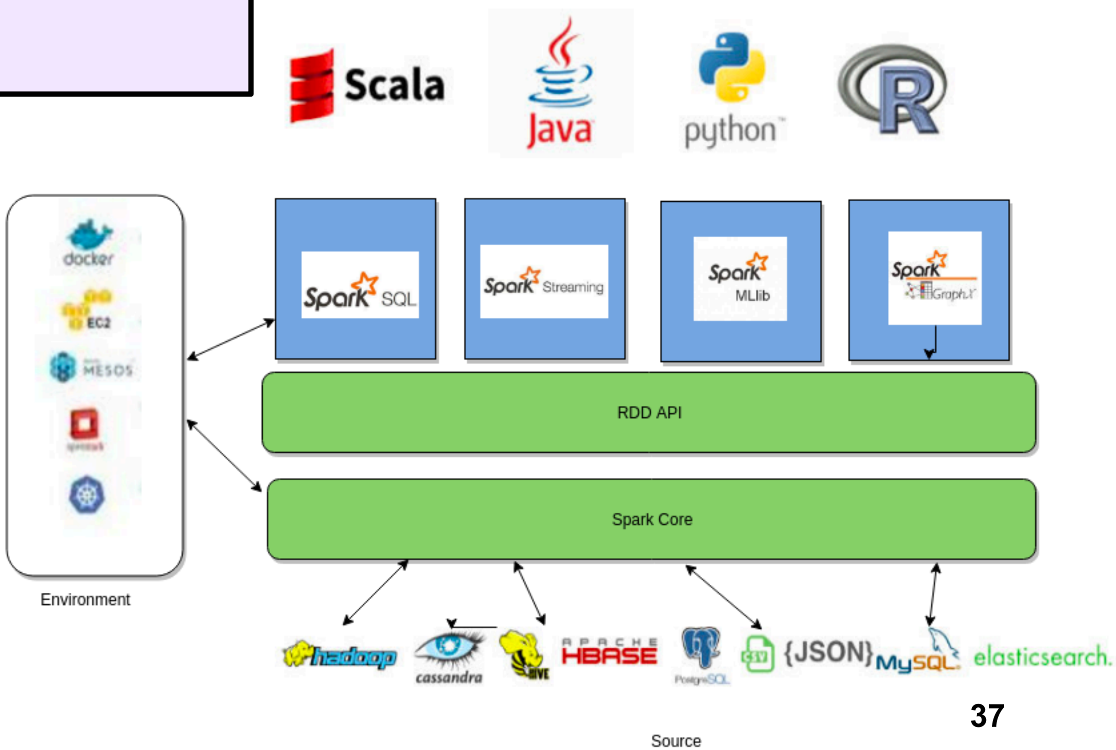
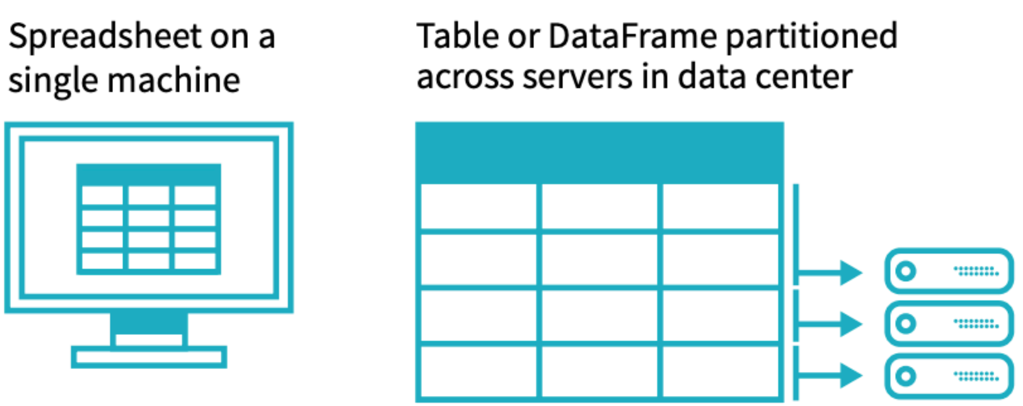


DataFrames

- A DataFrame represents a table of data, similar to tables in SQL, or DataFrames in pandas.
- Compared to RDDs, this is a higher level interface, e.g. it has transformations that resemble SQL operations.
  - DataFrames (and Datasets) are the recommended interface for working with Spark – they are easier to use than RDDs and almost all tasks can be done with them, while only rarely using the RDD functions.
  - However, all DataFrame operations are still ultimately compiled down to RDD operations by Spark.



DataFrames: example

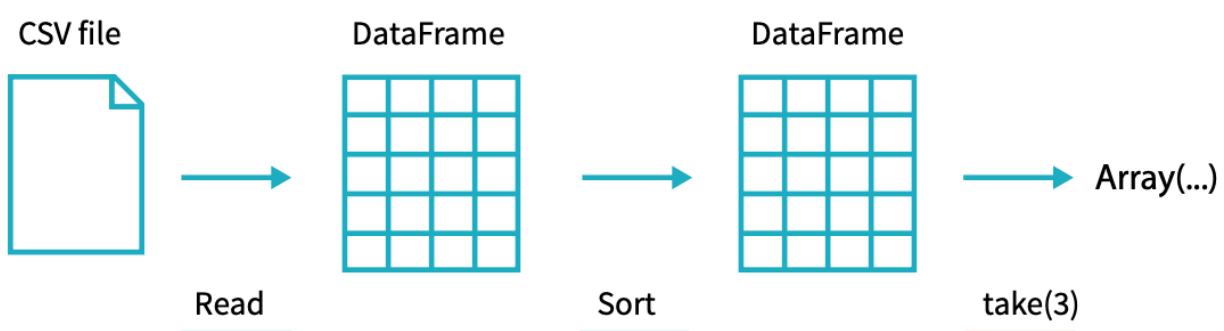
```
flightData2015 = spark\
.read\
.option("inferSchema", "true")\
.option("header", "true")\
.csv("/mnt/defg/flight-data/csv/2015-summary.csv")
```

- Reads in a DataFrame from a CSV file.

```
flightData2015.sort("count").take(3)
```

- Sorts by ‘count’ and output the first 3 rows (action)

```
Array([United States,Romania,15], [United States,Croatia...
```



DataFrames: transformations

- An easy way to transform DataFrames is to use SQL queries. This takes in a DataFrame and returns a DataFrame (the output of the query).

```
flightData2015.createOrReplaceTempView("flight_data_2015")
maxSql = spark.sql("""
SELECT DEST_COUNTRY_NAME, sum(count) as destination_total
FROM flight_data_2015
GROUP BY DEST_COUNTRY_NAME
ORDER BY sum(count) DESC
LIMIT 5
""")
maxSql.collect()
```

DataFrames: DataFrame interface

- We can also run the exact same query as follows:

```
from pyspark.sql.functions import desc
flightData2015\
.groupBy("DEST_COUNTRY_NAME")\
.sum("count")\
.withColumnRenamed("sum(count)", "destination_total")\
.sort(desc("destination_total"))\
.limit(5)\
.collect()
```

- Generally, these transformation functions (groupBy, sort, …) take in either strings or "column objects", which represent columns.
  - For example, "desc" here returns a column object.

Datasets

- Datasets are similar to DataFrames, but are type-safe.
  - In fact, in Spark (Scala), DataFrame is just an alias for Dataset[Row]
  - However, Datasets are not available in Python and R, since these are dynamically typed languages

```
case class Flight(DEST_COUNTRY_NAME: String,
ORIGIN_COUNTRY_NAME: String, count: BigInt)
val flightsDF = spark.read.parquet("/mnt/defg/flight-data/
parquet/2010-summary.parquet/")
val flights = flightsDF.as[Flight]
flights.collect()
```

- The Dataset `flights` is type safe – its type is the "Flight" class.
- Now when calling `collect()`, it will also return objects of the "Flight" class, instead of Row objects.

Example: Spark Notebook in Google Colab

- To experiment with simple Spark commands without needing to install / setup anything on your computer, you can run Spark on Google Colab
- See the simple example notebook at https://colab.research.google.com/drive/1qtNpkieNEUzyF2NnXTyqyGL3LQD1TVIl#scrollTo=pUgUMWYUKAU3

Spark Example.ipynb

File Edit View Insert Runtime Tools Help All changes saved

+ Code + Text

[53]

```
DataFrame[_c0: string, _c1: string, _c2: double, _c3: string, _c4: string, _c5: string, _c6: string
```

```
dat.select("*").toPandas()
```

	_c0	_c1	_c2	_c3	_c4	_c5	_c6	_c7	_c8	_c9	_c10	_c11	_c12	_c13	_c14	_c15
0	b	30.83	0.000	u	g	w	v	1.25	t	t	1	f	g	00202	0	+
1	a	58.67	4.460	u	g	q	h	3.04	t	t	6	f	g	00043	560	+
2	a	24.50	0.500	u	g	q	h	1.50	t	f	0	f	g	00280	824	+
3	b	27.83	1.540	u	g	w	v	3.75	t	t	5	t	g	00100	3	+
4	b	20.17	5.625	u	g	w	v	1.71	t	f	0	f	s	00120	0	+
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
685	b	21.08	10.085	y	p	e	h	1.25	f	f	0	f	g	00260	0	-
686	a	22.67	0.750	u	g	c	v	2.00	f	t	2	t	g	00200	394	-
687	a	25.25	13.500	y	p	ff	ff	2.00	f	t	1	t	g	00200	1	-
688	b	17.92	0.205	u	g	aa	v	0.04	f	f	0	f	g	00280	750	-
689	b	35.00	3.375	u	g	c	h	8.29	f	f	0	t	g	00000	0	-

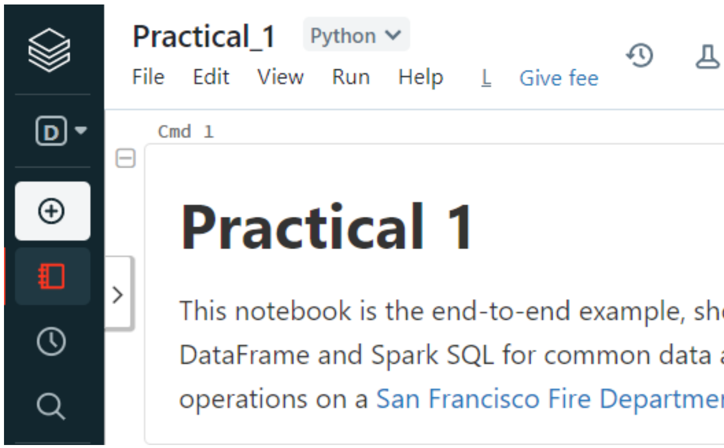
690 rows × 16 columns

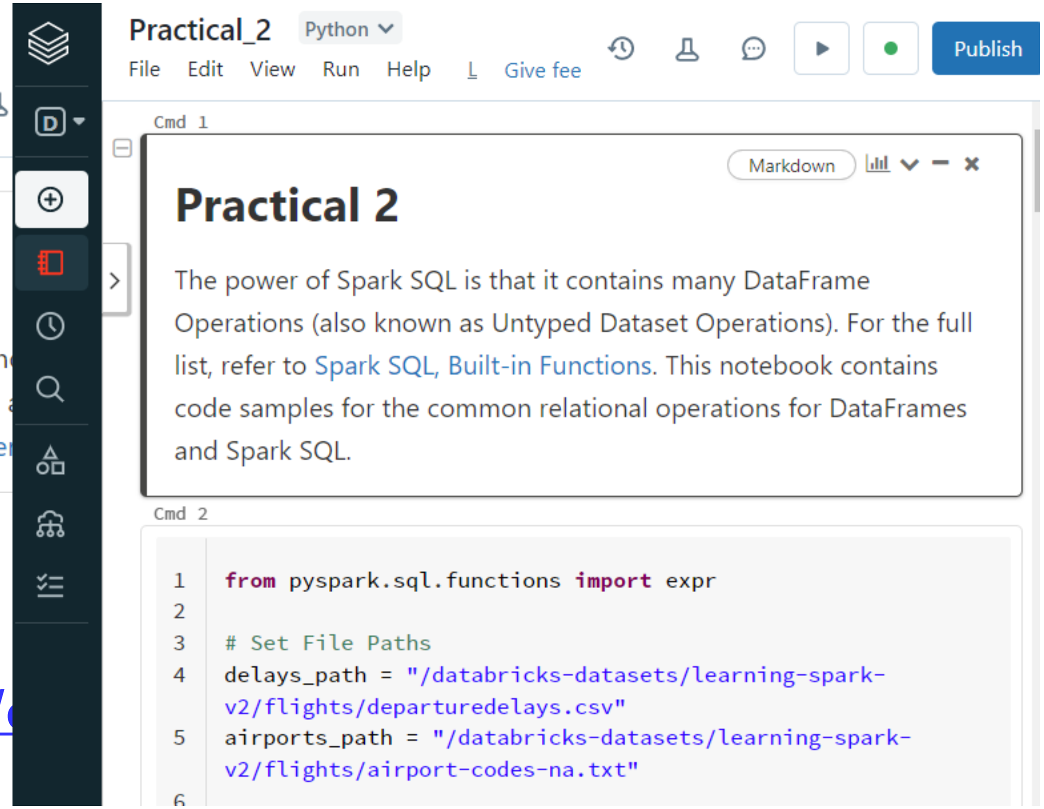
```
Welcome to
      ____              __
     / __/__  ___ _____/ /__
    _\ \/ _ \/ _ `/ __/  '_/
   /__ / .__/\_,_/_/ /_/\_\   version 3.1.2
      /_/

Using Python version 3.7.10 (default, Feb 26 2021 10:16:00)
Spark context Web UI available at http://192.168.79.2:4040
```

Example: Spark Notebooks in Databricks

- You need to sign up a Databricks community edition account (free)





- Source: https://github.com/

Demo_1: Spark Web U

```
df1 = spark.range(2, 10000000, 2)
df2 = spark.range(2, 10000000, 4)
df3 = df1.join(df2, ["id"])
df3.count()
```

(4) Spark Jobs

- Job 0 View (Stages: 1/1)
  - Stage 1: 8/8
- Job 1 View (Stages: 1/1)
  - Stage 0: 8/8
- Job 2 View (Stages: 1/1, 2 skipped)
  - Stage 2: 0/8 skipped
  - Stage 3: 0/8 skipped
  - Stage 4: 8/8
- Job 3 View (Stages: 1/1, 3 skipped)
  - Stage 5: 0/8 skipped
  - Stage 6: 0/8 skipped
  - Stage 7: 0/8 skipped
  - Stage 8: 1/1

df1: pyspark.sql.dataframe.DataFrame = [id: long]

df2: pyspark.sql.dataframe.DataFrame = [id: long]

df3: pyspark.sql.dataframe.DataFrame = [id: long]

```
Out[1]: 2500000
```

```
df1.show(10)
```

(1) Spark Jobs

```
+---+
| id|
+---+
|  2|
|  4|
|  6|
|  8|
| 10|
| 12|
| 14|
| 16|
| 18|
| 20|
+---+
```

```
df2.show(10)
```

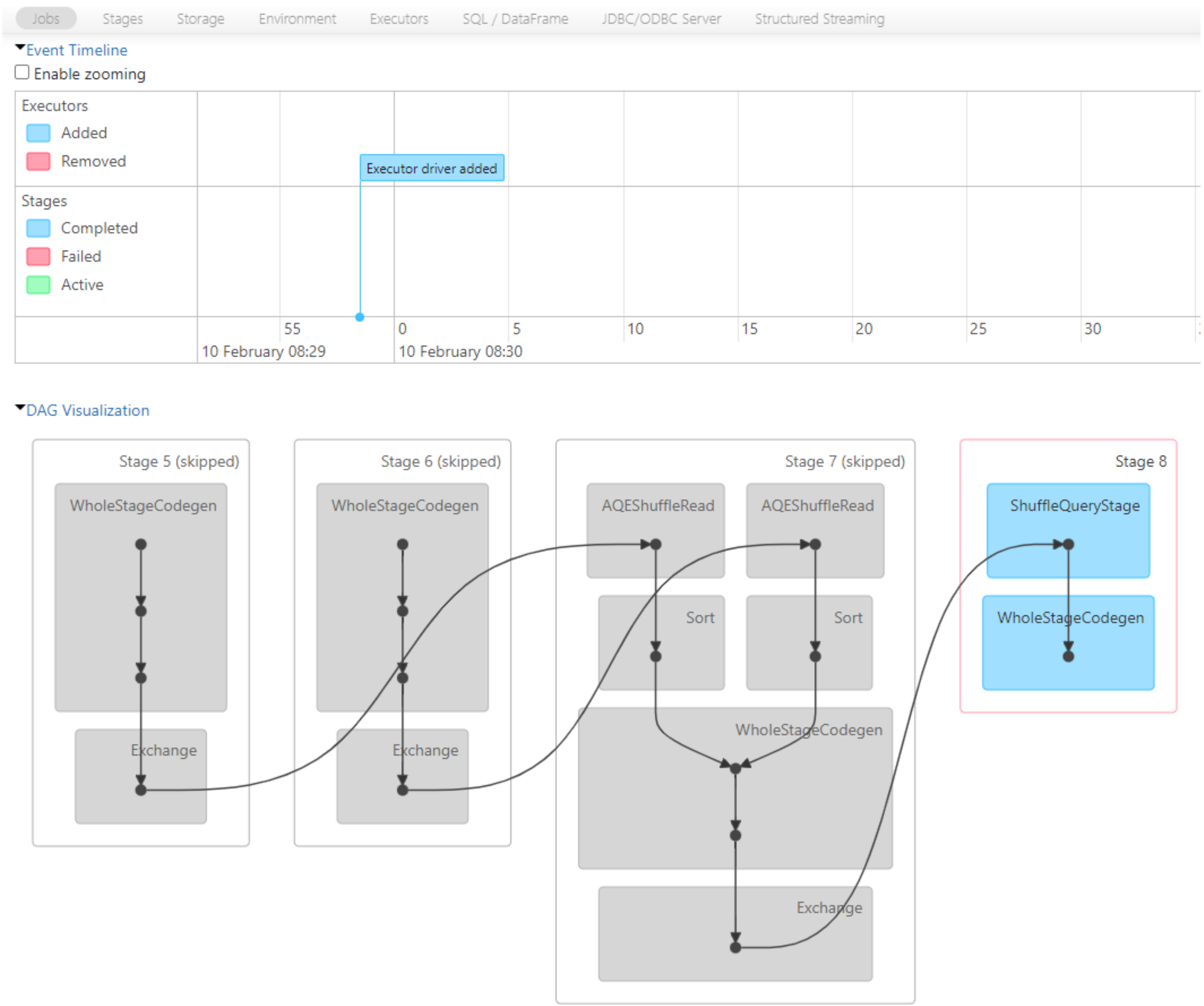
(1) Spark Jobs

```
+---+
| id|
+---+
|  2|
|  6|
| 10|
| 14|
| 18|
| 22|
| 26|
| 30|
| 34|
| 38|
+---+
```

```
df3.show(10)
```

(3) Spark Jobs

```
+---+
| id|
+---+
| 22|
| 26|
| 34|
| 50|
| 54|
| 94|
|110|
|126|
|130|
|190|
+---+
```



Jobs
Stages
Storage
Environment
Executors
SQL / DataFrame
JDBC/ODBC Server
Structured Streaming
Event Timeline
Enable zooming
Executors
Added
Removed
Executor driver added
Stages
Completed
Failed
Active
55
10 February 08:29
0
10 February 08:30
5
10
15
20
25
30
DAG Visualization
Stage 5 (skipped)
WholeStageCodegen
Exchange
Stage 6 (skipped)
WholeStageCodegen
Exchange
Stage 7 (skipped)
AQEShuffleRead
AQEShuffleRead
Sort
Sort
WholeStageCodegen
Exchange
Stage 8
ShuffleQueryStage
WholeStageCodegen

Jobs | Stages | Storage | Environment | Executors | SQL / DataFrame | JDBC/ODBC Server | Structured Streaming

Stages for All Jobs

Completed Stages: 4
Skipped Stages: 5

Fair Scheduler Pools (1)

Pool Name	Minimum Share	Pool Weight	Active Stages	Running Tasks	SchedulingMode
default	0	1	0	0	FIFO

Completed Stages (4)

Page: 1 — 1 Pages. Jump to 1 . Show 100 items in a page. G

Stage Id ▾	Pool Name	Description	Submitted	Duration	Tasks: Succeeded/Total	Input	Output	Shuffle Read	Shuffle Write
8	3168022962293687376	df1 = spark.range(2, 10000000, 2) df2 = spark.r... count at NativeMethodAccessorImpl.java:0 +details	2023/02/10 08:31:15	0.3 s	1/1			472.0 B	
4	3168022962293687376	df1 = spark.range(2, 10000000, 2) df2 = spark.r... $anonfun$withThreadLocalCaptured$1 at CompletableFuture.java:1604 +details	2023/02/10 08:31:05	9 s	8/8			36.5 MiB	472.0 B
1	3168022962293687376	df1 = spark.range(2, 10000000, 2) df2 = spark.r... $anonfun$withThreadLocalCaptured$1 at CompletableFuture.java:1604 +details	2023/02/10 08:30:53	3 s	8/8				12.2 MiB
0	3168022962293687376	df1 = spark.range(2, 10000000, 2) df2 = spark.r... $anonfun$withThreadLocalCaptured$1 at CompletableFuture.java:1604 +details	2023/02/10 08:30:52	8 s	8/8				24.3 MiB

Jobs | Stages | Storage | Environment | Executors | SQL / DataFrame | JDBC/ODBC Server | Structured Streaming

Executors

Show Additional Metrics

Summary

	RDD Blocks	Storage Memory	Disk Used	Cores	Active Tasks	Failed Tasks	Complete Tasks	Total Tasks	Task Time (GC Time)	Input	Shuffle Read	Shuffle Write	Excluded
Active(1)	0	0.0 B / 3.9 GiB	0.0 B	8	0	0	25	25	5.6 min (4 s)	0.0 B	36.5 MiB	36.5 MiB	0
Dead(0)	0	0.0 B / 0.0 B	0.0 B	0	0	0	0	0	0.0 ms (0.0 ms)	0.0 B	0.0 B	0.0 B	0
Total(1)	0	0.0 B / 3.9 GiB	0.0 B	8	0	0	25	25	5.6 min (4 s)	0.0 B	36.5 MiB	36.5 MiB	0

Executors

Show 20 entries — Search:

Executor ID	Address	Status	RDD Blocks	Storage Memory	Disk Used	Cores	Active Tasks	Failed Tasks	Complete Tasks	Total Tasks	Task Time (GC Time)	Input	Shuffle Read	Shuffle Write	Thread Dump	Heap Histogram	Exec Loss Reason
driver	10.172.213.39:43725	Active	0	0.0 B / 3.9 GiB	0.0 B	8	0	0	25	25	5.6 min (4 s)	0.0 B	36.5 MiB	36.5 MiB	Thread Dump	Heap Histogram	

Showing 1 to 1 of 1 entries — Previous | Next

Jobs | Stages | Storage | Environment | Executors | SQL / DataFrame | JDBC/ODBC Server | Structured Streaming

SQL / DataFrame

Completed Queries: 5

▾Completed Queries (5)

Page: 1   1 Pages. Jump to 1 . Show 100 item

ID ▾	Description	Submitted	Duration	Job IDs	Sub Execution IDs
4	show tables in `default` +details	2023/02/10 08:31:23	31 ms		
3	show tables in `default` +details	2023/02/10 08:31:22	0.1 s		
2	show databases +details	2023/02/10 08:31:21	52 ms		
1	df1 = spark.range(2, 10000000, 2) df2 = spark.r... +details	2023/02/10 08:30:48	27 s	[0][1][2][3]	
0	show databases +details	2023/02/10 08:30:39	41 s		

Jobs | Stages | Storage | Environment | Executors | SQL / DataFrame | JDBC/ODBC Server | Structured Streaming

Storage

Parquet IO Cache

Data Read from External Filesystem (All Formats)	Data Read from IO Cache (Cache Hits, Compressed)	Data Written to IO Cache (Compressed)	Cache Misses (Compressed)	True Cache Misses	Partial Cache Misses	Rescheduling Cache Misses	Cache Hit Ratio	Number of Local Scan Tasks	Number of Rescheduled Scan Tasks	Cache Metadata Manager Peak Disk Usage
0.0 B	0.0 B	0.0 B	0.0 B	0.0 B	0.0 B	0.0 B	0 %	0	0	0.0 B

Jobs | Stages | Storage | Environment | Executors | SQL / DataFrame | JDBC/ODBC Server | Structured Streaming

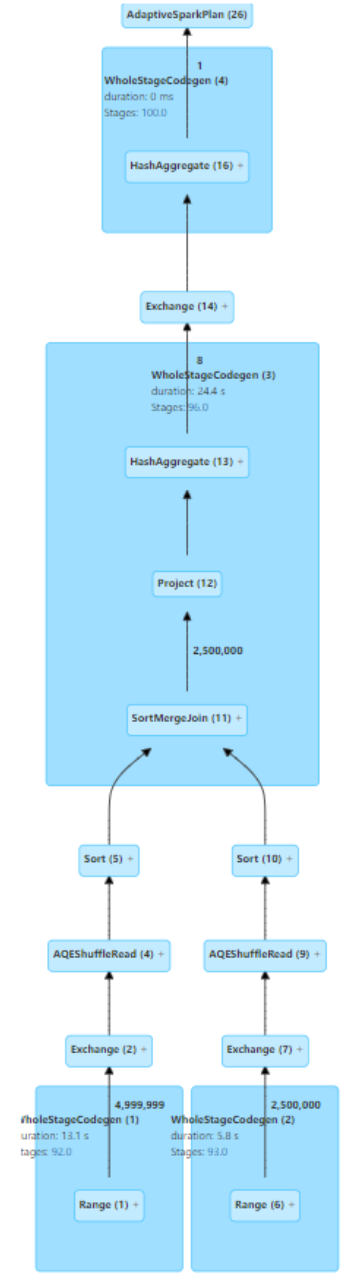
Environment

▾Runtime Information

Name	Value
Java Home	/usr/lib/jvm/zulu8-ca-amd64/jre
Java Version	1.8.0_345 (Azul Systems, Inc.)
Scala Version	version 2.12.14

▾Spark Properties

Name	Value
eventLog.rolloverIntervalSeconds	900
libraryDownload.sleepIntervalSeconds	5
libraryDownload.timeoutSeconds	180
spark.akka.frameSize	256
spark.app.id	local-1676017796375
spark.app.name	Databricks Shell
spark.app.startTime	1676017791391
spark.cleaner.referenceTracking.blocking	false
spark.databricks.acl.client	com.databricks.spark.sql.acl.client.SparkSqlAclClient
spark.databricks.acl.provider	com.databricks.sql.acl.ReflectionBackedAclProvider
spark.databricks.acl.scim.client	com.databricks.spark.sql.acl.client.DriverToWebappScimClient
spark.databricks.automl.serviceEnabled	true
spark.databricks.cloudProvider	AWS
spark.databricks.cloudfetch.hasRegionSupport	true
spark.databricks.cloudfetch.requesterClassName	*********(redacted)
spark.databricks.clusterSource	UI



Demo_2: Caching Data

```
from pyspark.sql.functions import col

df = spark.range(1 * 10000000).toDF("id").withColumn("square", col("id") * col("id"))
df.cache().count()
```

▸ (2) Spark Jobs

▸ df: pyspark.sql.dataframe.DataFrame = [id: long, square: long]

Out[12]: 10000000

Command took 8.90 seconds -- by aixin@comp.nus.edu.sg at 2/16/2023, 2:29:58 PM on Test

Jobs | Stages | Storage | Environment | Executors | SQL / DataFrame | JDBC/ODBC Server | Structured Streaming

Storage

Parquet IO Cache

Data Read from External Filesystem (All Formats)	Data Read from IO Cache (Cache Hits, Compressed)	Data Written to IO Cache (Compressed)	Cache Misses (Compressed)	True Cache Misses	Partial Cache Misses	Rescheduling Cache Misses	Cache Hit Ratio	Number of Local Scan Tasks	Number of Rescheduled Scan Tasks	Cache Metadata Manager Peak Disk Usage
321.5 MiB	0.0 B	0.0 B	0.0 B	0.0 B	0.0 B	0.0 B	0 %	0	0	0.0 B

▾RDDs

ID	RDD Name	Storage Level	Cached Partitions	Fraction Cached	Size in Memory	Size on Disk
42	In-memory table dfTable	Disk Memory Deserialized 1x Replicated	8	100%	86.2 MiB	0.0 B

```
df.count()
```

▸ (2) Spark Jobs

Out[13]: 10000000

Command took 0.61 seconds -- by aixin@comp.nus.edu.sg at 2/16/2023, 2:30:11 PM on Test

Acknowledgements

- CS4225 slides by He Bingsheng and Bryan Hooi
- Jules S. Damji, Brooke Wenig, Tathagata Das & Denny Lee, "Learning Spark: Lightning-Fast Data Analytics"
- Databricks, "The Data Engineer's Guide to Spark"
- https://www.pinterest.com/pin/739364463807740043/
- https://colab.research.google.com/github/jmbanda/BigDataProgramming_2019/blob/master/Chapter_5_Loading_and_Saving_Data_in_Spark.ipynb
- https://untitled-life.github.io/blog/2018/12/27/wide-vs-narrow-dependencies/