B0M33BDT
Big Data technologies
Spark - Basics

PROFINIT

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Agenda

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1. Spark Overview
2. How Spark works
3. Spark Dataframes
4. Spark Actions
5. Spark Architecture
6. How to start Spark and setup configuration

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The What, Why, and When of Apache Spark

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- **What:**
  - Unified engine for big data and machine learning
  - Distributed data processing engine -> up to petabytes of data up to thousands of physical or virtual machines
  - Open Source with over 1000 contributors from 250+ organizations
- **Why:**
  - High speed data querying, analysis, and transformation with large data sets.
  - Great for iterative algorithms (using a sequence of estimations based on the previous estimate).
  - Supports multiple languages (Java, Scala, R, Python)
  - Free of charge
- **When:**
  - When you're using functional programming (output of functions only depends on their arguments, not global states)
  - Performing ETL or SQL batch jobs with large data sets
  - Processing streaming
  - Machine Learning tasks

Spark – Facts

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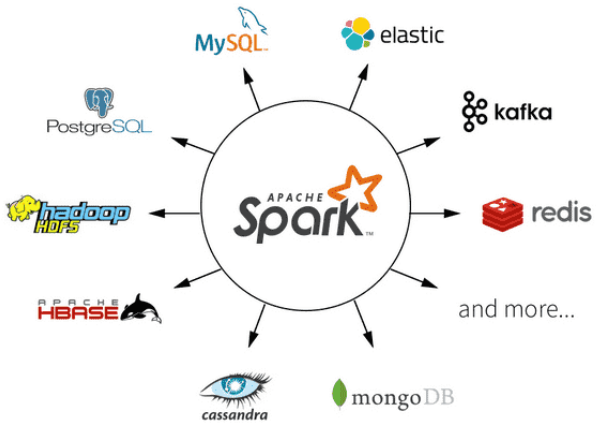
- In-memory Map-Reduce engine
- Written in Scala
- Fault-tolerant
- Connected with all major big data technologies
- Runs „Everywhere“

Google Cloud

aws

Microsoft Azure



Apache Spark evolution

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- **Spark 1.x – 2014 :**
  - Spark CORE - Fault-tolerant in memory computation engine
  - Spark RDD (Resilient Distributed Dataset) API
  - API for Streaming and Mlib
  - Spark SQL
- **Spark 2.x - 2016:**
  - Speedups the computation 5 to 20 times.
  - API for structured Streaming
  - API for graph data processing
  - SQL 2003 support
  - Datasets API over RDD
- **Spark 3.x - 2020:**
  - adaptive query execution, dynamic partition pruning and other optimizations
  - Significant improvements in pandas APIs, including Python type hints and additional pandas UDFs
  - Up to 40x speedup for calling R user-defined functions
  - SQL ANSI supports

When does Spark work best?

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- On distributed data systems or NoSQL Databases
- Collaboration – Data engineers, data scientist, BI analyst, ..
- Batch and streaming tasks

Common uses:

1. Calculation of client scores (risc score, fraud detection)
2. ETL or SQL batch jobs
3. Using streaming data to trigger a response
4. Machine Learning tasks
5. Graph algorithms

When not to use Spark ?

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- Small
- Low computing capacity (memory)
- Poorly parallelizable
- real-time

e.g.:

1. Modeling on small data
2. Ingesting data in a publish-subscribe model
3. Median calculation
4. JOIN of very big tables

How to learn spark

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- http://spark.apache.org
- Basics in Python | Scala | Java | R
- Help from friends, StackOverflow etc.
- OR **Just try it**

How to work with

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- Interactively
  - Command line (shell for both Python and Scala)
  - Zeppelin/Jupyter notebook
  - Pycharm, IntelliJ, …
- Batch / application
  - compiled .jar file
  - *.py file

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How Spark works

Logical point of view

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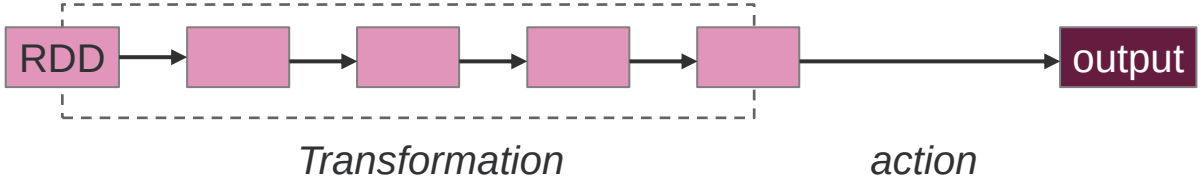

- **RDD:**
  - resilient distributed dataset - the abstractions of Spark. It is used to handle distributed collection of data elements (e.g.: rows in text file, data matrix, set of binary data) across all the nodes in a cluster.
  - is immutable
- **Transformation:**
  - are planned and optimized, but not evaluated
  - planned as DAG – Direct acyclic graph
- **Action:**
  - action is a trigger that started the whole process

Technical point of view

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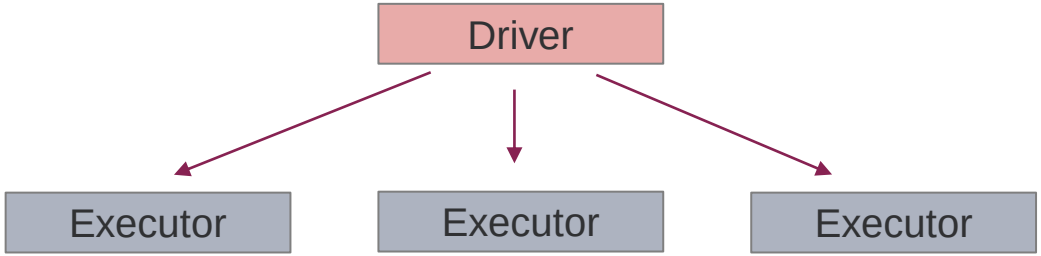

- **Driver:**
  - Control all processes
  - Convert user code to transformations and actions -> tasks
  - Distribute tasks across executors
- **Executor:**
  - „worker“ – run tasks and return result to a driver
- **Both run as JVM**

Example – word count:

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- Task: count number of word in document
- Source: text file splitted to lines
- Approach:
  - Load file from disk
  - Transformation of lines: line ⇨ split to words ⇨ split to items (word, 1)
  - Group items with the same word and sum up ones
- Result of transformation: RDD with items (word, frequency)

Example:

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```
lines = sc.textFile("bible.txt")

words = lines.flatMap(lambda line: line.split(" "))

items = words.map(lambda word: (word, 1))

counts = items.reduceByKey(lambda a, b: a + b)



counts.take(5)
```

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Spark Dataframes

Spark SQL and DataFrames (DataSets)

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- New from spark 2.x ⇨ Enhances the classical RDD approach
- Data structure **DataFrame** = „RDD with columns“
  - similar to database relation table
  - with metadata (field names, types)
  - works with columns –> SQL syntax can be used

RDD

1;Andrea;35;64.3;Praha
2;Martin;43;87.1;Ostrava
3;Simona;18;57.8;Brno

DataFrame

id	name	age	weight	city
1	Andrea	35	64.3	Praha
2	Martin	42	87.1	Ostrava
3	Simona	18	57.8	Brno

WHY use DataFrames

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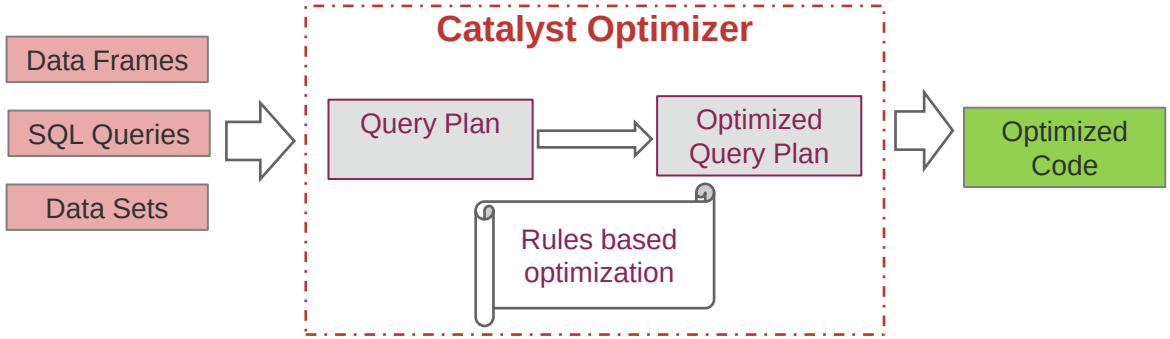
- Advantage over Spark RDD:
  - Dataframe API - shorter and easier code
  - Columns and Types
  - SQL languague can be used
  - Simplified work with databases
  - **Catalyst Optimizer can be applied**



⇨ Is faster

How to get a DataFrame?

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- transformation from existing RDD
  - if convertable
  - `sqlContext.createDataFrame(RDD, schema)`
- direct input of file
  - schema may be defined (Parquet, ORC) or inferred (CSV)
  - `sqlContext.read.format(format).load(path)`
- Hive query
  - `sqlContext.sql(sql_query)`

How to work with a DataFrame?

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1. registration of temporary table + SQL querying
   - `DF.registerTempTable("table")`
   - `sqlContext.sql("select * from table")`
2. SPARK API
   - `DF.operations`; select, filter, join, groupBy, sort...
3. Convert to RDD -> RDD operation (map, flatMap, shuffle, …) and then convert back -> Dataframe

SPARK API Cheat sheet

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Spark Session APIs
SparkSession.builder.appName(name)
SparkSession.builder.config([key, value, conf])
SparkSession.builder.enableHiveSupport()
SparkSession.builder.getOrCreate()
SparkSession.builder.master(master)
SparkSession.catalog
SparkSession.conf
SparkSession.createDataFrame(data[, schema, ...])
SparkSession.getActiveSession()
SparkSession.newSession()
SparkSession.range(start[, end, step, ...])
SparkSession.read
SparkSession.readStream
SparkSession.sparkContext
SparkSession.sql(sqlQuery)
SparkSession.stop()
SparkSession.streams
SparkSession.table(tableName)
SparkSession.udf
SparkSession.version

DataFrame APIs
DataFrame.agg(*exprs)
DataFrame.alias(alias)
DataFrame.approxQuantile(col, probabilities, ...)
DataFrame.cache()
DataFrame.checkpoint([eager])
DataFrame.coalesce(numPartitions)
DataFrame.colRegex(colName)
DataFrame.collect()
DataFrame.columns
DataFrame.corr(col1, col2[, method])
DataFrame.count()
DataFrame.cov(col1, col2)
DataFrame.createGlobalTempView(name)
DataFrame.createOrReplaceGlobalTempView(nam
DataFrame.createOrReplaceTempView(name)
DataFrame.createTempView(name)
DataFrame.crossJoin(other)
DataFrame.cube(*cols)
DataFrame.describe(*cols)
DataFrame.distinct()
DataFrame.drop(*cols)
DataFrame.dropDuplicates([subset])
DataFrame.drop_duplicates([subset])
...

Input and Output
DataFrameReader.csv(path[, schema, sep, ...])
DataFrameReader.format(source)
DataFrameReader.jdbc(url, table[, column, ...])
DataFrameReader.json(path[, schema, ...])
DataFrameReader.load([path, format, schema]
DataFrameReader.option(key, value)
DataFrameReader.options(**options)
DataFrameReader.orc(path[, mergeSchema, ...
DataFrameReader.parquet(*paths, **options)
DataFrameReader.schema(schema)
DataFrameReader.table(tableName)
DataFrameWriter.bucketBy(numBuckets, col)
DataFrameWriter.csv(path[, mode, ...])
DataFrameWriter.format(source)
DataFrameWriter.insertInto(tableName[, ...])
DataFrameWriter.jdbc(url, table[, mode, ...])
DataFrameWriter.json(path[, mode, ...])

Column APIs
Column.alias(*alias, **kwargs)
Column.asc()
Column.asc_nulls_first()
Column.asc_nulls_last()
Column.astype(dataType)
Column.between(lowerBound, upperBound)
Column.bitwiseAND(other)
Column.bitwiseOR(other)
Column.bitwiseXOR(other)
Column.cast(dataType)
Column.contains(other)
Column.desc()
Column.desc_nulls_first()
Column.desc_nulls_last()
Column.dropFields(*fieldNames)
Column.endswith(other)
Column.eqNullSafe(other)
Column.getField(name)
Column.getItem(key)
Column.isNotNull()
Column.isNull()

Functions
abs(col)
acos(col)
acosh(col)
add_months(start, months)
aggregate(col, initialValue, merge[, finish])
approxCountDistinct(col[, rsd])
approx_count_distinct(col[, rsd])
array(*cols)
array_contains(col, value)
array_distinct(col)
array_except(col1, col2)
array_intersect(col1, col2)
array_join(col, delimiter[, null_replacement])
array_max(col)
array_min(col)
array_position(col, value)
array_remove(col, element)
array_repeat(col, count)
array_sort(col)
array_union(col1, col2)
arrays_overlap(a1, a2)
arrays_zip(*cols)
asc(col)
asc_nulls_first(col)
asc_nulls_last(col)
ascii(col)
asin(col)
asinh(col)
assert_true(col[, errMsg])
atan(col)
atanh(col)
atan2(col1, col2)
avg(col)
base64(col)
bin(col)
bitwiseNOT(col)
broadcast(df)
bround(col[, scale])
bucket(numBuckets, col)
cbrt(col)
.....

Window
Window.currentRow
Window.orderBy(*cols)
Window.partitionBy(*cols)
Window.rangeBetween(start, end)
Window.rowsBetween(start, end)
Window.unboundedFollowing
Window.unboundedPreceding
WindowSpec.orderBy(*cols)
WindowSpec.partitionBy(*cols)
WindowSpec.rangeBetween(start, end)
WindowSpec.rowsBetween(start, end)

Grouping
GroupedData.agg(*exprs)
GroupedData.apply(udf)
GroupedData.applyInPandas()
GroupedData.avg(*cols)
GroupedData.cogroup(other)
GroupedData.count()
GroupedData.max(*cols)
GroupedData.mean(*cols)
GroupedData.min(*cols)
GroupedData.pivot(pivot_col[, values])
GroupedData.sum(*cols)

Example

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› Which USA state has the highest average temperature in summer?

Data sample:

```
station,month,day,hour,temperature,flag,latit,longit,elevation,state,name
AQW00061705,1,1,1,804,P,-14.3306,-170.7136,3.7,AS,PAGO PAGO WSO AP
AQW00061705,1,2,1,804,P,-14.3306,-170.7136,3.7,AS,PAGO PAGO WSO AP
AQW00061705,1,3,1,803,P,-14.3306,-170.7136,3.7,AS,PAGO PAGO WSO AP
AQW00061705,1,4,1,802,P,-14.3306,-170.7136,3.7,AS,PAGO PAGO WSO AP
AQW00061705,1,5,1,802,P,-14.3306,-170.7136,3.7,AS,PAGO PAGO WSO AP
```

Solution by RDD only

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```
tp_raw = sc.textFile('7-12.csv')

tp_raw = tp_raw.filter(lambda r: (r.split(',')[1] in
set('678')) & (r.split(',')[4] !=''))

tp = tp_raw.map(adjust_row)

tp_st = tp.reduceByKey(sum).map(lambda x:
(x[0],x[1][0]/x[1][1])).sortBy(lambda y: y[1], False)

tp_st.take(1)
```

```
def adjust_row(rlist):
    stat = rlist[9]
    tepl = (int(rlist[4])/10.0 -
    32)*5/9
    return (stat, (tepl, 1))
```

```
def sums(a, b):
    sumA = a[0]
    sumB = b[0]
    cntA = a[1]
    cntB = b[1]
    return (sumA + sumB, cntA +
    cntB)
```

Solution by DataFrame

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```
import pyspark.sql.functions as F

df_temp = spark.read.format("com.databricks.spark.csv").load('teplota7-12.csv')

df_filtered = df_temp.filter((df_temp['mesic'] >= 6) &
                             (df_temp['mesic'] <= 8)).select('stat', 'teplota').dropna()


df_celsius = df_filtered.withColumn('teplota', (df_filtered['teplota'] / 10.0 - 32) * 5 / 9)


df_avg = df_celsius.groupBy('stat').avg('teplota').toDF('stat', 'temp_avg')


df_desc = df_avg.orderBy(F.col('temp_avg').desc())

df_desc.show(1)
```

Solution by DataFrame

PROFINIT

```
df_temp.registerTempTable("t")

df_sql= sqlContext.sql("
select stat, avg((teplota/ 10.0 - 32) * 5 / 9) as temp_avg
from t
where mesic>5 and mesic<9 and teplota is not null
group by stat order by temp_avg desc")

df_sql.limit(1).show()
```

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Spark actions

Spark Actions

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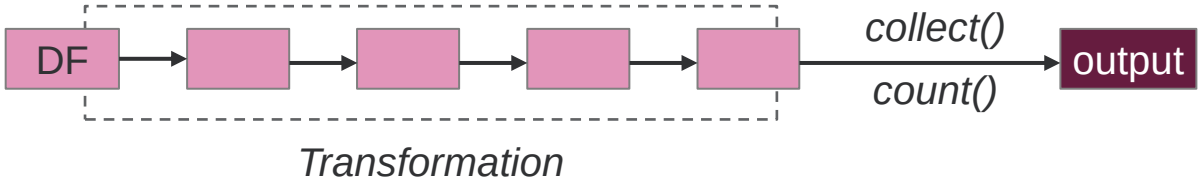
RDD	Dataframe	Description
take	take,show	Show first n rows
count	count	Count of rows
collect	collect	Show rdd/dataframe as list of rows
saveAsTextFile	saveAsTable, write	Save file/create table
…	…	



› Every action starts all steps of transformation from the beginning!

Spark caching

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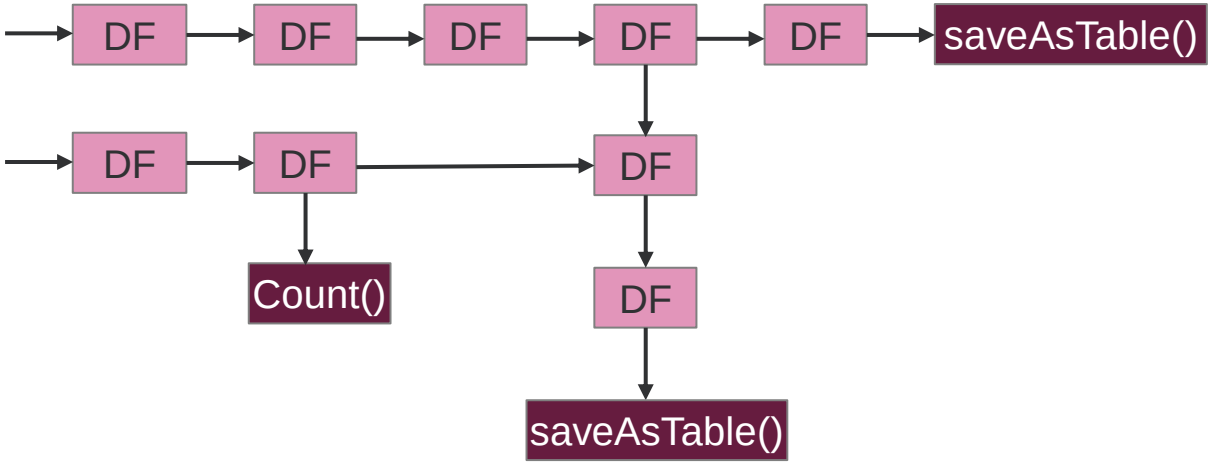

HOW to CACHE

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- **Methods:**
  - `persist()` (several options)
  - `cache()` (use persist with MEMORY_ONLY option)
  - `unpersist()` (release persisted data)

- **Persist options:**
  - MEMORY_ONLY – Default –> deserialized JVM memory
  - MEMORY_AND_DISK –> excessed partitions into disk.
  - MEMORY_ONLY_SER -> serialized JVM memory
  - MEMORY_AND_DISK_SER -> etc.

- Persist is not an action!

Example

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- Which USA state has the lowest average temperature in summer?

```
df_asc=df_avg.orderBy(F.col('temp_avg').asc())
df_asc.show(5)
```

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Spark Architecture

Important Terminologies of Apache Spark

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- SparkContext
  - It is the main entry point to spark core. Act as master of spark application
  - Getting the current status of spark application
  - Canceling the job and the stage
  - Running job synchronously or asynchronously
- Spark Application
  - It is a self-contained computation that runs user-supplied code to compute a result.
- Job
  - It parallels computation consisting of multiple tasks.
- Stage
  - Each job is divided into small sets of tasks which are known as **stage.**
- Task
  - It is a unit of work, which we sent to the executor. It is a single operation (map, filter, …) applied to a single partition.

Components of Spark Architecture

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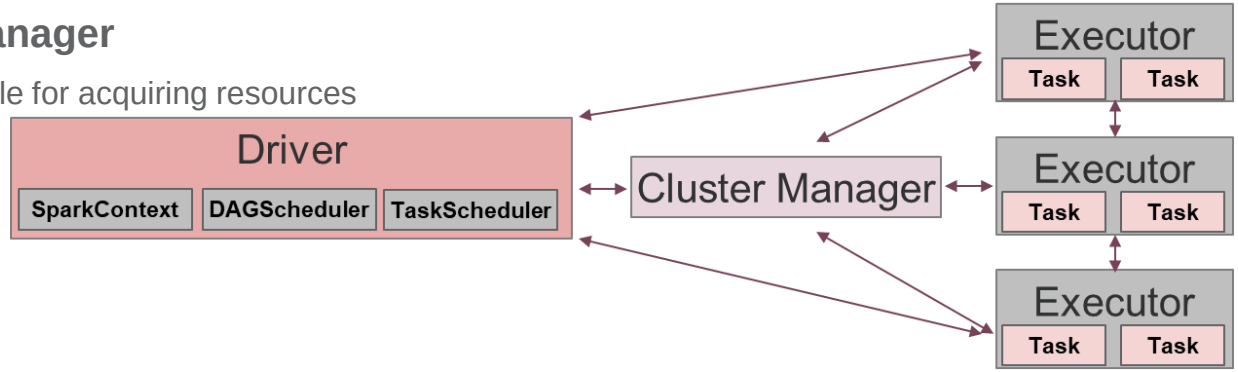
- **Driver**
  - It is a **master node**.
  - Translates user code into a specified job.
  - Schedules the job execution and negotiates with the cluster manager.
  - Stores the metadata about all RDDs as well as their partitions.
  - The key component is a SparkContext, others are DAG Scheduler, task scheduler, backend scheduler and block manager.
- **Executors**
  - They are distributed agents those are responsible for the execution of tasks
  - They perform all the data processing
- **Cluster Manager**
  - Responsible for acquiring resources



Spark Memory

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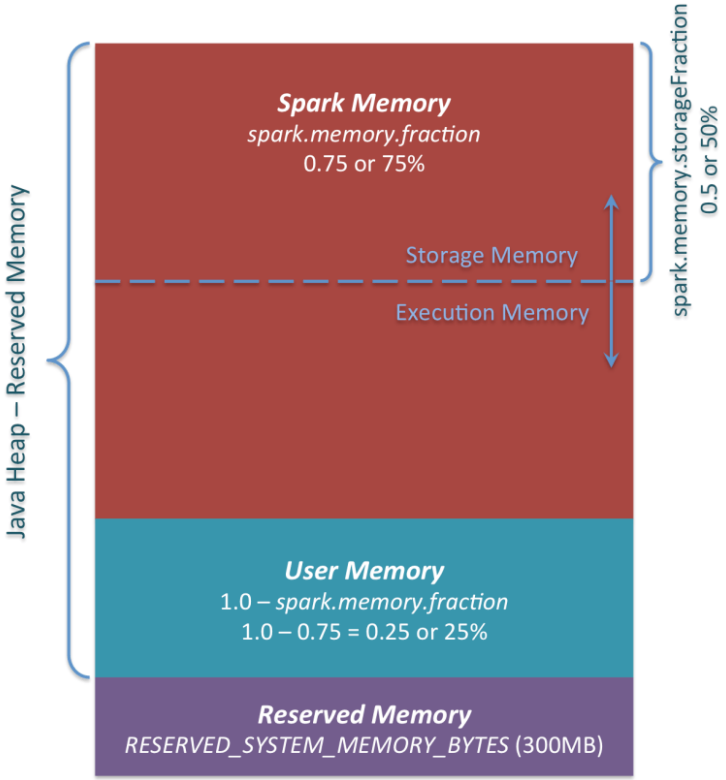

How are date data splitted – partitioning

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- **partition**
  - part of data managed in one task
  - default partition = 1 HDFS block = 1 task = 1 core
  - partition is ideally managed on the node where is stored
  - More partitions ⇨ more tasks ⇨ higher paralelization
    ⇨ smaller ⇨ lower efficiency ⇨ higher overhead
- **How to change it?**
  - in load: `sc.textFile(file, count_of_partitions)`
  - In the program:
    - `coalesce (count_of_partitions)`
    - `repartition(count_of_partitions)`
    - `partitionBy (count_of_partitions)`
- **Default for Joins:**
  - The default number of partitions to use when shuffling data for joins or aggregations.
  - `spark.sql.shuffle.partitions = 200`

Data locality & shuffling

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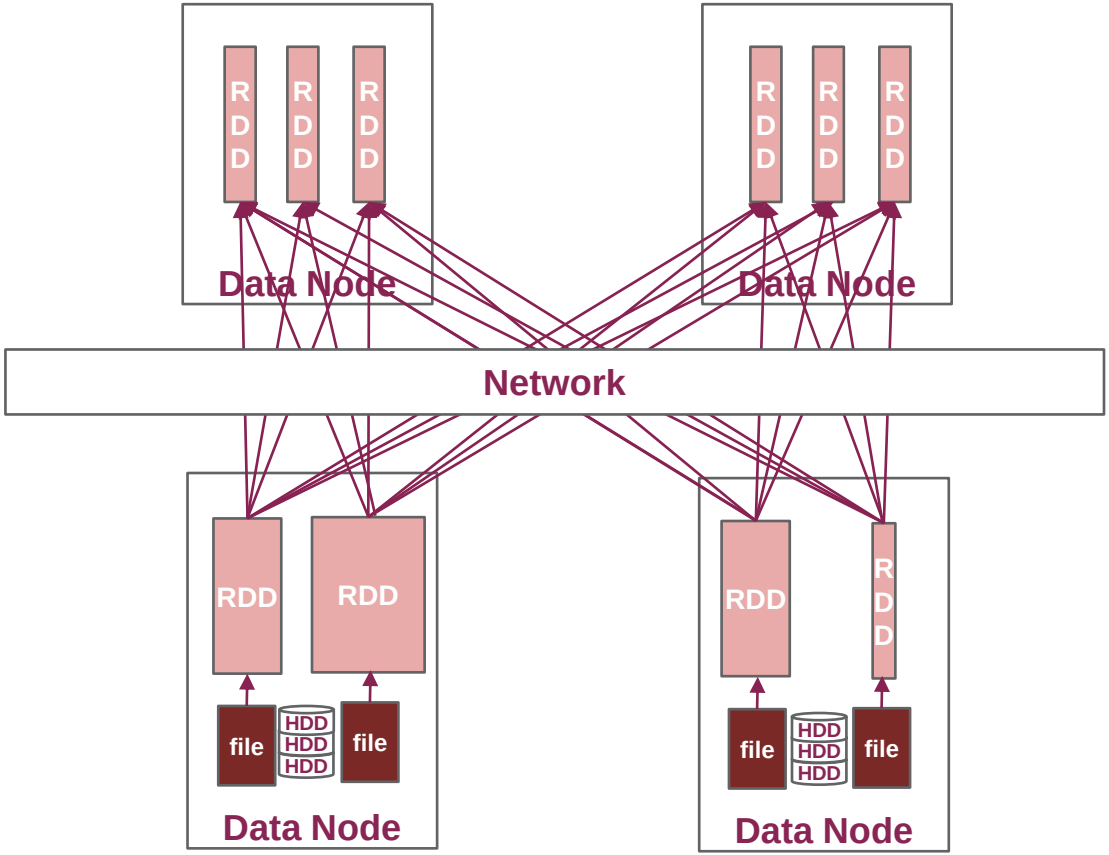

Example:

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› Count of rows for every USA state that is in source file?

```
df_temp.registerTempTable("t")
df_sql= sqlContext.sql("select * from t")


df_sql.groupBy('stat').count().show(100)
df_sql.repartition(2000).groupBy('stat').count().show(100)
```

6

Start and configuration

How to start Spark

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```
pyspark | spark-shell | spark-submit --param value
```

Useful parameters:

--name -> name of the application

--class -> The entry point for your application

--master -> The master URL for the cluster (local, Yarn, Mesos, ..)

--deploy_mode -> where the driver will be deployed (client/cluster)

--driver-memory -> memory for driver

--num-executors -> count of executors

--executor-cores -> count of cores for executor

--executor-memory -> memory for *executor*

How to start Spark

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Example:

```
./bin/spark-submit \
--master yarn
--deploy-mode client \
--name my_spark_application \
--driver-memory 1G \
--num-executors 3 \
--executor-cores 2 \
--executor-memory 3G
```

Example how to allocate resources

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General recomendation:

- --num-cores <= 5
- --executor-memory <= 64 GB

Cluster 6 nods, every 16 cores a 64 GB RAM

- Reserve 1 core a 1GB /node for OS
  rest is 6 *15 cores a 63 GB
- 1 core for spark Driver: 6 * 15 – 1 = 89 cores.
- 89 / 5 ~ 17 executors. Every node (except the one with driver) will have 3 executors.
- 63 GB / 3 ~ 21 GB memory per executor. Moreover count with memory overhead -> set up 19 GB per executor

Thank you

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