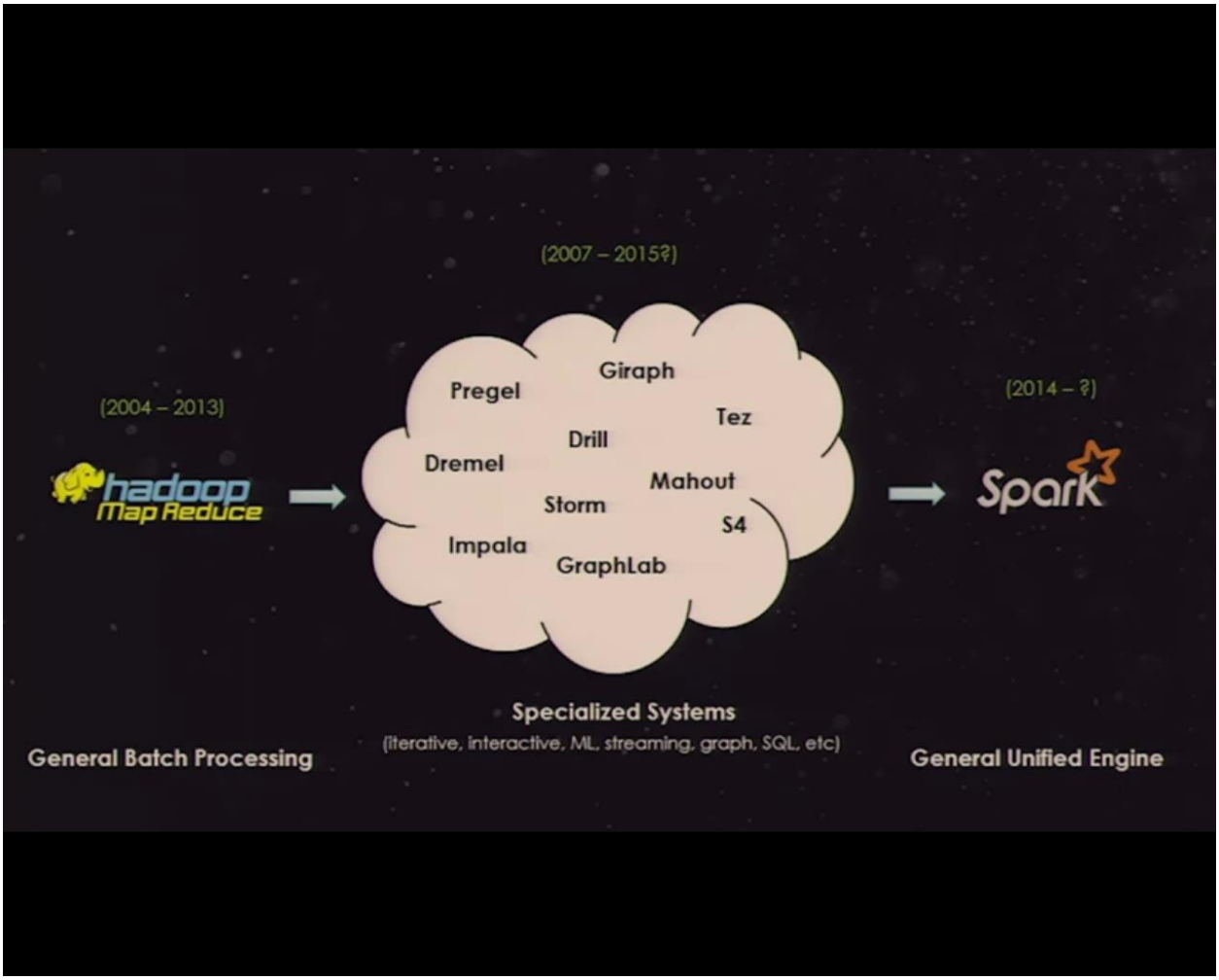
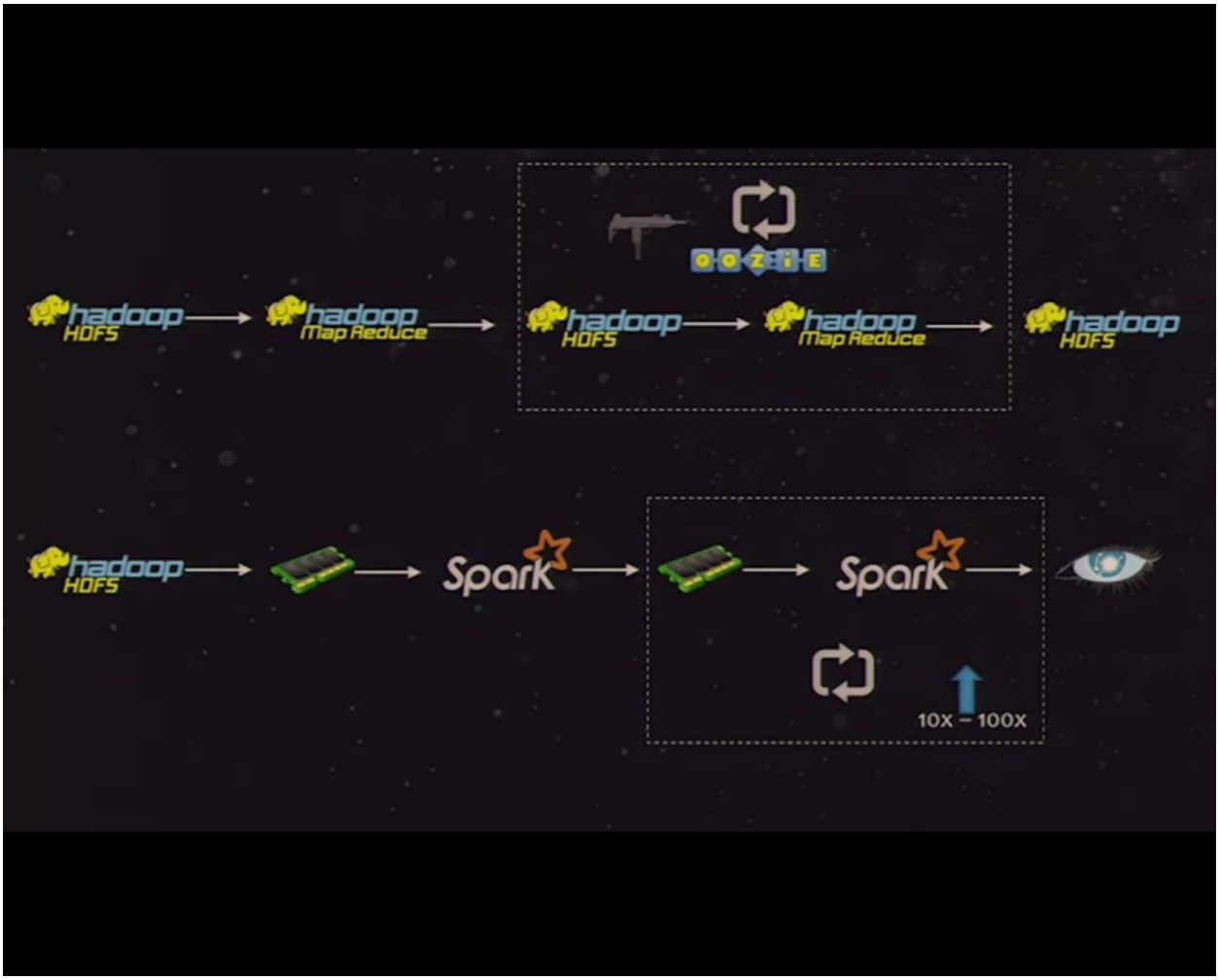
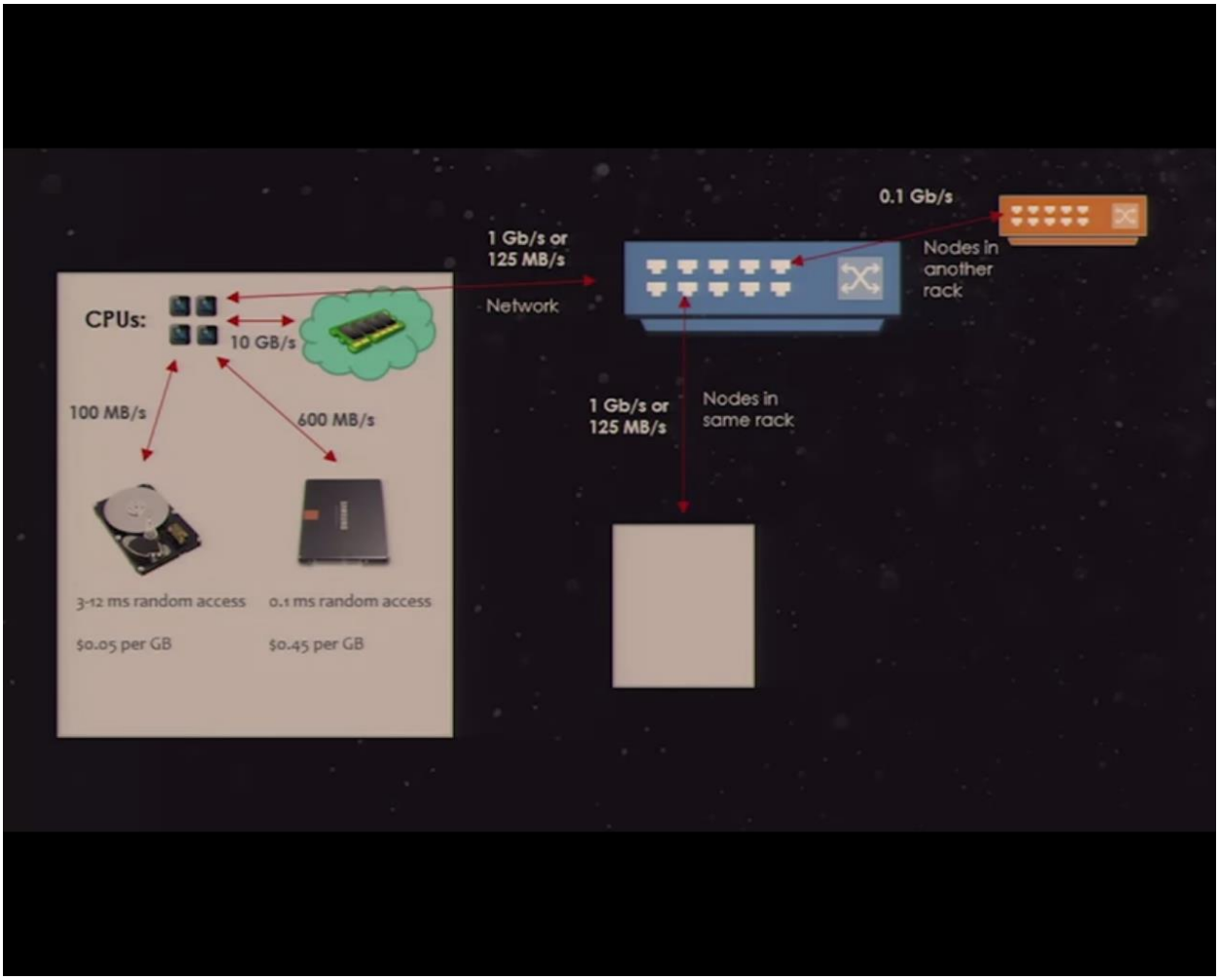
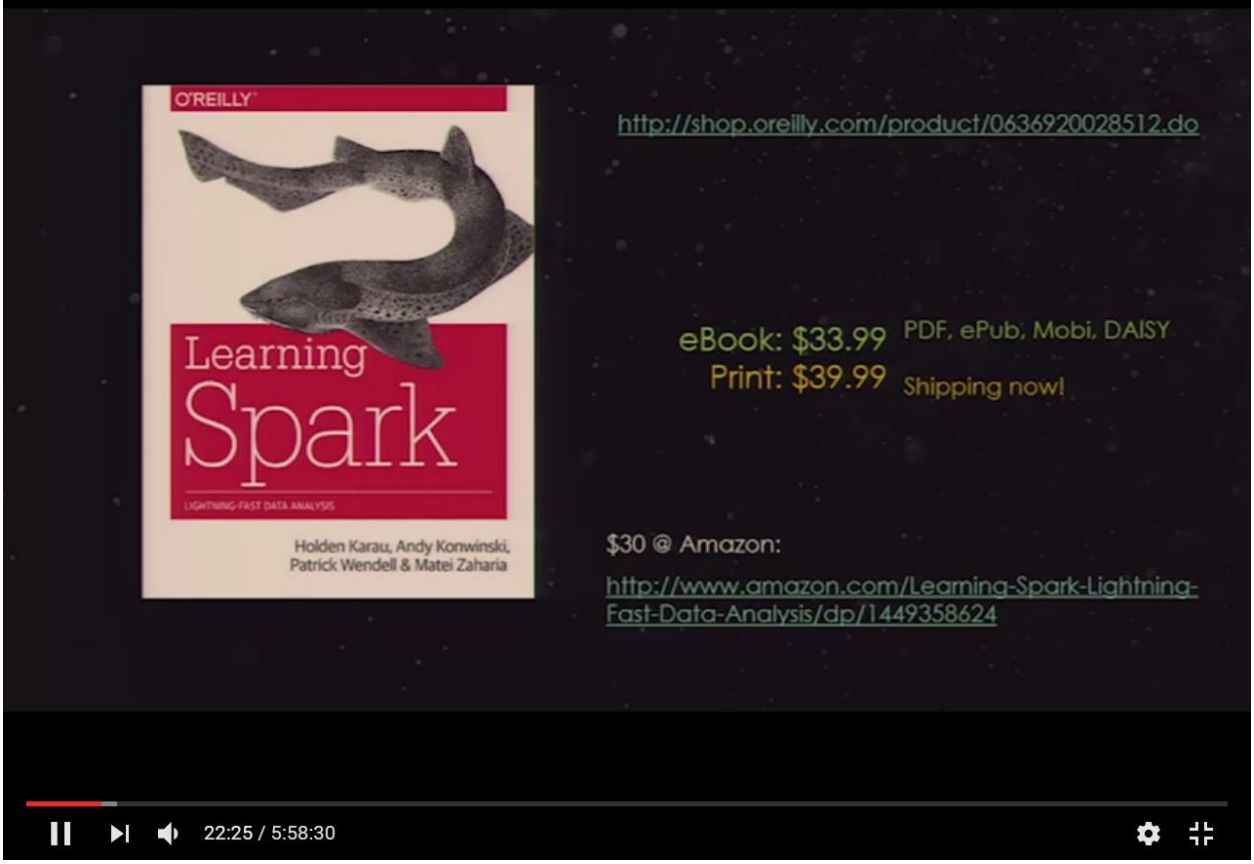
https://www.youtube.com/watch?v=7ooZ4S7Ay6Y


(2004 – 2013)
hadoop
Map Reduce
General Batch Processing
(2007 – 2015?)
Pregel
Giraph
Dremel
Drill
Tez
Mahout
Storm
S4
Impala
GraphLab
Specialized Systems
(iterative, interactive, ML, streaming, graph, SQL, etc)
(2014 – ?)
Spark
General Unified Engine

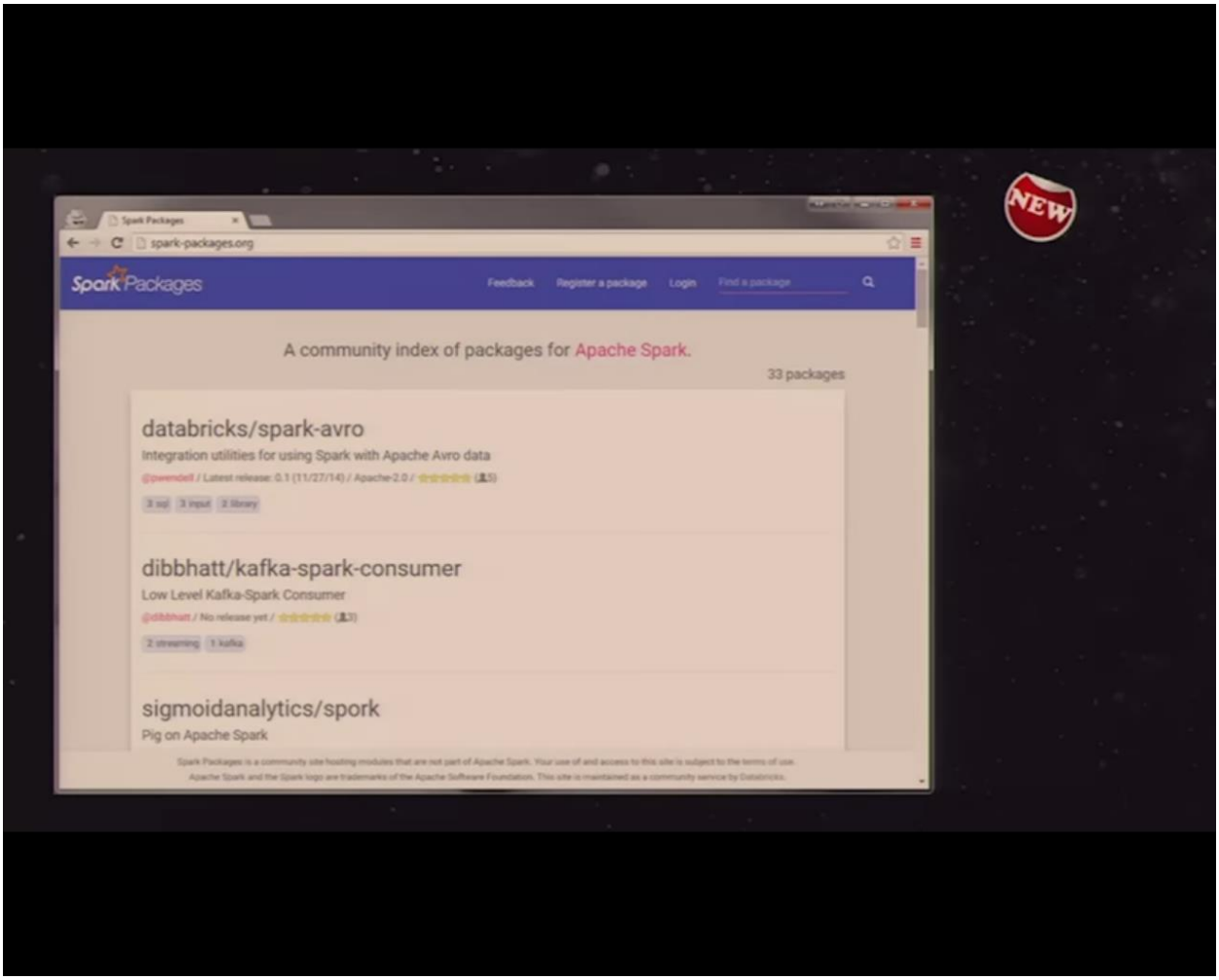

OOZIE
hadoop HDFS
hadoop Map Reduce
hadoop HDFS
hadoop Map Reduce
hadoop HDFS
hadoop HDFS
Spark
Spark
10x – 100x


0.1 Gb/s
1 Gb/s or
125 MB/s
Nodes in
another
rack
Network
CPUs:
10 GB/s
100 MB/s
600 MB/s
1 Gb/s or
125 MB/s
Nodes in
same rack
3-12 ms random access
$0.05 per GB
0.1 ms random access
$0.45 per GB

Advanced Apache Spark Training - Sameer Farooqui (Databricks)



22:25 / 5:58:30


NEW
Spark Packages
spark-packages.org
Spark Packages
Feedback
Register a package
Login
Find a package
A community index of packages for Apache Spark.
33 packages
databricks/spark-avro
Integration utilities for using Spark with Apache Avro data
3 sql
3 input
2 library
dibbhatt/kafka-spark-consumer
Low Level Kafka-Spark Consumer
2 streaming
1 kafka
sigmoidanalytics/spork
Pig on Apache Spark


more partitions = more parallelism
RDD
item-1
item-2
item-3
item-4
item-5
item-6
item-7
item-8
item-9
item-10
item-11
item-12
item-13
item-14
item-15
item-16
item-17
item-18
item-19
item-20
item-21
item-22
item-23
item-24
item-25
Ex
Ex
Ex


RDD w/ 4 partitions
Error, ts, msg1
Warn, ts, msg2
Error, ts, msg1
Info, ts, msg8
Warn, ts, msg2
Info, ts, msg8
Error, ts, msg3
Info, ts, msg5
Info, ts, msg5
Error, ts, msg4
Warn, ts, msg9
Error, ts, msg1
logLinesRDD
An RDD can be created 2 ways:
- Parallelize a collection
- Read data from an external source (S3, C*, HDFS, etc)

PARALLELIZE

```
# Parallelize in Python
wordsRDD = sc.parallelize([“fish“, “cats“, “dogs”])
```

```
// Parallelize in Scala
val wordsRDD= sc.parallelize(List("fish", "cats", "dogs"))
```

```
// Parallelize in Java
JavaRDD<String> wordsRDD = sc.parallelize(Arrays.asList(“fish“, “cats“, “dogs”));
```

- Take an existing in-memory collection and pass it to SparkContext's parallelize method
- Not generally used outside of prototyping and testing since it requires entire dataset in memory on one machine

READ FROM TEXT FILE

```python
# Read a local txt file in Python
linesRDD = sc.textFile("/path/to/README.md")
```

```scala
// Read a local txt file in Scala
val linesRDD = sc.textFile("/path/to/README.md")
```

```java
// Read a local txt file in Java
JavaRDD<String> lines = sc.textFile("/path/to/README.md");
```

- There are other methods to read data from HDFS, C*, S3, HBase, etc.


hadoop
HDFS
Error, ts, msg1
Warn, ts, msg2
Error, ts, msg1
Info, ts, msg8
Warn, ts, msg2
Info, ts, msg8
Error, ts, msg3
Info, ts, msg5
Info, ts, msg5
Error, ts, msg4
Warn, ts, msg9
Error, ts, msg1
logLinesRDD
(input/base RDD)
.filter(f(x))
Error, ts, msg1
Error, ts, msg1
Error, ts, msg3
Error, ts, msg4
Error, ts, msg1
errorsRDD

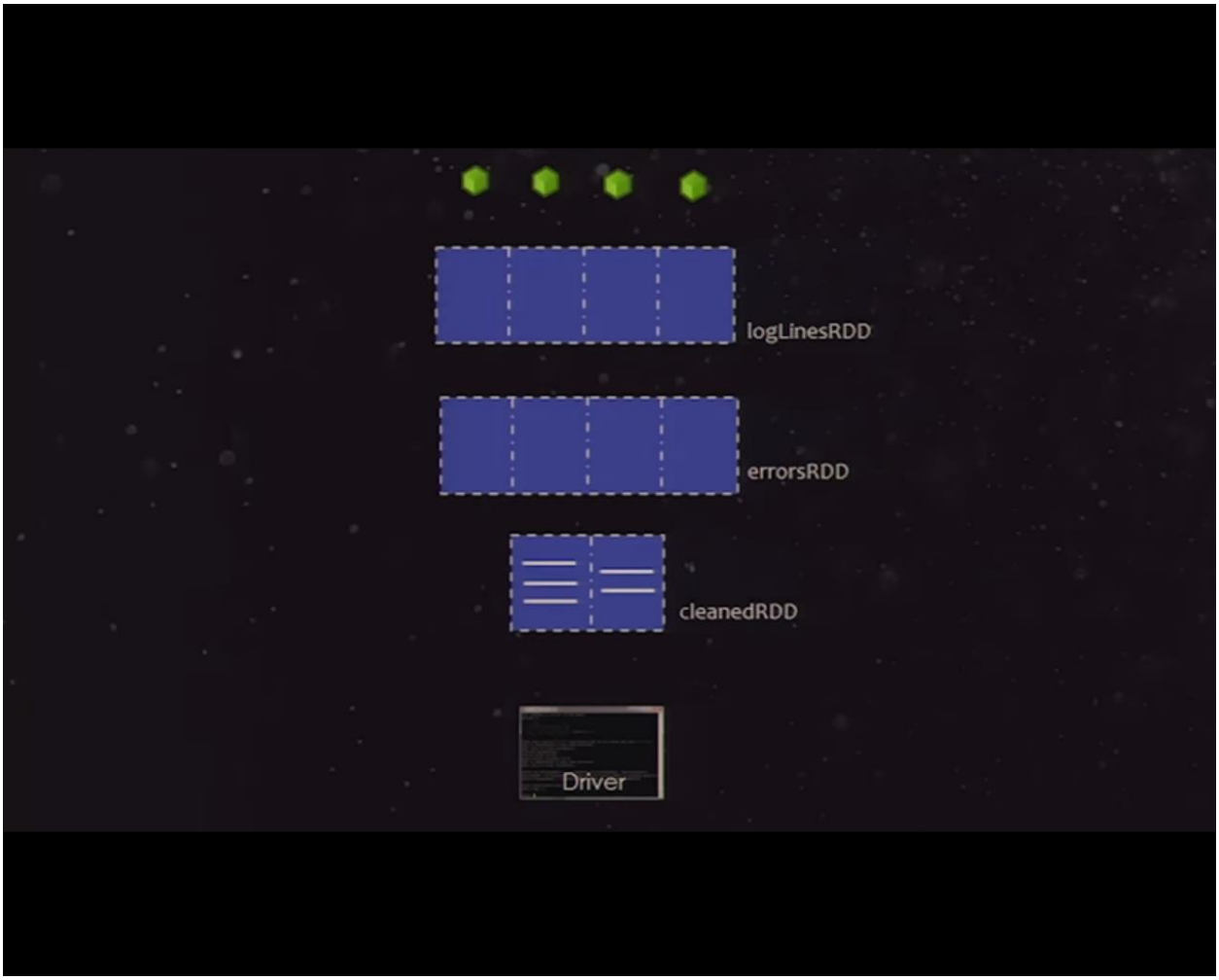

Error, ts, msg1
Error, ts, msg1
Error, ts, msg3
Error, ts, msg4
Error, ts, msg1
errorsRDD
.coalesce(2)
Error, ts, msg1
Error, ts, msg3
Error, ts, msg1
Error, ts, msg4
Error, ts, msg1
cleanedRDD
.collect( )
Driver


Execute DAG!
.collect( )
Driver

Don’t uses collect for terabyte of data RDD, instead save it on hdfs or sample the larger RDD in smaller one

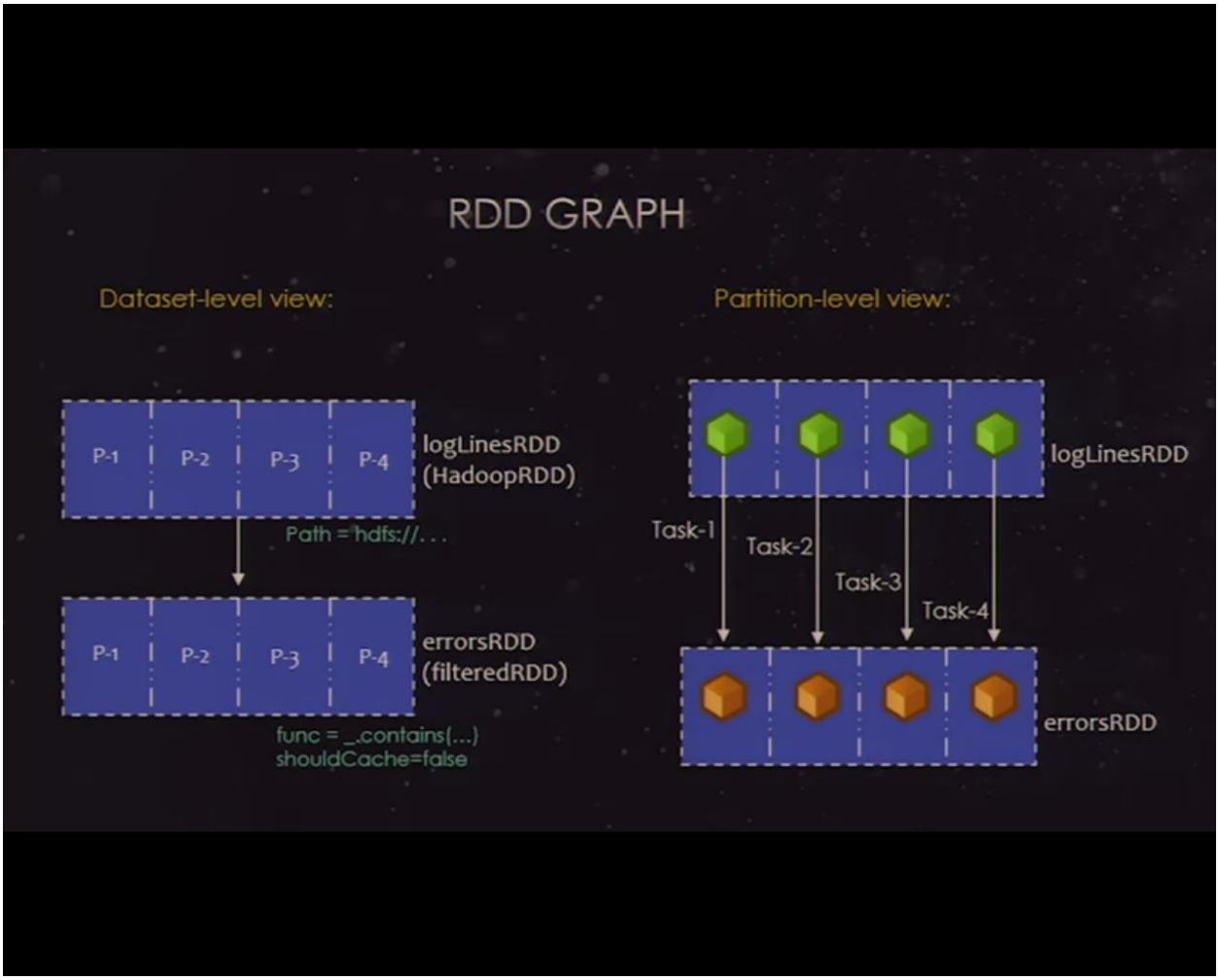
Once we completed execution of DAG we get rid of the RDD , solid line becomes dashed line (just for demonstration purpose)

After action all RDD disappear as we didn’t cache the RDD


logLinesRDD
errorsRDD
cleanedRDD
Driver

You need to know which RDD should be cached, the RDD which are going to be uses multiple times needs to be cached and of course the size of RDD is within the limit, in below example cleaned RDD is a good candidate of cache as we are using it 3 times

If whole RDD is not able to cached in memory the rest will go to underlined datasource, let say we have partition of 100 and only 30 partition RDD can store in memory during cache so rest 70 will go to underlined data source like hdfs


RDD GRAPH
Dataset-level view:
P-1
P-2
P-3
P-4
logLinesRDD
(HadoopRDD)
Path = hdfs://...
P-1
P-2
P-3
P-4
errorsRDD
(filteredRDD)
func = _.contains(...)
shouldCache=false
Partition-level view:
logLinesRDD
Task-1
Task-2
Task-3
Task-4
errorsRDD

LIFECYCLE OF A SPARK PROGRAM

1) Create some input RDDs from external data or parallelize a collection in your driver program.

2) Lazily transform them to define new RDDs using transformations like `filter()` or `map()`

3) Ask Spark to `cache()` any intermediate RDDs that will need to be reused.

4) Launch actions such as `count()` and `collect()` to kick off a parallel computation, which is then optimized and executed by Spark.

TRANSFORMATIONS (lazy)

`map()`	`intersection()`	`cartesion()`
`flatMap()`	`distinct()`	`pipe()`
`filter()`	`groupByKey()`	`coalesce()`
`mapPartitions()`	`reduceByKey()`	`repartition()`
`mapPartitionsWithIndex()`	`sortByKey()`	`partitionBy()`
`sample()`	`join()`	`...`
`union()`	`cogroup()`	`...`

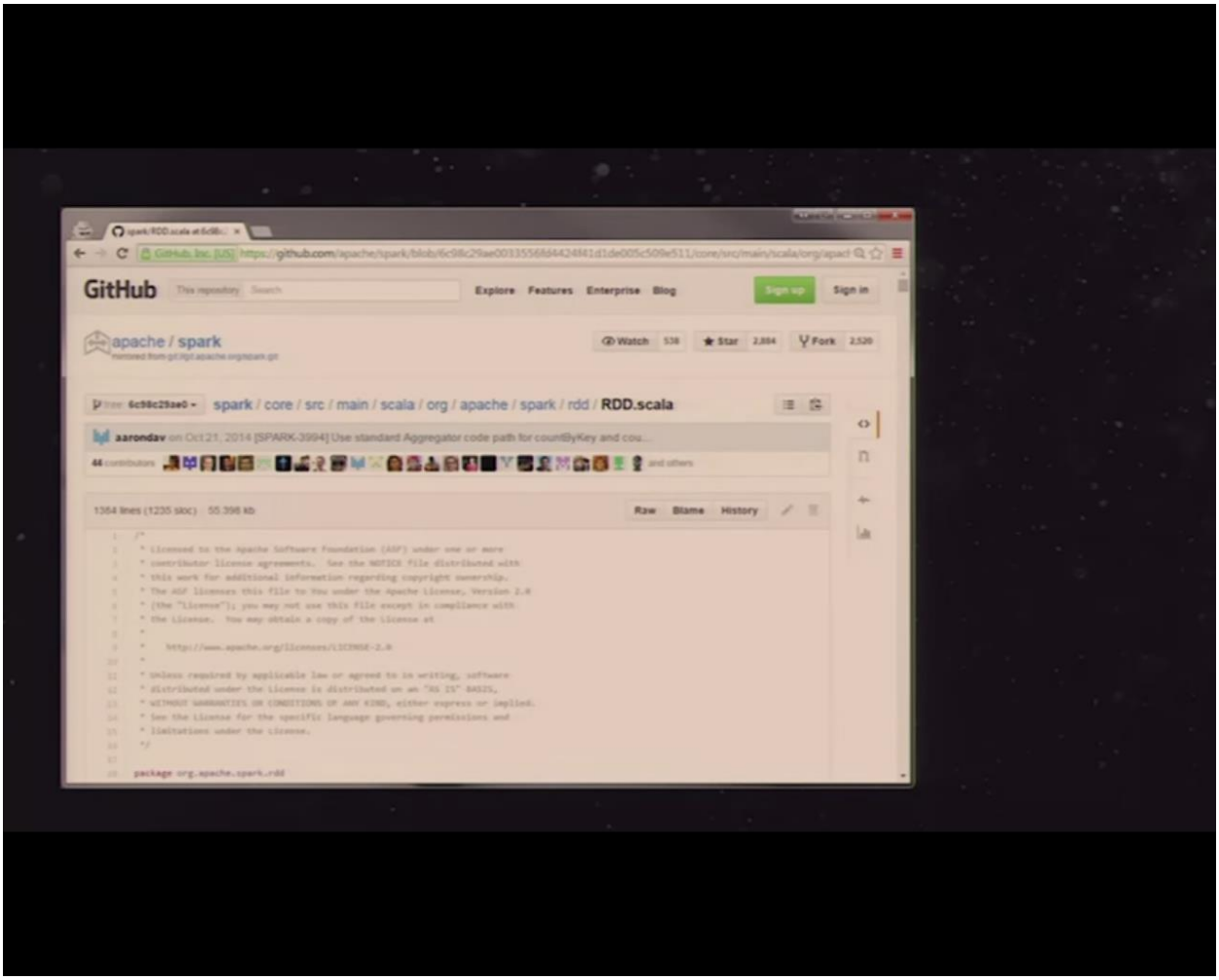
- Most transformations are element-wise (they work on one element at a time), but this is not true for all transformations

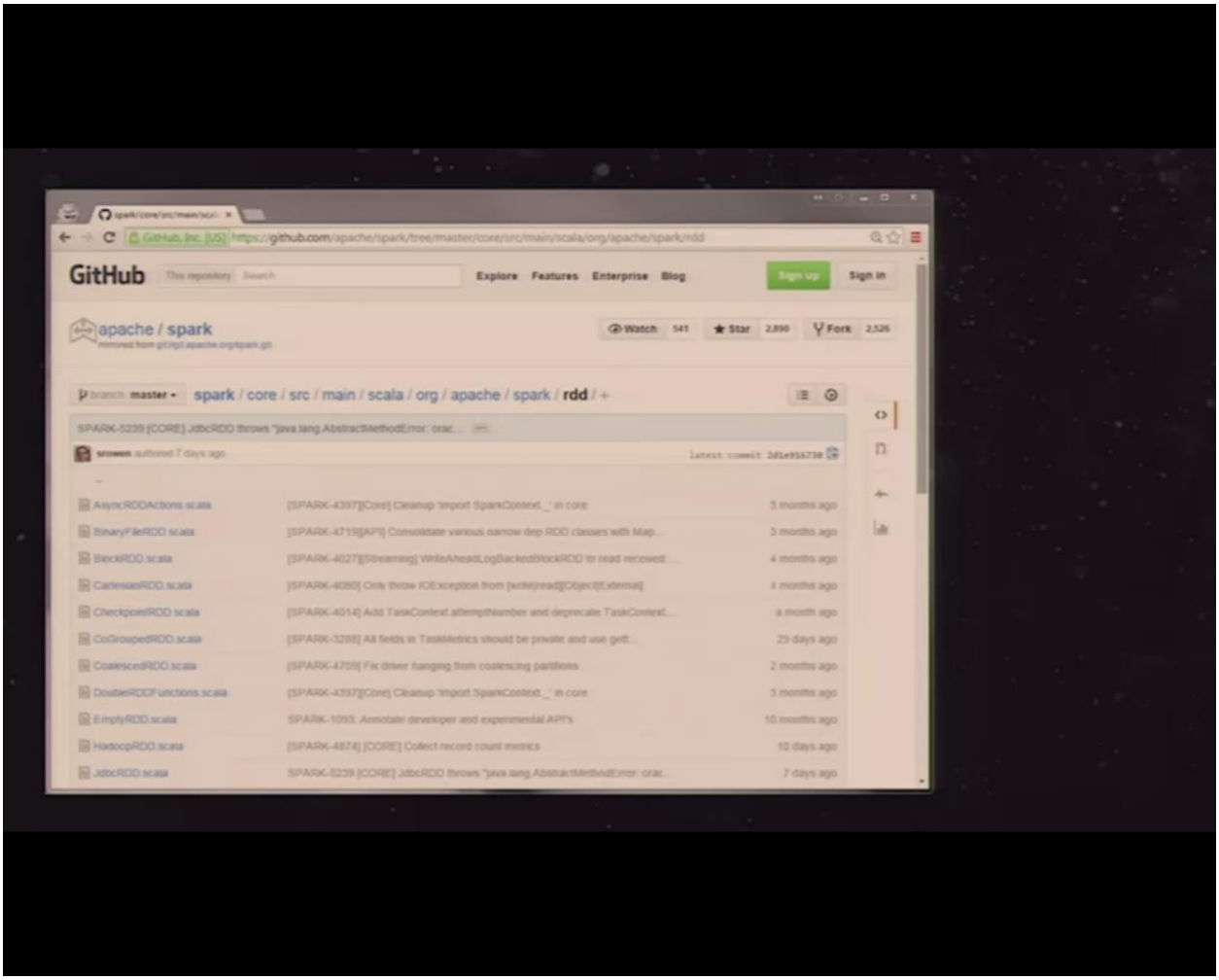
ACTIONS

```
reduce()
collect()
count()
first()
take()
takeSample()
saveToCassandra()
takeOrdered()
saveAsTextFile()
saveAsSequenceFile()
saveAsObjectFile()
countByKey()
foreach()
...
```

TYPES OF RDDS

- HadoopRDD
- FilteredRDD
- MappedRDD
- PairRDD
- ShuffledRDD
- UnionRDD
- PythonRDD
- DoubleRDD
- JdbcRDD
- JsonRDD
- SchemaRDD
- VertexRDD
- EdgeRDD
- CassandraRDD *(DataStax)*
- GeoRDD *(ESRI)*
- EsSpark *(ElasticSearch)*


GitHub
Explore
Features
Enterprise
Blog
Sign up
Sign in
apache / spark
spark / core / src / main / scala / org / apache / spark / rdd / RDD.scala
aarondav on Oct 21, 2014 [SPARK-3994] Use standard Aggregator code path for countByKey and cou...
Raw
Blame
History
package org.apache.spark.rdd


GitHub
Explore
Features
Enterprise
Blog
Sign up
Sign in
apache / spark
Watch
Star
Fork
branch: master
spark / core / src / main / scala / org / apache / spark / rdd /

RDD INTERFACE

* 1) Set of partitions ("splits")
* 2) List of dependencies on parent RDDs
* 3) Function to compute a partition given parents
* 4) Optional preferred locations
* 5) Optional partitioning info for k/v RDDs (Partitioner)

This captures all current Spark operations!

EXAMPLE: HADOOPRDD

* Partitions = one per HDFS block
* Dependencies = none
* Compute (partition) = read corresponding block

* preferredLocations (part) = HDFS block location
* Partitioner = none

EXAMPLE: FILTEREDRDD

* Partitions = same as parent RDD
* Dependencies = "one-to-one" on parent
* Compute (partition) = compute parent and filter it

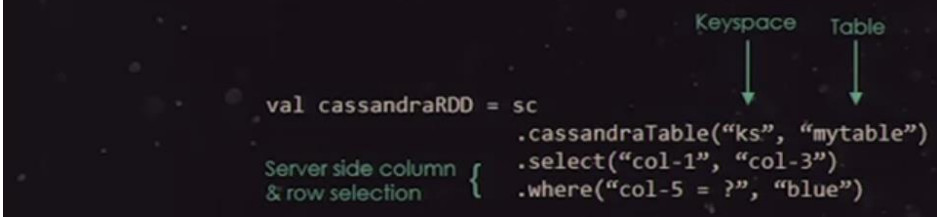
* preferredLocations (part) = none (ask parent)
* Partitioner = none

EXAMPLE: JOINEDRDD

* Partitions = One per reduce task
* Dependencies = "shuffle" on each parent
* Compute (partition) = read and join shuffled data

* preferredLocations (part) = none
* Partitioner = HashPartitioner(numTasks)

READING DATA USING THE C* CONNECTOR



INPUT SPLIT SIZE

(for dealing with wide rows)

Start the Spark shell by passing in a custom cassandra.input.split.size:

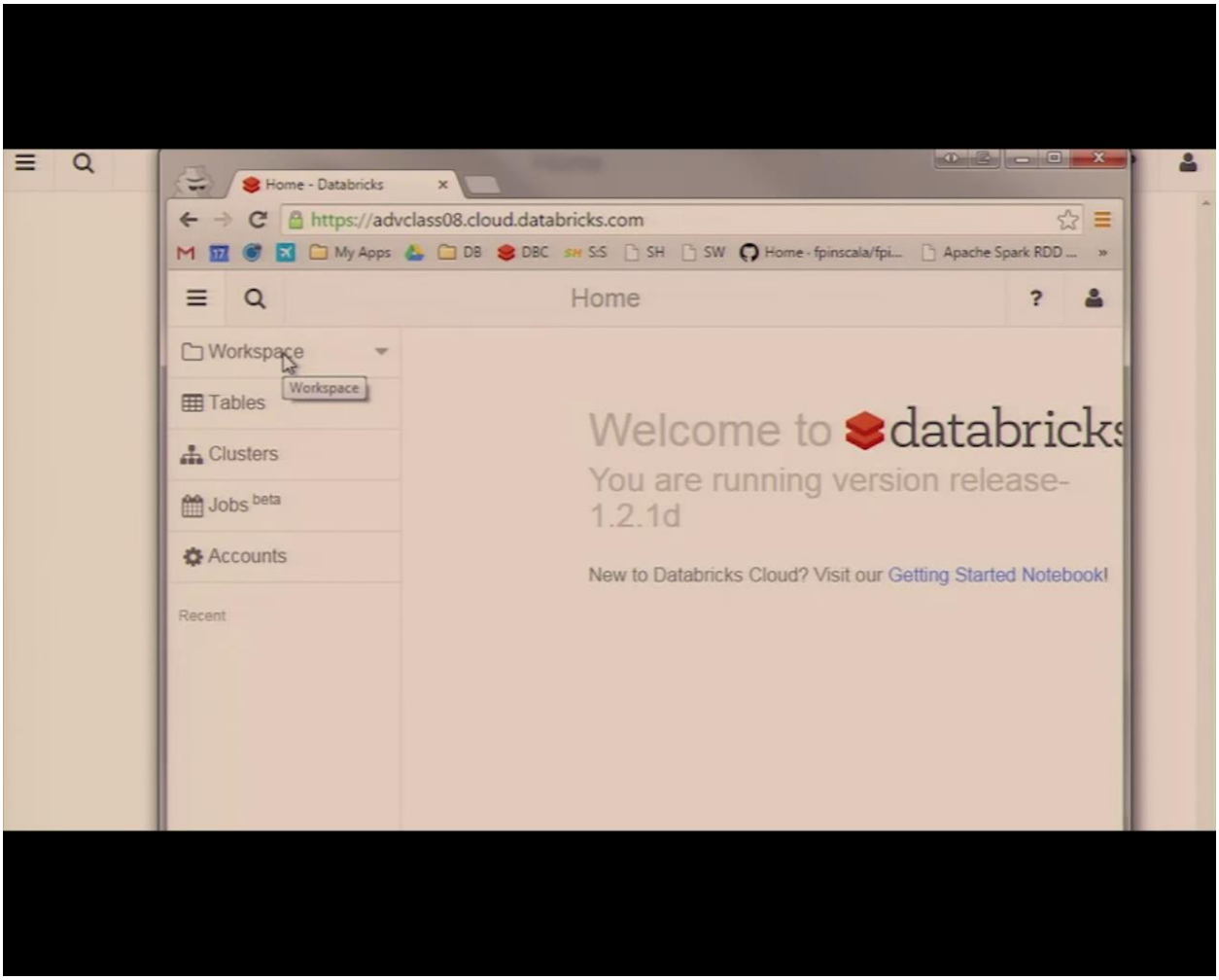
```
ubuntu@ip-10-0-53-24:~$ dse spark -Dspark.cassandra.input.split.size=2000
Welcome to
```

```
version 0.9.1

Using Scala version 2.10.3 (Java HotSpot(TM) 64-Bit Server VM, Java
1.7.0_51)
Type in expressions to have them evaluated.
Type :help for more information.
Creating SparkContext...
Created spark context..
Spark context available as sc.
Type in expressions to have them evaluated.
Type :help for more information.

scala>
```

The `cassandra.input.split.size` parameter defaults to 100,000. This is the approximate number of physical rows in a single Spark partition. If you have really wide rows (thousands of columns), you may need to lower this value. The higher the value, the fewer Spark tasks are created. Increasing the value too much may limit the parallelism level."

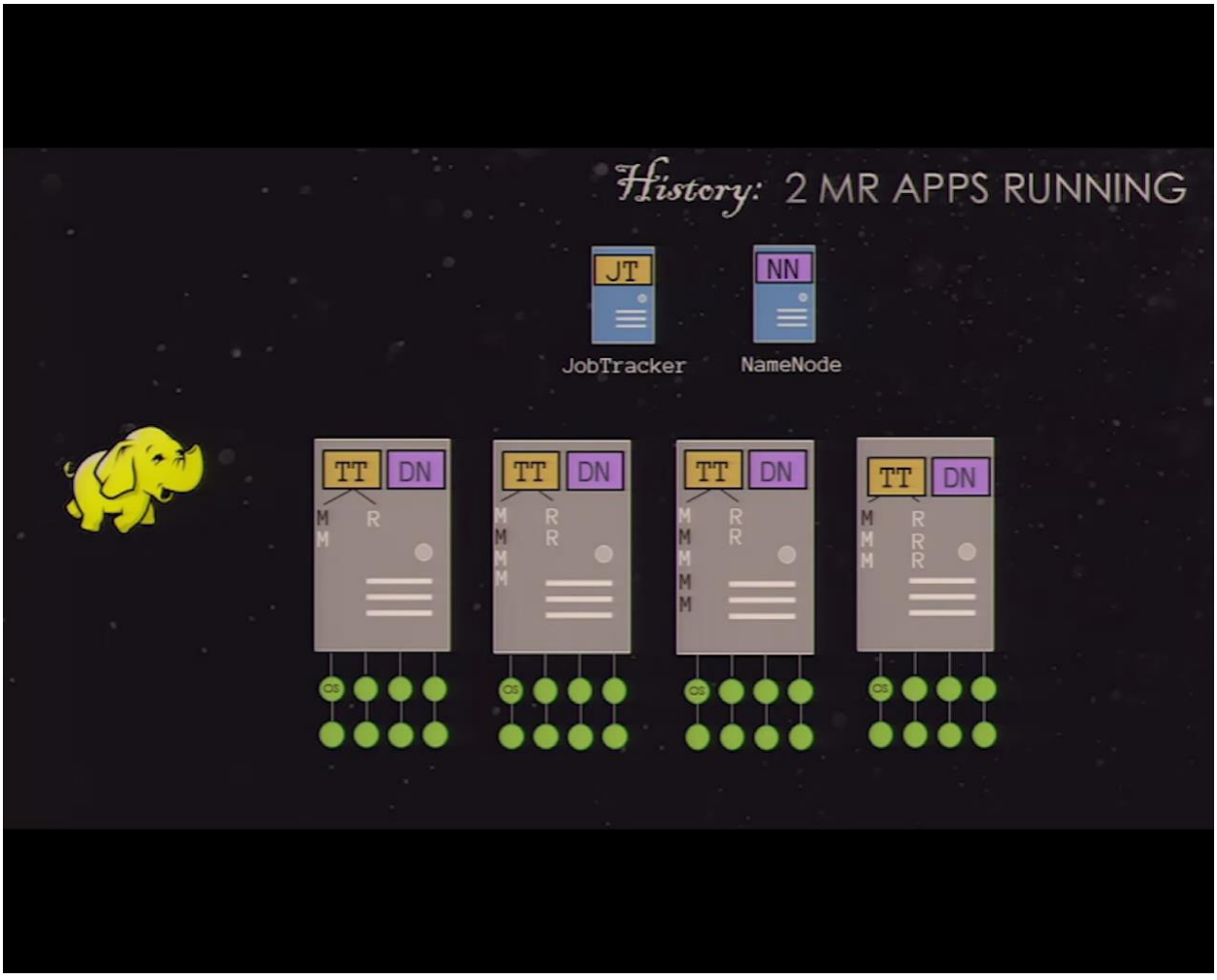

Home - Databricks
https://advclass08.cloud.databricks.com
My Apps
DB
DBC
SH
SW
Home - fpinscala/fpi...
Apache Spark RDD ...
Home
Workspace
Workspace
Tables
Clusters
Jobs beta
Accounts
Recent
Welcome to databricks
You are running version release-1.2.1d
New to Databricks Cloud? Visit our Getting Started Notebook!


WAYS TO RUN SPARK
- Local
Static Partitioning
- Standalone Scheduler
- YARN
Dynamic Partitioning
- Mesos

In map reduce there are different JVM to get the parallelism of the task while in spark we have different threads inside the executors

In Spark you have one executor JVM in each machine, inside the executor JVM you have slots, inside the slots tasks can run.

In Map reduce there are different slots for map phase and reduce phase; there are not generic slots which can use either map or reduce. at the time of map phase is running (which takes most of the time) ,slots for reduce phase are sit idle and no one can use it while in spark the slots are generic slots they can run map , reduce or other tasks



Local Mode

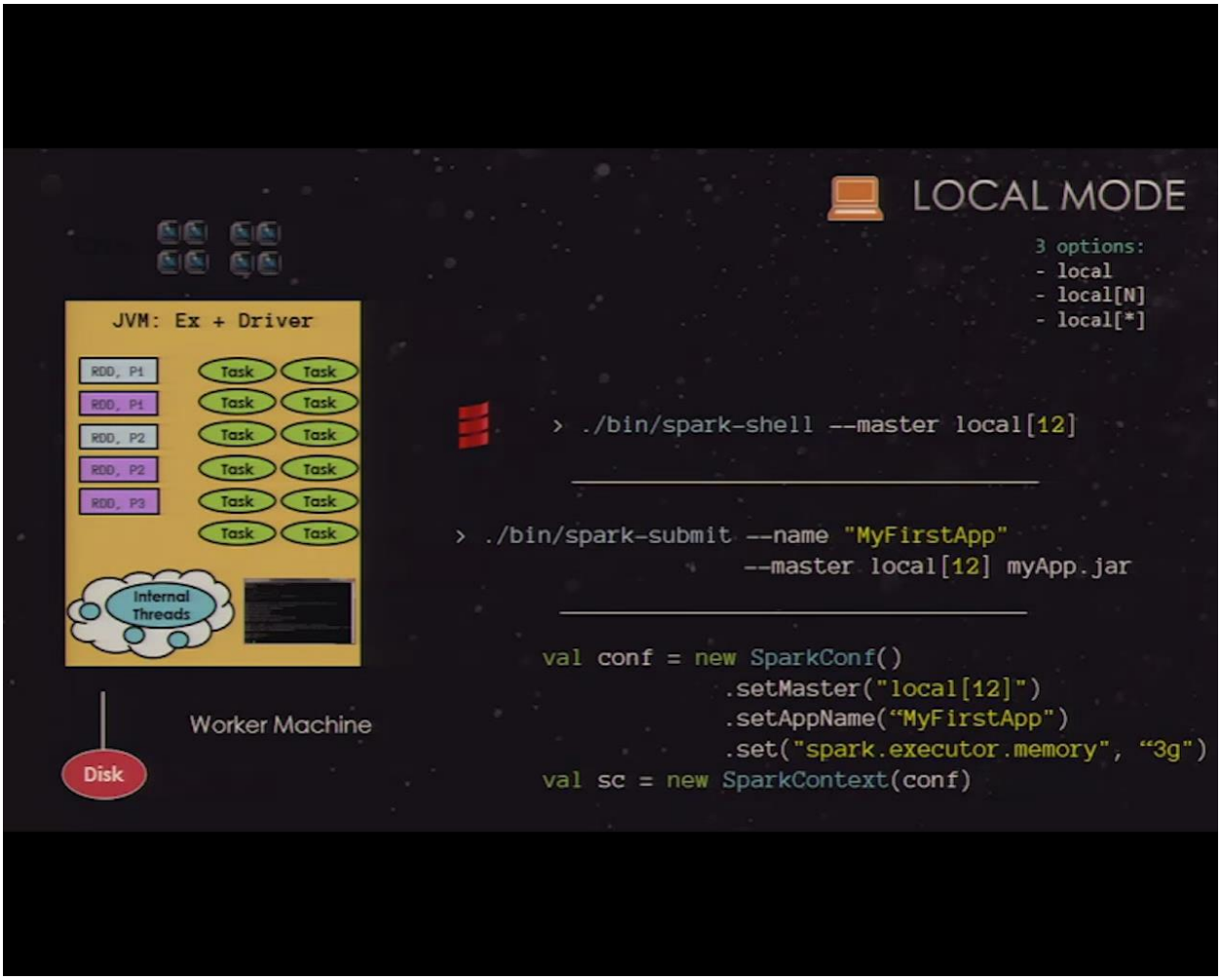
When you start Scala shell, it actually starts the JVM which execute the executor process and the driver process.

Tasks in sparks are called cores (threads) that we can run in parallel, its common mistake that we correlate it with CPU core, most of the time we think if we have machine with 8 CPU core, we will use 2 cores for OS and rest 6 cores for spark JVM which is not correct. Generally in spark we define cores in multiple of 2 or 3. And we can define core more than our CPU core if we have 6 CPU cores we can go with 12 or 18 tasks core.

We can pass the threads or tasks when we start spark-shell by defining local [N], N is number of cores

If we pass only local it means only one worker thread which is not enough.

If we pass local [*] , it means run worker threads as many as there are logical cores in the machine, once again it is not a good setting as we want to run more threads than CPU cores.

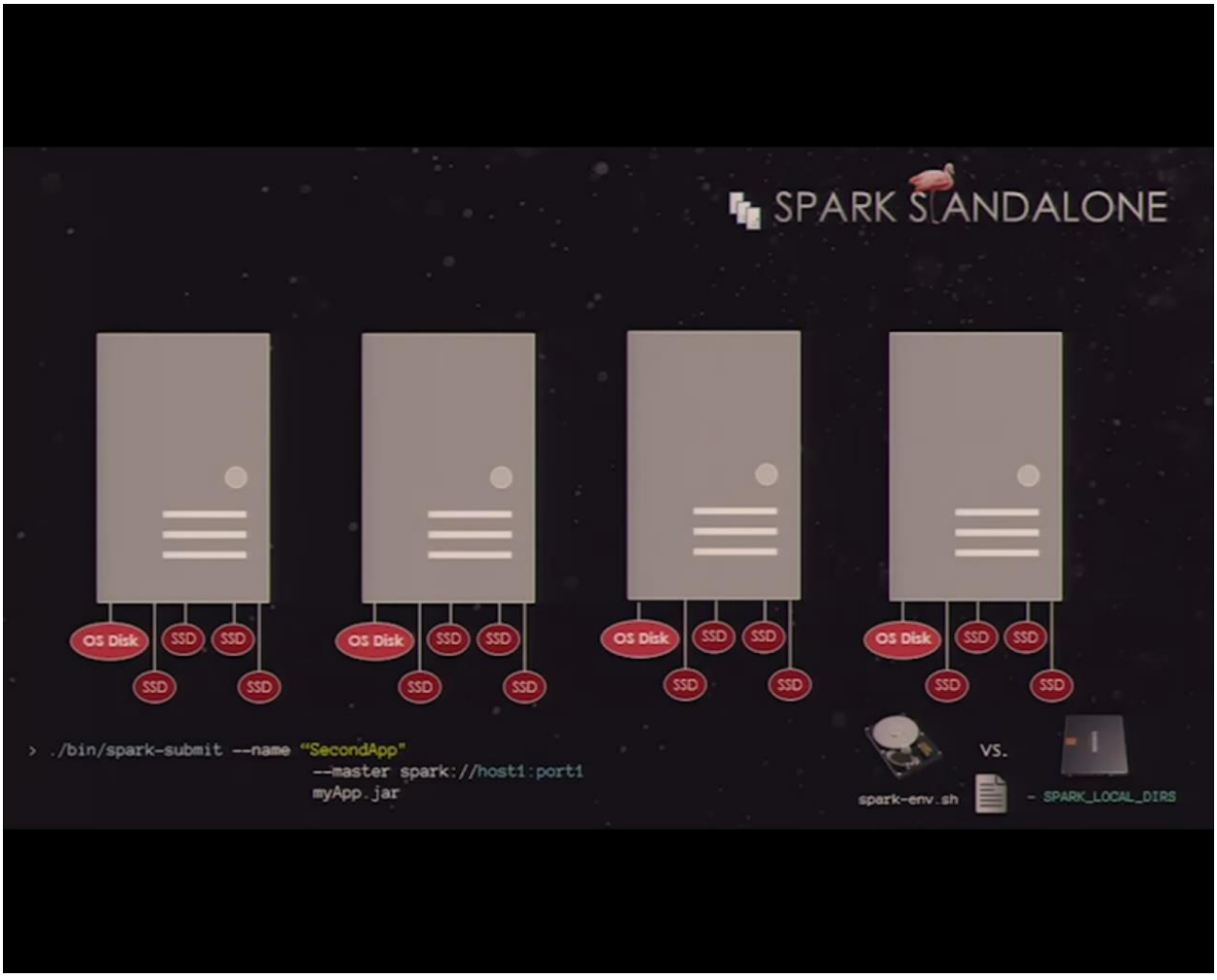


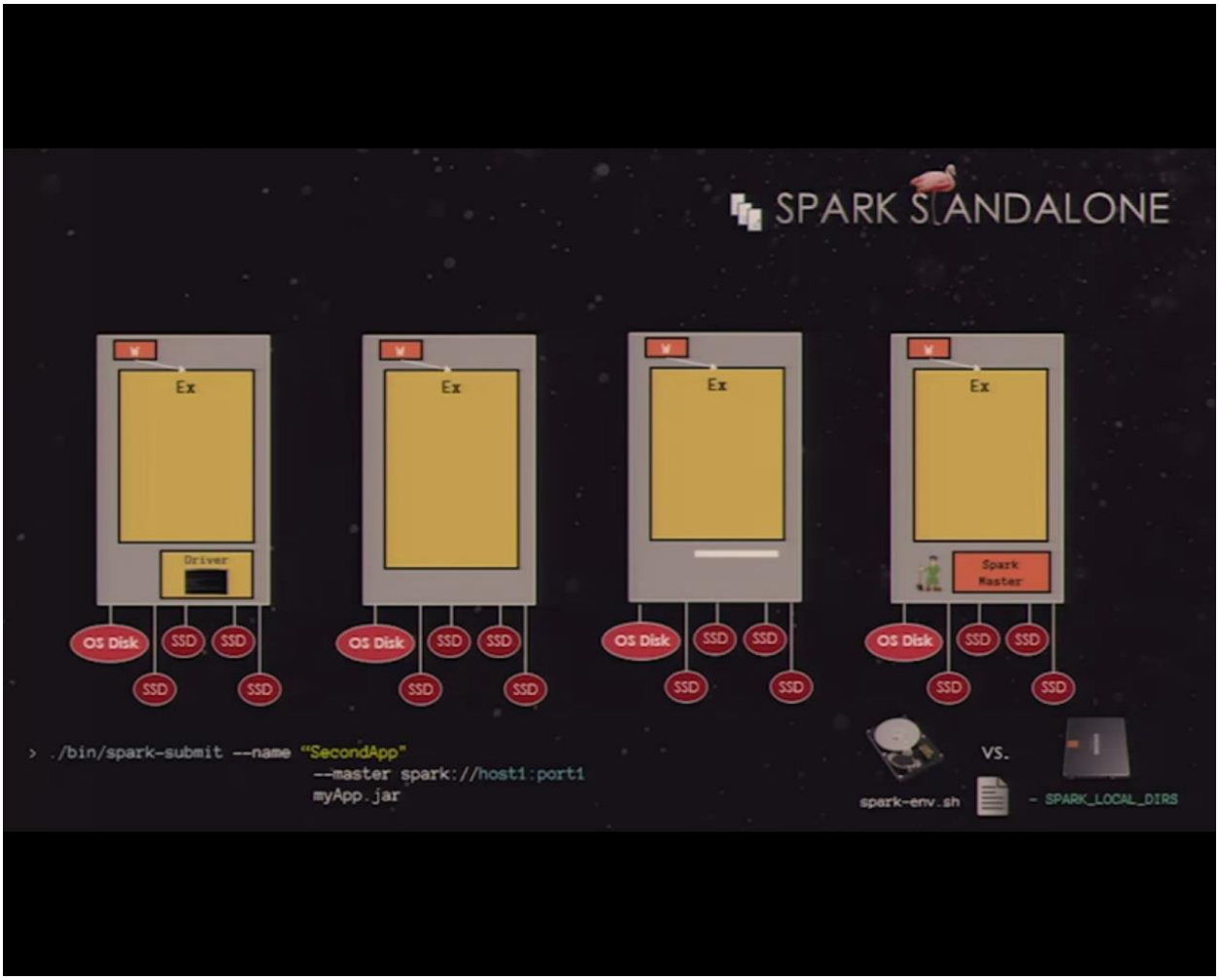
Code overwrites the number of thread submitted

Standalone mode

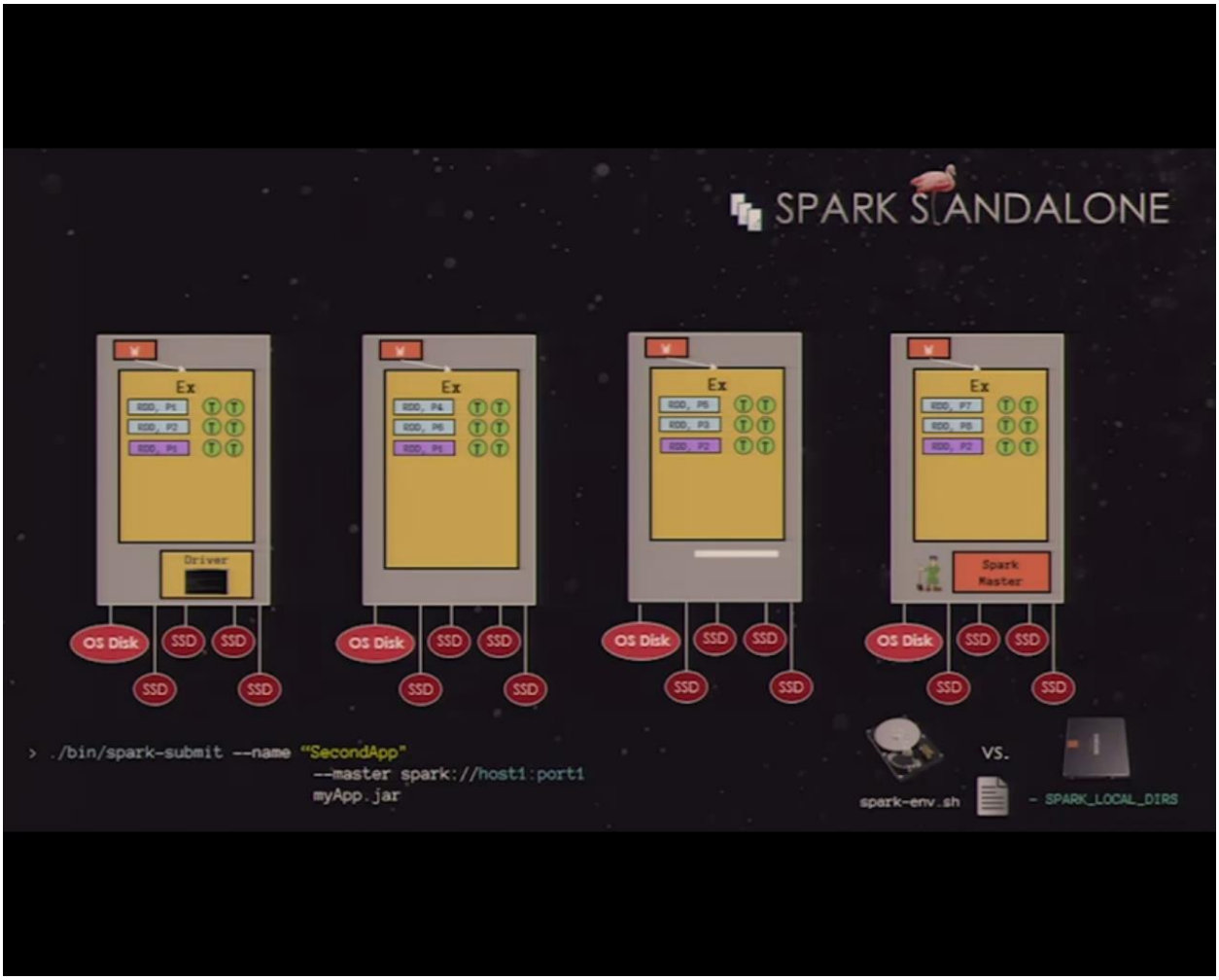
Example 4 node cluster

Spark-env.sh file has a property called SPARK_LOCAL_DIRS, which contains N, <N location of file mount points> what this property does is when RDD is very big and doesn't fit into memory, the rest portion are stored in those location which define in SPARK_LOCAL_DIRS. It is also used for intermediate shuffle data, like when map side operation runs and spills some data down to local disk and reducer come up and pull the data of the map spills over the network. So map side spills data goes down to this DIRS

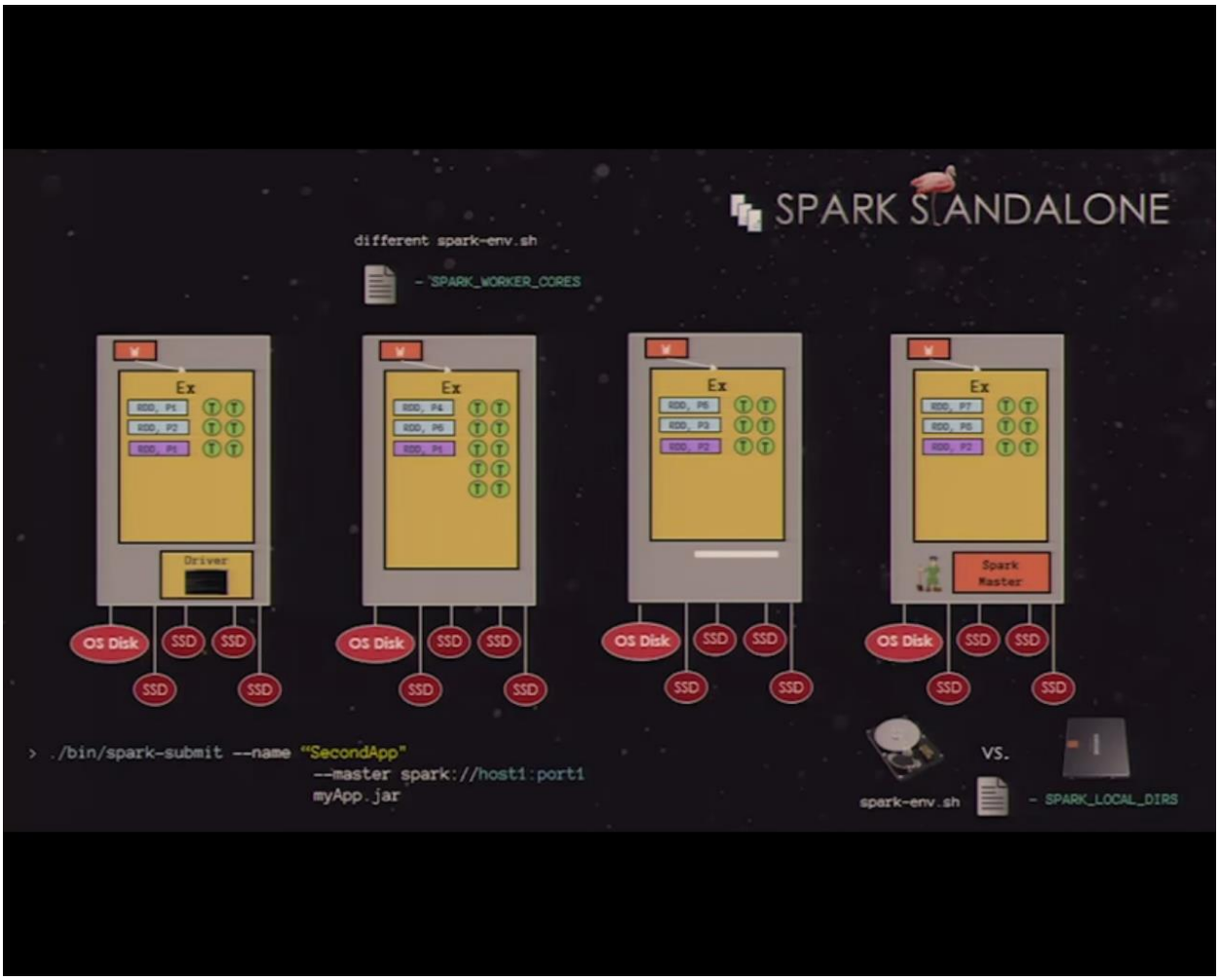


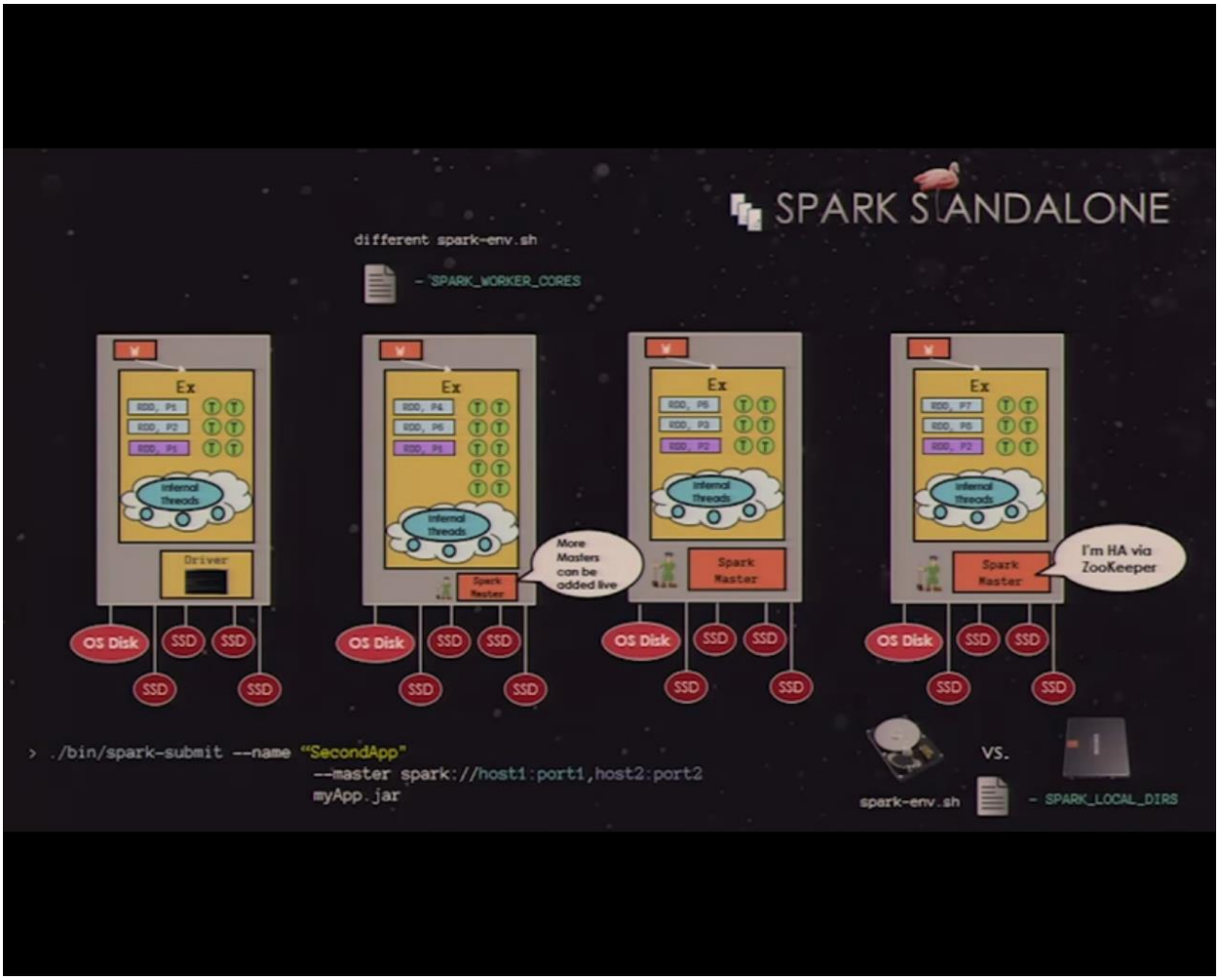


Yellow – spark application Orange – Default resource manager

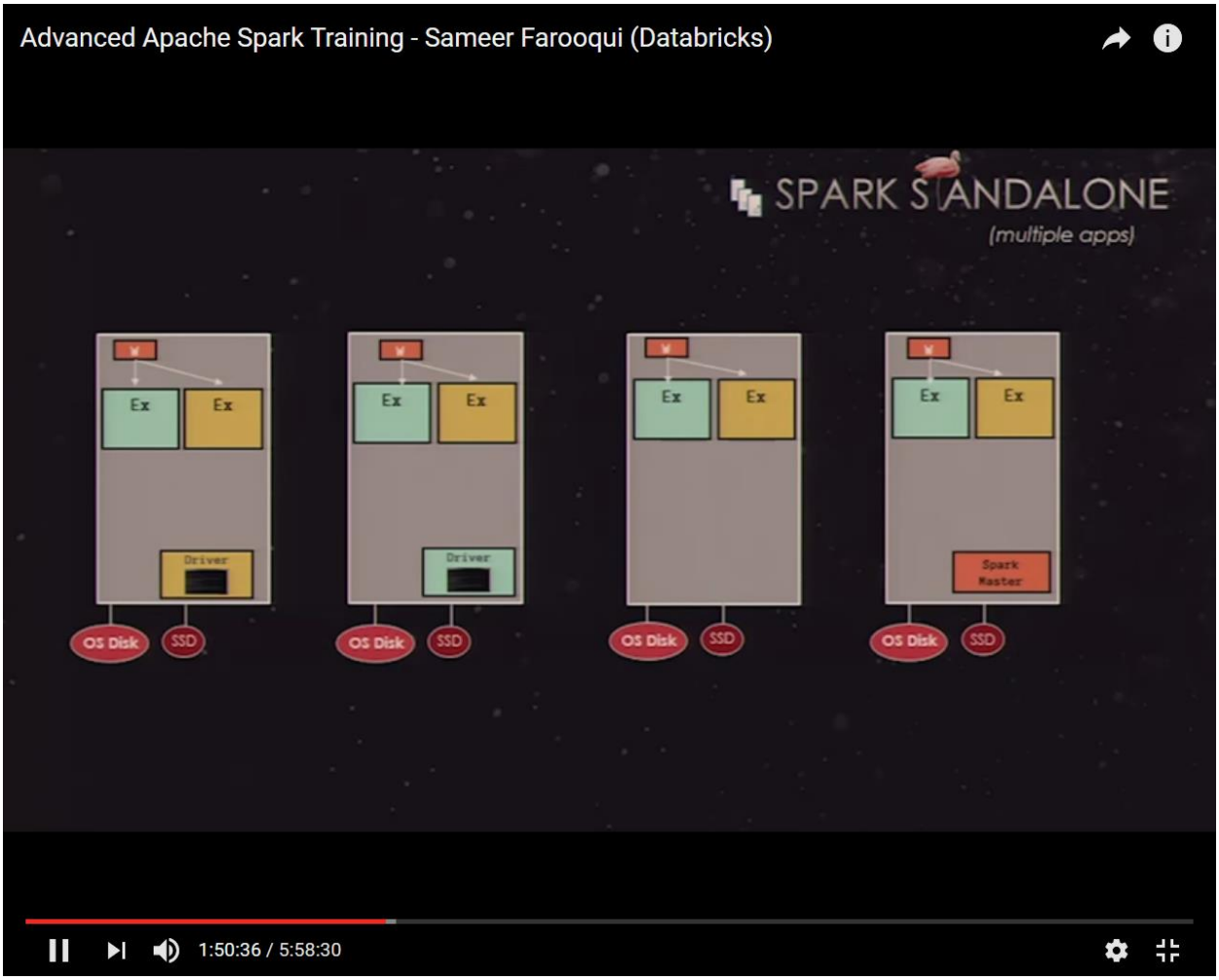

SPARK STANDALONE
W
Ex
RDD, P1
RDD, P2
RDD, P5
Driver
OS Disk
SSD
W
Ex
RDD, P4
RDD, P6
RDD, P1
OS Disk
SSD
W
Ex
RDD, P5
RDD, P3
RDD, P2
OS Disk
SSD
W
Ex
RDD, P7
RDD, P8
RDD, P2
Spark Master
OS Disk
SSD
> ./bin/spark-submit --name "SecondApp"
--master spark://host1:port1
myApp.jar
spark-env.sh
vs.
- SPARK_LOCAL_DIRS

If we have a machine with different configuration lets say in this example we have machine 2 with large CPU core than rest 3 we can set the more number of cores for second machine by specify properety SPARK_WORKER_CORES



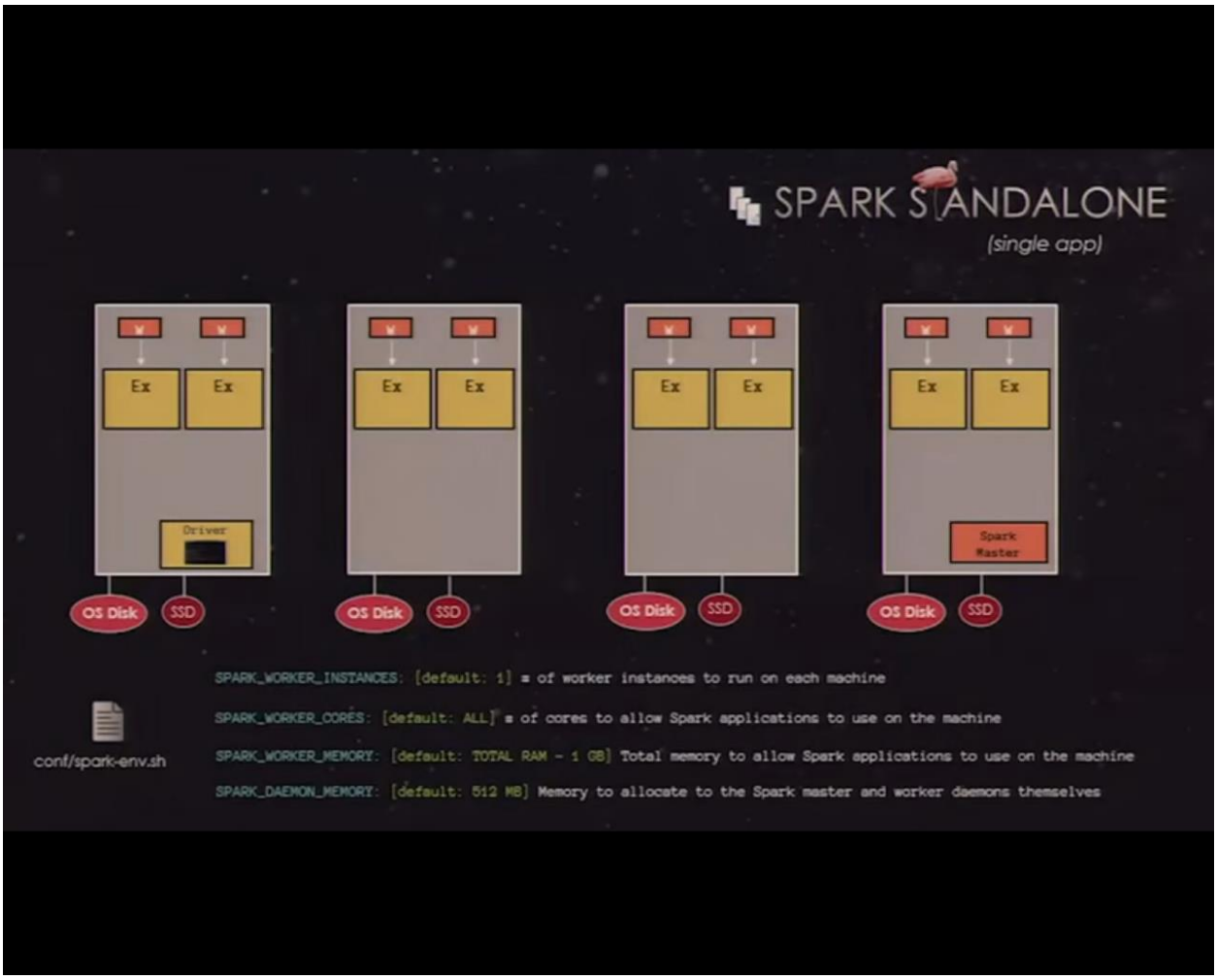

SPARK STANDALONE
different spark-env.sh
- SPARK_WORKER_CORES
W
Ex
RDD, P5
RDD, P2
RDD, P1
Internal threads
Driver
OS Disk
SSD
W
Ex
RDD, P4
RDD, P6
RDD, P1
Internal threads
Spark Master
More Masters can be added live
W
Ex
RDD, P6
RDD, P3
RDD, P2
Internal threads
Spark Master
W
Ex
RDD, P7
RDD, P6
RDD, P2
Internal threads
Spark Master
I'm HA via ZooKeeper
> ./bin/spark-submit --name "SecondApp"
--master spark://host1:port1,host2:port2
myApp.jar
spark-env.sh
VS.
- SPARK_LOCAL_DIRS

Multiple executors in standalone mode



One worker in standalone mode cannot start more than one executor. We cannot give more than 45 GB memory to one JVM.

If we only want to run one driver or one application and we have almost 125 GB memory



Here each worker starts two yellow executors but one worker cannot start two yellow executors, so we need to configure two workers in every machine

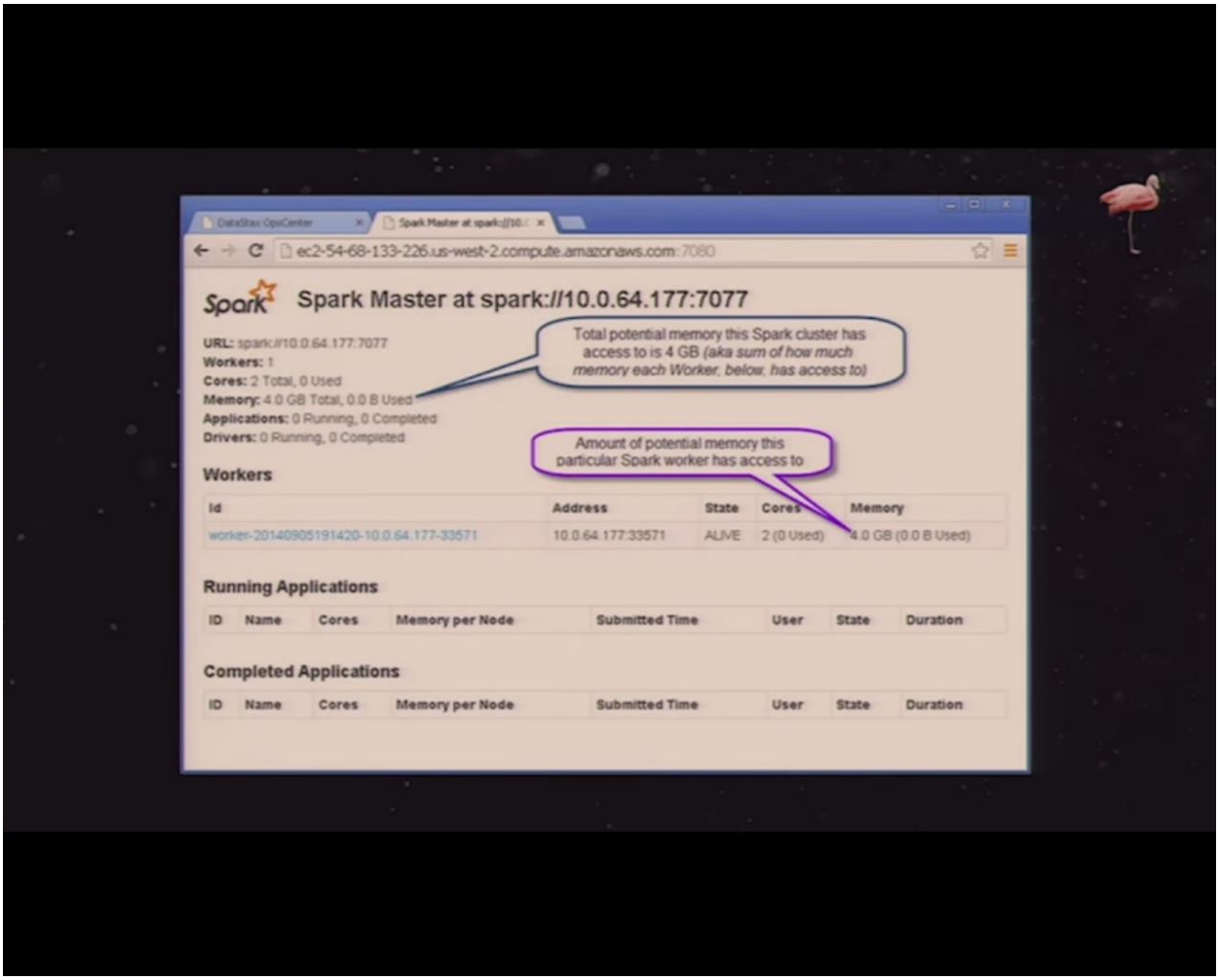
Set **SPARK_WORKER_INSTANCES**=2

SPARK_WORKERS_CORES - doesn't mean how many threads run in the worker JVM, it means how many cores can that worker give out to its underlying executors, so if value is configured as 12 and if start one executor with 6 cores so worker can still start another executor with 6 more cores.

SPARK_WORKER_MEMORY – means how much memory can worker give out to its underlying executors or JVM

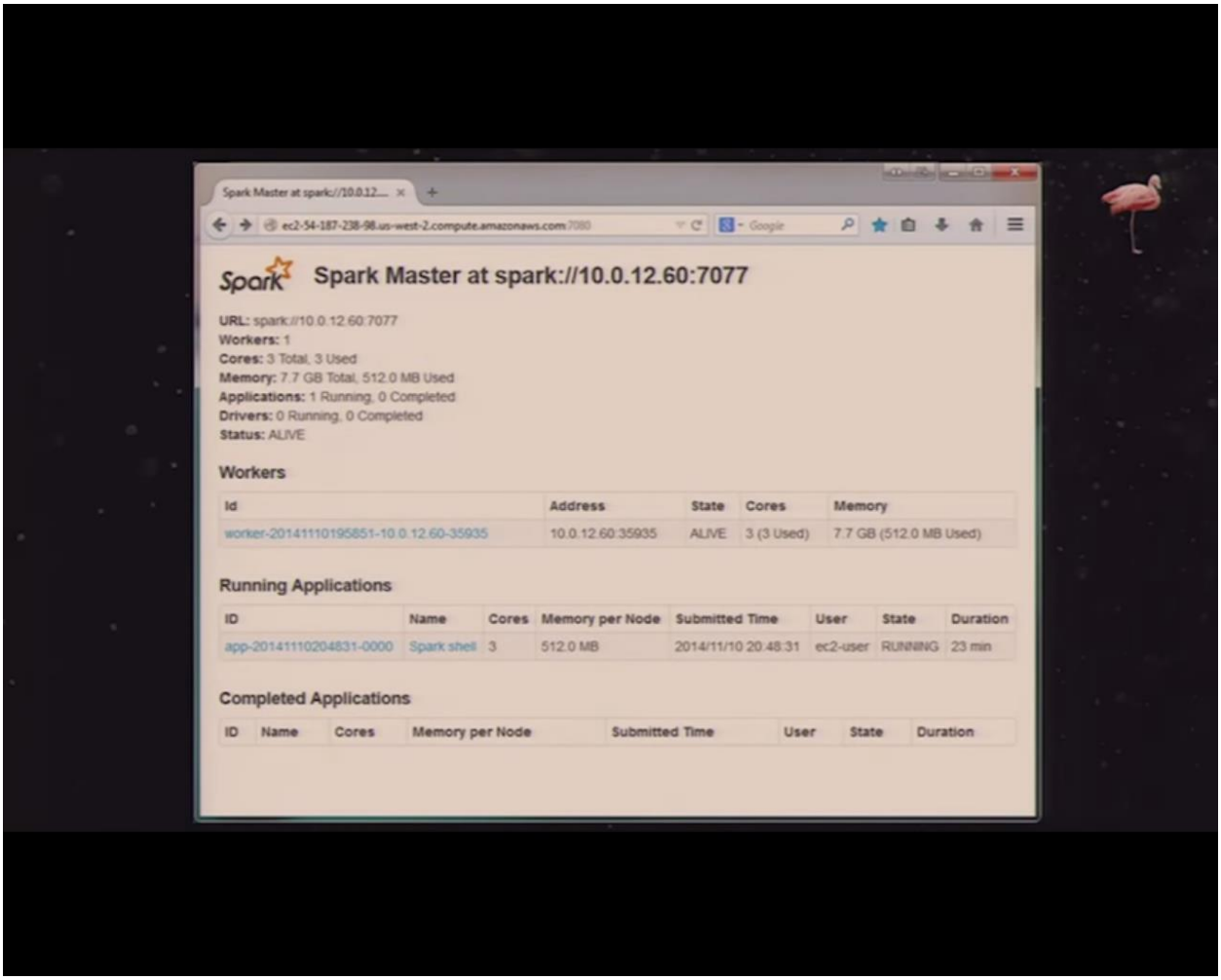
SPARK_DAEMON_MEMORY – is the memory to allocate to the actual spark master JVM and spark worker demons.

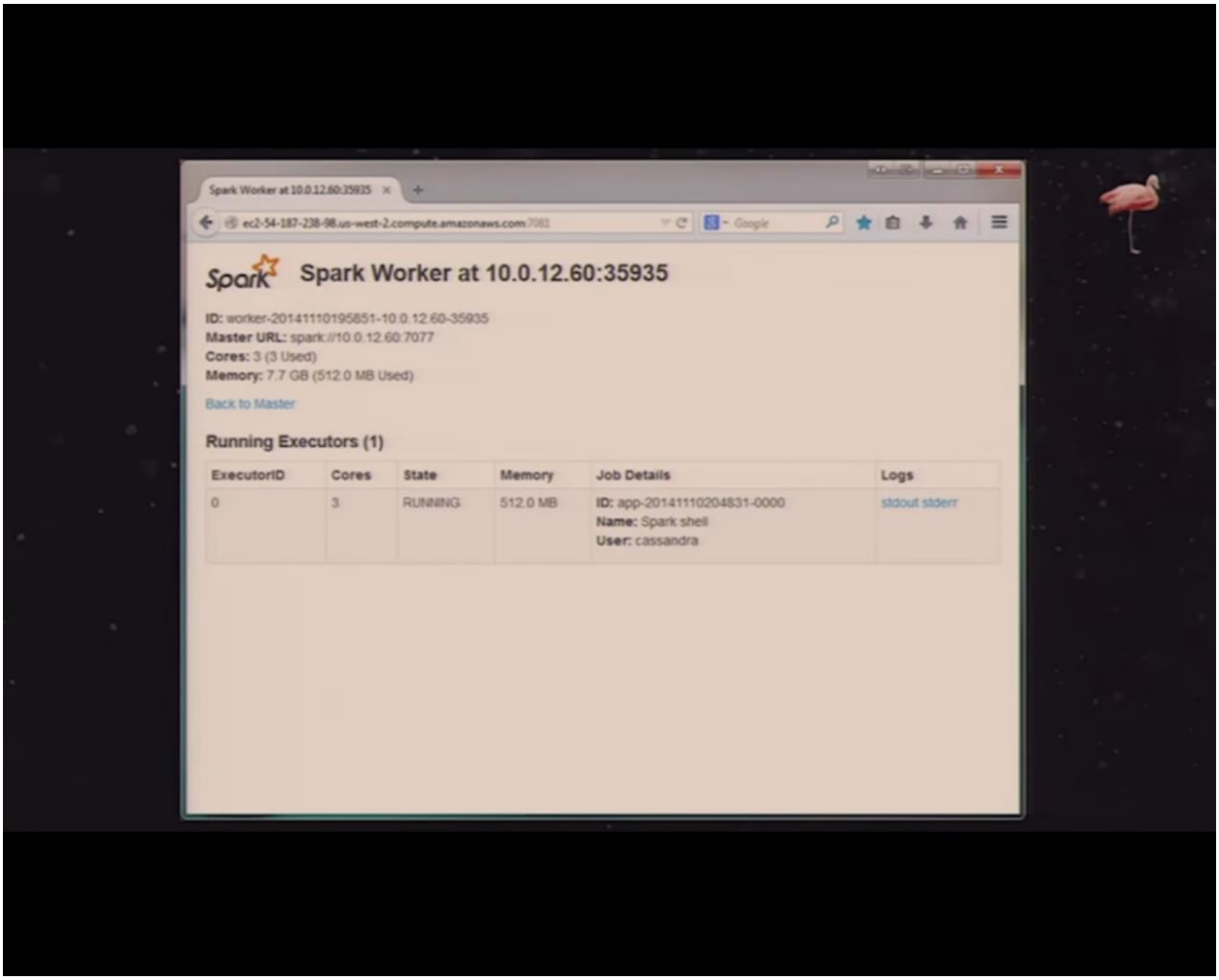
In standalone mode we cannot define number of executors and number of tasks/cores for each executor but we can define how many cores we want and spark load balancer distribute the cores across the cluster and divide the cores among executors


DataStax OpsCenter
Spark Master at spark://10.0
ec2-54-68-133-226.us-west-2.compute.amazonaws.com:7080
Spark Master at spark://10.0.64.177:7077
URL: spark://10.0.64.177:7077
Workers: 1
Cores: 2 Total, 0 Used
Memory: 4.0 GB Total, 0.0 B Used
Applications: 0 Running, 0 Completed
Drivers: 0 Running, 0 Completed
Total potential memory this Spark cluster has access to is 4 GB (aka sum of how much memory each Worker, below, has access to)
Amount of potential memory this particular Spark worker has access to
Workers
Id
Address
State
Cores
Memory
worker-20140905191420-10.0.64.177-33571
10.0.64.177:33571
ALIVE
2 (0 Used)
4.0 GB (0.0 B Used)
Running Applications
ID
Name
Cores
Memory per Node
Submitted Time
User
State
Duration
Completed Applications
ID
Name
Cores
Memory per Node
Submitted Time
User
State
Duration

Misconfiguration that we can see in UI below

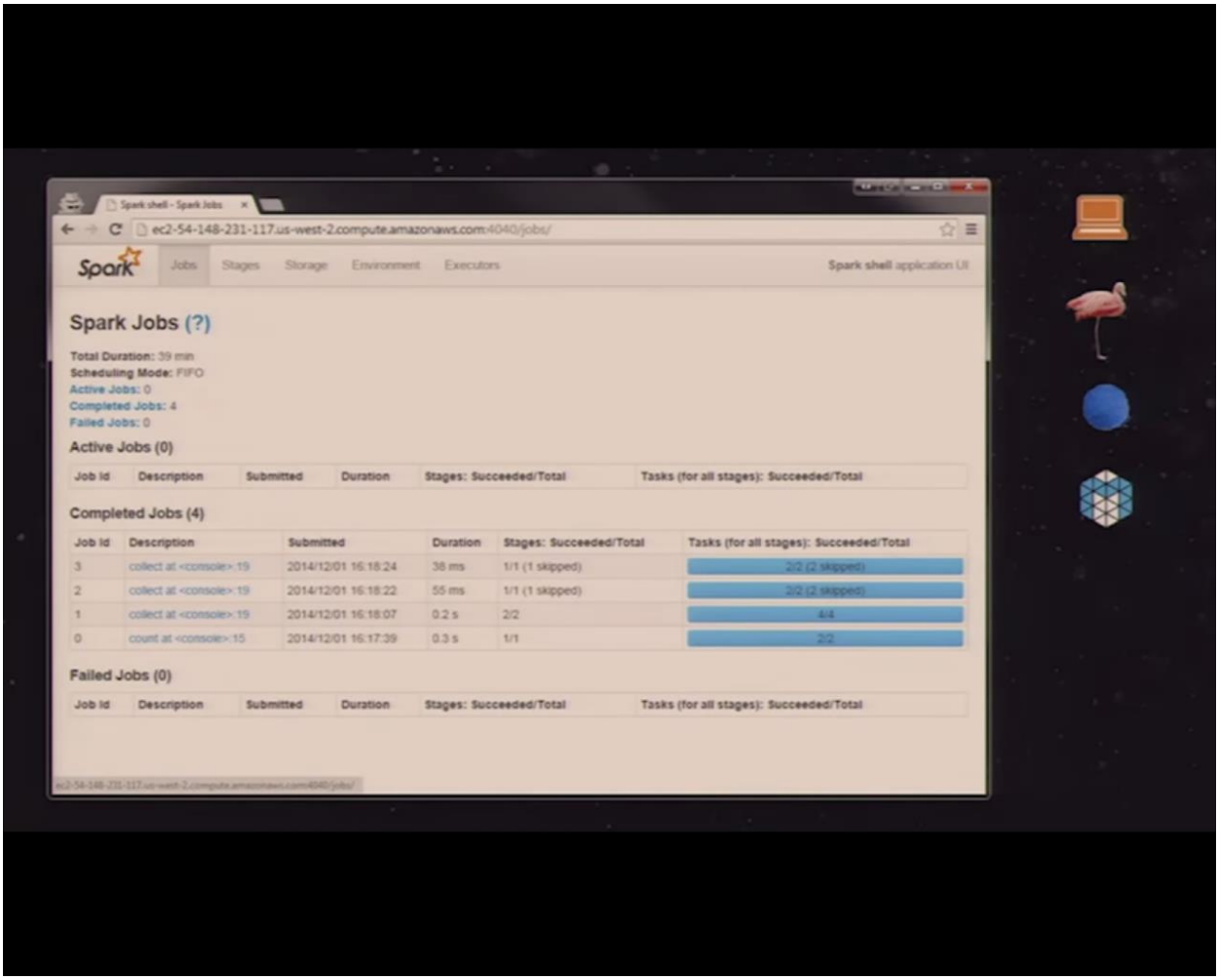
Here we can see there is only one worker is running and it can give at max 3 cores to its worker and we also can see there is one running application, this running application is nothing but one of the executor and we can see that all the 3 cores is being used by this executor but it only took 512 MB memory out of 7.7 GB. So if only one executor is running and it is using all three cores it should use all 7.7 GB of memory to boost the performance. So probably we set **spark.executor.memory** to 512 MB to fix this scenario increase it to around 7.6 GB



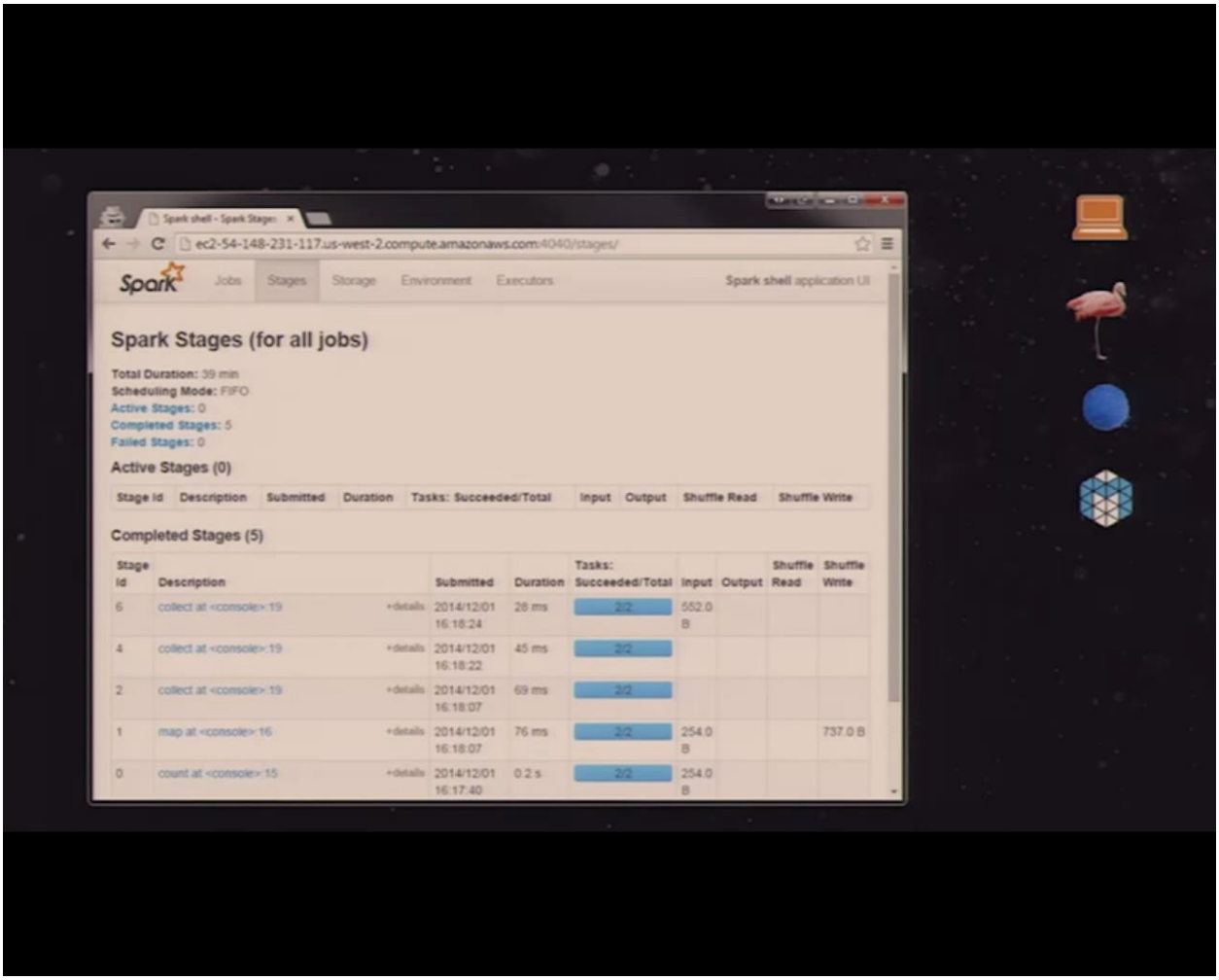

Spark Worker at 10.0.12.60:35935
ec2-54-187-238-98.us-west-2.compute.amazonaws.com:7081
Google
Spark Worker at 10.0.12.60:35935
ID: worker-20141110195851-10.0.12.60-35935
Master URL: spark://10.0.12.60:7077
Cores: 3 (3 Used)
Memory: 7.7 GB (512.0 MB Used)
Back to Master
Running Executors (1)
ExecutorID
Cores
State
Memory
Job Details
Logs
0
3
RUNNING
512.0 MB
ID: app-20141110204831-0000
Name: Spark shell
User: cassandra
stdout stderr

Spark Driver UI

Spark application is made of multiple jobs, every time we kickoff the action creates a new job



Stages of the job



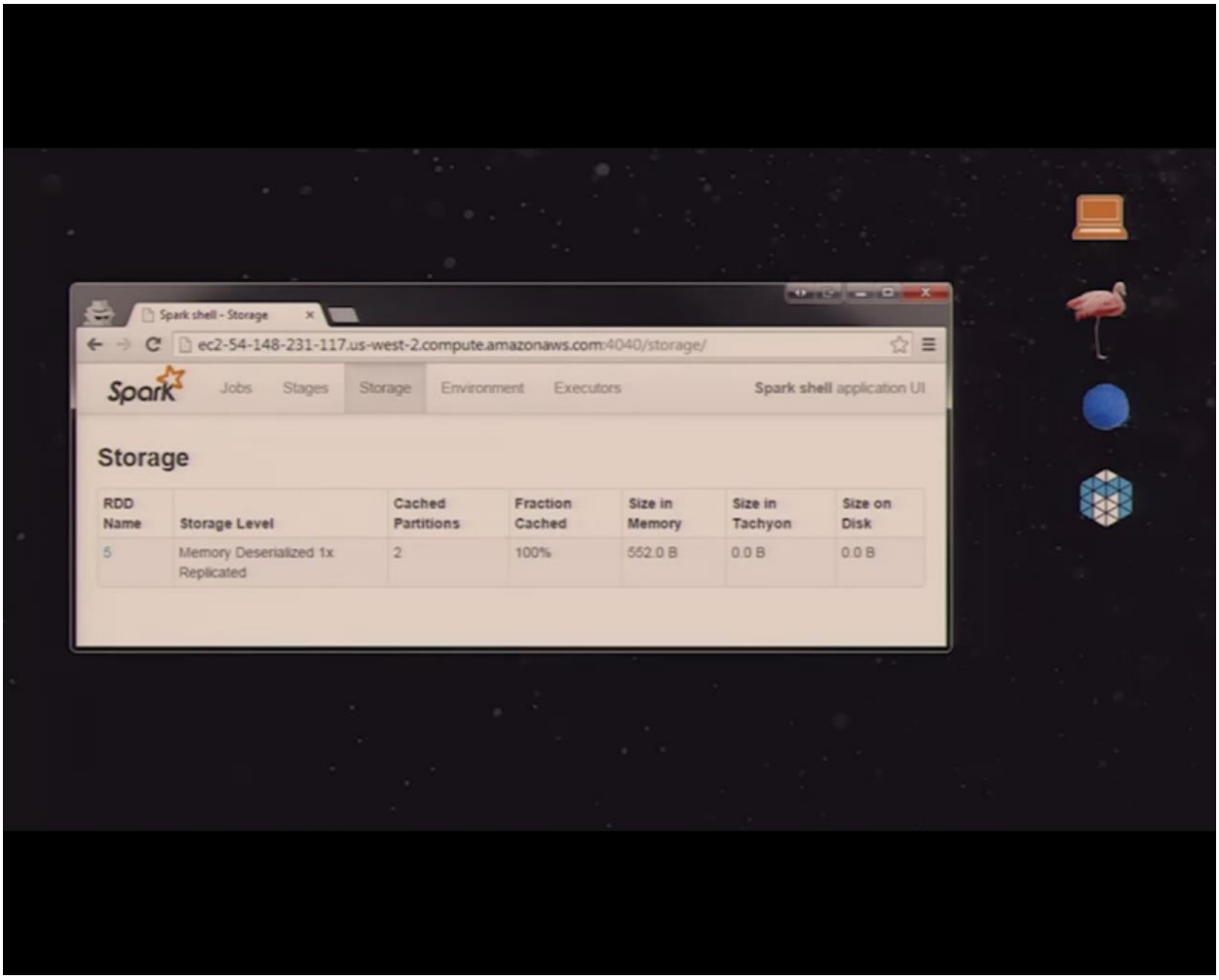
Stage decomposes one or more tasks

Storage Tab

Storage tab let us know the RDD that cached either in memory or in disk

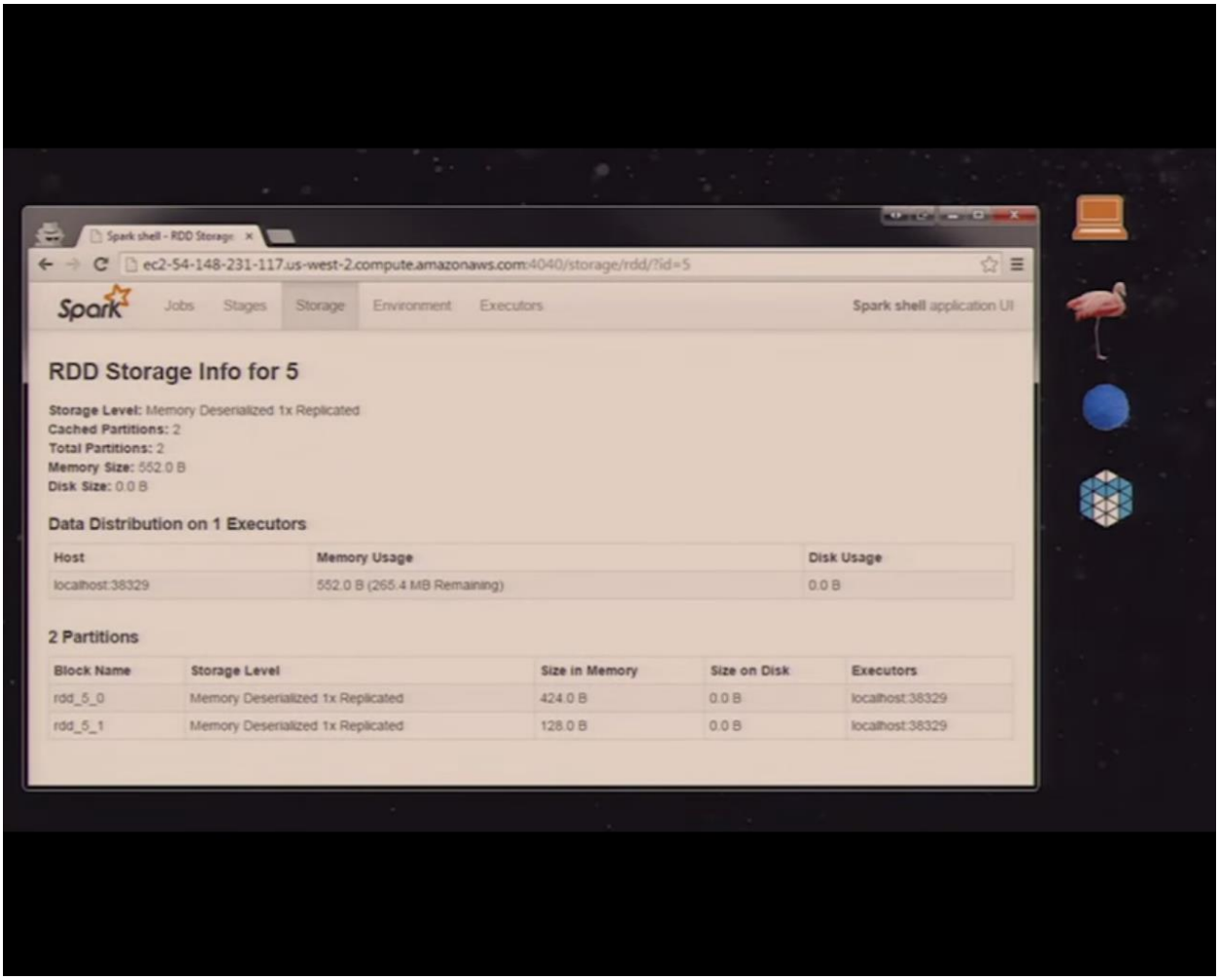
Here 2 partition is there in RDD and 100% is cached means both partitioned are cached and size in memory is 552 bytes.

We can get number of partition in RDD by calling getNumPartition method on RDD

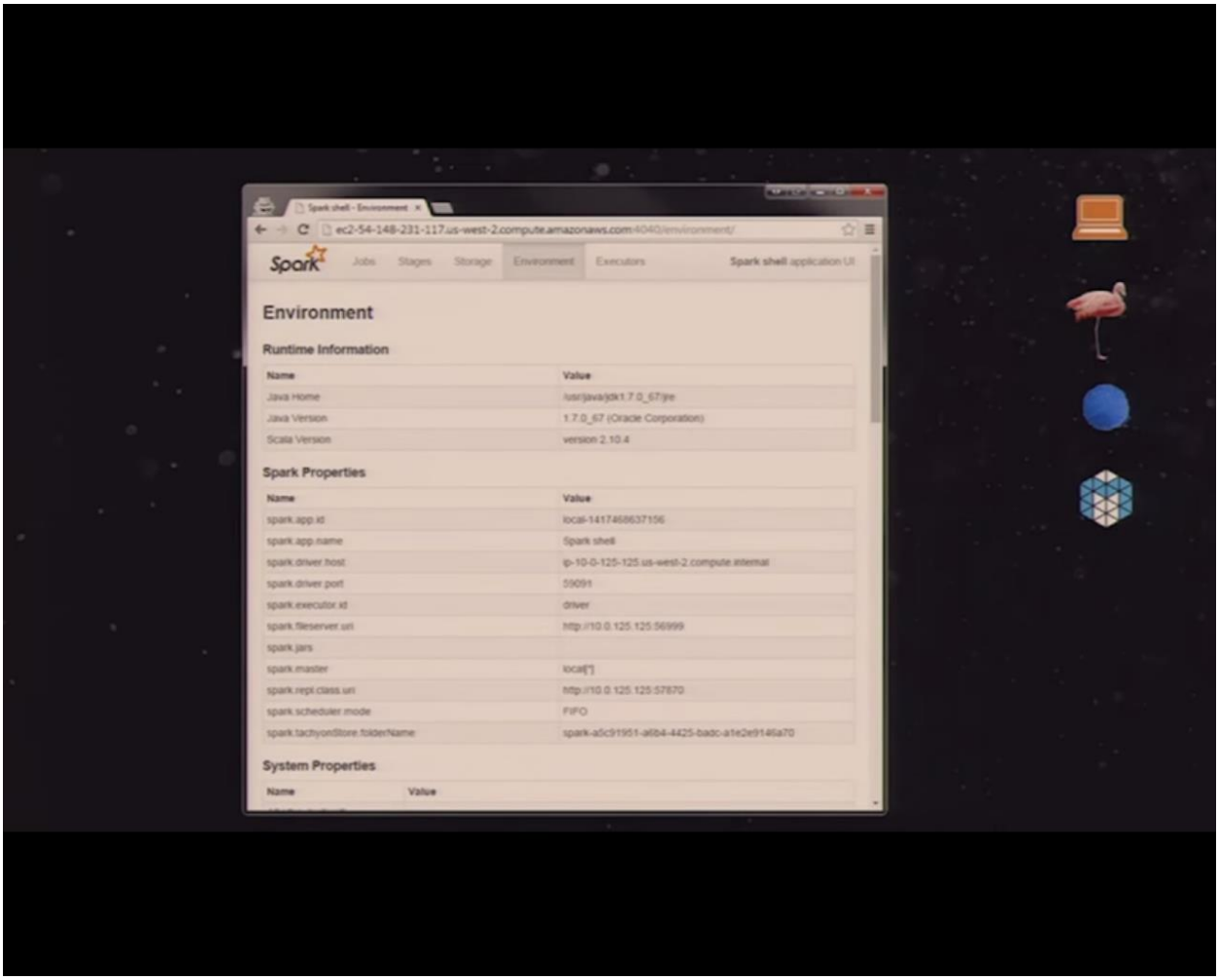


We can see more details of cached RDD

below; Data is distributed only one executor



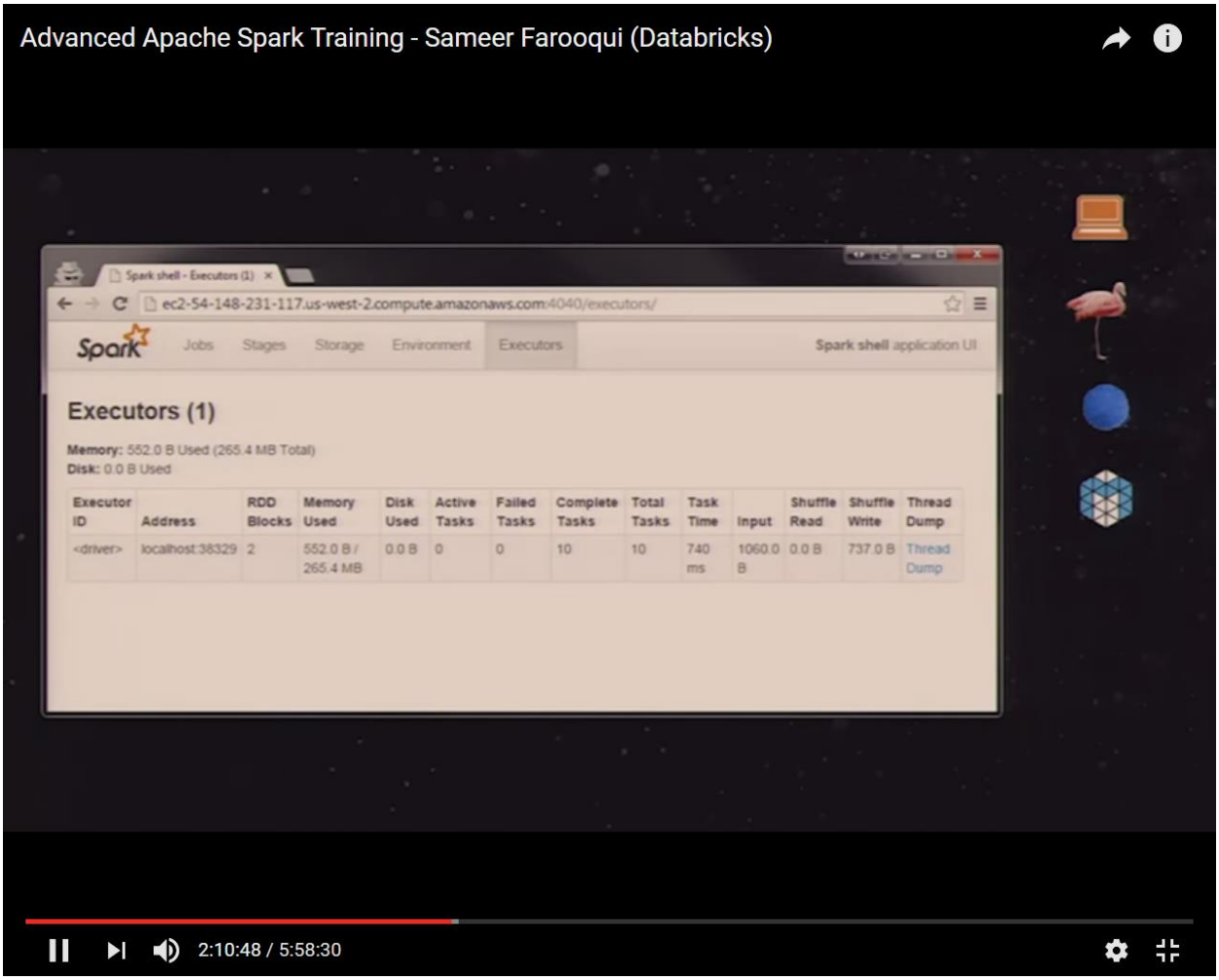
Environment



Setting – Default >> configuration file >>at the time of submit job >> in the spark source code

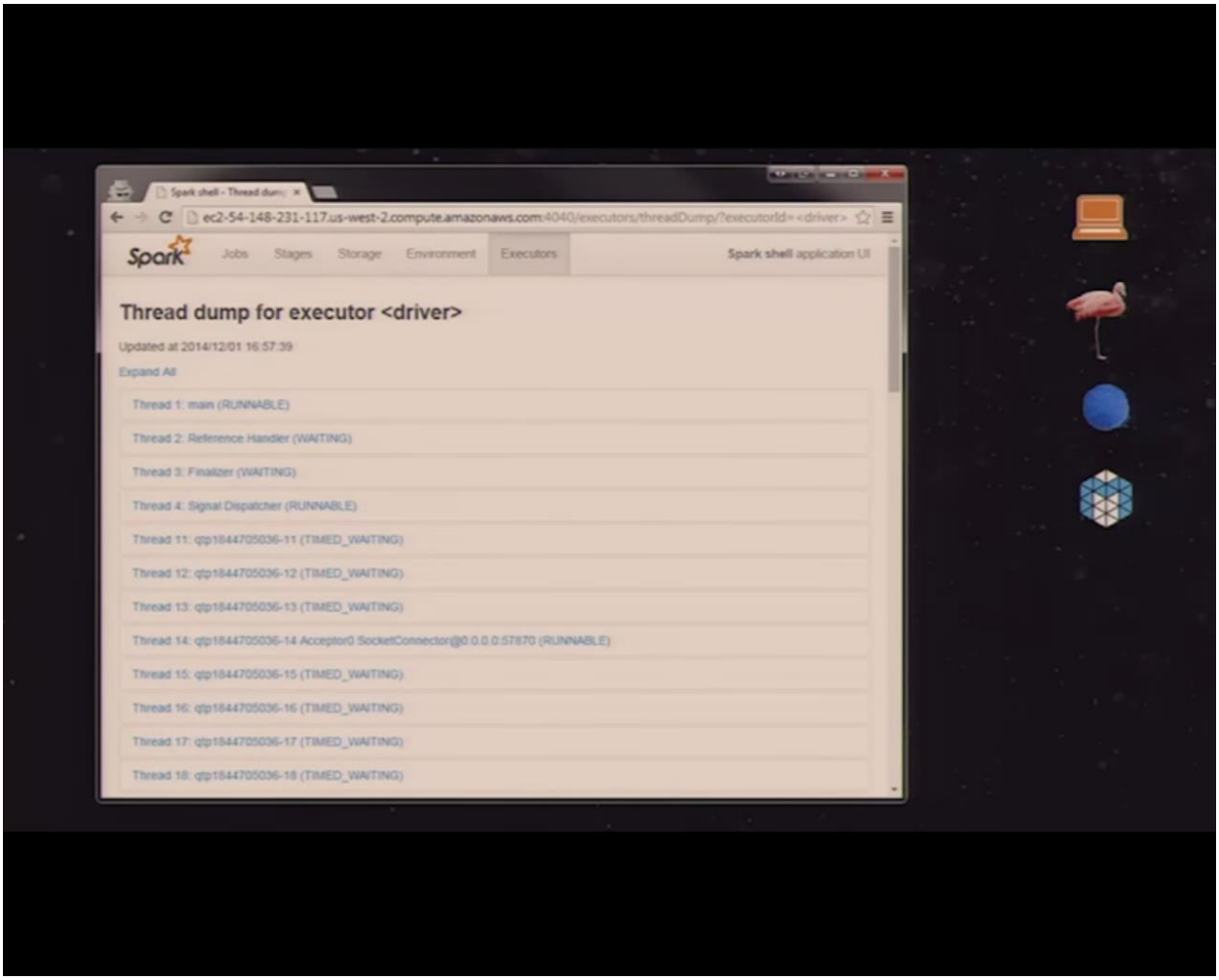
Highest precedence will override the settings of lower.

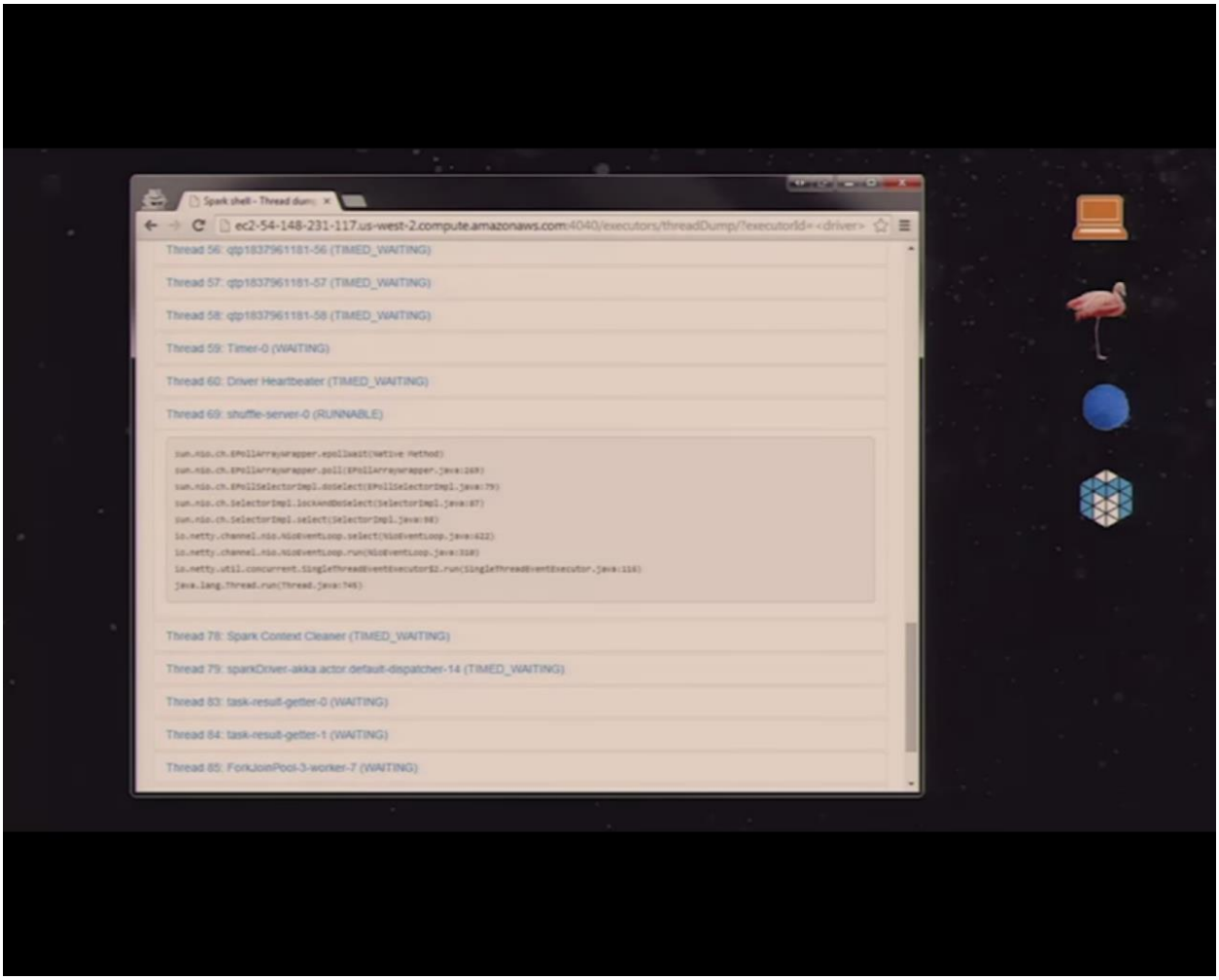
Executor tab



Thread Dump

We can collect stack thread from this tab

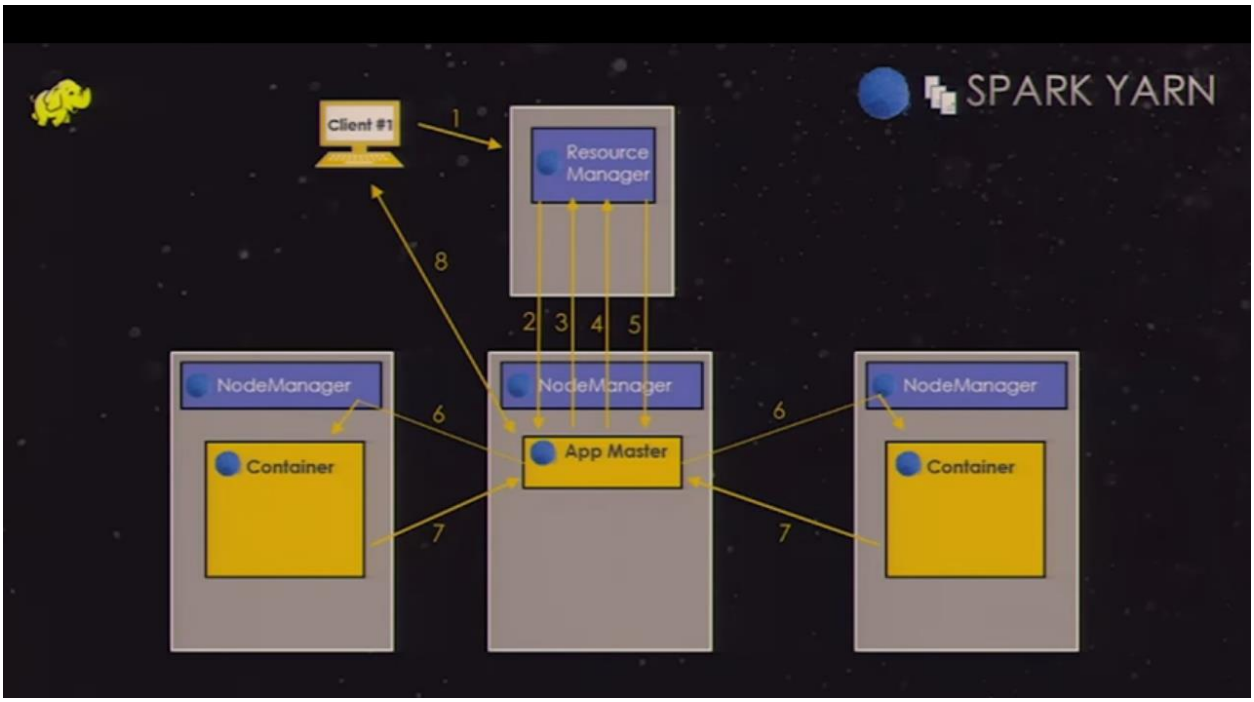



Spark shell - Thread dump
ec2-54-148-231-117.us-west-2.compute.amazonaws.com:4040/executors/threadDump/?executorId=<driver>
Thread 56: qtp1837961181-56 (TIMED_WAITING)
Thread 57: qtp1837961181-57 (TIMED_WAITING)
Thread 58: qtp1837961181-58 (TIMED_WAITING)
Thread 59: Timer-0 (WAITING)
Thread 60: Driver Heartbeater (TIMED_WAITING)
Thread 69: shuffle-server-0 (RUNNABLE)
sun.nio.ch.EPollArrayWrapper.epollWait(Native Method)
sun.nio.ch.EPollArrayWrapper.poll(EPollArrayWrapper.java:269)
sun.nio.ch.EPollSelectorImpl.doSelect(EPollSelectorImpl.java:79)
sun.nio.ch.SelectorImpl.lockAndDoSelect(SelectorImpl.java:87)
sun.nio.ch.SelectorImpl.select(SelectorImpl.java:98)
io.netty.channel.nio.NioEventLoop.select(NioEventLoop.java:622)
io.netty.channel.nio.NioEventLoop.run(NioEventLoop.java:310)
io.netty.util.concurrent.SingleThreadEventExecutor$2.run(SingleThreadEventExecutor.java:116)
java.lang.Thread.run(Thread.java:745)
Thread 78: Spark Context Cleaner (TIMED_WAITING)
Thread 79: sparkDriver-akka.actor.default-dispatcher-14 (TIMED_WAITING)
Thread 83: task-result-getter-0 (WAITING)
Thread 84: task-result-getter-1 (WAITING)
Thread 85: ForkJoinPool-3-worker-7 (WAITING)

YARN Mode

App Master is not going to do any of the work for your application it is like a job scheduler, App master communicate to the resource manager and ask for Container to schedule application, resource manager than hand over application master some keys and tokens to start the container

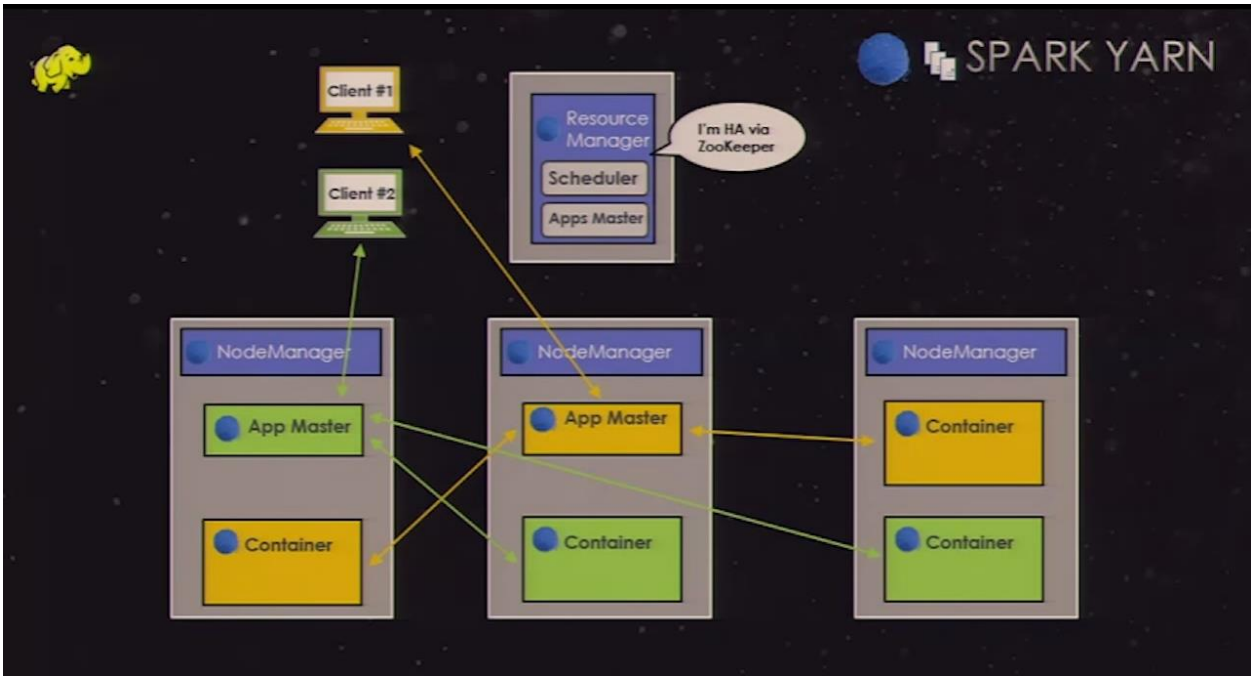
Example – one application running



Once App master get the control Resource manager work is over and App master directly communicate with client

Example – two different applications are running

Green and yellow and each App master has two containers doing the work for him



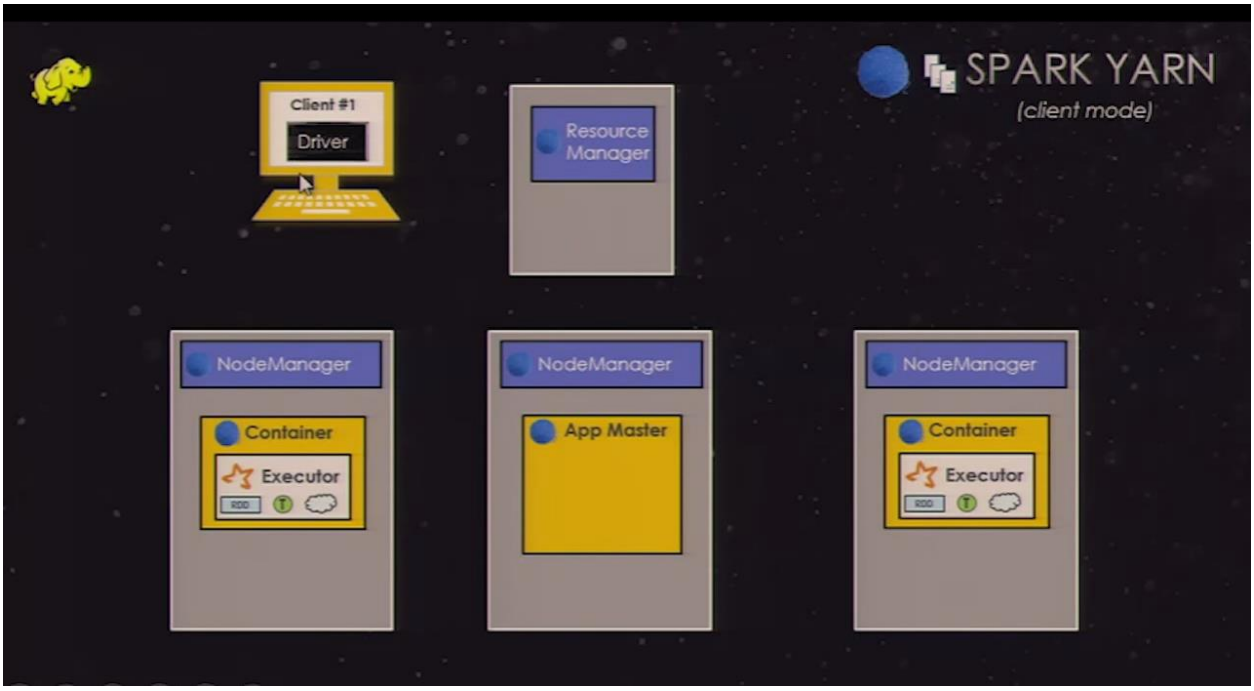
Resource manager has scheduler that decides where the App master will run and where these containers will schedule and has one Applications master

YARN –Client Mode

In client mode driver runs on the client machine, it's like you start scala and python shell on your laptop

So if you use collect method, the array shipped to client machine and you can see on your machine

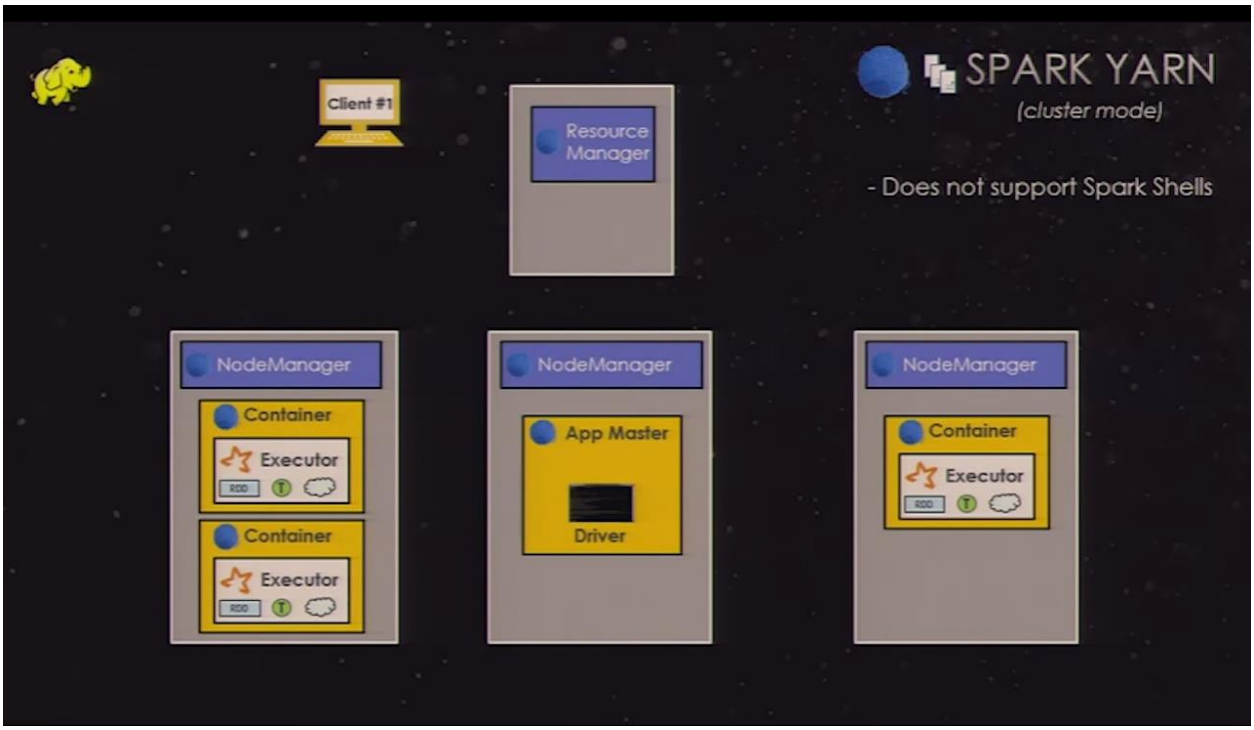
So two executors can direct contact with driver (same as standalone mode there we have workers and in yarn we have node manager), Resource manager is doing same what the spark-master is doing in standalone mode, RM is scheduling where the executor will run, however there is one more scheduler inside Driver that decide where the tasks will be scheduled within the executors



The problem is with this mode what if we remove our laptop from the cluster and left that would terminate the entire application because driver is disconnect with executors, remember Driver is available on our laptop in Client mode

YARN –Cluster Mode

In this mode client submit the application including the driver which might be like jar file or python script and then driver will run within the yarn application master itself. In this case we can't run spark shell so we can't use method like collect but we can save the result to HDFS



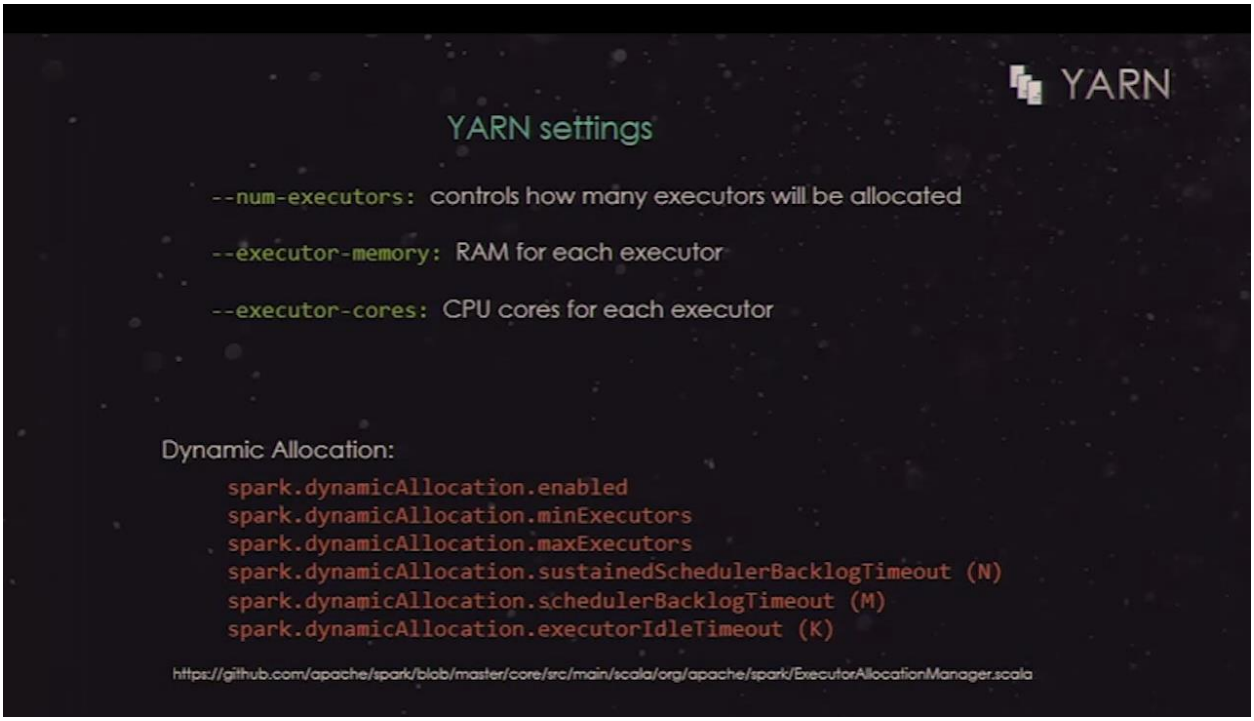
spark.dynamicAllocation.enabled – true / false
spark.dynamicAllocation.minExecutors - Lower bound on the number of executors (10)
spark.dynamicAllocation.maxExecutors - Upper bound on the number of executors (100)
spark.dynamicAllocation.sustainedSchedulerBacklogTimeout = 60
spark.dynamicAllocation.schedulerBacklogTimeout (M)
spark.dynamicAllocation.executorIdleTimeout (K)
spark.dynamicAllocation.initialExecutors - Number of executors to start with

If dynamic allocation is enabled so it start with 10 executors and after 60 sec (sustainedSchedulerBacklogTimeout) ,check if there is backlog for whole bunch of task built up in the driver which are not being scheduled yet than increase the number of executors little bit like 10 to 20.If schedulerBacklogTimeout hit may be 30 sec , again check backlogged tasks, if tasks are still pending increase number of executors exponentially and keep checking every 30 sec. after hit max we might need to release resources so check if any executor idle for executorIdleTimeout remove it and keep terminating until it come to minExecutors

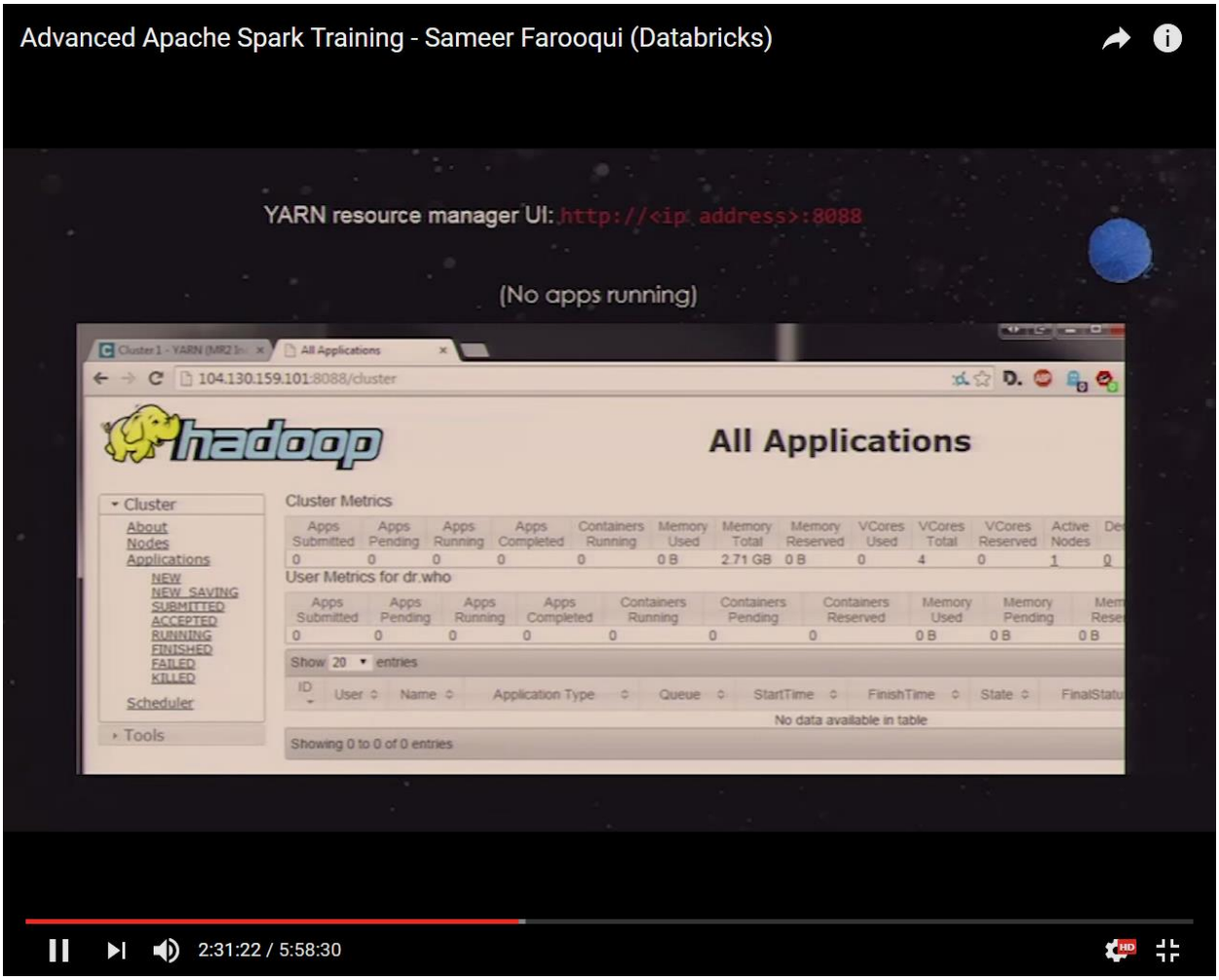
spark.dynamicAllocation.sustainedSchedulerBacklogTimeout (N) - If the backlog is sustained for this duration, add more executors, this is used only after the initial backlog timeout is exceeded

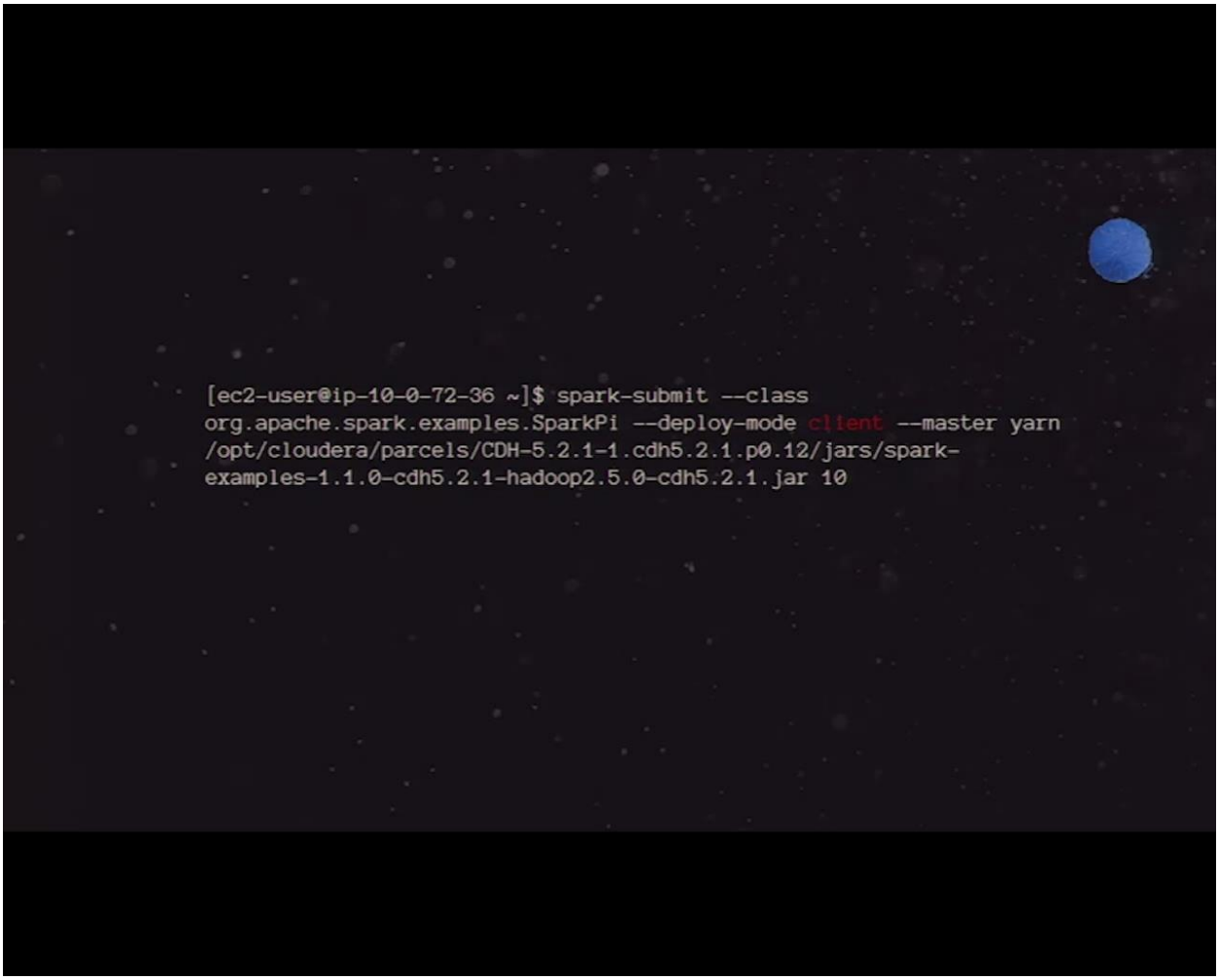
spark.dynamicAllocation.schedulerBacklogTimeout (M) - If there are backlogged tasks for this duration, add new executors

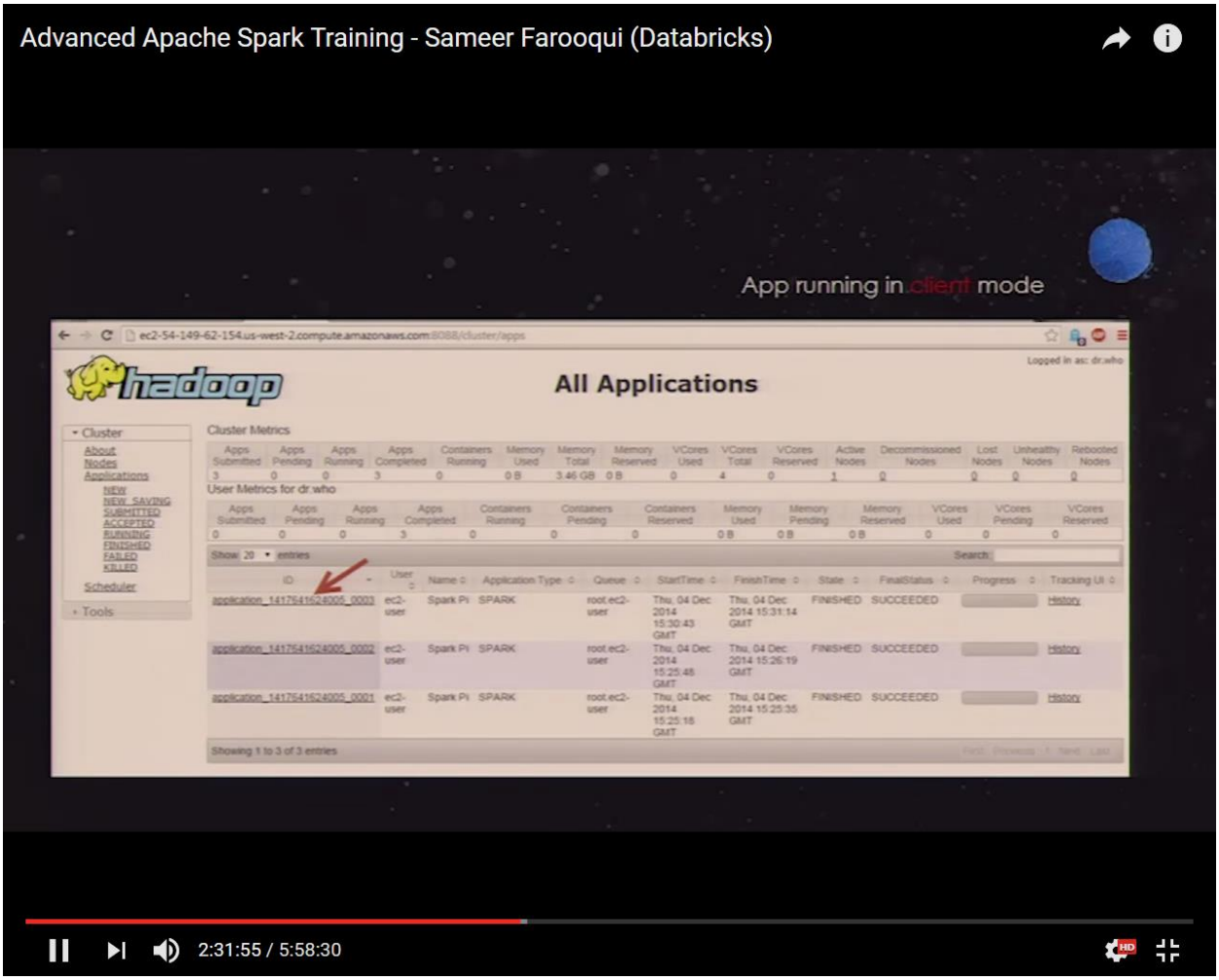
spark.dynamicAllocation.executorIdleTimeout (K) - If an executor has been idle for this duration, remove it



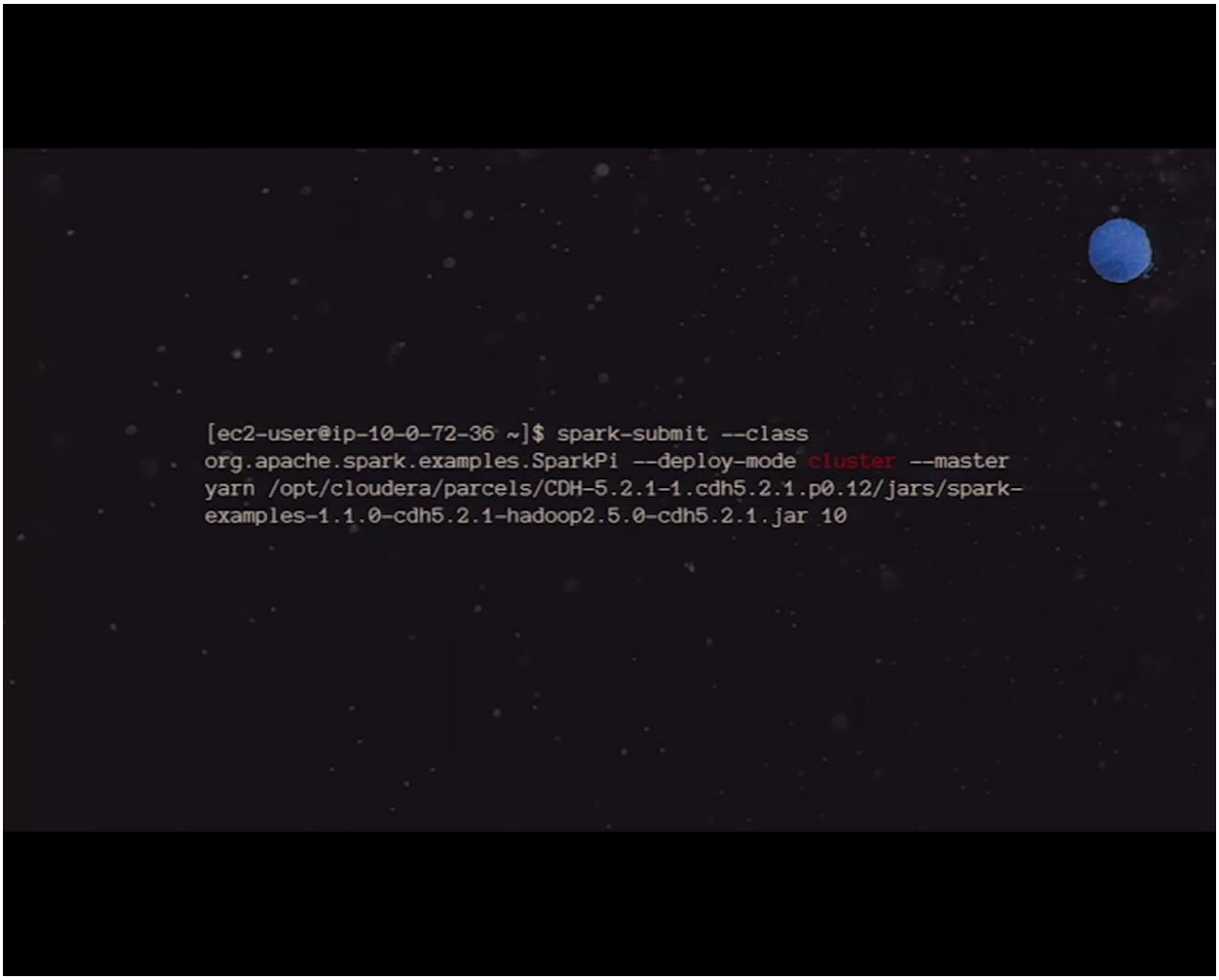
YARN Resource Manager UI

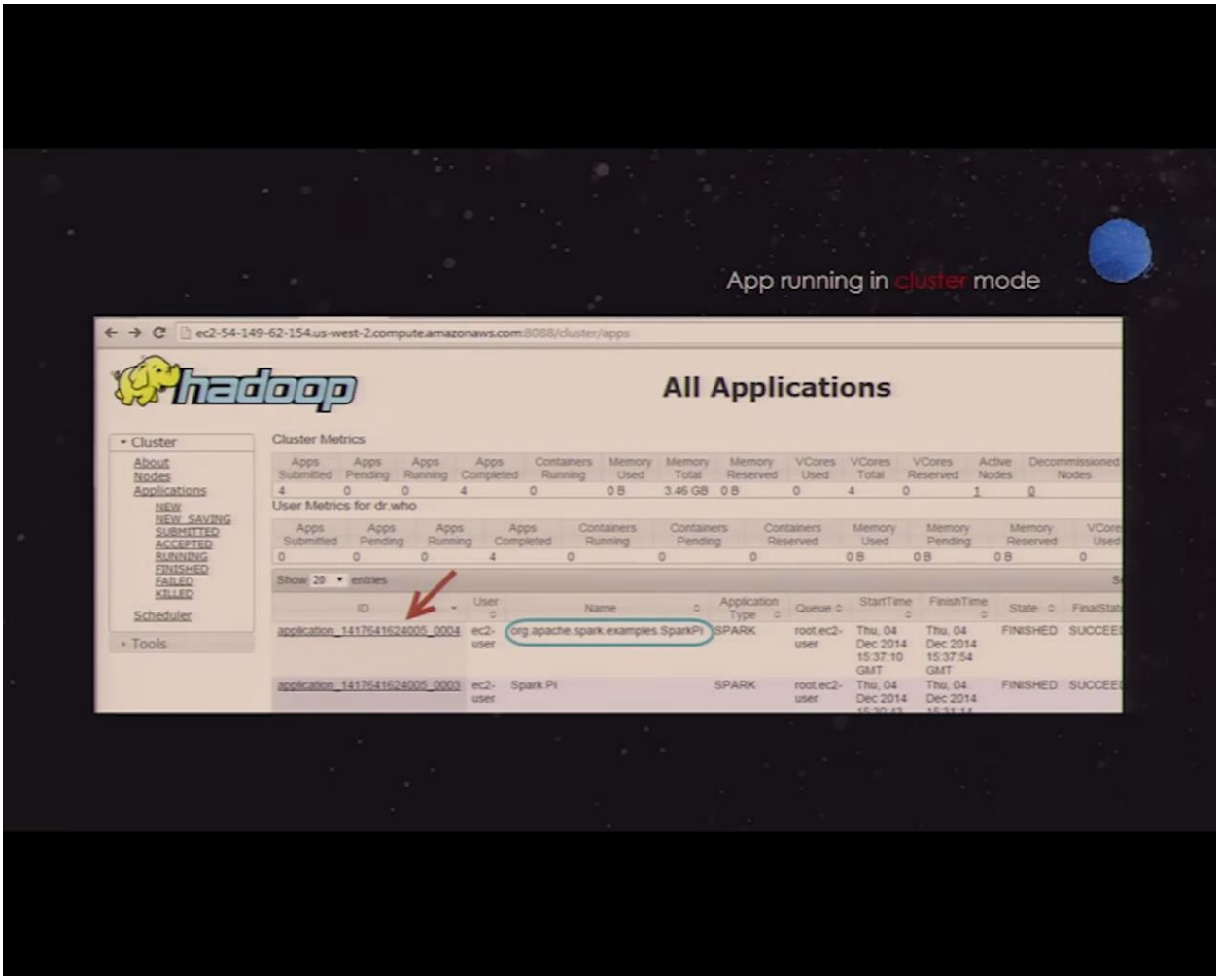


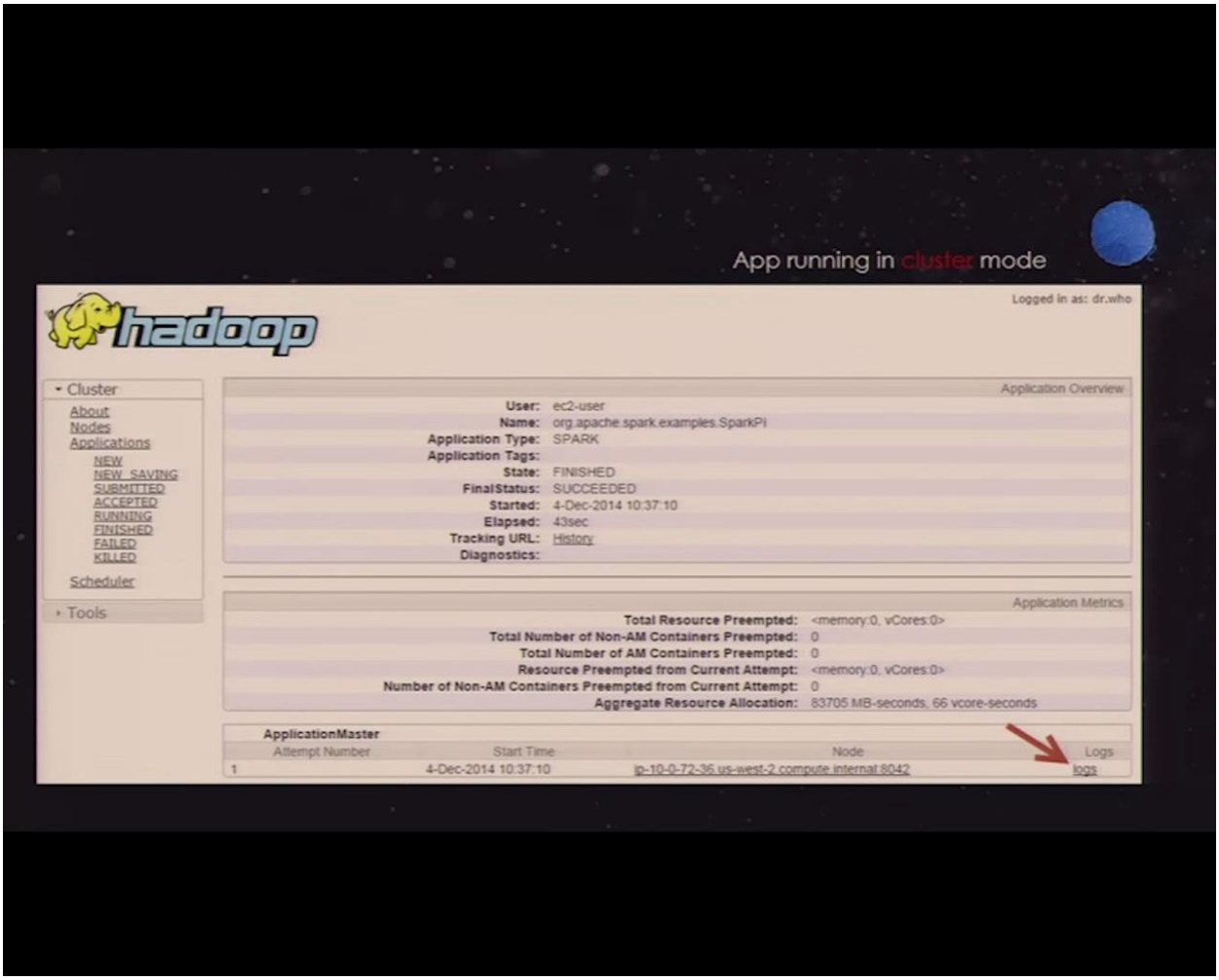

[ec2-user@ip-10-0-72-36 ~]$ spark-submit --class
org.apache.spark.examples.SparkPi --deploy-mode client --master yarn
/opt/cloudera/parcels/CDH-5.2.1-1.cdh5.2.1.p0.12/jars/spark-
examples-1.1.0-cdh5.2.1-hadoop2.5.0-cdh5.2.1.jar 10

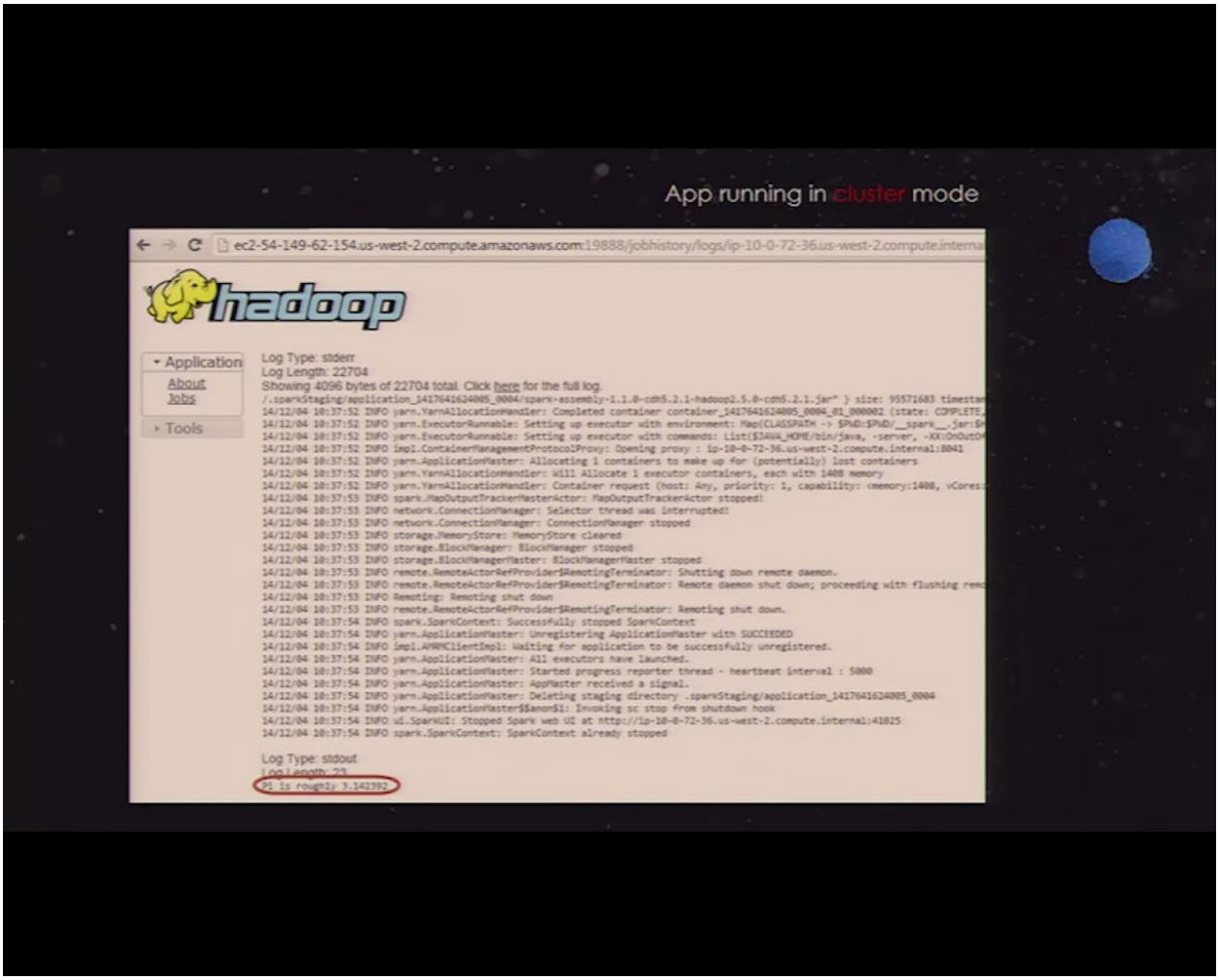

Advanced Apache Spark Training - Sameer Farooqui (Databricks)
App running in client mode
All Applications
2:31:55 / 5:58:30


ec2-54-149-62-154.us-west-2.compute.amazonaws.com:8088/cluster/app/application_1417641624005_0003
Logged in as: dr.who
hadoop
Cluster
About
Nodes
Applications
NEW
NEW_SAVING
SUBMITTED
ACCEPTED
RUNNING
FINISHED
FAILED
KILLED
Scheduler
Tools
Application Overview
User: ec2-user
Name: Spark Pi
Application Type: SPARK
Application Tags:
State: FINISHED
FinalStatus: SUCCEEDED
Started: 4-Dec-2014 10:30:43
Elapsed: 31sec
Tracking URL: History
Diagnostics:
Application Metrics
Total Resource Preempted: <memory:0, vCores:0>
Total Number of Non-AM Containers Preempted: 0
Total Number of AM Containers Preempted: 0
Resource Preempted from Current Attempt: <memory:0, vCores:0>
Number of Non-AM Containers Preempted from Current Attempt: 0
Aggregate Resource Allocation: 57388 MB-seconds, 45 vcore-seconds
ApplicationMaster
Attempt Number
Start Time
Node
Logs
1
4-Dec-2014 10:30:43
ip-10-0-72-36.us-west-2.compute.internal:8042
logs

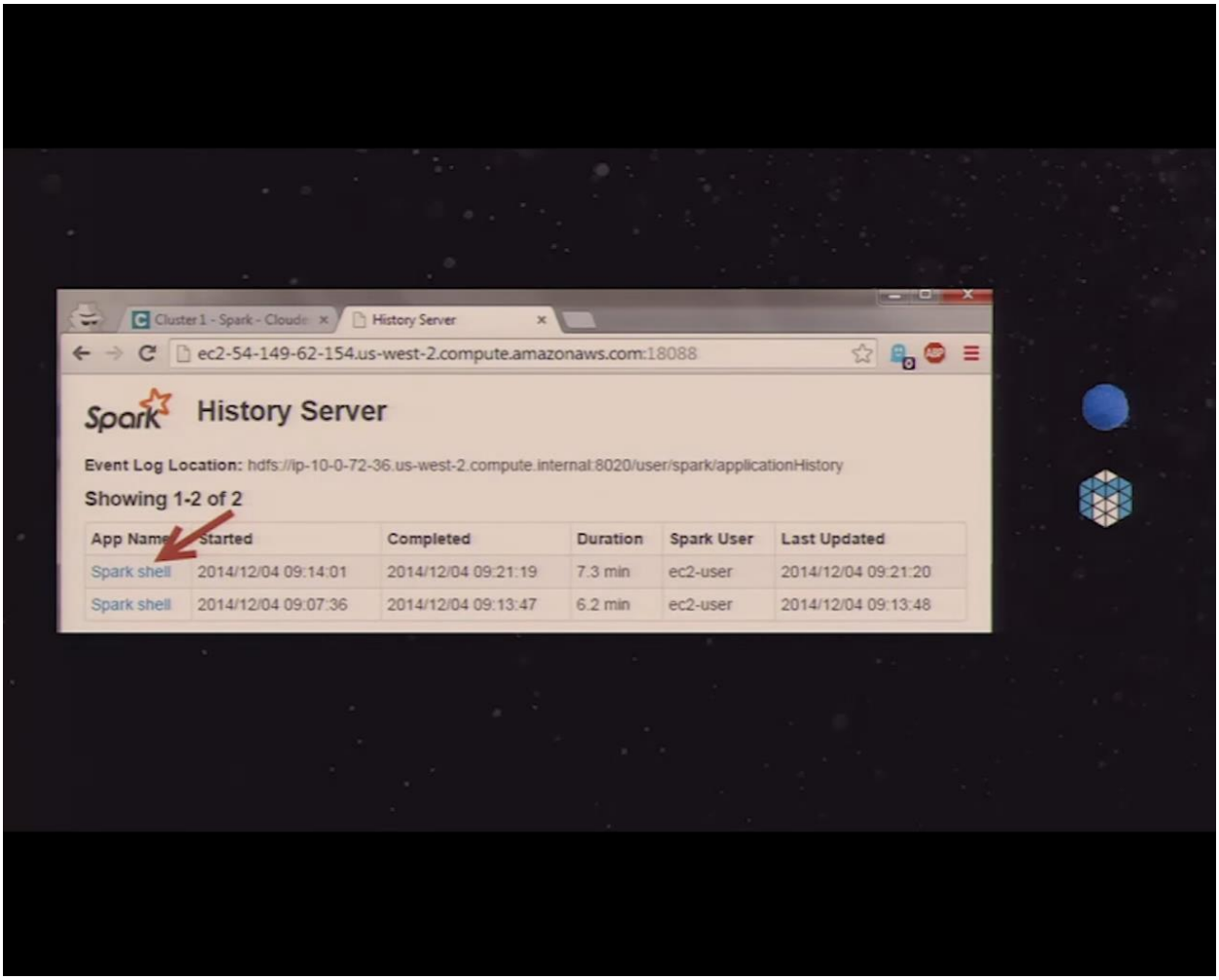

[ec2-user@ip-10-0-72-36 ~]$ spark-submit --class
org.apache.spark.examples.SparkPi --deploy-mode cluster --master
yarn /opt/cloudera/parcels/CDH-5.2.1-1.cdh5.2.1.p0.12/jars/spark-
examples-1.1.0-cdh5.2.1-hadoop2.5.0-cdh5.2.1.jar 10


App running in cluster mode
ec2-54-149-62-154.us-west-2.compute.amazonaws.com:8088/cluster/apps
hadoop
All Applications
Cluster
About
Nodes
Applications
NEW
NEW_SAVING
SUBMITTED
ACCEPTED
RUNNING
FINISHED
FAILED
KILLED
Scheduler
Tools
Cluster Metrics
Apps Submitted
Apps Pending
Apps Running
Apps Completed
Containers Running
Memory Used
Memory Total
Memory Reserved
VCores Used
VCores Total
VCores Reserved
Active Nodes
Decommissioned Nodes
4
0
0
4
0
0 B
3.46 GB
0 B
0
4
0
1
0
User Metrics for dr.who
Apps Submitted
Apps Pending
Apps Running
Apps Completed
Containers Running
Containers Pending
Containers Reserved
Memory Used
Memory Pending
Memory Reserved
VCore Used
0
0
0
4
0
0
0
0 B
0 B
0 B
0
Show 20 entries
ID
User
Name
Application Type
Queue
StartTime
FinishTime
State
FinalStat
application_1417641624005_0004
ec2-user
org.apache.spark.examples.SparkPi
SPARK
root.ec2-user
Thu, 04 Dec 2014 15:37:10 GMT
Thu, 04 Dec 2014 15:37:54 GMT
FINISHED
SUCCEE
application_1417641624005_0003
ec2-user
Spark Pi
SPARK
root.ec2-user
Thu, 04 Dec 2014
Thu, 04 Dec 2014
FINISHED
SUCCEE

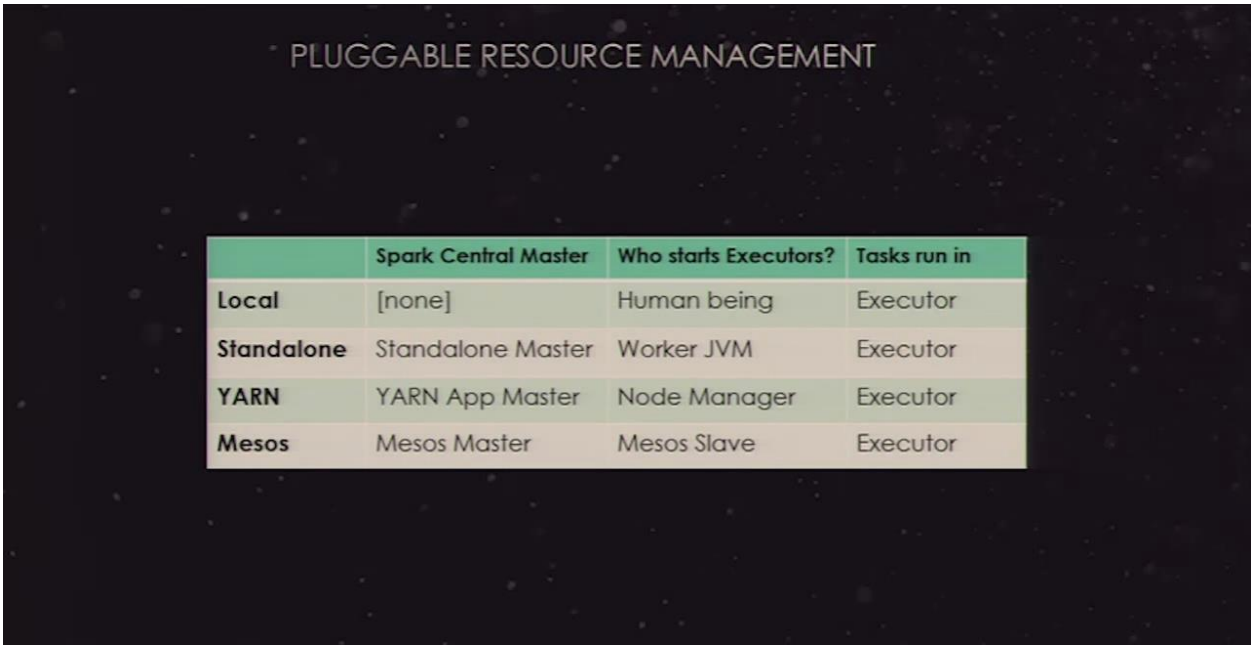

App running in cluster mode
hadoop
Logged in as: dr.who
Cluster
About
Nodes
Applications
NEW
NEW_SAVING
SUBMITTED
ACCEPTED
RUNNING
FINISHED
FAILED
KILLED
Scheduler
Tools
Application Overview
User: ec2-user
Name: org.apache.spark.examples.SparkPi
Application Type: SPARK
Application Tags:
State: FINISHED
FinalStatus: SUCCEEDED
Started: 4-Dec-2014 10:37:10
Elapsed: 43sec
Tracking URL: History
Diagnostics:
Application Metrics
Total Resource Preempted: <memory:0, vCores:0>
Total Number of Non-AM Containers Preempted: 0
Total Number of AM Containers Preempted: 0
Resource Preempted from Current Attempt: <memory:0, vCores:0>
Number of Non-AM Containers Preempted from Current Attempt: 0
Aggregate Resource Allocation: 83705 MB-seconds, 66 vcore-seconds
ApplicationMaster
Attempt Number
Start Time
Node
Logs
1
4-Dec-2014 10:37:10
ip-10-0-72-36.us-west-2.compute.internal:8042
logs

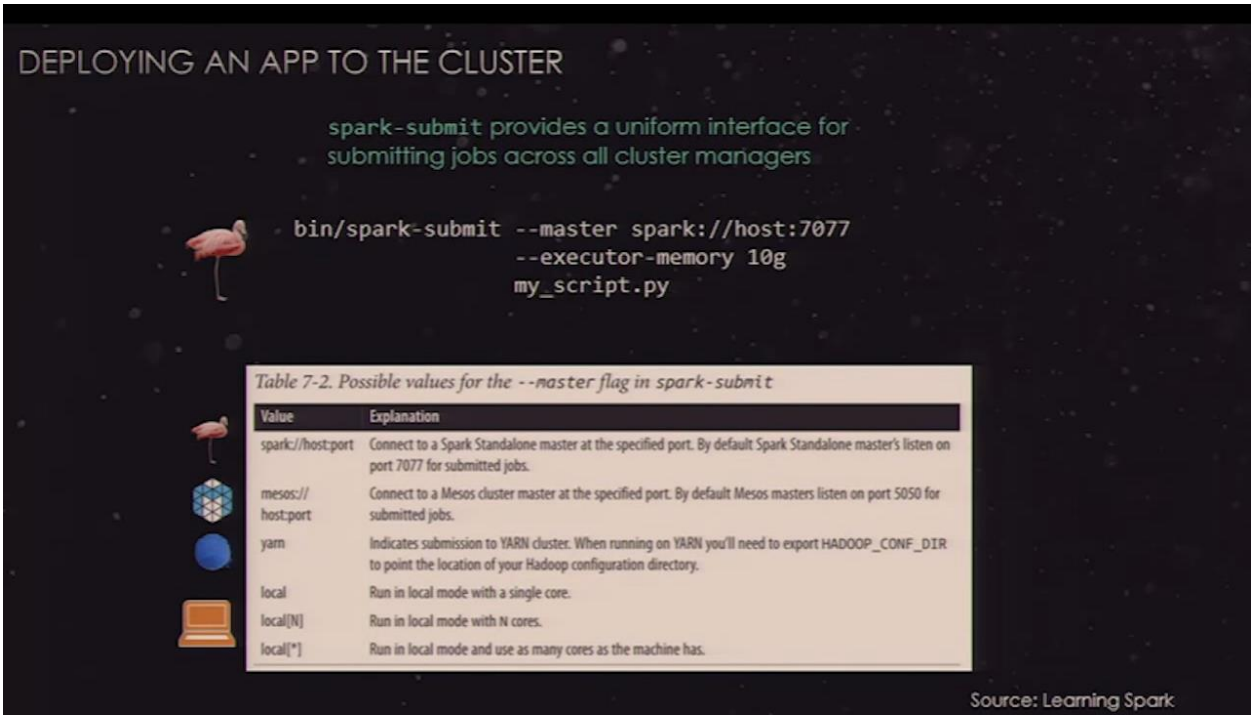

App running in cluster mode
ec2-54-149-62-154.us-west-2.compute.amazonaws.com:19888/jobhistory/logs/ip-10-0-72-36.us-west-2.compute.interna
hadoop
Application
About
Jobs
Tools
Log Type: stderr
Log Length: 22704
Showing 4096 bytes of 22704 total. Click here for the full log.
/.sparkStaging/application_1417641624005_0004/spark-assembly-1.1.0-cdh5.2.1-hadoop2.5.0-cdh5.2.1.jar" } size: 95571683 timestam
14/12/04 10:37:52 INFO yarn.YarnAllocationHandler: Completed container container_1417641624005_0004_01_000002 (state: COMPLETE,
14/12/04 10:37:52 INFO yarn.ExecutorRunnable: Setting up executor with environment: Map(CLASSPATH -> $PWD:$PWD/__spark__.jar:$
14/12/04 10:37:52 INFO yarn.ExecutorRunnable: Setting up executor with commands: List($JAVA_HOME/bin/java, -server, -XX:OnOutO
14/12/04 10:37:52 INFO impl.ContainerManagementProtocolProxy: Opening proxy : ip-10-0-72-36.us-west-2.compute.internal:8041
14/12/04 10:37:52 INFO yarn.ApplicationMaster: Allocating 1 containers to make up for (potentially) lost containers
14/12/04 10:37:52 INFO yarn.YarnAllocationHandler: Will Allocate 1 executor containers, each with 1408 memory
14/12/04 10:37:52 INFO yarn.YarnAllocationHandler: Container request (host: Any, priority: 1, capability: <memory:1408, vCores:
14/12/04 10:37:53 INFO spark.MapOutputTrackerMasterActor: MapOutputTrackerActor stopped!
14/12/04 10:37:53 INFO network.ConnectionManager: Selector thread was interrupted!
14/12/04 10:37:53 INFO network.ConnectionManager: ConnectionManager stopped
14/12/04 10:37:53 INFO storage.MemoryStore: MemoryStore cleared
14/12/04 10:37:53 INFO storage.BlockManager: BlockManager stopped
14/12/04 10:37:53 INFO storage.BlockManagerMaster: BlockManagerMaster stopped
14/12/04 10:37:53 INFO remote.RemoteActorRefProvider$RemotingTerminator: Shutting down remote daemon.
14/12/04 10:37:53 INFO remote.RemoteActorRefProvider$RemotingTerminator: Remote daemon shut down; proceeding with flushing rem
14/12/04 10:37:53 INFO Remoting: Remoting shut down
14/12/04 10:37:53 INFO remote.RemoteActorRefProvider$RemotingTerminator: Remoting shut down.
14/12/04 10:37:54 INFO spark.SparkContext: Successfully stopped SparkContext
14/12/04 10:37:54 INFO yarn.ApplicationMaster: Unregistering ApplicationMaster with SUCCEEDED
14/12/04 10:37:54 INFO impl.AMRMClientImpl: Waiting for application to be successfully unregistered.
14/12/04 10:37:54 INFO yarn.ApplicationMaster: All executors have launched.
14/12/04 10:37:54 INFO yarn.ApplicationMaster: Started progress reporter thread - heartbeat interval : 5000
14/12/04 10:37:54 INFO yarn.ApplicationMaster: AppMaster received a signal.
14/12/04 10:37:54 INFO yarn.ApplicationMaster: Deleting staging directory .sparkStaging/application_1417641624005_0004
14/12/04 10:37:54 INFO yarn.ApplicationMaster$$anon$1: Invoking sc stop from shutdown hook
14/12/04 10:37:54 INFO ui.SparkUI: Stopped Spark web UI at http://ip-10-0-72-36.us-west-2.compute.internal:41825
14/12/04 10:37:54 INFO spark.SparkContext: SparkContext already stopped
Log Type: stdout
Log Length: 23
Pi is roughly 3.142392

History server to keep track of your terminated jobs



Conclusion

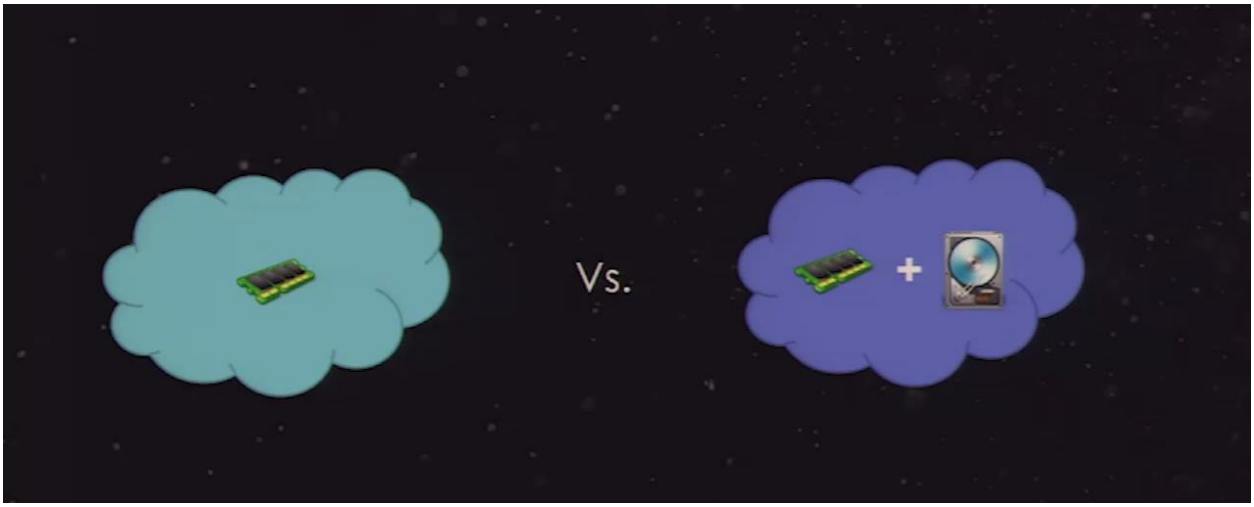




http://tinyurl.com/sparknycsurveyresults

Memory and persistence

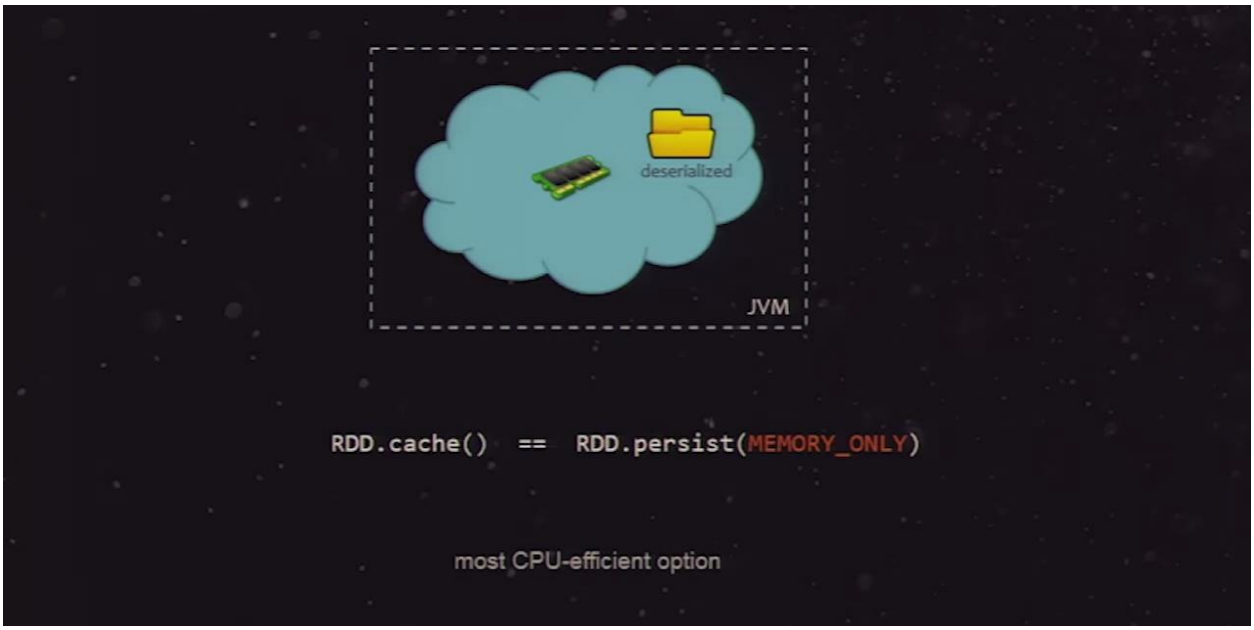
When we persist RDD in memory we can either persist memeory or memory+disk



cache() is just a shortcut of persist but when we do persist () we can pass lot more thing as argument

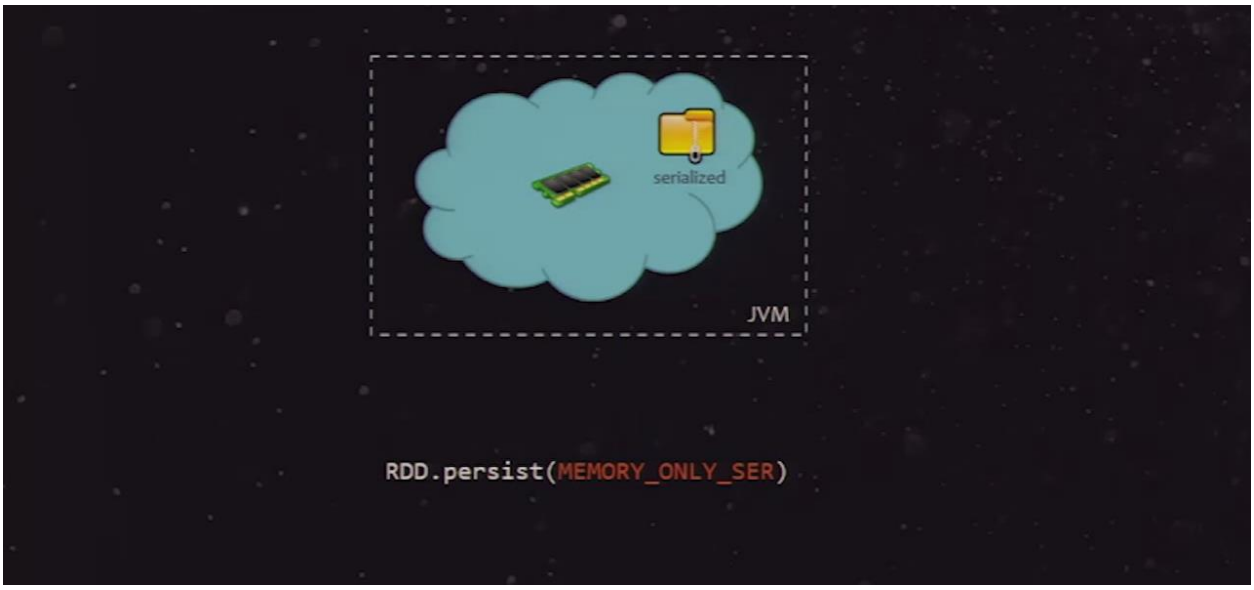
Memory Only

when we store RDD using cache or memory only it stores the RDD deserialized as java object inside the JVM, if certain partition of the RDD do not fit in memory then those partition will not be cached at all they are dropped not store on disk either and that RDD will be recomputed on the fly



Memory Only Serialized

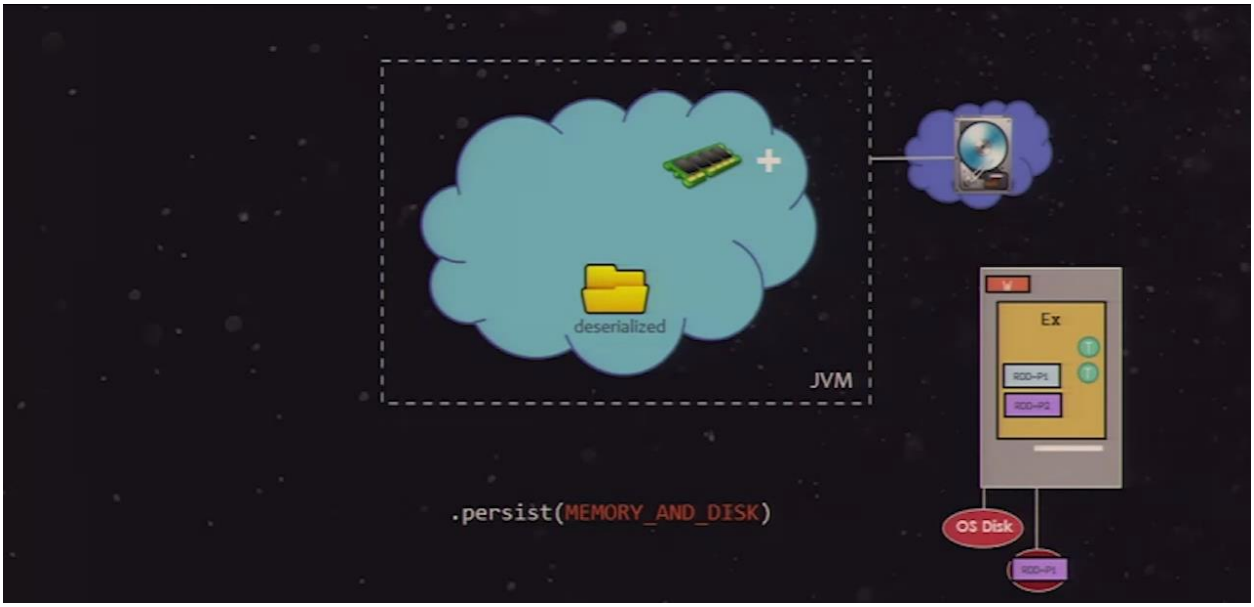
We can also persist RDD with memory only serialized , it creates serialized java object , one byte array per partition, this is generally more space efficient than memory only (de-serialized) RDD by default it uses java serialization process to store RDD in memory. But it is little bit slow because cost of serializing object. It reduced the cost of GC because many individual records can be stored as a single serialized buffer



Memory and Disk

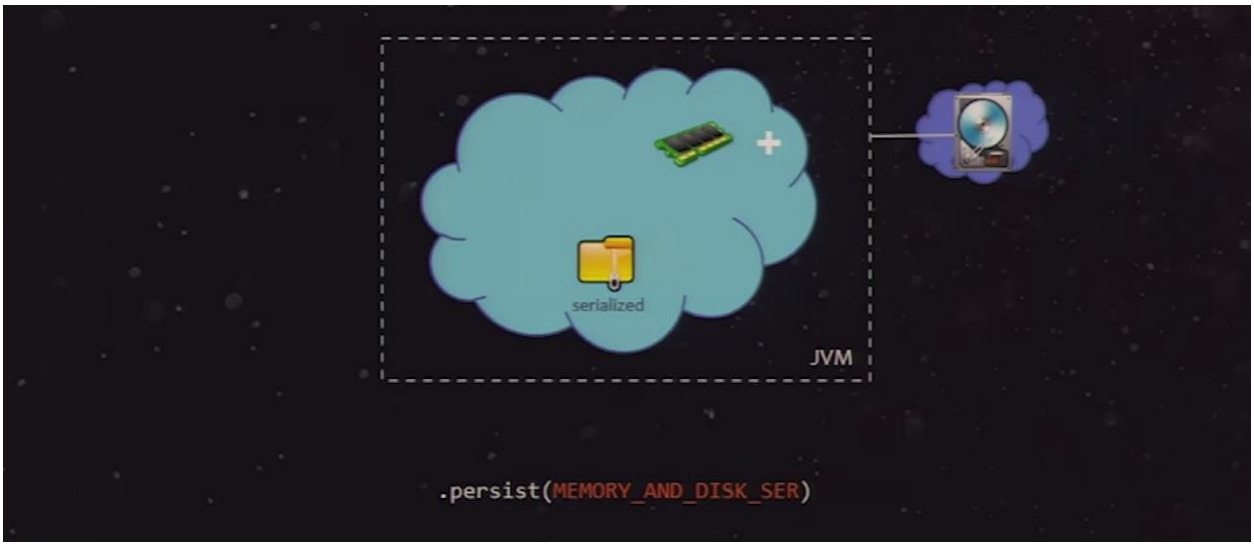
In this case its going to try store RDD in de-serialized form in the JVM memory and if the RDD partition don't fit in memory it stores it in disk in serialized form instead

When it goes down to disk it will always be serialized



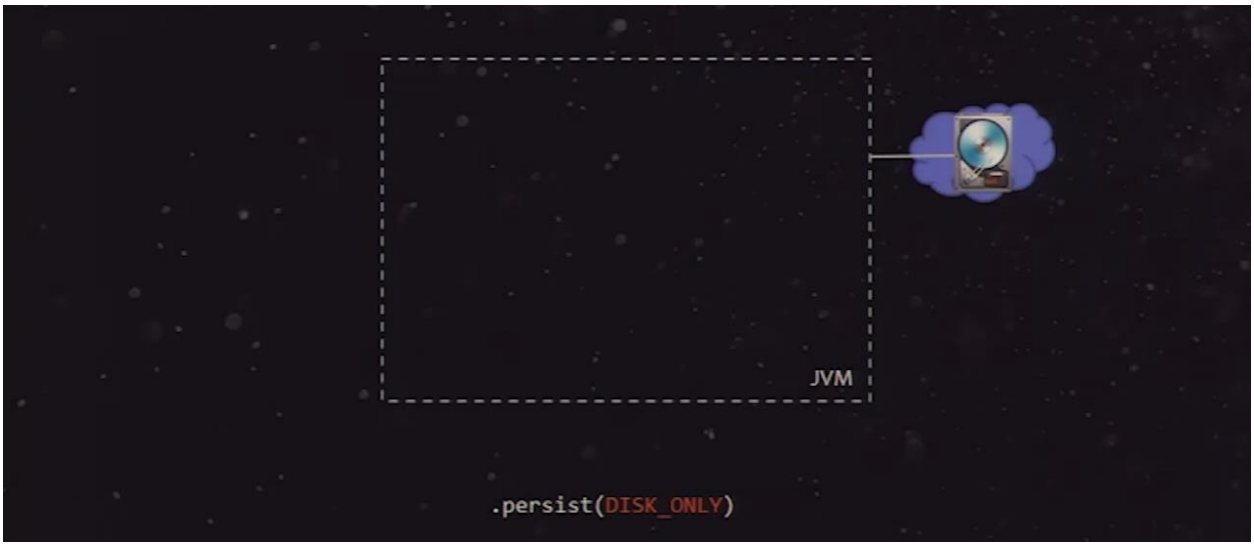
Memory and Disk Serialized

In this case RDD partition stores in serialization form on both memory and disk



Disk Only

RDD persist only on disk

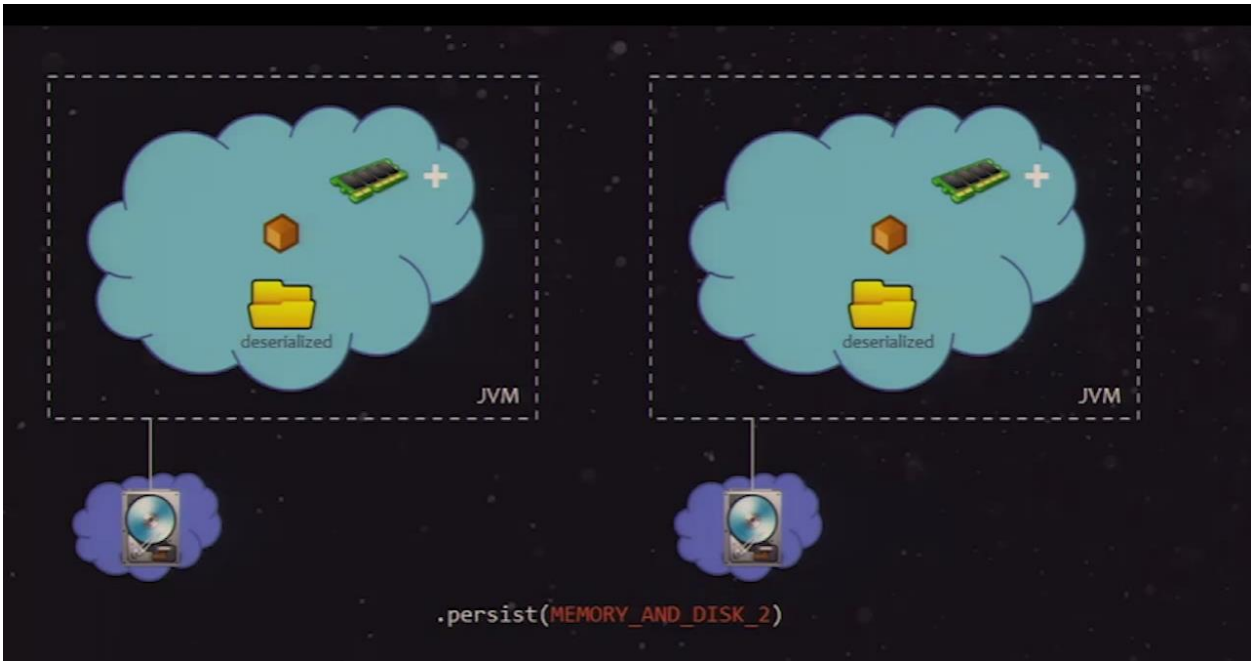


Memory only 2

This stores RDD partitions as de-serialized java objects in two different JVMS, you can use this if your RDD is extremely costly to recreate and if you lose one partition of RDD. In general don't use this

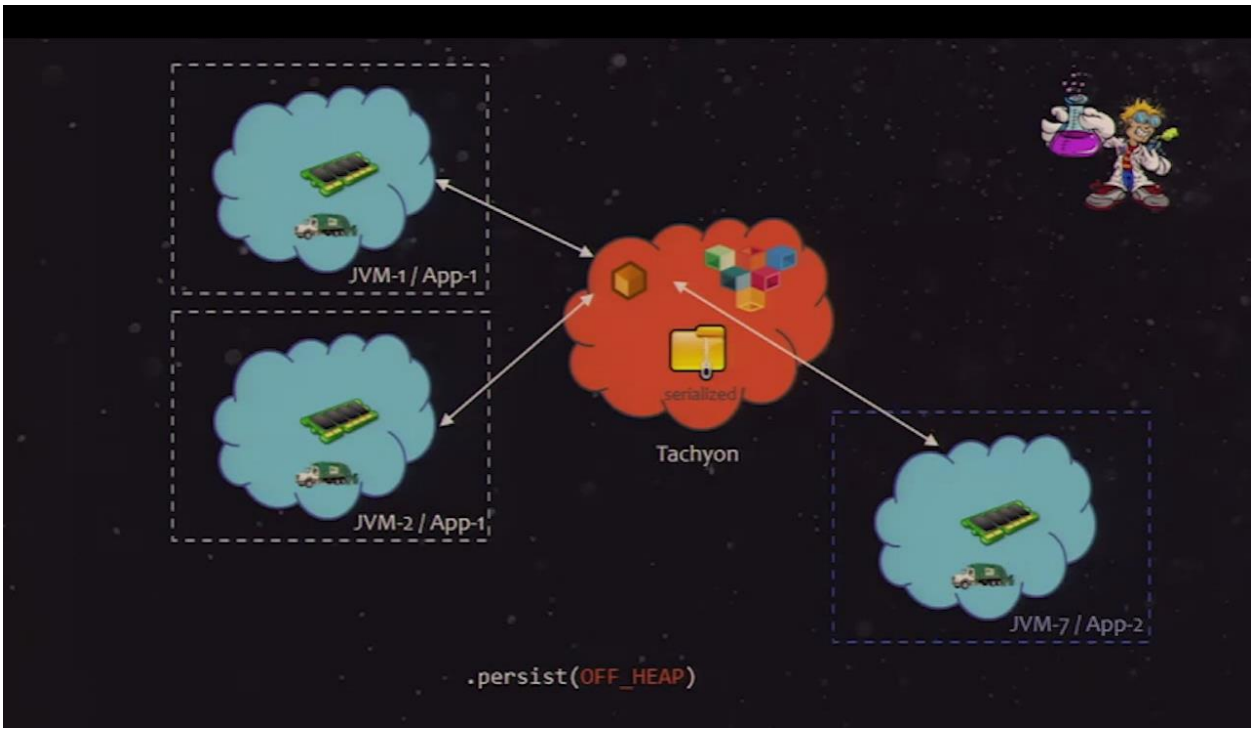
Memory and disk 2

In this Case it stored partition in both location



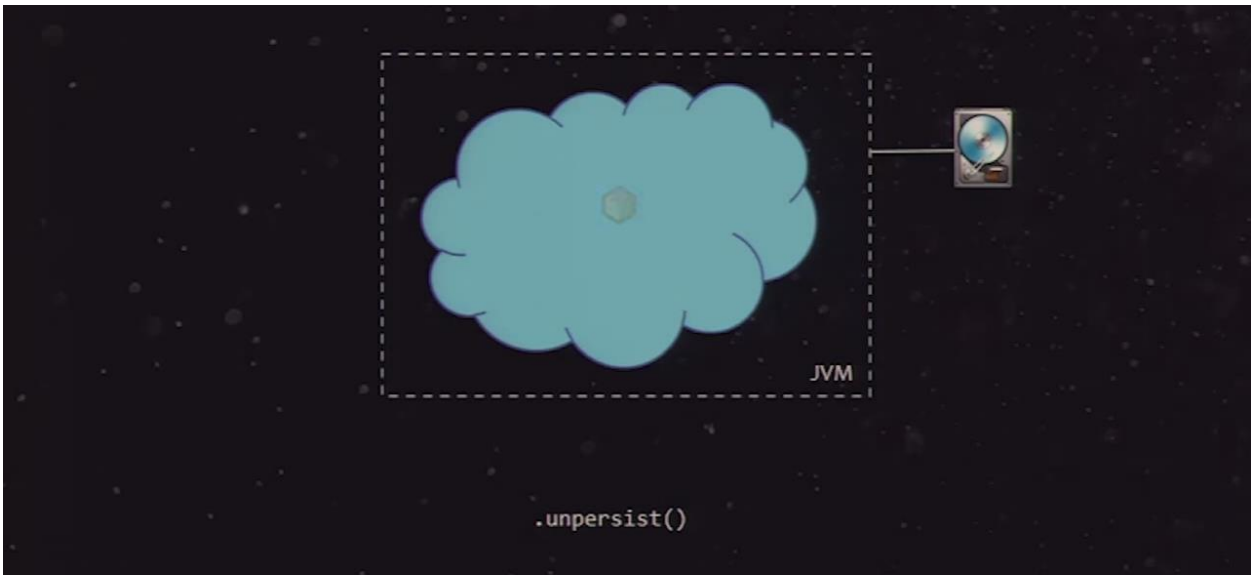
Off Heap

If you use OFF_HEAP, RDD will store in tachyon in serialized form, in this case RDD continue living in Tachyon even if executor JVM crashes

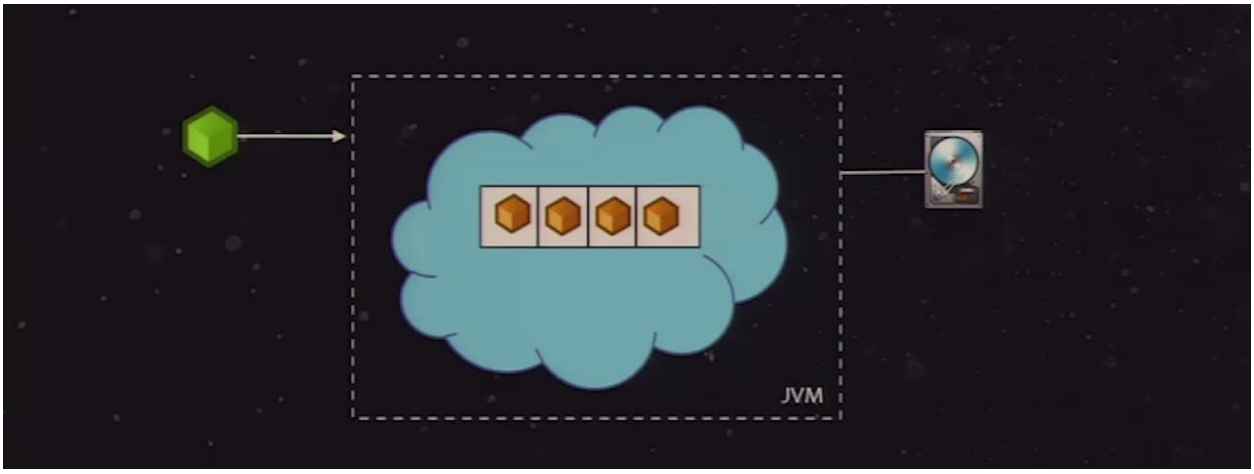


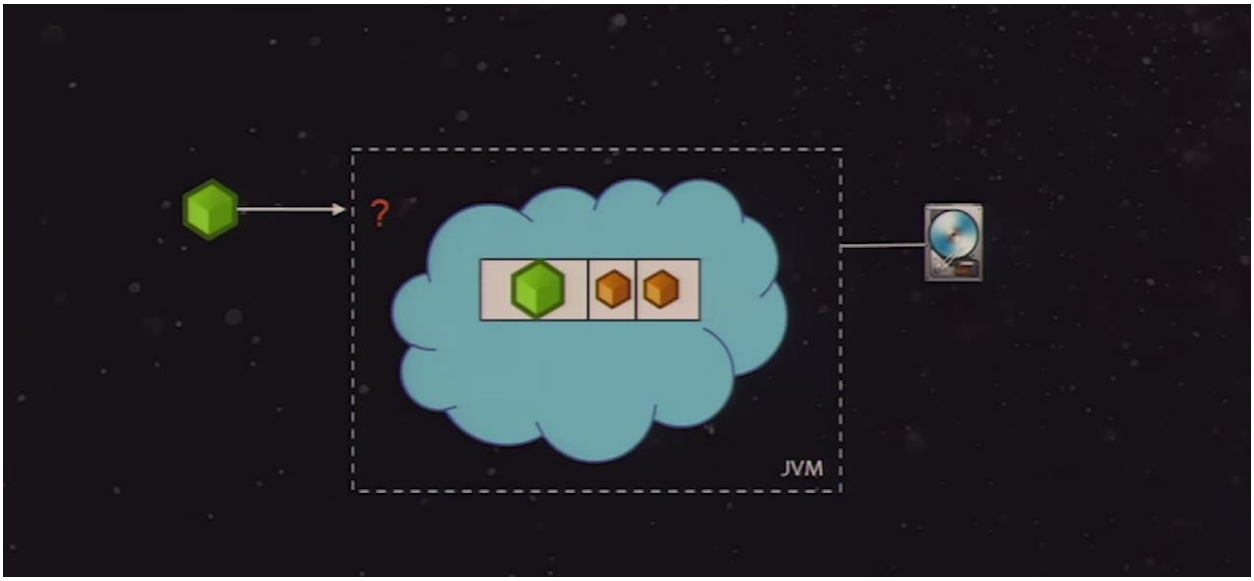
Unpersist

Remove forcefully out of memory



When executor JVM is full and you need to make room for a new partition then using least recently used (LRU) algo it removes some old partition and make room for new partition



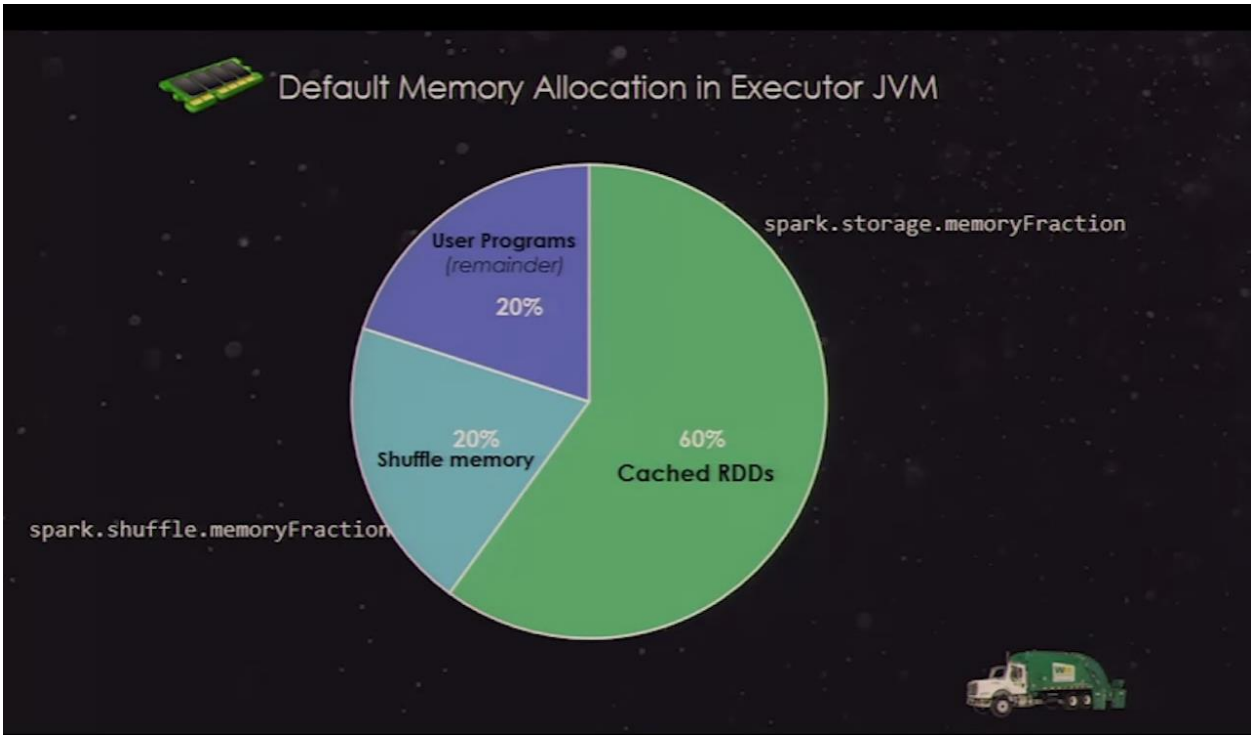


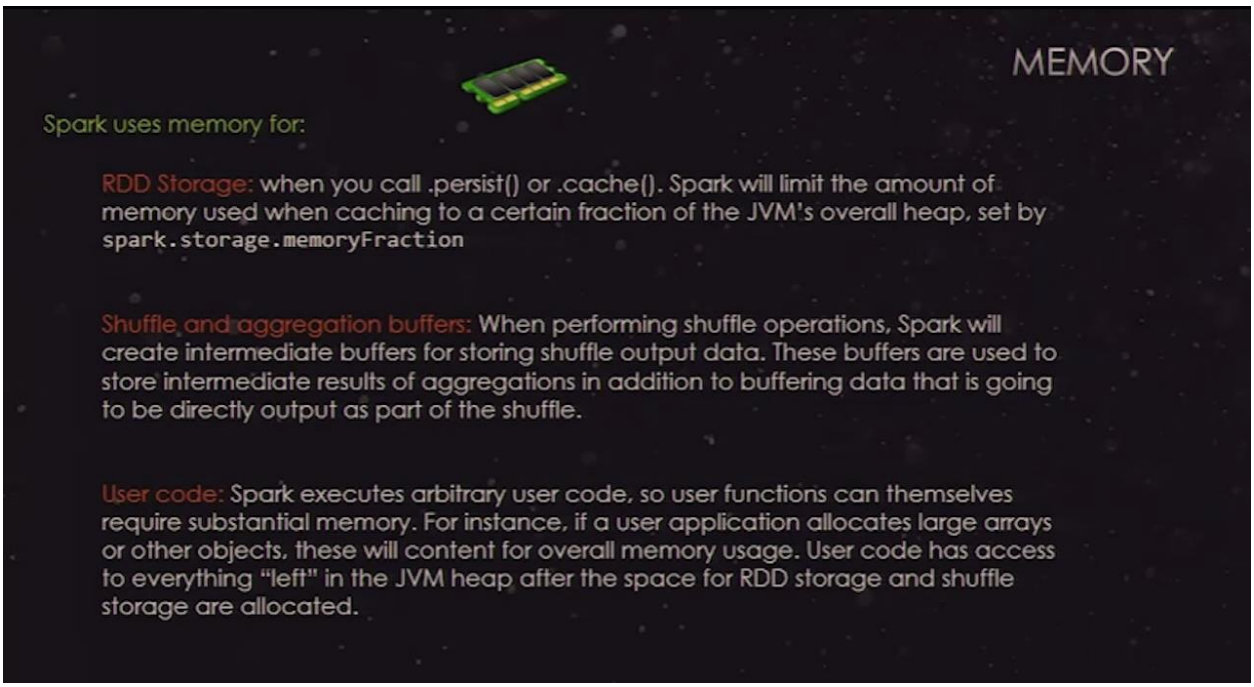
- If RDD fits in memory, choose MEMORY_ONLY
- If not, use MEMORY_ONLY_SER w/ fast serialization library
- Don't spill to disk unless functions that computed the datasets are very expensive or they filter a large amount of data. (recomputing may be as fast as reading from disk)
- Use replicated storage levels sparingly and only if you want fast fault recovery (maybe to serve requests from a web app)

Remember!

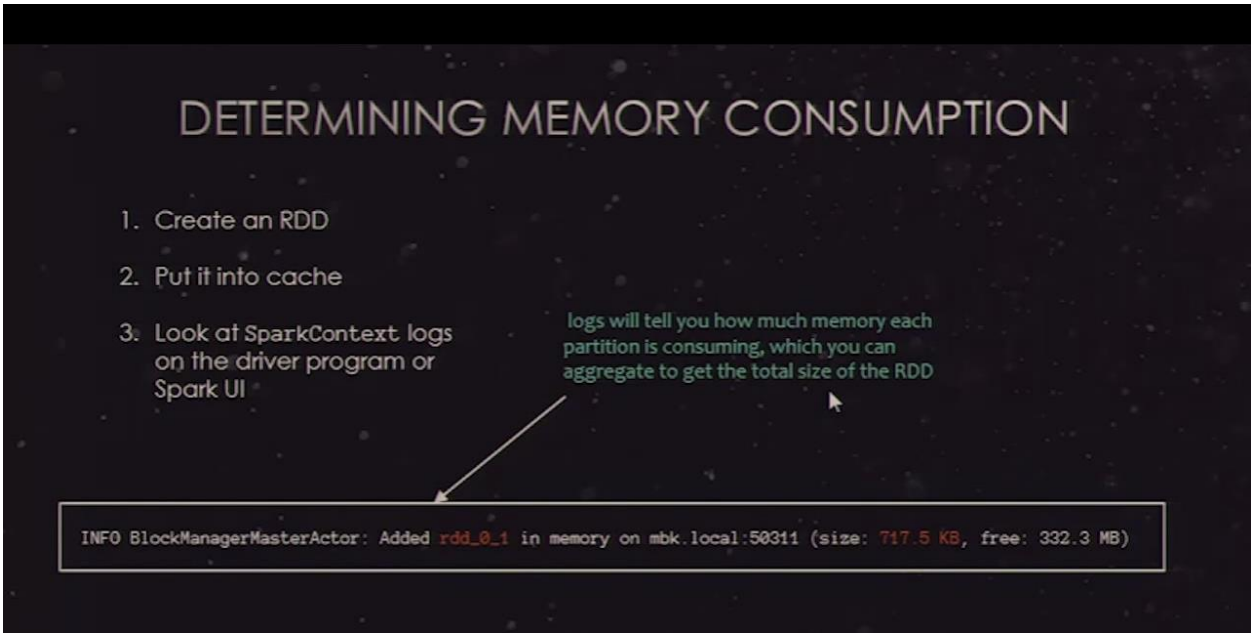
Intermediate data is automatically persisted during shuffle operations

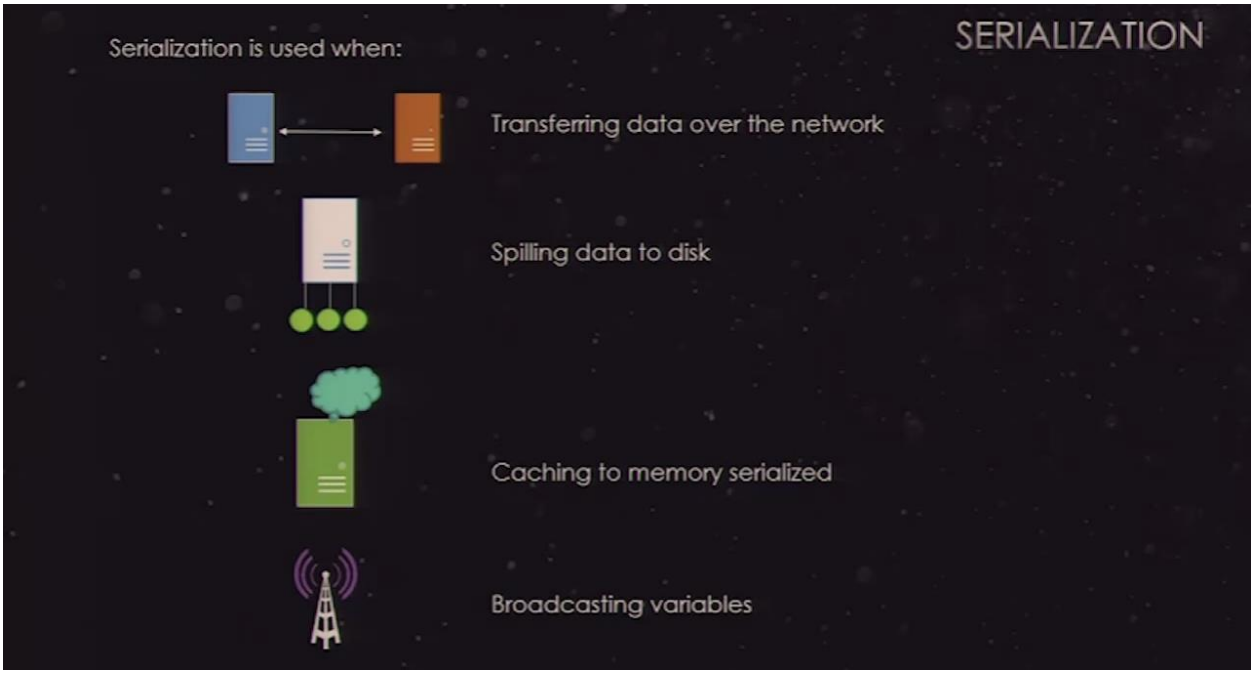
PySpark: stored objects will always be serialized with Pickle library, so it does not matter whether you choose a serialized level.


Default Memory Allocation in Executor JVM
User Programs
(remainder)
20%
spark.storage.memoryFraction
20%
Shuffle memory
60%
Cached RDDs
spark.shuffle.memoryFraction

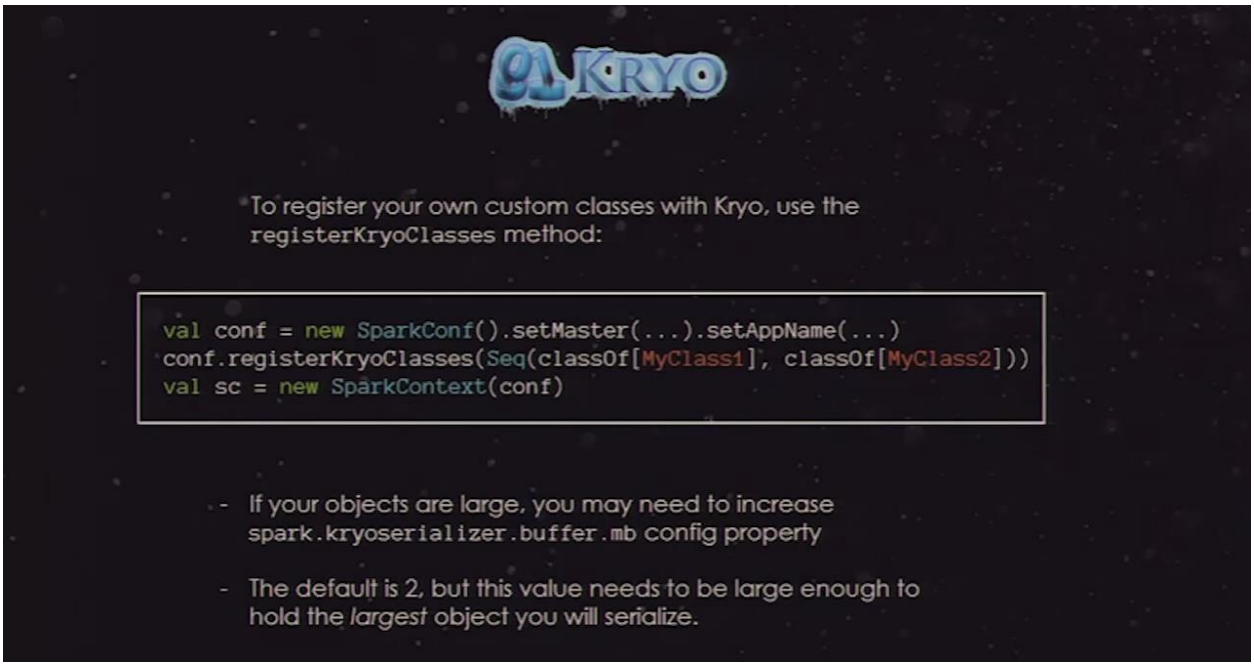

MEMORY
Spark uses memory for:
RDD Storage: when you call .persist() or .cache(). Spark will limit the amount of memory used when caching to a certain fraction of the JVM's overall heap, set by spark.storage.memoryFraction
Shuffle and aggregation buffers: When performing shuffle operations, Spark will create intermediate buffers for storing shuffle output data. These buffers are used to store intermediate results of aggregations in addition to buffering data that is going to be directly output as part of the shuffle.
User code: Spark executes arbitrary user code, so user functions can themselves require substantial memory. For instance, if a user application allocates large arrays or other objects, these will content for overall memory usage. User code has access to everything "left" in the JVM heap after the space for RDD storage and shuffle storage are allocated.

This says partition 1 of RDD 0 consumed 717 KB memory

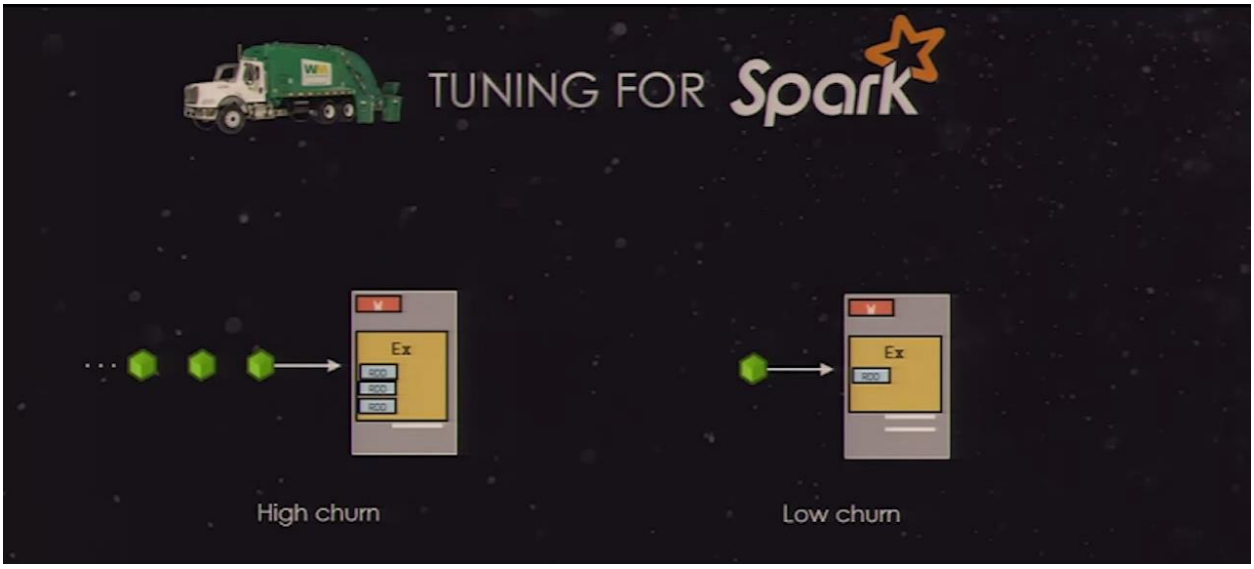


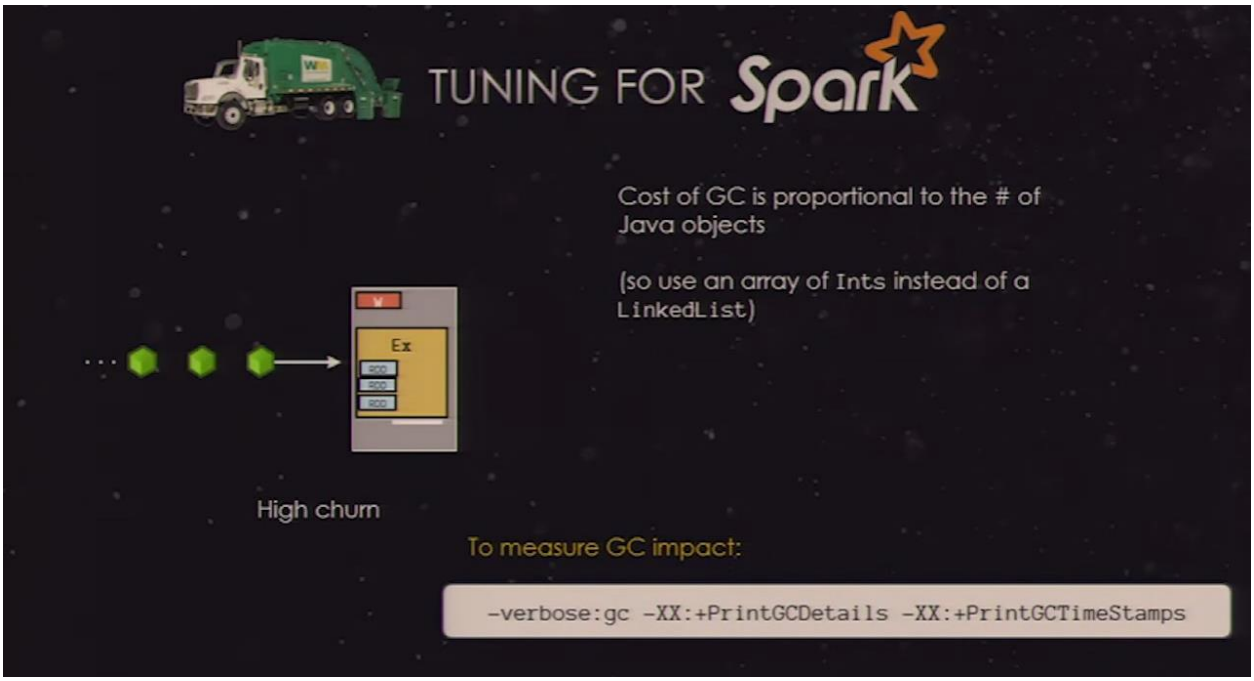


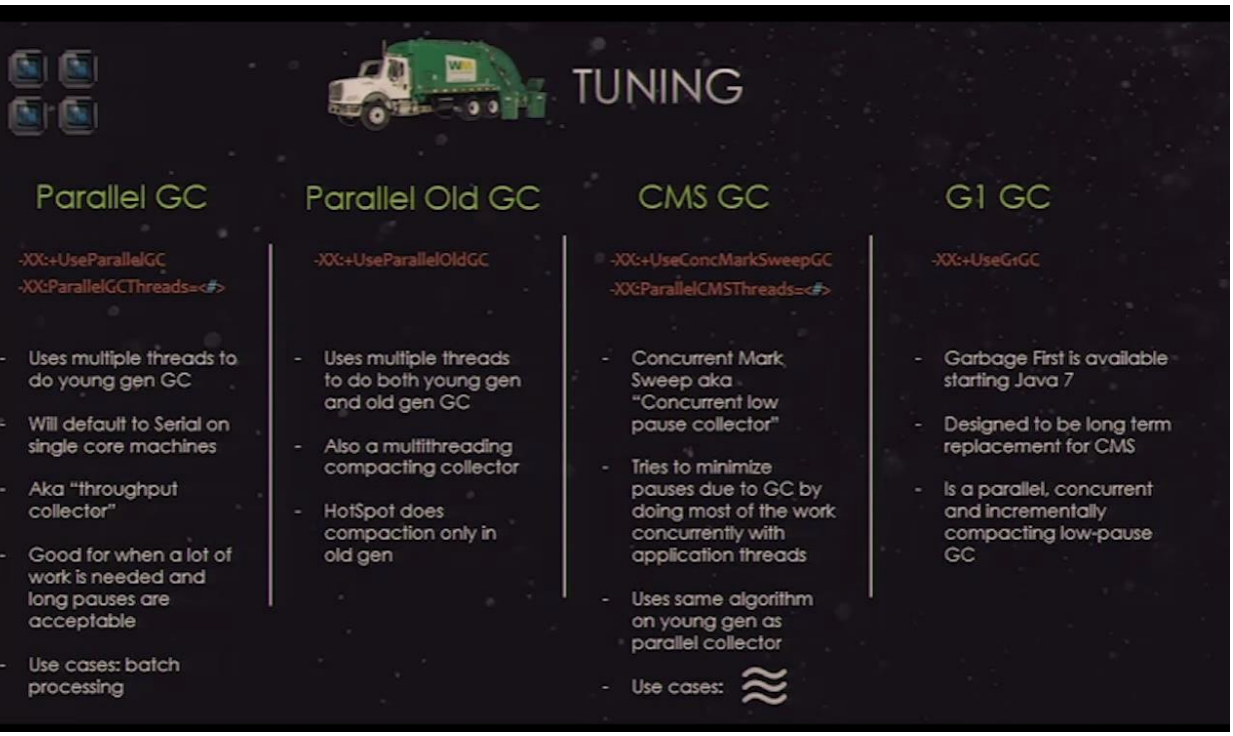
By default it uses java serialization which is slow



Tuning for Spark

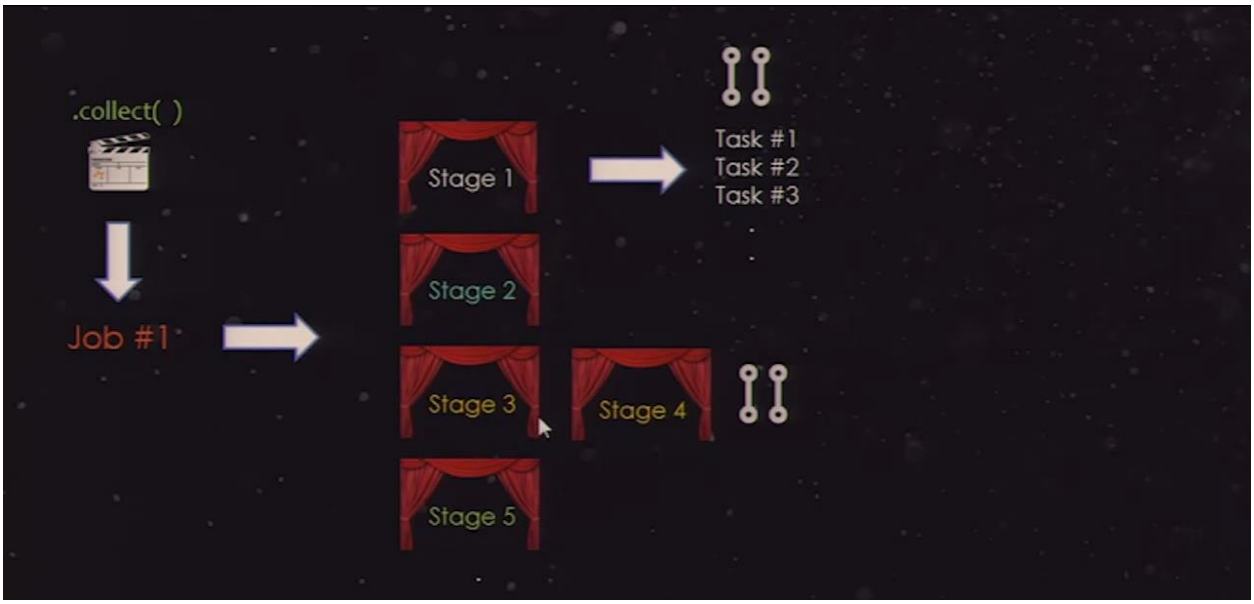





TUNING
Parallel GC
-XX:+UseParallelGC
-XX:ParallelGCThreads=<#>
- Uses multiple threads to do young gen GC
- Will default to Serial on single core machines
- Aka "throughput collector"
- Good for when a lot of work is needed and long pauses are acceptable
- Use cases: batch processing
Parallel Old GC
-XX:+UseParallelOldGC
- Uses multiple threads to do both young gen and old gen GC
- Also a multithreading compacting collector
- HotSpot does compaction only in old gen
CMS GC
-XX:+UseConcMarkSweepGC
-XX:ParallelCMSThreads=<#>
- Concurrent Mark Sweep aka "Concurrent low pause collector"
- Tries to minimize pauses due to GC by doing most of the work concurrently with application threads
- Uses same algorithm on young gen as parallel collector
- Use cases:
G1 GC
-XX:+UseG1GC
- Garbage First is available starting Java 7
- Designed to be long term replacement for CMS
- Is a parallel, concurrent and incrementally compacting low-pause GC

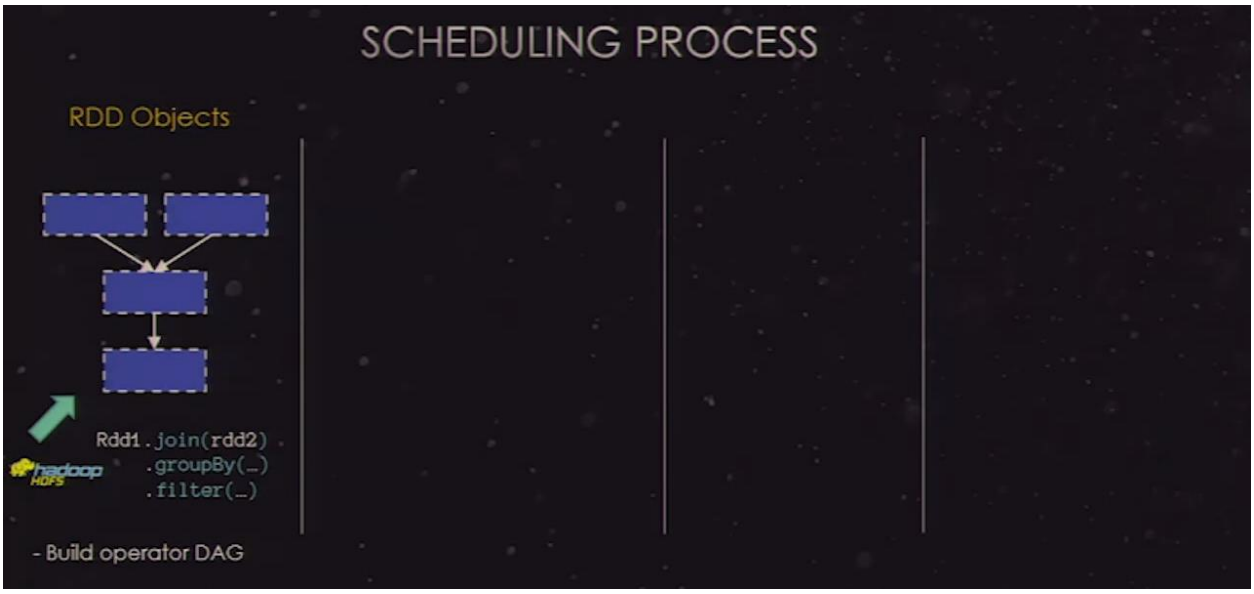
Jobs – Stack- Tasks

If you call an action like collect it trigger a Job to run, if you click on a job id in spark UI , you can see job is made of multiple stages ,some stages runs parallel (stage3,4) , inside the stage there are multiple tasks which run in parallel , each task operating on one partition do some processing on parent RDD and emits a new child partition out.

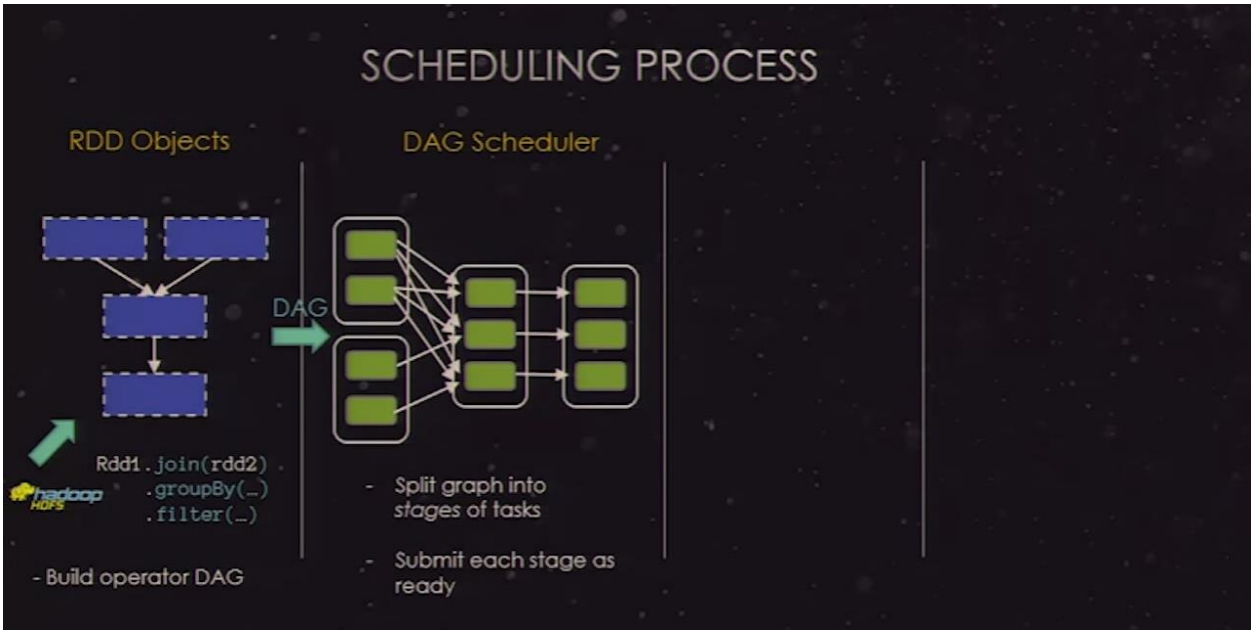


Scheduling process

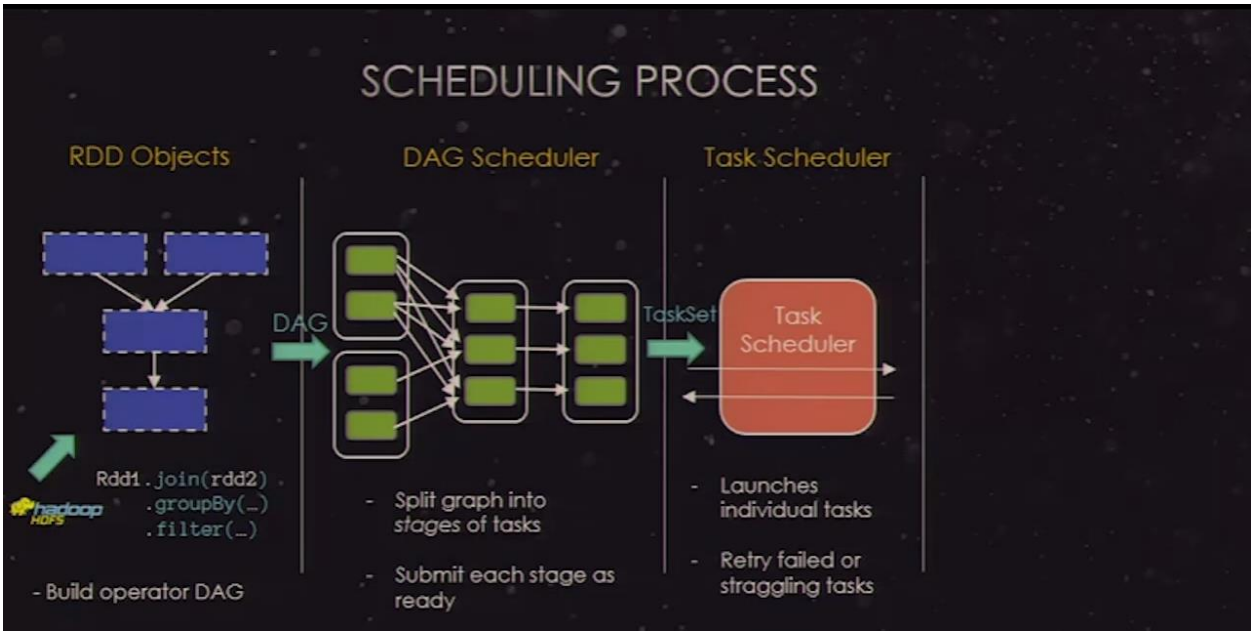
When you do lazy operation on RDD it will create DAG (Directed Acyclic Graph)

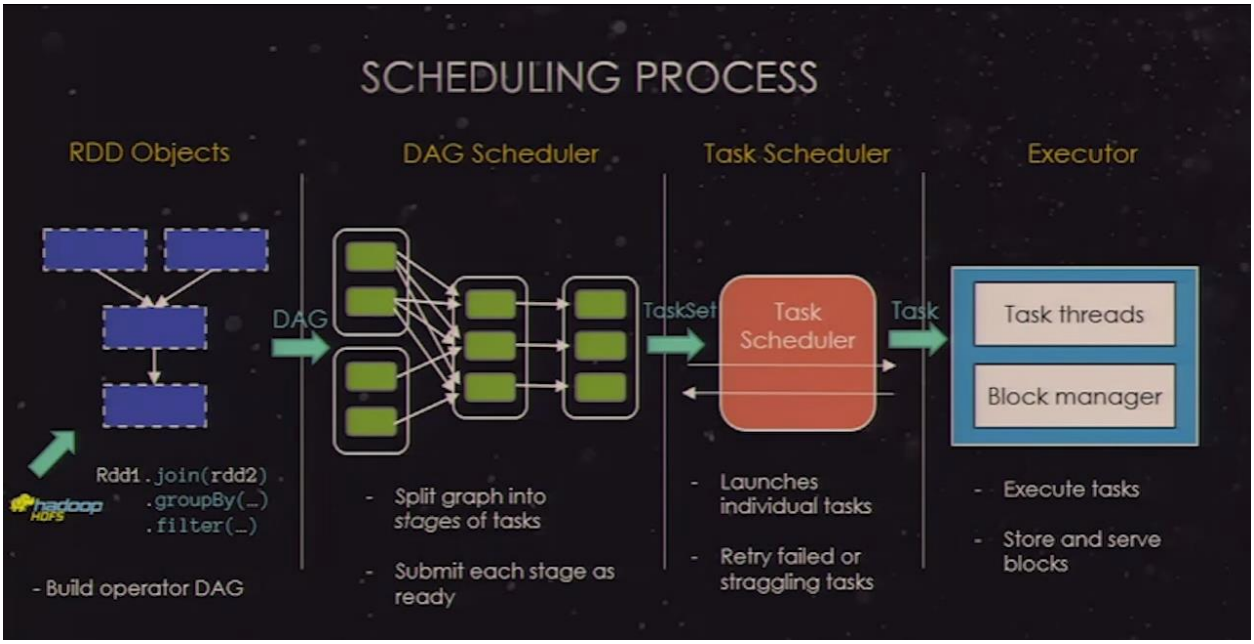


When we call action on RDD , spark driver JVM will figure out how to carve up that DAG into stage boundaries , basically creates different stages. That done by the DAG schedular



Each stage will submitted to task scheduler , task scheduler looks out of stage and schedule individual task to run on individual executor





LINEAGE

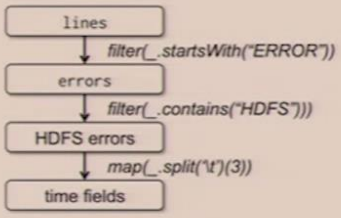


Figure 1: Lineage graph for the third query in our example. Boxes represent RDDs and arrows represent transformations.

```
lines = spark.textFile("hdfs://...")
errors = lines.filter(_.startsWith("ERROR"))
errors.persist()
```

LINEAGE

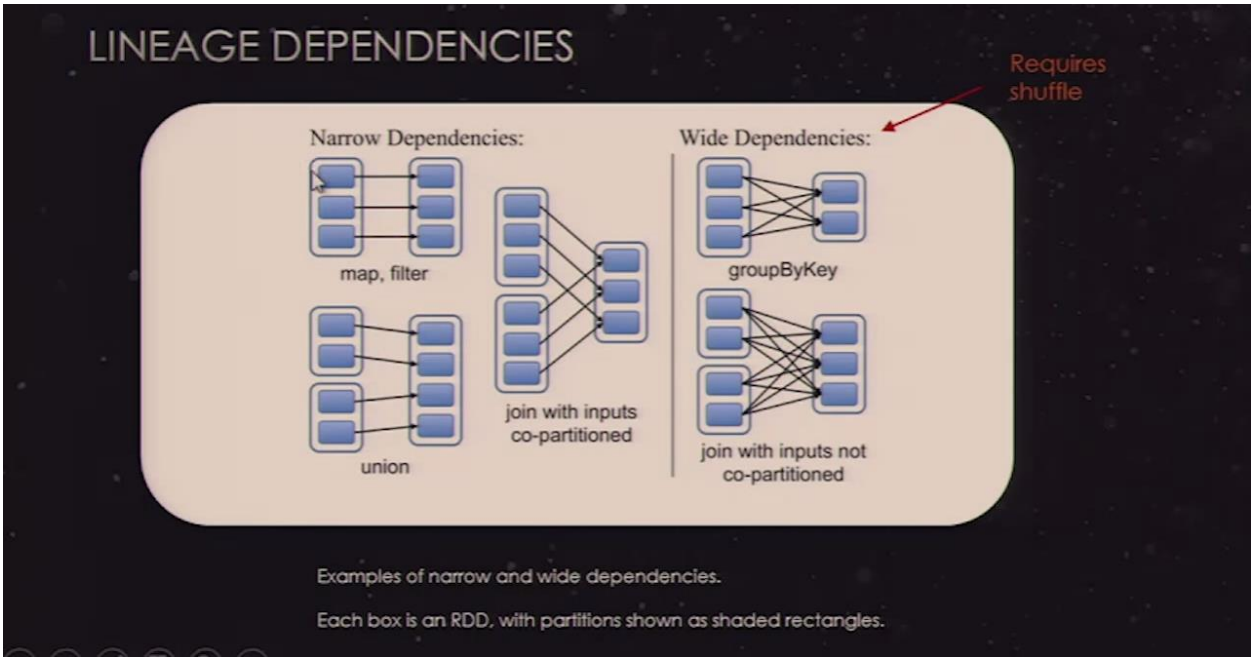
"One of the challenges in providing RDDs as an abstraction is choosing a representation for them that can track lineage across a wide range of transformations."

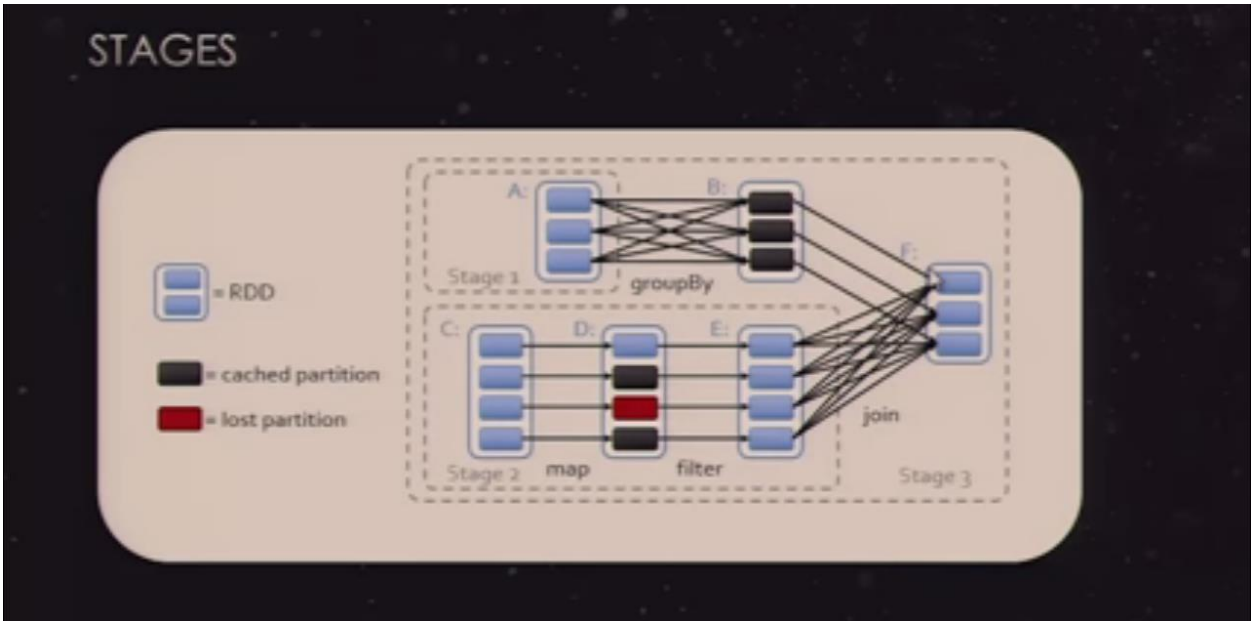
"The most interesting question in designing this interface is how to represent dependencies between RDDs."

"We found it both sufficient and useful to classify dependencies into two types:

- 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."

In narrow dependencies parent RDD is made up of just one child RDD while in wide parent made up of multiple Childs





LINEAGE

Dependencies: Narrow vs Wide

"This distinction is useful for two reasons:

1) Narrow dependencies allow for pipelined execution on one cluster node, which can compute all the parent partitions. For example, one can apply a map followed by a filter on an element-by-element basis.

In contrast, wide dependencies require data from all parent partitions to be available and to be shuffled across the nodes using a MapReduce-like operation.

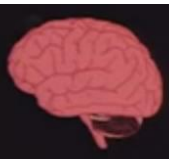
2) Recovery after a node failure is more efficient with a narrow dependency, as only the lost parent partitions need to be recomputed, and they can be recomputed in parallel on different nodes. In contrast, in a lineage graph with wide dependencies, a single failed node might cause the loss of some partition from all the ancestors of an RDD, requiring a complete re-execution."

To display the lineage of an RDD, Spark provides a `toDebugString` method:

```
scala> input.toDebugString

res85: String =
(2) data.text MappedRDD[292] at textFile at <console>:13
 | data.text HadoopRDD[291] at textFile at <console>:13

scala> counts.toDebugString
res84: String =
(2) ShuffledRDD[296] at reduceByKey at <console>:17
 +-(2) MappedRDD[295] at map at <console>:17
    | FilteredRDD[294] at filter at <console>:15
    | MappedRDD[293] at map at <console>:15
    | data.text MappedRDD[292] at textFile at <console>:13
    | data.text HadoopRDD[291] at textFile at <console>:13
```



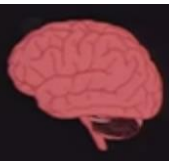
How do you know if a shuffle will be called on a Transformation?

- repartition , join, cogroup, and any of the *By or *ByKey transformations can result in shuffles
- If you declare a numPartitions parameter, it'll probably shuffle
- If a transformation constructs a shuffledRDD, it'll probably shuffle
- combineByKey calls a shuffle (so do other transformations like groupByKey, which actually end up calling combineByKey)

Note that repartition just calls coalese w/ True:

RDD.scala

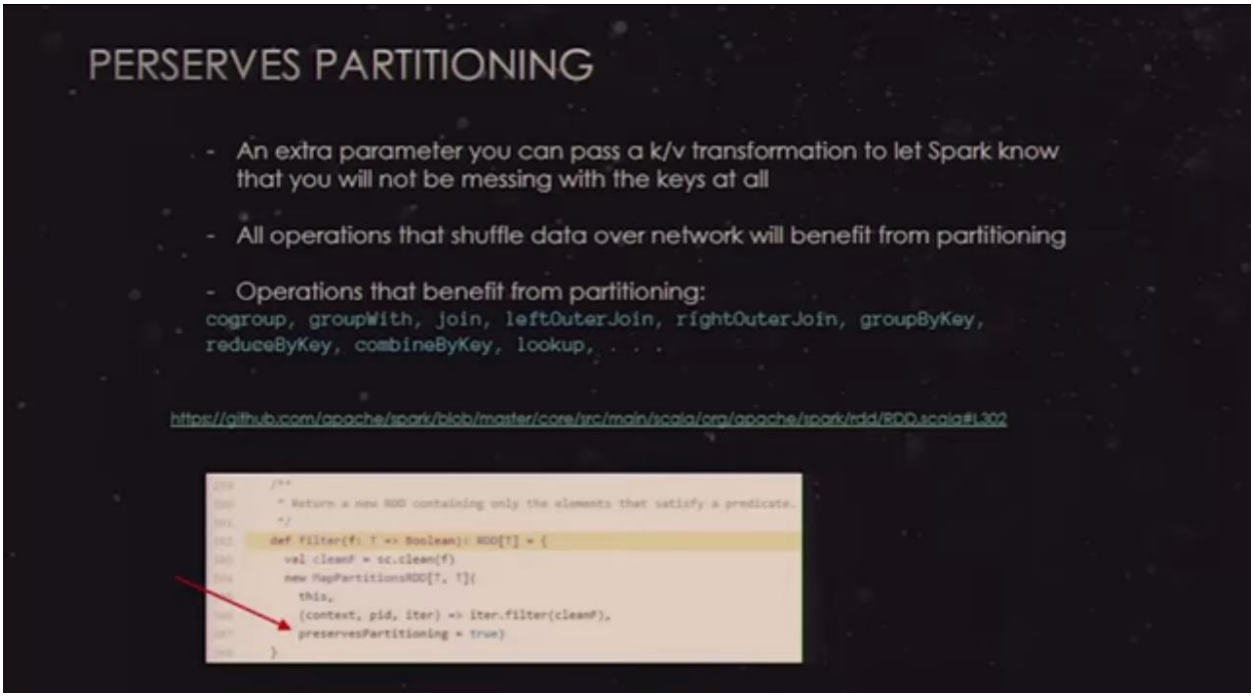
```
def repartition(numPartitions: Int)(implicit
ord: Ordering[T] = null): RDD[T] = {
    coalesce(numPartitions, shuffle = true)
}
```

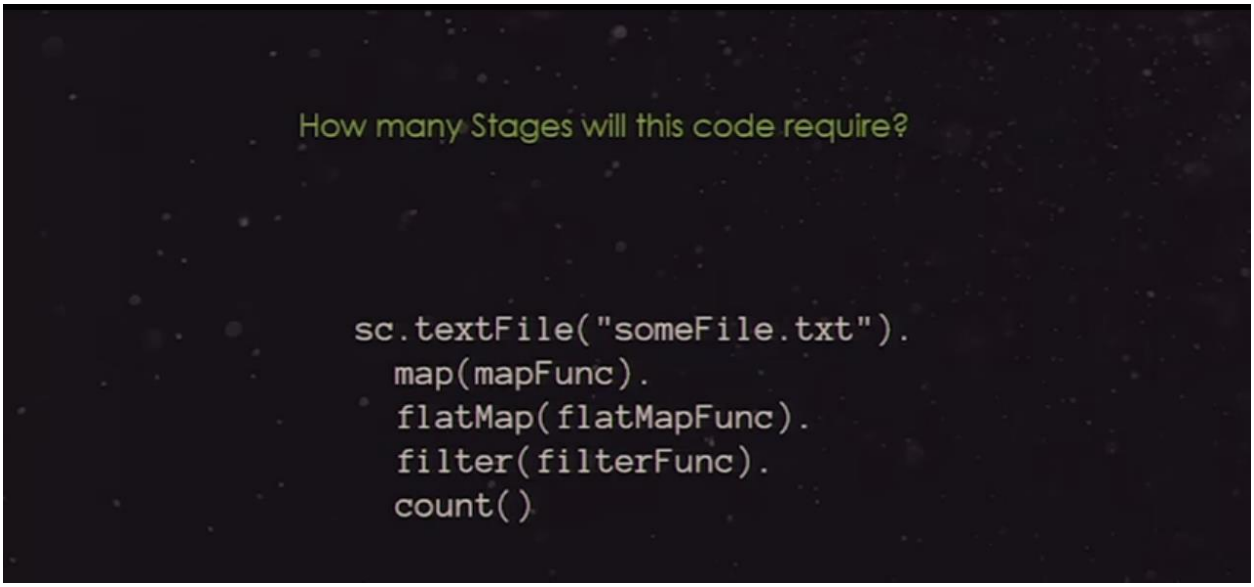


How do you know if a shuffle will be called on a Transformation?

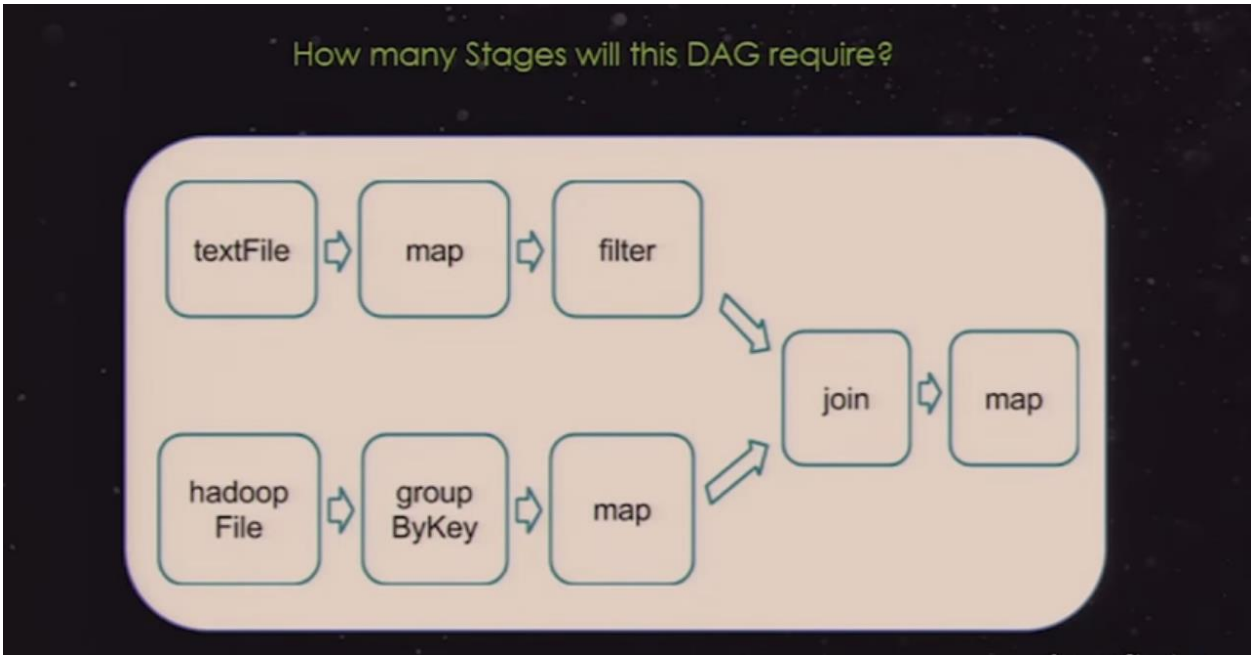
Transformations that use "numPartitions" like distinct will probably shuffle:

```
def distinct(numPartitions: Int)(implicit ord: Ordering[T] =
null): RDD[T] =
    map(x => (x, null)).reduceByKey((x, y) => x,
numPartitions).map(_._1)
```

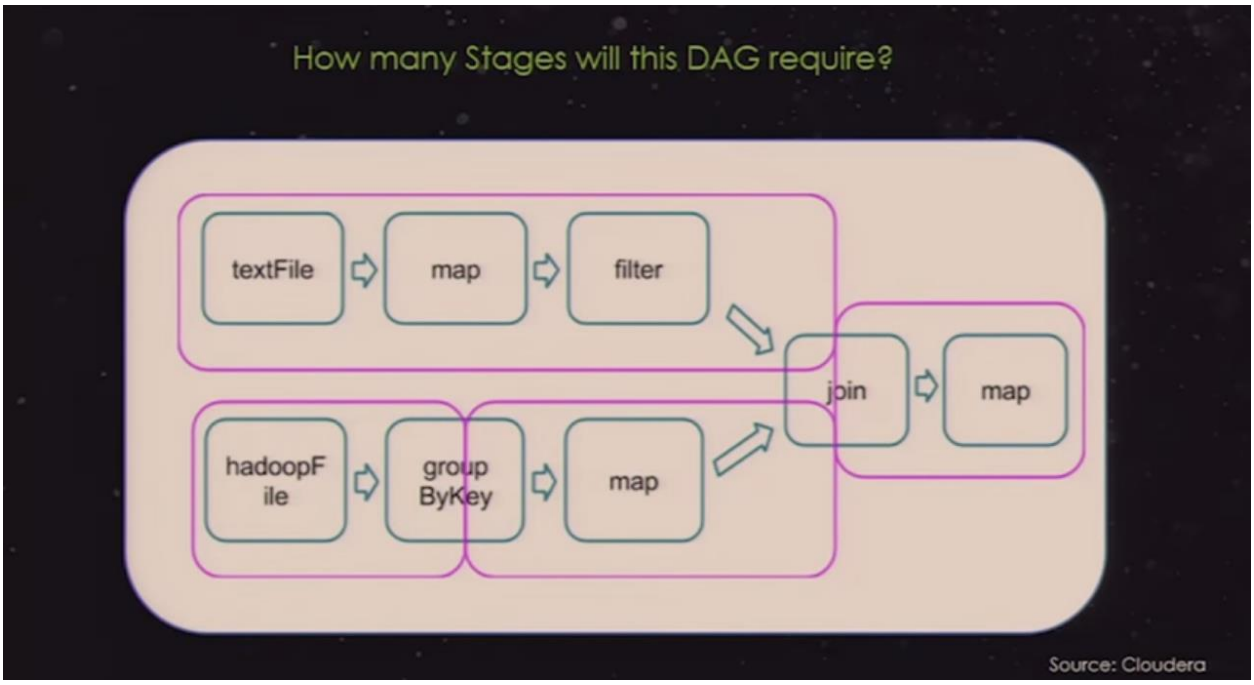




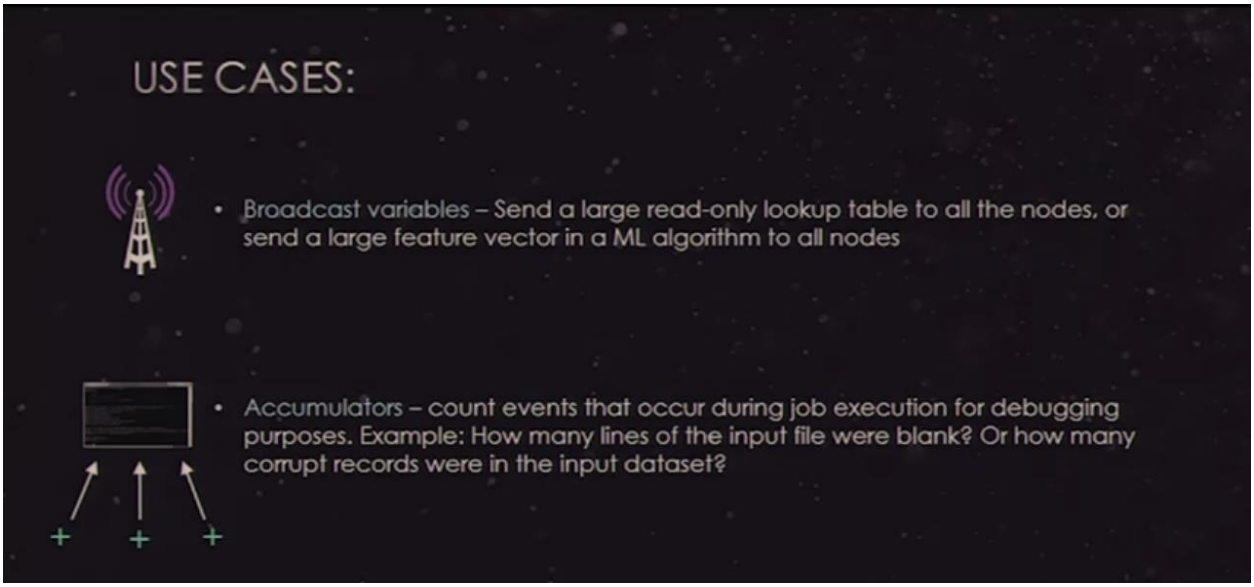
Map, Flatmap and filter all require narrow transformation so this will require only one stage

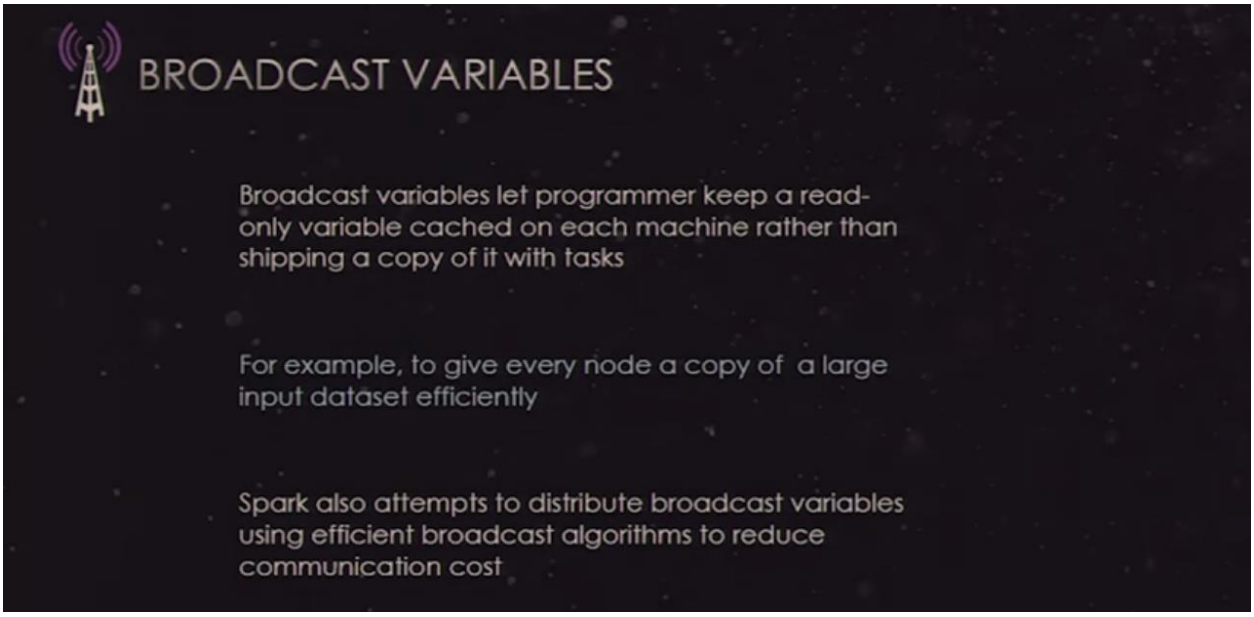


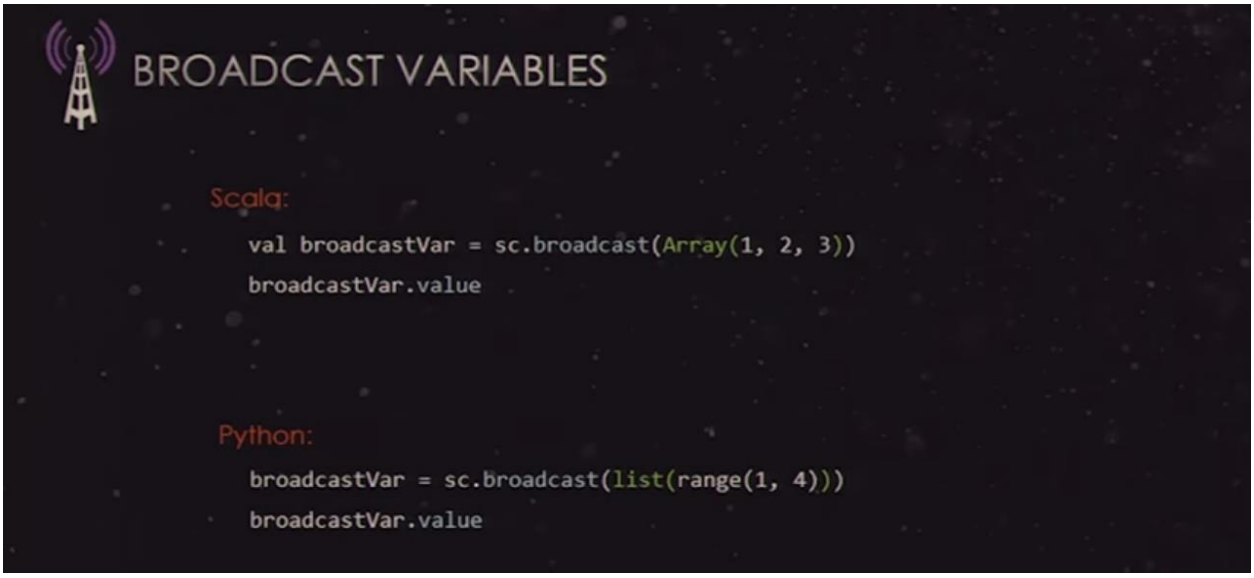
3 stages, groupBykey causes a shuffle so group By key one of the stage boundaries , join also cause a shuffle as well

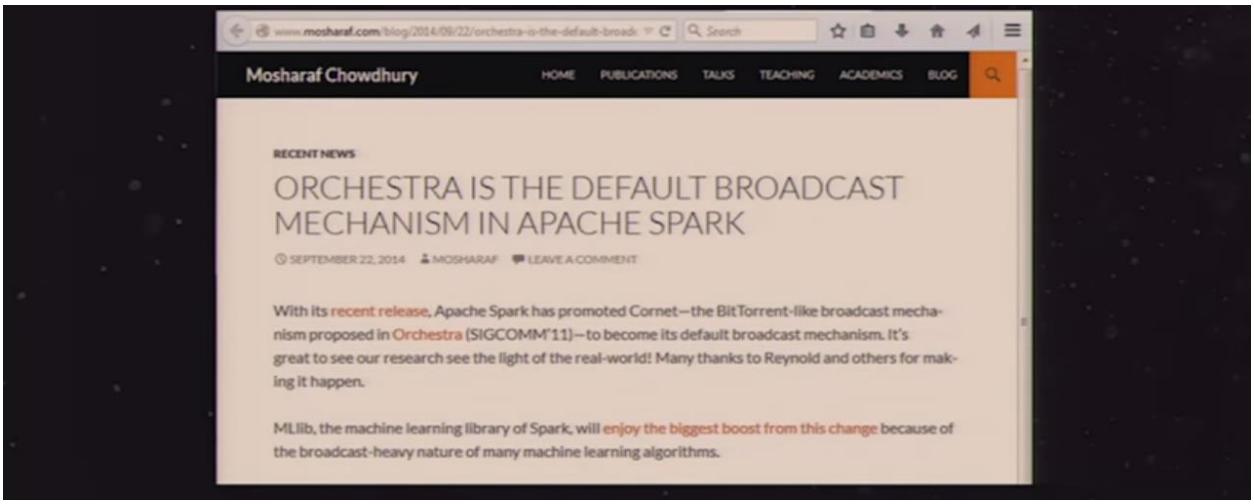


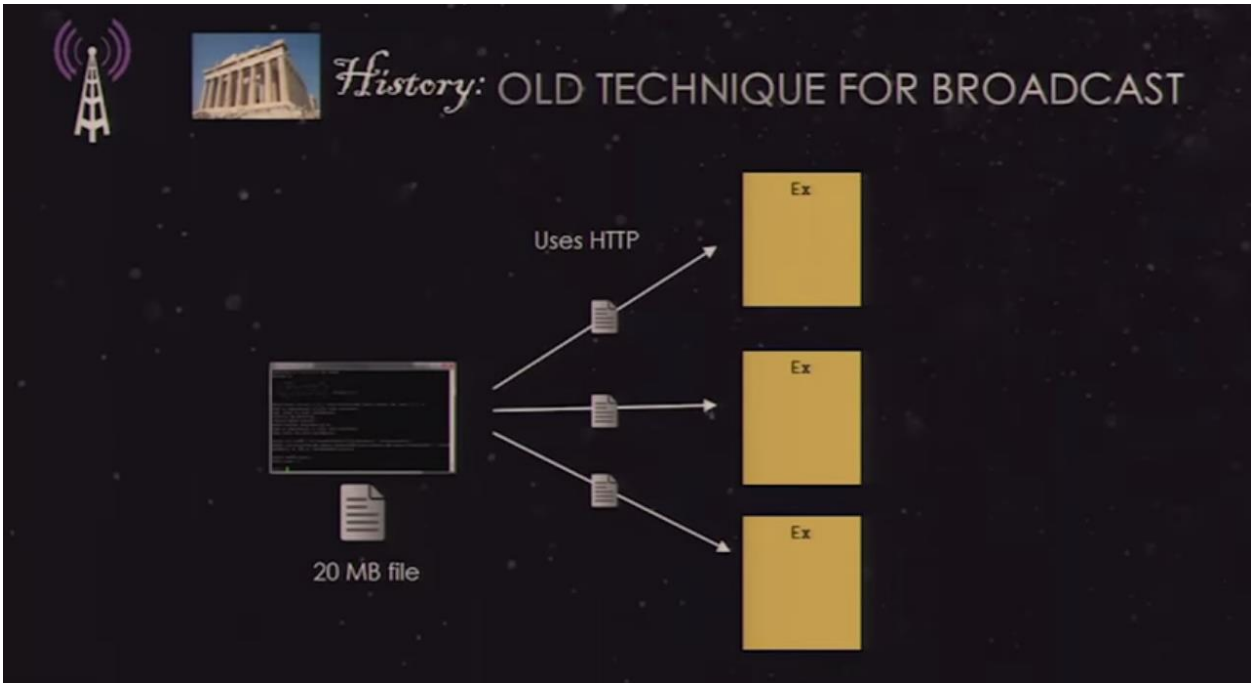
Broadcast and Accumulators



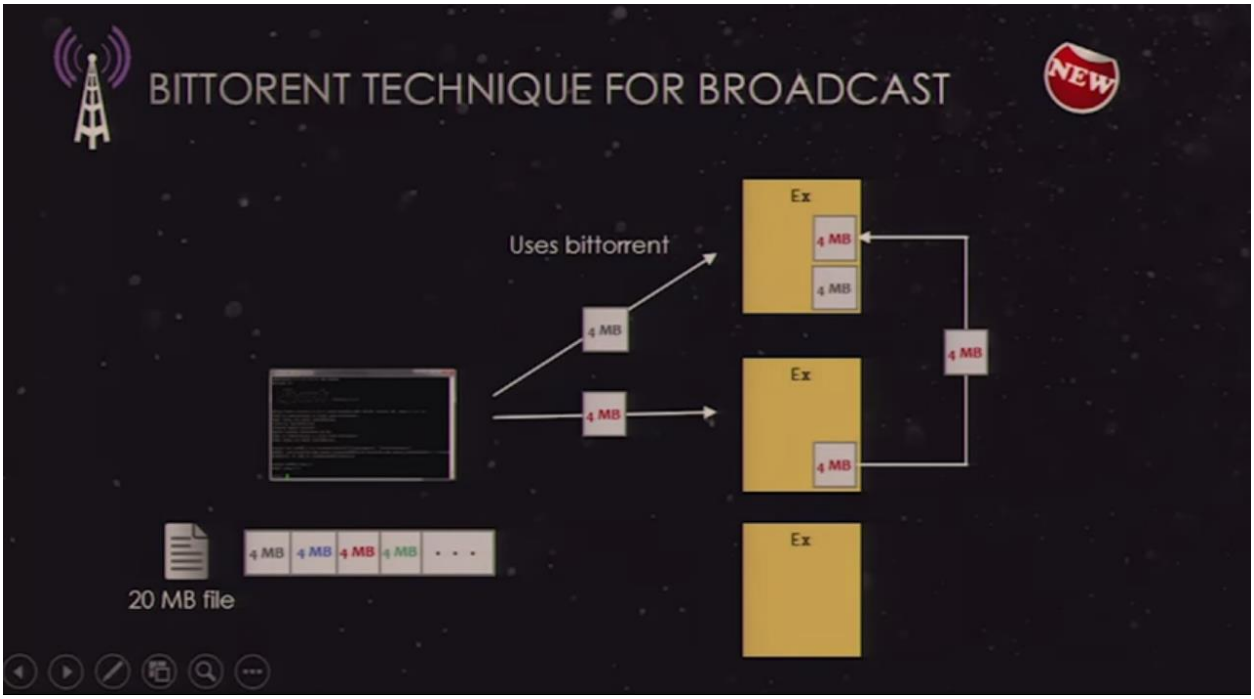


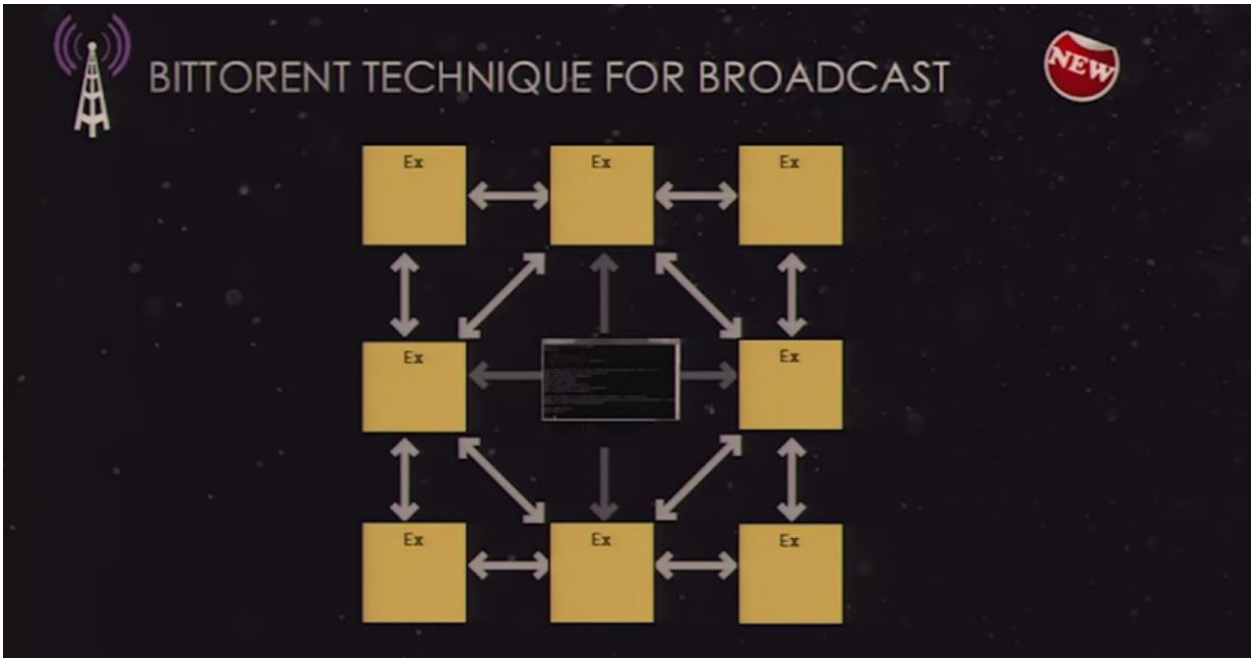

BROADCAST VARIABLES
Scala:
val broadcastVar = sc.broadcast(Array(1, 2, 3))
broadcastVar.value
Python:
broadcastVar = sc.broadcast(list(range(1, 4)))
broadcastVar.value

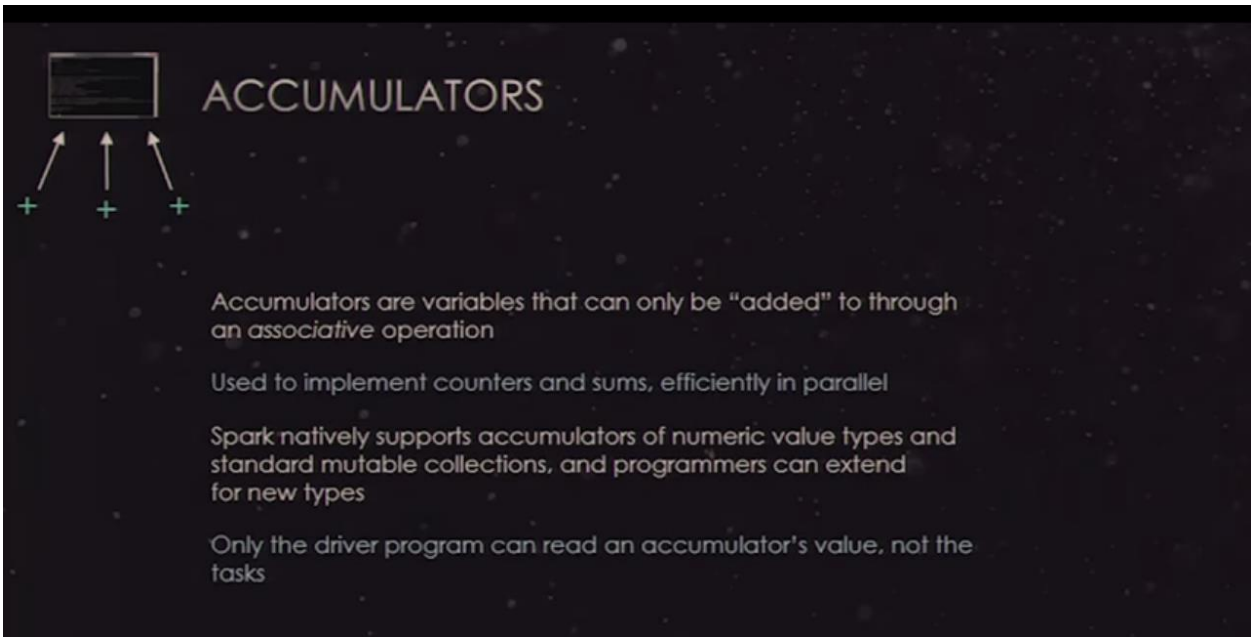

Mosharaf Chowdhury
HOME
PUBLICATIONS
TALKS
TEACHING
ACADEMICS
BLOG
RECENT NEWS
ORCHESTRA IS THE DEFAULT BROADCAST MECHANISM IN APACHE SPARK
SEPTEMBER 22, 2014
MOSHARAF
LEAVE A COMMENT
With its recent release, Apache Spark has promoted Cornet—the BitTorrent-like broadcast mechanism proposed in Orchestra (SIGCOMM'11)—to become its default broadcast mechanism. It's great to see our research see the light of the real-world! Many thanks to Reynold and others for making it happen.
MLlib, the machine learning library of Spark, will enjoy the biggest boost from this change because of the broadcast-heavy nature of many machine learning algorithms.

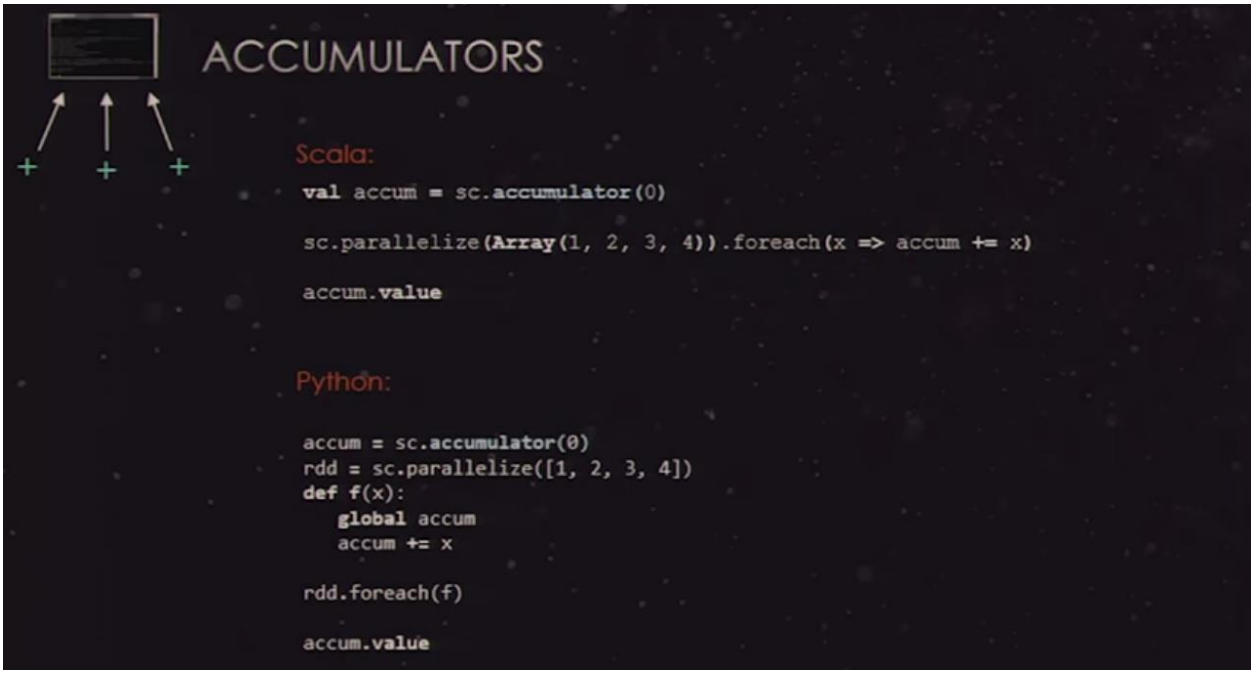


All executors coordinate with each other to get the full 20 MB files

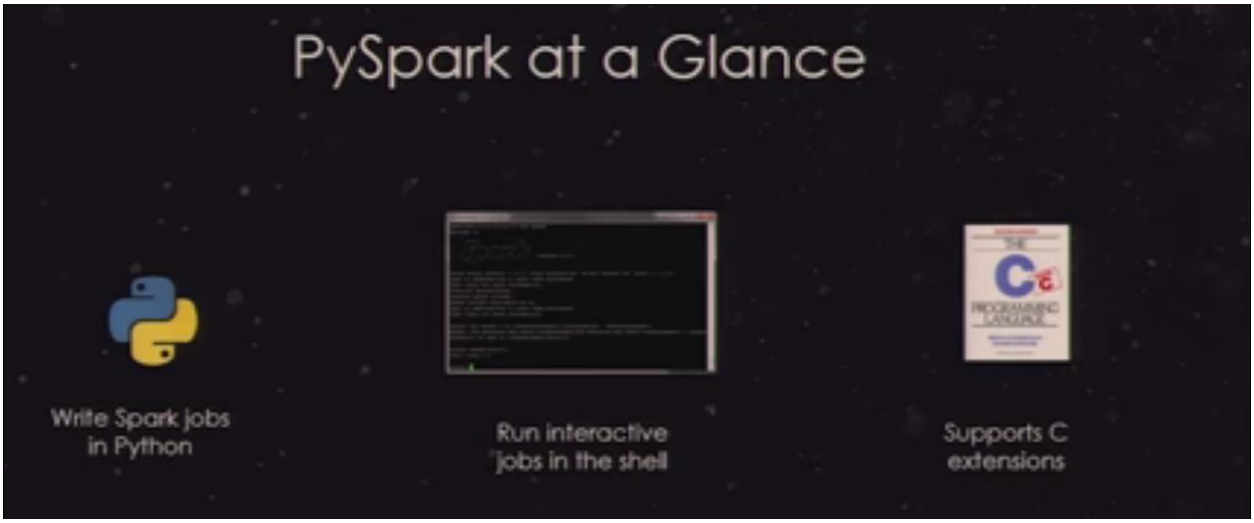


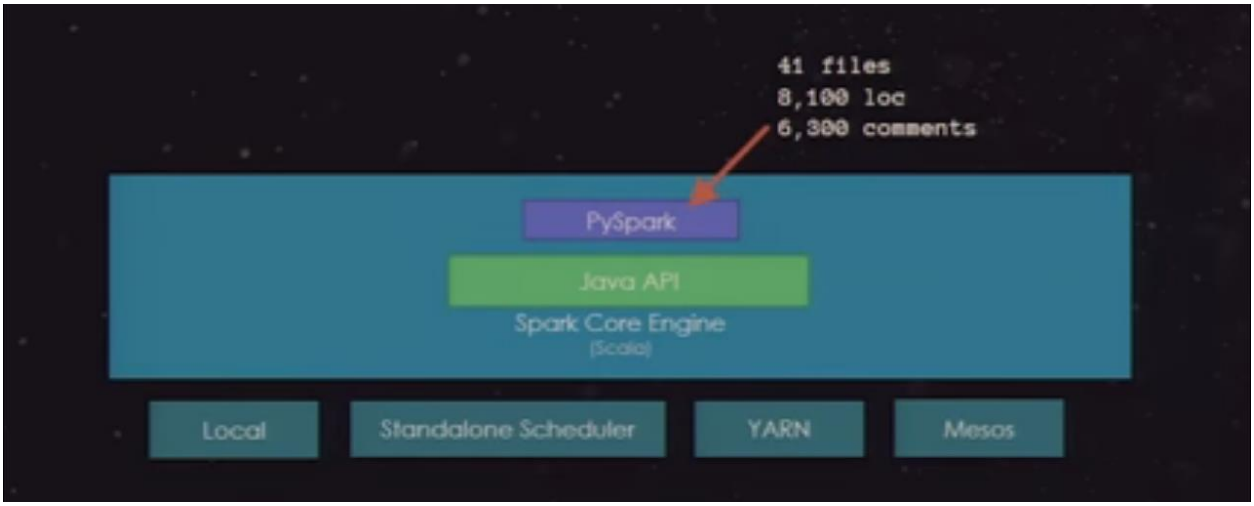

BITTORENT TECHNIQUE FOR BROADCAST
NEW
Ex
Ex
Ex
Ex
Ex
Ex
Ex
Ex

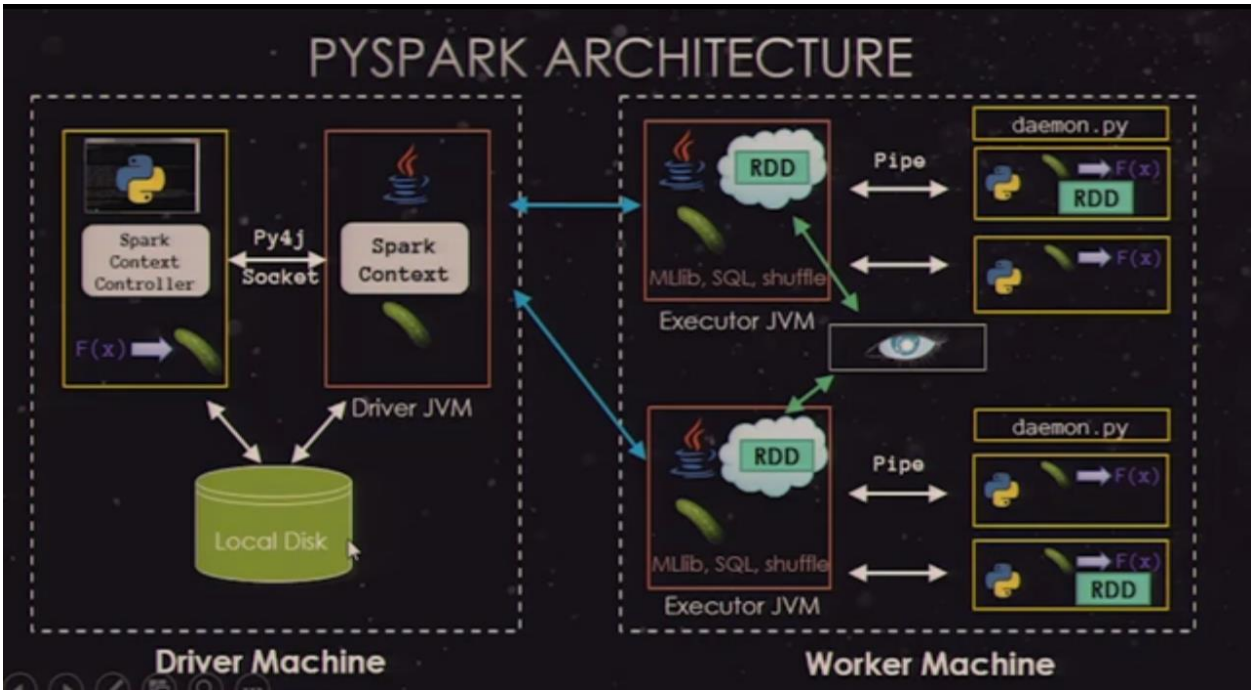

ACCUMULATORS
+
+
+
Accumulators are variables that can only be "added" to through an *associative* operation
Used to implement counters and sums, efficiently in parallel
Spark natively supports accumulators of numeric value types and standard mutable collections, and programmers can extend for new types
Only the driver program can read an accumulator's value, not the tasks


ACCUMULATORS
+
+
+
Scala:
val accum = sc.accumulator(0)
sc.parallelize(Array(1, 2, 3, 4)).foreach(x => accum += x)
accum.value
Python:
accum = sc.accumulator(0)
rdd = sc.parallelize([1, 2, 3, 4])
def f(x):
global accum
accum += x
rdd.foreach(f)
accum.value

Python API

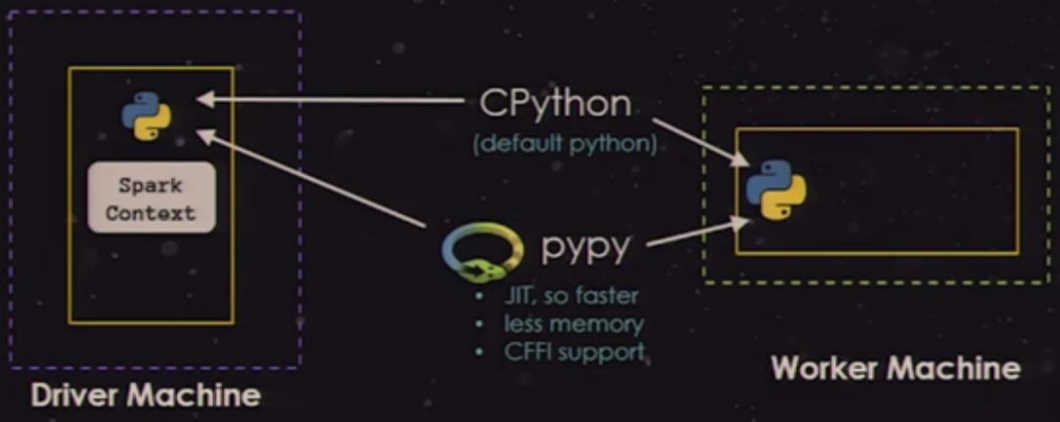

PySpark at a Glance
Write Spark jobs in Python
Run interactive jobs in the shell
Supports C extensions


41 files
8,100 loc
6,300 comments
PySpark
Java API
Spark Core Engine
(Scala)
Local
Standalone Scheduler
YARN
Mesos


PYSPARK ARCHITECTURE
Spark Context Controller
F(x)
Py4j Socket
Spark Context
Driver JVM
Local Disk
Driver Machine
RDD
Pipe
MLlib, SQL, shuffle
Executor JVM
daemon.py
F(x)
RDD
Worker Machine


hadoop HDFS
HadoopRDD
MappedRDD
PythonRDD
Data is stored as Pickled objects in an RDD[Array[Byte]]
RDD[Array[, , ,]]
(100 KB – 1MB each picked object)

Choose Your Python Implementation




```
$ PYSPARK_DRIVER_PYTHON=pypy PYSPARK_PYTHON=pypy ./bin/pyspark
```

OR

```
$ PYSPARK_DRIVER_PYTHON=pypy PYSPARK_PYTHON=pypy ./bin/spark-submit wordcount.py
```

The performance speed up will depend on work load (from 20% to 3000%).

Here are some benchmarks:

Job	CPython 2.7	PyPy 2.3.1	Speed up
Word Count	41 s	15 s	2.7 x
Sort	46 s	44 s	1.05 x
Stats	174 s	3.6 s	48 x

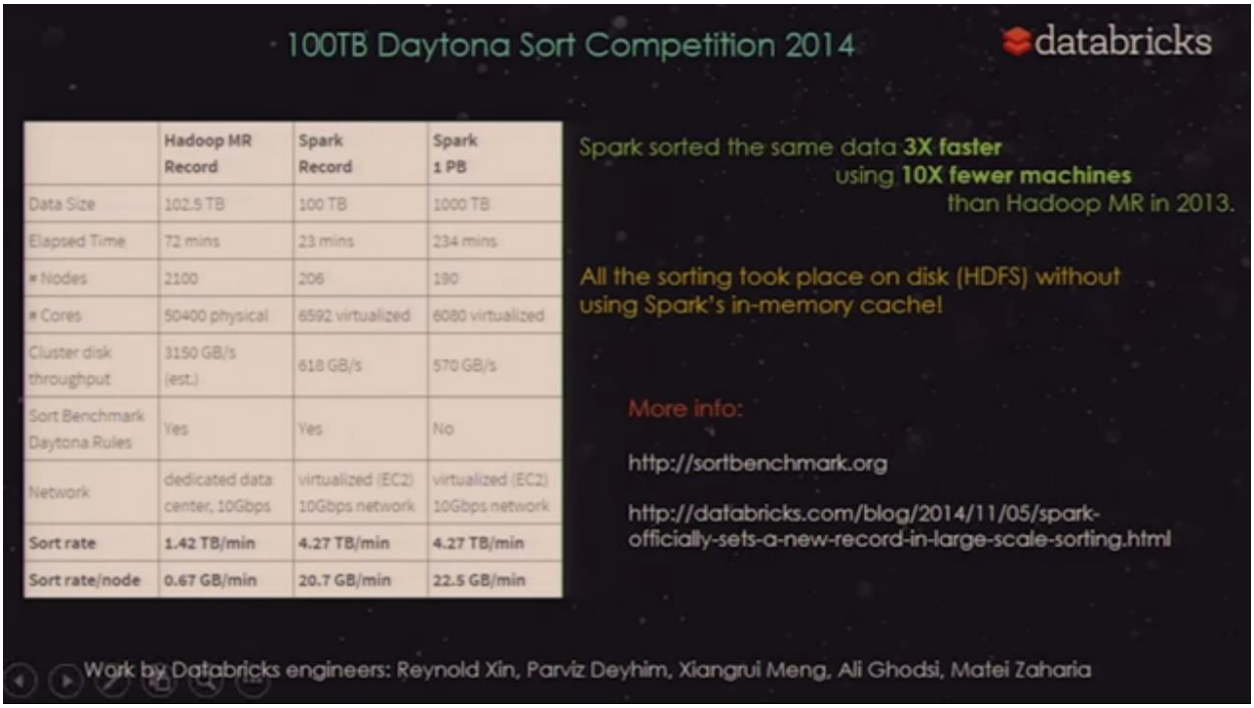
Here is the code used for benchmark:

```
rdd = sc.textFile("text")
def wordcount():
    rdd.flatMap(lambda x:x.split('/'))\
        .map(lambda x:(x,1)).reduceByKey(lambda x,y:x+y).collectAsMap()
def sort():
    rdd.sortBy(lambda x:x, 1).count()
def stats():
    sc.parallelize(range(1024), 20).flatMap(lambda x: xrange(5024)).stats()
```

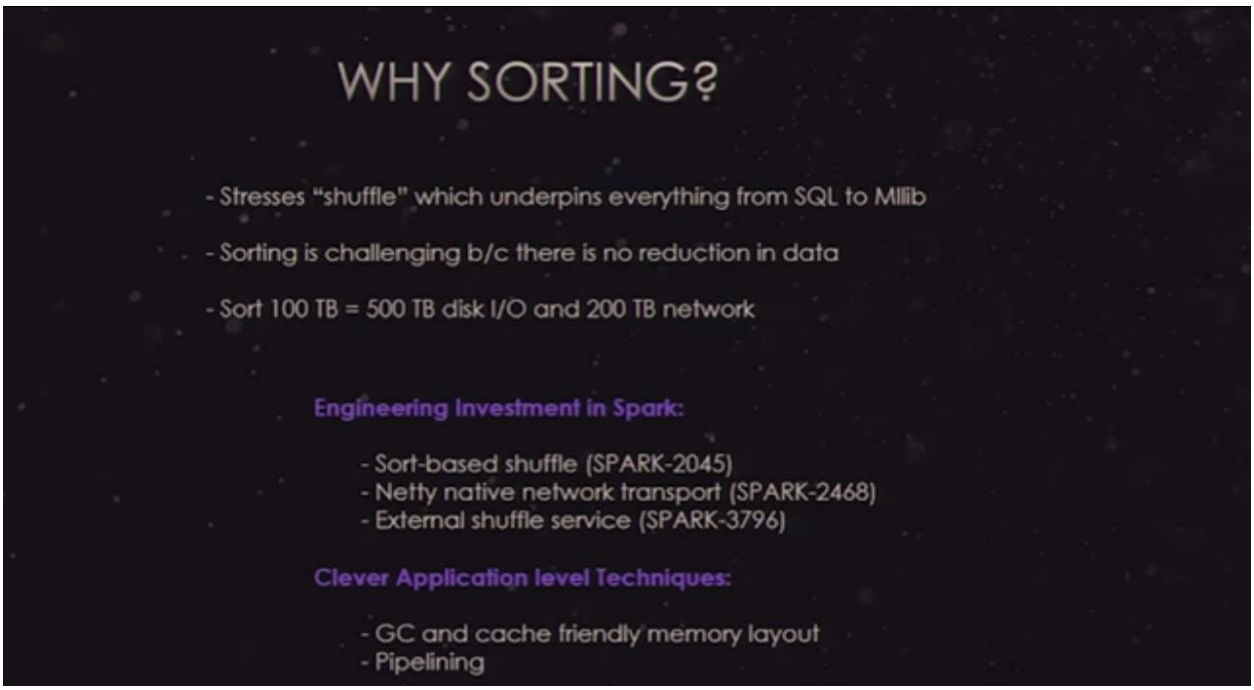
https://github.com/apache/spark/pull/2144

spark.python.worker.memory	512m	Amount of memory to use per python worker process during aggregation, in the same format as JVM memory strings (e.g. 512m, 2g). If the memory used during aggregation goes above this amount, it will spill the data into disks.

New Shuffle Implementation

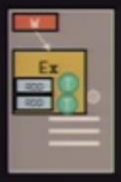


	Hadoop MR Record	Spark Record	Spark 1 PB
Data Size	102.5 TB	100 TB	1000 TB
Elapsed Time	72 mins	23 mins	234 mins
# Nodes	2100	206	190
# Cores	50400 physical	6592 virtualized	6080 virtualized
Cluster disk throughput	3150 GB/s (est.)	618 GB/s	570 GB/s
Sort Benchmark Daytona Rules	Yes	Yes	No
Network	dedicated data center, 10Gbps	virtualized (EC2) 10Gbps network	virtualized (EC2) 10Gbps network
Sort rate	**1.42 TB/min**	**4.27 TB/min**	**4.27 TB/min**
Sort rate/node	**0.67 GB/min**	**20.7 GB/min**	**22.5 GB/min**



TECHNIQUE USED FOR 100 TB SORT

- Intel Xeon CPU E5 2670 @ 2.5 GHz w/ 32 cores
- 244 GB of RAM
- 8 x 800 GB SSD and RAID 0 setup formatted with /ext4
- ~9.5 Gbps (*1.1 GBps*) bandwidth between 2 random nodes



EC2: I2.8xlarge

(206 workers)

- 32 slots per machine
- 6,592 slots total

- Each record: 100 bytes (10 byte key & 90 byte value)
- OpenJDK 1.7
- HDFS 2.4.1 w/ short circuit local reads enabled
- Apache Spark 1.2.0
- Speculative Execution off
- Increased Locality Wait to infinite
- Compression turned off for input, output & network
- Used Unsafe to put all the data off-heap and managed it manually (i.e. never triggered the GC)

=

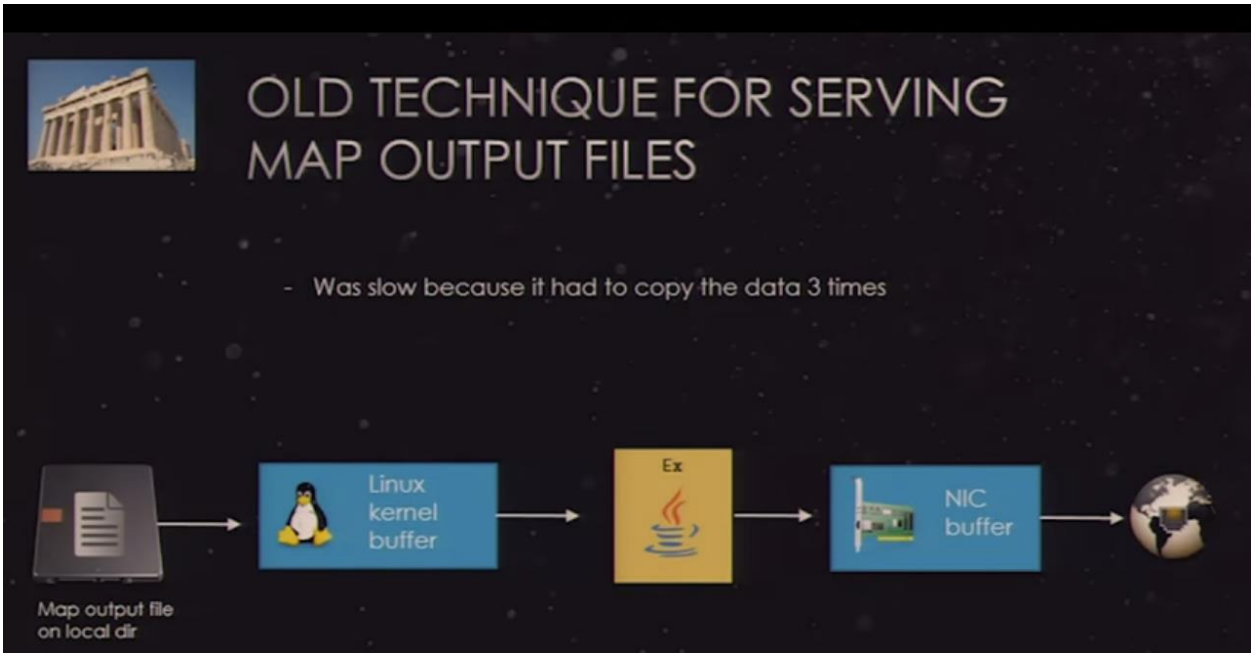
`groupByKey`

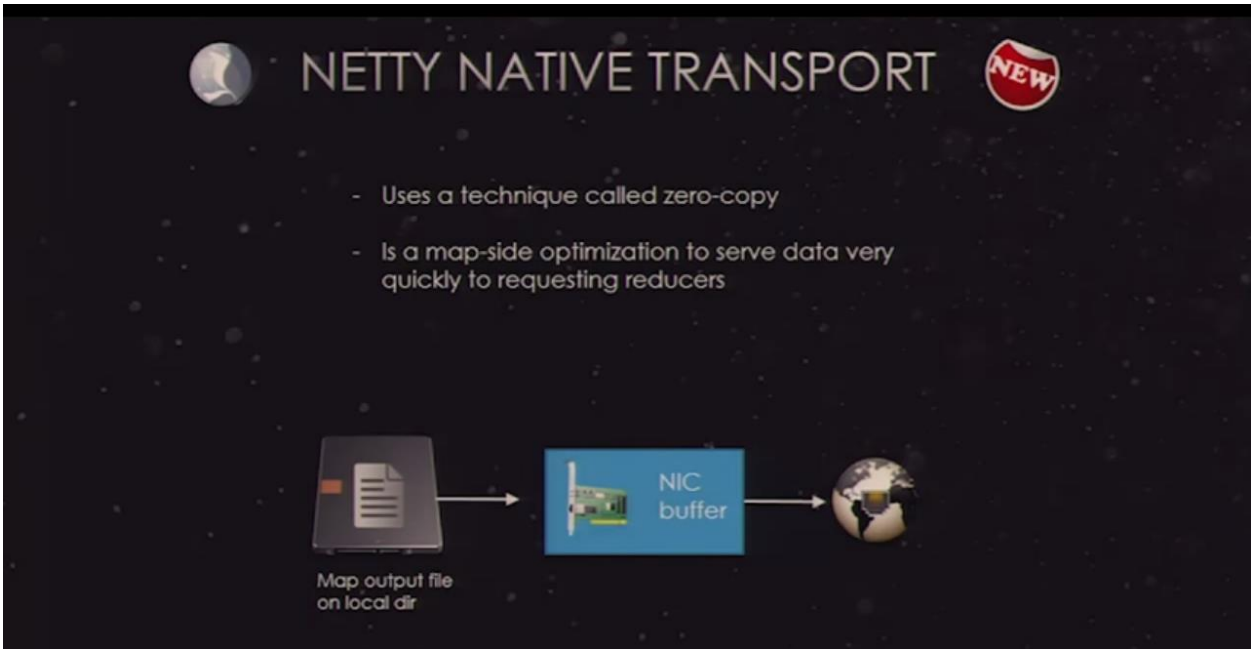
`sortByKey`

`reduceByKey`

```
spark.shuffle.spill=false
```

(Affects reducer side and keeps all the data in memory)

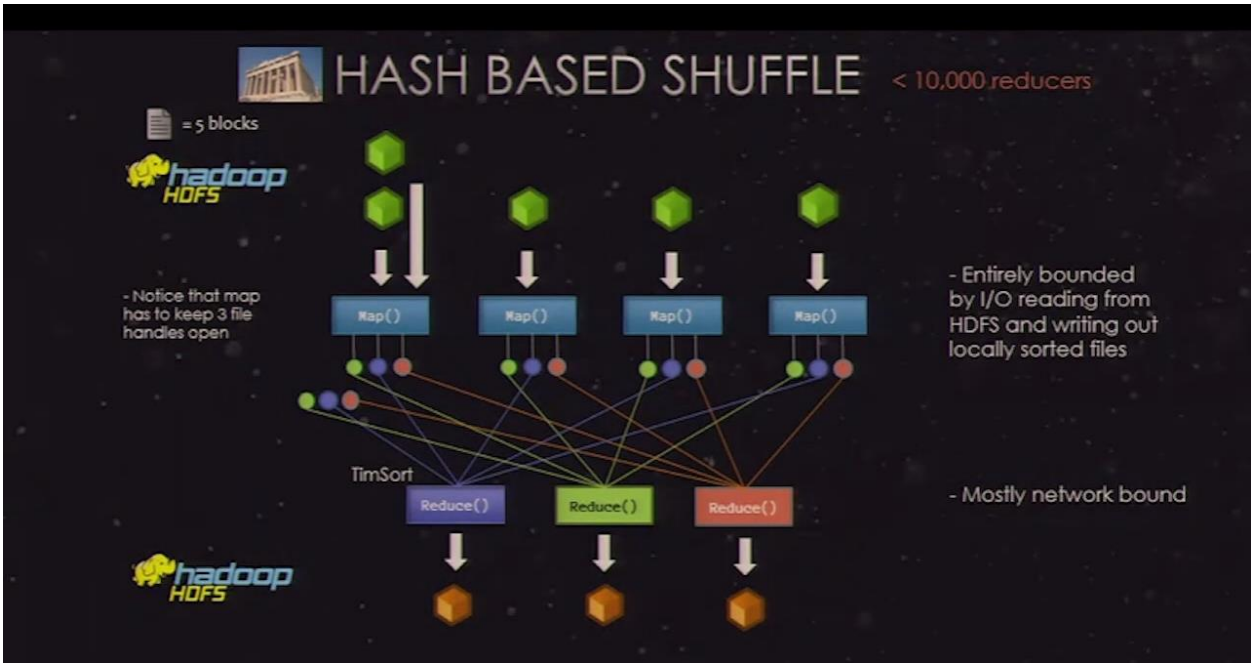

OLD TECHNIQUE FOR SERVING MAP OUTPUT FILES
- Was slow because it had to copy the data 3 times
Linux kernel buffer
Ex
NIC buffer
Map output file on local dir


NETTY NATIVE TRANSPORT
NEW
- Uses a technique called zero-copy
- Is a map-side optimization to serve data very quickly to requesting reducers
NIC buffer
Map output file on local dir

Hash Based Shuffle

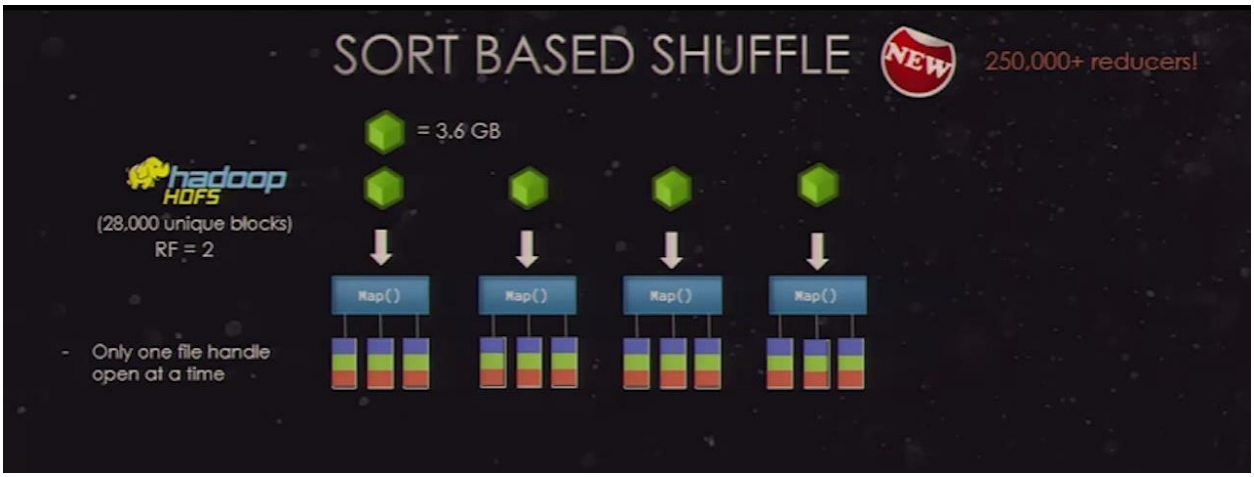
Main issue in below example is map side has to open three file handles open, more number of file handles open, buffer management become costly

Reduce phase is totally network bound as it need to pull the data over network

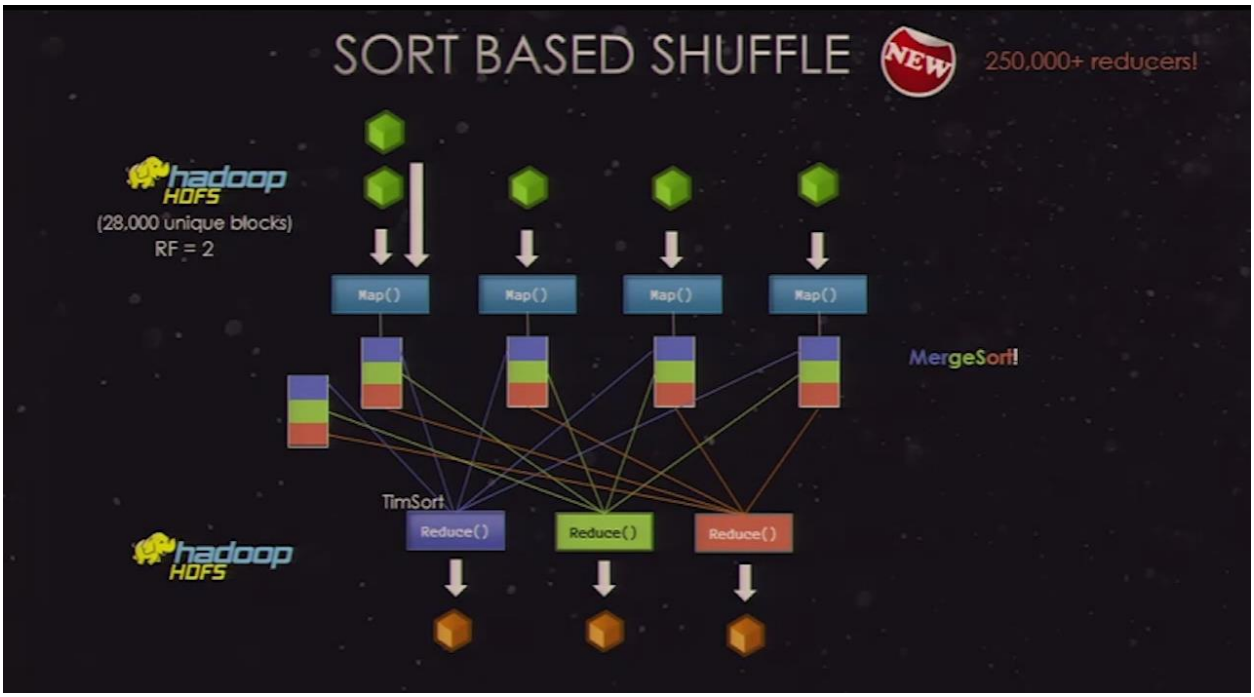


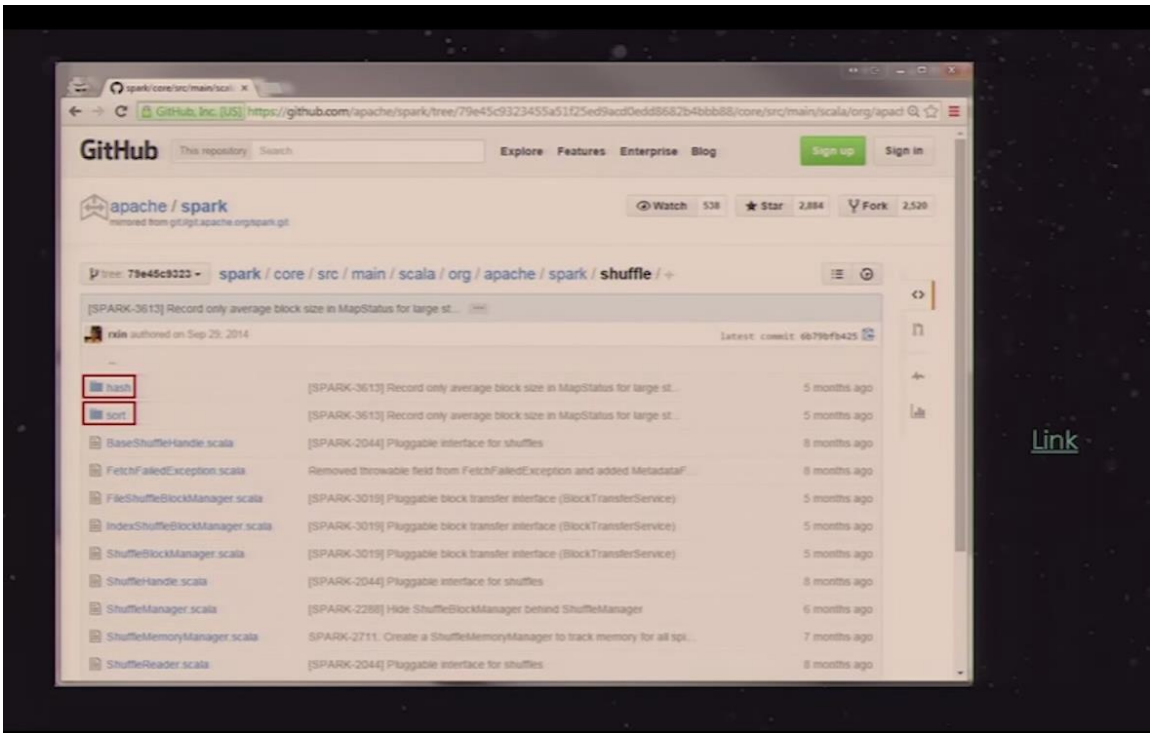
Sort Based Shuffle

Only open one file handle at a time and keep sorted all the data



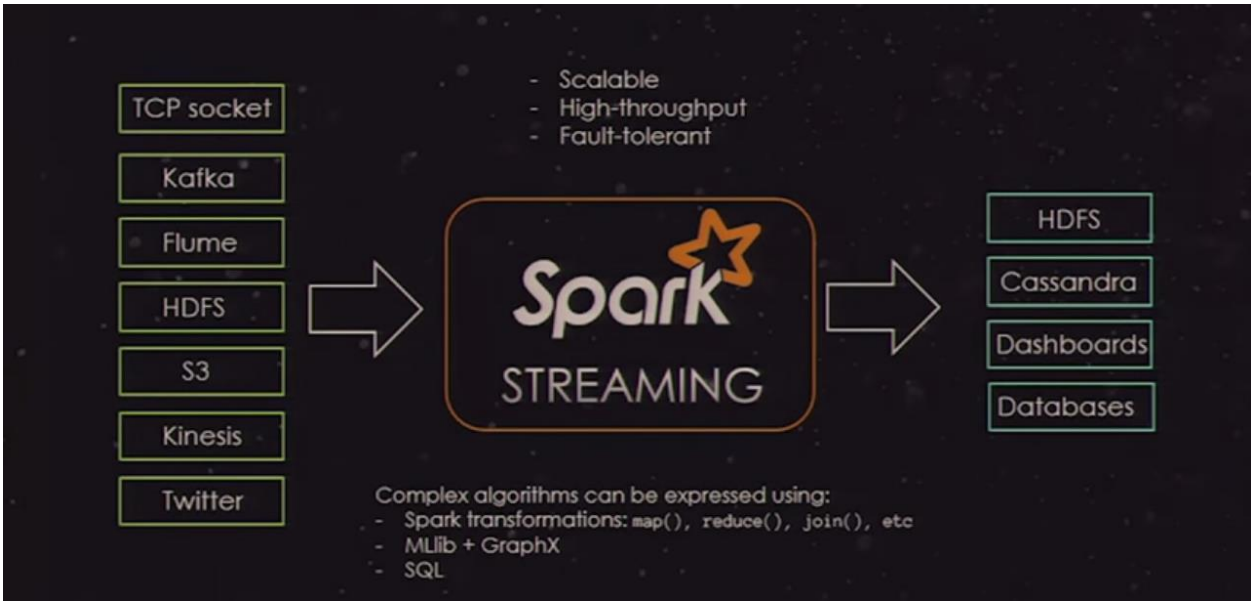
Later do the merge sort to combine all the map files in one large file

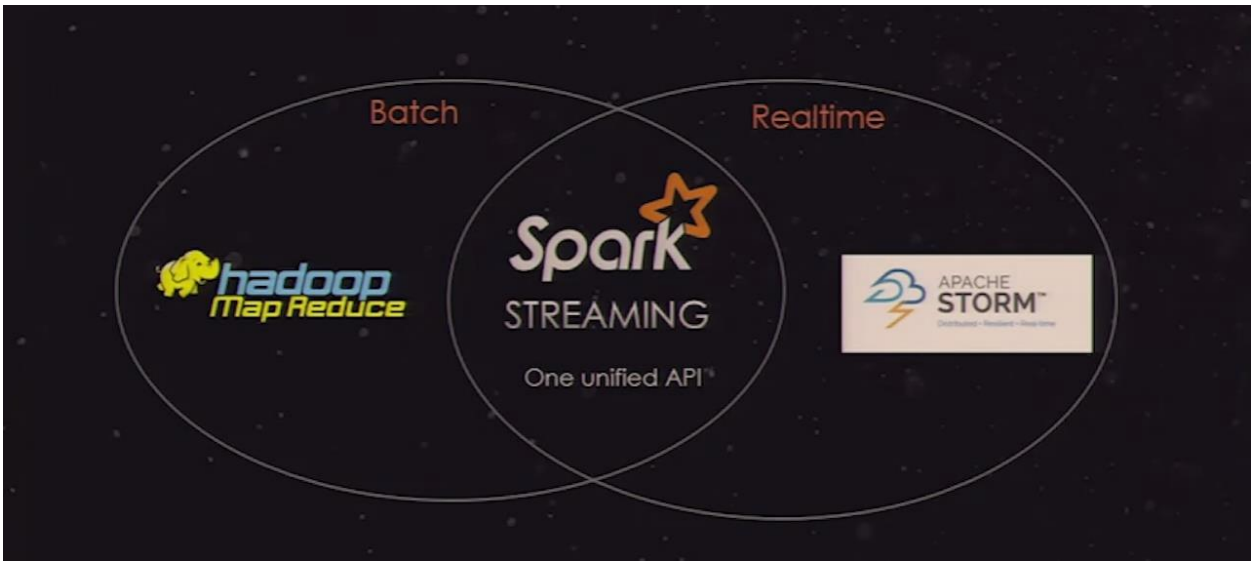



GitHub
Explore
Features
Enterprise
Blog
Sign up
Sign in
apache / spark
Watch 538
Star 2,884
Fork 2,520
spark / core / src / main / scala / org / apache / spark / shuffle /
[SPARK-3613] Record only average block size in MapStatus for large st...
rxin authored on Sep 29, 2014
latest commit 6b79bfb425
hash
sort
BaseShuffleHandle.scala
FetchFailedException.scala
FileShuffleBlockManager.scala
IndexShuffleBlockManager.scala
ShuffleBlockManager.scala
ShuffleHandle.scala
ShuffleManager.scala
ShuffleMemoryManager.scala
ShuffleReader.scala

Link

Spark Streaming





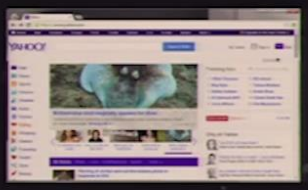
Tathagata Das (TD)

- Lead developer of Spark Streaming + Committer on Apache Spark core
- Helped re-write Spark Core internals in 2012 to make it 10x faster to support Streaming use cases
- On leave from UC Berkeley PhD program
- Ex: Intern @ Amazon, Intern @ Conviva, Research Assistant @ Microsoft Research India
- 1 guy; does not scale

Spark
STREAMING

- Scales to 100s of nodes
- Batch sizes as small at half a second
- Processing latency as low as 1 second
- Exactly-once semantics no matter what fails

USE CASES (live statistics)



Page views

Kafka for buffering

Spark STREAMING

Spark for processing

USE CASES (Anomaly Detection)

Smart meter readings

Join 2 live data sources

FLUME

Spark STREAMING

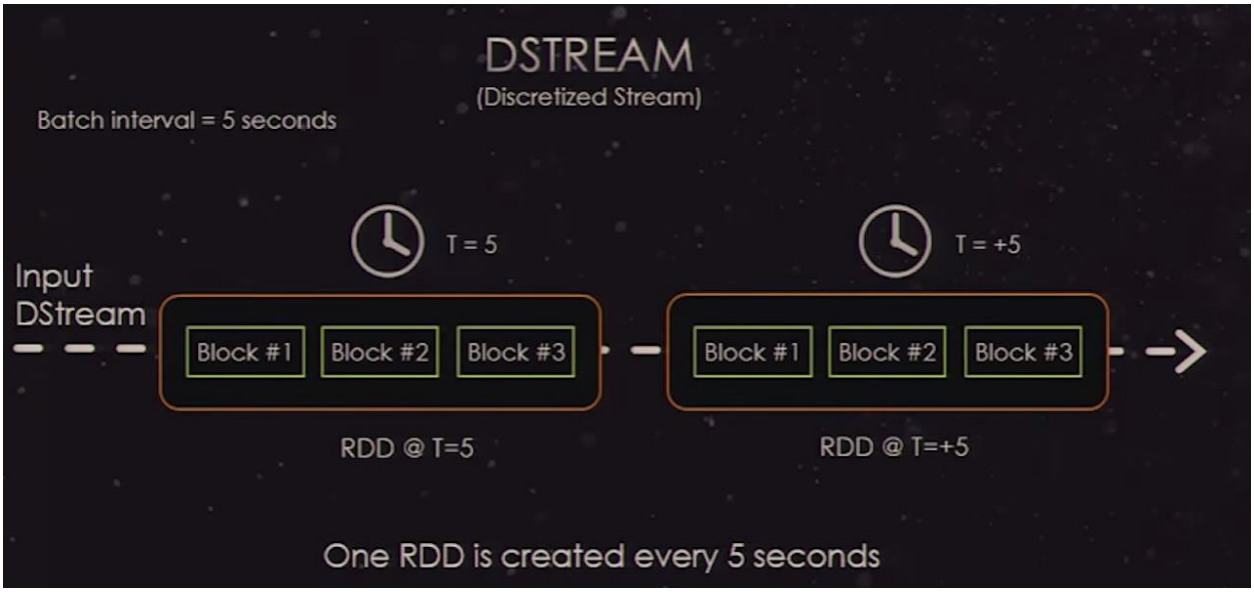
Batches every X seconds

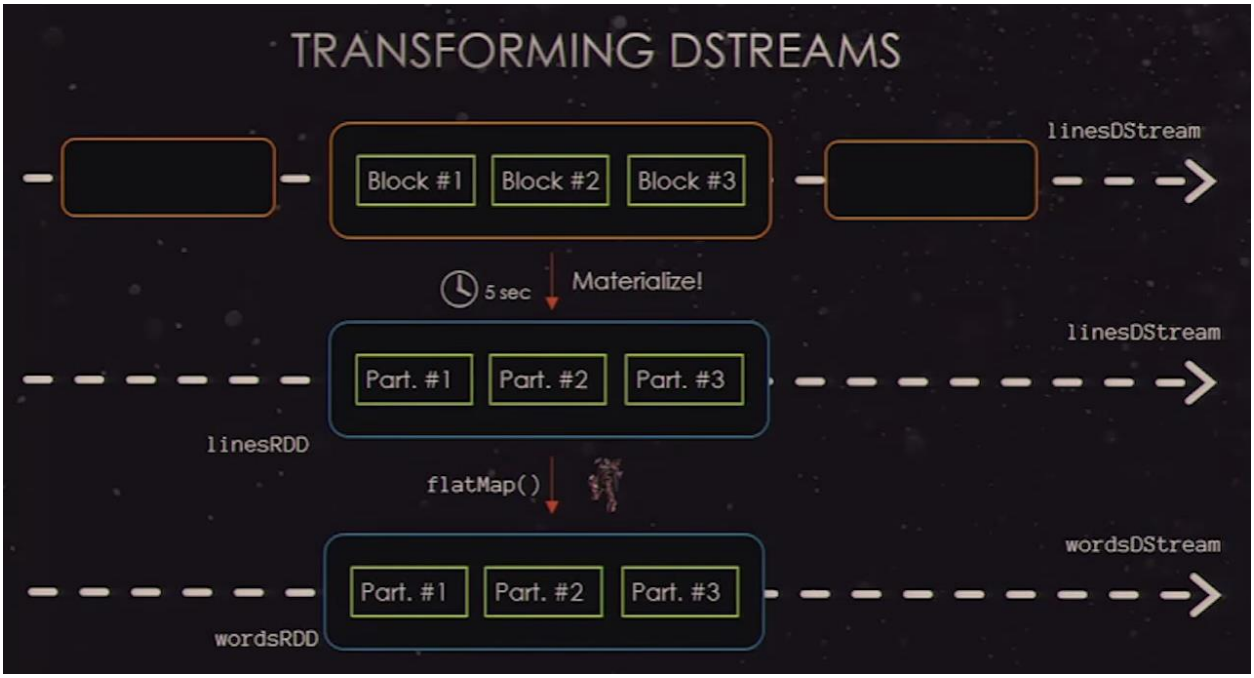
Input data stream

Spark STREAMING

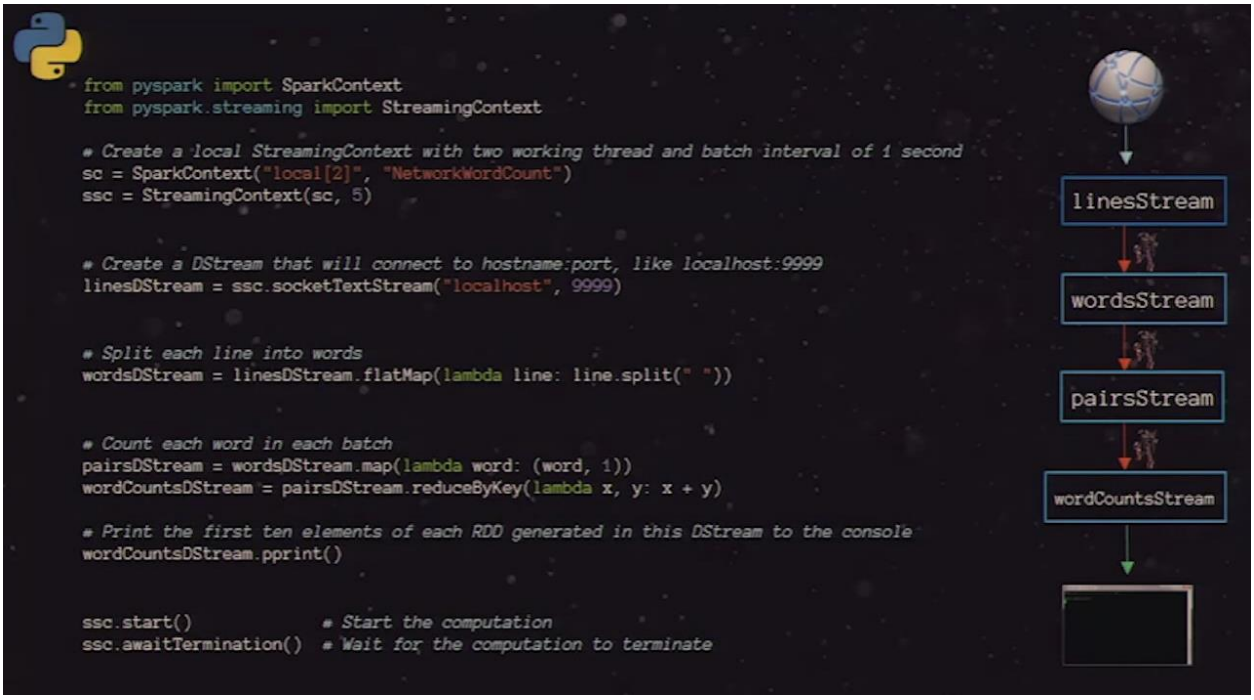
Spark CORE

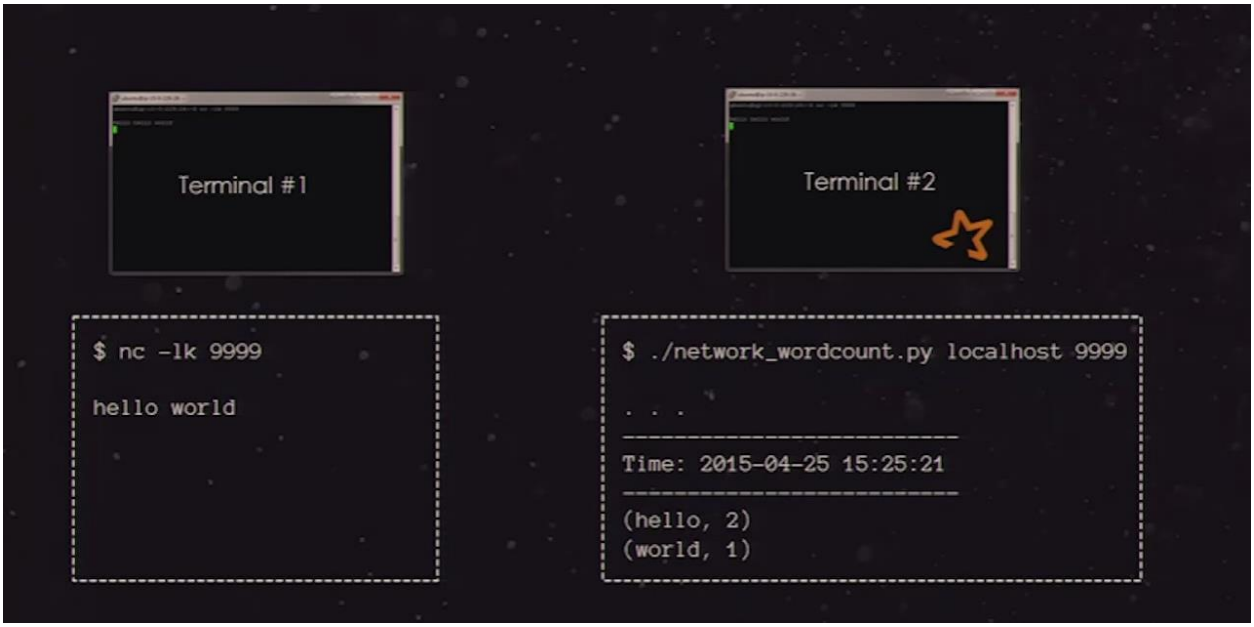
Batches of processed data


DSTREAM
(Discretized Stream)
Batch interval = 5 seconds
T = 5
T = +5
Input DStream
Block #1
Block #2
Block #3
Block #1
Block #2
Block #3
RDD @ T=5
RDD @ T=+5
One RDD is created every 5 seconds


TRANSFORMING DSTREAMS
linesDStream
Block #1
Block #2
Block #3
5 sec
Materialize!
linesDStream
Part. #1
Part. #2
Part. #3
linesRDD
flatMap()
wordsDStream
Part. #1
Part. #2
Part. #3
wordsRDD

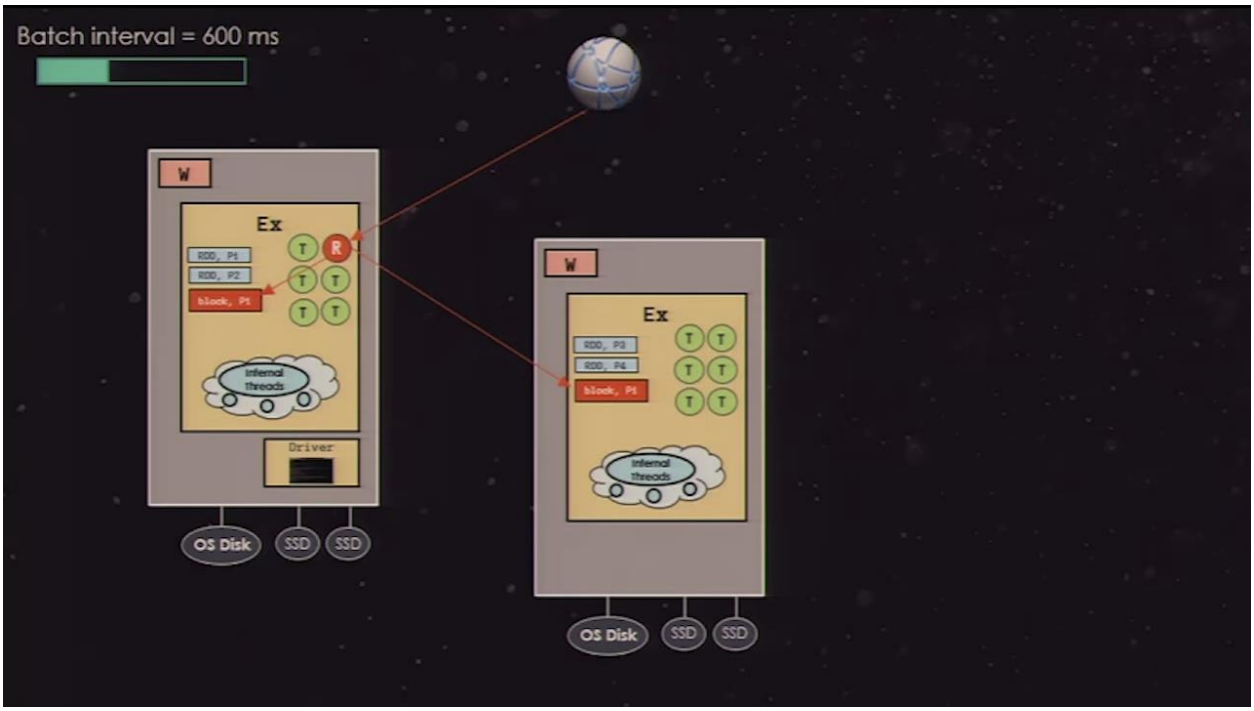
Batch interval of 5 seconds



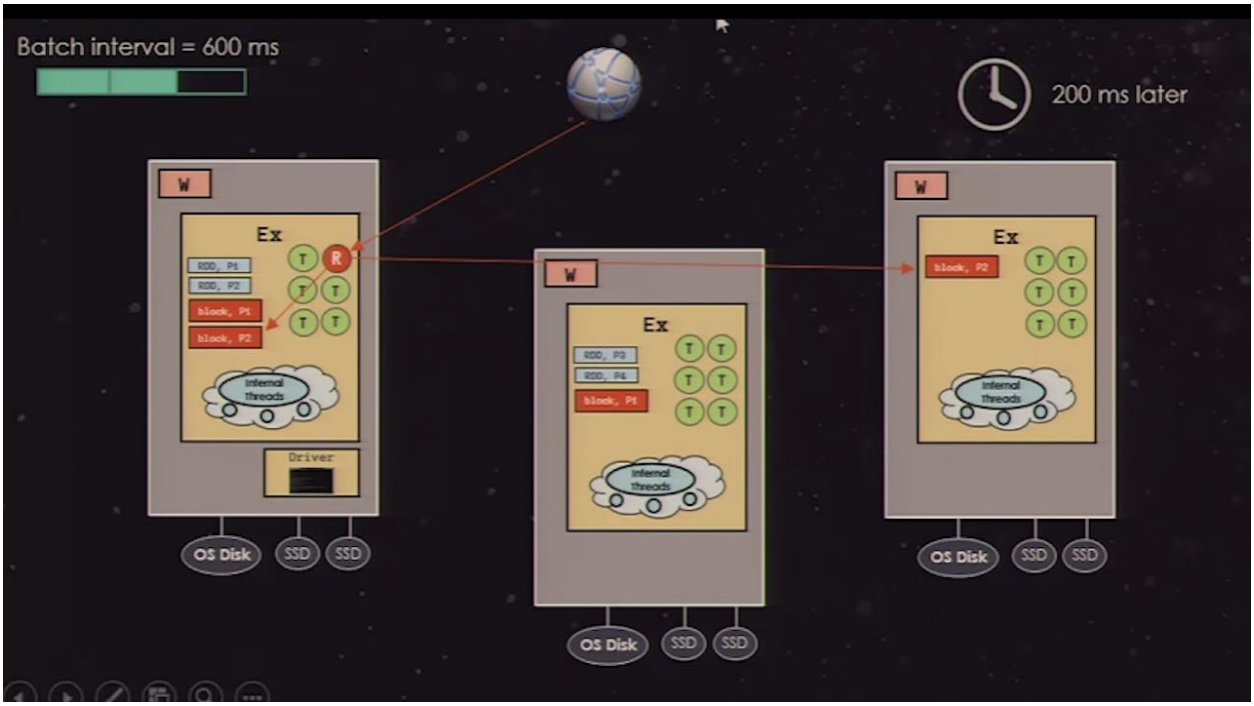


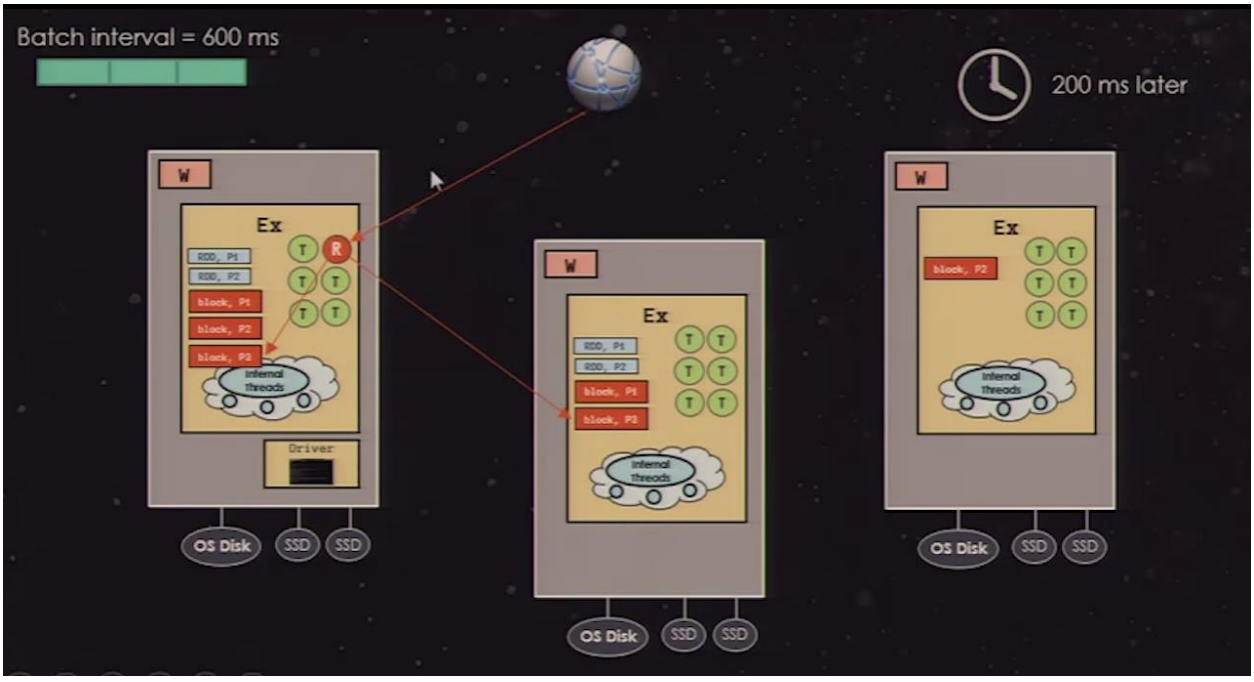
Spark streaming use a receiver to listening on specific IP and port (e.g. 9999) or pulling data from kafka ,flume or twitter , Receiver thread will write out a block (like partition) and copy of the block in a different executor JVM

Here our batch interval is 600ms, whatever data is come in first 200ms will create the first block

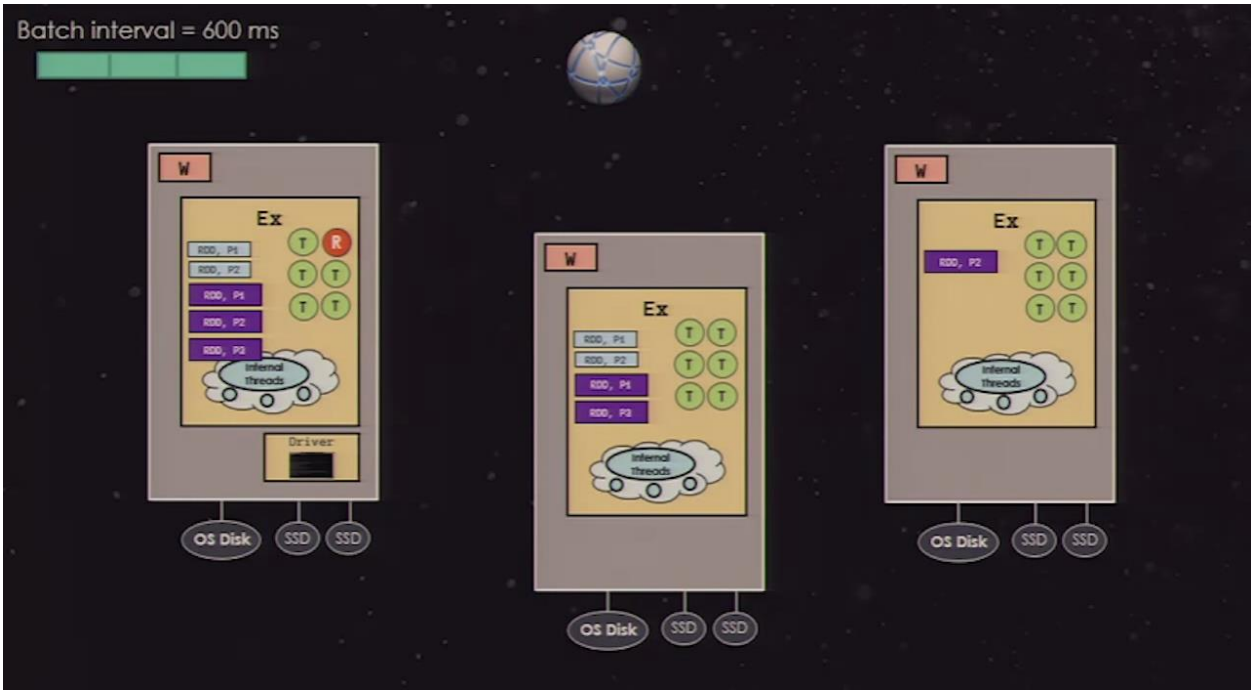


The same receiver continues listening for the next 200ms and creates one new block and continues the same till 600ms.

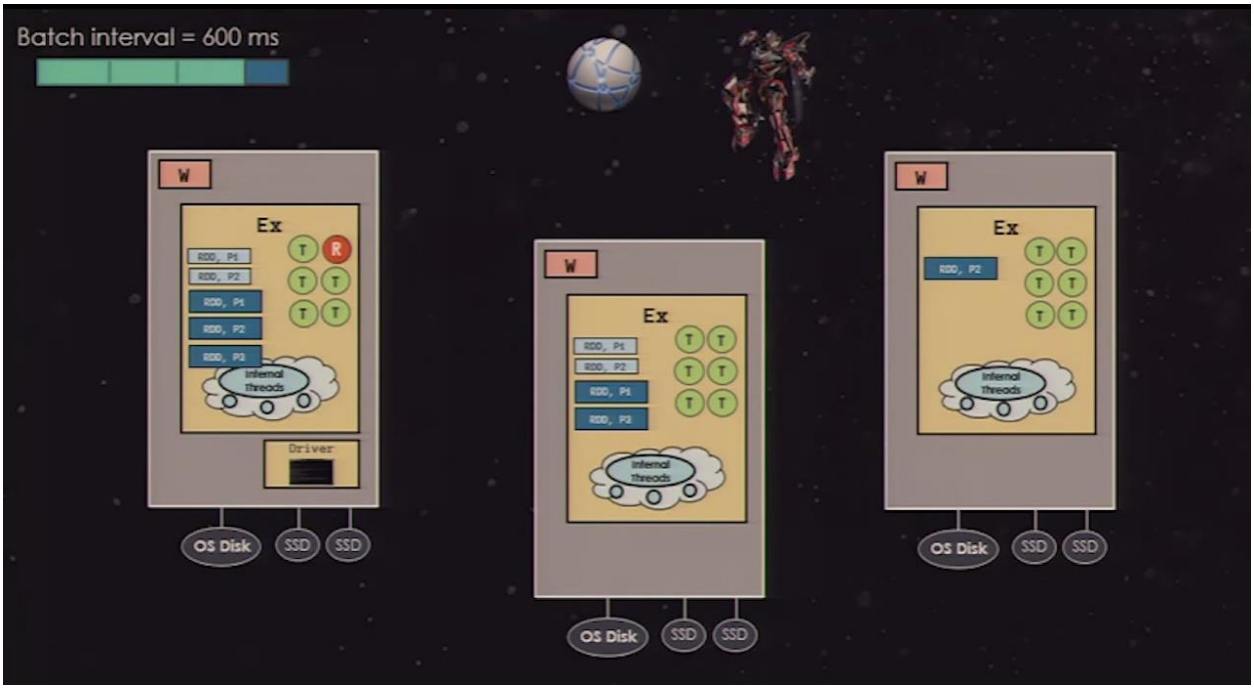




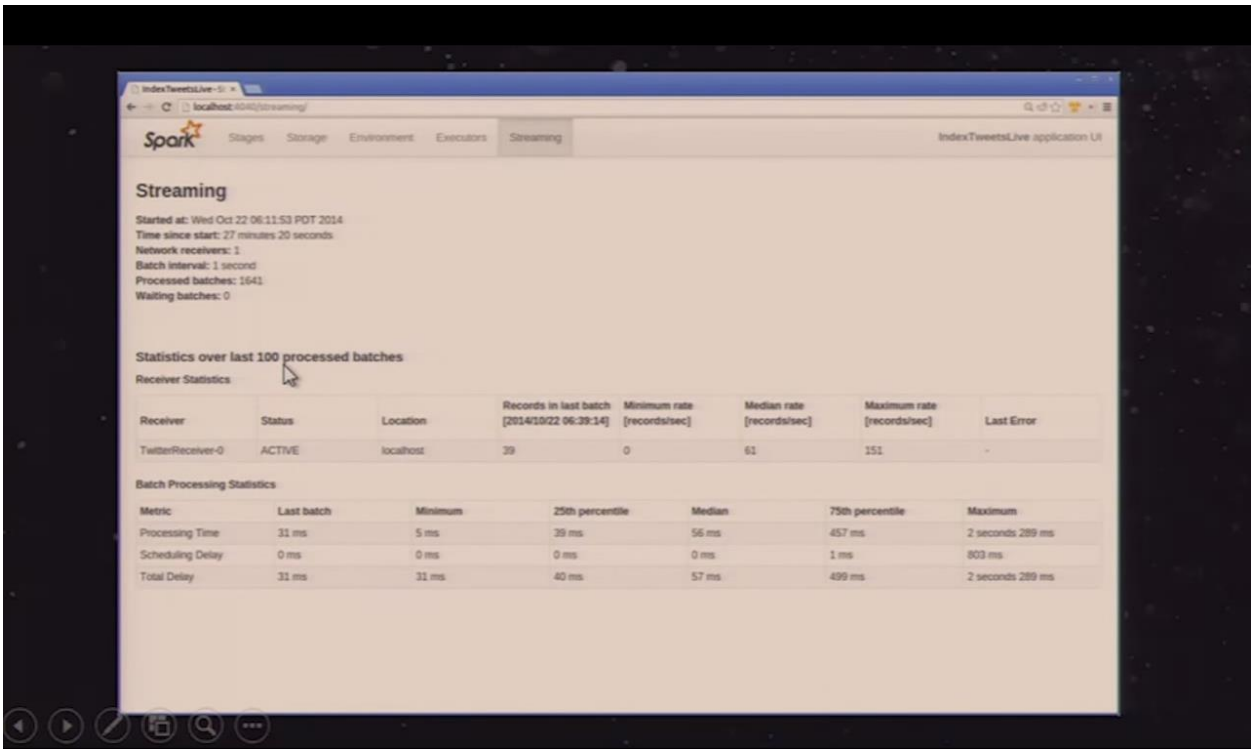
Now we hit our batch interval period, so now it’s time to materialized and make the RDD



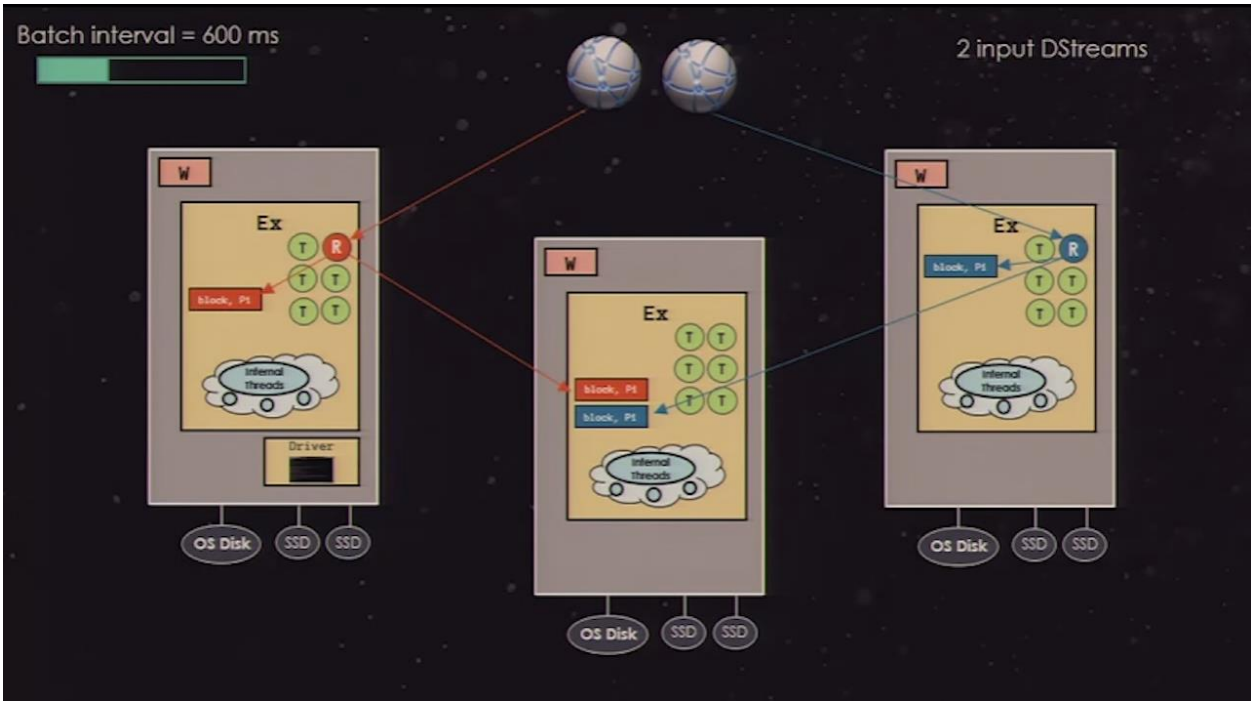
Now on these RDD we are applying transformation function, those transformation we applied is processing latency, this happens after the batch interval over. By that time receiver continue to listen new data, so ideally before creating new RDD, processing for transformation for previous RDD get completed otherwise we will fall behind, so if our processing latency is too high like 6 sec and batch interval is 5 sec then we need to re architecture that, need to decrease batch interval so that processing latency go down.

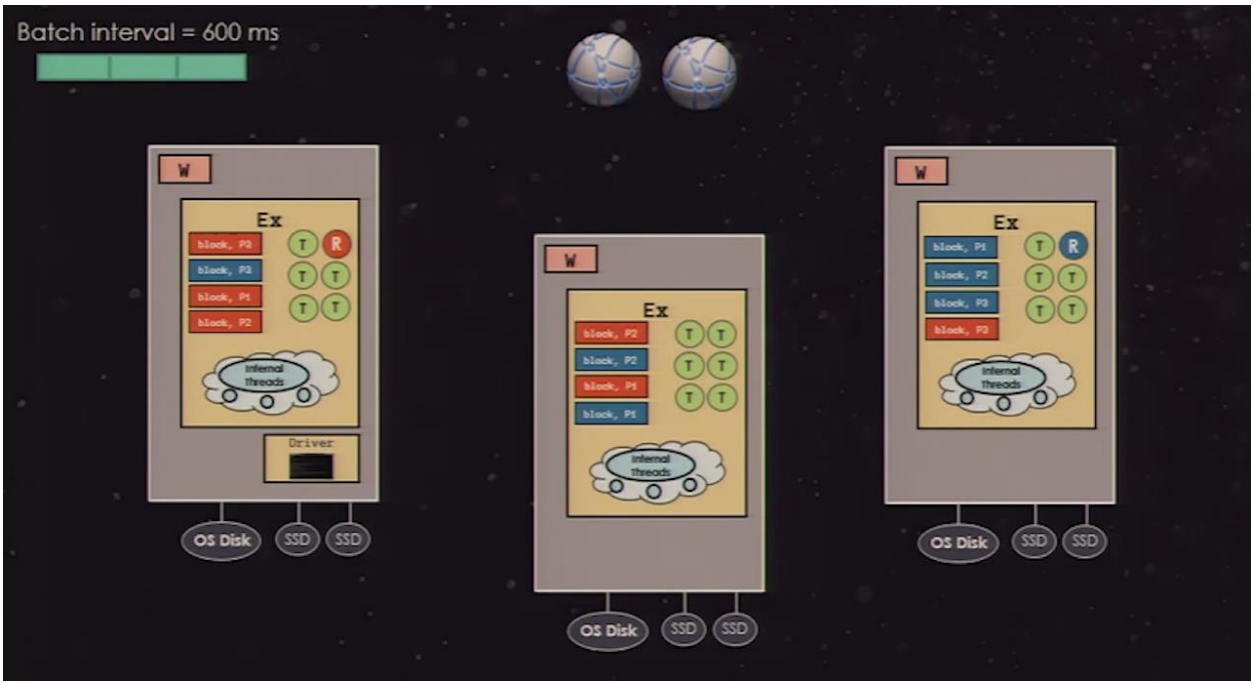


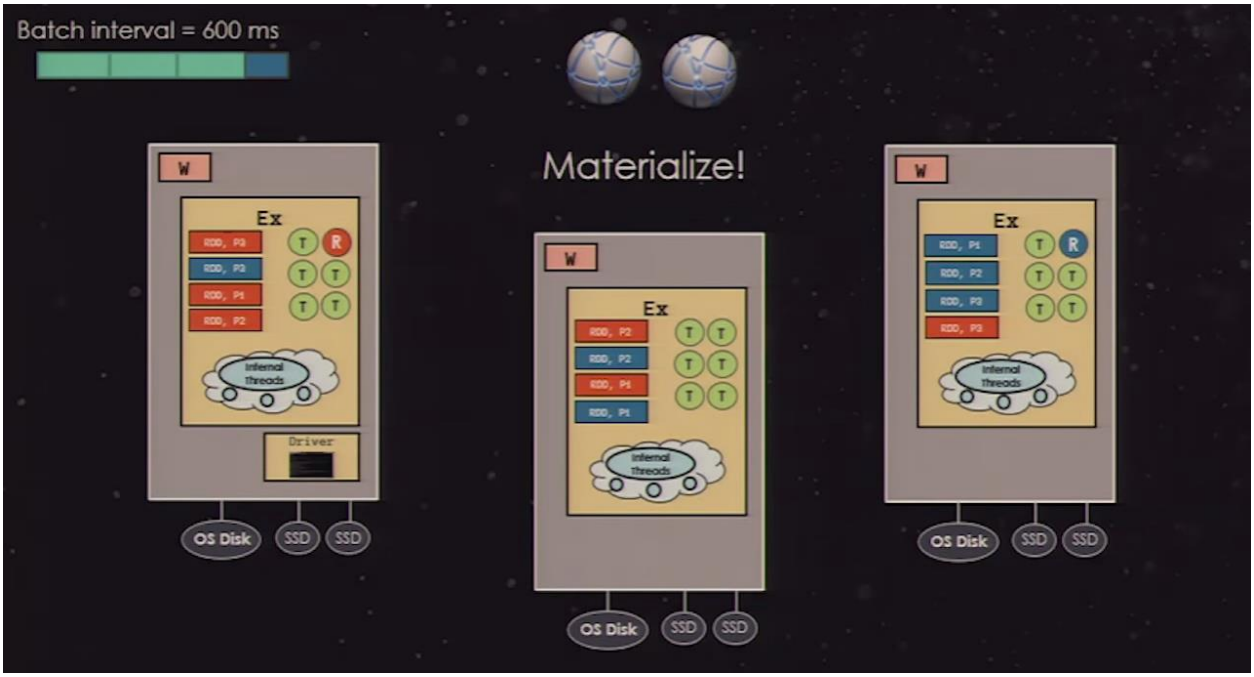
Spark stream UI

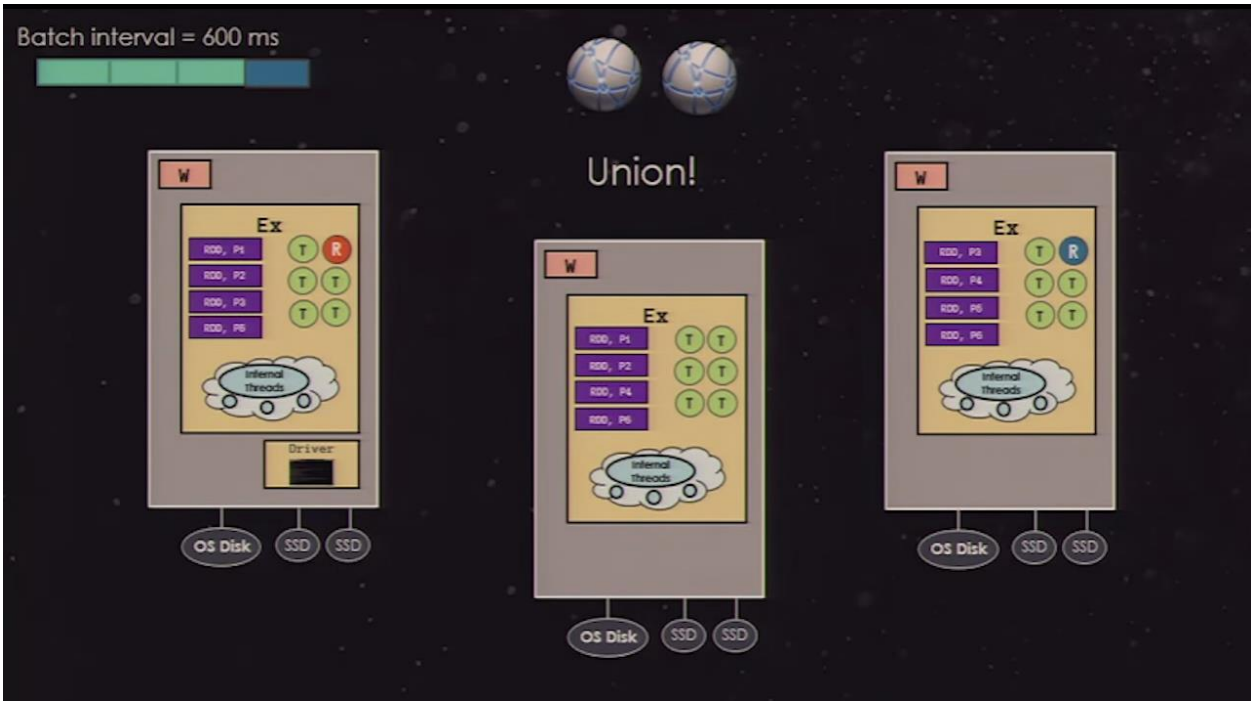


We can set multiple receivers (may be two different kafka topics)






Batch interval = 600 ms
Materialize!
W
Ex
RDD, P3
RDD, P2
RDD, P1
RDD, P2
T
R
Internal Threads
Driver
OS Disk
SSD
SSD


Batch interval = 600 ms
Union!
W
Ex
RDD, P1
RDD, P2
RDD, P3
RDD, P6
RDD, P4
T
R
Internal Threads
Driver
OS Disk
SSD
SSD


BASIC
- File systems
- Socket Connections
- Akka Actors
Sources directly available in StreamingContext API
ADVANCED
- Kafka
- Flume
- Twitter
Requires linking against extra dependencies
CUSTOM
- Anywhere
Requires implementing user-defined receiver


TRANSFORMATIONS ON DSTREAMS
map(f(x))
reduce(f(x))
union(otherStream)
updateStateByKey(f(x))*
flatMap(f(x))
join(otherStream, [numTasks])
filter(f(x))
cogroup(otherStream, [numTasks])
repartition(numPartitions)
transform(f(x))
count()
reduceAByKey(f(x) , [numTasks])
countByValue()

TRANSFORMATIONS ON DSTREAMS

pairs = (word, 1) (cat, 1)

`updateStateByKey( f(x) )*` : allows you to maintain arbitrary state while continuously updating it with new information.

To use:

1) Define the state
(an arbitrary data type)

2) Define the state update function
(specify with a function how to update the state using the previous state and new values from the input stream)

* Requires a checkpoint directory to be configured

To maintain a running count of each word seen in a text data stream (here running count is an integer type of state):

```
def updateFunction(newValues, runningCount):
    if runningCount is None:
        runningCount = 0
    return sum(newValues, runningCount)  # add the
        # new values with the previous running count
        # to get the new count

runningCounts = pairs.updateStateByKey(updateFunction)
```

TRANSFORMATIONS ON DSTREAMS

`transform( f(x) )` : can be used to apply any RDD operation that is not exposed in the DStream API.

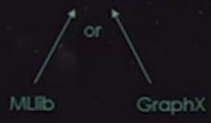
```
spamInfoRDD = sc.pickleFile(...) # RDD containing spam information

# join data stream with spam information to do data cleaning
cleanedDStream = wordCounts.transform(lambda rdd:
                                      rdd.join(spamInfoRDD).filter(...))
```

For example:

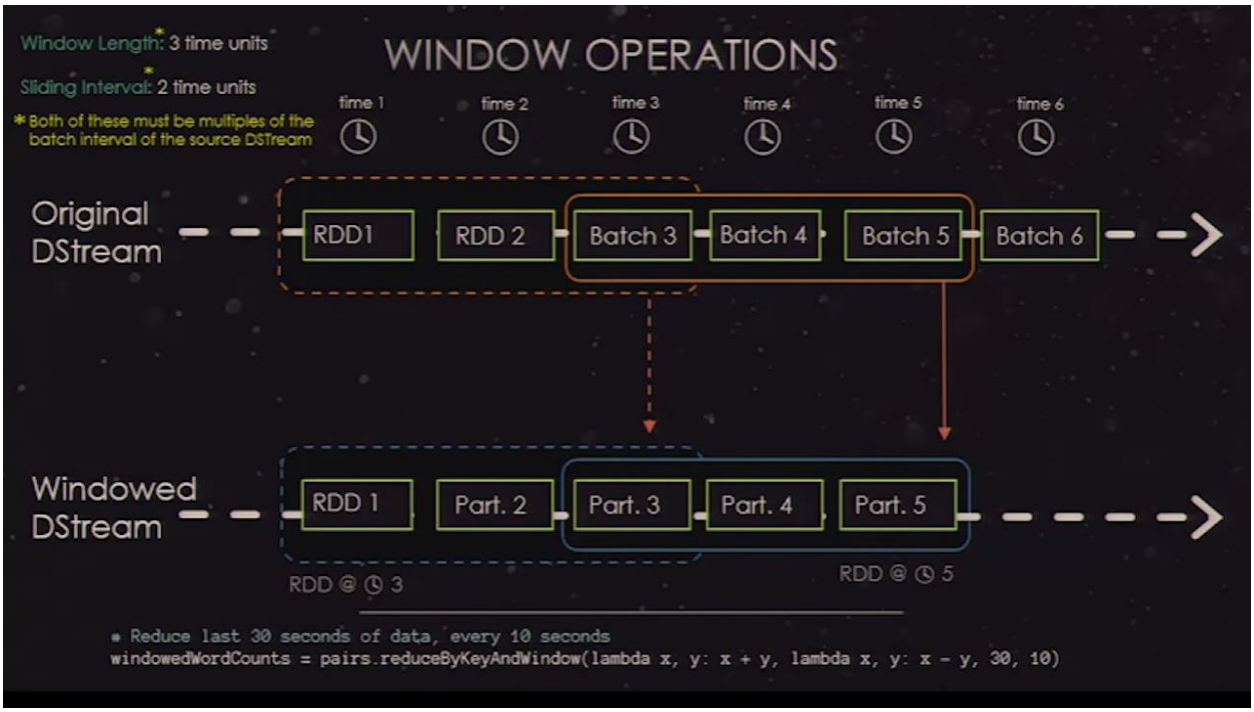
- Functionality to join every batch in a data stream with another dataset is not directly exposed in the DStream API.

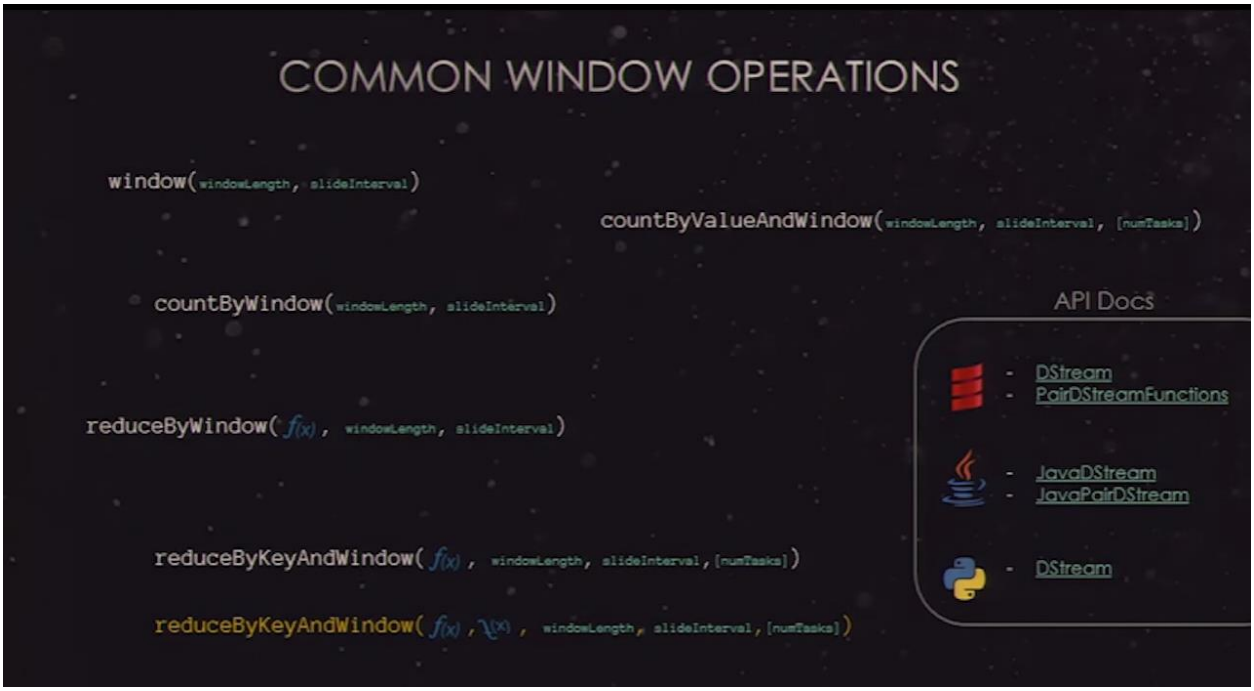
- If you want to do real-time data cleaning by joining the input data stream with pre-computed spam information and then filtering based on it.



We can set window length and sliding interval

If you want to do analysis on all the data came in last 30 sec and you want to do that analysis every 10 sec





OUTPUT OPERATIONS ON DSTREAMS

print()

foreachRDD($f(x)$)

saveAsTextFile(prefix, [suffix])

saveAsObjectFiles(prefix, [suffix])

saveAsHadoopFiles(prefix, [suffix])