FAKULTÄT FÜR MATHEMATIK, INFORMATIK UND STATISTIK
INSTITUT FÜR INFORMATIK

LMU LUDWIG-MAXIMILIANS-UNIVERSITÄT MÜNCHEN

LEHRSTUHL FÜR DATENBANKSYSTEME UND DATA MINING

Lecture Notes to

Big Data Management and Analytics

Winter Term 2017/2018

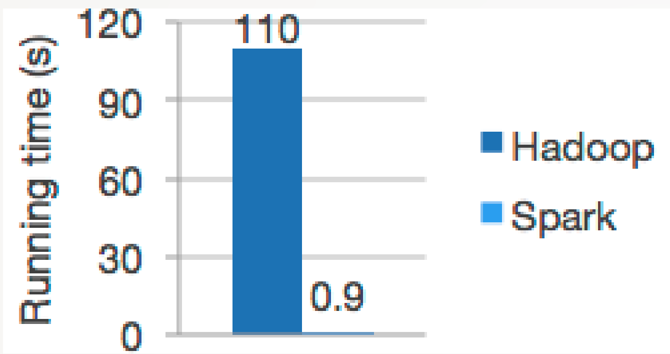
Apache Spark

DBS

Motivation

Spark becomes new standard for the MR applications:

- Logistic regression in Hadoop and Spark:

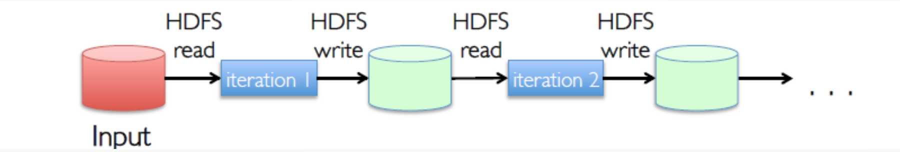


- Cloudera replaces classic MR framework with Spark
- IBM puts 3500 Researches to work on Spark related projects

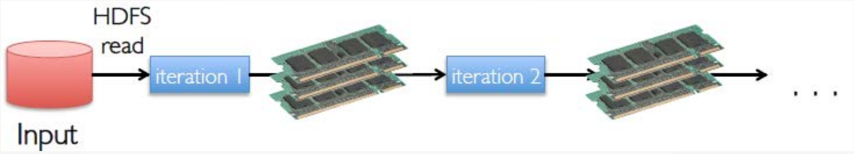
Motivation

Most of the Algorithms require a chain of MR steps:

- Tedious to program
- Writes to disk and reads from disk between steps are expensive



- Idea: Use memory instead of disk



Apache Spark

- Keeps data between operations in-memory
- Lot of convenience functions (e.g. filter, join)
- No restrictions for the operations order from the framework (not just Map->Reduce)
- Spark program is a pipeline of operations on distributed datasets (RDD)
- API: Java, Scala, Python, R

Resilient Distributed Dataset (RDD)

- Read-only collection of objects
- Partitioned across machines
- Enables operations on partitions in parallel
- Creation:
  - Parallelizing a collection
  - Data from files (e.g. HDFS)
  - As result of transformation of another RDD

```
In [25]: numbers=sc.parallelize([1,2,3,4,5,6,7,8,9,10])

In [26]: numbers
Out[26]: ParallelCollectionRDD[21] at parallelize at PythonRDD.scala:391
```

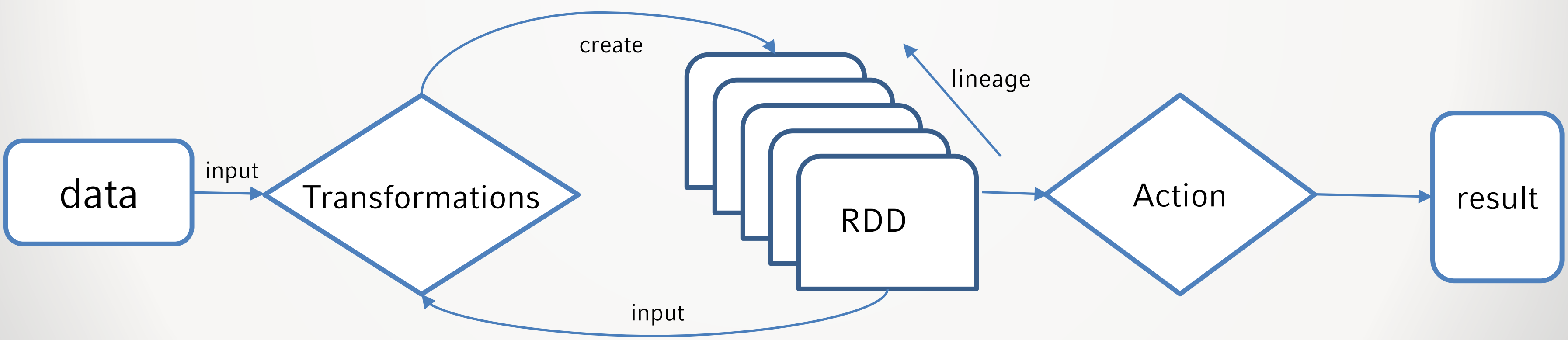
Resilient Distributed Dataset (RDD)

- Number of partitions determines parallelism level
- Can be cached in memory between operations
- Graph based representation (Lineage)
- Fault-Tolerant
  - In case of machine failure:
    RDD can be reconstructed

RDD Transformations and actions

Two types of operations:

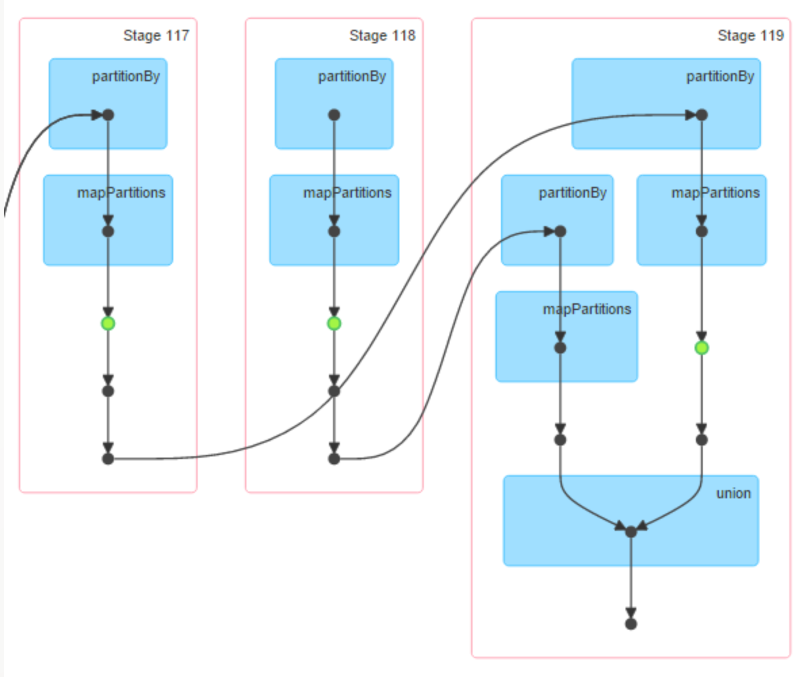
- Transformations (lazily evaluated)
- Actions (trigger transformations)



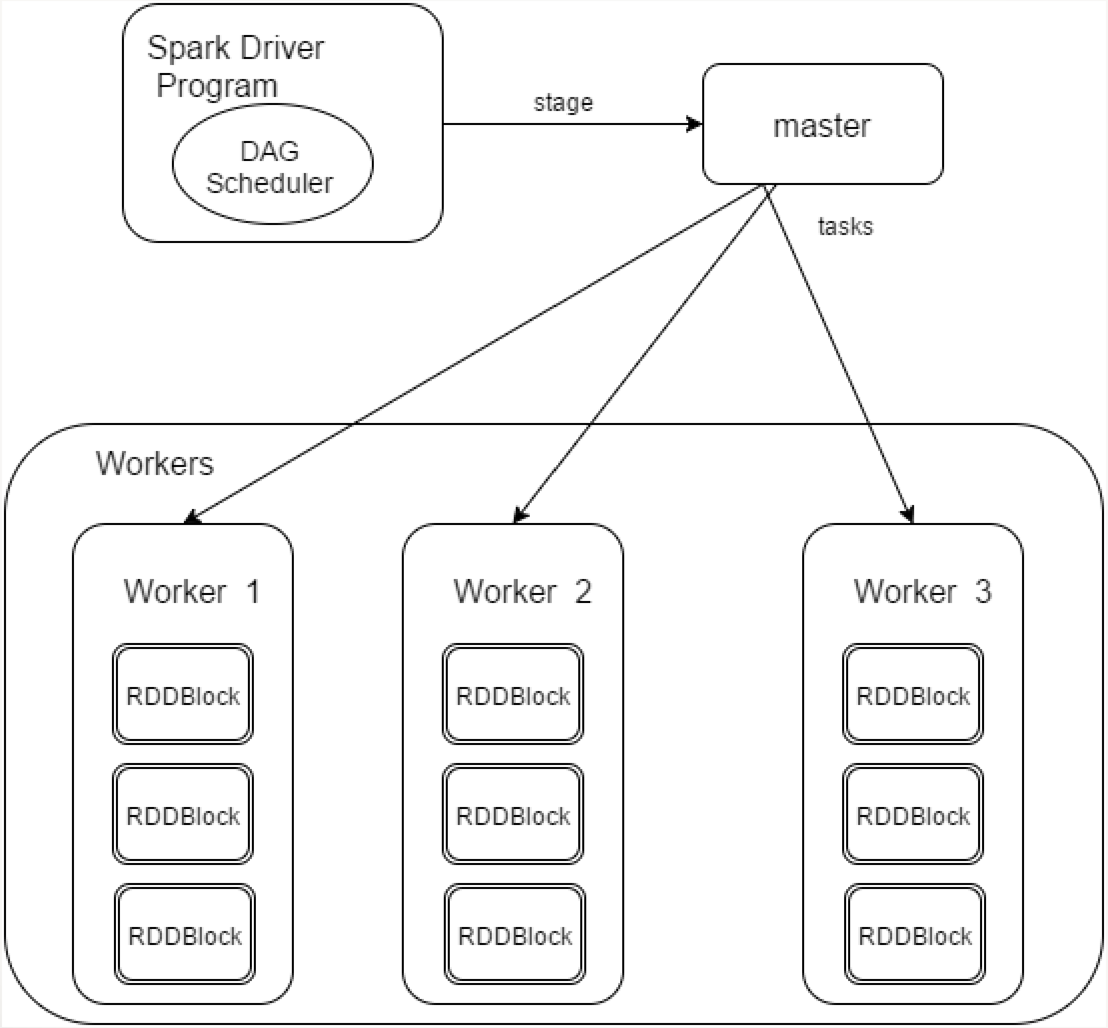
RDD Transformations and actions

Transformations

- Recipe how the new dataset is generated from the existing one
- Lazily evaluated
- Organized as Directed Acyclic Graph
- The required calculations are optimized
- DAG Scheduler defines stages for execution
- Each stage comprises tasks based on particular data partitions

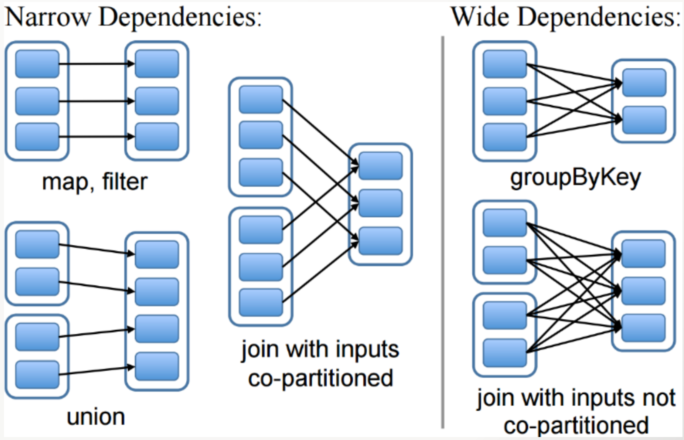


Architecture



RDD narrow and wide dependencies

- Narrow dependency
  - Each partition of the new RDD depends on partitions located on the same worker (transformation is executed locally on the workers)
- Wide dependency
  - New partition depends on partitions on several workers (shuffle necessary)



Shuffle

- internal map and reduce tasks
  to organize and aggregate data

- large costs
  - in memory data structures consume a lot of memory
    => disk I/O (shuffle spill) + garbage collection
  - many intermediate files on disk (for RDD reconstruction in case of failure) => garbage collection
  - data serialization
  - network I/O

- reduce the amount of data to be transferred in the shuffle phase by pre-aggregation

Lettercount examples

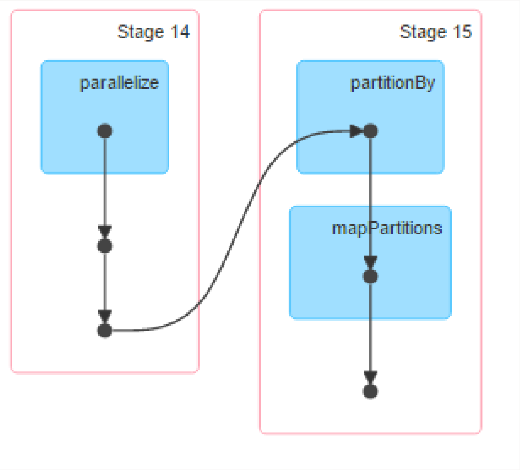
```
In [17]: data = sc.parallelize(list('dfasdfasdfasdfasdgafsgasfgasfgafgasfdgafgafafga'))

In [18]: data.map(lambda letter: (letter, 1))\
   ....: .reduceByKey(lambda f_count, s_count: f_count + s_count)\
   ....: .collect()
Out[18]: [('g', 8), ('f', 12), ('a', 13), ('s', 8), ('d', 6)]
```

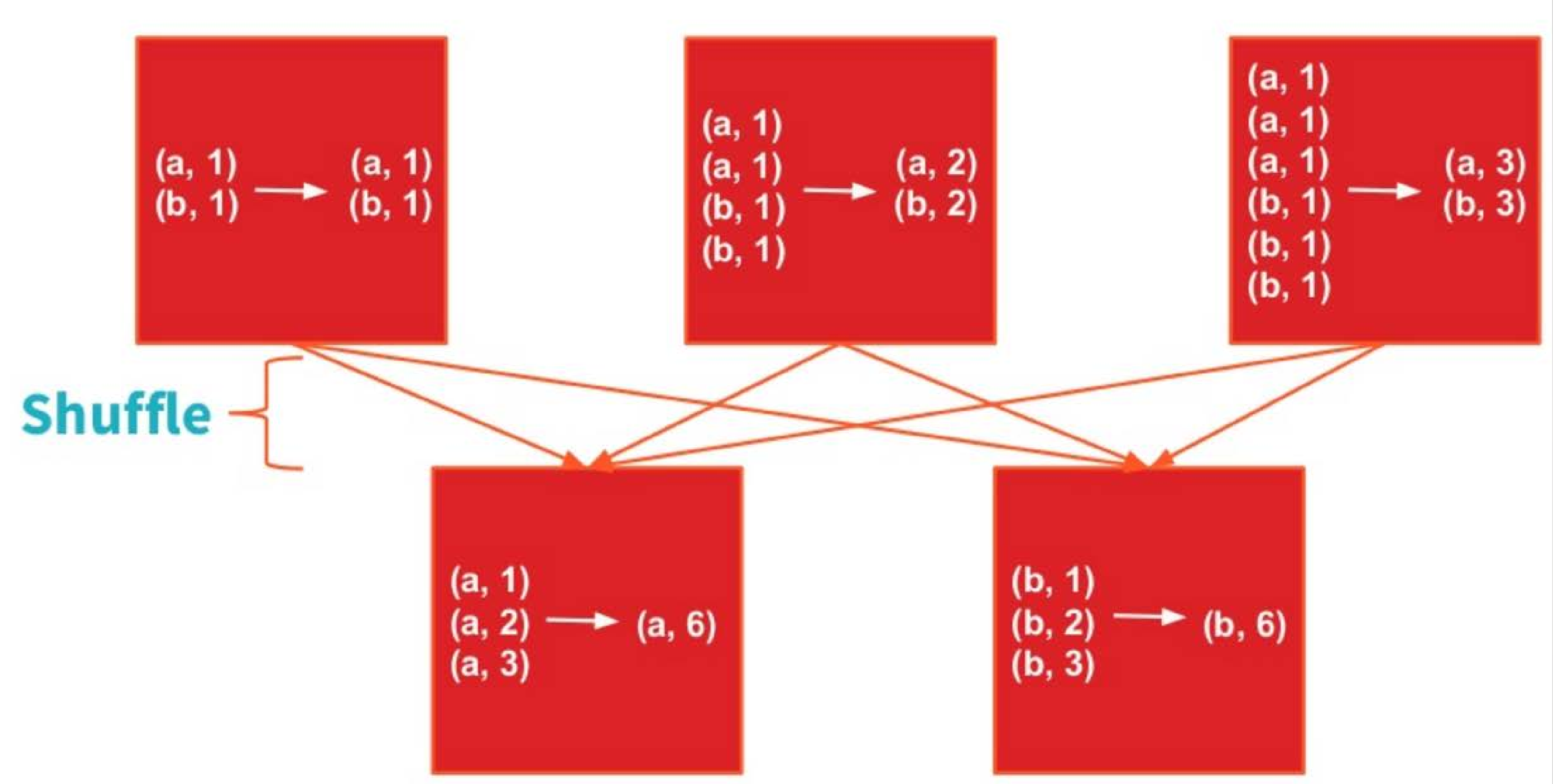
transformations

actions

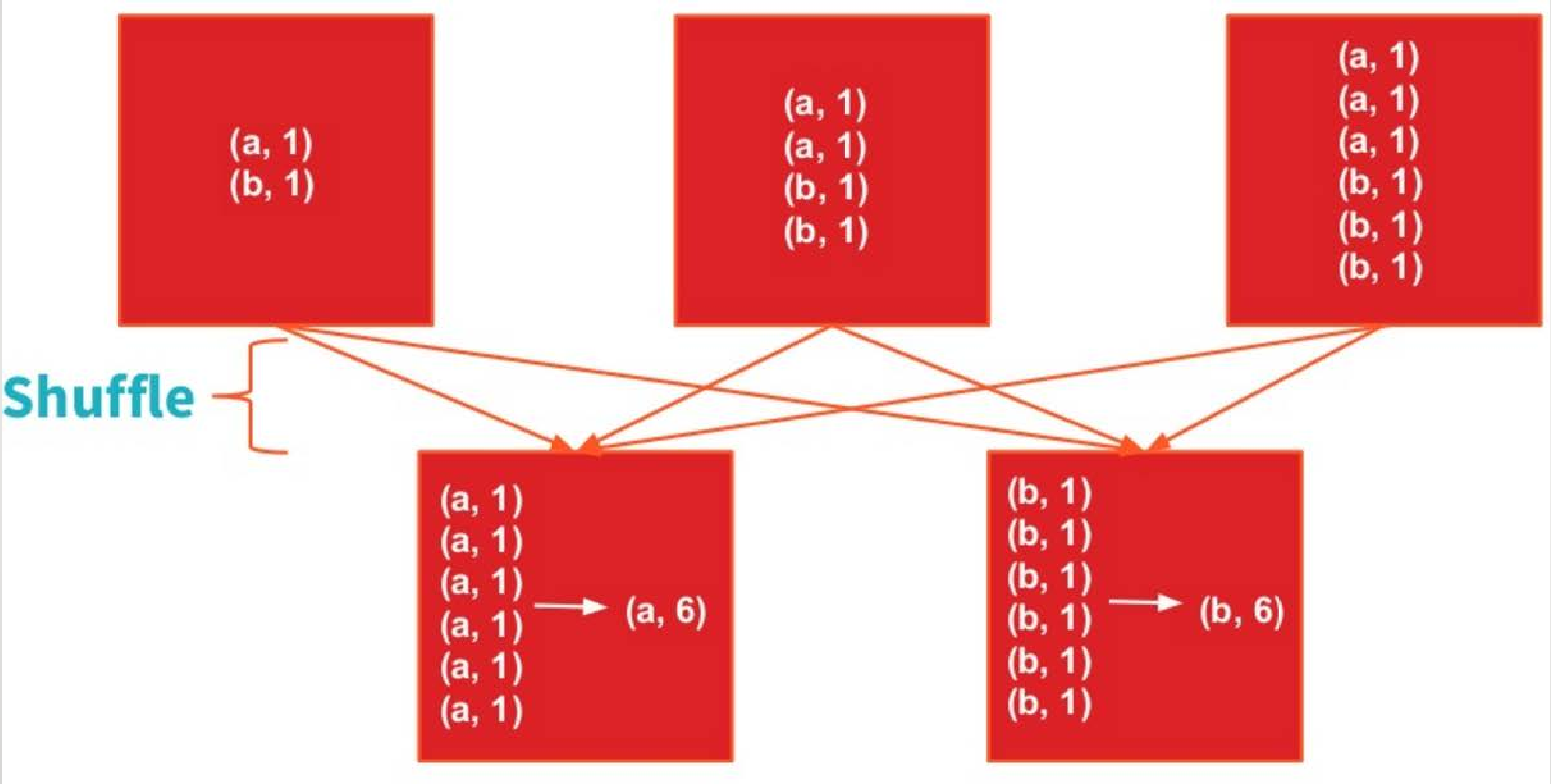
```
In [20]: data.map(lambda letter: (letter, 1))\
.groupByKey()\
.mapValues(lambda count_list:sum(count_list))\
.collect()
Out[20]: [('g', 8), ('f', 12), ('a', 13), ('s', 8), ('d', 6)]
```



Shuffle reduceByKey

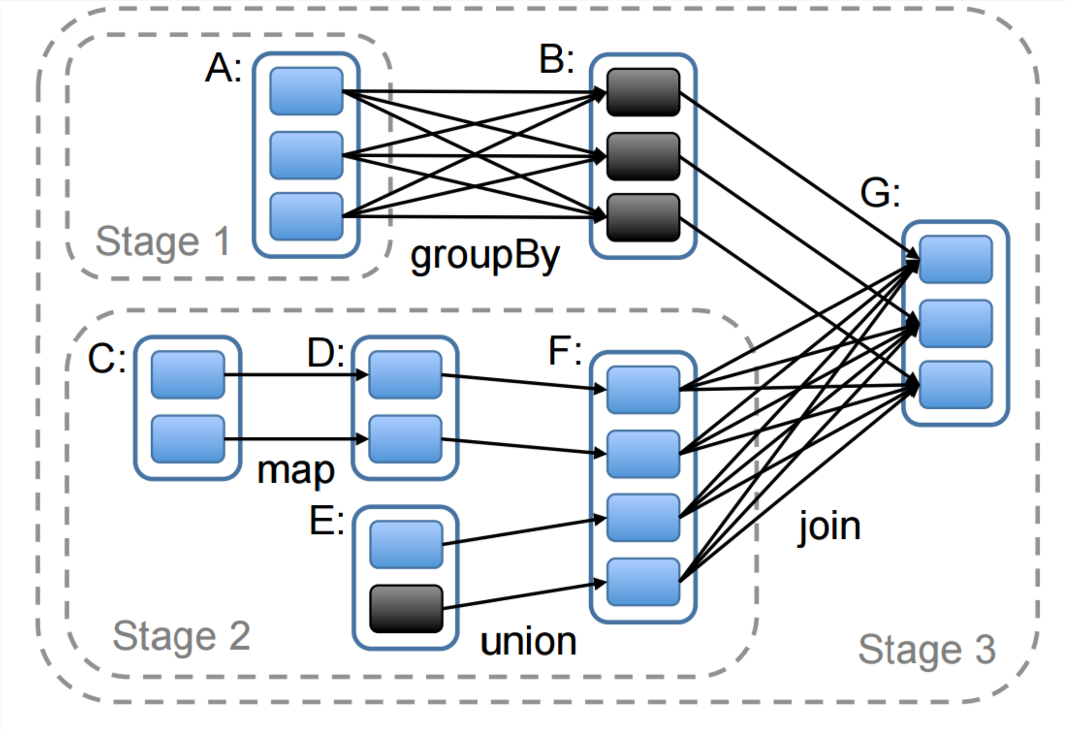


Shuffle groupByKey



RDD Persistence

Precomputed RDDs are reused



B was computed and is reused, stage 1 is skipped

RDD Persistence

- Computed RDD are held in memory as deserialized Java objects

- Old data partitions are dropped in least-recently-used fashion to free memory. Discarded RDD is recomputed if it is needed again.

- To advise Spark to keep RDD in memory call cache() or persist() operations on it

RDD Persistence

- RDD can be persisted differently by passing argument to persist function (in python persisted objects are always serialized):
  - As deserialized java objects in memory (default)
  - As deserialized java objects in memory and on disk
  - Serialized java objects in memory
  - Serialized java objects in memory and on disk
  - Serialized on disk
  - Off Heap

RDD Persistence

- Off heap RDD persistence:
  - RDDs are persisted outside of Java Heap
  - Reduces the JVM Garbage Collection pauses
- Tachyon
  - Memory-centric distributed storage system
  - Lineage function
  - Enables data sharing between different jobs
  - Data is safe even if computation crashes

Shared variables

- The driver program passes the functions to the cluster
- If passed function uses variables defined in driver program, these are copied to each worker

```
In [201]: a = 3

In [202]: numbers = sc.parallelize([1,2,3,4])

In [203]: numbers.map(lambda n: n + a).collect()
Out[203]: [4, 5, 6, 7]
```

- Updates on these variables are not allowed

```
In [195]: a=[3]

In [196]: numbers=sc.parallelize([1,2,3,4])

In [197]: numbers.foreach(lambda n: a.append(n))

In [198]: a
Out[198]: [3]
```

Shared variables

- The necessary common data is broadcasted within each stage
- Within the stage the data is serialized and is desirialized before each task
- Broadcast variables are used to avoid multiple broadcasting and de/serialization
- Broadcast variable is shipped once and is cached deserialized
- Broadcast variable should not be modified, but can be recreated

Shared variables

Example broadcast variable:

```
In [219]: dict = {'dog' : 'hund', 'he' : 'er', 'weather' : 'wetter', 'is' : 'ist', 'good' : 'gut'}

In [220]: broadcasted_dict = sc.broadcast(dict)

In [221]: data = sc.parallelize( ['weather', 'is', 'good'] )

In [222]: data.map(lambda word: broadcasted_dict.value[word]).collect()
Out[222]: ['wetter', 'ist', 'gut']

In [223]: dict['good']='sehr gut'

In [224]: data.map(lambda word: broadcasted_dict.value[word]).collect()
Out[224]: ['wetter', 'ist', 'gut']

In [225]: broadcasted_dict = sc.broadcast(dict)

In [226]: data.map(lambda word: broadcasted_dict.value[word]).collect()
Out[226]: ['wetter', 'ist', 'sehr gut']
```

Shared variables

- Accumulators are only updatable shared variables in Spark
- Associative add operation on accumulator is allowed
- Own add operation for new types are allowed
- Tasks can update Accumulator value, but only driver program can read it
- Accumulator update is applied when action is executed
- Task updates accumulator each time action is called
- Restarted tasks update accumulator only once

Shared variables

Accumulator example:

```
In [257]: accum = sc.accumulator(0)

In [258]: data = sc.parallelize([1,2,3,4])

In [259]: def add_to_acc(acc, to_add ):
    acc.add(to_add)
    return to_add
   .....:

In [260]: res = data.map(lambda n: add_to_acc(accum,n))

In [261]: accum.value
Out[261]: 0

In [262]: res.collect()
Out[262]: [1, 2, 3, 4]

In [263]: accum.value
Out[263]: 10

In [264]: res.count()
Out[264]: 4

In [265]: accum.value
Out[265]: 20
```

Other relevant spark projects

- Spark streaming
  - Objects from stream are processed in small groups (batches)
  - Similar to batch processing

- Spark SQL
  - Processing of structured data (SchemaRDD)
  - Data is stored in columns and is analyzed in SQL manner
  - Data is still RDD and can be processed by other Spark frameworks
  - JDBC/ODBC interface

Other relevant spark projects

- GraphX
  - Distributed computations on Graphs

- Machine Learning Libraries
  - Mlib
  - H20 (Sparkling water)
  - Keystone ML

Sources

- http://www.datacenterknowledge.com/archives/2015/09/09/cloudera-aims-to-replace-mapreduce-with-spark-as-default-hadoop-framework/
- http://spark.apache.org/images/logistic-regression.png
- https://www-03.ibm.com/press/us/en/pressrelease/47107.wss
- Zaharia, Matei, et al. "Resilient distributed datasets: A fault-tolerant abstraction for in-memory cluster computing." *Proceedings of the 9th USENIX conference on Networked Systems Design and Implementation.* USENIX Association, 2012.
- http://de.slideshare.net/databricks/strata-sj-everyday-im-shuffling-tips-for-writing-better-spark-programs?related=1