Motivation

Spark becomes new standard for the MR applications:

- Logistic regression in Hadoop and Spark:
  
  ![Graph showing running time comparison between 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

```python
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

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

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)]

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
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 deserialized 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:

```python
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:

```python
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://spark.apache.org/images/logistic-regression.png


• http://de.slideshare.net/databricks/strata-sj-everyday-im-shuffling-tips-for-writing-better-spark-programs?related=1