Chapter 4:

Apache Spark

Lecture Notes
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Based on lectures by
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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
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
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
- Lazy 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

Spark Driver Program

DAG Scheduler

master

stage

tasks

Workers

Worker 1

RDDBlock

RDDBlock

RDDBlock

Worker 2

RDDBlock

RDDBlock

RDDBlock

Worker 3

RDDBlock

RDDBlock

RDDBlock
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('dfasdfsdfasdfsdfgasgfasfgasfdgafgafgafga'))

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

((a, 1), (a, 1), (a, 2), (a, 3), (b, 1), (b, 2), (b, 3))

Shuffle

((a, 1), (a, 2), (a, 3), (b, 1), (b, 2), (b, 3))
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

```python
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

```python
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:

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


