6CS030 Lecture 7

SQL on Hadoop

Hadoop Stack 'Zoo':

- Apache Spark
- Apache HBase
- Apache Pig
- Apache Hive

SQL on Hadoop

- MapReduce is very complex when compared to SQL
- Need for a more database-like setup on top of Hadoop
- Various projects can be used on top of Hadoop
  - See http://hadoop.apache.org/ for a list.
- Sometimes referred to as a “Zoo”
- ZooKeeper provides a high-performance coordination service for distributed applications

SQL on Hadoop

- HBase
  - https://hbase.apache.org
- Pig
  - https://pig.apache.org/
- Hive
  - https://hive.apache.org/
- Spark
  - https://spark.apache.org/

HBase

- First Hadoop database inspired by Google's Bigtable
- Runs on top of HDFS
- NoSQL alike data storage platform
  - No typed columns, triggers, advanced query capabilities, etc.
- Offers a simplified structure and query language in a way that is highly scalable and can tackle large volumes

HBase

- Similar to RDBMSs, HBase organizes data in tables with rows and columns
- HBase table consists of multiple rows
- A row consists of a row key and one or more columns with values associated with them
- Rows in a table are sorted alphabetically by the row key

HBase

- Each column in HBase is denoted by a column family and qualifier (separated by a colon, ‘:’)
- A column family physically co-locates a set of columns and their values
- Every row has the same column families, but not all column families need to have a value per row
- Each cell in a table is hence defined by a combination of the row key, column family and column qualifier, and a timestamp

HBase

- Example: HBase table to store and query users
- The row key will be the user id
- column families:qualifiers
  - name:first
  - name:last
  - email (without a qualifier)

HBase

```
hbase(main):001:0> create 'users', 'name', 'email'
0 row(s) in 2.8350 seconds

=> Hbase::Table - users



hbase(main):002:0> describe 'users'
Table users is ENABLED
users
COLUMN FAMILIES DESCRIPTION
{NAME => 'email', BLOOMFILTER => 'ROW', VERSIONS => '1', IN_MEMORY => 'false', K
EEP_DELETED_CELLS => 'FALSE', DATA_BLOCK_ENCODING => 'NONE', TTL => 'FOREVER', C
OMPRESSION => 'NONE', MIN_VERSIONS => '0', BLOCKCACHE => 'true', BLOCKSIZE => '6
5536', REPLICATION_SCOPE => '0'}
{NAME => 'name', BLOOMFILTER => 'ROW', VERSIONS => '1', IN_MEMORY => 'false', KE
EP_DELETED_CELLS => 'FALSE', DATA_BLOCK_ENCODING => 'NONE', TTL => 'FOREVER', CO
MPRESSION => 'NONE', MIN_VERSIONS => '0', BLOCKCACHE => 'true', BLOCKSIZE => '65
536', REPLICATION_SCOPE => '0'}
2 row(s) in 0.3250 seconds
```

Examples from: www.pdbmbook.com

HBase

```
hbase(main):006:0> put 'users', 'seppe', 'name:first', 'Seppe'
0 row(s) in 0.0200 seconds

hbase(main):007:0> put 'users', 'seppe', 'name:last', 'vanden Broucke'
0 row(s) in 0.0330 seconds

hbase(main):008:0> put 'users', 'seppe', 'email', 'seppe.vandenbroucke@kuleuven'
0 row(s) in 0.0570 seconds

hbase(main):009:0> scan 'users'
ROW                    COLUMN+CELL
 seppe                 column=email:, timestamp=1495293082872, value=seppe.vanden
                       broucke@kuleuven.be
 seppe                 column=name:first, timestamp=1495293050816, value=Seppe
 seppe                 column=name:firstt, timestamp=1495293047100, value=Seppe
 seppe                 column=name:last, timestamp=1495293067245, value=vanden Broucke

1 row(s) in 0.1170 seconds

hbase(main):011:0> get 'users', 'seppe'
COLUMN                         CELL
 email:                        timestamp=1495293082872, value=seppe.vandenbroucke@kuleuven.be
 name:first                    timestamp=1495293050816, value=Seppe
 name:last                     timestamp=1495293067245, value=vanden Broucke
4 row(s) in 0.1250 seconds
```

HBase

- HBase’s query facilities are very limited
- Essentially a key-value, distributed data store with simple get/put operations
- Includes facilities to write MapReduce programs
- HBase (similar to Hadoop) doesn’t perform well on less than 5 HDFS DataNodes with an additional NameNode
  - only makes the effort worthwhile when you can invest in, set up and maintain at least 6-10 nodes

Pig

- Yahoo! Developed "Pig", which was made open source as Apache Pig in 2007
- High-level platform for creating programs that run on Hadoop which uses MapReduce underneath
  - The language used is Pig Latin
- Resembles the querying facilities of SQL

Pig

```
timesheet = LOAD 'timesheet.csv' USING PigStorage(',');

raw_timesheet = FILTER timesheet by $0 > 100;

timesheet_logged = FOREACH raw_timesheet GENERATE $0 AS
driverId, $2 AS hours_logged, $3 AS miles_logged;

grp_logged = GROUP timesheet_logged by driverId;

sum_logged = FOREACH grp_logged GENERATE group as driverId,
SUM(timesheet_logged.hours_logged) as sum_hourslogged,
SUM(timesheet_logged.miles_logged) as sum_mileslogged;
```

Pig

- Some have argued that RDBMSs and SQL are substantially faster than MapReduce – and hence Pig
- Pig Latin is relatively procedural versus declarative SQL
- No wide adoption

Hive

- Initially developed by Facebook but open-sourced afterwards
- Data warehouse solution offering SQL querying facilities on top of Hadoop
- Converts SQL-like queries to a MapReduce pipeline
- Also offers a JDBC and ODBC interface
- Can run on top of HDFS, as well as other file systems

Hive

- Hive Metastore stores metadata for each table such as its schema and location on HDFS (using an RDBMS)
- Driver service is responsible to receive and handle incoming queries
  - query is first converted to an abstract syntax tree, which is then converted to a directed acyclic graph representing an execution plan
  - the directed acyclic graph will contain a number of MapReduce stages and tasks
- Optimizer optimizes the directed acyclic graph
- Executer sends MapReduce stages to Hadoop’s resource manager (e.g. YARN) and monitor their progress

Hive

- HiveQL does not completely follow the full SQL-92 standard
  - E.g., lacks strong support for indexes, transactions, materialized views, and only has limited subquery support
- Example:
  ```
  SELECT genre, SUM(nrPages) FROM
  books GROUP BY genre
  ```
- HiveQL also allows to query data sets other than structured tables

Hive

```
CREATE TABLE docs (line STRING); -- create a docs table

-- load in file from HDFS to docs table, overwrite existing
data:
LOAD DATA INPATH '/testfile.txt' OVERWRITE INTO TABLE docs;

-- perform word count
SELECT word, count(1) AS count
FROM ( -- split each line in docs into words
  SELECT explode(split(line, '\s')) AS word FROM docs
) t
GROUP BY t.word
ORDER BY t.word;
```

Hive

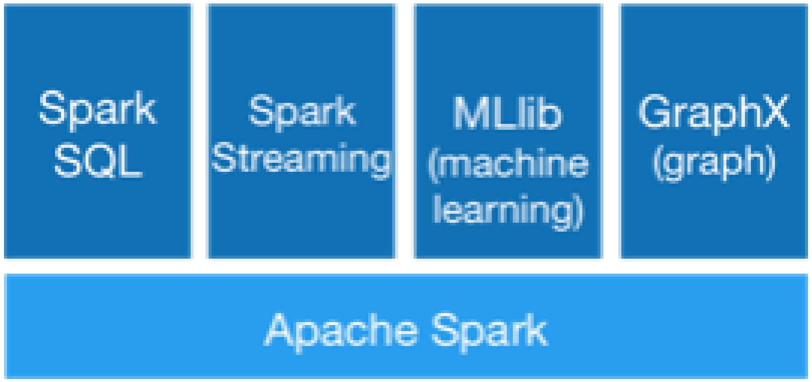
- One difference with traditional RDBMS is that Hive does not enforce the schema at the time of loading the data
  - Hive: schema-on-read
  - RDBMS: schema-on-write
- Recent versions of Hive support full ACID transaction management
- Performance and speed of SQL queries still forms the main disadvantage of Hive today
  - Solutions to bypass MapReduce (e.g. Apache Tez, Cloudera Impala, Facebook Presto)

Apache Spark

- Open-source alternative for MapReduce
- New programming paradigm centered on a data structure called the Resilient Distributed Dataset (RDD)
  - RDDs can enable the construction of iterative programs that have to visit a data set multiple times, as well as more interactive or exploratory programs
  - RDD is a fundamental data structure of Spark
  - Each dataset in RDD is divided into logical partitions that can be computed on different nodes of the cluster
  - Is maintained in a fault tolerant way
  - RDDs can contain any type of Python, Java or Scala objects, including user-defined classes.
- Many orders of magnitude faster than MapReduce implementations
- Rapidly adopted by many Big Data vendors

Apache Spark

- Similar to Hadoop, Spark works with HDFS and requires a cluster manager (e.g. YARN)
- Key components
  - Spark Core
  - Spark SQL
  - MLib, Spark Streaming, GraphX



Spark Core

- Foundation for all other components
- Provides functionality for task scheduling and a set of basic data transformations
- Can be used through many programming languages
  - For example: Java, Python, Scala and R
- RDDs are the primary data abstraction in Spark
  - designed to support in-memory data storage and operations, distributed across a cluster
- Can be used to handle JSON and CSV data

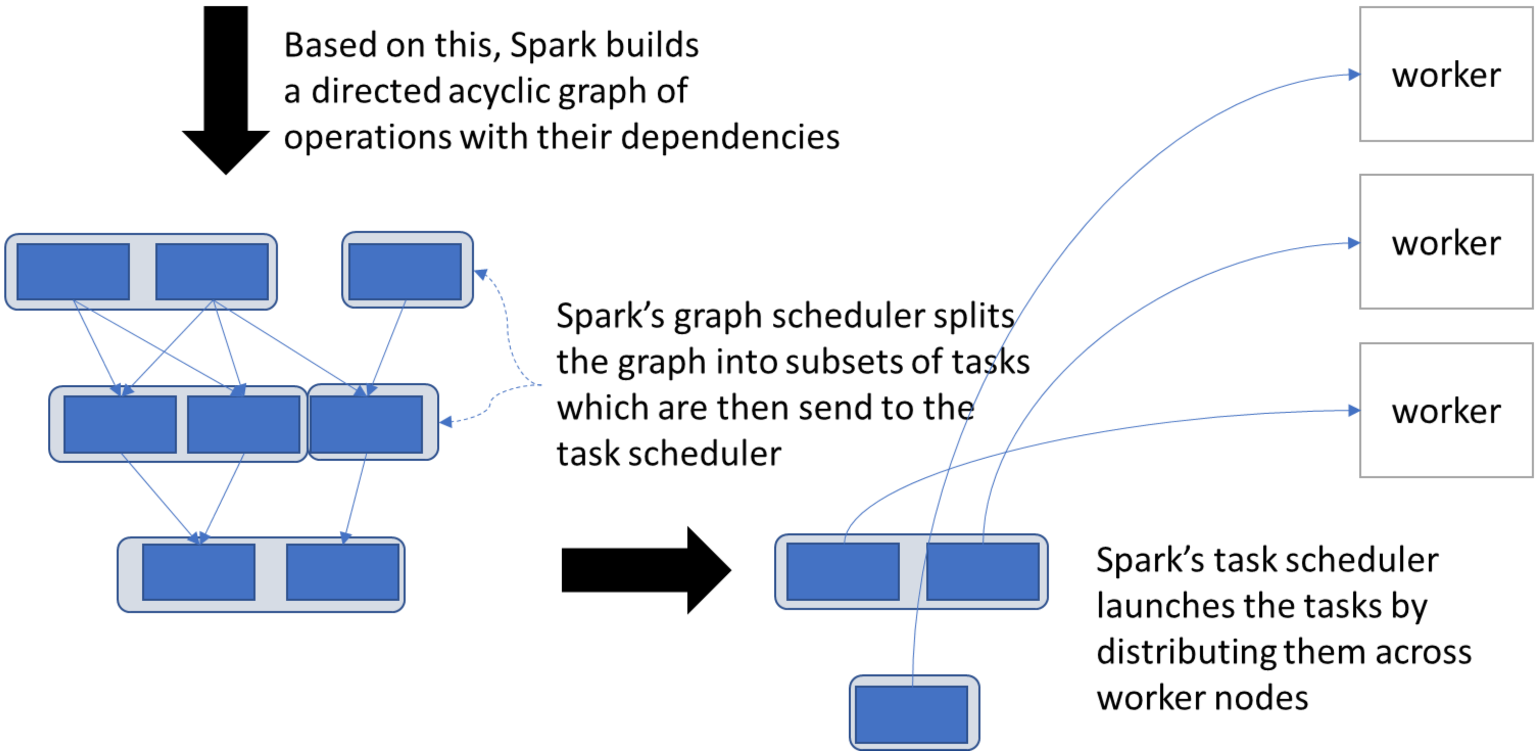
Spark Core

- Once data is loaded into an RDD, two basic types of operations can be performed:
  - Transformation which creates a new RDD through changing the original one
  - Actions which measure but do not change the original data
- Transformations are lazily evaluated
  - executed when a subsequent action has a need for the result
  - So can mean errors do not immediately appear
    - E.g., file does not exist
- RDDs will also be kept as long as possible in memory
- A chain of RDD operations gets compiled by Spark into a directed acyclic graph but which is then spread out and calculated over the cluster

Spark Core

A programmer writes a Spark program using its API:

```
rdd1.join(rdd2).groupBy(…).filter(…)
```



Spark Core – Map Reduce

- Spark's RDD API is relatively easy to work with compared to writing MapReduce programs

```
# Load in an RDD from a text file, the RDD will represent a
# collection  of text strings
#(one for each line)
text_file = sc.textFile("testfile.txt")

# Count the word occurrences
counts = text_file.flatMap(lambda line: line.split("
.map(lambda word: (word, 1)) \
.reduceByKey(lambda a, b: a + b)

# counts is a PythonRDD
# Need loop to print items:
for x in counts.collect():
    print x
```

Let's combine our testfile1 and testfile2
cat test* > testfile.txt

(u'A', 1)
(u'ago', 1)
(u'episode', 1)
(u'far', 2)
(u'away', 1)
(u'long', 1)
(u'a', 1)
(u'Another', 1)
(u'Star', 1)
(u'galaxy', 1)
(u'of', 1)
(u'in', 1)
(u'Wars', 1)
(u'time', 1)

Spark SQL

- Spark SQL runs on top of Spark Core and introduces another data abstraction called DataFrames
- DataFrames can be created from RDDs by specifying a schema on how to structure the data elements in the RDD, or can be loaded in directly from various sorts of file formats
- Even although DataFrames continue to use RDDs behind the scenes, they represent themselves to the end user as a collection of data organized into named columns
- You can run Spark directly using:
  - pyspark – uses Python
  - spark-shell – uses Scala
  - spark-sql – to run SQL queries
  - spark-submit – to run a program file, such as Python
- Or can access it via a programming language, such as Java
- See here for information:
  - https://spark.apache.org/docs/latest/sql-programming-guide.html

Spark SQL – Handling JSON (pyspark)

```
# Create a DataFrame object by reading in a file
df = spark.read.json("student.json")
df.show()
+----+---------------+--------------------+------+
| age|         course|               email|  name|
+----+---------------+--------------------+------+
|null|BSc Horticulture|                null|   Tom|
|  45| MSc Agriculture|                null| Helen|
|  30|            null|S.Carter.borchest...| Alice|
|  21|BSc Horticulture|                null|Johnny|
+----+---------------+--------------------+------+
```

student.json:

```
{"name":"Tom",
    "course": "BSc Horticulture"}
{"name":"Helen", "age":45,
    "course": "MSc Agriculture"}
{"name":"Alice", "age":30,
"email":"S.Carter@borchester.ac.uk"}
{"name":"Johnny", "age":21,
    "course": "BSc Horticulture"}
```

```
# DataFrames are structured in columns and rows:
df.printSchema()
root
 |-- age: long (nullable = true)
 |-- course: string (nullable = true)
 |-- email: string (nullable = true)
 |-- name: string (nullable = true)
```

Spark SQL (pyspark)

```
df.select("name").show()
+-------+
|   name|
+-------+
|    Tom|
|  Helen|
|  Alice|
| Johnny|
+-------+

# SQL-like operations can now easily be expressed:
df.select(df['name'], df['age'] + 1).show()
+------+---------+
|  name|(age + 1)|
+------+---------+
|   Tom|     null|
| Helen|       46|
| Alice|       31|
|Johnny|       22|
+------+---------+
```

Spark SQL (pyspark)

```
df.filter(df['age'] > 21).show()
--+---------------+--------------------+-----+
|age|          course|                 email| name|
+---+---------------+--------------------+-----+
| 45|MSc Agriculture|                  null|Helen|
| 30|           null|S.Carter.borchest...|Alice|
+---+---------------+--------------------+-----+
```

```
df.groupBy("course").count().show()
+----------------+-----+
|          course|count|
+----------------+-----+
| MSc Agriculture|    1|
|            null|    1|
|BSc Horticulture|    2|
+----------------+-----+
```

Spark SQL (pyspark)

- Spark implements a full SQL query engine which can convert SQL statements to a series of RDD transformations and actions

- First Register the DataFrame as a SQL temporary view:

```
df.createOrReplaceTempView("student")
```

Can then use SQL like syntax:

```
sqlDF = spark.sql("SELECT name, age, course FROM student WHERE age > 21")

sqlDF.show()
```

You can not just type the SQL Code at the command line

```
+-----+---+---------------+
| name|age|         course|
+-----+---+---------------+
|Helen| 45|MSc Agriculture|
|Alice| 30|           null|
+-----+---+---------------+
```

See Workbook for further examples

MLlib, Spark Streaming and GraphX

- There are lots of other Spark tools to help work with Big Data:
  - MLlib is Spark’s machine learning library
    - offers classification, regression, clustering, and recommender system algorithms
  - Spark Streaming uses Spark Core and its scheduling engine to perform streaming analytics
    - provides a high-level concept called `DStream`, which represents a continuous stream of data
  - GraphX is Spark’s component implementing programming abstractions to deal with graph based structures
    - based on the RDD abstraction
    - comes with a set of fundamental operators and algorithms to work with graphs and simplify graph analytics tasks

MLlib, Spark Streaming and GraphX

- Example: Word counting

```
from pyspark import SparkContext
from pyspark.streaming import StreamingContext
sc = SparkContext("local[2]", "StreamingWordCount")
ssc = StreamingContext(sc, 1)

# Create a DStream that will connect to server.mycorp.com:9999 as a source
lines = ssc.socketTextStream("server.mycorp.com ", 9999)

# Split each line into words
words = lines.flatMap(lambda line: line.split(" "))

# Count each word in each batch
pairs = words.map(lambda word: (word, 1))
wordCounts = pairs.reduceByKey(lambda x, y: x + y)

# Print out first ten elements of each RDD generated in the wordCounts Dstream
wordCounts.pprint()

# Start the computation
ssc.start()
ssc.awaitTermination()
```

Conclusion

- This lecture has looked at:
  - SQL on Hadoop
  - Apache Spark

- This week's workbook will look at using:
  - Further Hadoop examples
    - How to use CSV files
  - Apache Spark
    - SQL queries
    - JSON and CSV data