Spark & Spark SQL

High-Speed In-Memory Analytics over Hadoop and Hive Data

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Slides adopted from Matei Zaharia (MIT) and Oliver Vagner (TGI Fridays)
What is Spark?

http://spark.apache.org

Not a modified version of Hadoop

**Separate, fast, MapReduce-like engine**
- **In-memory** data storage for very fast iterative queries
- General execution graphs and powerful optimizations
- Up to 40x faster than Hadoop

Compatible with Hadoop’s storage APIs
- Can read/write to any Hadoop-supported system, including HDFS, HBase, SequenceFiles, etc
What is **Spark SQL**?
(Formally called Shark)

Port of Apache **Hive** to run on **Spark**

Compatible with existing Hive data, metastores, and queries (HiveQL, UDFs, etc)

Similar speedups of up to **40x**
Project History [latest: v1.1]

Spark project started in 2009 at UC Berkeley AMP lab, open sourced 2010

Became Apache Top-Level Project in Feb 2014

Shark/Spark SQL started summer 2011

Built by 250+ developers and people from 50 companies

Scale to 1000+ nodes in production

In use at Berkeley, Princeton, Klout, Foursquare, Conviva, Quantifind, Yahoo! Research, ...
Why a New Programming Model?

MapReduce greatly simplified big data analysis

But as soon as it got popular, users wanted more:

» More complex, multi-stage applications (e.g. iterative graph algorithms and machine learning)
» More interactive ad-hoc queries
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Require faster data sharing across parallel jobs
Up for debate… as of 10/7/2014

Is MapReduce dead?

Google Dumps MapReduce in Favor of New Hyper-Scale Analytics System


http://www.reddit.com/r/compsci/comments/296aqr/on_the_death_of_mapreduce_at_google/

As an employee, I was surprised by this headline, considering I just ran some mapreduces this past week. After digging further, this headline and article is rather inaccurate.

Cloud DataFlow is the external name for what is internally called Flume.

Flume is a layer that runs on top of MapReduce that abstracts away the complexity into something that is much easier.
Data Sharing in MapReduce

Input

HDFS read → iter. 1 → HDFS read → iter. 2 → ... → HDFS write

HDFS read → query 1 → result 1
HDFS read → query 2 → result 2
HDFS read → query 3 → result 3

...
Data Sharing in MapReduce

Input

HDFS read → iter. 1 → HDFS read → iter. 2 → HDFS write → ...

Input

HDFS read

query 1 → result 1

query 2 → result 2

query 3 → result 3

Slow due to replication, serialization, and disk IO
Data Sharing in Spark

Input

iter. 1

iter. 2

... 

Distributed memory

one-time processing

query 1

query 2

query 3

...
Data Sharing in Spark

Input

iter. 1 → iter. 2 → ... 

Distributed memory

one-time processing

query 1

query 2

query 3

... 

10-100× faster than network and disk
Spark Programming Model

Key idea: resilient distributed datasets (RDDs)
- Distributed collections of objects that can be cached in memory across cluster nodes
- Manipulated through various parallel operators
- Automatically rebuilt on failure

Interface
- Clean language-integrated API in Scala
- Can be used interactively from Scala, Python console
- Supported languages: Java, Scala, Python, R
http://www.scala-lang.org/old/faq/4

Functional programming in D3: http://sleptons.blogspot.com/2015/01/functional-programming-d3js-good-example.html

Scala vs Java 8: http://kukuruku.co/hub/scala/java-8-vs-scala-the-difference-in-approaches-and-mutual-innovations
Example: Log Mining

Load error messages from a log into memory, then interactively search for various patterns

http://www.slideshare.net/normation/scala-dreaded
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```scala
lines = spark.textFile("hdfs://...")
errors = lines.filter(_.startsWith("ERROR"))
messages = errors.map(_.split("\t")(2))
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cachedMsgs.filter(_.contains("bar")).count

... 
```

Result: full-text search of Wikipedia in <1 sec (vs 20 sec for on-disk data)

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cachedMsgs.filter(_.contains("bar")).count

Result: scaled to 1 TB data in 5-7 sec (vs 170 sec for on-disk data)

http://www.slideshare.net/normation/scala-dreaded
Fault Tolerance

RDDs track the series of transformations used to build them (their *lineage*) to recompute lost data.

E.g.: `messages = textFile(...).filter(_.contains("error")).map(_.split("\t")(2))`
val data = spark.textFile(...).map(readPoint).cache()

var w = Vector.random(D)

for (i <- 1 to ITERATIONS) {
    val gradient = data.map(p =>
        (1 / (1 + exp(-p.y*(w dot p.x))) - 1) * p.y * p.x
    ).reduce(_ + _)
    w -= gradient
}

println("Final w: " + w)
Example: Logistic Regression

```scala
def logreg(w: Vector, data: Array[(Double, Double)]) = 
  data.map { p =>
    (1 / (1 + exp(-p._1 * w * p._2))) - 1
  } .map { x => x * w }
  .reduce(_+_) 
```
Example: Logistic Regression

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Logistic Regression Performance

Number of Iterations

- Hadoop
- Spark

127 s / iteration
first iteration 174 s
further iterations 6 s
Supported Operators

map        reduce        sample
filter     count         cogroup
groupBy    reduceByKey   take
sort       groupByKey    partitionBy
join       first         pipe
leftOuterJoin  union    save
rightOuterJoin  cross    ...

Spark Users

CON VIVA

foursquare

quantifind

KLOUT

Yahoo!

Research

University of California Berkeley

Princeton University

UCSF
Spark SQL: Hive on Spark
Motivation

Hive is great, but Hadoop’s execution engine makes even the smallest queries take minutes

Scala is good for programmers, but many data users only know SQL

Can we extend Hive to run on Spark?
Hive Architecture

- **Meta store**

- **Client**
  - CLI
  - JDBC

- **Driver**
  - SQL Parser
  - Query Optimizer
  - Physical Plan
  - Execution

- **MapReduce**

- **HDFS**
Spark SQL Architecture

[Engle et al, SIGMOD 2012]
Efficient In-Memory Storage

Simply caching Hive records as Java objects is inefficient due to high per-object overhead

Instead, Spark SQL employs column-oriented storage using **arrays of primitive types**
Efficient In-Memory Storage

Simply caching Hive records as Java objects is inefficient due to high per-object overhead.

Instead, Spark SQL employs column-oriented storage using arrays of primitive types.

**Benefit:** similarly compact size to serialized data, but >5x faster to access.
Using Spark SQL

CREATE TABLE mydata_cached AS SELECT ...

Run standard HiveQL on it, including UDFs
» A few esoteric features are not yet supported

Can also call from Scala to mix with Spark
BENCHMARK QUERY 1

SELECT * FROM grep WHERE field LIKE '%XYZ%';
Benchmark Query 2

SELECT sourceIP, AVG(pageRank), SUM(adRevenue) AS earnings
FROM rankings AS R, userVisits AS V
ON R.pageURL = V.destURL
WHERE V.visitDate BETWEEN '1999-01-01' AND '2000-01-01'
GROUP BY V.sourceIP
ORDER BY earnings DESC
LIMIT 1;

Shark (cached) 126s
Shark 270s
Hive 447s
What’s Next?

Recall that Spark’s model was motivated by two emerging uses (interactive and multi-stage apps).

Another emerging use case that needs fast data sharing is **stream processing**

» Track and update state in memory as events arrive

» Large-scale reporting, click analysis, spam filtering, etc
Streaming Spark

Extends Spark to perform streaming computations

Runs as a series of small (~1 s) batch jobs, keeping state in memory as fault-tolerant RDDs

Intermix seamlessly with batch and ad-hoc queries

tweetStream
  .flatMap(_.toLowerCase.split)
  .map(word => (word, 1))
  .reduceByWindow("5s", _ + _)

[Zaharia et al, HotCloud 2012]
Streaming Spark

Extends Spark to perform streaming computations

Runs as a series of small (~1 s) batch jobs, keeping state in memory as fault-tolerant RDDs

Intermix seamlessly with batch and ad-hoc queries

Result: can process 42 million records/second (4 GB/s) on 100 nodes at sub-second latency

[Zaharia et al, HotCloud 2012]
Streaming Spark

Extends Spark to perform streaming computations

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  .map(word => (word, 1))
  .reduceByWindow(5, _ + _)

[Zaharia et al, HotCloud 2012]
Spark Streaming

Create and operate on RDDs from live data streams at set intervals

Data is divided into batches for processing

Streams may be combined as a part of processing or analyzed with higher level transforms
Behavior with Not Enough RAM

<table>
<thead>
<tr>
<th>% of working set in memory</th>
<th>Iteration time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cache disabled</td>
<td>68.8</td>
</tr>
<tr>
<td>25%</td>
<td>58.1</td>
</tr>
<tr>
<td>50%</td>
<td>40.7</td>
</tr>
<tr>
<td>75%</td>
<td>29.7</td>
</tr>
<tr>
<td>Fully cached</td>
<td>11.5</td>
</tr>
</tbody>
</table>
Standalone

Hadoop 2.x (YARN)

Hadoop V1 (SIMR)
MLlib

Scalable machine learning library

Interoperates with NumPy

Available algorithms in 1.0

» Linear Support Vector Machine (SVM)
» Logistic Regression
» Linear Least Squares
» Decision Trees
» Naïve Bayes
» Collaborative Filtering with ALS
» K-means
» Singular Value Decomposition
» Principal Component Analysis
» Gradient Descent
GraphX

Parallel graph processing

Extends RDD -> Resilient Distributed Property Graph
  » Directed multigraph with properties attached to each vertex and edge

Limited algorithms
  » PageRank
  » Connected Components
  » Triangle Counts

Alpha component
Commercial Support

Databricks

» Not to be confused with DataStax
» Found by members of the AMPLab
» Offering
  • Certification
  • Training
  • Support
  • DataBricks Cloud