Distributed Computing with Spark

Reza Zadeh

ICME
INSTITUTE for COMPUTATIONAL & MATHEMATICAL ENGINEERING
at STANFORD UNIVERSITY

databricks
Spark
Problem

Data growing faster than processing speeds

Only solution is to parallelize on large clusters

» Wide use in both enterprises and web industry

How do we program these things?
Outline

Data flow vs. traditional network programming
Limitations of MapReduce
Spark computing engine
Machine Learning Example
Current State of Spark Ecosystem
Built-in Libraries
Data flow vs. traditional network programming
Traditional Network Programming

Message-passing between nodes (e.g. MPI)

Very difficult to do at scale:

» How to split problem across nodes?
  • Must consider network & data locality
» How to deal with failures? (inevitable at scale)
» Even worse: stragglers (node not failed, but slow)
» Ethernet networking not fast
» Have to write programs for each machine

Rarely used in commodity datacenters
Data Flow Models

Restrict the programming interface so that the system can do more automatically

Express jobs as graphs of high-level operators
  » System picks how to split each operator into tasks and where to run each task
  » Run parts twice fault recovery

Biggest example: MapReduce
Example MapReduce Algorithms

Matrix-vector multiplication
Power iteration (e.g. PageRank)
Gradient descent methods
Stochastic SVD
Tall skinny QR

Many others!
Why Use a Data Flow Engine?

Ease of programming
  » High-level functions instead of message passing

Wide deployment
  » More common than MPI, especially “near” data

Scalability to very largest clusters
  » Even HPC world is now concerned about resilience

Examples: Pig, Hive, Scalding, Storm
Limitations of MapReduce
Limitations of MapReduce

MapReduce is great at one-pass computation, but inefficient for multi-pass algorithms

No efficient primitives for data sharing
  » State between steps goes to distributed file system
  » Slow due to replication & disk storage
Example: Iterative Apps

Commonly spend 90% of time doing I/O
Example: PageRank

Repeatedly multiply sparse matrix and vector

Requires repeatedly hashing together page adjacency lists and rank vector

Neighbors (id, edges)

Ranks (id, rank)

iteration 1

iteration 2

iteration 3

Same file grouped over and over
Result

While MapReduce is simple, it can require asymptotically more communication or I/O.
Spark computing engine
Spark Computing Engine

Extends a programming language with a distributed collection data-structure
  » “Resilient distributed datasets” (RDD)

Open source at Apache
  » Most active community in big data, with 50+ companies contributing

Clean APIs in Java, Scala, Python, R
Resilient Distributed Datasets (RDDs)

Main idea: Resilient Distributed Datasets
» Immutable collections of objects, spread across cluster
» Statically typed: RDD[T] has objects of type T

```scala
val sc = new SparkContext()
val lines = sc.textFile("log.txt")  // RDD[String]

// Transform using standard collection operations
val errors = lines.filter(_.startsWith("ERROR"))
val messages = errors.map(_.split(\t')(2))

messages.saveAsTextFile("errors.txt")
```

lazily evaluated
kicks off a computation
Key Idea

Resilient Distributed Datasets (RDDs)

» Collections of objects across a cluster with user controlled partitioning & storage (memory, disk, ...)
» Built via parallel transformations (map, filter, ...)
» The world only lets you make make RDDs such that they can be:

Automatically rebuilt on failure
// Scala:
val lines = sc.textFile(...)
lines.filter(x => x.contains("ERROR")).count()

// Java (better in java8!):
JavaRDD<String> lines = sc.textFile(...);
lines.filter(new Function<String, Boolean>() {
    Boolean call(String s) {
      return s.contains("error");
    }
  }).count();
Fault Tolerance

RDDS track *lineage* info to rebuild lost data

```python
file.map(lambda rec: (rec.type, 1))
  .reduceByKey(lambda x, y: x + y)
  .filter(lambda (type, count): count > 10)
```
Fault Tolerance

RDDS track lineage info to rebuild lost data

```
file.map(lambda rec: (rec.type, 1))
  .reduceByKey(lambda x, y: x + y)
  .filter(lambda (type, count): count > 10)
```
Partitioning

RDDS know their partitioning functions

```java
file.map(lambda rec: (rec.type, 1))
.reduceByKey(lambda x, y: x + y)
.filter(lambda (type, count): count > 10)
```

Known to be hash-partitioned

Also known
Machine Learning example
Logistic Regression

\[ w \leftarrow w - \alpha \cdot \sum_{i=1}^{n} g(w; x_i, y_i) \]

```scala
val points = spark.textFile(...).map(parsePoint).cache()
var w = Vector.zeros(d)
for (i <- 1 to numIterations) {
  val gradient = points.map { p =>
    (1 / (1 + exp(-p.y * w.dot(p.x)) - 1)) * p.y * p.x
  }.reduce(_ + _)
  w -= alpha * gradient
}
```
Logistic Regression Results

100 GB of data on 50 m1.xlarge EC2 machines
Behavior with Less RAM

- Iteration time (s) vs % of working set in memory

- 0%: 68.8
- 25%: 58.1
- 50%: 40.7
- 75%: 29.7
- 100%: 11.5
Benefit for Users

**Same engine** performs data extraction, model training and interactive queries

Separate engines

```
DFS read  parse  DFS write
DFS read  train  DFS write
DFS read  query  DFS write
```

Spark

```
DFS read  parse  train  query
```

```
> python
Scala
DFS
```
State of the Spark ecosystem
Spark Community

Most active open source community in big data

200+ developers, 50+ companies contributing

Contributors in past year
Project Activity

Activity in past 6 months
Built-in libraries
Standard Library for Big Data

Big data apps lack libraries of common algorithms

Spark’s generality + support for multiple languages make suitable to offer this

Much of future activity will be in these libraries
A General Platform

Standard libraries included with Spark

Spark SQL
Spark Streaming real-time
GraphX graph
MLlib machine learning

Spark Core
Machine Learning Library (MLlib)

points = context.sql("select latitude, longitude from tweets")
model = KMeans.train(points, 10)
MLlib algorithms

**classification:** logistic regression, linear SVM, naïve Bayes, classification tree

**regression:** generalized linear models (GLMs), regression tree

**collaborative filtering:** alternating least squares (ALS), non-negative matrix factorization (NMF)

**clustering:** k-means

**decomposition:** SVD, PCA

**optimization:** stochastic gradient descent, L-BFGS
GraphX
GraphX

General graph processing library

Build graph using RDDs of nodes and edges

Large library of graph algorithms with composable steps
GraphX Algorithms

Collaborative Filtering
  » Alternating Least Squares
  » Stochastic Gradient Descent
  » Tensor Factorization

Structured Prediction
  » Loopy Belief Propagation
  » Max-Product Linear Programs
  » Gibbs Sampling

Community Detection
  » Triangle-Counting
  » K-core Decomposition
  » K-Truss

Graph Analytics
  » PageRank
  » Personalized PageRank
  » Shortest Path
  » Graph Coloring

Semi-supervised ML
  » Graph SSL
  » CoEM

Classification
  » Neural Networks
Spark Streaming

Run a streaming computation as a **series** of very small, deterministic batch jobs

- Chop up the live stream into batches of X seconds
- Spark treats each batch of data as RDDs and processes them using RDD operations
- Finally, the processed results of the RDD operations are returned in batches
Spark Streaming

Run a streaming computation as a series of very small, deterministic batch jobs

- Batch sizes as low as ½ second, latency ~ 1 second
- Potential for combining batch processing and streaming processing in the same system
Spark SQL

// Run SQL statements
val teenagers = context.sql(
  "SELECT name FROM people WHERE age >= 13 AND age <= 19"
)

// The results of SQL queries are RDDs of Row objects
val names = teenagers.map(t => "Name: " + t(0)).collect()
Spark SQL

Enables loading & querying structured data in Spark

From Hive:
```python
c = HiveContext(sc)
rows = c.sql("select text, year from hivetable")
rows.filter(lambda r: r.year > 2013).collect()
```

From JSON:
```python
c.jsonFile("tweets.json").registerAsTable("tweets")
c.sql("select text, user.name from tweets")
```
Conclusions
Spark and Research

Spark has all its roots in research, so we hope to keep incorporating new ideas!
Conclusion

Data flow engines are becoming an important platform for numerical algorithms

While early models like MapReduce were inefficient, new ones like Spark close this gap

More info: spark.apache.org