Parallel Programming with Spark

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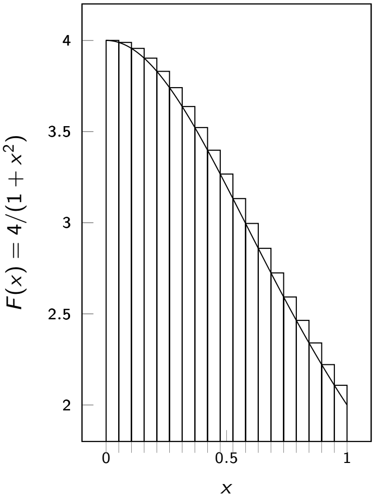
Previously on Parallel Programming

OpenMP: an API for writing multi-threaded applications

- A set of compiler directives and library routines for parallel application programmers
- Greatly simplifies writing multi-threaded programs in Fortran and C/C++
- Standardizes last 20 years of symmetric multiprocessing (SMP) practice

Compute π using Numerical Integration



Let $F(x) = 4/(1 + x^2)$

$$\pi = \int_0^1 F(x)dx$$

Approximate the integral as a sum of rectangles:

$$\sum_{i=0}^{N} F(x_i)\Delta x \approx \pi$$

where each rectangle has width Δx and height $F(x_i)$ at the middle of interval i

Example: π Program with OpenMP

```c
#include <stdio.h>
#include <omp.h>                                    // header
const long N = 100000000;
#define NUM_THREADS 4                               // #threads
int main () {
    double sum = 0.0;
    double delta_x = 1.0 / (double) N;
    omp_set_num_threads(NUM_THREADS);               // set #threads
#pragma omp parallel for reduction(+:sum)           // parallel for
    for (int i = 0; i < N; i++) {
        double x = (i+0.5) * delta_x;
        sum += 4.0 / (1.0 + x*x);
    }
    double pi = delta_x * sum;
    printf("pi is %f\n", pi);
}
```

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How to parallelize the π program on distributed clusters?

Outline

Why Spark?

Spark Concepts

Tour of Spark Operations

Job Execution

Spark MLlib

Why Spark?

Apache Hadoop Ecosystem

Component	Hadoop
Resource Manager	YARN
Storage	HDFS
Batch	**MapReduce**
Streaming	Flume
Columnar Store	HBase
SQL Query	Hive
Machine Learning	Mahout
Graph	Giraph
Interactive	Pig

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... mostly focused on large on-disk datasets: great for **batch** but **slow**

Many Specialized Systems

MapReduce doesn't compose well for large applications, and so *specialized* systems emerged as workarounds

Component	Hadoop	Specialized
Resource Manager	YARN	
Storage	HDFS	RAMCloud
Batch	MapReduce	
Streaming	Flume	Storm
Columnar Store	HBase	
SQL Query	Hive	
Machine Learning	Mahout	DMLC
Graph	Giraph	PowerGraph
Interactive	Pig	

Goals

A new ecosystem

- leverages current generation of commodity hardware
- provides fault tolerance and parallel processing at scale
- easy to use and combines SQL, Streaming, ML, Graph, etc.
- compatible with existing ecosystems

Berkeley Data Analytics Stack

being built by AMPLab to make sense of Big Data[1]

Component	Hadoop	Specialized	BDAS
Resource Manager	YARN		Mesos
Storage	HDFS	RAMCloud	Tachyon
Batch	MapReduce		**Spark**
Streaming	Flume	Storm	Streaming
Columnar Store	HBase		Parquet
SQL Query	Hive		SparkSQL
Approximate SQL			BlinkDB
Machine Learning	Mahout	DMLC	MLlib
Graph	Giraph	PowerGraph	GraphX
Interactive	Pig		built-in

[1] https://amplab.cs.berkeley.edu/software/

Spark Concepts

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Fast and expressive cluster computing system compatible with Hadoop

- Works with many storage systems: local FS, HDFS, S3, SequenceFile, ...

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- In-memory computing primitives
- General computation graphs

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Improves usability through rich Scala/Java/Python APIs and interactive shell Often 2-10x less code

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- Built through parallel *transformations* (`map`, `filter`, ...)
- Automatically rebuilt on failure
- Controllable persistence (e.g. caching in RAM) for reuse

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Transformations (e.g. `map`, `filter`, `reduceByKey`, `join`)

- Lazy operations to build RDDs from other RDDs

Actions (e.g. `collect`, `count`, `save`)

- Return a result or write it to storage

Learning Spark

Download the binary package and uncompress it

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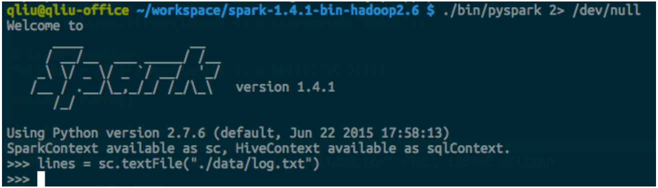
Interactive Shell (**easist way**): `./bin/pyspark`

- modified version of Scala/Python interpreter
- runs as an app on a Spark cluster or can run locally



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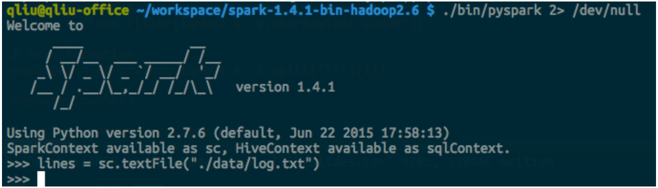


Standalone Programs: `./bin/spark-submit <program>`

- Scala, Java, and Python

This talk: mostly Python

Example: Log Mining

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

DEMO:

```
lines = sc.textFile("hdfs://...") #load from HDFS

# transformation
errors = lines.filter(lambda s: s.startswith("ERROR"))

# transformation
messages = errors.map(lambda s: s.split('\t')[1])

messages.cache()

# action; compute messages now
messages.filter(lambda s: "life" in s).count()

# action; reuse cached messages
messages.filter(lambda s: "work" in s).count()
```

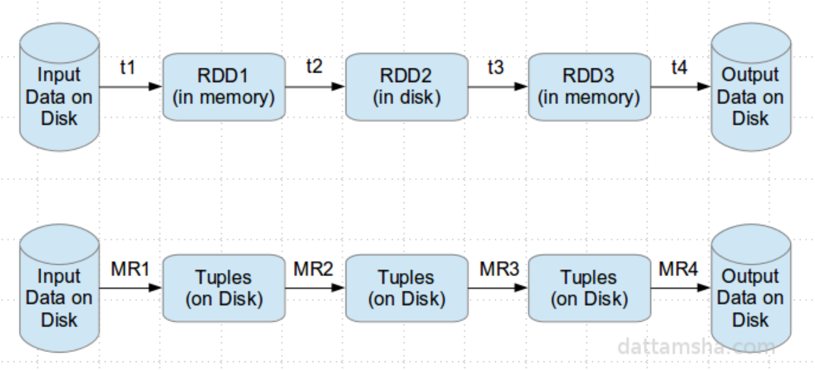
RDD Fault Tolerance

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


```
msgs = sc.textFile("hdfs://...")
         .filter(lambda s:
            s.startswith("ERROR"))
         .map(lambda s: s.split('\t')[1])
```

Spark vs. MapReduce

- Spark keeps intermediate data in memory
- Hadoop only supports map and reduce, which may not be efficient for join, group, ...
- Programming in Spark is easier



Tour of Spark Operations

Spark Context

- Main entry point to Spark functionality
- Created for you in **Spark shell** as variable `sc`
- In standalone programs, you'd make your own:

```
from pyspark import SparkContext

sc = SparkContext(appName="ExampleApp")
```

Creating RDDs

- Turn a local collection into an RDD
  `rdd = sc.parallelize([1, 2, 3])`

- Load text file from local FS, HDFS, or other storage systems
  ```
  sc.textFile("file:///path/file.txt")
  sc.textFile("hdfs://namenode:9000/file.txt")
  ```

- Use any existing Hadoop InputFormat
  ```
  sc.hadoopFile(keyClass, valClass, inputFmt,
  conf)
  ```

Basic Transformations

```
nums = sc.parallelize([1, 2, 3])

# Pass each element through a function
squares = nums.map(lambda x: x*x)
# => {1, 4, 9}

# Keep elements passing a predicate
even = squares.filter(lambda x: x%2 == 0)
# => {4}

# Map each element to zero or more others
nums.flatMap(lambda x: range(x))
# => {0, 0, 1, 0, 1, 2}
```

Basic Actions

```
nums = sc.parallelize([1, 2, 3])

# Retrieve RDD contents as a local collection
nums.collect()                 # => [1, 2, 3]

# Return first K elements
nums.take(2)                   # => [1, 2]

# Count number of elements
nums.count()                   # => 3

# Merge elements with an associative function
nums.reduce(lambda a, b: a+b) # => 6

# Write elements to a text file
nums.saveAsTextFile("hdfs://host:9000/file")
```

Example: π Program in Spark

Compute

$$\sum_{i=0}^{N} F(x_i)\Delta x \approx \pi$$

where $F(x) = 4/(1 + x^2)$

```
N = 100000000
delta_x = 1.0 / N

print sc.parallelize(xrange(N))          # i
    .map(lambda i: (i+0.5) * delta_x)    # x_i
    .map(lambda x: 4 / (1 + x**2))       # F(x_i)
    .reduce(lambda a, b: a+b) * delta_x # pi
```

Working with Key-Value Pairs

A few special transformations operate on RDDs of key-value paris: `reduceByKey`, `join`, `groupByKey`, ...

Python pair (2-tuple) syntax:

```
pair = (a, b)
```

Accessing pair elements:

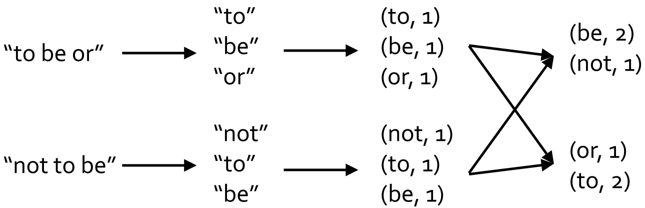
```
pair[0] # => a
pair[1] # => b
```

Some Key-Value Operations

```
val pets = sc.parallelize([('cat', 1), ('dog',
    1), ('cat', 2)])

pets.reduceByKey(lambda a, b: a+b)
# => [('cat', 3), ('dog', 1)]

pets.groupByKey()
# => [('cat', [1, 2]), ('dog', [1])]

pets.sortByKey()
# => [('cat', 1), ('cat', 2), ('dog', 1)]
```

Example: Word Count

```
lines = sc.textFile("...")
counts = lines.flatMap(lambda s: s.split())
              .map(lambda w: (w, 1))
              .reduceByKey(lambda a, b: a+b)
```



Other RDD Operations

`sample()`: deterministically sample a subset

`join()`: join two RDDs

`union()`: merge two RDDs

`cartesian()`: cross product

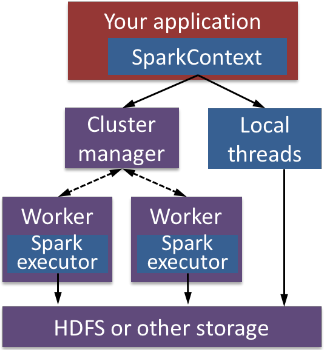
`pipe()`: pass through external program

See Programming Guide for more:
http://spark.apache.org/docs/latest/programming-guide.html

Job Execution

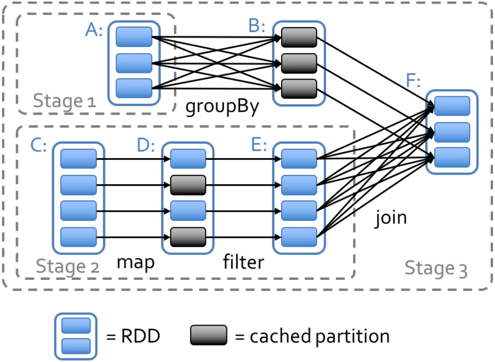
Software Components

- Spark runs as a library in your program (1 instance per app)
- Runs tasks locally or on cluster
  - Mesos, YARN or standalone mode
- Accesses storage systems via Hadoop InputFormat API
  - Can use HBase, HDFS, S3, ...



Task Scheduler

- General task graphs
- Automatically pipelines functions
- Data locality aware
- Partitioning aware to avoid shuffles



Advanced Features

- Controllable partitioning
  - Speed up joins against a dataset
- Controllable storage formats
  - Keep data serialized for efficiency, replicate to multiple nodes, cache on disk
- Shared variables: broadcasts, accumulators
- See online docs for details!

Launching on a Cluster

On a private cloud

- Standalone Deploy Mode: simplest Spark cluster

```
vim conf/slaves # add hostnames of slaves
./sbin/start-all.sh
```

- Mesos
- YARN

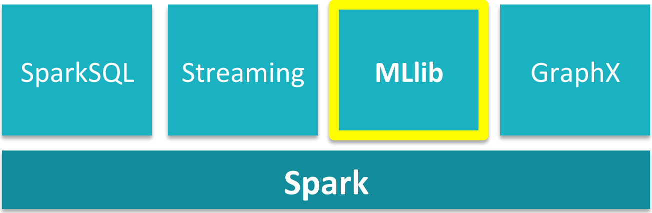
Running Spark on EC2

- Prepare your AWS account
- `./ec2/spark-ec2 -k <keypair> -i <key-file> -s <num-slaves> launch <cluster-name>`

Spark MLlib

Machine Learning Library (MLlib)

A scalable machine learning library consisting of common learning algorithms and utilities



These libraries are implemented using Spark APIs in Scala and included in Spark codebase

Functionality of Spark MLlib

Classification
- Logistic regression
- Naive Bayes
- Streaming logistic regression
- Linear SVMs
- Decision trees
- Random forests
- Gradient-boosted trees

Regression
- Ordinary least squares
- Ridge regression
- Lasso
- Isotonic regression
- Decision trees
- Random forests
- Gradient-boosted trees
- Streaming linear methods

Clustering
- Gaussian mixture models
- K-Means
- Streaming K-Means
- Latent Dirichlet Allocation
- Power Iteration Clustering

Recommendation
- Alternating Least Squares

Feature extraction & selection
- Word2Vec
- Chi-Squared selection
- Hashing term frequency
- Inverse document frequency
- Normalizer
- Standard scaler
- Tokenizer

Statistics
- Pearson correlation
- Spearman correlation
- Online summarization
- Chi-squared test
- Kernel density estimation

Linear algebra
- Local dense & sparse vectors & matrices
- Distributed matrices
    - Block-partitioned matrix
    - Row matrix
    - Indexed row matrix
    - Coordinate matrix
- Matrix decompositions

Frequent itemsets
- FP-growth

Model import/export

Example: k-means clustering

Given $(\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n)$, partition the n samples into k sets $\mathbf{S} = \{S_1, S_2, \ldots, S_k\}$ so as to minimize the within-cluster sum of squares (WCSS):

$$\arg\min_{\mathbf{S}} \sum_{i=1}^{k} \sum_{\mathbf{x} \in S_i} \|\mathbf{x} - \boldsymbol{\mu}_i\|^2$$

where $\boldsymbol{\mu}_i$ is the mean of points in S_i.

Algorithm: initialize $\boldsymbol{\mu}_i$, then iterate till converge

- **Assignment**: assign each sample to the cluster with nearest mean
- **Update**: calculate the new means

Example: k-means clustering

Main API: `pyspark.mllib.clustering.KMeans.train()`
Parameters:

- `rdd`: stores training samples
- `k`: number of clusters
- `maxIterations`: maximum number of iterations
- `initializationMode`: random or `k-means||`
- `runs`: number of times to run k-means
- `initializationSteps`: number of steps in `k-means||`
- `epsilon`: distance threshold of convergence

Example: k-means clustering

```
$ cat data/mllib/kmeans_data.txt
0.0 0.0 0.0
0.1 0.1 0.1
0.2 0.2 0.2
9.0 9.0 9.0
9.1 9.1 9.1
9.2 9.2 9.2
```

```
from pyspark import SparkContext
from pyspark.mllib.clustering import KMeans, KMeansModel
from numpy import array
from math import sqrt

sc = SparkContext(appName = "K-Means")

# Load and parse the data
data = sc.textFile("data/mllib/kmeans_data.txt")
parsedData = data.map(lambda line: array(map(float,
    line.split())))
```

Example: k-means clustering

```
# Build the model (cluster the data)
clusters = KMeans.train(parsedData, 2, maxIterations=10,
        runs=10, initializationMode="random")

# Evaluate clustering by computing WCSS
def error(point):
    center = clusters.centers[clusters.predict(point)]
    return sqrt(sum([x**2 for x in (point - center)]))

WCSS = parsedData.map(error).reduce(lambda x, y: x + y)
print("Within Set Sum of Squared Error = " + str(WCSS))

# Save and load model
clusters.save(sc, "myModelPath")
sameModel = KMeansModel.load(sc, "myModelPath")
```

References

- Zaharia, M., et al. (2012). Resilient distributed datasets: A fault-tolerant abstraction for in-memory cluster computing. In NSDI.
- Spark Docs: link
- Spark Programming Guide: link
- Example code: link
- Parallel Programming with Spark (Part 1 & 2) - Matei Zaharia: YouTube