Why Spark?

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Background

UC Berkeley's Research Centers

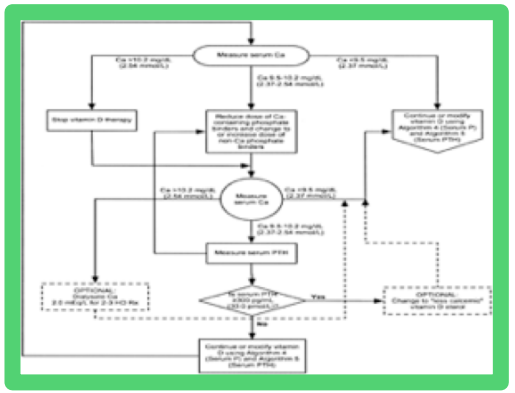
Requirements

- A common vision
- About 5 years
- At least three faculty
- A dozen students

Years	Title	Profs: Director, Co-PIs	Students
1977–1981	X-Tree: Tree Multiprocessor	Despain, Patterson, Sequin	12
1980–1984	RISC: Reduced Instructions	Patterson, Ousterhout, Sequin	17
1983–1986	SOAR: Smalltalk On A RISC	Patterson, Ousterhout	22
1985–1989	SPUR: Symbolic Processing Using RISCs	Patterson, Fateman, Hilfinger, Hodges, Katz, Ousterhout	21
1988–1992	RAID: Redundant Array of Inexpensive Disks	Katz, Ousterhout, Patterson, Stonebraker	16
1993–1998	NOW: Network of Workstations	Culler, Anderson, Brewer, Patterson	25
1997–2002	IRAM: Intelligent RAM	Patterson, Kubiatowicz, Wawrzynek, Yelick	12
2001–2005	ROC: Recovery Oriented Computing Systems	Patterson, Fox	11
2005–2011	RAD Lab: Reliable Adaptive Distributed Computing Lab	Patterson, Fox, Jordan, Joseph, Katz, Shenker, Stoica	30
2007–2013	Par Lab: Parallel Computing Lab	Patterson, Asanovic, Demmel, Fox, Keutzer, Kubiatowicz, Sen, Yelick	40
2011–2017	AMP Lab: Algorithms, Machines, and People	Franklin, Jordan, Joseph, Katz, Patterson, Recht, Shenker, Stoica	40
2013–2018	ASPIRE Lab	Asanovic, Alon, Bachrach, Demmel, Fox, Keutzer, Nikolic, Patterson, Sen, Wawrzynek	40

AMPLab's Vision

Make sense of BIG DATA by tightly integrating algorithms, machines, and people



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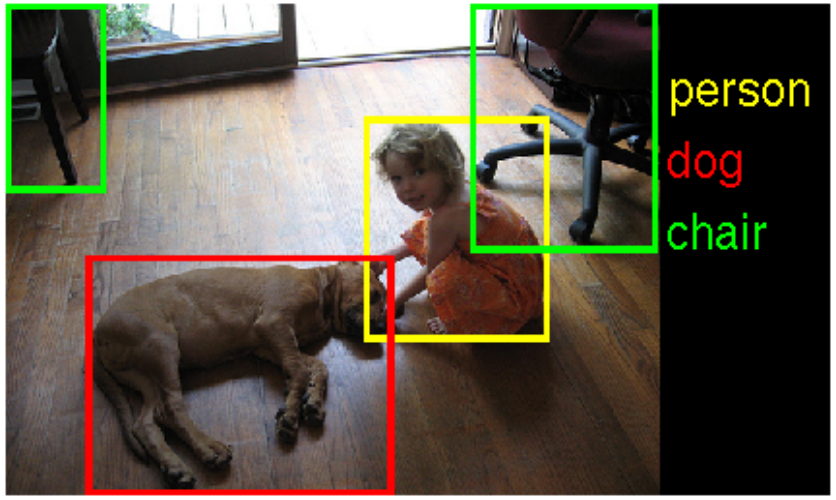
Example: Extract Value From Image Data

What are in the image?



How to solve the problem?

Deep Learning (Algorithms)
GPU Cluster (Machines)
ImageNet (People)

Spark's Initial Idea

Algorithms + Machines

- Run ML Algorithms on Hadoop

Why is it slow?

1. The algorithms are iterative (i.e., multiple scans of data)
2. MapReduce writes/reads data to/from **disk** at each iteration

Solution

- Keep data in **memory**

How About Fault Tolerance?

Resilient Distributed Datasets (RDD)

Main Idea: Logging the transformations (used to build an RDD) rather than the RDD itself

Zaharia et al. Resilient Distributed Datasets: A Fault-Tolerant Abstraction for In-Memory Cluster Computing. NSDI 2012: 15-28

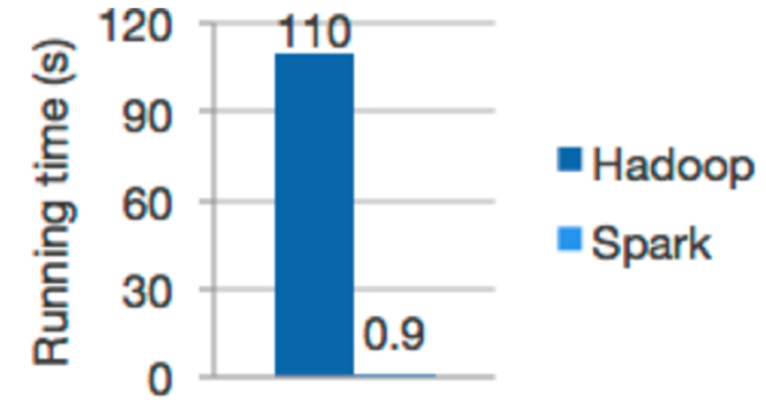
Why Spark?

Fast 

Easy to Use 

What Makes Spark *Fast*?

In-memory Computation



Logistic regression in Hadoop and Spark

What you save?

- Serialization/Deserialization
- Compression/Decompression
- I/O cost

“CPU (and not I/O) is often the bottleneck”

Ousterhout et al. Making Sense of Performance in Data Analytics Frameworks. NSDI 2015: 293-307

Hardware Trends

	2010	2016	
Storage	50+MB/s (HDD)	500+MB/s (SSD)	10X
Network	1Gbps	10Gbps	10X
CPU	~3GHz	~3GHz	☹

What Makes Spark *Fast*?

Project Tungsten: Bringing Apache Spark Closer to Bare Metal

by Reynold Xin and Josh Rosen
Posted in **ENGINEERING BLOG** | April 28, 2015

1. Memory Management and Binary Processing
2. Cache-aware computation
3. Code generation

Why Spark?

Fast 

Easy to Use 

What Makes Spark *Easy-to-Use*?

Over 80 High-level Operators

WordCount (Mapreduce)

```
import java.io.IOException;
import java.util.StringTokenizer;

import org.apache.hadoop.conf.Configuration;
import org.apache.hadoop.conf.Configured;
import org.apache.hadoop.fs.Path;
import org.apache.hadoop.io.IntWritable;
import org.apache.hadoop.io.LongWritable;
import org.apache.hadoop.io.Text;
import org.apache.hadoop.mapreduce.Job;
import org.apache.hadoop.mapreduce.Mapper;
import org.apache.hadoop.mapreduce.Reducer;
import org.apache.hadoop.mapreduce.lib.input.TextInputFormat;
import org.apache.hadoop.mapreduce.lib.output.TextOutputFormat;
import org.apache.hadoop.util.Tool;
import org.apache.hadoop.util.ToolRunner;

public class WordCount extends Configured implements Tool {

    public static class TokenizerMapper
    extends Mapper<LongWritable, Text, Text, IntWritable>{

        private final static IntWritable one = new IntWritable(1);
        private Text word = new Text();

        @Override
        public void map(LongWritable key, Text value, Context context
                ) throws IOException, InterruptedException {
            StringTokenizer itr = new StringTokenizer(value.toString());
            while (itr.hasMoreTokens()) {
                word.set(itr.nextToken());
                context.write(word, one);
            }
        }
    }
```

```
public static class IntSumReducer
extends Reducer<Text, IntWritable, Text, IntWritable> {
    private IntWritable result = new IntWritable();

    @Override
    public void reduce(Text key, Iterable<IntWritable> values,
            Context context
            ) throws IOException, InterruptedException {
        int sum = 0;
        for (IntWritable val : values) {
            sum += val.get();
        }
        result.set(sum);
        context.write(key, result);
    }
}

public static void main(String[] args) throws Exception {
    int res = ToolRunner.run(new Configuration(), new WordCount(), args);
    System.exit(res);
}

@Override
public int run(String[] args) throws Exception {
    Configuration conf = this.getConf();
    Job job = Job.getInstance(conf, "word count");
    job.setJarByClass(WordCount.class);

    job.setInputFormatClass(TextInputFormat.class);

    job.setMapperClass(TokenizerMapper.class);
    job.setCombinerClass(IntSumReducer.class);
    job.setReducerClass(IntSumReducer.class);

    job.setOutputKeyClass(Text.class);
    job.setOutputValueClass(IntWritable.class);
    job.setOutputFormatClass(TextOutputFormat.class);
    TextInputFormat.addInputPath(job, new Path(args[0]));
    TextOutputFormat.setOutputPath(job, new Path(args[1]));

    return job.waitForCompletion(true) ? 0 : 1;
}
}
```

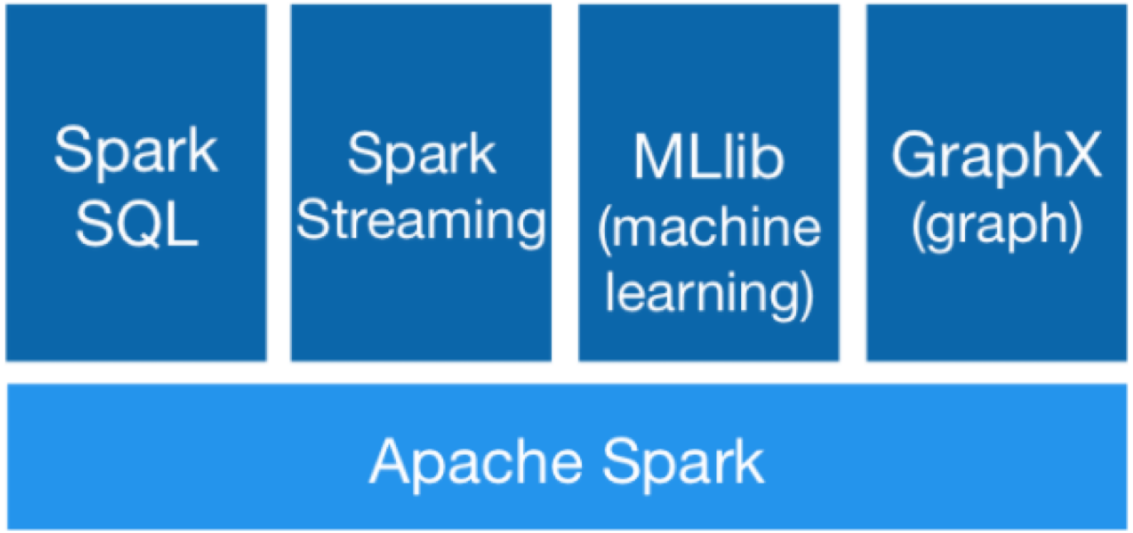
WordCount (Spark)

```
text_file = spark.textFile("hdfs://...")

text_file.flatMap(lambda line: line.split())
    .map(lambda word: (word, 1))
    .reduceByKey(lambda a, b: a+b)
```

What Makes Spark *Easy-to-Use*?

Unified Engine



Easy to manage, learn, and combine functionality

Analogy

Specialized Devices

Unified Device

What Makes Spark *Easy-to-Use*?

Integrate Broadly

Languages: Scala, python, R, Java

The Big Data world is diversified

Data Sources: cassandra, MySQL, elastic, APACHE HBASE, HIVE, S3, PostgreSQL, JSON

Environments: AWS, docker, Google Cloud Platform, openstack, MESOS, hadoop YARN, Azure

Summary

A brief history of Spark
- UC Berkeley's AMPLab
- Spark's Initial Idea

Spark is fast
- In-memory Computation
- Tungsten Project

Spark is easy-to-use
- High-level Operators
- Unified Engine
- Integrate Broadly