# Apache Spark in 2015 and Beyond

Reynold Xin (@rxin) ApacheCon, Apr 16, 2015



### Who am I?

Reynold Xin

Spark PMC member

Databricks co-founder & architect

UC Berkeley AMPLab PhD (on leave)



### **About Databricks**

Founded by creators of Spark and is the largest contributor to Spark

Databricks Cloud (in limited availability)

- Fully managed Spark clusters (one-click launch)
- Interactive workspace
- Production data pipelines
- 3<sup>rd</sup> party applications

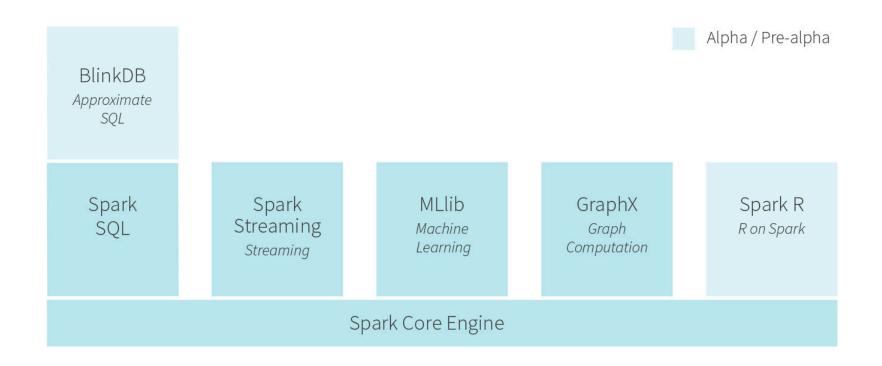


### Show of Hands!

How familiar are you with Spark?

- A. Heard of it, but haven't used it before.
- B. Kicked the tires with some basics.
- C. Worked or working on a POC.
- D. Worked or working on a production deployment.





Fast and general engine for distributed data processing



# 2014: an Amazing Year for Spark

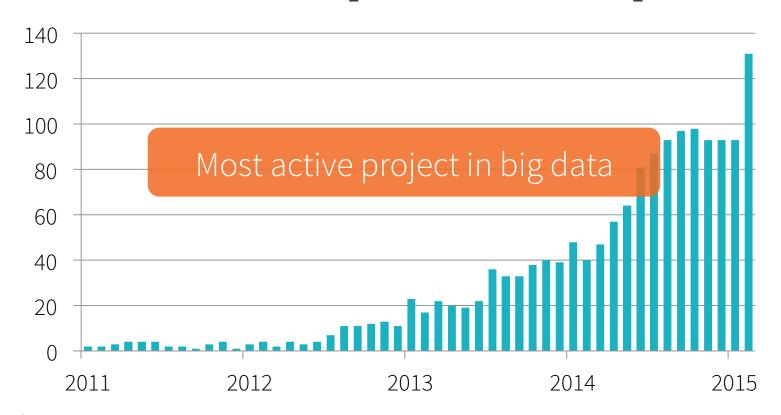
Total contributors: 150 → 500

Lines of code:  $190K \rightarrow 370K$ 

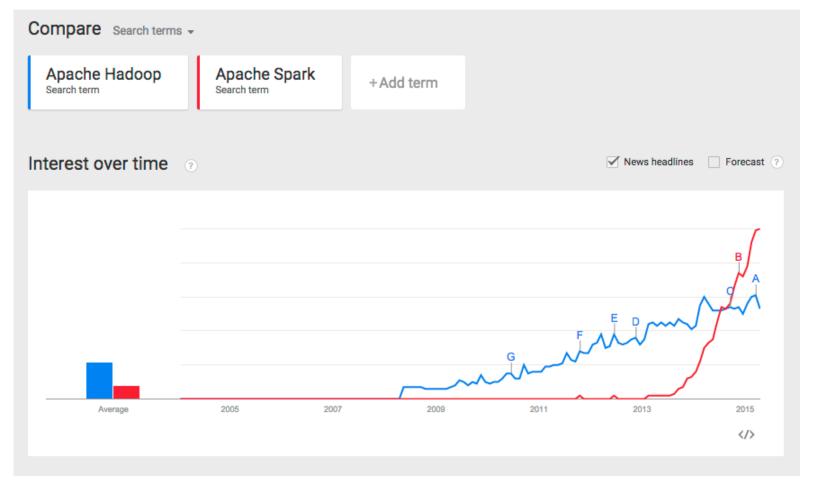
500+ active production deployments



# Contributors per Month to Spark









### 2014 Focus

Richer libraries

Core engine: stability, performance, and enterprise readiness



### Libraries in 2014

Spark SQL

GraphX

Java 8 closure support

Random forests

Python streaming

Streaming MLlib

. . .



# Core Engine in 2014

Revamped "shuffle" and network transport

Higher throughput and lower memory usage

Much better memory estimation and management

harder to get OutOfMemoryError

Enterprise Readiness

YARN integration, security, ...

# On-Disk Sort Record: Time to sort 100TB

2013 Record: Hadoop

2100 machines



72 minutes

2014 Record: Spark 207 machines



23 minutes



# Continuing in 2015

Performance & robustness

### Security

Option to encrypt all communication (control & data planes)

### Usability

Visualization and debugging tools

# Continuing in 2015

#### MLlib

Many new algorithms

#### GraphX

Java API

#### Streaming

- Stronger integration with Kafka, etc

#### SQL

Performance improvements, robustness

### New Directions in 2015

Data Science

Making it easier for wider class of users

Platform Interfaces

Scaling the ecosystem



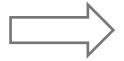
# From MapReduce to Spark

```
public static class WordCountMapClass extends MapReduceBase
  implements Mapper<LongWritable, Text, Text, IntWritable> {
  private final static IntWritable one = new IntWritable(1);
  private Text word = new Text();
  public void map (LongWritable key, Text value,
                  OutputCollector<Text, IntWritable> output,
                  Reporter reporter) throws IOException
    String line = value.toString();
    StringTokenizer itr = new StringTokenizer(line);
   while (itr.hasMoreTokens()) {
      word.set(itr.nextToken());
      output.collect(word, one);
public static class WorkdCountReduce extends MapReduceBase
  implements Reducer<Text, IntWritable, Text, IntWritable> {
  public void reduce(Text key, Iterator<IntWritable> values,
                     OutputCollector<Text, IntWritable> output,
                     Reporter reporter) throws IOException {
    int sum = 0;
    while (values.hasNext()) {
      sum += values.next().get();
    output.collect(key, new IntWritable(sum));
```

# Beyond Hadoop Users

#### Early adopters







Users

Understands MapReduce & functional APIs

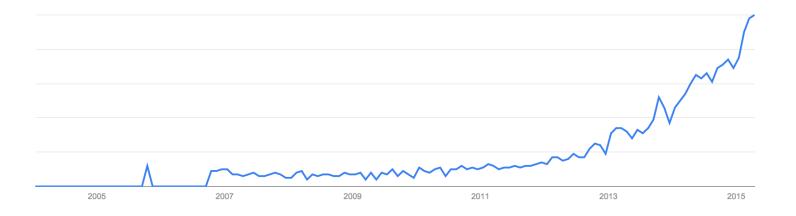


Data Scientists Statisticians R users ... PyData



### Data Frames

De facto data processing abstraction for data science (R and Python)



Google Trends for "dataframe"



### Spark DataFrames

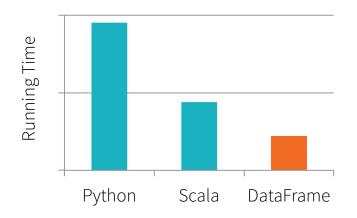
Similar API to data frames in R and Pandas

Automatically optimized via Spark SQL

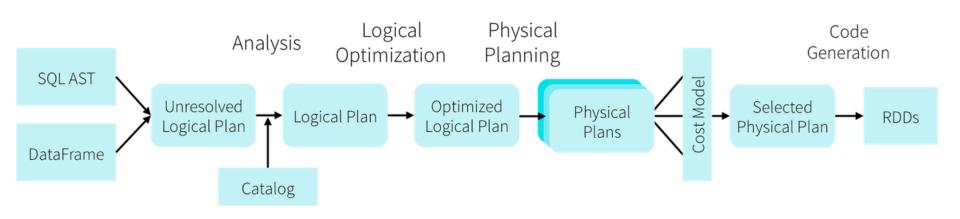
Out in Spark 1.3

```
df = jsonFile("tweets.json")

df[df["user"] == "matei"]
   .groupBy("date")
   .sum("retweets")
```



# Convergence of SQL and DataFrames



DataFrames and SQL share the same optimization/execution pipeline

Maximize code reuse & share optimization efforts

### PySpark RDD vs DataFrame

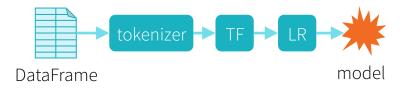
```
pdata.map(lambda x: (x.dept, [x.age, 1])) \
    .reduceByKey(lambda x, y: [x[0] + y[0], x[1] + y[1]]) \
    .map(lambda x: [x[0], x[1][0] / x[1][1]]) \
    .collect()
```

```
data.groupBy("dept").avg("age")
```

# Machine Learning Pipelines

High-level API inspired by SciKit-Learn

Featurization, evaluation, parameter search



```
tokenizer = Tokenizer()
tf = HashingTF(numFeatures=1000)
lr = LogisticRegression()

pipe = Pipeline([tokenizer, tf, lr])
model = pipe.fit(df)
```

# R Interface (SparkR)

Spark 1.4 (June)

Exposes DataFrames, and ML library in R

```
df = jsonFile("tweets.json")
summarize(
  group_by(
    df[df$user == "matei",],
    "date"),
  sum("retweets"))
```



### Data Science at Scale

Higher level interfaces in Scala, Java, Python, R

Drastically easier to program Big Data

With APIs similar to single-node tools



### New Directions in 2015

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# Spark Mailing Lists (Mar 2015)

2,577 user:

dev:

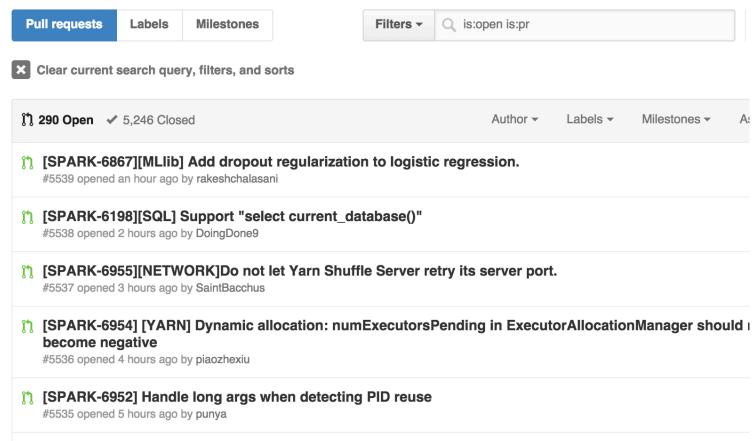
456

issues: 4,473

reviews: 9,993







### Feature Requests and Patches

Can I add this new API zipWithIndexWithContext to RDD?

I want support for HBase/Cassandra/Accumulo/...

I want this algorithm for machine learning...



### Platformization

Standardize interfaces for integration points (so implementations can run in many versions to come)

Make it as easy as possible to consume these implementations that are not in Apache Spark repo

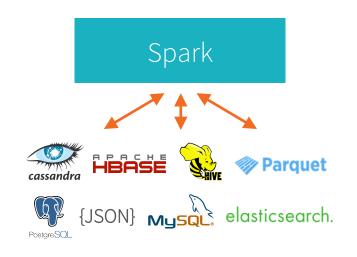


### External Data Sources

Platform API to plug smart data sources into Spark

Returns DataFrames usable in Spark apps or SQL

Pushes logic into sources



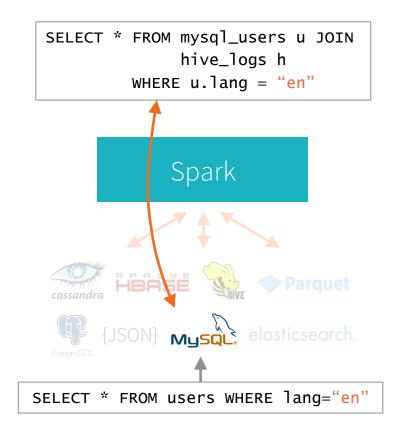


### External Data Sources

Platform API to plug smart data sources into Spark

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```
/**
160
       * ::DeveloperApi::
161
       * A BaseRelation that can eliminate unneeded columns and filter using selected
162
       * predicates before producing an RDD containing all matching tuples as Row objects.
163
       *
164
       * The actual filter should be the conjunction of all `filters`,
165
       * i.e. they should be "and" together.
166
       *
167
       * The pushed down filters are currently purely an optimization as they will all be evaluated
168
       * again. This means it is safe to use them with methods that produce false positives such
169
       * as filtering partitions based on a bloom filter.
170
       */
171
      @DeveloperApi
172
      trait PrunedFilteredScan {
173
        def buildScan(requiredColumns: Array[String], filters: Array[Filter]): RDD[Row]
174
175
```

# **Existing Data Sources**

built-in





{ JSON }









Postgre**SQL** 

external















and more ...

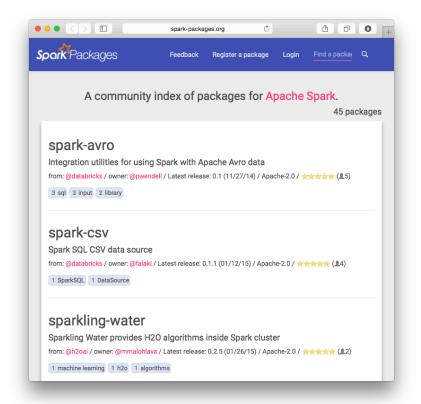


# Spark Packages

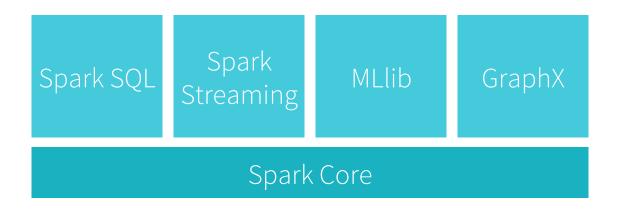
Community index of third party packages

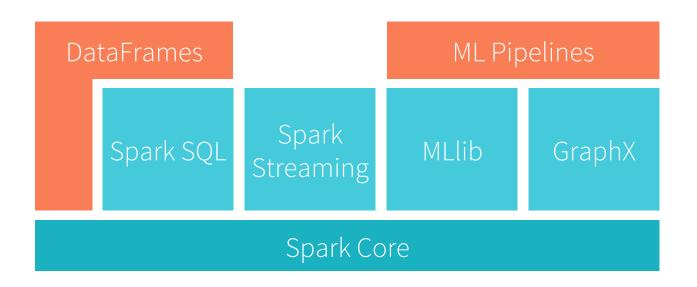
bin/spark-shell --packages databricks/spark-csv:0.2

spark-packages.org

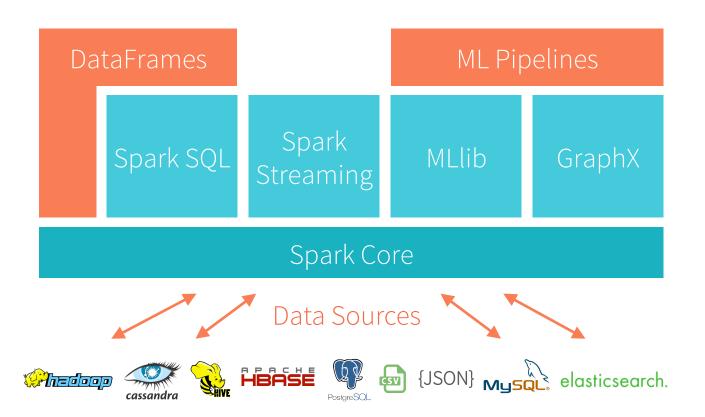












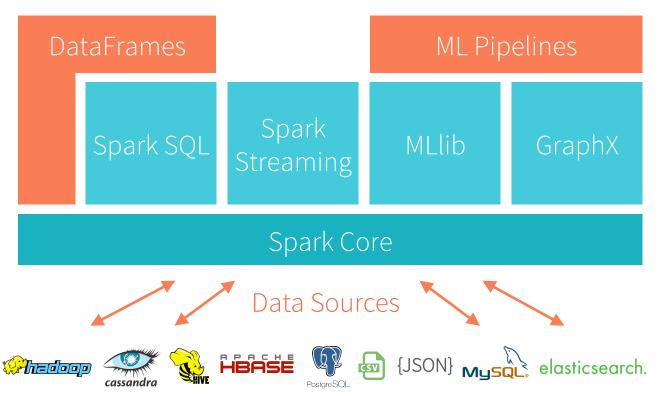














Goal: unified engine across data sources, workloads and environments







REGISTER AGENDA SPARK TRAINING VENUE JOB BOARD

#### DAY 1 - SPARK SUMMIT 2015

TIME	06/15/2015		
07:00 AM - 09:00 AM	Registration		
09:00 AM - 12:00 PM	Keynotes		
12:00 PM - 12:00 PM	Lunch		
	TRACK A - Developer	TRACK B - Data Science	TRACK C - Applications
01:00 PM - 01:30 PM	Beyond SQL: Spark SQL Abstractions For The Common Spark Job Michael Armbrust (Databricks)	Large-scale Lasso and Elastic-Net Regularized Generalized Linear Models DB Tsai (Alpine Data Labs) 30 min	Use of Spark MLlib for Predicting the Offlining of Digital Media Christopher Burdorf (NBC Universal) 30 min
	TRACK A - Developer	TRACK B - Data Science	TRACK C - Applications
	Spark-on-YARN: The	Hybrid Community Detection for Web-scale	Spark and Spark Streaming at Netflix

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