

Distributed ML in Apache® Spark™

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Who am I?

Apache Spark committer & PMC member

Software Engineer @ Databricks

Ph.D. in Machine Learning from Carnegie Mellon

Apache Spark

- General engine for big data computing
- Fast
- Easy to use
- APIs in Python, Scala, Java & R

Open source

- Apache Software Foundation
- 1000+ contributors
- 200+ companies & universities

Spark SQL

Streaming

MLlib

GraphX



Largest cluster:
8000 Nodes (Tencent)

NOTABLE USERS THAT PRESENTED AT SPARK SUMMIT
2015 SAN FRANCISCO

Source: Slide 5 of Spark Community Update



Databricks

We're hiring!

Founded by the creators of Apache Spark

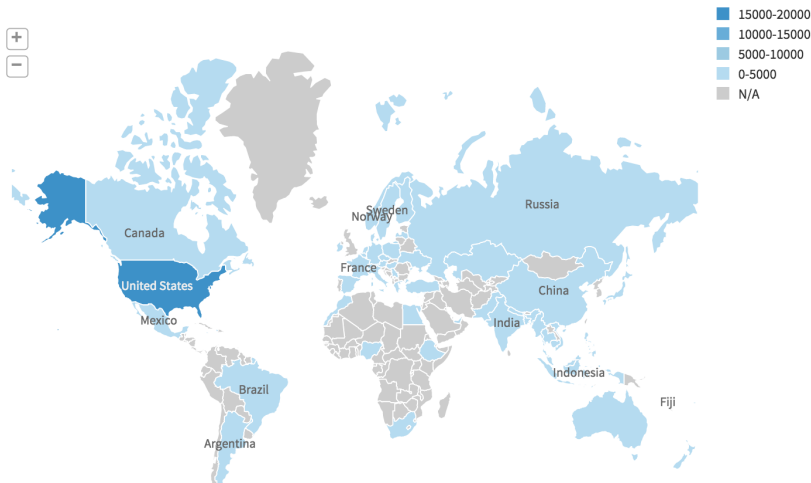
Offers hosted service

- Spark on EC2
- Notebooks
- Visualizations
- Cluster management
- Scheduled jobs

Mobile Devices by Geography (Sample Data)

This is a world map of number of mobile phones by country from a sample dataset

```
> select m.ClientID, c.CountryCode3, m.DeviceMake  
from mobile_sample m  
join countrycodes c  
on m.Country = c.Country
```



This talk: DataFrames in MLlib

Common issues within Big ML projects

- Custom, strict data format
- Library encourages developing via scripts
- Lots of work on low-level optimizations
- Hard to bridge R&D – Production gap
- Single-language APIs

MLlib: Spark's ML library

Goals

Scale-out ML
Standard library
Extensible API

Data utilities

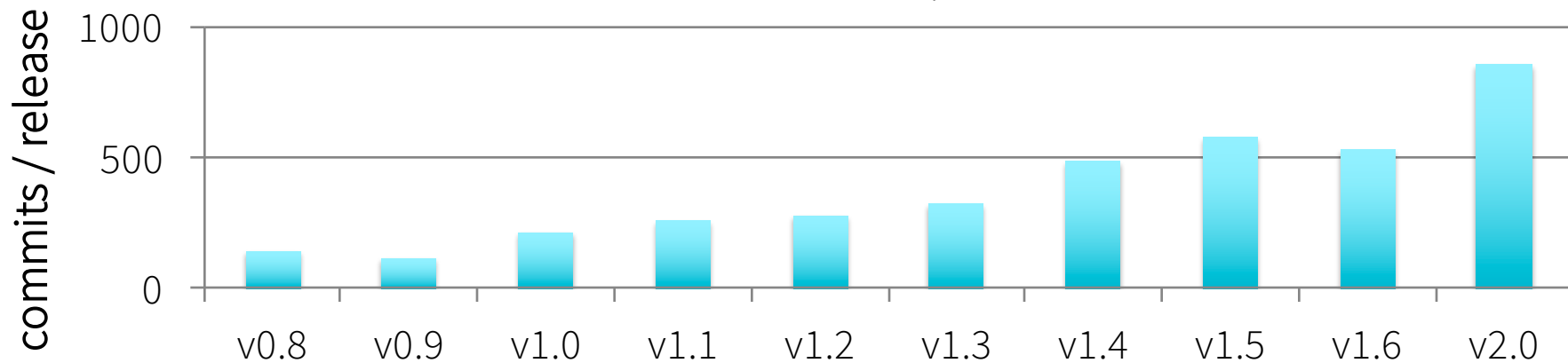
Featurization
Statistics
Linear algebra

Learning tasks

Classification
Regression
Recommendation
Clustering
Frequent itemsets

Workflow utilities

Model import/export
Pipelines
DataFrames
Cross validation



Spark DataFrames & Datasets

dept	age	name
Bio	48	H Smith
CS	34	A Turing
Bio	43	B Jones
Chem	61	M Kennedy

Data grouped into
named columns

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

DSL for common tasks

- Project, filter, aggregate, join, ...
- 100+ functions available
- User-Defined Functions (UDFs)

Datasets: Strongly typed DataFrames

This talk: DataFrames in MLlib

Data sources & ETL

ML Pipelines

Under the hood: optimizations

Model persistence

Multiple language support

Data sources & ETL

Data scientists spend 50-80% of their time on data munging.*

DataFrames support easy manipulation of big data

- Standard DataFrame/SQL ops
- Methods for null/NaN vals
- Statistical methods
- Conversions: R data.frame, Python Pandas

Many data sources

built-in



external



and more ...

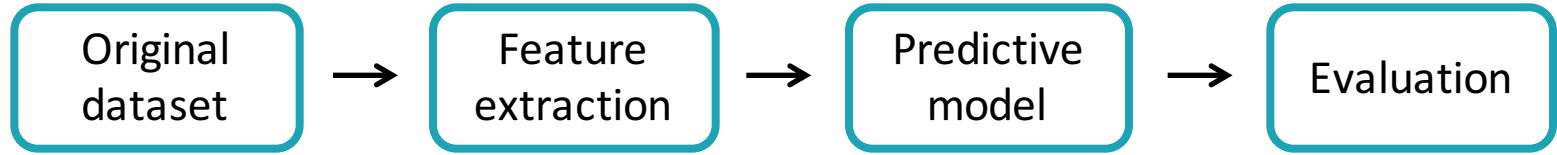
* Lohraug. "For Big-Data Scientists, 'Janitor Work' Is Key Hurdle to Insights." NYTimes, 8/18/2014.

ML Pipelines

DataFrames: unified ML dataset API

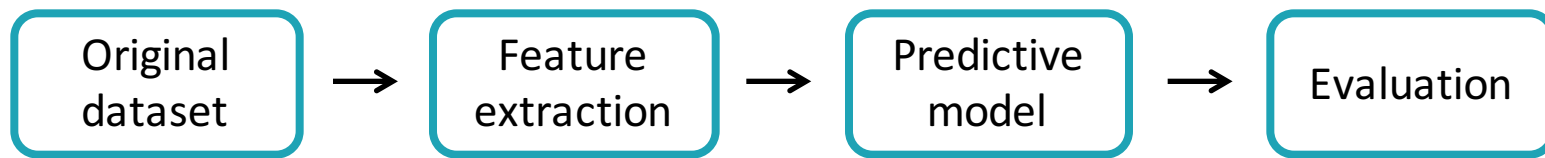
- Flexible types
- Add & remove columns during Pipeline execution

Load data



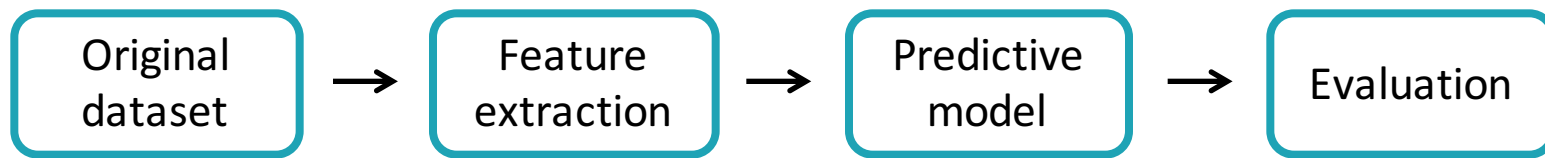
Text	Label
I bought the game...	4
Do NOT bother try...	1
this shirt is aweso...	5
never got it. Seller...	1
I ordered this to...	3

Extract features



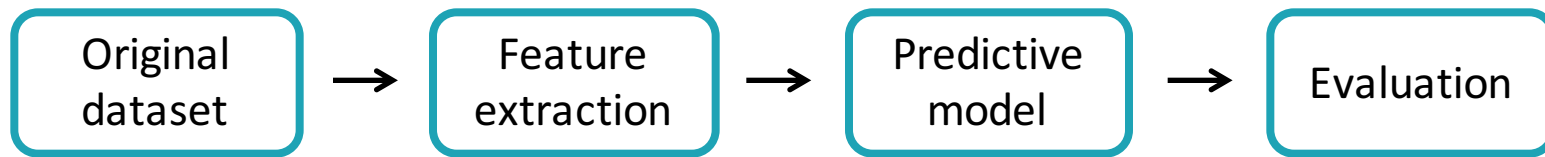
Text	Label	Words	Features
I bought the game...	4	"i", "bought",...	[1, 0, 3, 9, ...]
Do NOT bother try...	1	"do", "not",...	[0, 0, 11, 0, ...]
this shirt is aweso...	5	"this", "shirt"	[0, 2, 3, 1, ...]
never got it. Seller...	1	"never", "got"	[1, 2, 0, 0, ...]
I ordered this to...	3	"i", "ordered"	[1, 0, 0, 3, ...]

Fit a model



Text	Label	Words	Features	Prediction	Probability
I bought the game...	4	"i", "bought",...	[1, 0, 3, 9, ...]	4	0.8
Do NOT bother try...	1	"do", "not",...	[0, 0, 11, 0, ...]	2	0.6
this shirt is aweso...	5	"this", "shirt"	[0, 2, 3, 1, ...]	5	0.9
never got it. Seller...	1	"never", "got"	[1, 2, 0, 0, ...]	1	0.7
I ordered this to...	3	"i", "ordered"	[1, 0, 0, 3, ...]	4	0.7

Evaluate



Text	Label	Words	Features	Prediction	Probability
I bought the game...	4	"i", "bought",...	[1, 0, 3, 9, ...]	4	0.8
Do NOT bother try...	1	"do", "not",...	[0, 0, 11, 0, ...]	2	0.6
this shirt is aweso...	5	"this", "shirt"	[0, 2, 3, 1, ...]	5	0.9
never got it. Seller...	1	"never", "got"	[1, 2, 0, 0, ...]	1	0.7
I ordered this to...	3	"i", "ordered"	[1, 0, 0, 3, ...]	4	0.7

ML Pipelines

DataFrames: unified ML dataset API

- Flexible types
- Add & remove columns during Pipeline execution
- Materialize columns lazily
- Inspect intermediate results

DataFrame optimizations

Catalyst query optimizer

Predicate pushdown
Join selection
...

Project Tungsten

- Memory management
- Code generation

Off-heap
Avoid JVM GC
Compressed format

Combine operations into single,
efficient code blocks

Under the hood: optimizations

Current use of DataFrames

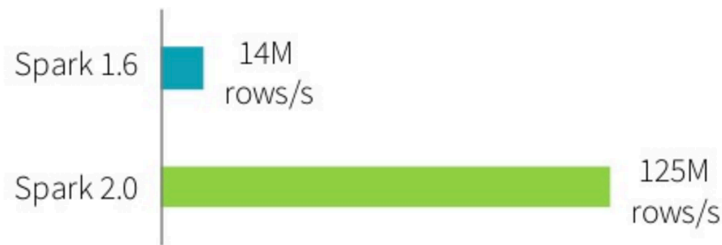
- API
- Transformations & predictions

Feature transformation & model prediction are phrased as User-Defined Functions (UDFs)

- Catalyst query optimizer
- Tungsten memory management + code generation

Whole-stage code generation

- Fuse across multiple operators



Implementations on DataFrames

Prototypes

- Belief propagation
- Connected components

Current challenge: DataFrame query plans do not have iteration as a top-level concept

Eventual goal: Port all ML algorithms to run on top of DataFrames → speed & scalability

ML persistence

Data Science

Prototype (Python/R)
Create model



Software Engineering

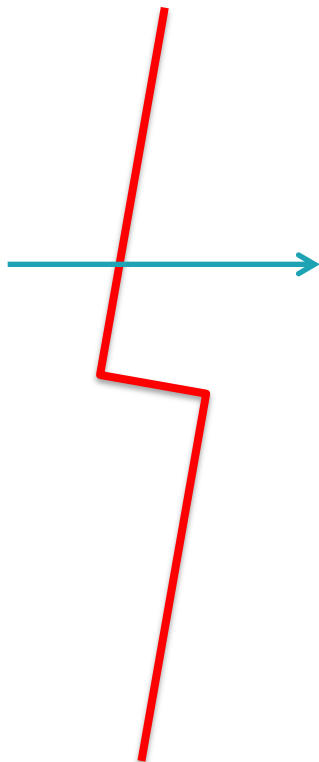
Re-implement model for
production (Java)
Deploy model

ML persistence

Data Science

Prototype (Python/R)
Create Pipeline

- Extract raw features
- Transform features
- Select key features
- Fit multiple models
- Combine results to make prediction



Software Engineering

Re-implement Pipeline for
production (Java)
Deploy Pipeline

- Extra implementation work
- Different code paths
- Synchronization overhead

With ML persistence...

Data Science

Software Engineering

Prototype (Python/R)
Create Pipeline

Load Pipeline (Scala/Java)
`Model.load("s3n://...")`
Deploy in production

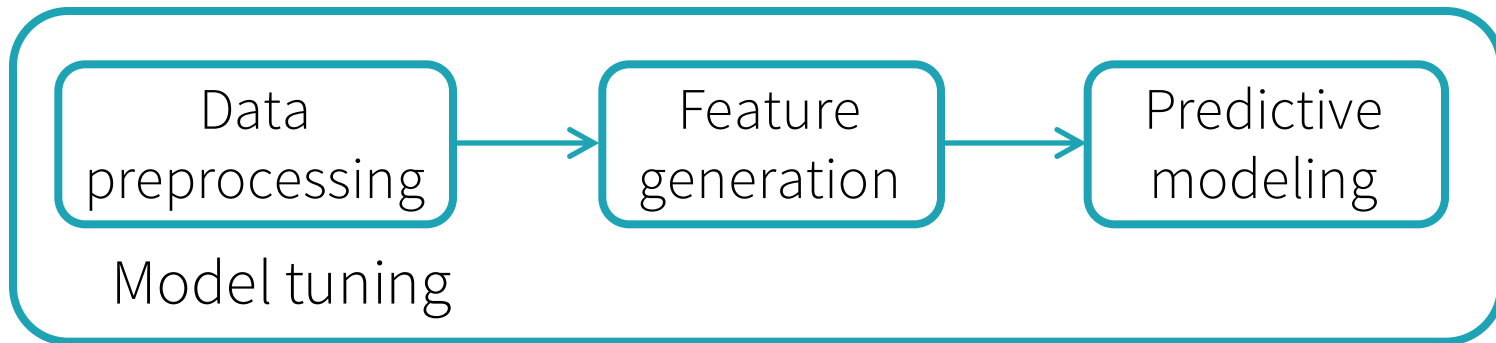
Persist model or Pipeline:
`model.save("s3n://...")`

ML persistence status

Single implementation for
all Spark language APIs:
Scala, Java, Python, R

	“recipe” Unfitted	“result” Fitted
Model	✓	✓
Pipeline	✓	✓

Supported in MLlib’s
RDD-based API



ML persistence status

Near-complete coverage in all Spark language APIs

- Scala & Java: complete
- Python: complete except for 2 algorithms
- R: complete for existing APIs

Single underlying implementation of models

Exchangeable data format

- JSON for metadata
- Parquet for model data (coefficients, etc.)

Multiple language support

APIs in Scala, Java, Python, R

- Scala (& Java): implementation
- Python & R: wrappers for Scala

DataFrames provide:

- Uniform API across languages
- Data serialization
 - Store data off-heap, accessible from JVM
 - Transfer to & from Python & R handled by DataFrames, not MLlib

Summary: DataFrames in MLlib

Data sources & ETL

ML Pipelines

Under the hood: optimizations

Model persistence

Multiple language support

Research & development topics

- Query optimization for ML/Graph algorithms
 - Caching, communication, serialization, compression
- Iteration as a first-class concept in DataFrames
- Optimized model tuning
- Spark + GPUs
- Asynchronous communication within Spark

What's next?

Prioritized items on the 2.1 roadmap JIRA (SPARK-15581):

- Critical feature completeness for the DataFrame-based API
 - Multiclass logistic regression
 - Frequent pattern mining
- Python API parity & R API expansion
- Scaling & speed for key algorithms: trees, forests, and boosting

GraphFrames

- Release for Spark 2.0
- Speed improvements (join elimination, connected components)

Get started

Get involved

- JIRA <http://issues.apache.org>
- mailing lists <http://spark.apache.org>
- Github <http://github.com/apache/spark>
- Spark Packages <http://spark-packages.org>

Many thanks to the community
for contributions & support!

Learn more

- What's coming in Apache Spark 2.0
<http://databricks.com/blog/2016/06/01>
- MOOCs on EdX <http://databricks.com/spark/training>

Try out Apache Spark 2.0 preview
in Databricks Community Edition
<http://databricks.com/ce>

Thank you!

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