Practical Machine Learning Pipelines with MLlib

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About Spark MLlib

Started in UC Berkeley AMPLab

- Shipped with Spark 0.8

Currently (Spark 1.3)

- Contributions from 50+ orgs, 100+ individuals
- Good coverage of algorithms

classification	feature extraction, selection
regression	statistics
clustering	linear algebra
recommendation	frequent itemsets

MLlib's Mission

MLlib's mission is to make practical machine learning easy and scalable.

- Capable of learning from large-scale datasets
- Easy to build machine learning applications

How can we move beyond this list of algorithms and help users developer real ML workflows?

Outline

ML workflows

Pipelines

Roadmap

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ML workflows

Pipelines

Roadmap

Example: Text Classification

Goal: Given a text document, predict its topic.

Dataset: "20 Newsgroups"
From UCI KDD Archive

Features

```
Subject: Re: Lexan Polish?
Suggest McQuires #1 plastic
polish.  It will help somewhat
but nothing will remove deep
scratches without making it
worse than it already is.
McQuires will do something...
```

text, image, vector, ...

Label

1: about science
0: not about science

CTR, inches of rainfall, ...

Training & Testing

Training

Given labeled data:
RDD of (features, label)

```
Subject: Re: Lexan Polish?
Suggest McQuires #1 plastic
polish.  It will help...
```
Label 0

```
Subject: RIPEM FAQ
RIPEM is a program which
performs Privacy Enhanced...
```
Label 1

...

Learn a model.

Testing/Production

Given new unlabeled data:
RDD of features

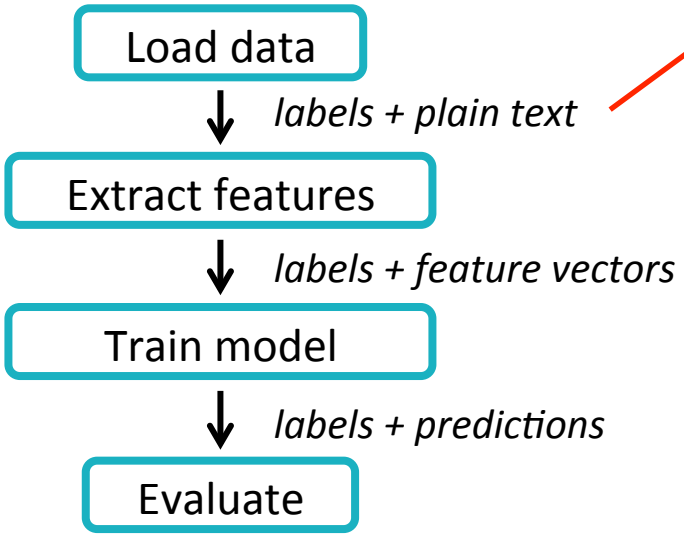
```
Subject: Apollo Training
The Apollo astronauts also
trained at (in) Meteor...
```
→ Label 1

```
Subject: A demo of Nonsense
How can you lie about
something that no one...
```
→ Label 0

Use model to make predictions.

Example ML Workflow

Training



Pain point

Create many RDDs

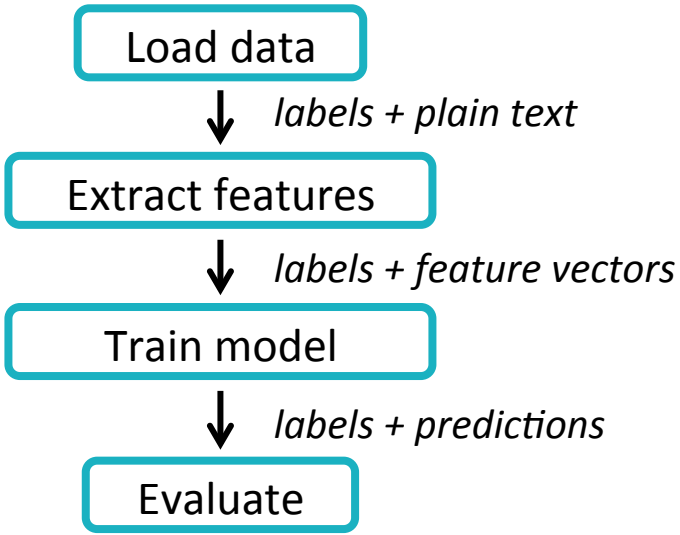
```
val labels: RDD[Double] =
  data.map(_.label)

val features: RDD[Vector]
val predictions: RDD[Double]
```

Explicitly unzip & zip RDDs

```
labels.zip(predictions).map {
  if (_._1 == _._2) ...
}
```

Example ML Workflow

Training



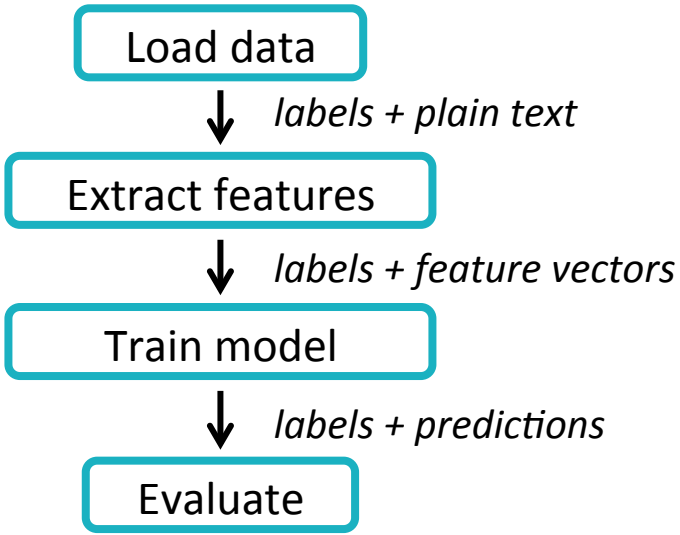
Pain point

Write as a script

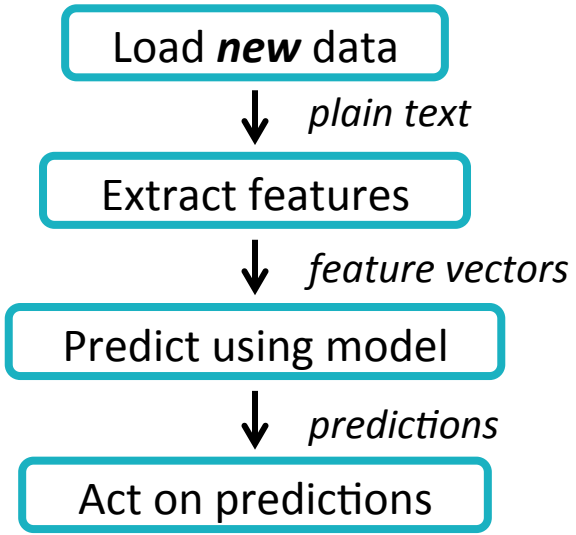
- Not modular
- Difficult to re-use workflow

Example ML Workflow

Training



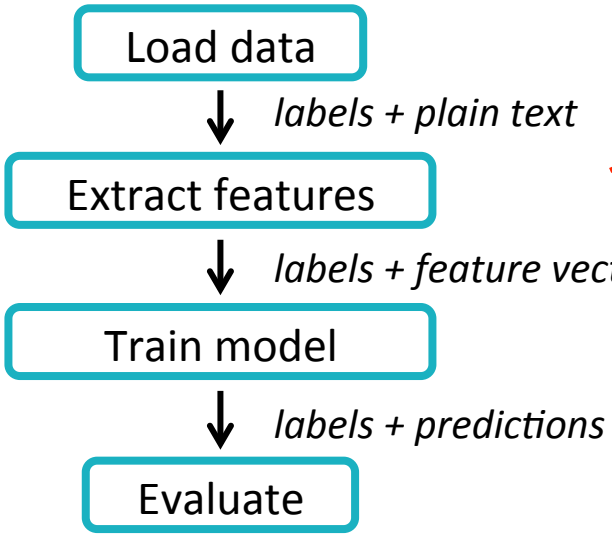
Testing/Production



Almost identical workflow

Example ML Workflow

Training



Pain point

Parameter tuning

- Key part of ML
- Involves training many models
  - For different splits of the data
  - For different sets of parameters

Pain Points

Create & handle many RDDs and data types
Write as a script
Tune parameters

Enter...

Pipelines!

in Spark 1.2 & 1.3

Outline

ML workflows

Pipelines

Roadmap

Key Concepts

DataFrame: The ML Dataset

Abstractions: Transformers, Estimators, & Evaluators

Parameters: API & tuning

DataFrame: The ML Dataset

DataFrame: RDD + schema + DSL

Named columns with types

```
label: Double
text: String
words: Seq[String]
features: Vector
prediction: Double
```

label	text	words	features
0	This is ...	[“This”, “is”, …]	[0.5, 1.2, …]
0	When we ...	[“When”, ...]	[1.9, -0.8, …]
1	Knuth was ...	[“Knuth”, …]	[0.0, 8.7, …]
0	Or you ...	[“Or”, “you”, …]	[0.1, -0.6, …]

DataFrame: The ML Dataset

DataFrame: RDD + schema + DSL

Named columns with types

Domain-Specific Language

```
# Select science articles
sciDocs =
  data.filter("label" == 1)

# Scale labels
data("label") * 0.5
```

DataFrame: The ML Dataset

DataFrame: RDD + schema + DSL

BIG data

Named columns with types

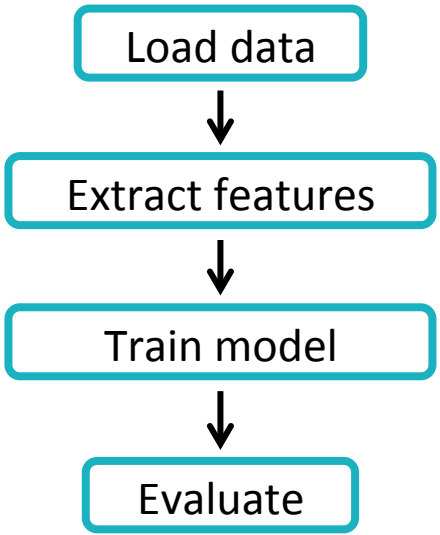
Domain-Specific Language

- Shipped with Spark 1.3
- APIs for Python, Java & Scala (+R in dev)
- Integration with Spark SQL
  - Data import/export
  - Internal optimizations

~~Pain point: Create & handle many RDDs and data types~~

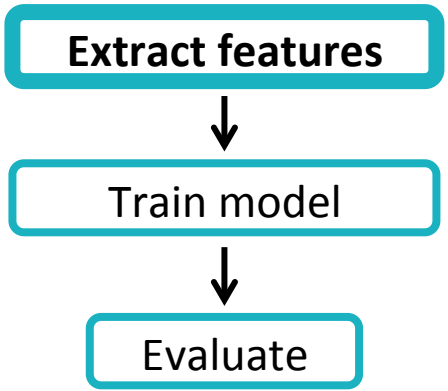
Abstractions

Training

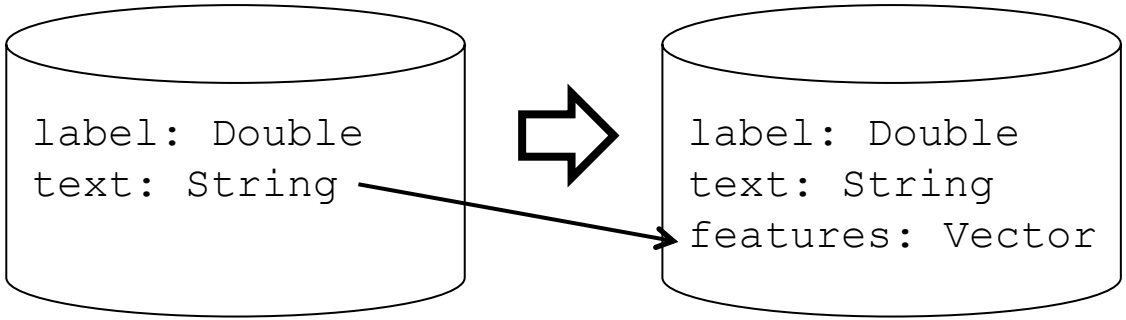


Abstraction: Transformer

Training



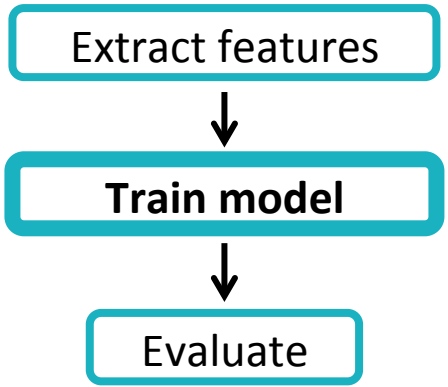

```
def transform(DataFrame): DataFrame
```

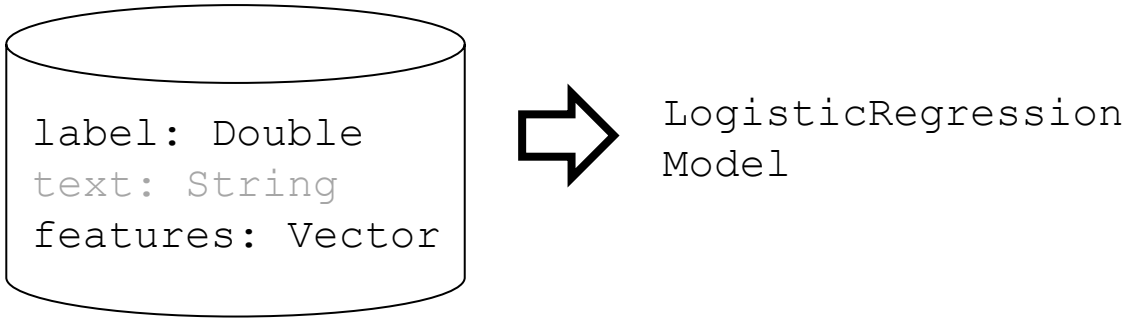


Abstraction: Estimator

Training

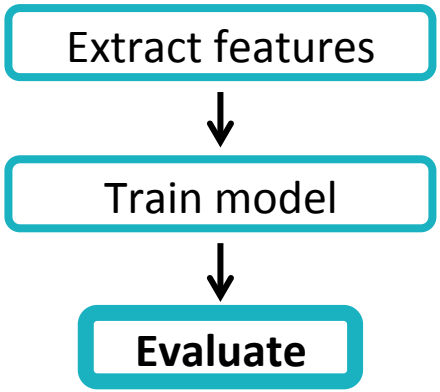
```
def fit(DataFrame): Model
```



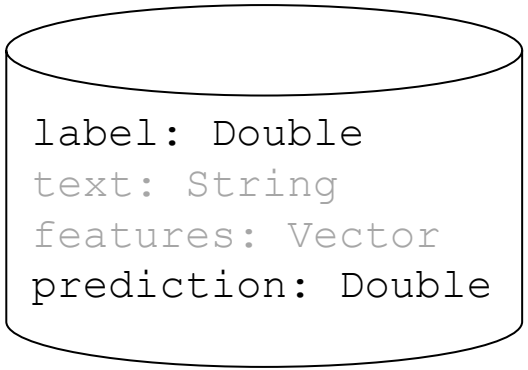


Abstraction: Evaluator

Training




```
def evaluate(DataFrame): Double
```

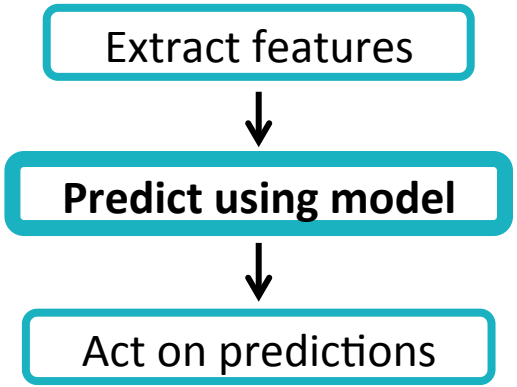


Metric:

```
accuracy
AUC
MSE
...
```

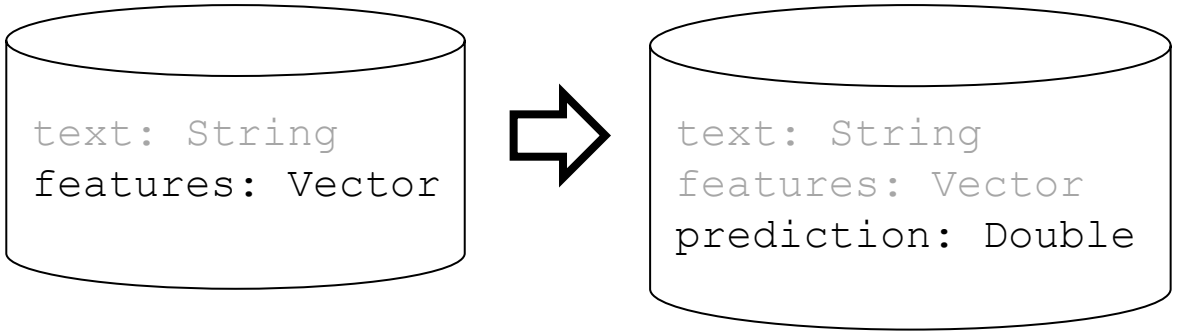
Abstraction: Model

Testing/Production



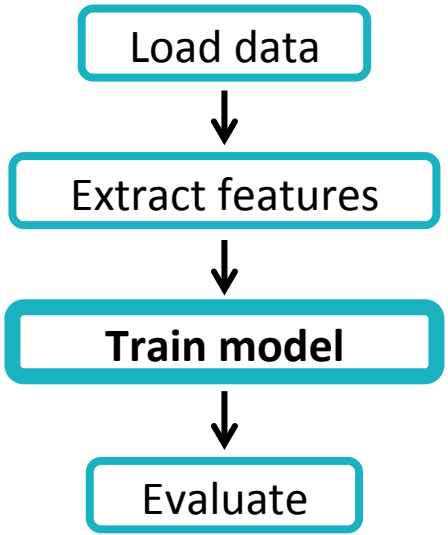
Model is a type of Transformer

```
def transform(DataFrame): DataFrame
```

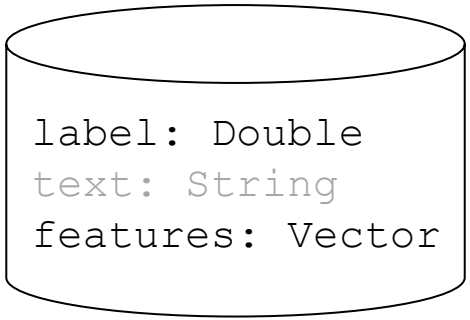


(Recall) Abstraction: Estimator

Training

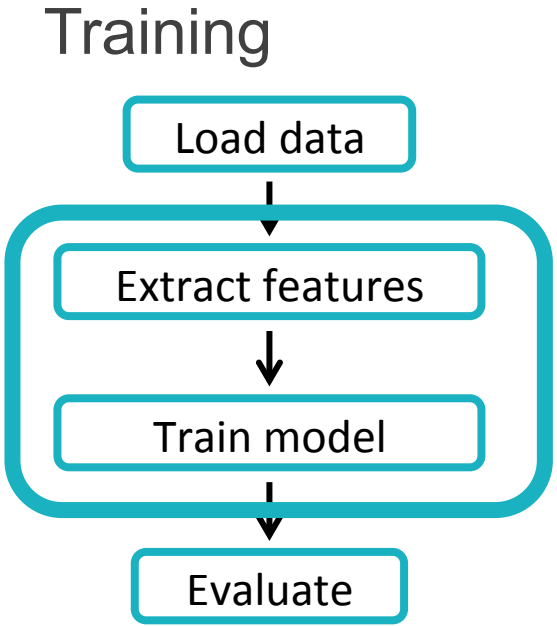



```
def fit(DataFrame): Model
```



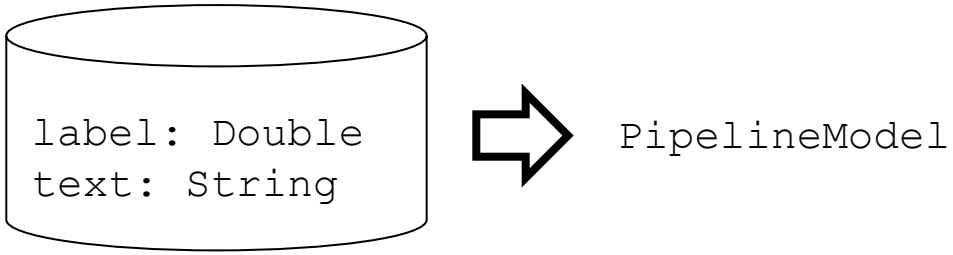
```
LogisticRegression
Model
```

Abstraction: Pipeline



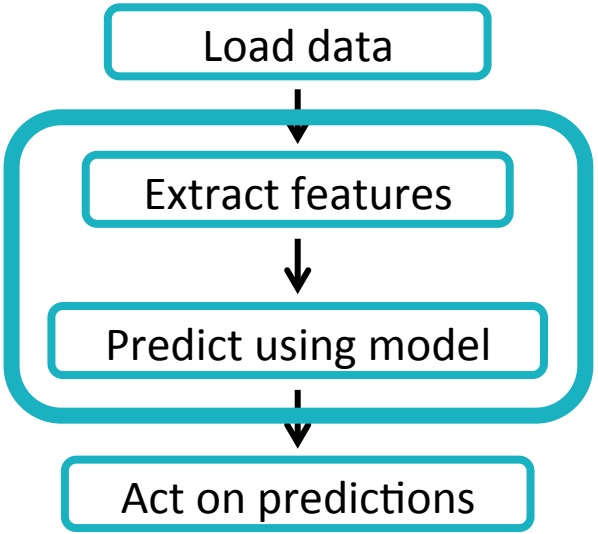
Pipeline is a type of Estimator

```
def fit(DataFrame): Model
```



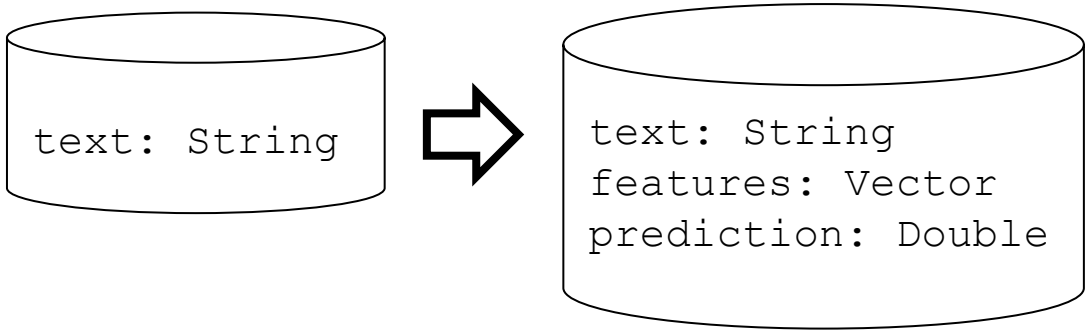
Abstraction: PipelineModel

Testing/Production



PipelineModel is a type of Transformer

```
def transform(DataFrame): DataFrame
```



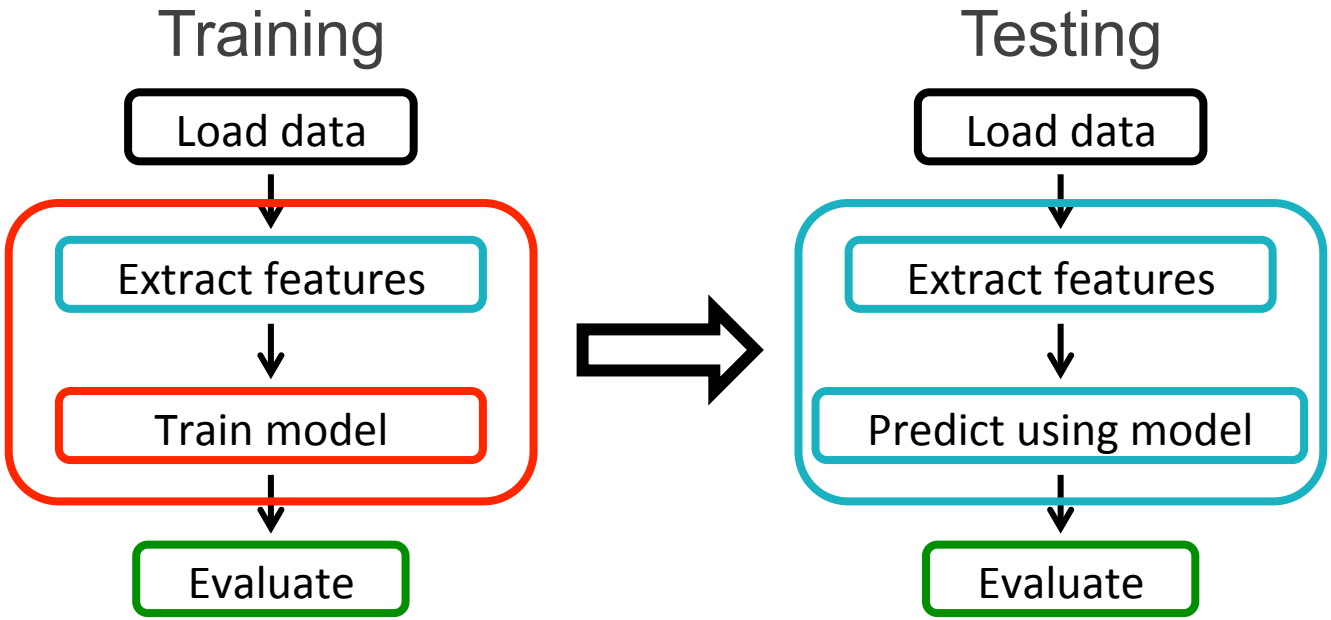
Abstractions: Summary

DataFrame

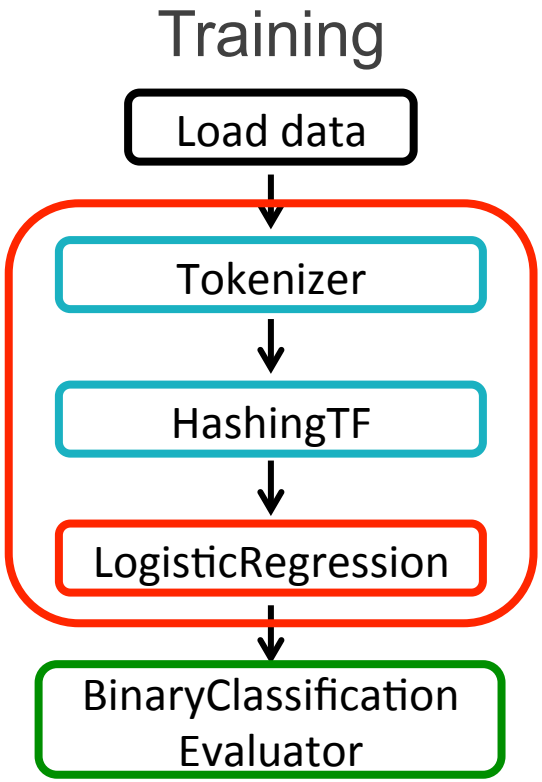
Transformer

Estimator

Evaluator



Demo



DataFrame

Transformer

Transformer

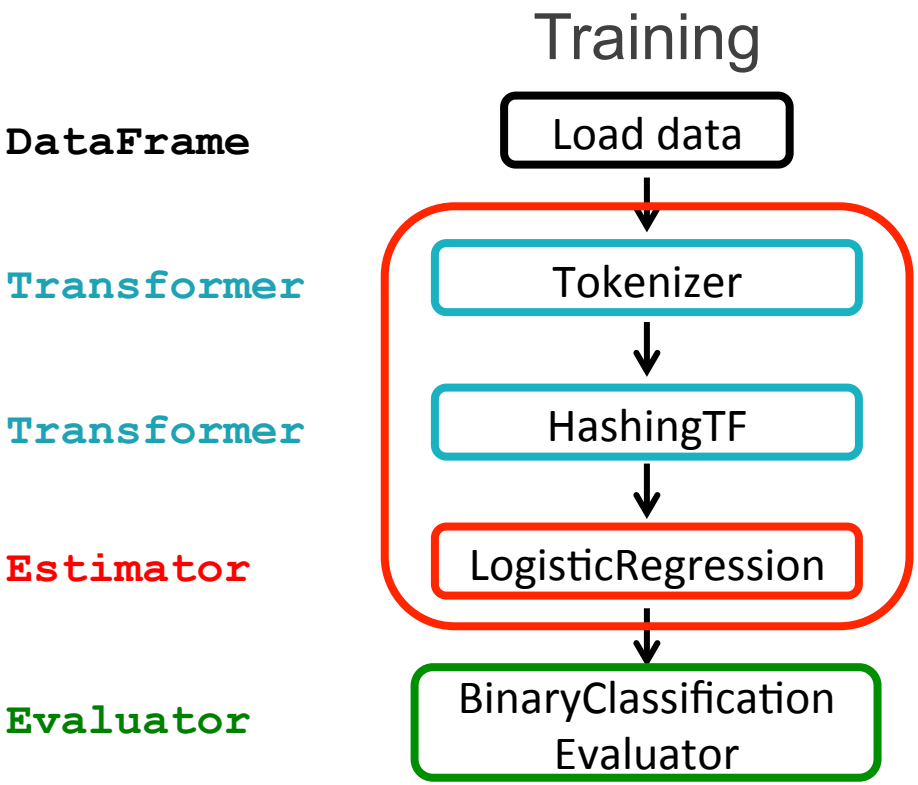
Estimator

Evaluator

Current data schema

```
label: Double
text: String

words: Seq[String]

features: Vector

prediction: Double
```

Demo



Pain point: Write as a script

Parameters

Standard API

- Typed
- Defaults
- Built-in doc
- Autocomplete

```
> hashingTF.numFeatures

    org.apache.spark.ml.param.IntParam =
     numFeatures: number of features
     (default: 262144)

> hashingTF.setNumFeatures(1000)

> hashingTF.getNumFeatures
```

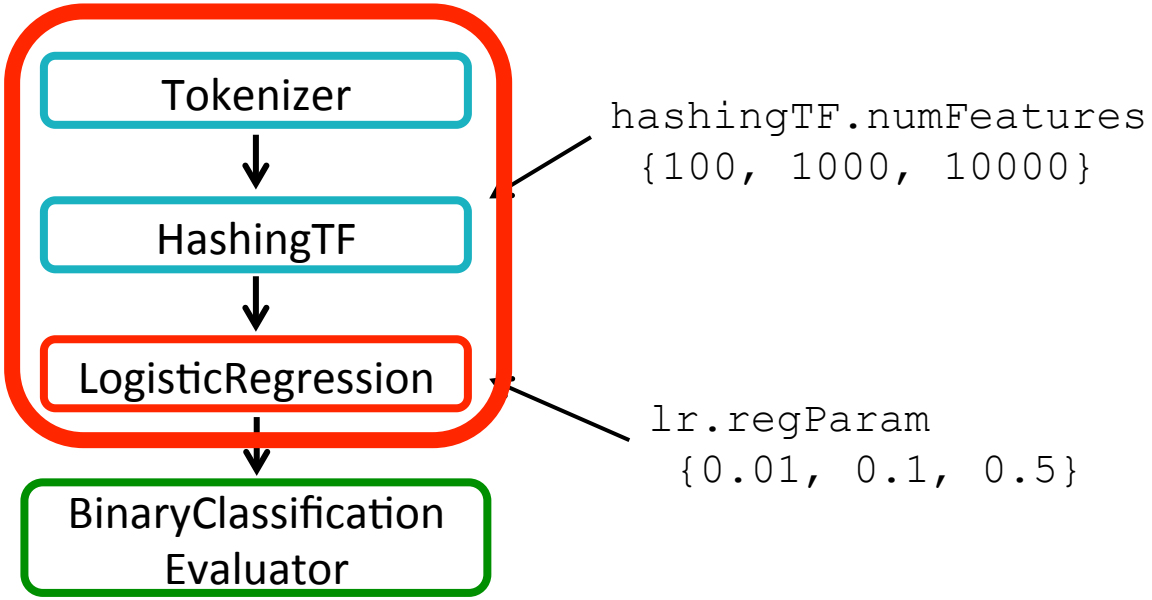
Parameter Tuning

Given:

- Estimator
- Parameter grid
- Evaluator

Find best parameters

`CrossValidator`



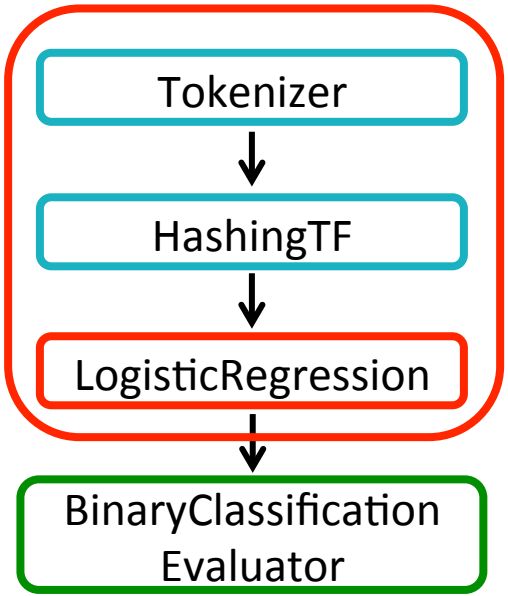
Parameter Tuning

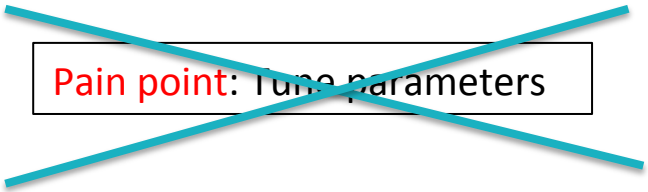
Given:

- Estimator
- Parameter grid
- Evaluator

Find best parameters

`CrossValidator`





Pipelines: Recap

DataFrame → *Create & handle many RDDs and data types*
Abstractions → *Write as a script*
Parameter API → *Tune parameters*

Also
- Python, Scala, Java APIs
- Schema validation
- User-Defined Types*
- Feature metadata*
- Multi-model training optimizations*

Inspirations

scikit-learn
+ Spark DataFrame, Param API

MLBase (Berkeley AMPLab)
Ongoing collaborations

** Groundwork done; full support WIP.*

Outline

ML workflows

Pipelines

Roadmap

Roadmap

`spark.mllib`: Primary ML package

`spark.ml`: High-level Pipelines API for algorithms in `spark.mllib` (*experimental in Spark 1.2-1.3*)

Near future

- Feature attributes
- Feature transformers
- More algorithms under Pipeline API

Farther ahead

- Ideas from AMPLab MLBase (auto-tuning models)
- SparkR integration

Outline

- **ML workflows**
- **Pipelines**
  - **DataFrame**
  - **Abstractions**
  - **Parameter tuning**
- **Roadmap**

Spark documentation
http://spark.apache.org/

Pipelines blog post
https://databricks.com/blog/2015/01/07

Thank you!

databricks™