

Strata+ Hadoop

WORLD

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Building Machine Learning Apps with Spark

Vartika / Jayant

strataconf.com

#StrataHadoop

Download & Install

- <http://spark.apache.org/downloads.html>
- `export PATH=$PATH:/Users/<username>/spark-2.0.2-bin-hadoop2.7/bin`
- `spark-shell --driver-memory 2G --executor-memory 2G --executor-cores 2`

<https://github.com/WhiteFangBuck/strata-2016-singapore>

About Us

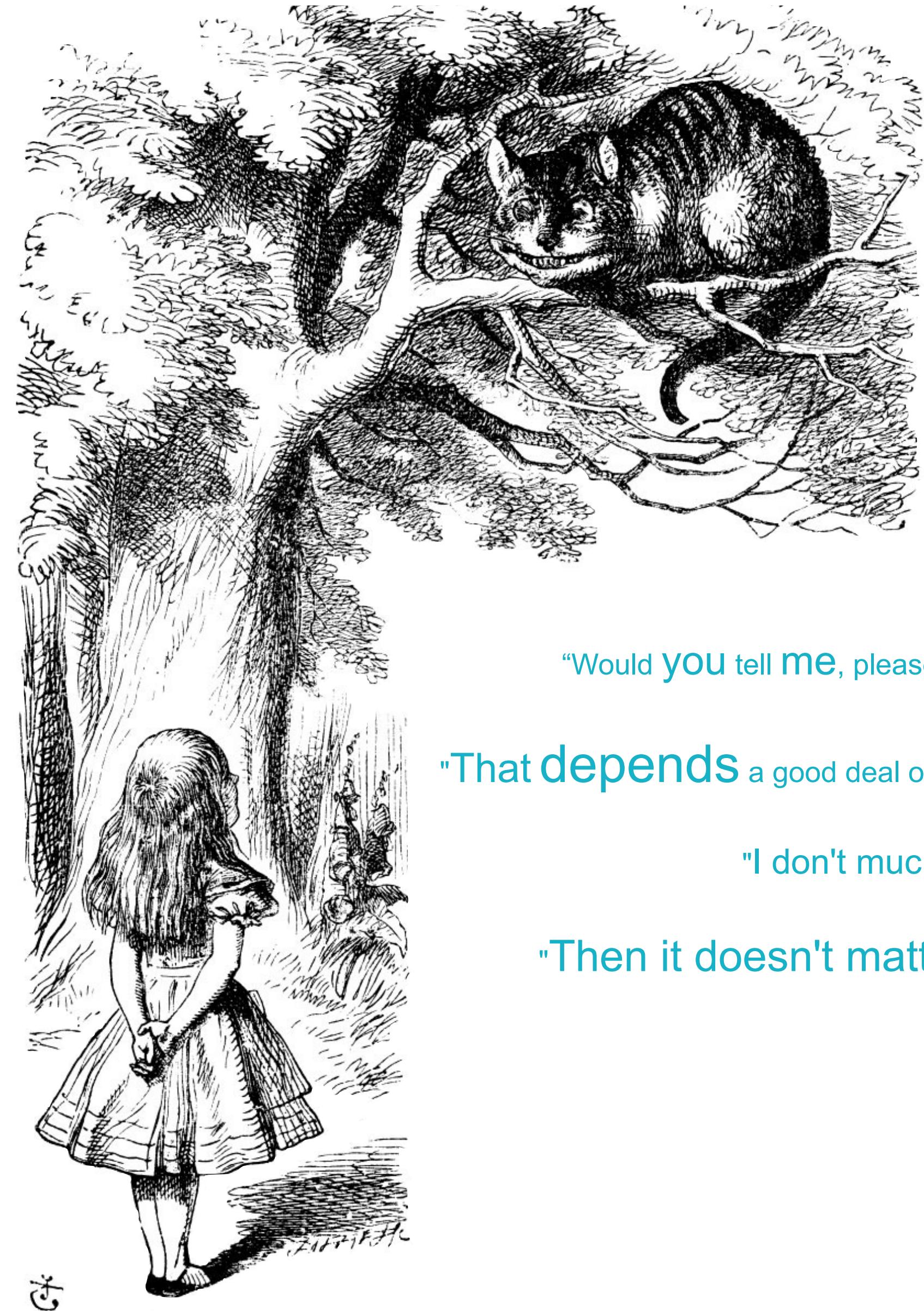
Vartika Singh is a Solutions Architect at Cloudera with over 10 years of experience in applying machine learning techniques to big data problems.

Jayant is the CEO of Sparkflows.io with over 10 years of experience building big data products and applying machine learning.

Prev : Cloudera / Yahoo / eBay

Logistics

- spark-shell
- Easy to see intermediate results/No set up time
- If you like copy paste
 - scala> :pa
 - // Entering paste mode (ctrl-D to finish)
 - // Nothing pasted, nothing gained.
 - scala>



"Would you tell me, please, which road do I take?"

"That depends a good deal on where you want to get to."

"I don't much care where –"

"Then it doesn't matter which way you go."

A Data Scientists Nightmare



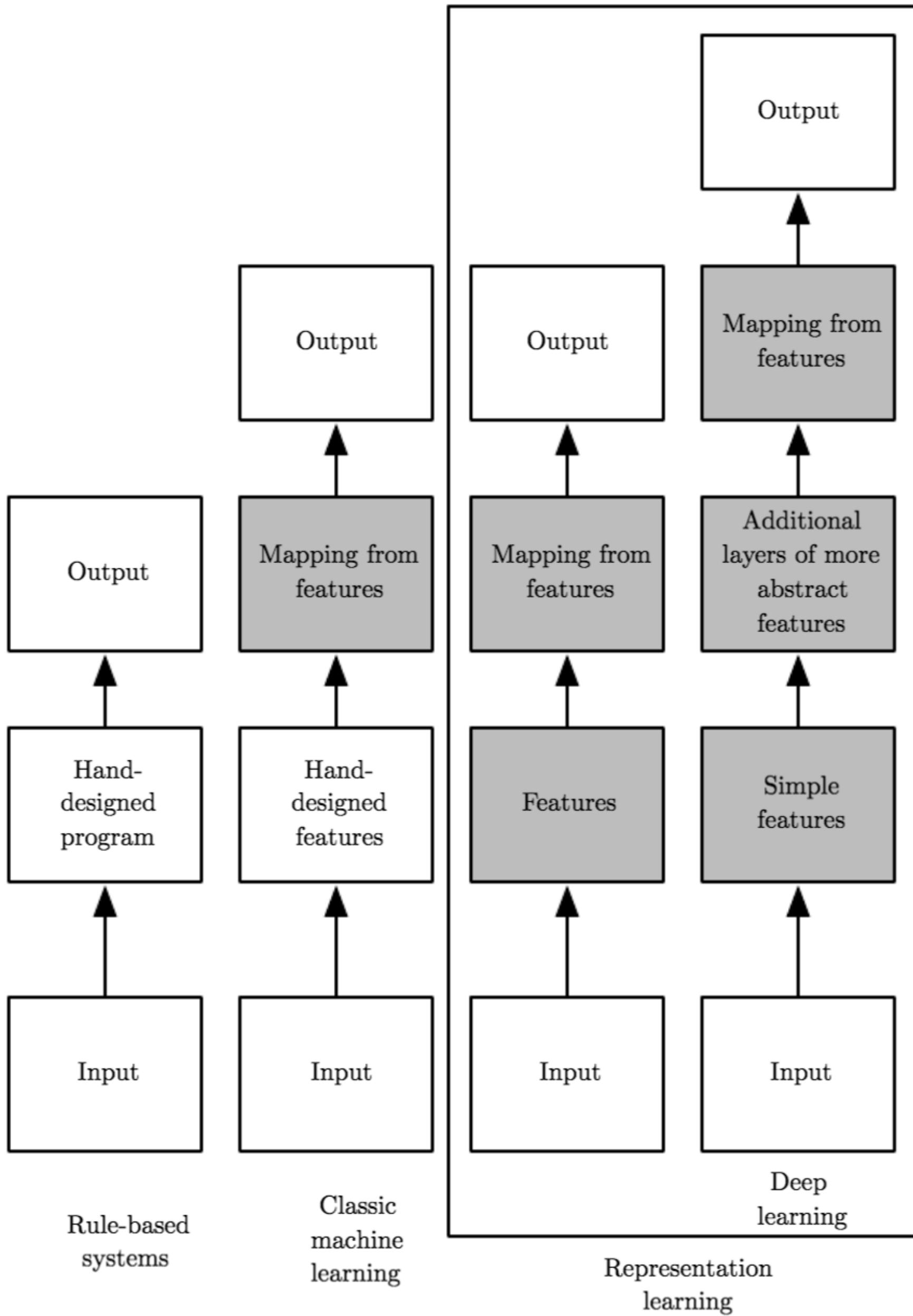
#StrataHadoop



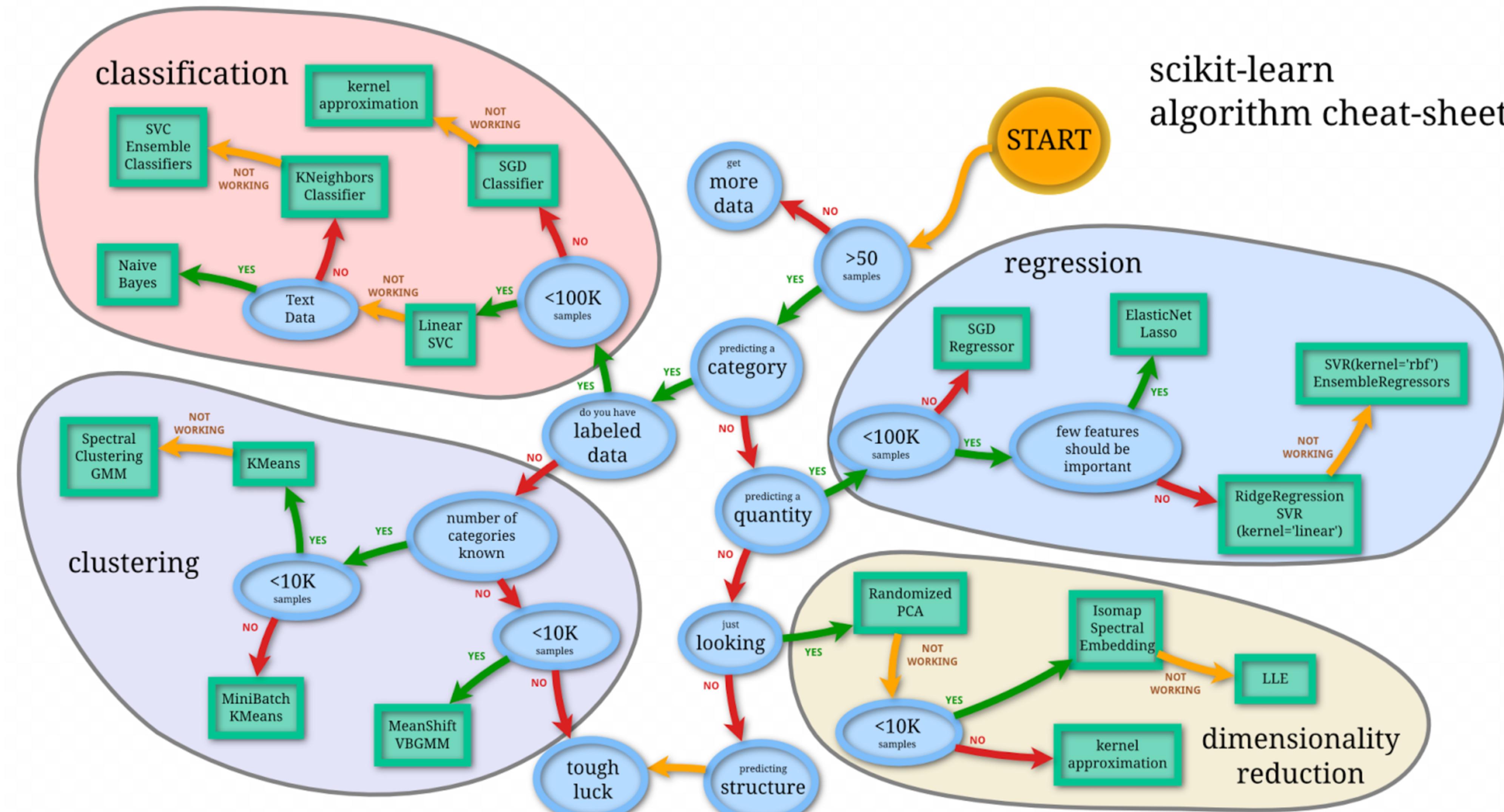
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Which Algorithm???!!!!

- Class of algorithms
 - Supervised
 - Unsupervised
- Examples
 - Supervised: Classification, Regression
 - Unsupervised: Clustering



Which Algorithm???!!!!



ML/MLLib

- The MLlib RDD-based API is now in maintenance mode.
- As of Spark 2.0, the RDD-based APIs in the spark.mllib package have entered maintenance mode. The primary Machine Learning API for Spark is now the DataFrame-based API in the spark.ml package.

What are the implications?

- MLlib will still support the RDD-based API in spark.mllib with bug fixes.
- MLlib will not add new features to the RDD-based API.
- In the Spark 2.x releases, MLlib will add features to the DataFrames-based API to reach feature parity with the RDD-based API.
- After reaching feature parity (roughly estimated for Spark 2.2), the RDD-based API will be deprecated.

Why is MLlib switching to the DataFrame-based API?

- DataFrames provide a more user-friendly API than RDDs. The many benefits of DataFrames include Spark Datasources, SQL/DataFrame queries, Tungsten and Catalyst optimizations, and uniform APIs across languages.
- The DataFrame-based API for MLlib provides a uniform API across ML algorithms and across multiple languages.
- DataFrames facilitate practical ML Pipelines, particularly feature transformations. See the Pipelines guide for details.

CDH Stack - Typical Machine Learning

- Data Ingest Load
- Feature Extraction
- Training/Tuning the model
- Prediction/Inference

- Split each document's text into words.
- Convert each document's words into a numerical feature vector.
- Learn a prediction model using the feature vectors and labels.

ML Pipelines and Workflow

- Facilitates a quick and easy assembly and configuration of practical machine learning pipelines.
- Are like DAG of nodes – sequence of stages – Estimators and Transformers.
- Can be saved and loaded when needed.
- Hyperparameter Tuning
- Flexible coding and Easy debugging – Use DataFrames

Let's Talk about features

- A feature is an individual measurable property of a phenomenon being observed.
- Choosing informative, discriminating and independent features is a crucial step for effective algorithms.
 - Many possible featurizations
 - Choice can drastically affect the performance.
- Feature Extractors
- Feature Transformers
- Feature Selectors

Capacity and Hypothesis Space

- Models with insufficient capacity are unable to solve complex tasks. Models with high capacity can solve complex tasks, but when their capacity is higher than needed to solve the present task they may overfit.

Linear - Underfitting

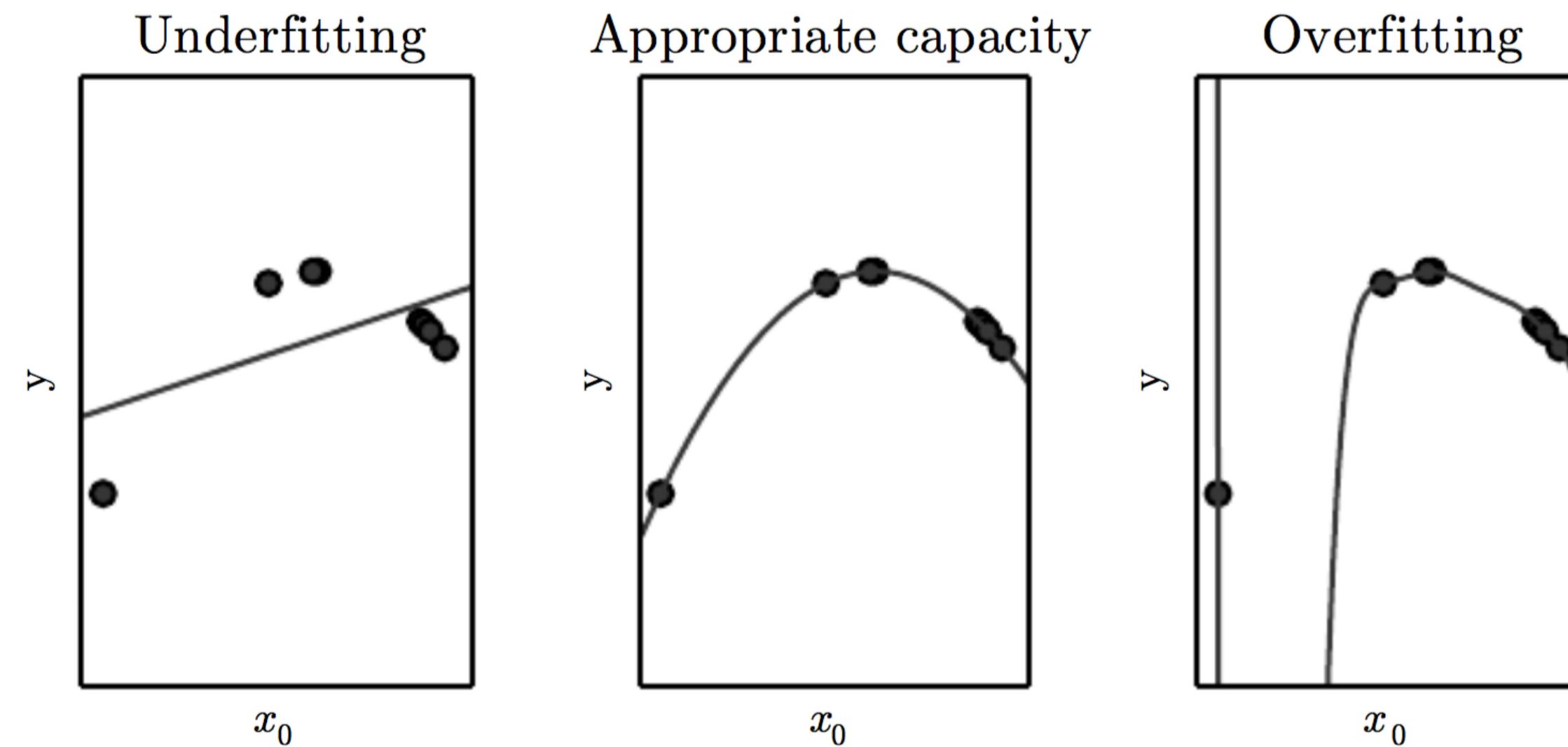
Degree-9 - Overfitting

Quadratic - Appropriate

- Representational Capacity

- Effective Capacity

- Occam's razor (c. 1287-1347). This principle states that among competing hypotheses that explain known observations equally well, one should choose the “simplest” one.



Extractors - TFIDF

<https://github.com/apache/spark/blob/master/examples/src/main/scala/org/apache/spark/examples/ml/TfidfExample.scala>

label	sentence
0	Hi I heard about Spark
0	I wish Java could use case classes
1	Logistic regression models are neat

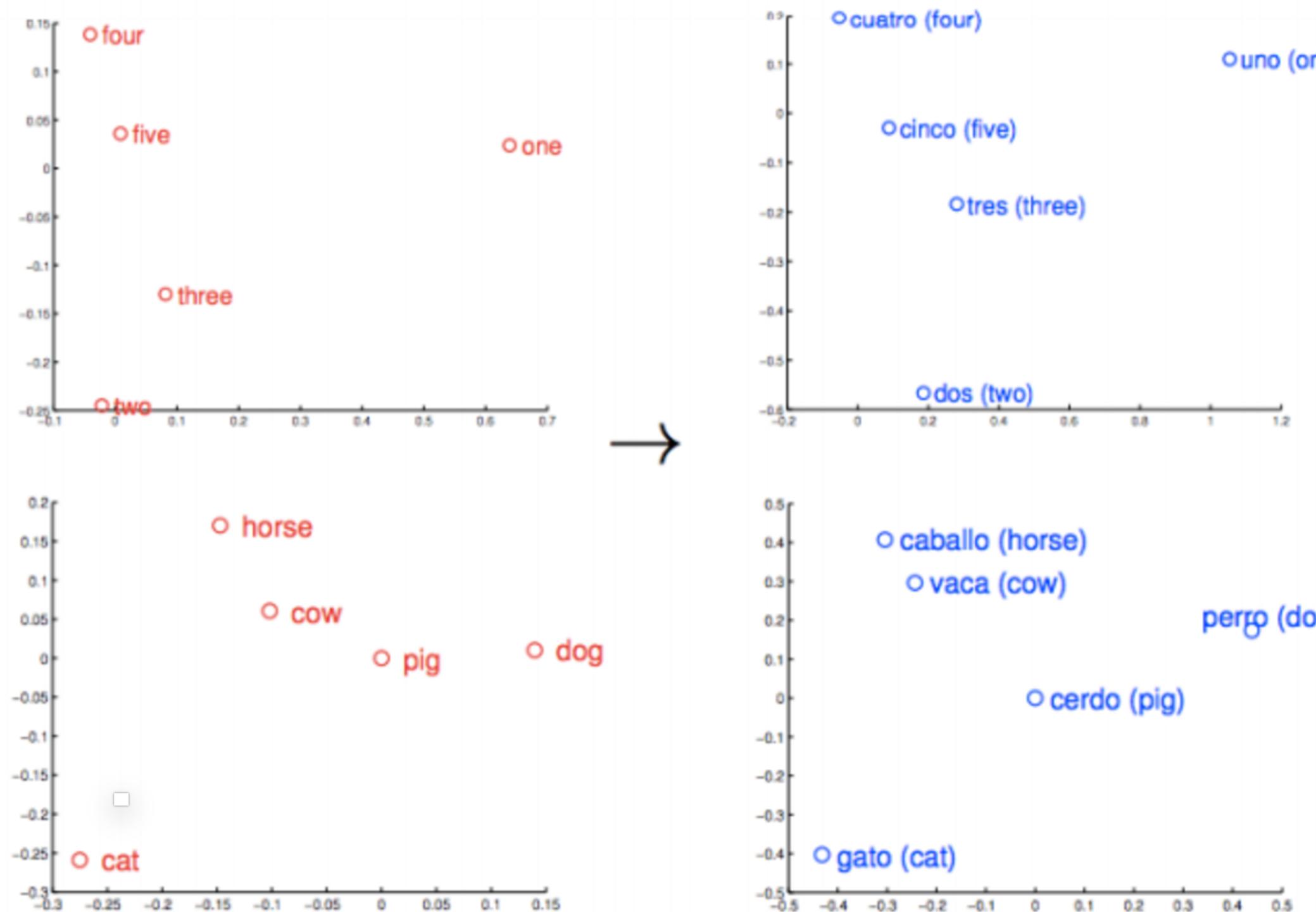
label	sentence	words
0	Hi I heard about Spark	[hi, i, heard, about, spark]
0	I wish Java could use case classes	[i, wish, java, could, use, case, classes]
1	Logistic regression models are neat	[logistic, regression, models, are, neat]

label	sentence	words	rawFeatures
0	Hi I heard about Spark	[hi, i, heard, about, spark]	(100,[5,29,57,60,77], [1.0,1.0,1.0,1.0,1.0])
0	I wish Java could use case classes	[i, wish, java, could, use, case, classes]	(100,[9,13,29,42,67,89,95], [1.0,1.0,1.0,1.0,1.0,1.0,1.0])
1	Logistic regression models are neat	[logistic, regression, models, are, neat]	(100,[4,38,86,93,95], [1.0,1.0,1.0,1.0,1.0])

label	sentence	words	rawFeatures	Re Scaled Data
0	Hi I heard about Spark	[hi, i, heard, about, spark]	(100,[5,29,57,60,77],[1.0,1.0,1.0,1.0,1.0])	(100,[5,29,57,60,77], [0.6931471805599453,0.28768207245178085,0.6931471805599453,0.6931471805599453,0.6931471805599453])
0	I wish Java could use case classes	[i, wish, java, could, use, case, classes]	(100,[9,13,29,42,67,89,95], [1.0,1.0,1.0,1.0,1.0,1.0,1.0])	(100,[9,13,29,42,67,89,95], [0.6931471805599453,0.6931471805599453,0.28768207245178085,0.6931471805599453,0.6931471805599453,0.28768207245178085])
1	Logistic regression models are neat	[logistic, regression, models, are, neat]	(100,[4,38,86,93,95],[1.0,1.0,1.0,1.0,1.0])	(100,[4,38,86,93,95], [0.6931471805599453,0.6931471805599453,0.6931471805599453,0.6931471805599453,0.28768207245178085])

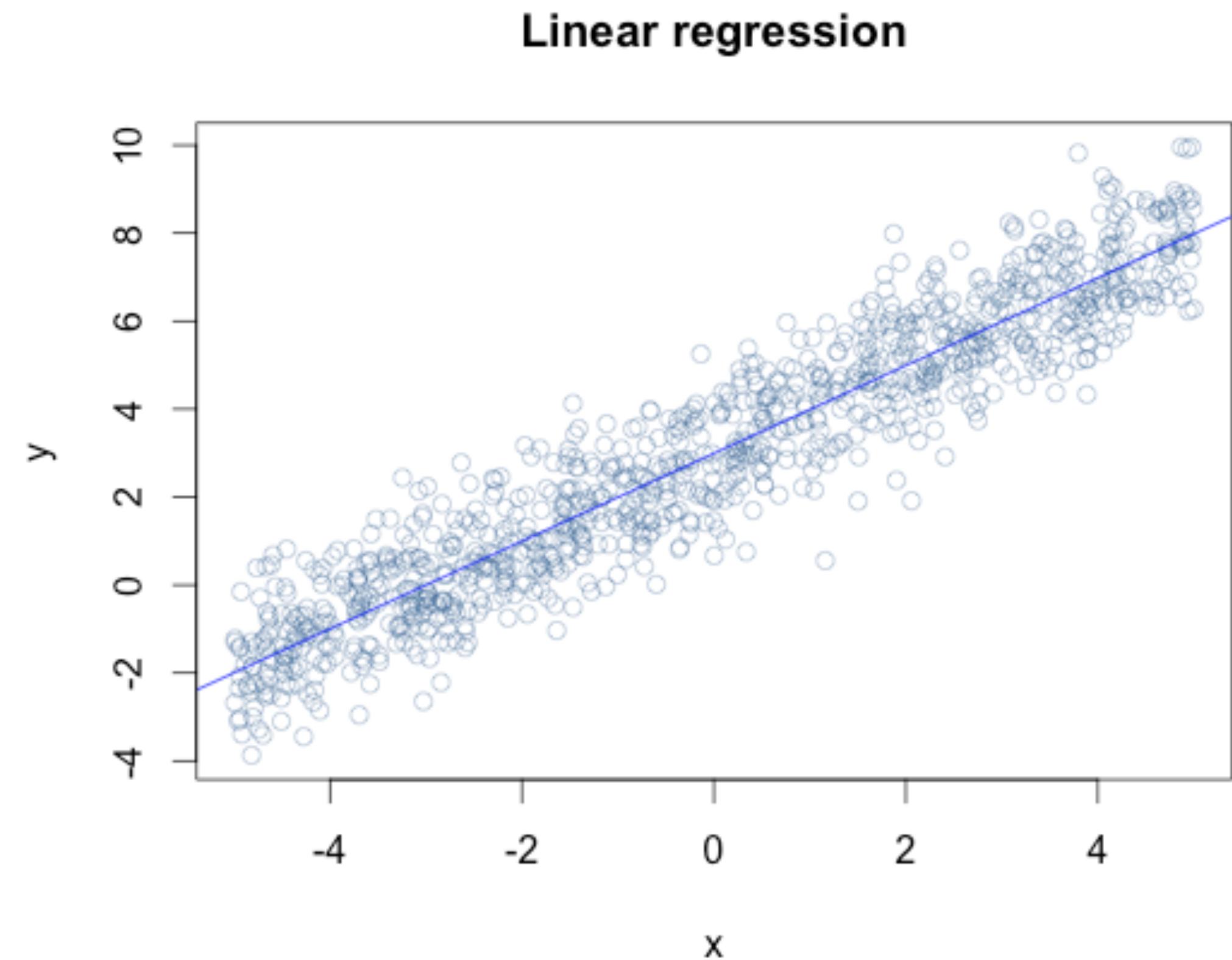
Extractors - Word2Vec

<http://spark.apache.org/docs/latest/ml-features.html#word2vec>



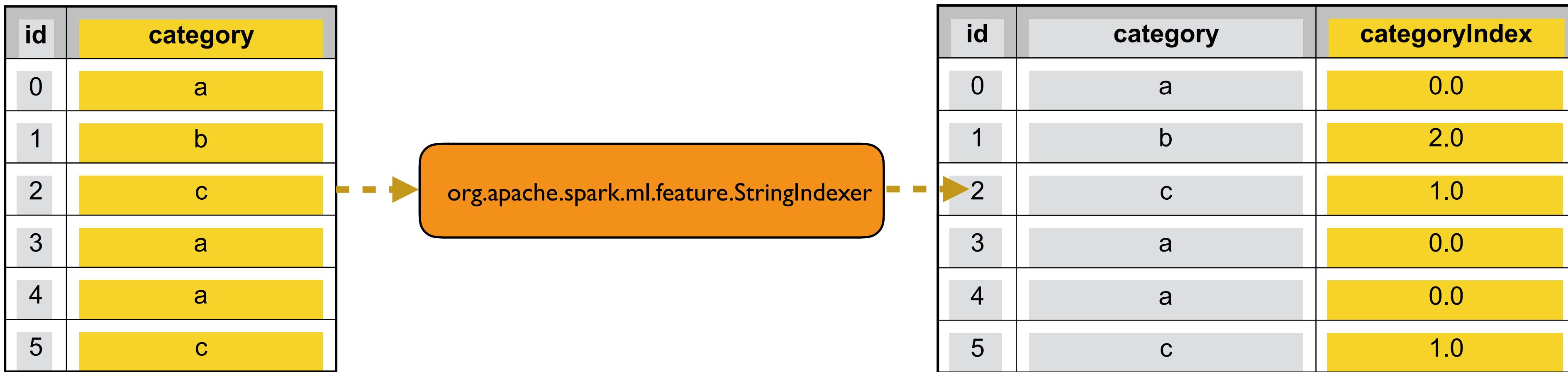
Regression - Linear Methods

- Modeling the relationship between a scalar dependent variable y and one or more explanatory variables (or independent variables) denoted X . $\Rightarrow \hat{y} = w^T x$, where $w \in R^n$, is a vector of parameters.
- The relationships are modeled using linear predictor functions whose unknown model parameters are estimated from the data.
- Parameters are values that control the behavior of the system.



Transformers - StringIndexer

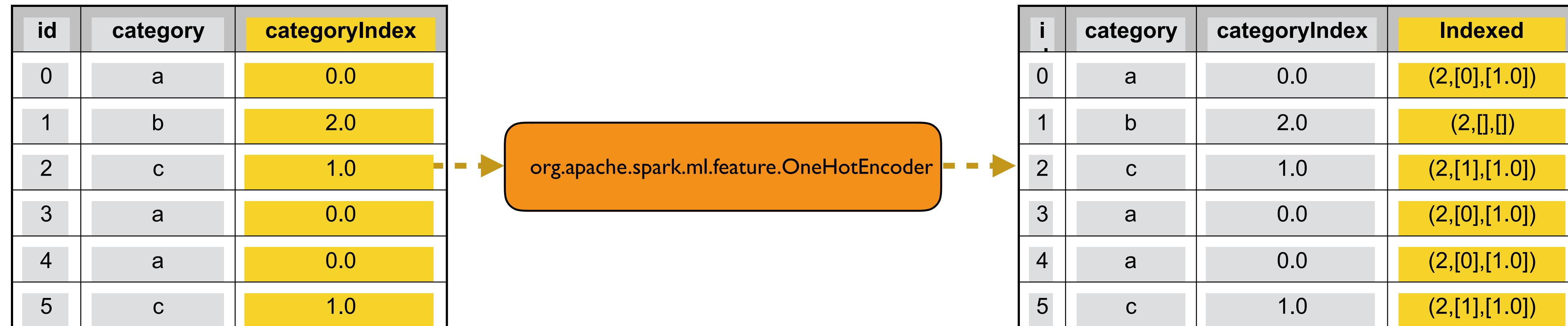
<http://spark.apache.org/docs/latest/ml-features.html#stringindexer>



- Encodes a string column of labels to a column of label indices.
- The indices are in [0, numLabels), ordered by label frequencies.
- StringIndexer.handleInvalid

Transformers - OneHotEncoding

<http://spark.apache.org/docs/latest/ml-features.html#onehotencoder>

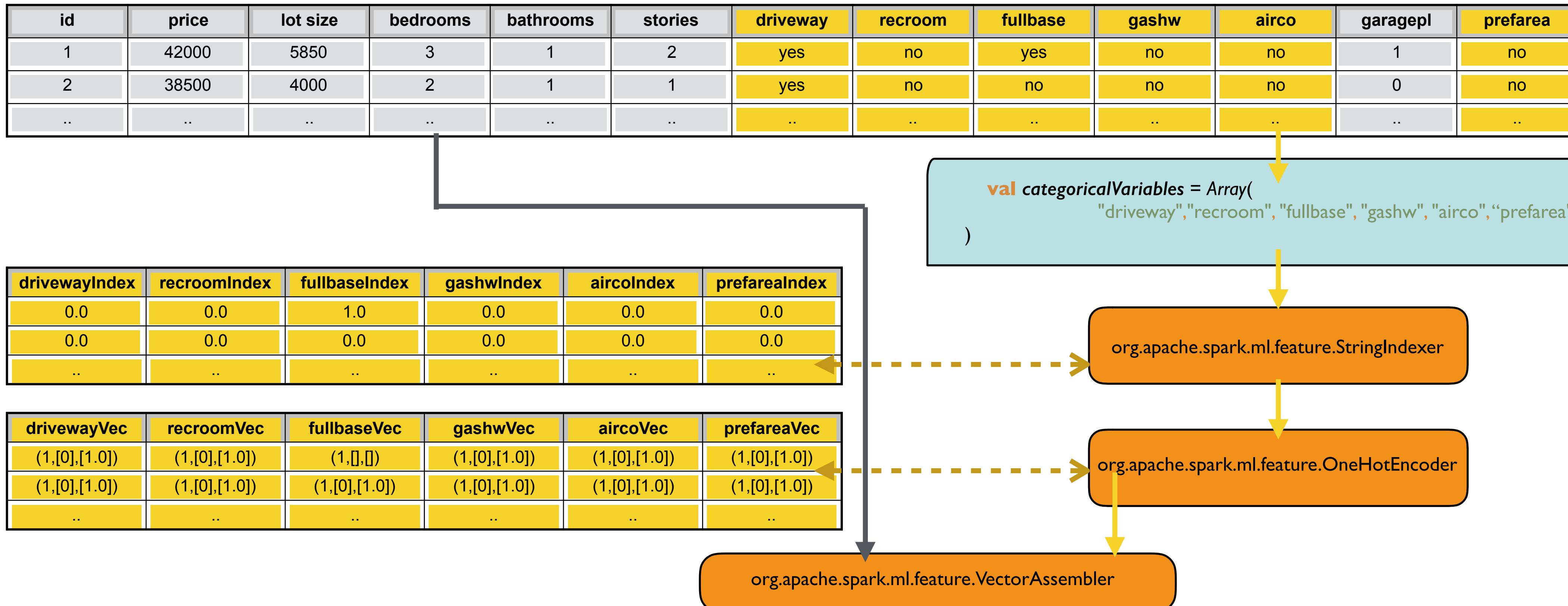


Transformers - Few More that we will use

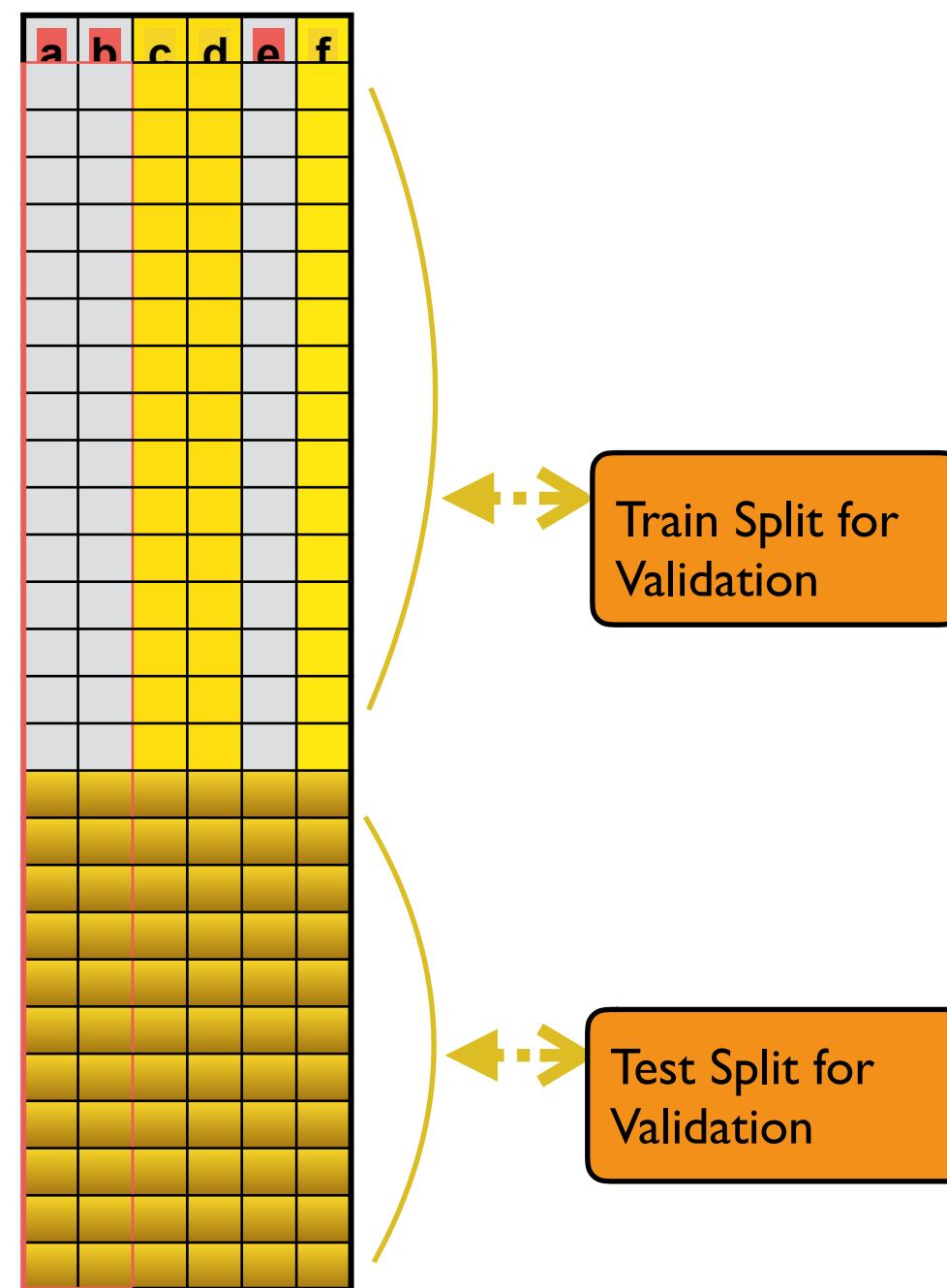
- Standard Scaler
- n-Gram
- VectorIndexer
- Stemming
- VectorAssembler

Working with the data

- Categorical Variables



Model Selection and Tuning



- Use data to find the best model or parameters for a given task.
- Can be done for single estimator or an entire pipeline.
- Require
 - Estimator -> algorithm to tune
 - ParamMap -> set of parameters to tune over
 - Evaluator -> metric to measure how well a fitted Model does on *holdout* data
- Can be done via CrossValidation or TrainValidation Split
 - CrossValidation
 - Goes over multiple folds of data.
 - Slower but more reliable
 - TrainValidation split
 - Evaluate combination of parameters only once.
 - Faster but less reliable

CrossValidation Split

- Split Data into folds
- Fits the estimator on all the folds
- After identifying the best parammap, it re-fits the estimator using the best param map

Linear Regression - Train and Predict

```
case class X(  
    id: String, price: Double, lotsize: Double,  
    bedrooms: Double, bathrms: Double, stories: Double,  
    driveway: String, recroom: String, fullbase: String,  
    gashw: String, airco: String, garagepl: Double, prefarea: String)
```

The case class to map the data in to

```
val paramGrid = new ParamGridBuilder()  
    .addGrid(lr.regParam, Array(0.1, 0.01, 0.001))  
    .addGrid(lr.fitIntercept)  
    .addGrid(lr.elasticNetParam, Array(0.0, 1.0))
```

Construct the Parameter Grid

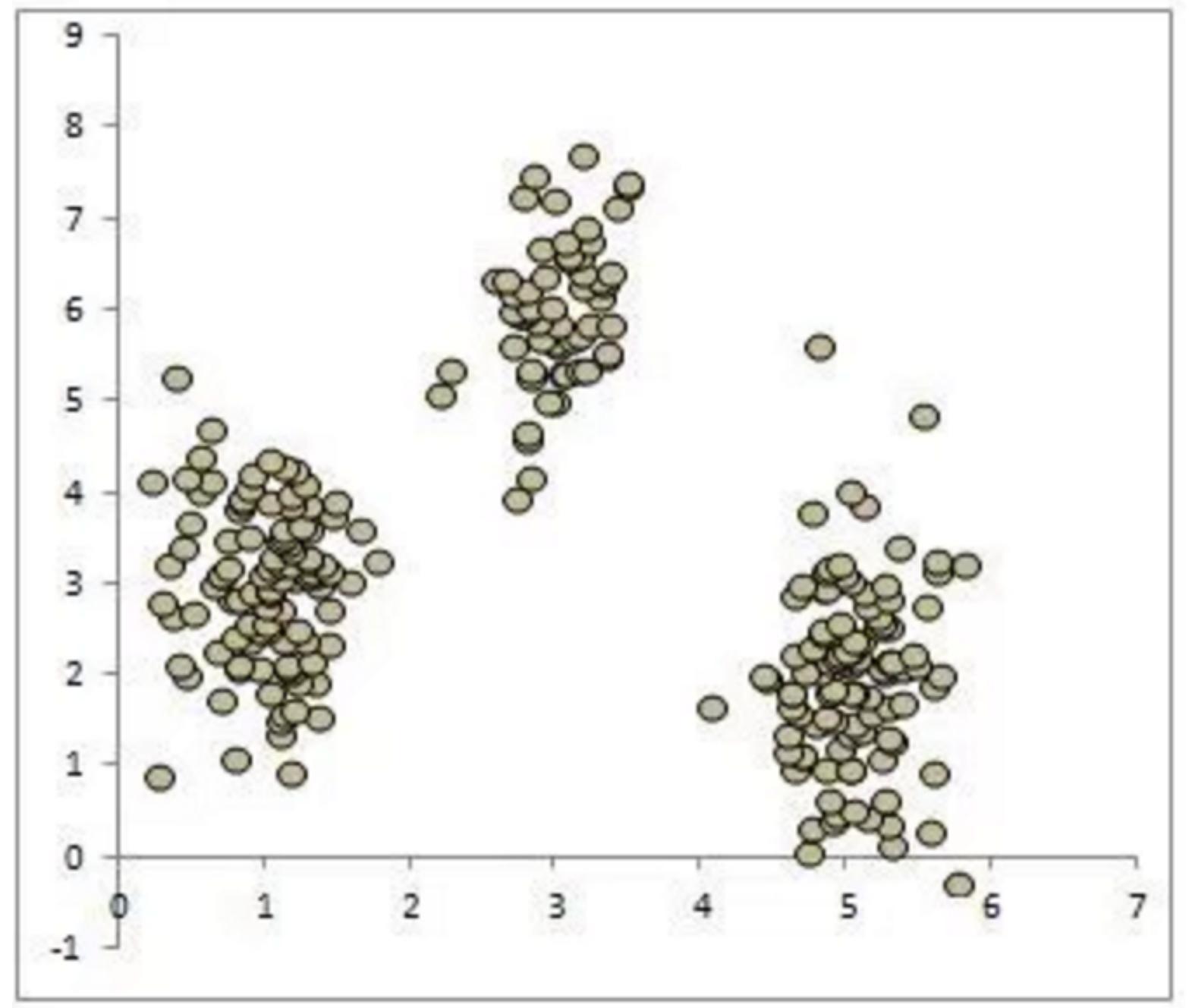
```
val tvs = new TrainValidationSplit()  
    .setEstimator( pipeline )  
    .setEvaluator( new RegressionEvaluator()  
        .setLabelCol("price") )  
    .setEstimatorParamMaps(paramGrid)  
    .setTrainRatio(0.75)
```

Form the Validator

```
val Array(training, test) = data.randomSplit(Array(0.75, 0.25), seed = 12345)  
val model = tvs.fit(training)
```

Split and train the data

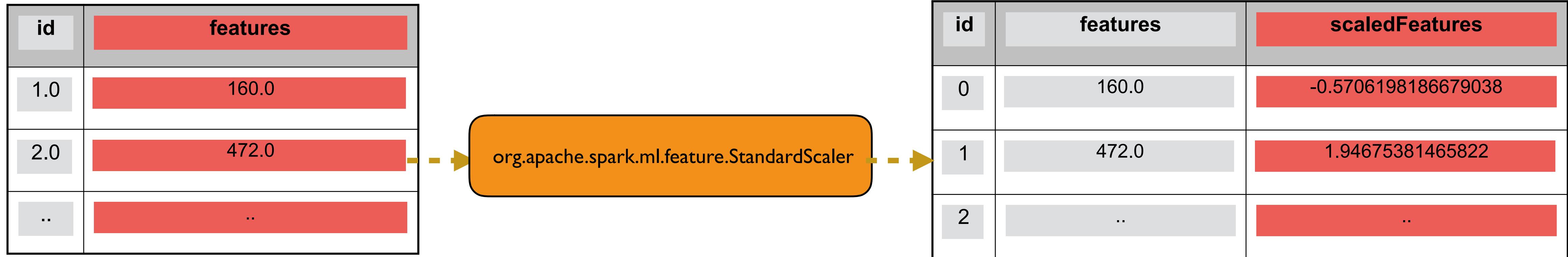
Clustering



- A good clustering has predictive power.
- Predictions while uncertain, are useful, because we believe that the underlying cluster labels are meaningful and can help us take meaningful actions.
- Failures of the cluster model may highlight interesting objects that deserve special attention, a.k.a outliers.
- Dimensionality reduction.
- Compression

Transformers - StandardScaler

<http://spark.apache.org/docs/latest/ml-features.html#standardscaler>



- Amounts to computing summary statistics.
- MinMaxScaler/MaxAbsScaler

KMeans - Reading the data and scaling

```
val ds = spark.read.option("inferSchema", "true").option("header", "true").option("nullValue", "?").csv("data/mtcars.csv")
```

Infer the schema from the header

_c0	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
Mazda RX4	21.0	6	160.0	110	3.9	2.62	16.46	0	1	4	4
Cadillac Fleetwood	10.4	8	472.0	205	2.93	5.25	17.98	0	0	3	4
..



org.apache.spark.ml.feature.StandardScaler



_c0	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
Mazda RX4	0.1508848246 4765615	..	-0.5706198186 679038	-0.6103995674 815357
Cadillac Fleetwood	-1.6078826159 18843	..	.9467538146582	2.0775047648 356484
..

Looking at the results

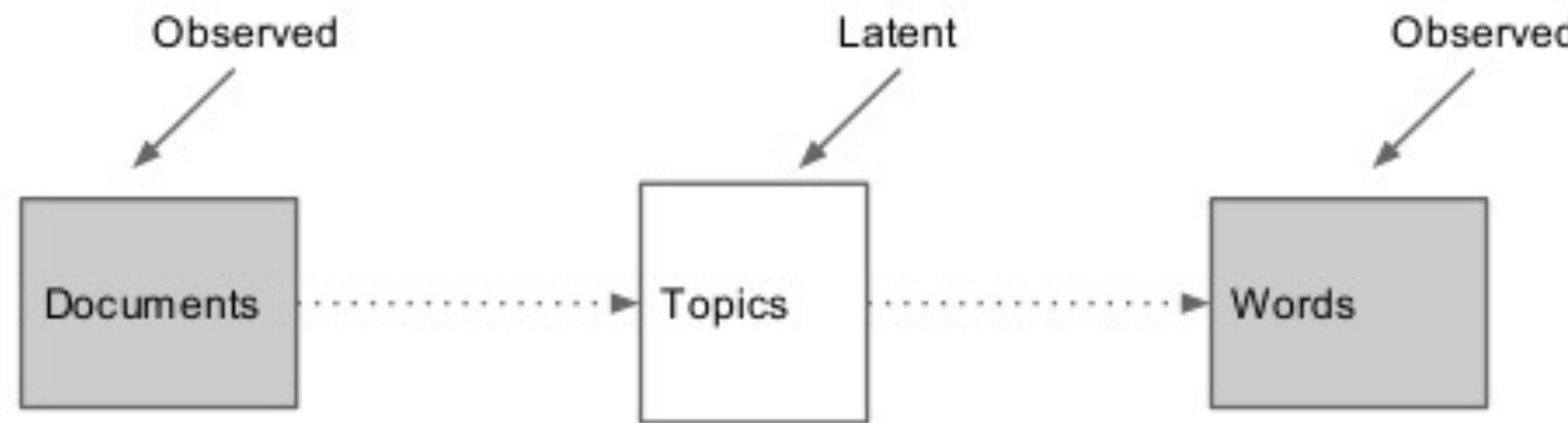
Cluster 1	
Duster 360,[14.3,8.0,360.0,245.0,3.21,3.57],9]	
[Merc 450SE,[16.4,8.0,275.8,180.0,3.07,4.07],9]	
[Merc 450SL,[17.3,8.0,275.8,180.0,3.07,3.73],9]	
[Merc 450SLC,[15.2,8.0,275.8,180.0,3.07,3.78],9]	
[Dodge Challenger,[15.5,8.0,318.0,150.0,2.76,3.52],9]	
[AMC Javelin,[15.2,8.0,304.0,150.0,3.15,3.435],9]	

Cluster 2	
[Datsun 710,[22.8,4.0,108.0,93.0,3.85,2.32],3]	
[Merc 240D,[24.4,4.0,146.7,62.0,3.69,3.19],3]	
[Merc 230,[22.8,4.0,140.8,95.0,3.92,3.15],3]	
[Toyota Corona,[21.5,4.0,120.1,97.0,3.7,2.465],3]	
[Volvo 142E,[21.4,4.0,121.0,109.0,4.11,2.78],3]	

Cluster 3	
[Cadillac Fleetwood,[10.4,8.0,472.0,205.0,2.93,5.25],5]	
[Lincoln Continental,[10.4,8.0,460.0,215.0,3.0,5.424],5]	
[Chrysler Imperial,[14.7,8.0,440.0,230.0,3.23,5.345],5]	

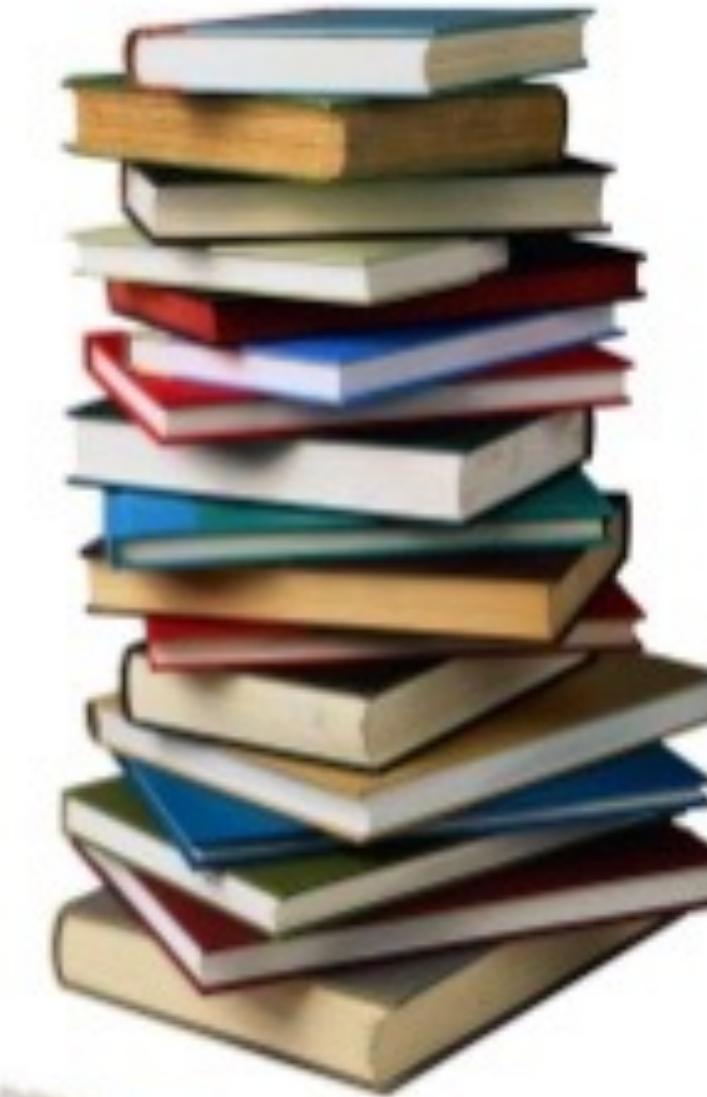
Clustering - LDA

Goal of Topic Modeling



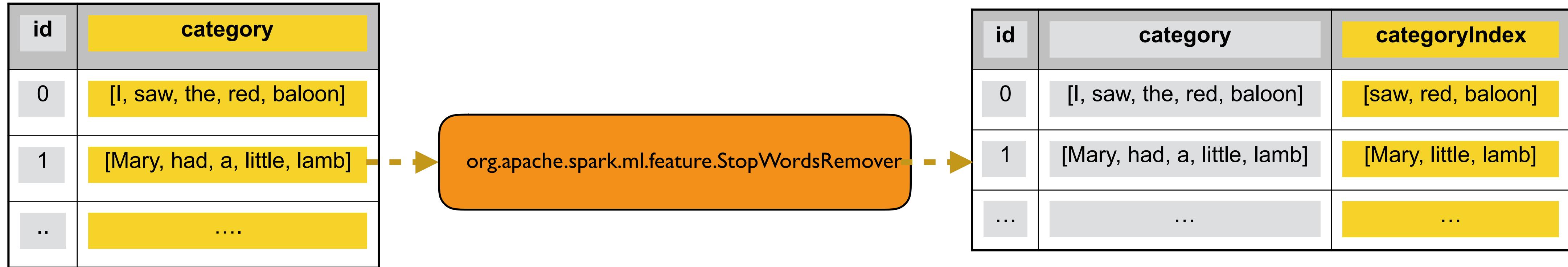
Documents are about several topics at the same time.
Topics are associated with different words.

Topics in the documents are expressed through the words
that are used.



Transformers - StopWordsRemover

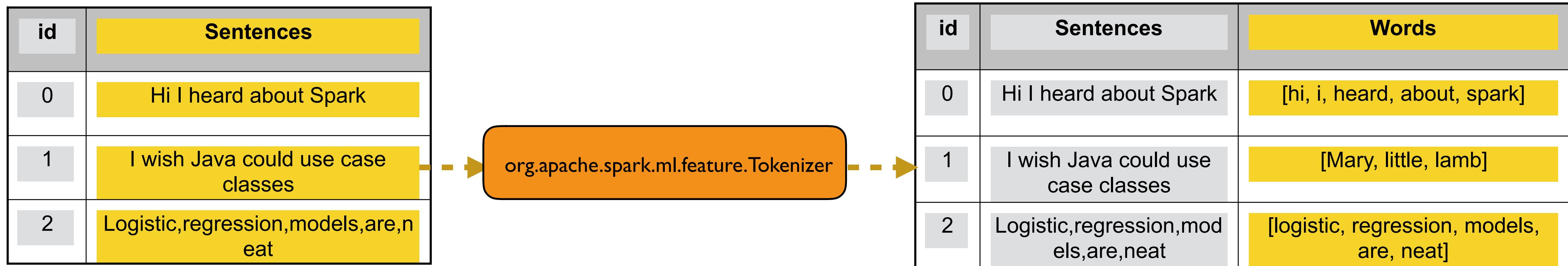
<http://spark.apache.org/docs/latest/ml-features.html#stopwordsremover>



- `StopWordsRemover.loadDefaultStopWords(language)`
- `StopWordsRemover.caseSensitive` - false by default
- `StopWordsRemover.stopWords(..)`

Transformers - Tokenizer

<http://spark.apache.org/docs/latest/ml-features.html#tokenizer>



- `RegexTokenizer` allows more advanced tokenization based on regular expression (regex)
- Can set parameter “gaps” to false indicating the regex “pattern” denotes “tokens” rather than splitting gaps

Extractors - CountVectorizer

spark.apache.org/docs/latest/ml-features.html#countvectorizer

Examples

Assume that we have the following DataFrame with columns `id` and `texts`:

<code>id</code>	<code>texts</code>
---	-----
0	<code>Array("a", "b", "c")</code>
1	<code>Array("a", "b", "b", "c", "a")</code>

each row in `texts` is a document of type `Array[String]`. Invoking `fit` of `CountVectorizer` produces a `CountVectorizerModel` with vocabulary `(a, b, c)`. Then the output column “`vector`” after transformation contains:

<code>id</code>	<code>texts</code>	<code> vector</code>
---	-----	-----
0	<code>Array("a", "b", "c")</code>	<code> (3,[0,1,2],[1.0,1.0,1.0])</code>
1	<code>Array("a", "b", "b", "c", "a")</code>	<code> (3,[0,1,2],[2.0,2.0,1.0])</code>

Get to know the data - sample email

Re: Short-fuse NSC Washfax

BW60M;10/R,PART
B5,B6 qqey<

I approve sendaresponse! OfLM!,, Cheryl D <CD9.OXCc: Sullivan, Jacob J <iI67>~ 15:56:09~FWv~8FYI - See below!jDKoh, Harold Hongju5:F"071:50I#%rBTMacmanus, Joseph E; F4; Syed, Zia S;>T; SPberg!4mes B; Amory, Elizabeth R; Ashraf, MadeehaMDonoghueanTownley,Whphen G; Johnson, Clifton M;R%@pector, Phillip M! ~ Since ourUc(is due bac"thi@by Tues, IL sto clear)4brief proposedTb%xhe

q@4received earlix<his weekend fromZ\$Ops ctr. aMax2xVcc
MKoh<he Legal Adviser^e ite 64202201 C St. NW-xingtA[DC 20520-,@02 647 9598 offic!mobil 7096 H
V@Macris, Gregory Pai)V;v5u
VF-; iMxEs-O_SWO-Only; SES_DutyDeputies!aent: Sat \$5 17:01:41nColleageL

Aua#\$attached sq5()yWh!Ho<Situation Room a C time agoa>(Per instruc)sIExecSec S staff,e{isQwarōaa copy
e#
is;JbyaTassis in
any way necryQ(I8)f(or Watch OEEk&kZ]
2

*2*4*04:0 Nf
Y Blackb^

Some house-keeping

- Get the word distribution
- Clean up the data
 - DataFrame => UDF => Word Distribution again to get a new stop word list

```
val cleanData = udf ({ text: String => text.replaceAll("[^A-Za-z ]", " ")})
```

- Splitting
- Stemming

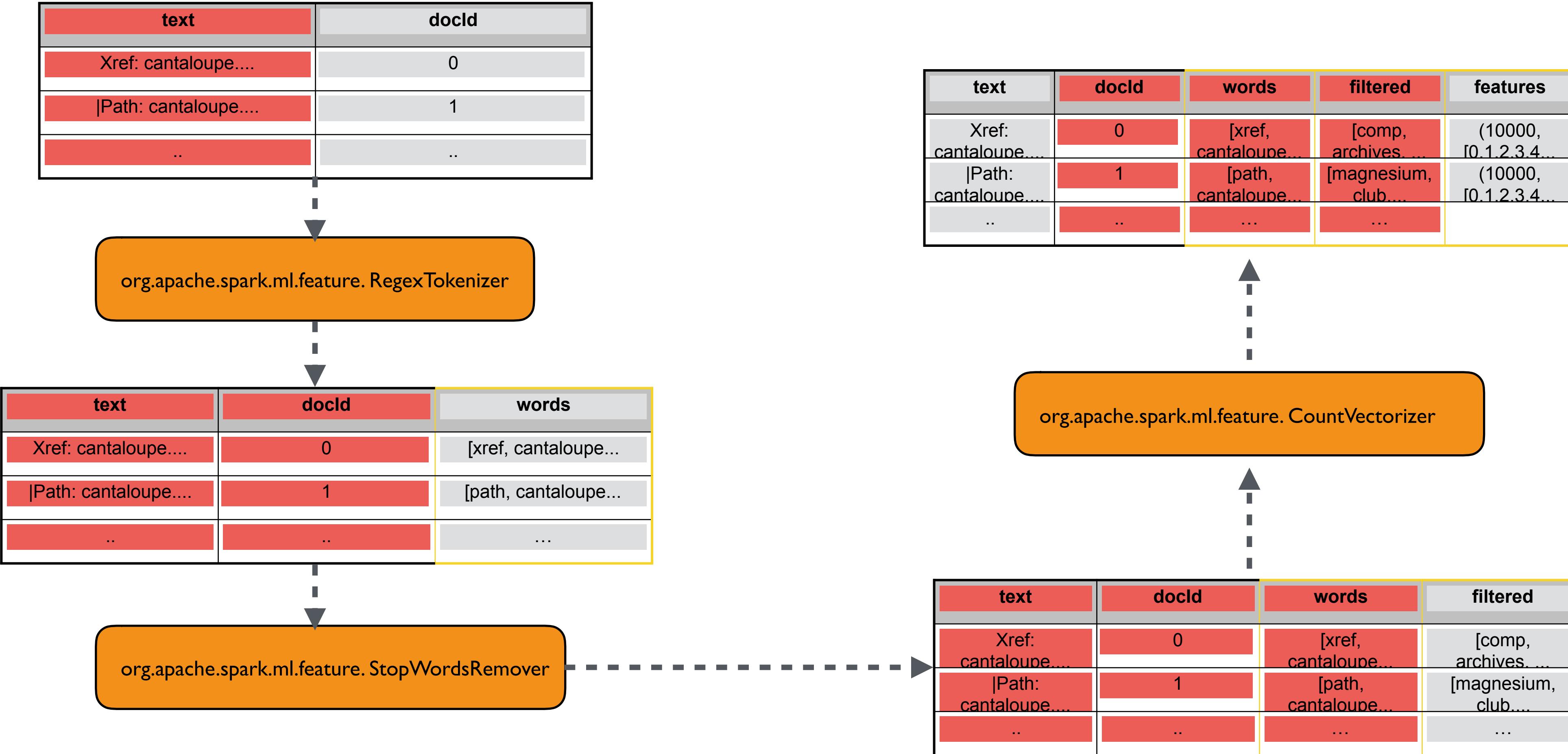
TOPIC 4	
saudi king rest slipped	0.18592574
reuters saudi king rest	0.18592574
king rest slipped disc	0.18592574
mcdonough denis mcdonough denis	0.15367810
denis mcdonough denis mcdonough	0.11988294
crowley philip reines philippe	0.03178703
reines philippe crowley philip	0.00381955
hanley monica hanleymr jake	0.00111982
decided iftar tonite unga	0.00109838

TOPIC 9	
benghazi agreement benghazi agreement	0.45488224
agreement benghazi agreement benghazi	0.41133721
hanley monica hanleymr jake	0.00112136
decided iftar tonite unga	0.00109987
hanley monica hanleymr left	0.00106407
samuelson heather toiv nora	0.00104709
pascual carlos mexico city	0.00102610
jeffrey feltman feltman jeffrey	0.00100359
laszczyc joanne toiv nora	0.00099235
lona valmoro direct valmoro	0.00098503

Middle East Dominates



Preparing the data



Looking at the results

Topic 1	
space	0.012660059181
nasa	0.005330283688
program	0.005239824606
available	0.005144048115
system	0.004966346014
data	0.004792352055

Topic 2	
colorado	0.02660943268
guns	0.01395920562
ucsu	0.01308461546
udel	0.01298423116
firearms	0.01224593594
intercon	0.01082974947

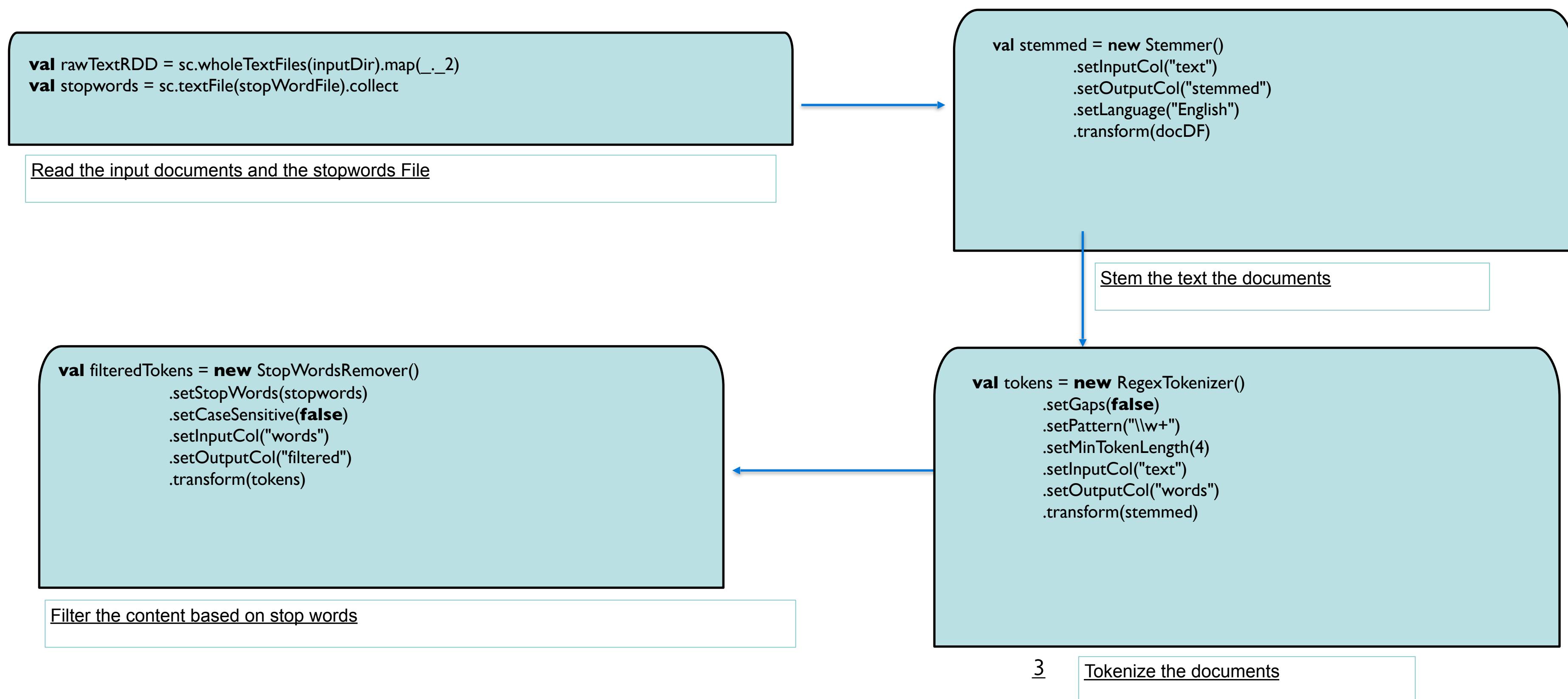
Topic 3	
people	0.00774559688
turkish	0.00763194932
israel	0.00673282049
mideast	0.00664783679
jewish	0.00590779415
jews	0.00563967327

Topic 4	
news	0.020640614429
baseball	0.019538283096
sport	0.012547926648
game	0.010113930332
subject	0.009844881506
organization	0.009577969868

Topic 5	
duke	0.013943643237
team	0.009899371553
hockey	0.008075055082
sport	0.008021120554
news	0.007865084086
ulowell	0.007315961791
league	0.007098242372
baseball	0.006199597687

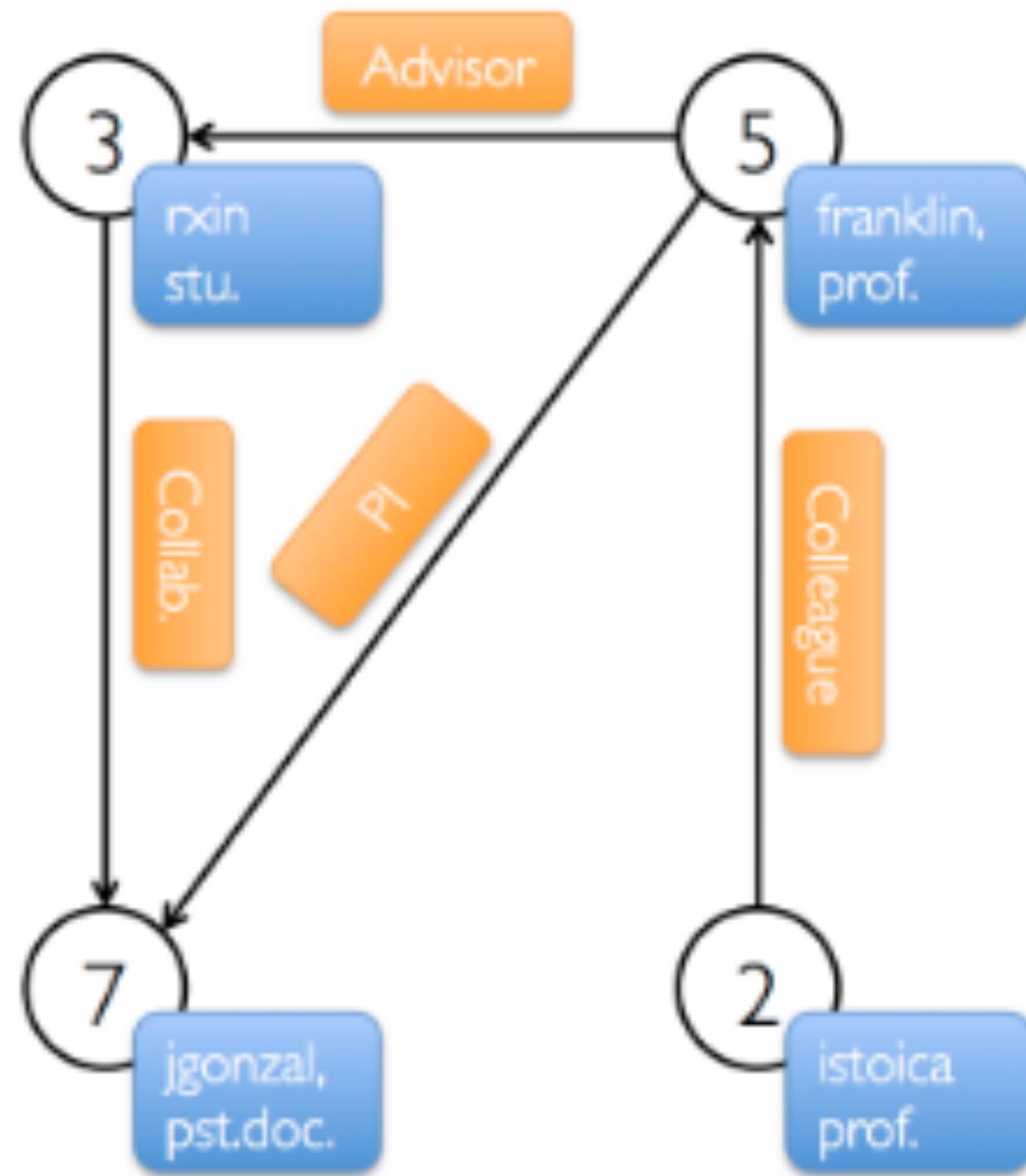
Topic 6	
rutgers	0.025988077707
christian	0.017065131308
religion	0.013231107212
writes	0.009754402317
talk	0.009659720709
lines	0.009513981142

Topic Modeling - Code Walk-through





Property Graph



Vertex Table

Id	Property (V)
3	(rxin, student)
7	(jgonzal, postdoc)
5	(franklin, professor)
2	(istoica, professor)

Edge Table

SrcId	DstId	Property (E)
3	7	Collaborator
5	3	Advisor
2	5	Colleague
5	7	PI

- User defined objects attached to each vertex and edge
- VertexId : 64 bit long identifier
- Type signature
 - `val userGraph: Graph[(String, String), String]`

```
class Graph[VD, ED] {  
    val vertices: VertexRDD[VD]  
    val edges: EdgeRDD[ED]  
}
```

- VertexRDD extends RDD[(VertexID, VD)]
- EdgeRDD extends RDD[Edge[ED]]

Graph Builders

GraphLoader.edgeListFile	provides a way to load a graph from a list of edges on disk 2.1 4.1
Graph.apply	allows creating a graph from RDDs of vertices and edges
Graph.fromEdges	allows creating a graph from only an RDD of edges, automatically creating any vertices mentioned by edges and assigning them the default value
Graph.fromEdgeTuples	allows creating a graph from only an RDD of edge tuples, assigning the edges the value 1, and automatically creating any vertices mentioned by edges and assigning them the default value

Graph Operators

Property Operators

- **mapVertices**
- **mapEdges**
- **mapTriplets**

Structural Operators

- **reverse**
- **subGraph**
- **mask**

Join Operators

- **joinVertices**
- **outerJoinVertices**

Neighborhood Aggregation

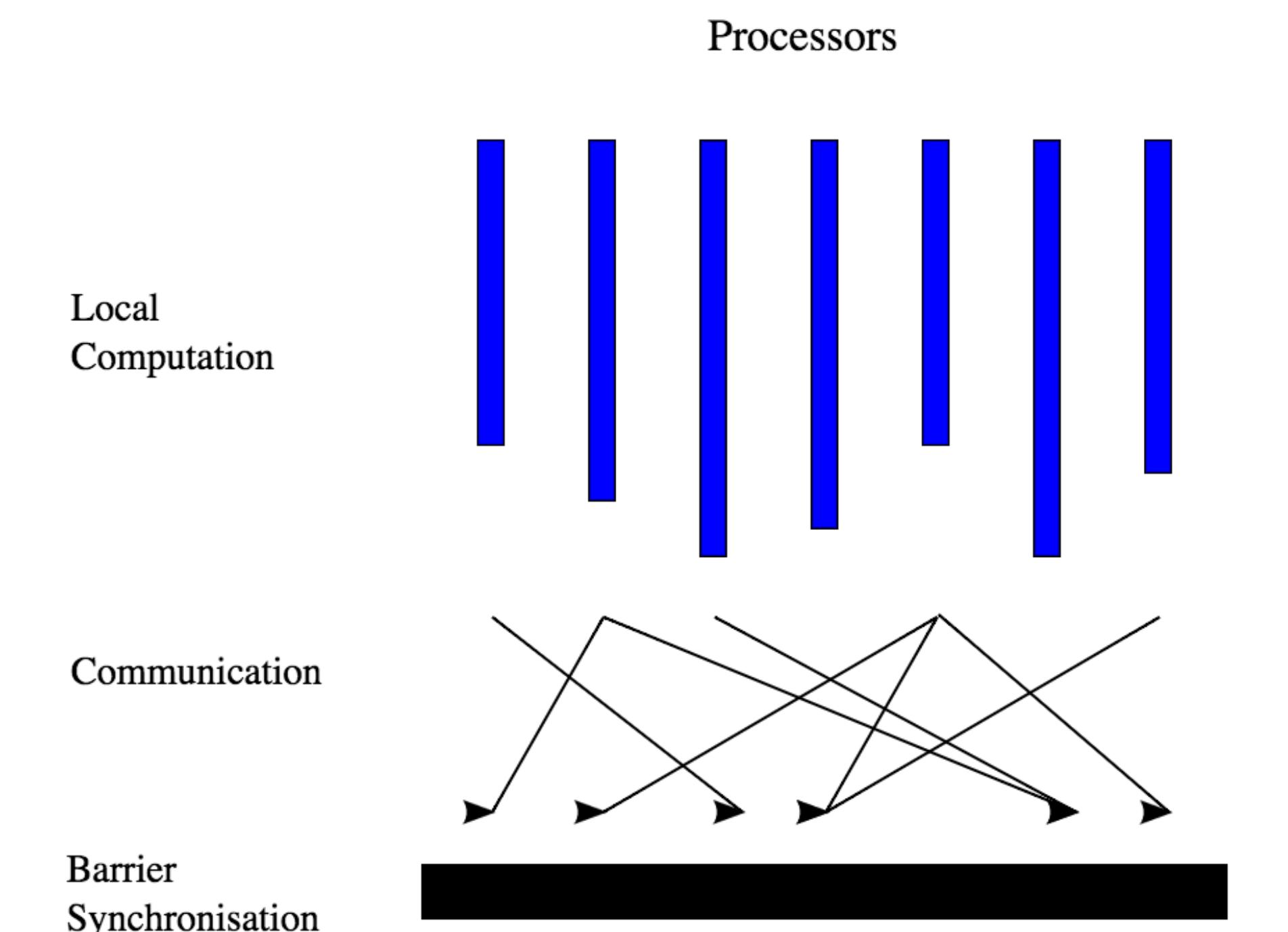
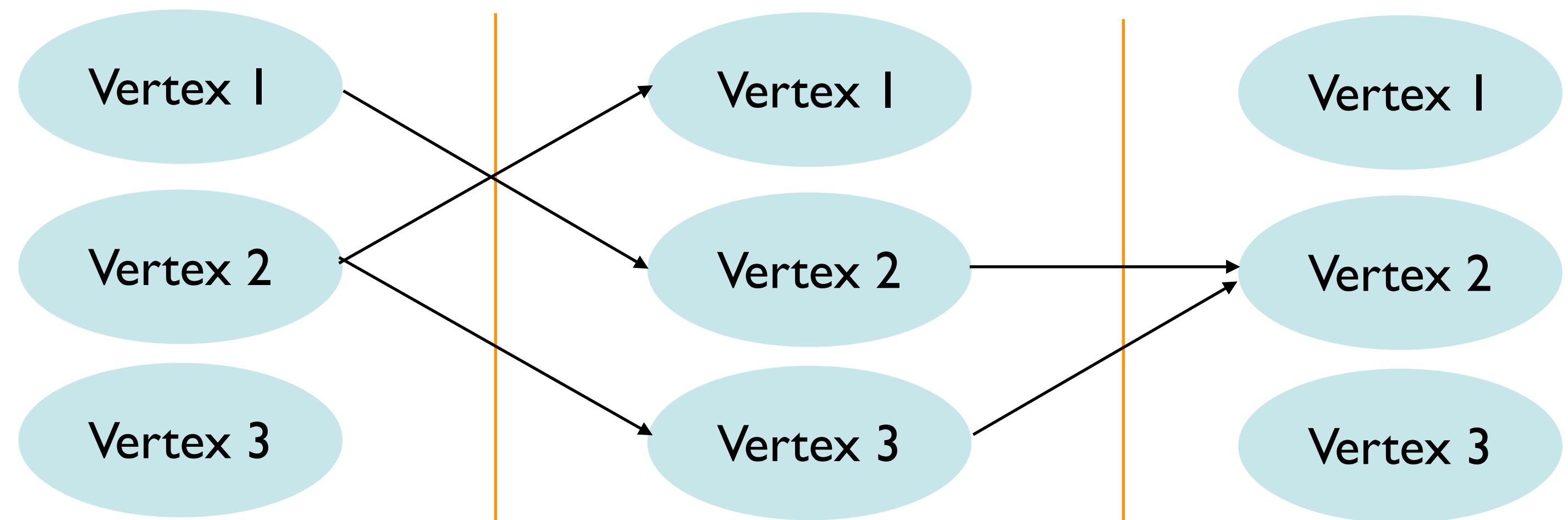
- **aggregateMessages**
- **collectingNeighbors**

Graph Algorithms

- **Page Rank**
- **Connected Components**
- **Triangle Counting**

Pregel API

- Many important graph algorithms iteratively recompute the properties of each vertex until a fixed-point condition is reached
- Pregel operator in GraphX is a bulk-synchronous parallel messaging abstraction
- It executes a series of super-steps:
 - Vertices receive inbound messages from the previous super-step
 - Compute the new value
 - Send messages to the neighboring vertices in the next super-step

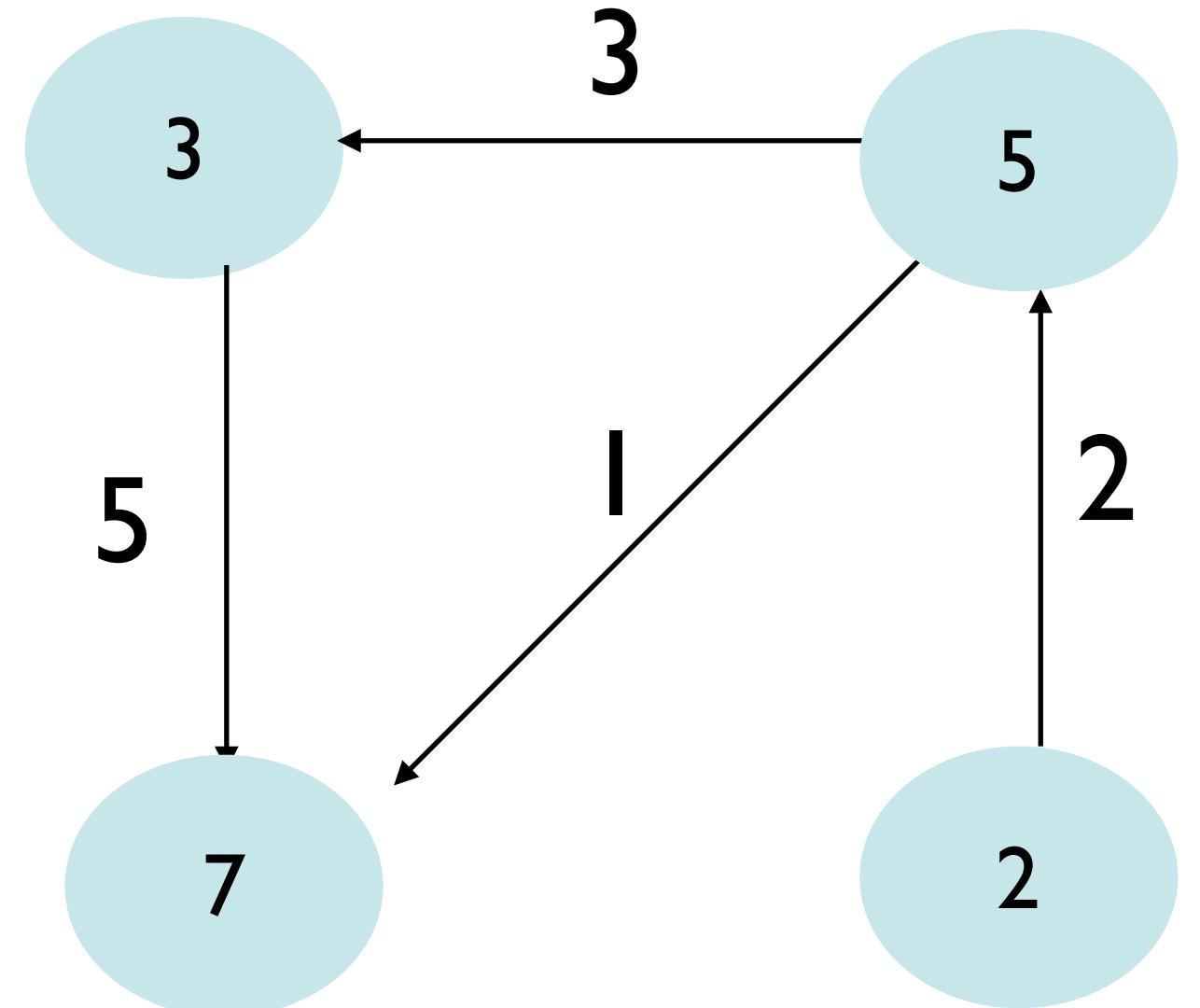


https://en.wikipedia.org/wiki/Bulk_synchronous_parallel

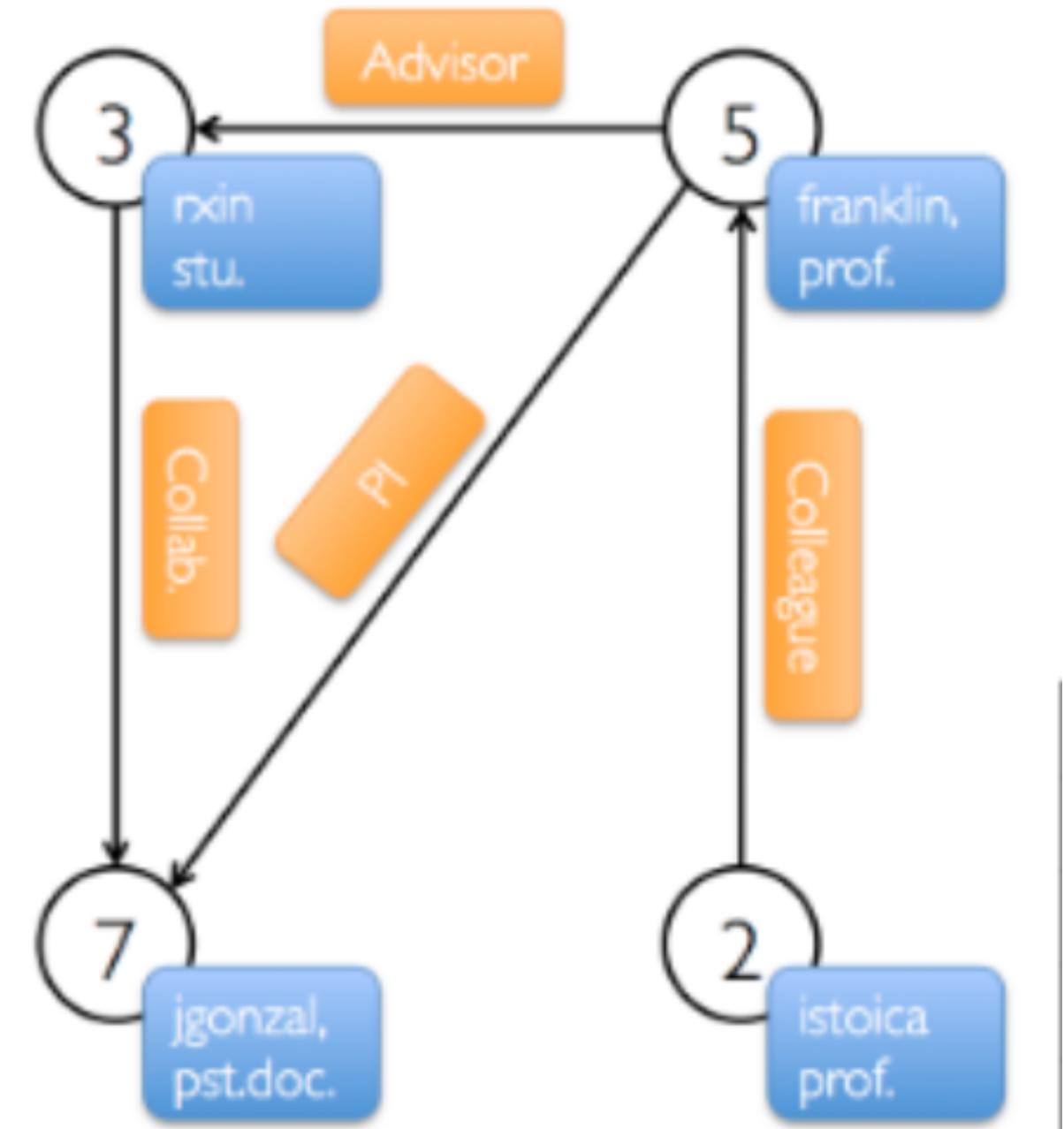
Pregel takes two argument lists (graph.pregel (list1) (list2))

- The first argument list contains configuration parameters including
 - **the initial message**
 - **the maximum number of iterations**
 - **the edge direction in which to send messages (by default along out edges).**
- The second argument list contains the **user defined functions** for
 - **receiving messages (the vertex program vprog)**
 - **computing messages (sendMsg)**
 - **and combining messages (mergeMsg)**

Pregel API

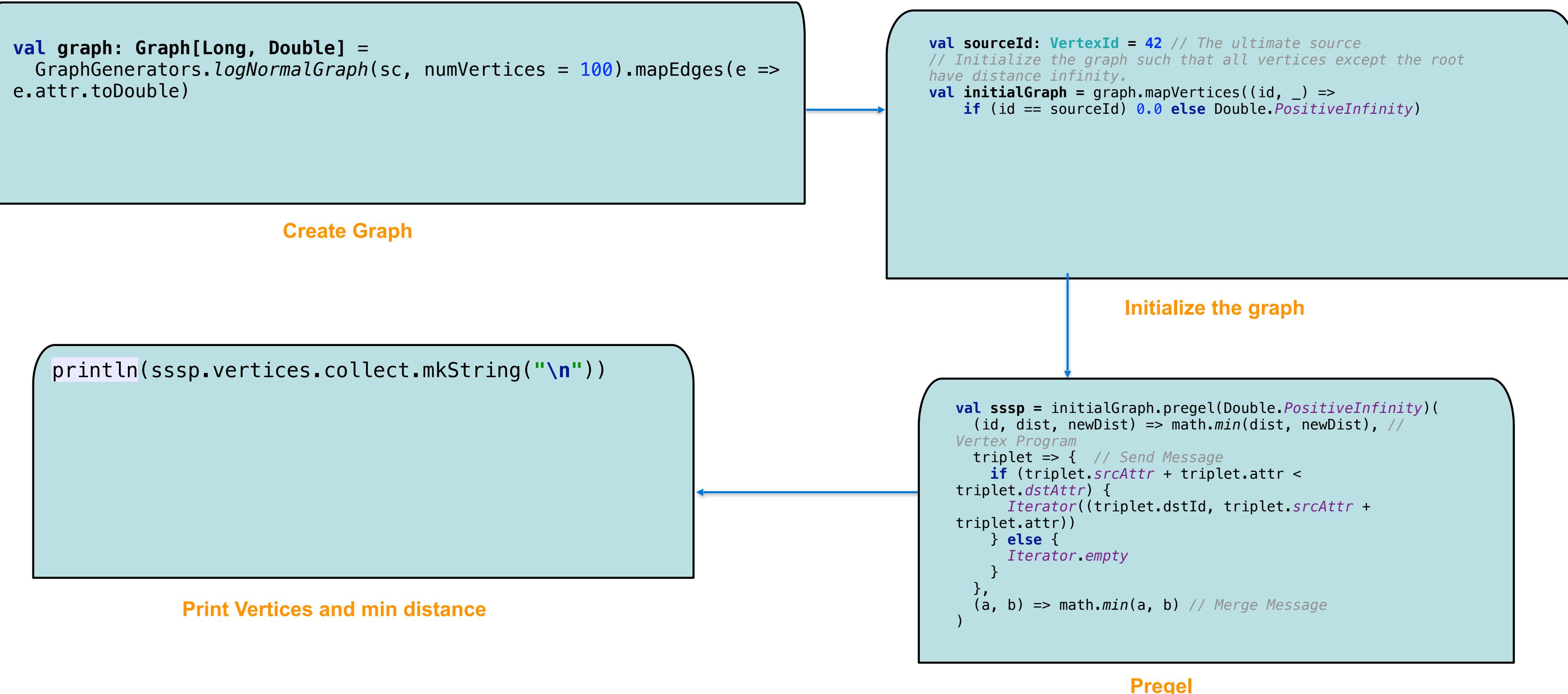


Property Graph



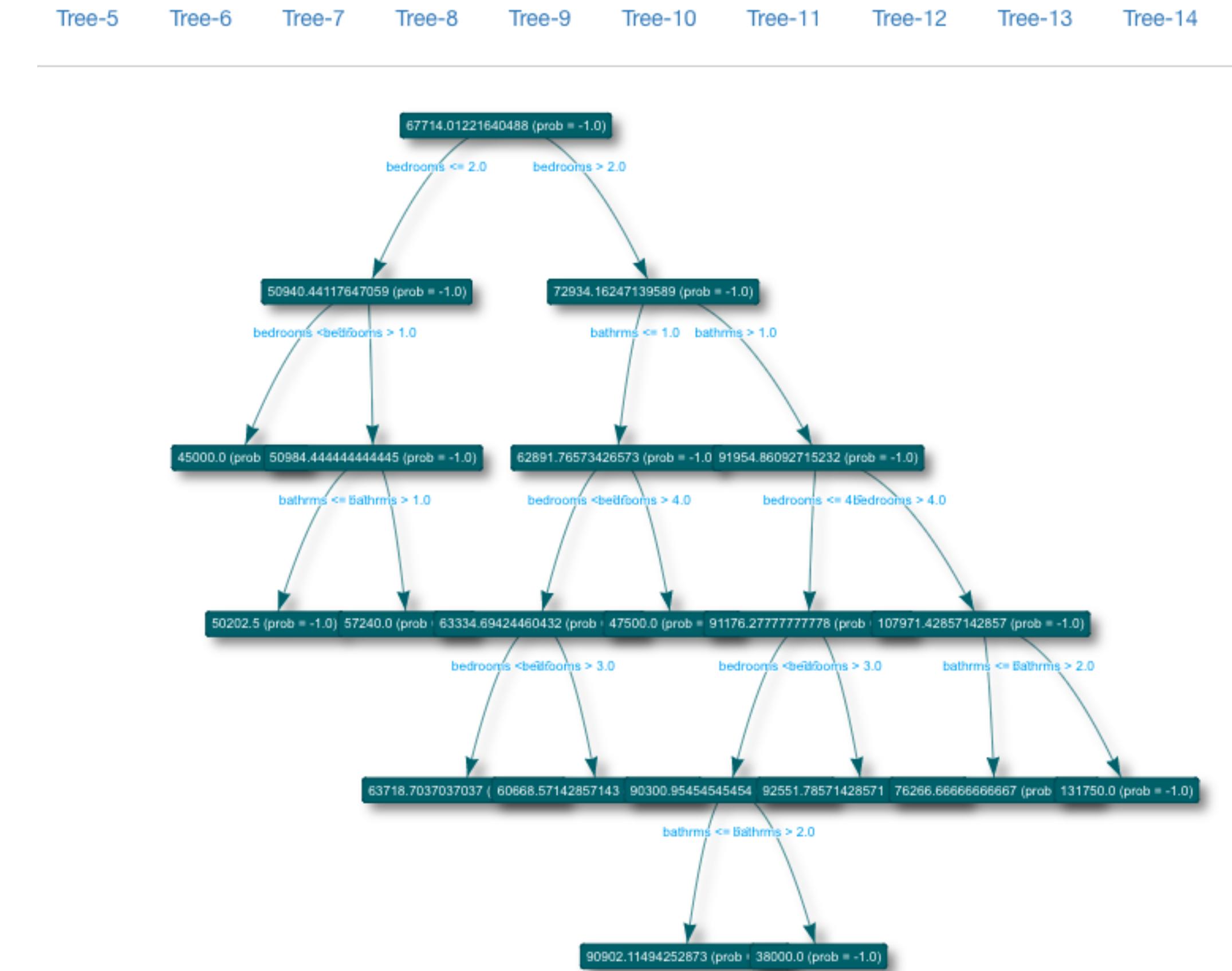
https://en.wikipedia.org/wiki/Bulk_synchronous_parallel

Pregel - Code Walk-through



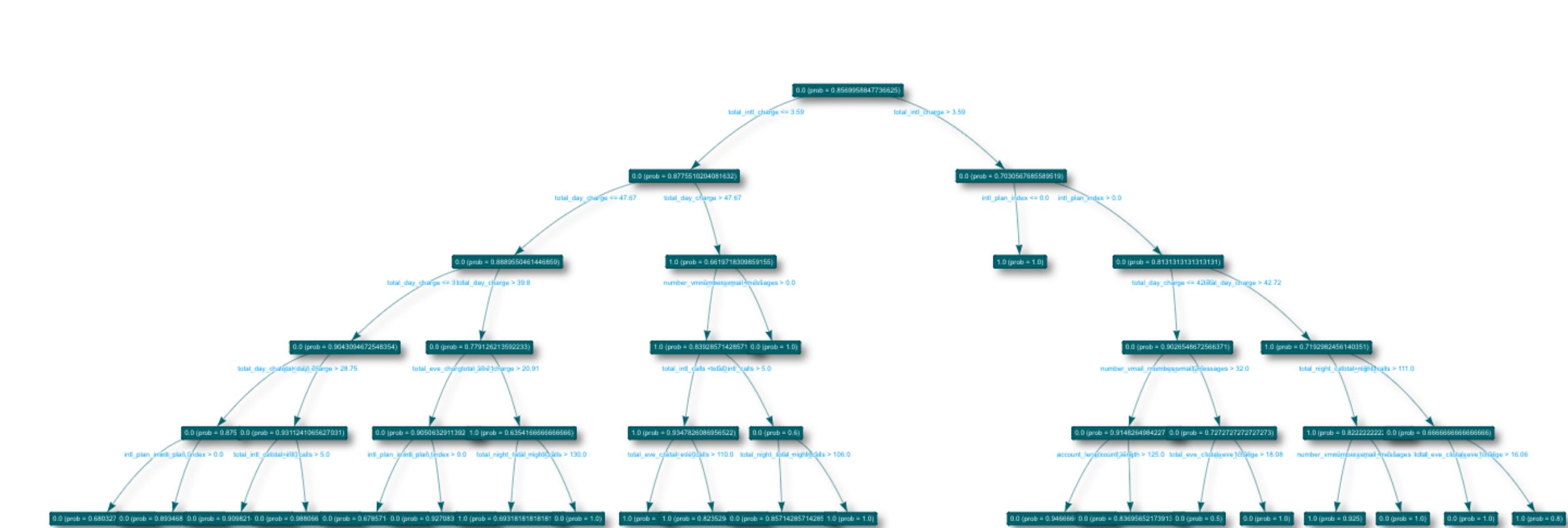
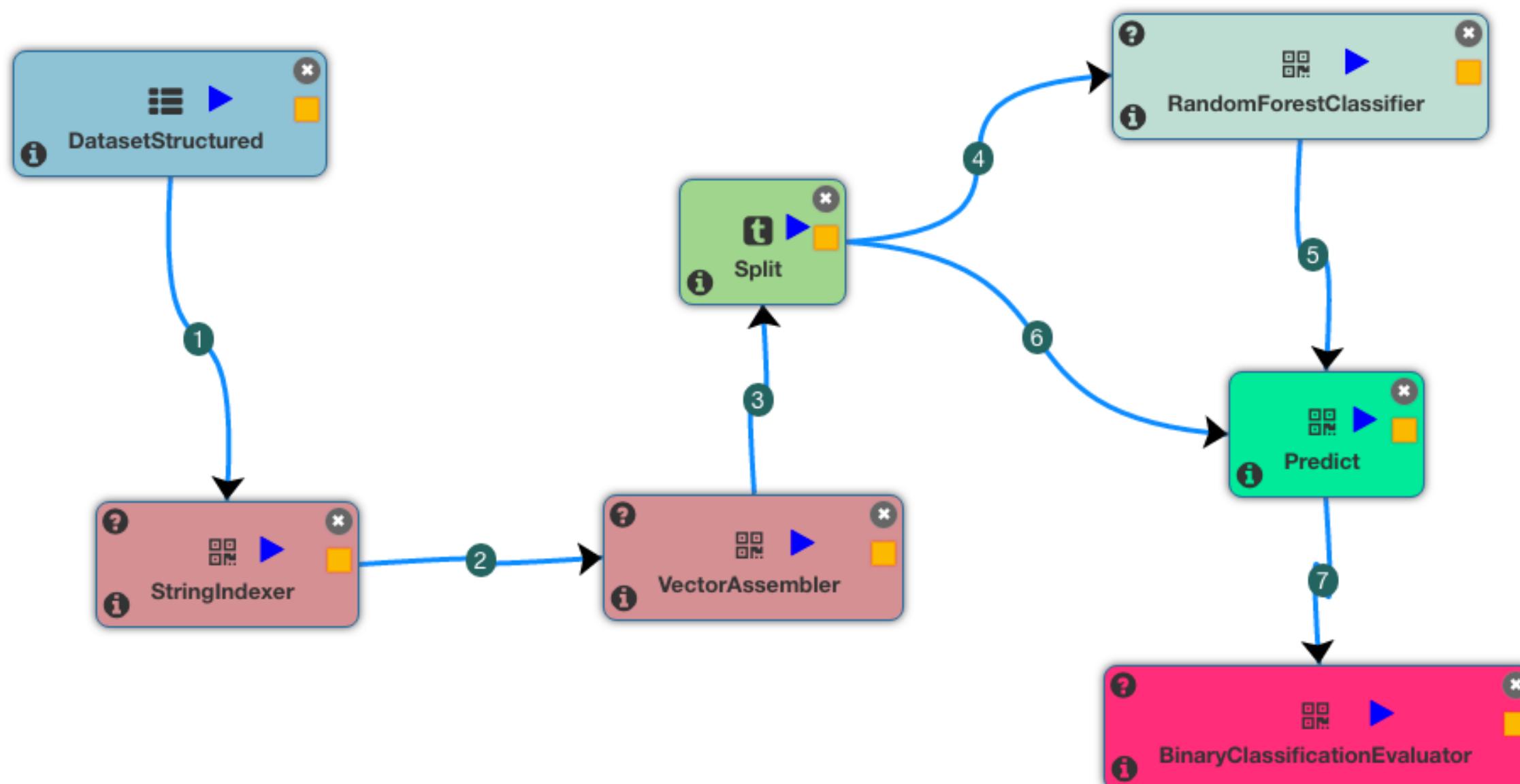
Classification - Random Forest

- Random forests or random decision forests are an ensemble learning method for classification, regression and other tasks, that operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees.

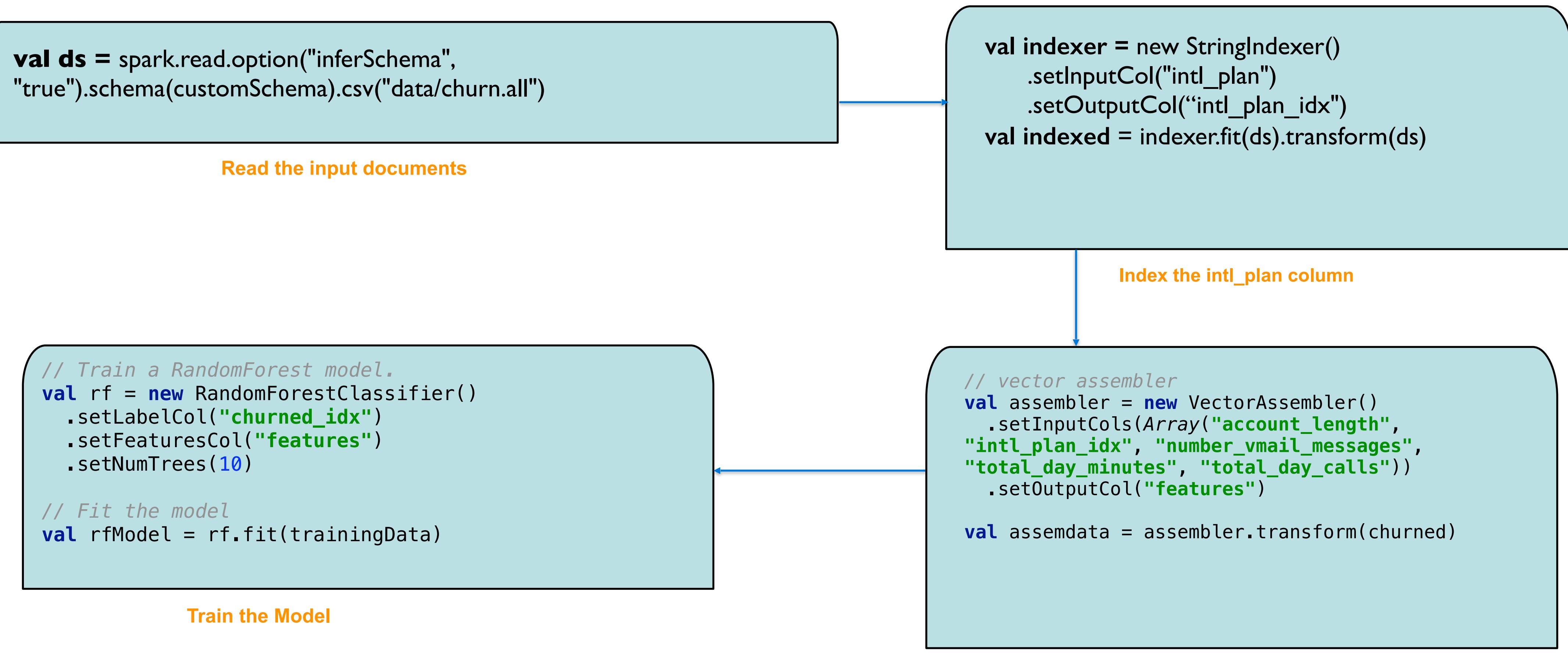


Classification - Churn Prediction for Telco

state	account_length	area_code	phone_number	intl_plan	voice_mail_plan	number_vmail_messages	total_day_minutes	total_day_calls	total_day_charge	total_eve_minutes	total_intl_charge	number_customer_service_calls	churned
StringType	DoubleType	DoubleType	StringType	StringType	StringType	DoubleType	DoubleType	DoubleType	DoubleType	DoubleType	DoubleType	DoubleType	StringType
OH	107.0	415.0	371-7191	no	yes	26.0	161.6	123.0	27.47	195.5	3.7	1.0	False.
NJ	137.0	415.0	358-1921	no	no	0.0	243.4	114.0	41.38	121.2	3.29	0.0	False.
OH	84.0	408.0	375-9999	yes	no	0.0	299.4	71.0	50.9	61.9	1.78	2.0	False.
OK	75.0	415.0	330-6626	yes	no	0.0	166.7	113.0	28.34	148.3	2.73	3.0	False.
AL	118.0	510.0	391-8027	yes	no	0.0	223.4	98.0	37.98	220.6	1.7	0.0	False.
MA	121.0	510.0	255-0002	no	yes	24.0	218.2	88.0	37.09	318.5	2.03	3.0	False.

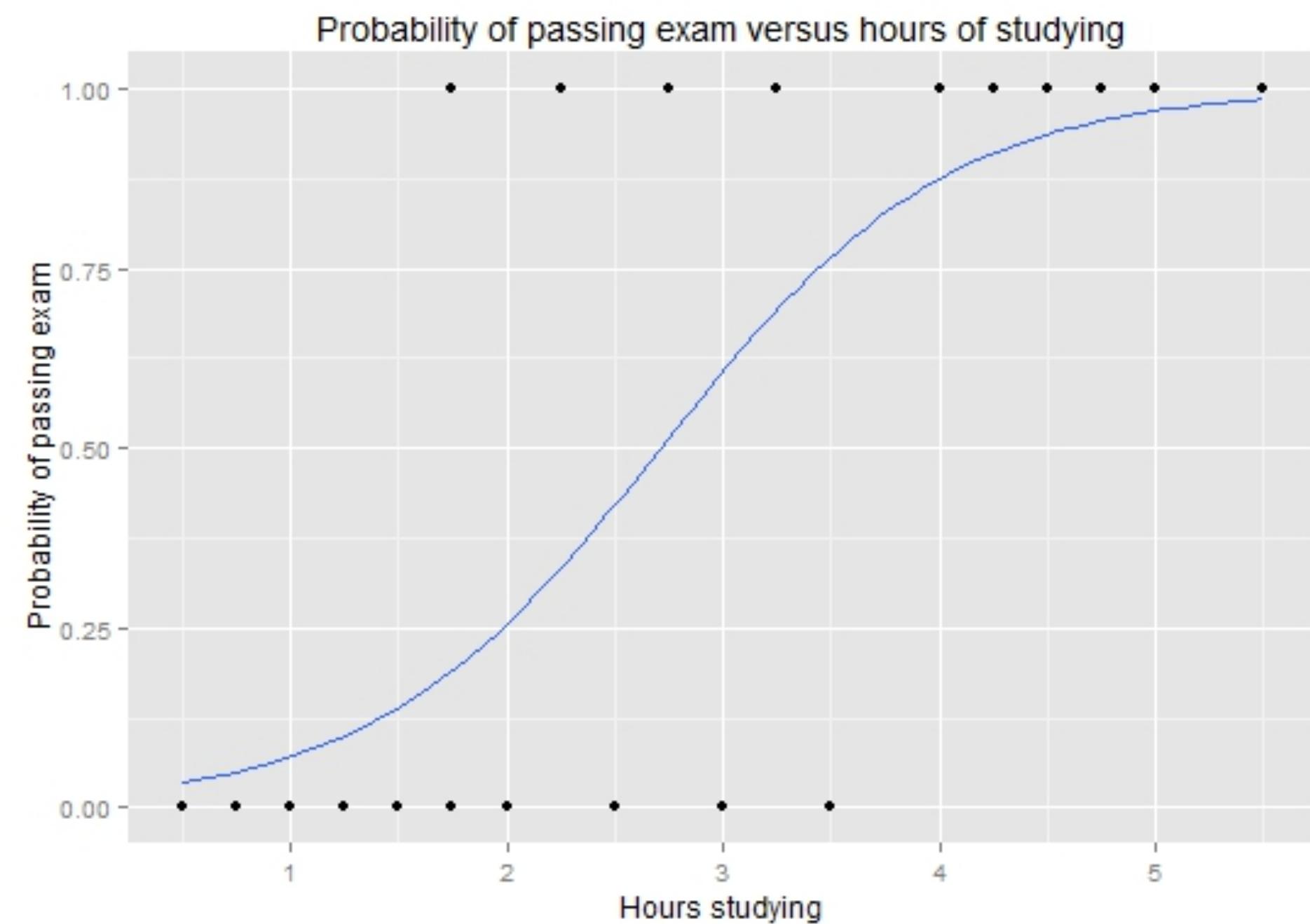


Random Forest - Code Walk-through



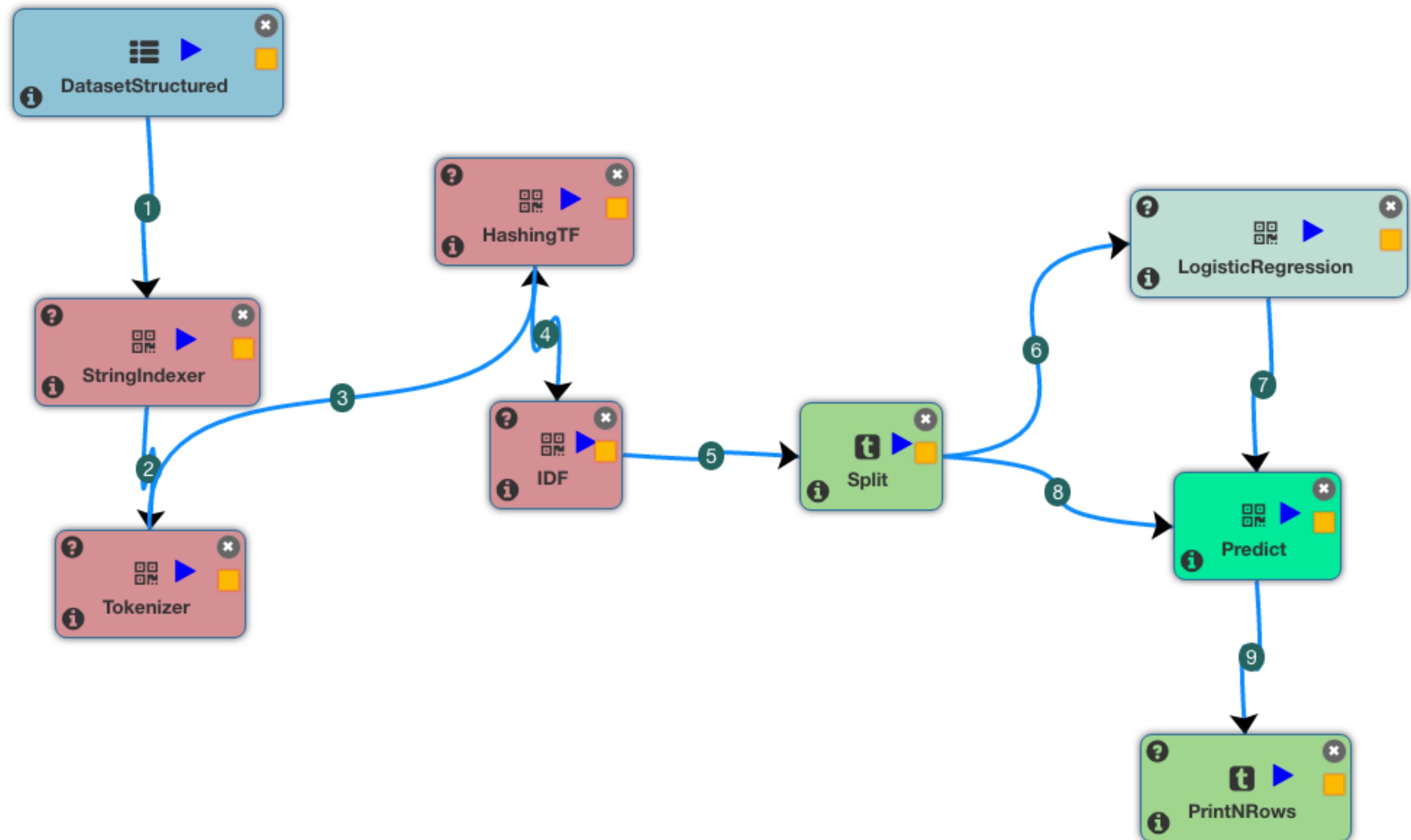
Classification - Logistic Regression

- Logistic regression measures the relationship between the categorical dependent variable and one or more independent variables by estimating probabilities using a logistic function, which is the cumulative logistic distribution.



Spam Detection

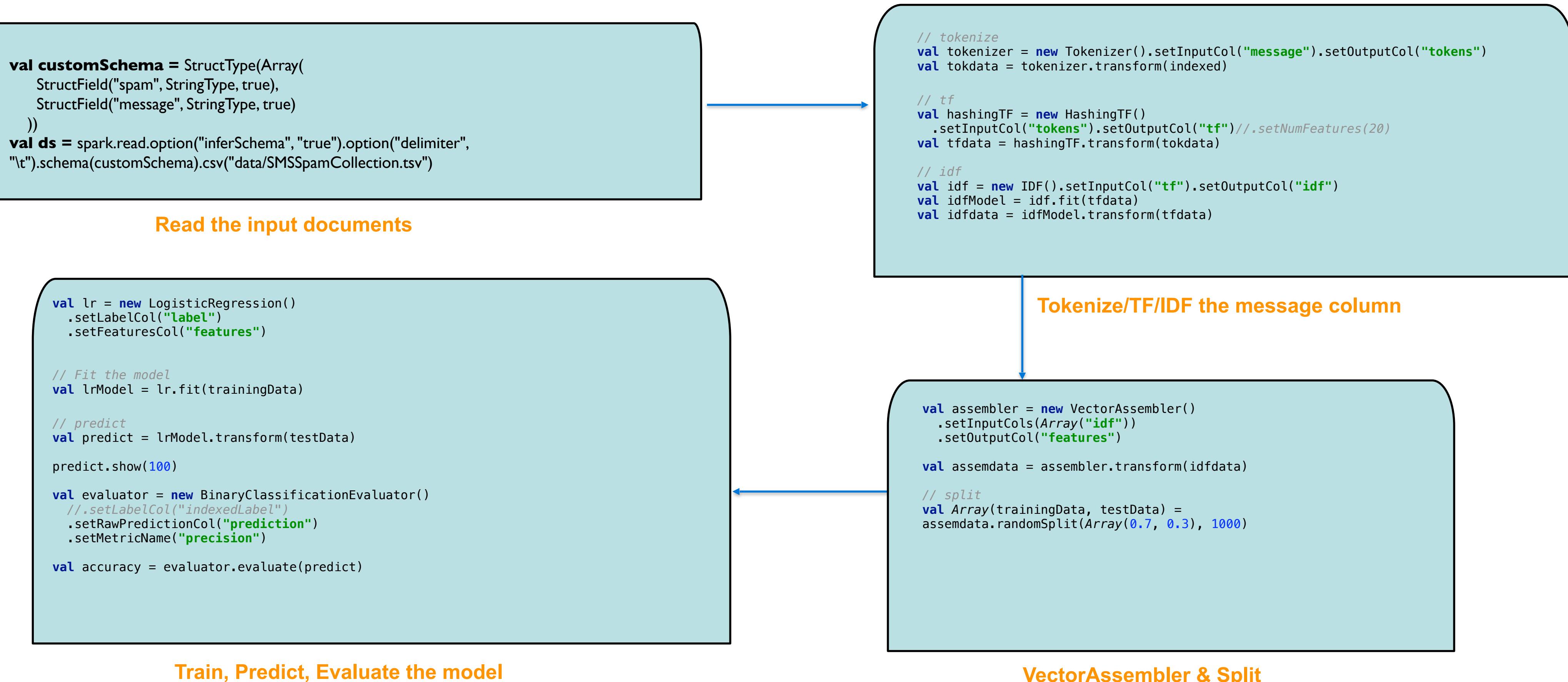
spam	message
StringType	StringType
ham	Ok lar... Joking wif u oni...
spam	Free entry in 2 a wkly comp to win FA Cup final tkts 21st May 2005. Text FA to 87121 to receive entry question(std txt rate)T&C's apply 08452810075over18's
ham	U dun say so early hor... U c already then say...
ham	Nah I don't think he goes to usf, he lives around here though
spam	FreeMsg Hey there darling it's been 3 week's now and no word back! I'd like some fun you up for it still? Tb ok! XxX std chgs to send, £1.50 to rcv
ham	Even my brother is not like to speak with me. They treat me like aids patent.
ham	As per your request 'Melle Melle (Oru Minnaminunginte Nurungu Vettam)' has been set as your callertune for all Callers. Press *9 to copy your friends Callertune
spam	WINNER!! As a valued network customer you have been selected to receivea £900 prize reward! To claim call 09061701461. Claim code KL341. Valid 12 hours only.



LogisticRegression

Label Column : spam_idx Intercept : -13.549728579531946 Coefficients : [-1.5268677627599565,-0.2372794241775128,-1.1072674016618658,-0.718543651988402,-1.2060471817854415,-0.5121405670718475,

Logistic Regression - Code Walk-through



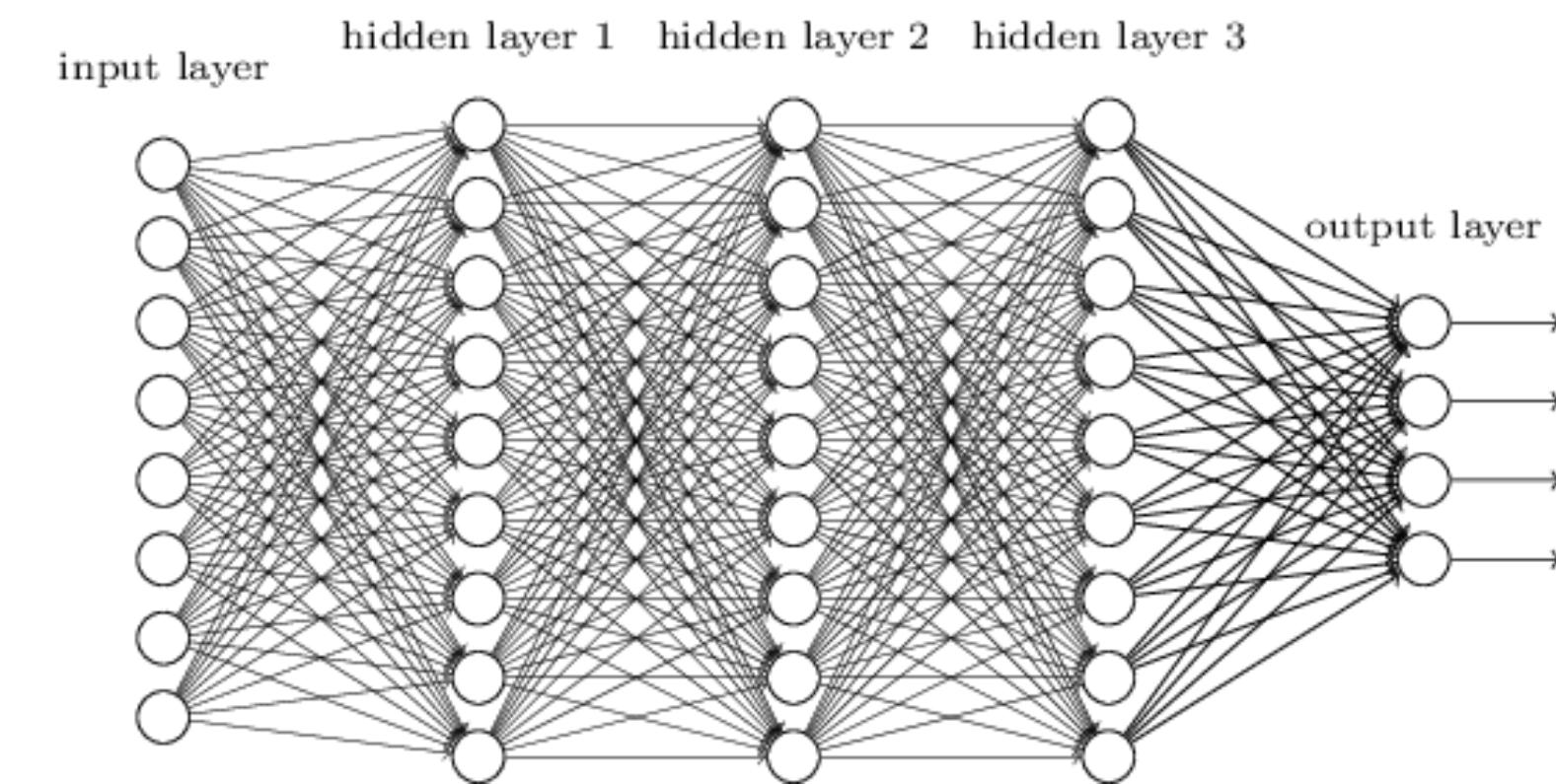
Spam Detection

LogisticRegression

Label Column : spam_idx Intercept : -13.549728579531946 Coefficients : [-1.5268677627599565,-0.2372794241775128,-1.1072674016618658,-0.718543651988402,-1.2060471817854415,-0.5121405670718475,

spam	message	spam_idx	ner	tf	idf	rawPrediction	probability	prediction
StringType	StringType	DoubleType	ArrayType(StringType,true)	org.apache.spark.mllib.linalg.VectorUDT@f71b0bce	org.apache.spark.mllib.linalg.VectorUDT@f71b0	org.apache.spark.mllib.linalg.VectorUDT@f71b0bce	org.apache.spark.mllib.linalg.VectorUDT@f71b0bce	DoubleType
ham	Ok lar... Joking wif u oni...	0.0	WrappedArray(ok, lar..., joking, wif, u, oni...)	(1000,[117,401,508,548,596,716],[1.0,1.0,1.0,1.0,1.0,1.0])	(1000,[117,401,508,548,596,716],[1.8800133667])	[28.976524354438865,-28.976524354438865]	[0.9999999999997395,2.6040862723062254E-13]	0.0
ham	U dun say so early hor... U c already then say...	0.0	WrappedArray(u, dun, say, so, early, hor..., u, c, already, then, say...)	(1000,[91,99,117,371,643,676,837,872,941,995],[1.0,1.0,2.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0])	(1000,[91,99,117,371,643,676,837,872,941,995])	[20.939194751756823,-20.939194751756823]	[0.999999991942075,8.057925791066503E-10]	0.0
ham	As per your request 'Melle Melle (Oru Minnaminunginte Nurungu Vettam)' has been set as your callertune for all Callers. Press *9 to copy your friends Callertune	0.0	WrappedArray(as, per, your, request, 'melle, melle, (oru, minnaminunginte, nurungu, vettam)', has, been, set, as, your, callertune, for, all, callers., press, *9, to, copy, your, friends, callertune)	(1000,[63,66,122,123,267,329,359,434,573,577,673,685,707,762,798,806,820,877,917,943,955,962], [1.0,1.0,2.0,3.0,1.0])	(1000,[63,66,122,123,267,329,359,434,573,577, [3.371799124996704,3.8037909874382967,5.6])	[18.539452471207944,-18.539452471207944]	[0.999999911198952,8.880104783324248E-9]	0.0
spam	Had your mobile 11 months or more? U R entitled to Update to the latest colour mobiles with camera for Free! Call The Mobile Update Co FREE on 08002986030	1.0	WrappedArray(had, your, mobile, 11, months, or, more?, u, r, entitled, to, update, to, the, latest, colour, mobiles, with, camera, for, free!, call, the, mobile, update, co, free, on, 08002986030)	(1000, [47,51,101,114,117,123,180,324,329,338, [47,51,101,114,117,123,180,324,329,338,468,496,501,541,551,555,568,577,707,734,737,801,819,866,982], [1.0,1.0])	(1000,[47,51,101,114,117,123,180,324,329,338, [4.5297279908212325,3.4592865791198193,3.1])	[-33.55460470089267,33.55460470089267]	[2.6755947551760234E-15,0.9999999999999973]	1.0

Deep Learning



Deep Learning - Exploring Trends



- Thus far finding the algorithmic basis for process of creating visual experiences through complex interplay between the content and style of an image, as done by humans, is unknown and there exists no artificial system with similar capabilities.
- However, in other key areas of visual perception such as object and face recognition near-human performance by DNN.
- Path forward to an algorithmic understanding of how humans create and perceive artistic imagery.

Reference: <http://arxiv.org/pdf/1508.06576v1.pdf>

Finer Points

- A major source of difficulty in many real-world AI applications is that many of the factors of variation influence every single piece of data we are able to observe.
 - Example of car: Color in night, viewing angle
- It can be very difficult to extract such high-level, abstract features from raw data.
- When is it nearly as difficult to obtain a representation as to solve the original problem, representation learning does not, at first glance seem to help us.
- Deep Learning, solves this central problem in representation learning by introducing representations that are expressed in terms of other, simpler representations .
- Deep learning allows the computer to build complex concepts out of simpler concepts.

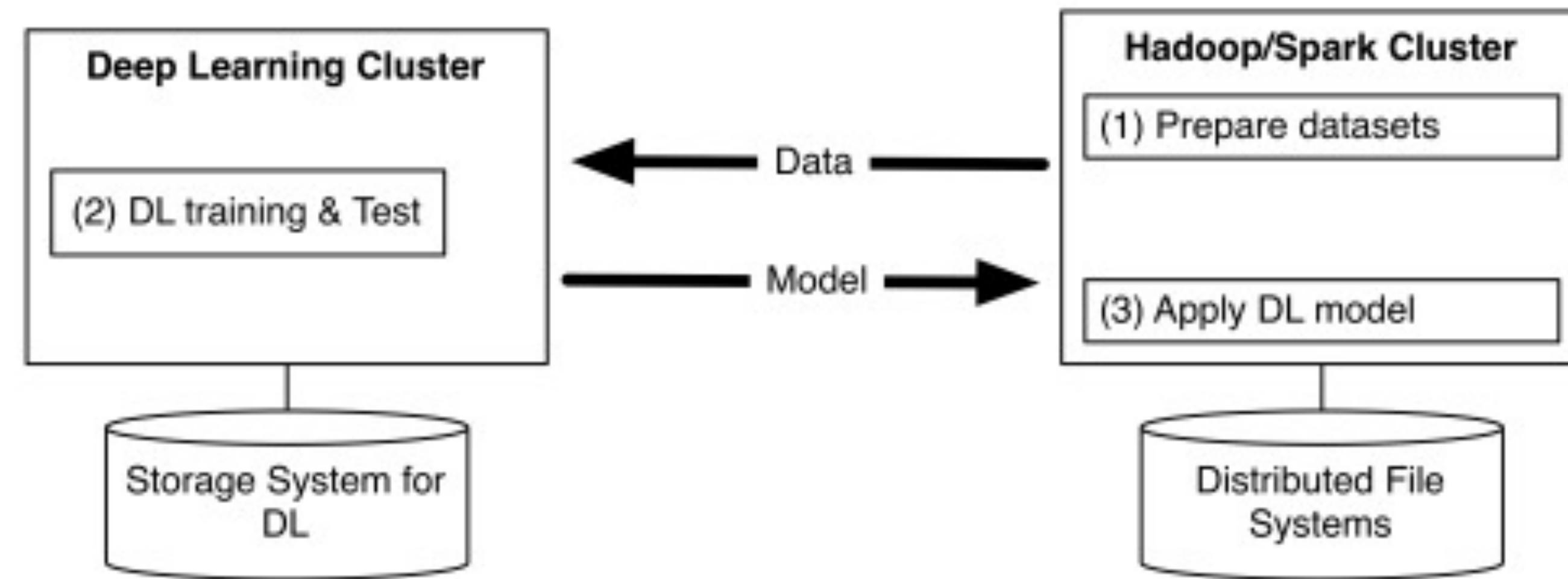
CPU and GPU - Best of both worlds!

- CaffeOnSpark
- DeepLearning4j

- GPU is Optimized for taking huge batches of data and performing the same operation over and over
- GPUs are special purpose and can compute vector maths, matrix maths, pixel transforms and rendering jobs about 10-100x faster than the equivalent CPU

- Architecturally, the CPU is composed of just few cores with lots of cache memory that can handle a few software threads at a time.
- They excel in serial tasks, branching operations and file operations.

Typical Scenario

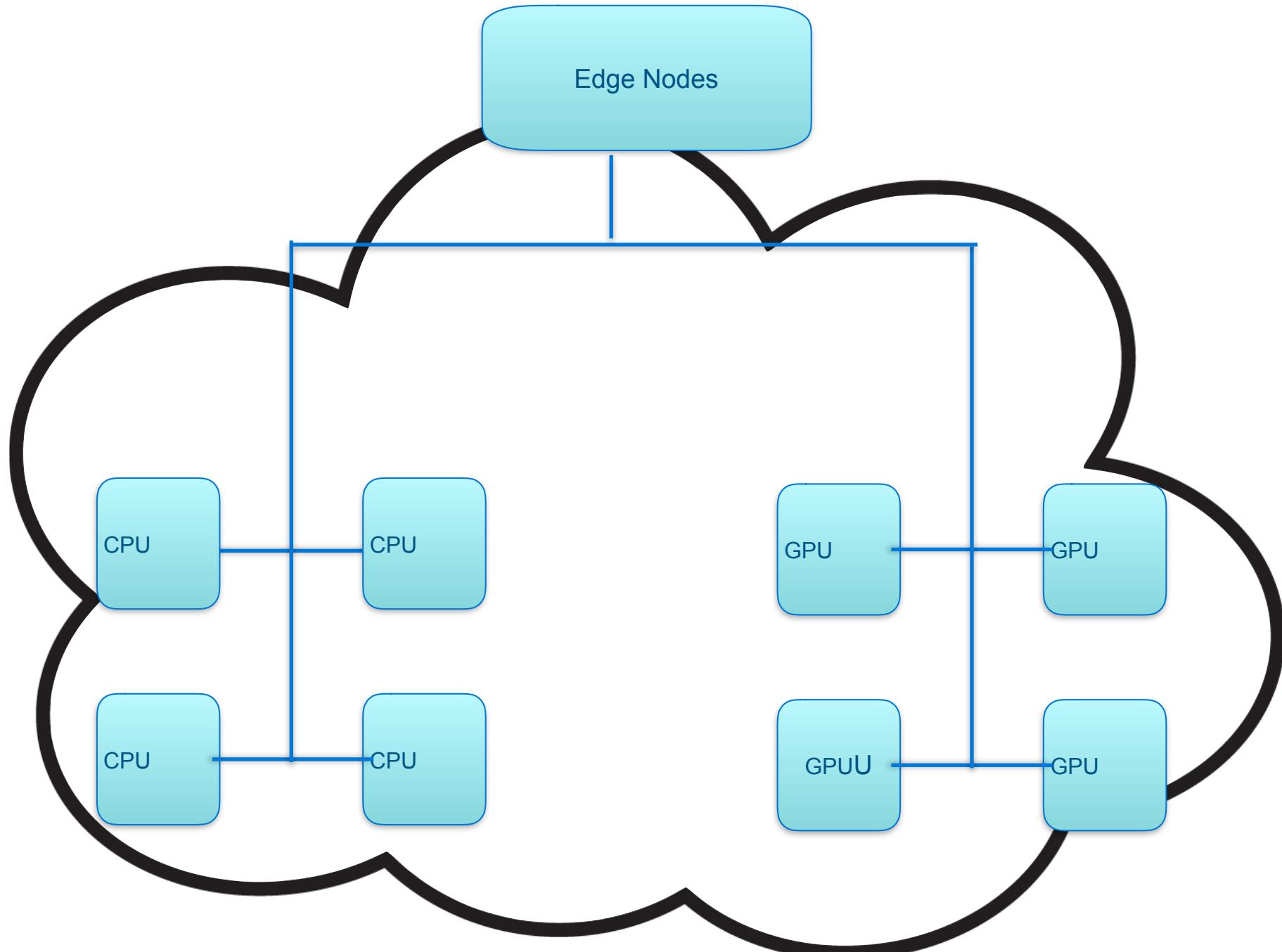


- Large data transfers
- Complicated pipelines

Intro to Caffe

- Developed by Berkley Vision and Learning Center
- Caffe defines a net layer-by-layer in its own model schema.
- As data and derivatives flow through the network in the forward and backward passes Caffe stores, communicates, and manipulates the information as **blobs**:
 - the blob is the standard array and unified memory interface for the framework.
 - The layer comes next as the foundation of both model and computation.
 - The net follows as the collection and connection of layers.
 - The details of blob describe how information is stored and communicated in and across layers and nets.
- We will go over the details of these components in more detail.

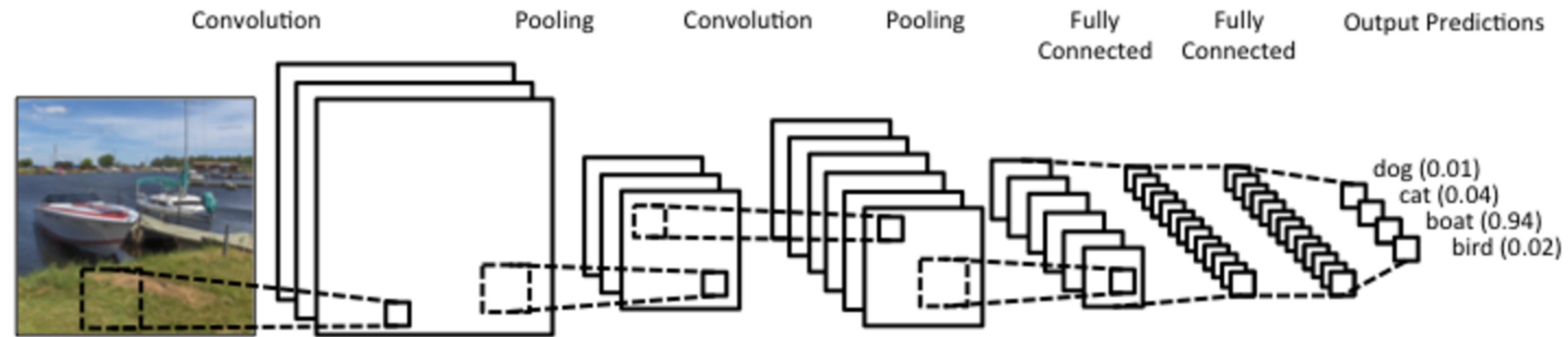
CaffeOnSpark



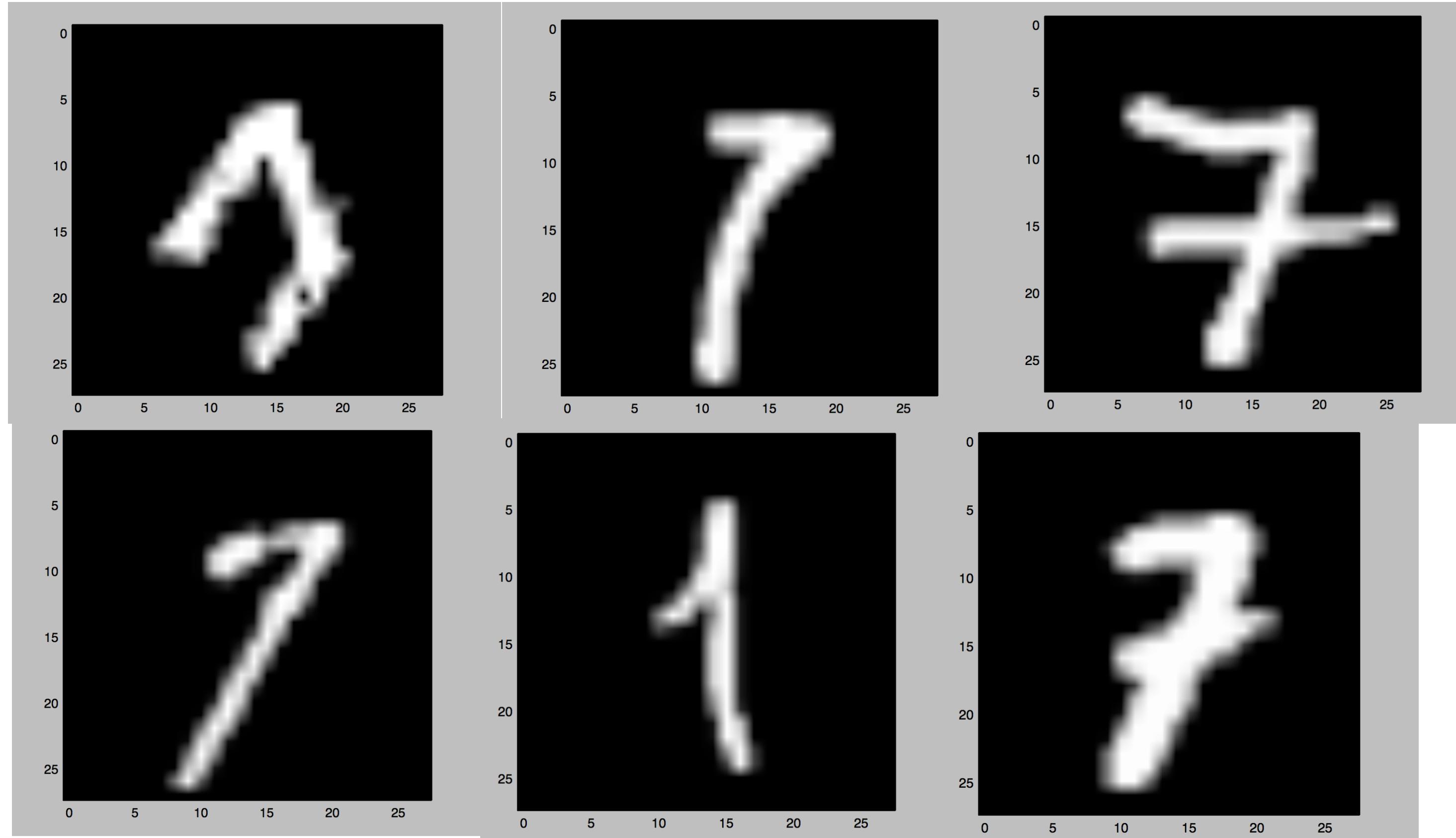
- Launch Caffe engines on GPU devices or CPU devices within the Spark executor.
- Invokes a JNI layer with fine-grain memory management.
- Unlike traditional Spark applications, CaffeOnSpark executors communicate to each other via MPI allreduce style interface via TCP/Ethernet or RDMA/Infiniband.
- This Spark+MPI architecture enables CaffeOnSpark to achieve similar performance as dedicated deep learning clusters.
- Checkpointing: CaffeOnSpark enables training state being snapshotted periodically, thus we could resume from previous state after a failure of a CaffeOnSpark job.

Basis of it all - Conv Neural Nets

- Convolution can be thought of as a sliding window function applied to a matrix, also known as kernel/filter/feature detector.
- CNNs are basically just several layers of convolutions with nonlinear activation functions like ReLU or tanh applied to the results.
- Convolutions over the input layer is used to compute the output, which results in local connections, where each region of the input is connected to a neuron in the output.
- During the training phase, a CNN automatically learns the values of its filters based on the task you want to perform.
- Example: In Image Classification a CNN may learn to detect edges from raw pixels in the first layer, then use the edges to detect simple shapes in the second layer, and then use these shapes to detect higher-level features, such as facial shapes in higher layers. The last layer is then a classifier that uses these high-level features.
- Locality Invariance and Composition



Getting evaluations from checkpoint data



Take aways

- Deep learning allows the computer to build complex concepts out of simpler concepts.
- Choices in CDH stack
 - SparkML
 - MLLib
- Other new exciting technologies
 - Tensor flow
 - Caffe
- Use the algorithms to unlock the value in data as oppose to lock yourself with a specific technology
- For Examples of Technology Application:
 - <http://github.mtv.cloudera.com/DataScience/nlp>

Thank you!!!! :)