Machine Learning in Spark

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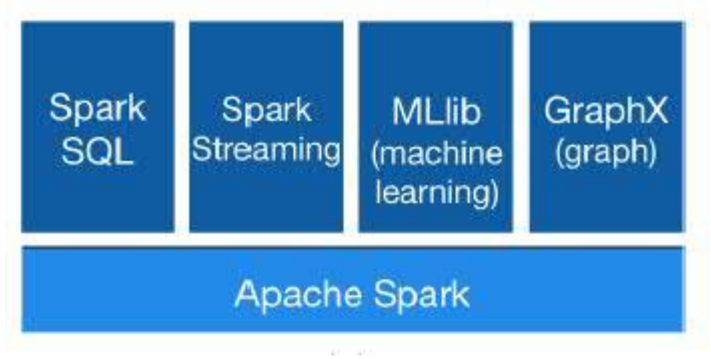
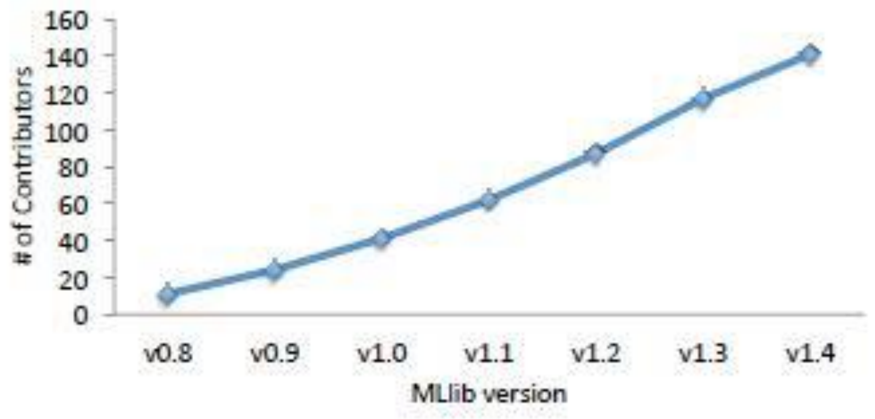
IBM Research -- Haifa

Spark MLLib

Large Scale Machine Learning on Apache Spark





Meng et.al. "MLLib: Machine Learning in Apache Spark", arXiv:1505:06807, 2015

Why MLLib?

Mahout?

LIBLINEAR?

H_2O?

Vowpal Wabbit?

MATLAB?

R?

GraphLab?

scikit-learn?

Weka?

Xiangrui Meng, *MLLib: scalable machine learning on Spark*, Spark Workshop April 2014, http://stanford.edu/~rezab/sparkworkshop/

Machine Learning Algorithms

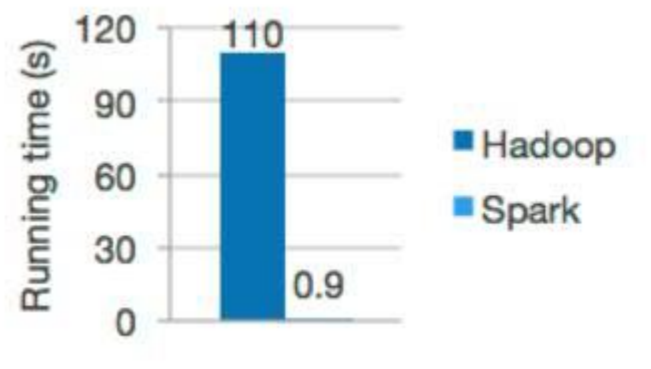
- Classification
  - Logistic regression
  - Linear support vector machine (SVM)
  - Naïve Bayes
  - Decision trees and forests
- Regression
  - Generalized linear regression (GLM)
- Recommendation
  - Alternating least squares (ALS)
- Clustering
  - K-means and Streaming K-means
  - Gaussian mixture
  - Power iteration clustering (PIC)
  - Latent Dirichlet allocation (LDA)
- Dimensionality reduction
  - Singular value decomposition (SVD)
  - Principal component analysis (PCA)
- Feature extraction & selection
- …

See: https://spark.apache.org/docs/latest/mllib-guide.html

Performance of MLLib

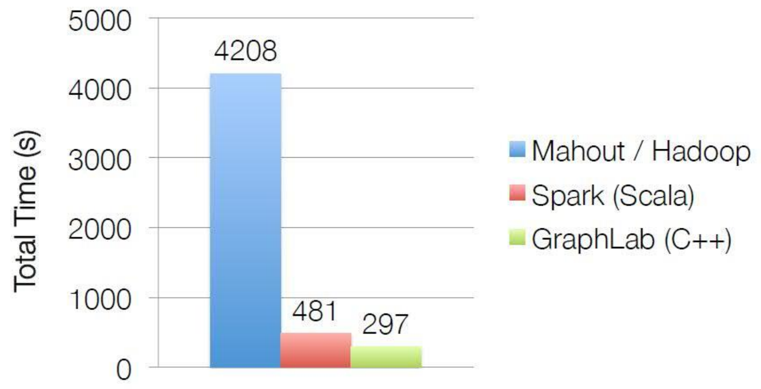
- It is built on Apache Spark, a fast and general engine for large-scale data processing.
- Run programs up to 100x faster than Hadoop MapReduce in memory, or 10x faster on disk.

Logistic Regression



Logistic regression in Hadoop and Spark

ALS Results



Reza Zadeh, CME 323: Distributed Algorithms and Optimization, Stanford University, http://stanford.edu/~rezab/dao/
https://spark.apache.org/

Performance of MLLib

- Speed-up between MLLib versions

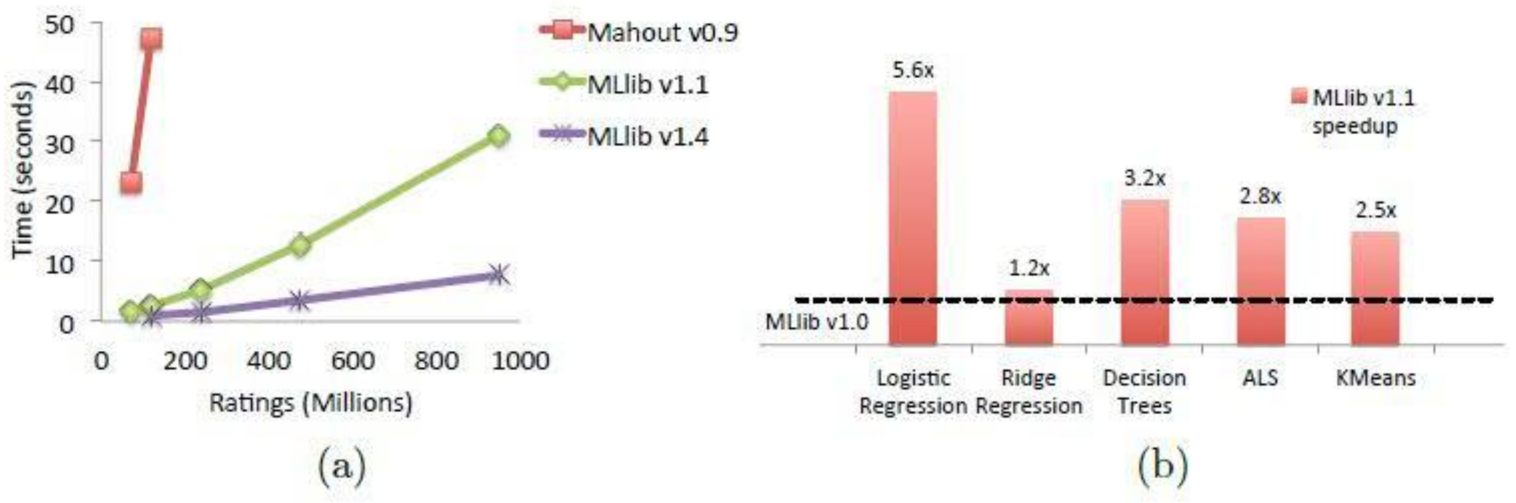


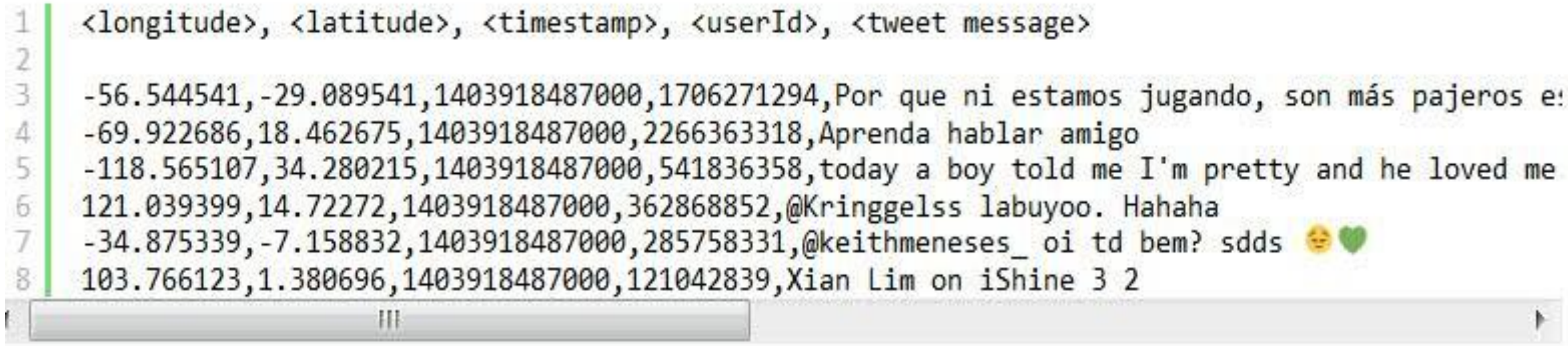
Figure 2: (a) Benchmarking results for ALS. (b) MLlib speedup between versions.

Meng et.al. "MLLib: Machine Learning in Apache Spark", arXiv:1505:06807, 2015

Example: K-Means Clustering

Goal:

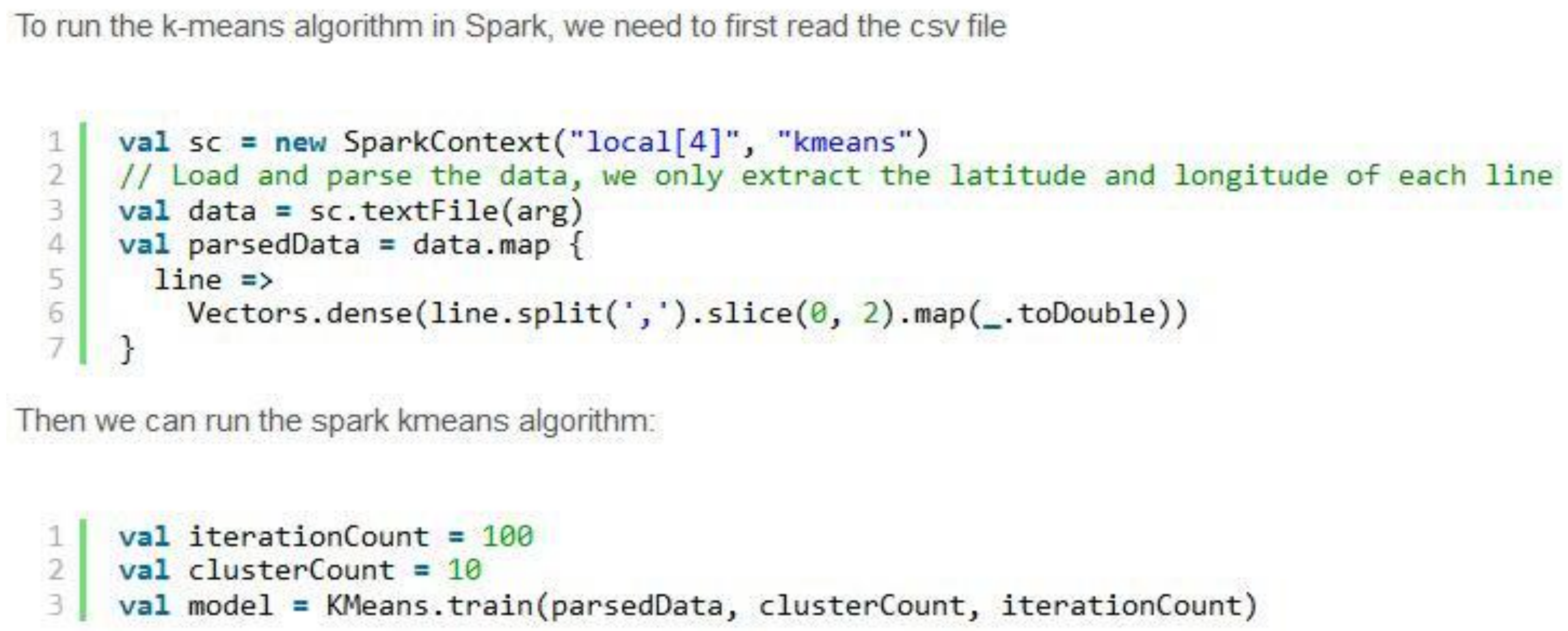
Segment tweets into clusters by geolocation using Spark MLLib K-means clustering



```
<longitude>, <latitude>, <timestamp>, <userId>, <tweet message>

-56.544541,-29.089541,1403918487000,1706271294,Por que ni estamos jugando, son más pajeros e
-69.922686,18.462675,1403918487000,2266363318,Aprenda hablar amigo
-118.565107,34.280215,1403918487000,541836358,today a boy told me I'm pretty and he loved me
121.039399,14.72272,1403918487000,362868852,@Kringgelss labuyoo. Hahaha
-34.875339,-7.158832,1403918487000,285758331,@keithmeneses_ oi td bem? sdds 😌💚
103.766123,1.380696,1403918487000,121042839,Xian Lim on iShine 3 2
```

https://chimpler.wordpress.com/2014/07/11/segmenting-audience-with-kmeans-and-voronoi-diagram-using-spark-and-mllib/

Example: K-Means Clustering



To run the k-means algorithm in Spark, we need to first read the csv file

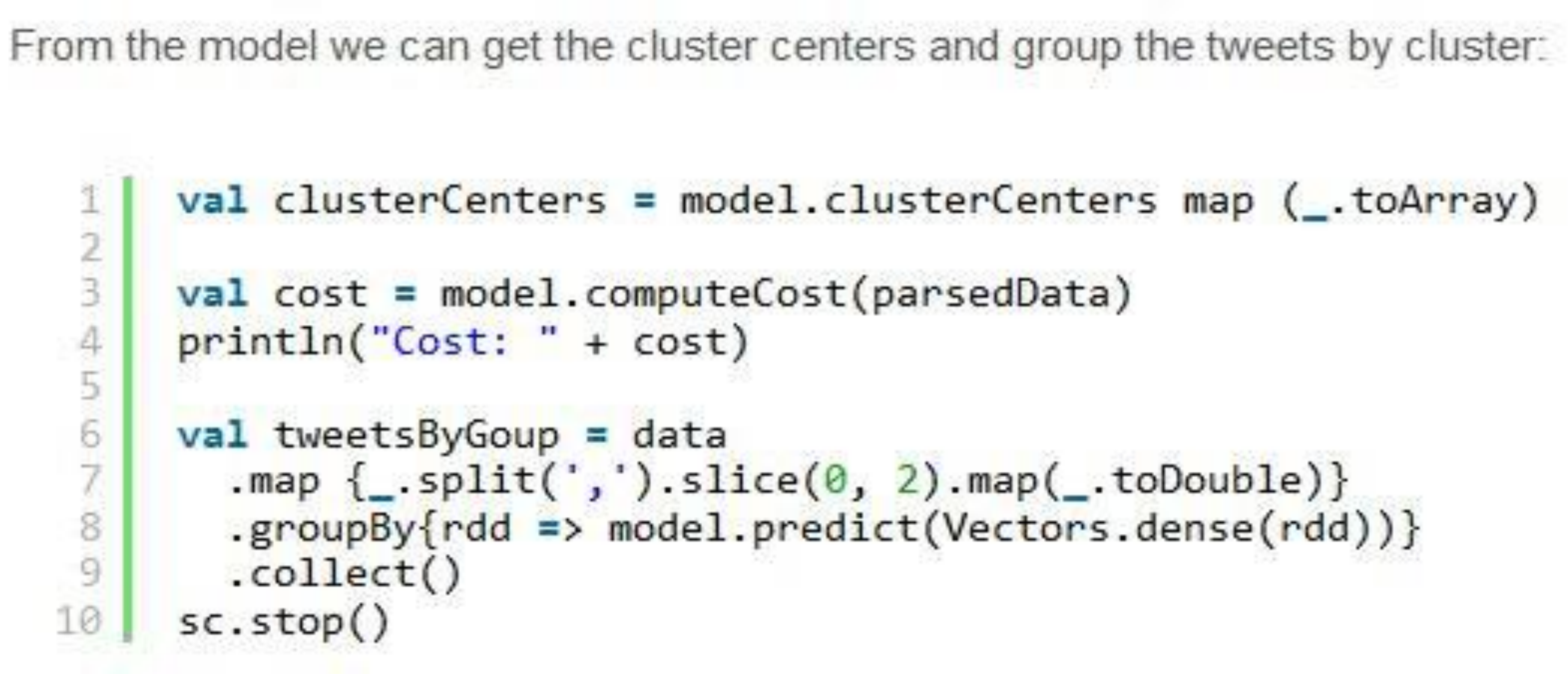
```scala
val sc = new SparkContext("local[4]", "kmeans")
// Load and parse the data, we only extract the latitude and longitude of each line
val data = sc.textFile(arg)
val parsedData = data.map {
  line =>
    Vectors.dense(line.split(',').slice(0, 2).map(_.toDouble))
}
```

Then we can run the spark kmeans algorithm:

```scala
val iterationCount = 100
val clusterCount = 10
val model = KMeans.train(parsedData, clusterCount, iterationCount)
```

https://chimpler.wordpress.com/2014/07/11/segmenting-audience-with-kmeans-and-voronoi-diagram-using-spark-and-mllib/

Example: K-Means Clustering

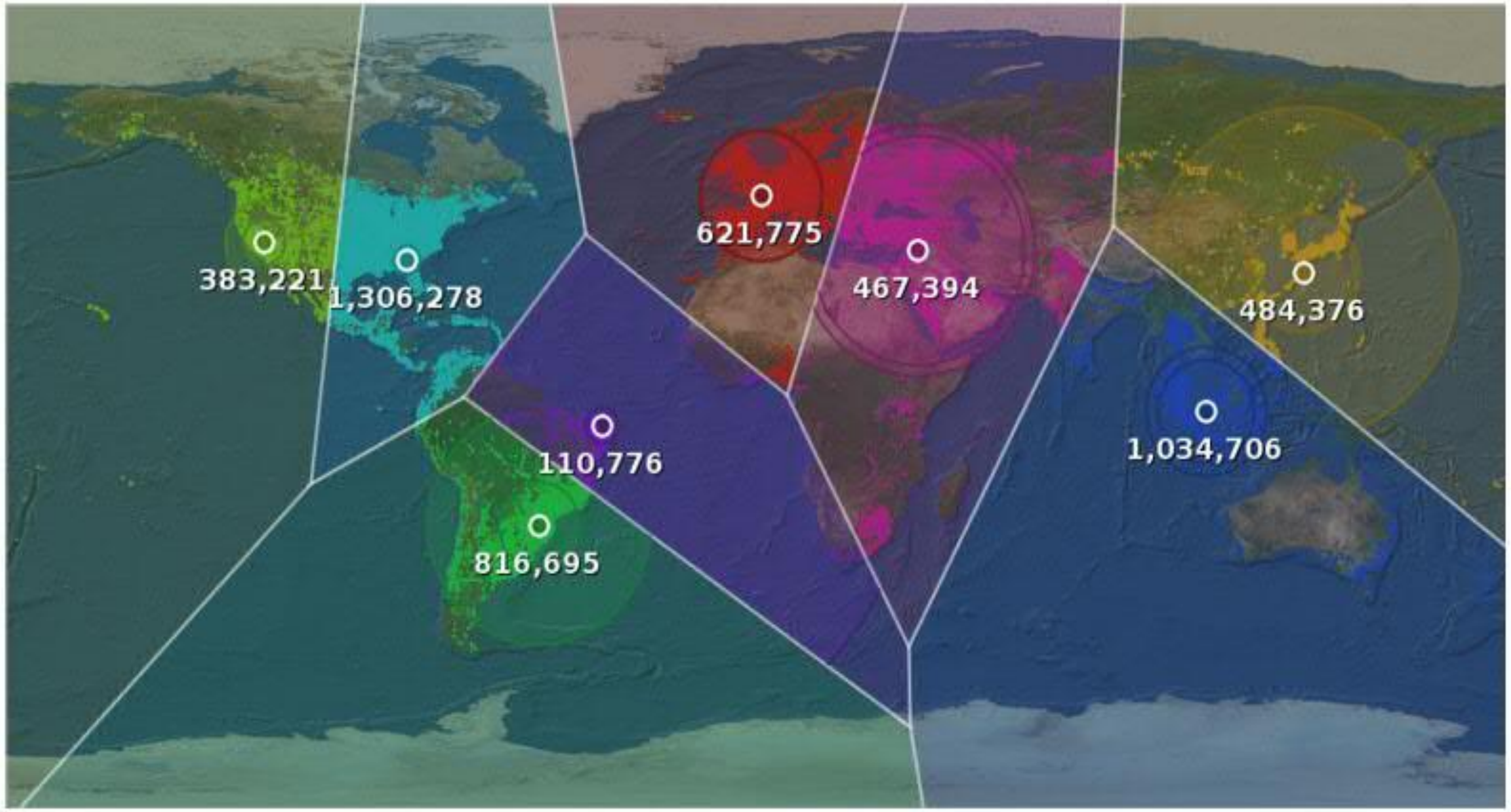


From the model we can get the cluster centers and group the tweets by cluster:

```
val clusterCenters = model.clusterCenters map (_.toArray)

val cost = model.computeCost(parsedData)
println("Cost: " + cost)

val tweetsByGoup = data
  .map {_.split(',').slice(0, 2).map(_.toDouble)}
  .groupBy{rdd => model.predict(Vectors.dense(rdd))}
  .collect()
sc.stop()
```

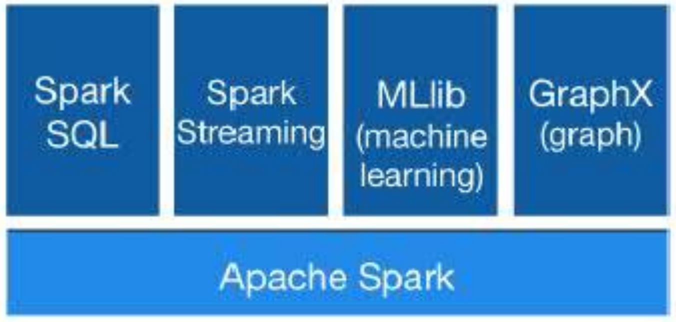
https://chimpler.wordpress.com/2014/07/11/segmenting-audience-with-kmeans-and-voronoi-diagram-using-spark-and-mllib/

Example: K-Means Clustering



https://chimpler.wordpress.com/2014/07/11/segmenting-audience-with-kmeans-and-voronoi-diagram-using-spark-and-mllib/

Spark Ecosystem
Spark SQL & MLLib

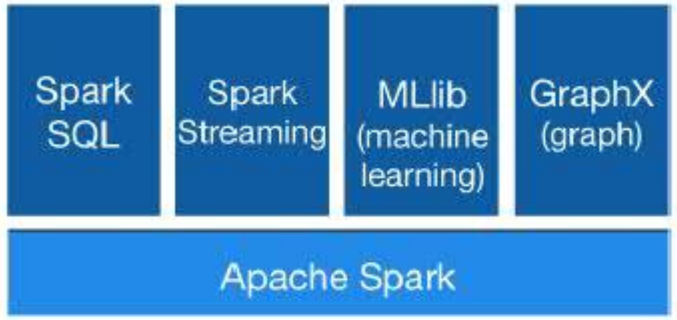


```
// Data can easily be extracted from existing sources,
// such as Apache Hive.
val trainingTable = sql("""
  SELECT e.action,
         u.age,
         u.latitude,
         u.longitude
  FROM Users u
  JOIN Events e
  ON u.userId = e.userId""")

// Since `sql` returns an RDD, the results of the above
// query can be easily used in MLlib.
val training = trainingTable.map { row =>
  val features = Vectors.dense(row(1), row(2), row(3))
  LabeledPoint(row(0), features)
}

val model = SVMWithSGD.train(training)
```

// SVM using Stochastic Gradient Descent

Xiangrui Meng, *MLLib: scalable machine learning on Spark*, Spark Workshop April 2014, http://stanford.edu/~rezab/sparkworkshop/

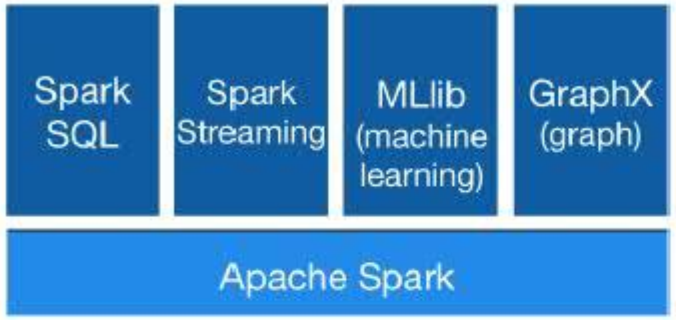
Spark Ecosystem
Spark Streaming & MLLib



```
// collect tweets using streaming

// train a k-means model
val model: KMmeansModel = ...

// apply model to filter tweets
val tweets = TwitterUtils.createStream(ssc, Some(authorizations(0)))
val statuses = tweets.map(_.getText)
val filteredTweets =
  statuses.filter(t => model.predict(featurize(t)) == clusterNumber)

// print tweets within this particular cluster
filteredTweets.print()
```

Xiangrui Meng, *MLLib: scalable machine learning on Spark*, Spark Workshop April 2014, http://stanford.edu/~rezab/sparkworkshop/

Spark Ecosystem GraphX & MLLib

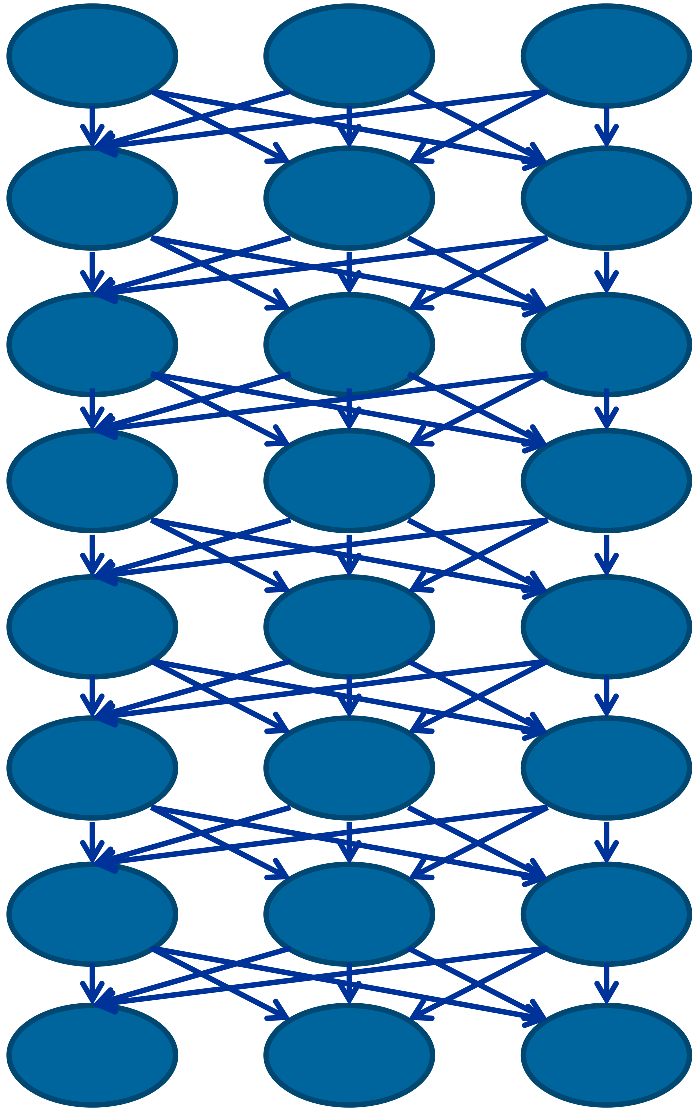


```
// assemble link graph
val graph = Graph(pages, links)
val pageRank: RDD[(Long, Double)] = graph.staticPageRank(10).vertices

// load page labels (spam or not) and content features
val labelAndFeatures: RDD[(Long, (Double, Seq((Int, Double))))] = ...
val training: RDD[LabeledPoint] =
  labelAndFeatures.join(pageRank).map {
    case (id, ((label, features), pageRank)) =>
      LabeledPoint(label, Vectors.sparse(features ++ (1000, pageRank))
}

// train a spam detector using logistic regression
val model = LogisticRegressionWithSGD.train(training)
```

Xiangrui Meng, *MLLib: scalable machine learning on Spark*, Spark Workshop April 2014, http://stanford.edu/~rezab/sparkworkshop/

Machine Learning Pipeline with Spark

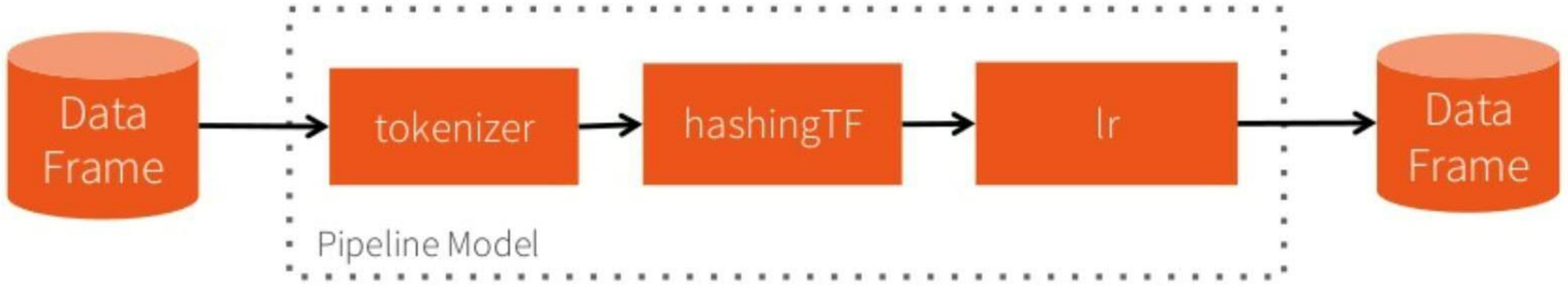
- Data pre-processing
- Feature extraction
- Model fitting
- Model training
- Validation
- Model prediction



Machine Learning Pipeline with Spark

```
// create pipeline
tok = Tokenizer(in="text", out="words")
tf = HashingTF(in="words", out="features")
lr = LogisticRegression(maxIter=10, regParam=0.01)
pipeline = Pipeline(stages=[tok, tf, lr])
```

```
// train pipeline
df = sqlCtx.table("training")
model = pipeline.fit(df)

// make predictions
df = sqlCtx.read.json("/path/to/test")
model.transform(df)
  .select("id", "text", "prediction")
```

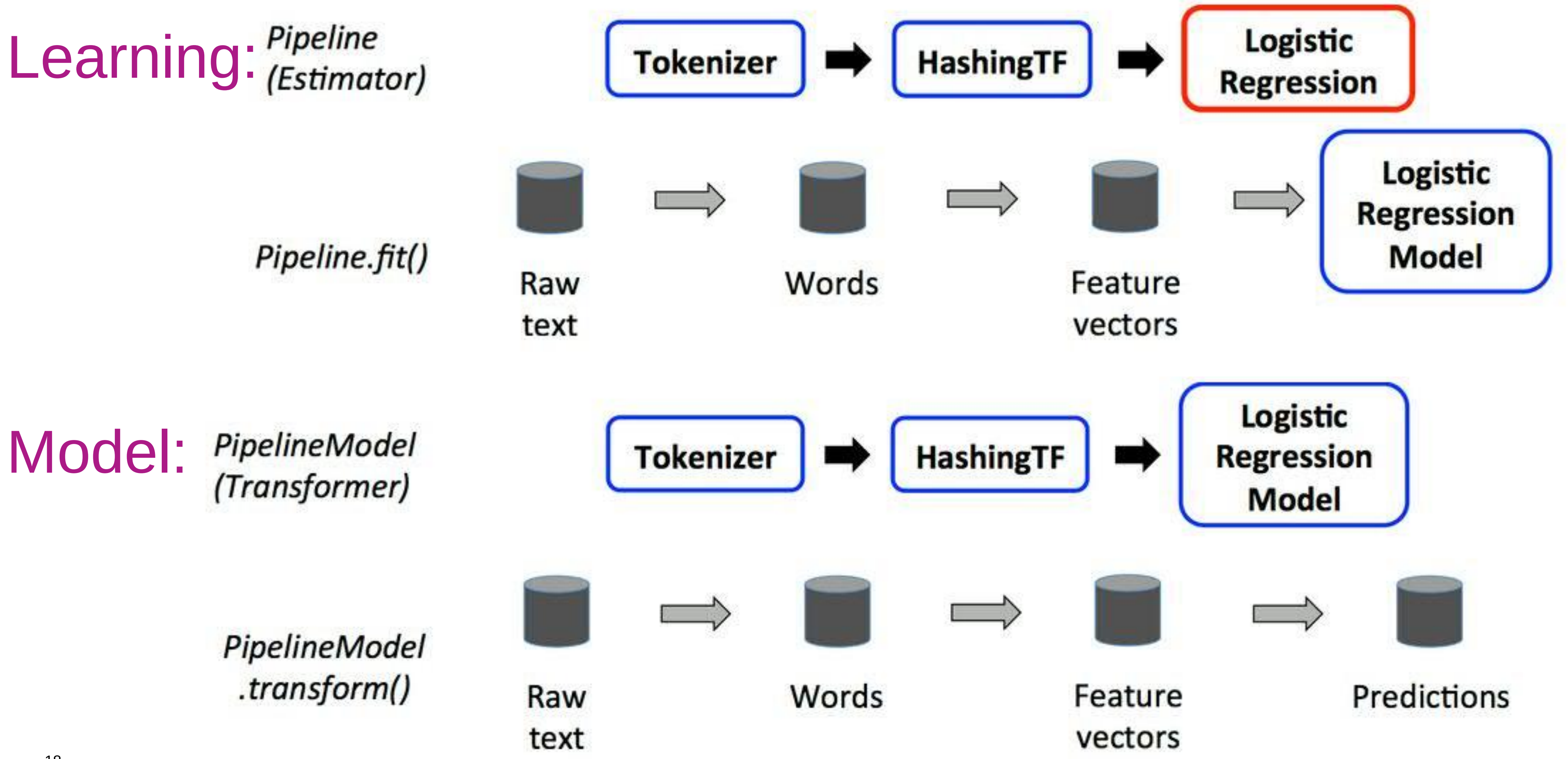


Patrick Wendell, Matei Zaharia, "Spark community update", https://spark-summit.org/2015/events/keynote-1/

Machine Learning Pipeline with Spark

- **ML Dataset:**
  - DataFrame from Spark SQL
    could have different columns storing text, feature vectors, true labels, and predictions
- **Transformer:**
  - Feature transformers (e.g., OneHotEncoder)
  - Trained ML models (e.g., LogisticRegressionModel)
- **Estimator:**
  - ML algorithms for training models (e.g., LogisticRegression)
- **Evaluator:**
  - Evaluate predictions and compute metrics, useful for tuning algorithm parameters
    (e.g., BinaryClassificationEvaluator)
- **Pipeline:** chains multiple Transformers and Estimators together to specify an ML workflow

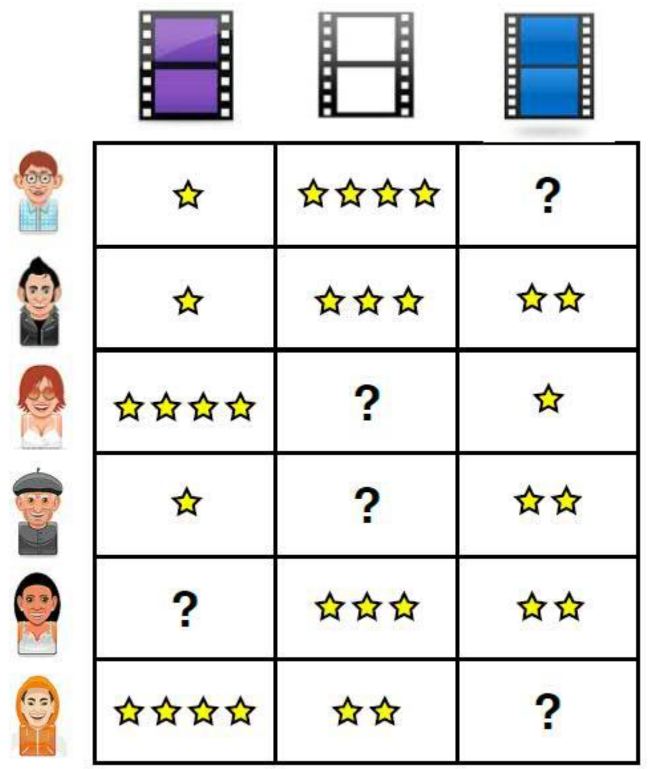
Machine Learning Pipeline with Spark



https://spark.apache.org/docs/latest/ml-guide.html

Example: Alternating Least Squares (ALS)

Collaborative filtering



	★	★★★★	?
	★	★★★	★★
	★★★★	?	★
	★	?	★★
	?	★★★	★★
	★★★★	★★	?

- Recover a rating matrix from a subset of its entries.

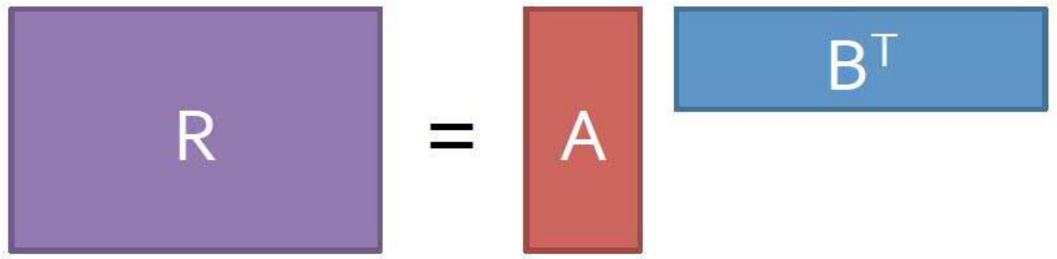
ALS Implementation in MLlib

How to scale to 100,000,000,000 ratings?

Xiangrui Meng, *MLLib: scalable machine learning on Spark*, Spark Workshop April 2014, http://stanford.edu/~rezab/sparkworkshop/

Example: Alternating Least Squares (ALS)

Model R as product of user and movie feature matrices A and B of size U×K and M×K



Alternating Least Squares (ALS)

» Start with random A & B

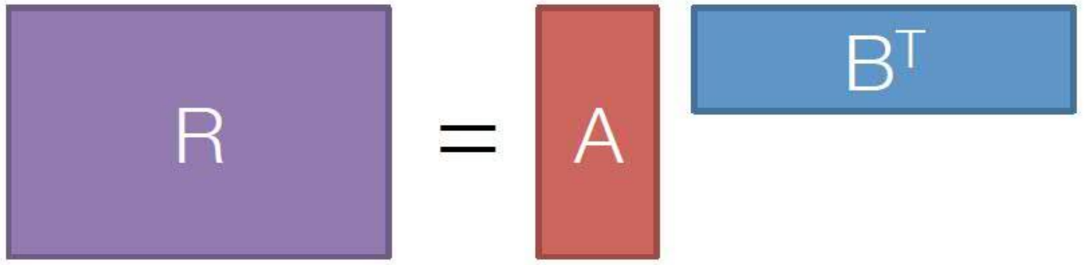
» Optimize user vectors (A) based on movies

» Optimize movie vectors (B) based on users

» Repeat until converged

Reza Zadeh, CME 323: Distributed Algorithms and Optimization, Stanford University, http://stanford.edu/~rezab/dao/

Example: Alternating Least Squares (ALS)

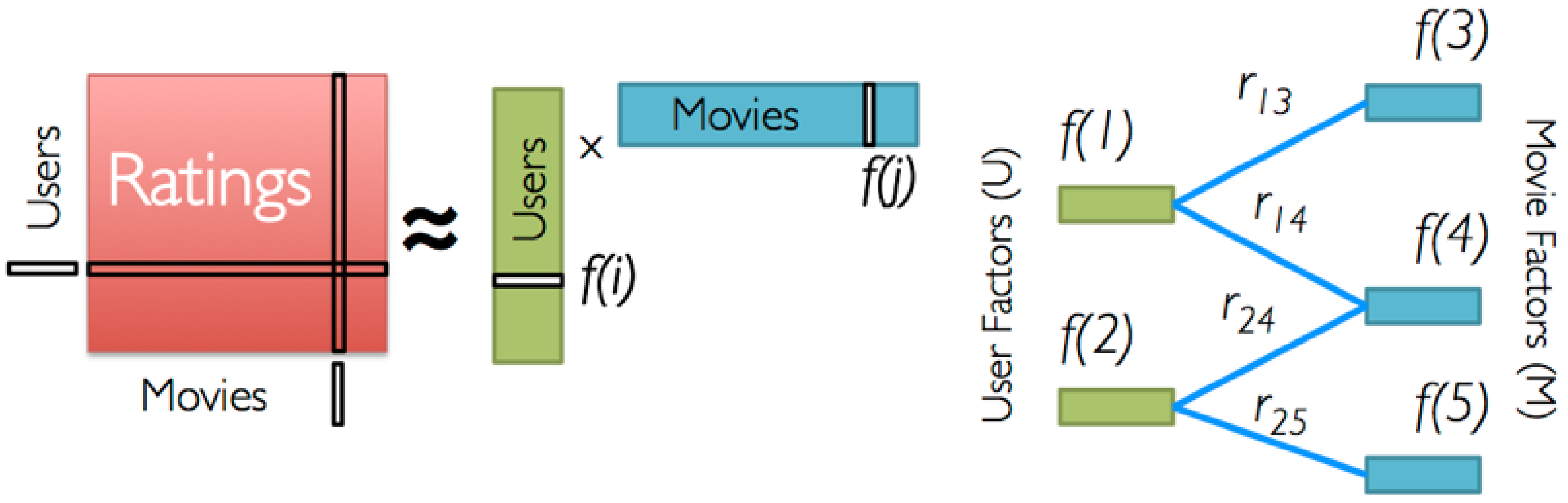


1. Start with random A_1, B_1
2. Solve for A_2 to minimize $||R - A_2B_1^T||$
3. Solve for B_2 to minimize $||R - A_2B_2^T||$
4. Repeat until convergence

Reza Zadeh, CME 323: Distributed Algorithms and Optimization, Stanford University, http://stanford.edu/~rezab/dao/

Example: Alternating Least Squares (ALS)

Low-Rank Matrix Factorization:



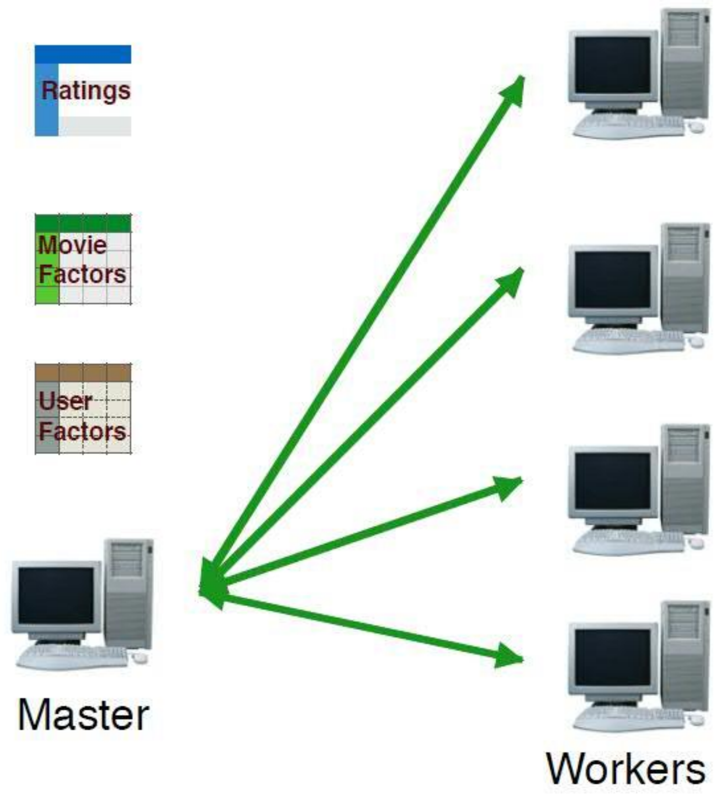
Iterate:

$$f[i] = \arg\min_{w \in \mathbb{R}^d} \sum_{j \in \mathrm{Nbrs}(i)} \left(r_{ij} - w^T f[j]\right)^2 + \lambda \|w\|_2^2$$

Xiangrui Meng, *MLLib: scalable machine learning on Spark*, Spark Workshop April 2014, http://stanford.edu/~rezab/sparkworkshop/

Example: Alternating Least Squares (ALS)

Broadcast everything

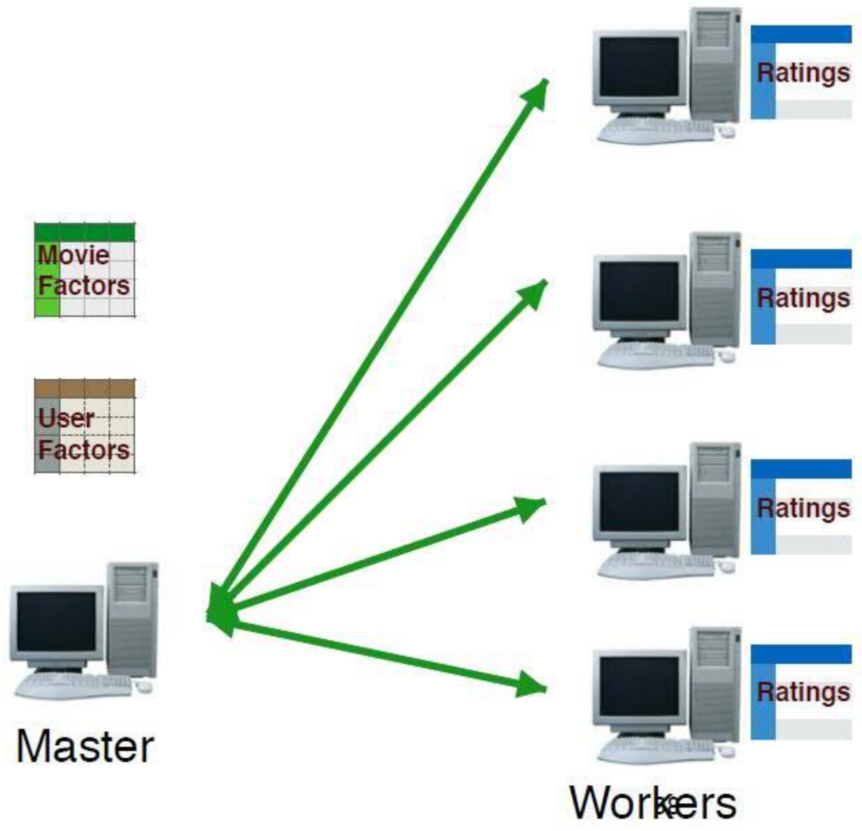


- Master loads (small) data file and initializes models.
- Master broadcasts data and initial models.
- At each iteration, updated models are broadcast again.
- Works OK for small data.
- Lots of communication overhead - doesn't scale well.

Xiangrui Meng, *MLLib: scalable machine learning on Spark*, Spark Workshop April 2014, http://stanford.edu/~rezab/sparkworkshop/

Example: Alternating Least Squares (ALS)

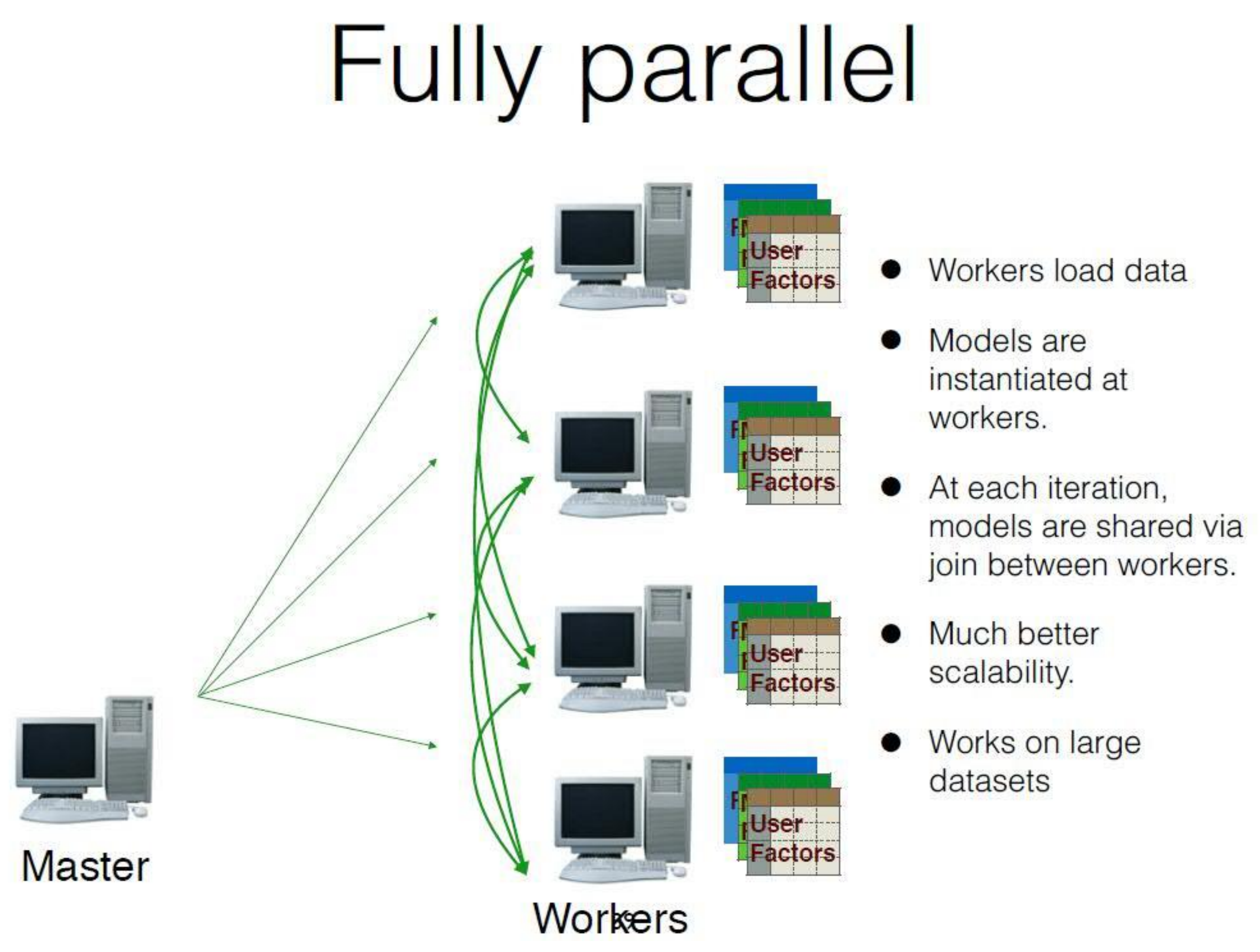
Data parallel



- Workers load data
- Master broadcasts initial models
- At each iteration, updated models are broadcast again
- Much better scaling
- Works on large datasets
- Works well for smaller models. (low K)

Xiangrui Meng, *MLLib: scalable machine learning on Spark*, Spark Workshop April 2014, http://stanford.edu/~rezab/sparkworkshop/

Example: Alternating Least Squares (ALS)



Fully parallel

- Workers load data
- Models are instantiated at workers.
- At each iteration, models are shared via join between workers.
- Much better scalability.
- Works on large datasets

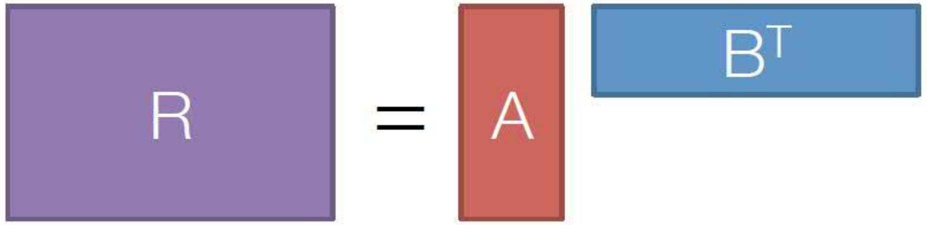
Xiangrui Meng, *MLLib: scalable machine learning on Spark*, Spark Workshop April 2014, http://stanford.edu/~rezab/sparkworkshop/

Implementation of ALS in Spark MLLib

ALS on Spark

Matei Zaharia,
Joey Gonzales,
Virginia Smith

- ~~broadcast everything~~
- ~~data parallel~~
- ~~fully parallel~~
- block-wise parallel



Cache 2 copies of R in memory, one partitioned by rows and one by columns

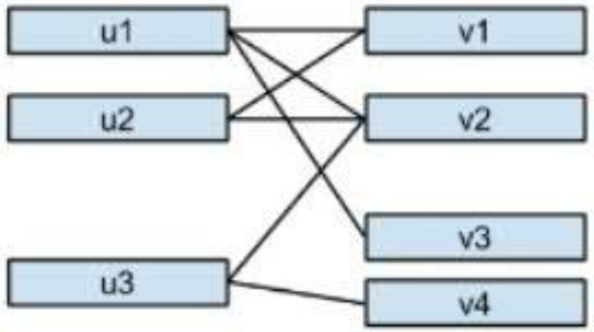
Keep A & B partitioned in corresponding way

Operate on blocks to lower communication

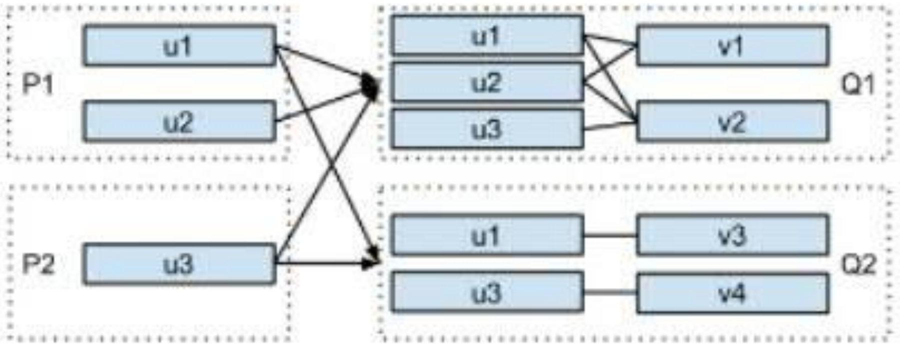
Xiangrui Meng, *MLLib: scalable machine learning on Spark*, Spark Workshop April 2014, http://stanford.edu/~rezab/sparkworkshop/
Reza Zadeh, CME 323: Distributed Algorithms and Optimization, Stanford University, http://stanford.edu/~rezab/dao/

Implementation of ALS in Spark MLLib

Communication: All-to-All vs. Communication: Block-to-Block



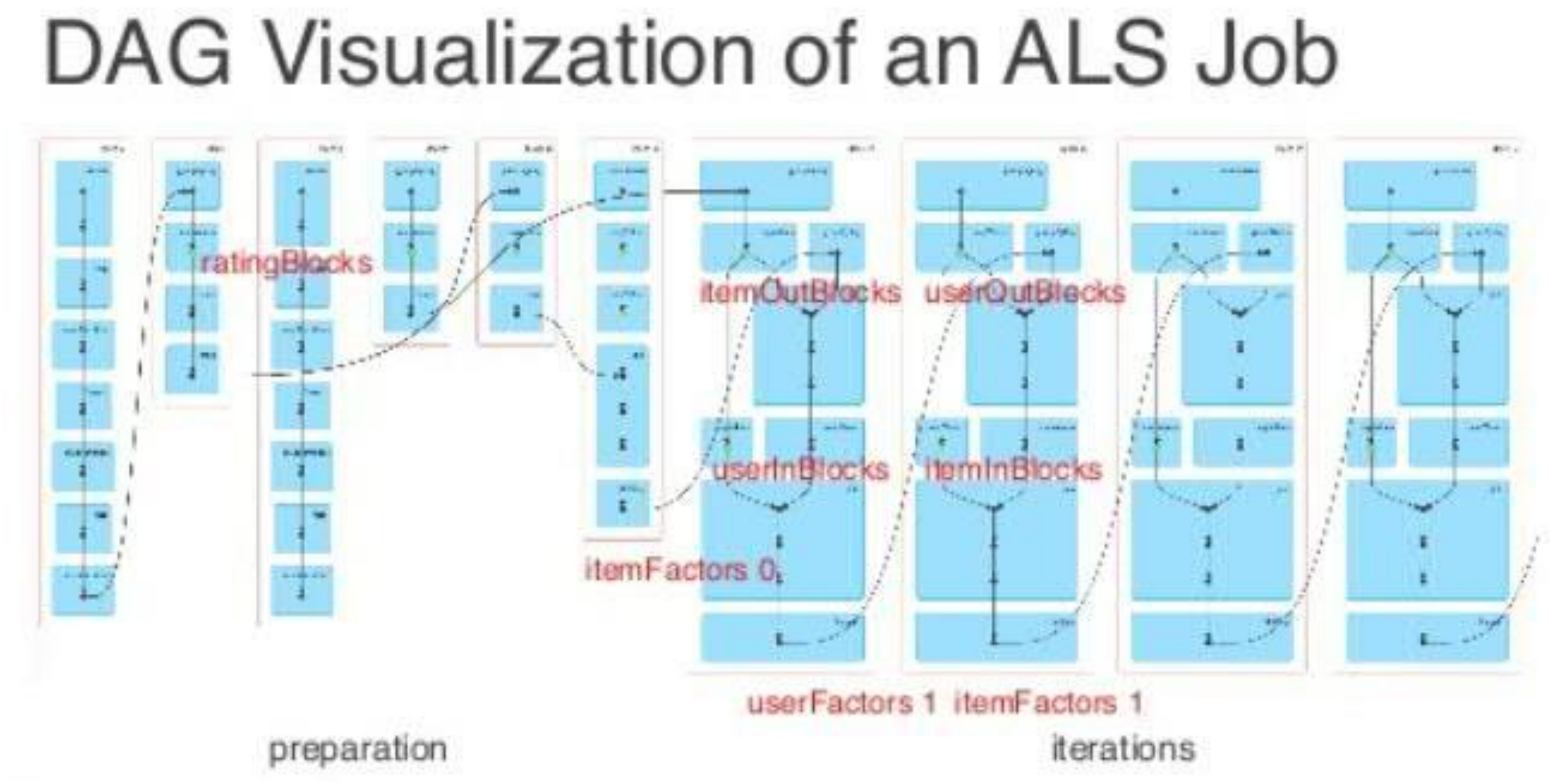
- users: u1, u2, u3; items: v1, v2, v3, v4
- shuffle size: O(nnz k) (nnz: number of nonzeros, i.e., rating
- sending the same factor multiple times



- Shuffle size is significantly reduced.
- We cache two copies of ratings — InBlocks for users and InBlocks for items.

Xiangrui Meng, "A more scalable way of making recommendations with MLLib", Spark Summit 2015, http://www.slideshare.net/SparkSummit/a-more-scaleable-way-of-making-recommendations-with-mllib-xiangrui-meng

Implementation of ALS in Spark MLLib



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References

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