- Performance / Scalability?
- Simple development environment?
- Integration with other data processing components?

LIBLINEAR?

Vowpal Wabbit?

scikit-learn?

Mahout?

Matlab?

Weka?
MLlib

+ Simple development environment (Spark)
+ Scalable and fast
+ Part of Apache Spark Ecosystem

SparkSQL  Spark  Streaming  MLlib (machine learning)  GraphX (graph)

Apache Spark
Overview
Examples
Roadmap
MLbase and MLlib

MLbase Goal: Simplify development and deployment of ML pipelines

- **MLOpt**: Autotuners for ML pipelines
- **MLI**: Experimental API to simplify ML development
- **MLlib**: Spark’s core ML library
MLbase and MLlib

**MLbase Goal:**
Simplify development and deployment of ML pipelines

---

**MLOpt**
Autotuners for ML pipelines

**MLI**
Experimental API to simplify ML development

**MLlib**
Spark's core ML library

---

MLOpt and MLI are experimental testbed
See video of Evan Spark's talk from Day 2 of Spark Summit
Active Development

Initial Release

• Developed by AMPLab (11 contributors)
• Shipped with Spark v0.8 (Sep 2013)
Active Development

Initial Release
- Developed by AMPLab (11 contributors)
- Shipped with Spark v0.8 (Sep 2013)

Current Version
- 48 contributors from various organizations
- Shipped with Spark v1.0 (May 2014)
Algorithms in v0.8

• **classification**: logistic regression, linear support vector machines (SVM)

• **regression**: linear regression

• **collaborative filtering**: alternating least squares (ALS)

• **clustering**: k-means

• **optimization**: stochastic gradient descent (SGD)
Algorithms in v1.0

• **classification**: logistic regression, linear support vector machines (SVM), naive Bayes, decision trees

• **regression**: linear regression, regression trees

• **collaborative filtering**: alternating least squares (ALS)

• **clustering**: k-means

• **optimization**: stochastic gradient descent (SGD), limited-memory BFGS (L-BFGS)

• **dimensionality reduction**: singular value decomposition (SVD), principal component analysis (PCA)
Distributed Decision Trees

- Interpretable, supports categorical variables / missing data, ensembles are top performers
- Classification and regression
- Scales to massive datasets
- See video of Manish Amde’s talk from Day 1 of Spark Summit
What else is new in v1.0?

• Improved user guide
• Code examples / templates
• API stability
• Sparse data support
• Distributed matrices
• Binary classification model evaluation
User guide: Improved Organization

Machine Learning Library (MLlib)

MLlib is a Spark implementation of some common machine learning algorithms and utilities, including classification, regression, clustering, collaborative filtering, dimensionality reduction, as well as underlying optimization primitives:

- **Basics**
  - data types
  - summary statistics
- **Classification and regression**
  - linear support vector machine (SVM)
  - logistic regression
  - linear least squares, Lasso, and ridge regression
  - decision tree
  - naive Bayes
- **Collaborative filtering**
  - alternating least squares (ALS)
- **Clustering**
  - k-means
- **Dimensionality reduction**
  - singular value decomposition (SVD)
  - principal component analysis (PCA)
- **Optimization**
  - stochastic gradient descent
  - limited-memory BFGS (L-BFGS)
**User guide: Improved Organization**

**Scala**  **Java**  **Python**

**NaiveBayes** implements multinomial naive Bayes. It takes an RDD of **LabeledPoint** and an optionally smoothing parameter `lambda` as input, and output a **NaiveBayesModel**, which can be used for evaluation and prediction.

```python
from pyspark.mllib.regression import LabeledPoint
from pyspark.mllib.classification import NaiveBayes

# an RDD of LabeledPoint
data = sc.parallelize([  
    LabeledPoint(0.0, [0.0, 0.0])  
    ... # more labeled points
])

# Train a naive Bayes model.
model = NaiveBayes.train(data, 1.0)

# Make prediction.
prediction = model.predict([0.0, 0.0])
```
Code examples

Useful as templates for standalone applications
Code examples

Useful as templates for standalone applications

MovieLensALS: an example app for ALS on MovieLens data.
Usage: MovieLensALS [options] <input>

--rank <value>
  rank, default: 10
--numIterations <value>
  number of iterations, default: 20
--lambda <value>
  lambda (smoothing constant), default: 1.0
--kryo
  use Kryo serialization
--implicitPrefs
  use implicit preference
<input>
  input paths to a MovieLens dataset of ratings
Code examples

Useful as templates for standalone applications

In “examples/” folder with sample datasets
- binary classification (SVM and logistic regression)
- decision tree
- naive Bayes
- k-means
- linear regression
- tall-and-skinny PCA and SVD
- collaborative filtering
API Stability

• Following Spark core, MLlib is guaranteeing binary compatibility for all 1.x releases on stable APIs

• For changes in experimental and developer APIs, we will provide migration guide between releases

• Unified API docs for various Spark components
Exploiting Sparsity

Sparse data is prevalent

- Text processing: bag-of-words, n-grams
- Collaborative Filtering: ratings matrix
- Graphs: adjacency matrix
- Genomics: SNPs, variant calling
Exploiting Sparsity

Sparse data is prevalent
- Text processing: bag-of-words, n-grams
- Collaborative Filtering: ratings matrix
- Graphs: adjacency matrix
- Genomics: SNPs, variant calling

MLlib supports sparse storage and computation
- classification
- k-means
- summary statistics

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<td>values</td>
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Exploiting Sparsity

Sparse data is prevalent

- Text processing: bag-of-words, n-grams
- Collaborative Filtering: ratings matrix
- Graphs: adjacency matrix
- Genomics: SNPs, variant calling

MLlib supports sparse storage and computation

- classification
- k-means
- summary statistics

See video of Xiangrui Meng’s talk from Day 1 of Spark Summit
Exploiting sparsity in k-means

Training set:

- 12 million examples
- 500 features
- sparsity: 10%

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40GB savings in storage, 4x speedup in computation
Overview
Examples
Roadmap
K-means clustering: Partition observations into k clusters
K-means clustering: Partition observations into k clusters
K-means clustering: Partition observations into k clusters

Compute/initialize cluster centers
K-means clustering: Partition observations into k clusters

Compute/initialize cluster centers

Assign cluster membership
K-means clustering: Partition observations into k clusters

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Compute/initialize cluster centers

Assign cluster membership
K-means clustering: Partition observations into k clusters

Compute/initialize cluster centers

Assign cluster membership
K-means (scala)

// Load and parse the data.
val data = sc.textFile("kmeans_data.txt")
val parsedData = data.map(_.split(' ')).map(_.toDouble)).cache()

// Cluster the data into five classes using KMeans.
val clusters = KMeans.train(parsedData, 5, numIterations = 20)

// Compute the sum of squared errors.
val cost = clusters.computeCost(parsedData)
println("Sum of squared errors = " + cost)
K-means (python)

# Load and parse the data
data = sc.textFile("kmeans_data.txt")
parsedData = data.map(lambda line:
    array([[float(x) for x in line.split(' ')]]).cache()
)

# Build the model (cluster the data)
clusters = KMeans.train(parsedData, 5, maxIterations = 20,
    runs = 1, initialization_mode = "kmeans||")

# Evaluate clustering by computing the sum of squared errors
def error(point):
    center = clusters.centers[clusters.predict(point)]
    return sqrt(sum([x**2 for x in (point - center)]))

cost = parsedData.map(lambda point: error(point)).reduce(lambda x, y: x + y)
print("Sum of squared error = " + str(cost))
Dimensionality reduction + K-means

// compute principal components
val points: RDD[Vector] = ...
val mat = RowMatrix(points)
val pc = mat.computePrincipalComponents(20)

// project points to a low-dimensional space
val projected = mat.multiply(pc).rows

// train a k-means model on the projected data
val model = KMeans.train(projected, 10)
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()
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)

See video of Aaron Davidson’s talk at last month’s Hadoop Summit for extended demo:
http://youtu.be/sPhyePwo7FA
Collaborative Filtering

**Goal**: Recover a matrix from a subset of its entries

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Collaborative Filtering

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**Goal**: Recover a matrix from a subset of its entries
Reducing Degrees of Freedom

- **Problem**: Impossible without additional information
- $mn$ degrees of freedom
Reducing Degrees of Freedom

- **Problem**: Impossible without additional information
  - $mn$ degrees of freedom

- **Solution**: Assume small # of factors determine preference

\[ m n = \text{‘Low-rank’} \]
Reducing Degrees of Freedom

- **Problem**: Impossible without additional information
  - \( mn \) degrees of freedom

- **Solution**: Assume small \# of factors determine preference
  - \( O(m + n) \) degrees of freedom
  - Linear storage costs

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\end{array}
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\end{array}
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\[
\text{‘Low-rank’}
\]
Alternating Least Squares
Alternating Least Squares
Alternating Least Squares
Alternating Least Squares
Alternating Least Squares

Training error for first user = (● - □□□□) + (● - □□□□□□)

28
Alternating Least Squares

Training error for first user = ( \[ \text{user factor} \times \text{movie factor} \] ) + ( \[ \text{user factor} \times \text{movie factor} \] )

ALS: alternate between updating user and movie factors
Alternating Least Squares

Training error for first user = \((\text{red} - \text{light blue}) + (\text{red} - \text{light yellow})\)

ALS: alternate between updating user and movie factors

Update 1st user: find \(\text{light yellow}\) that minimizes training error (reduces to standard linear regression problem)
Alternating Least Squares

Training error for first user = ( \color{red}{-} - \color{green}{\Box} ) + ( \color{blue}{-} - \color{orange}{\Box} )

ALS: alternate between updating user and movie factors

Update 1st user: find \color{orange}{\Box} that minimizes training error (reduces to standard linear regression problem)

Can update all users in parallel!
Collaborative filtering

// Load and parse the data
val data = sc.textFile("mllib/data/als/test.data")
val ratings = data.map(_.split(',')) match {
  case Array(user, item, rate) =>
    Rating(user.toInt, item.toInt, rate.toDouble)
}

// Build the recommendation model using ALS
val numIterations = 20
val rank = 10
val regularizer = 0.01
val model = ALS.train(ratings, rank, numIterations, regularizer)

// Evaluate the model on rating data
val usersProducts = ratings.map { case Rating(user, product, rate) =>
  (user, product)
}
val predictions = model.predict(usersProducts)
Today’s Exercise

• Load 1M/10M ratings from MovieLens
• Specify YOUR ratings on examples
• Split examples into training/validation
• Fit a model (Python or Scala)
• Improve model via parameter tuning
• Get YOUR recommendations
Overview
Examples
Roadmap
Next release (v1.1)

Spark has 3-month release cycle

July 25: cut-off for new features
MLlib roadmap for v1.1

Standardize interfaces (MLbase/MLI)
Parallel model training for autotuning (MLbase/MLOpt)

Statistical toolbox
  • descriptive statistics, sampling, hypothesis testing

Learning algorithms
  • Non-negative matrix factorization, Sparse SVD, Multiclass decision tree, Random Forests?, …

Optimization algorithms
  • ADMM, Accelerated gradient methods
Beyond v1.1?

Scalable implementations of standard ML algorithms and optimization primitives

User-friendly documentation and consistent APIs

Support for machine learning pipeline development
  • Autotuning (MLbase/MLOpt), feature extractors, code examples
Beyond v1.1?

Scalable implementations of standard ML algorithms and optimization primitives

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Feedback and Contributions Encouraged!
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Thank You!