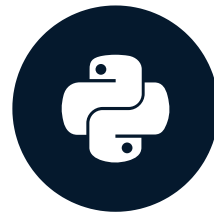


# Introduction to the MovieLens dataset

BUILDING RECOMMENDATION ENGINES WITH PYSPARK



**Jamen Long**

Data Scientist at Nike

# MovieLens dataset

F. Maxwell Harper and Joseph A. Konstan. 2015

The MovieLens Datasets: History and Context.

ACM Transactions on Interactive Intelligent Systems (TiiS) 5, 4, Article 19 (December 2015), 19

Pages. DOI=<http://dx.doi.org/10.1145/2827872>

# MovieLens summary stats

F. Maxwell Harper and Joseph A. Konstan. 2015

The MovieLens Datasets: History and Context.

ACM Transactions on Interactive Intelligent Systems (TiiS) 5, 4, Article 19 (December 2015), 19

Pages. DOI=<http://dx.doi.org/10.1145/2827872>

**Ratings:** 20,000,000+

**Users:** 138,493

**Movies:** 27,278

# Explore the data

```
df.show()  
df.columns()
```

# MovieLens sparsity

$$\textit{Sparsity} = \frac{\textit{Number of Ratings in Matrix}}{(\textit{Number of Users}) \times (\textit{Number of Movies})}$$

# Sparsity: numerator

```
# Number of ratings in matrix  
numerator = ratings.count()
```

# Sparsity: users and movies

```
# Distinct users and movies
users = ratings.select("userId").distinct().count()
movies = ratings.select("movieId").distinct().count()
```

# Sparsity: denominator

```
# Number of ratings in matrix
numerator = ratings.count()

# Distinct users and movies
users = ratings.select("userId").distinct().count()
movies = ratings.select("movieId").distinct().count()
# Number of ratings matrix could contain if no empty cells
denominator = users * movies
```



# Sparsity

```
# Number of ratings in matrix
numerator = ratings.count()

# Distinct users and movies
users = ratings.select("userId").distinct().count()
movies = ratings.select("movieId").distinct().count()

# Number of ratings matrix could contain if no empty cells
denominator = users * movies

#Calculating sparsity
sparsity = 1 - (numerator*1.0 / denominator)
print ("Sparsity: "), sparsity
```

Sparsity: .998

# The `.distinct()` method

```
ratings.select("userId").distinct().count()
```

```
671
```

# GroupBy method

```
# Group by userId  
ratings.groupBy("userId")
```

# GroupBy method

```
# Num of song plays by userId  
ratings.groupBy("userId").count().show()
```

```
+-----+-----+  
|userId|count|  
+-----+-----+  
|   148|   76|  
|   243|   12|  
|    31|  232|  
|   137|   16|  
|   251|   19|  
|    85|  752|  
|    65|  737|
```

# GroupBy method min

```
from pyspark.sql.functions import min, max, avg

# Min num of song plays by userId
msd.groupBy("userId").count()
    .select(min("count")).show()
```

```
+-----+
|min(count)|
+-----+
|          1|
+-----+
```

# GroupBy method max

```
# Max num of song plays by userId
ratings.groupBy("userId").count()
        .select(max("count")).show()
```

```
+-----+
|max(count)|
+-----+
|      1162|
+-----+
```

# GroupBy method avg

```
# Avg num of song plays by userId
ratings.groupBy("userId").count()
        .select(avg("count")).show()
```

```
+-----+
|avg(count)|
+-----+
| 233.34579|
+-----+
```

# Filter method

```
# Removes users with less than 20 ratings
ratings.groupBy("userId").count().filter(col("count") >= 20).show()
```

```
+-----+-----+
|userId|count|
+-----+-----+
|    148|    76|
|     31|   232|
|     85|   752|
|     65|   737|
|     53|   190|
|    133|   302|
|    296|    74|
```

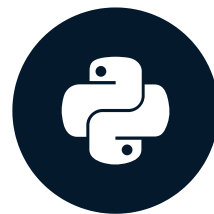


# Let's practice!

BUILDING RECOMMENDATION ENGINES WITH PYSPARK

# ALS model buildout on MovieLens Data

BUILDING RECOMMENDATION ENGINES WITH PYSPARK



**Jamen Long**

Data Scientist at Nike

# Fitting a basic model

```
# Split data
(training_data, test_data) = movie_ratings.randomSplit([0.8, 0.2])

# Build ALS model
from pyspark.ml.recommendation import ALS

als = ALS(userCol="userId", itemCol="movieId", ratingCol="rating",
          rank=25, maxIter=100, regParam=.05, nonnegative=True,
          coldStartStrategy="drop", implicitPrefs=False)

# Fit model to training data
model = als.fit(training_data)

# Generate predictions on test_data
predictions = model.transform(test_data)

# Tell Spark how to evaluate predictions
evaluator = RegressionEvaluator(metricName="rmse", labelCol="rating",
                               predictionCol="prediction")

# Obtain and print RMSE
rmse = evaluator.evaluate(predictions)
print ("RMSE: "), rmse
```

RMSE: 1.45

# Intro to ParamGridBuilder and CrossValidator

```
ParamGridBuilder()
```

```
CrossValidator()
```

# ParamGridBuilder

```
# Imports ParamGridBuilder package
from pyspark.ml.tuning import ParamGridBuilder
# Creates a ParamGridBuilder
param_grid = ParamGridBuilder()
```

# Adding Hyperparameters to the ParamGridBuilder

```
# Imports ParamGridBuilder package
from pyspark.ml.tuning import ParamGridBuilder

# Creates a ParamGridBuilder, and adds hyperparameters
param_grid = ParamGridBuilder()
    .addGrid(als.rank, [])
    .addGrid(als.maxIter, [])
    .addGrid(als.regParam, [])
```

# Adding Hyperparameter Values to the ParamGridBuilder

```
# Imports ParamGridBuilder package
from pyspark.ml.tuning import ParamGridBuilder

# Creates a ParamGridBuilder, and adds hyperparameters and values
param_grid = ParamGridBuilder()
    .addGrid(als.rank, [5, 40, 80, 120])
    .addGrid(als.maxIter, [5, 100, 250, 500])
    .addGrid(als.regParam, [.05, .1, 1.5])
    .build()
```

# CrossValidator

```
# Imports CrossValidator package
from pyspark.ml.tuning import CrossValidator

# Creates cross validator and tells Spark what to use when training # and evaluating
cv = CrossValidator(estimator = als,
                    estimatorParamMaps = param_grid,
                    evaluator = evaluator,
                    numFolds = 5)
```



# CrossValidator instantiation and estimator

```
# Imports CrossValidator package
from pyspark.ml.tuning import CrossValidator

# Instantiates a cross validator
cv = CrossValidator()
```

# CrossValidator ParamMaps

```
# Imports CrossValidator package
from pyspark.ml.tuning import CrossValidator

# Tells Spark what to use when training a model
cv = CrossValidator(estimator = als,
                    estimatorParamMaps = param_grid,
                    )
```

# CrossValidator

```
# Imports CrossValidator package
from pyspark.ml.tuning import CrossValidator

# Tells Spark what alg, hyperparameter values, how to evaluate
# each model and number of folds to use during training
cv = CrossValidator(estimator = als,
                    estimatorParamMaps = param_grid,
                    evaluator = evaluator,
                    numFolds = 5)
```

# Random split

```
# Create training and test set (80/20 split)
(training, test) = movie_ratings.randomSplit([0.8, 0.2])

# Build generic ALS model without hyperparameters
als = ALS(userCol="userId", itemCol="movieId", ratingCol="rating",
          coldStartStrategy="drop", nonnegative = True,
          implicitPrefs = False)
```

# ParamGridBuilder

```
# Create training and test set (80/20 split)
(training, test) = movie_ratings.randomSplit([0.8, 0.2])

# Build generic ALS model without hyperparameters
als = ALS(userCol="userId", itemCol="movieId", ratingCol="rating",
          coldStartStrategy="drop", nonnegative = True,
          implicitPrefs = False)

# Tell Spark what values to try for each hyperparameter
from pyspark.ml.tuning import ParamGridBuilder
param_grid = ParamGridBuilder()
    .addGrid(als.rank, [5, 40, 80, 120])
    .addGrid(als.maxIter, [5, 100, 250, 500])
    .addGrid(als.regParam, [.05, .1, 1.5])
    .build()
```

# Evaluator

```
# Create training and test set (80/20 split)
(training, test) = movie_ratings.randomSplit([0.8, 0.2])

# Build generic ALS model without hyperparameters
als = ALS(userCol="userId", itemCol="movieId", ratingCol="rating",
          coldStartStrategy="drop", nonnegative = True,
          implicitPrefs = False)

# Tell Spark what values to try for each hyperparameter
from pyspark.ml.tuning import ParamGridBuilder
param_grid = ParamGridBuilder()
    .addGrid(als.rank, [5, 40, 80, 120])
    .addGrid(als.maxIter, [5, 100, 250, 500])
    .addGrid(als.regParam, [.05, .1, 1.5])
    .build()

# Tell Spark how to evaluate model performance
evaluator = RegressionEvaluator(metricName="rmse", labelCol="rating",
                                predictionCol="prediction")
```

# CrossValidator

```
# Build generic ALS model without hyperparameters
als = ALS(userCol="userId", itemCol="movieId", ratingCol="rating",
          coldStartStrategy="drop", nonnegative = True,
          implicitPrefs = False)

# Tell Spark what values to try for each hyperparameter
from pyspark.ml.tuning import ParamGridBuilder
param_grid = ParamGridBuilder()
    .addGrid(als.rank, [5, 40, 80, 120])
    .addGrid(als.maxIter, [5, 100, 250, 500])
    .addGrid(als.regParam, [.05, .1, 1.5])
    .build()

# Tell Spark how to evaluate model performance
evaluator = RegressionEvaluator(metricName="rmse", labelCol="rating",
                               predictionCol="prediction")

# Build cross validation step using CrossValidator
from pyspark.ml.tuning import CrossValidator
cv = CrossValidator(estimator = als,
                    estimatorParamMaps = param_grid,
                    evaluator = evaluator,
                    numFolds = 5)
```

# Best model

```
# Tell Spark what values to try for each hyperparameter
from pyspark.ml.tuning import ParamGridBuilder
param_grid = ParamGridBuilder()
    .addGrid(als.rank, [5, 40, 80, 120])
    .addGrid(als.maxIter, [5, 100, 250, 500])
    .addGrid(als.regParam, [.05, .1, 1.5])
    .build()

# Tell Spark how to evaluate model performance
evaluator = RegressionEvaluator(metricName="rmse", labelCol="rating",
    predictionCol="prediction")

# Build cross validation step using CrossValidator
from pyspark.ml.tuning import CrossValidator
cv = CrossValidator(estimator = als,
    estimatorParamMaps = param_grid,
    evaluator = evaluator,
    numFolds = 5)

# Run the cv on the training data
model = cv.fit(training)

# Extract best combination of values from cross validation
best_model = model.bestModel
```



# Predictions and performance evaluation

```
# Extract best combination of values from cross validation
best_model = model.bestModel

# Generate test set predictions and evaluate using RMSE
predictions = best_model.transform(test)
rmse = evaluator.evaluate(predictions)

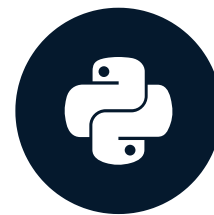
# Print evaluation metrics and model parameters
print ("**Best Model**")
print ("RMSE = "), rmse
print ("  Rank: "), best_model.rank
print ("  MaxIter: "), best_model._java_obj.parent().getMaxIter()
print ("  RegParam: "), best_model._java_obj.parent().getRegParam()
```

# Let's practice!

BUILDING RECOMMENDATION ENGINES WITH PYSPARK

# Model Performance Evaluation and Output Cleanup

BUILDING RECOMMENDATION ENGINES WITH PYSPARK



**Jamen Long**  
Data Scientist at Nike

# Root mean squared error

$$\text{RMSE} = \sqrt{\frac{\sum (y_{\text{pred}} - y_{\text{actual}})^2}{N}}$$

# Pred vs actual

```
+-----+-----+
|pred|actual|
+-----+-----+
|    5|    4.5|
|    3|    3.5|
|    4|     4|
|    2|     1|
+-----+-----+
```

# Pred vs actual: difference

```
+-----+-----+-----+
|pred|actual|diff|
+-----+-----+-----+
|  5 |   4.5 | 0.5 |
|  3 |   3.5 |-0.5 |
|  4 |    4 | 0.0 |
|  2 |    1 | 1.0 |
+-----+-----+-----+
```

# Difference squared

```
+-----+-----+-----+-----+
|pred|actual|diff|diff_sq|
+-----+-----+-----+-----+
|  5 |  4.5 | 0.5 |  0.25 |
|  3 |  3.5 |-0.5 |  0.25 |
|  4 |    4 | 0.0 |  0.00 |
|  2 |    1 | 1.0 |  1.00 |
+-----+-----+-----+-----+
```

# Sum of difference squared

```
+-----+-----+-----+-----+
|pred|actual|diff|diff_sq|
+-----+-----+-----+-----+
|  5 |   4.5 | 0.5 |   0.25 |
|  3 |   3.5 |-0.5 |   0.25 |
|  4 |    4 | 0.0 |   0.00 |
|  2 |    1 | 1.0 |   1.00 |
+-----+-----+-----+-----+
```

```
sum of diff_sq = 1.5
```



# Average of difference squared

```
+-----+-----+-----+-----+
|pred|actual|diff|diff_sq|
+-----+-----+-----+-----+
|  5 |   4.5 | 0.5 |   0.25 |
|  3 |   3.5 |-0.5 |   0.25 |
|  4 |    4 | 0.0 |   0.00 |
|  2 |    1 | 1.0 |   1.00 |
+-----+-----+-----+-----+
```

sum of diff\_sq = 1.5

avg of diff\_sq = 1.5 / 4 = 0.375

# RMSE

```
+-----+-----+-----+-----+
|pred|actual|diff|diff_sq|
+-----+-----+-----+-----+
|  5 |   4.5 | 0.5 |   0.25 |
|  3 |   3.5 |-0.5 |   0.25 |
|  4 |    4 | 0.0 |   0.00 |
|  2 |    1 | 1.0 |   1.00 |
+-----+-----+-----+-----+
```

sum of diff\_sq = 1.5

avg of diff\_sq = 1.5 / 4 = 0.375

RMSE = sq root of avg of diff\_sq = 0.61

# Recommend for all users

```
# Generate top n recommendations for all users  
recommendForAllUsers(n) # n is an integer
```

# Unclean recommendation output

```
ALS_recommendations.show()
```

```
+-----+-----+
|userId| recommendations|
+-----+-----+
|  360|[[65037, 4.491346]...|
|  246|[[3414, 4.8967672]...|
|  346|[[4565, 4.9247236]...|
|  476|[[83318,4.9556283]...|
|  367|[[4632, 4.7018986]...|
|  539|[[1172, 5.2528191]...|
|  599|[[6413, 4.7284415]...|
|  220|[[80, 4.4857406]...|
```

# Cleaning up recommendation output

```
ALS_recommendations.registerTempTable("ALS_recs_temp")

clean_recs = spark.sql("SELECT userId,
                        movieIds_and_ratings.movieId AS movieId,
                        movieIds_and_ratings.rating AS prediction
                        FROM ALS_recs_temp
                        LATERAL VIEW explode(recommendations) exploded_table
                        AS movieIds_and_ratings")
```

# Explode function

```
exploded_recs = spark.sql("SELECT uderId,  
                                explode(recommendations) AS MovieRec  
                                FROM ALS_recs_temp")  
  
exploded_recs.show()
```

```
+-----+-----+  
|userId|                                MovieRec|  
+-----+-----+  
|   360|{"movieId": 65037, "rating": 4.4913464}|  
|   360|{"movieId": 59684, "rating": 4.4832921}|  
|   360|{"movieId": 31435, "rating": 4.4822811}|  
|   360|{"movieId": 593, "rating": 4.456215}|  
|   360|{"movieId": 67504, "rating": 4.4028492}|  
|   360|{"movieId": 83411, "rating": 4.3391834}|
```

# Adding lateral view

```
ALS_recommendations.registerTempTable("ALS_recs_temp")

clean_recs = spark.sql("SELECT userId,
                        movieIds_and_ratings.movieId AS movieId,
                        movieIds_and_ratings.rating AS prediction
                        FROM ALS_recs_temp
                        LATERAL VIEW explode(recommendations) exploded_table
                        AS movieIds_and_ratings")
```

# Explode and lateral view together

```
ALS_recommendations.registerTempTable("ALS_recs_temp")

clean_recs = spark.sql("SELECT userId,
                        movieIds_and_ratings.movieId AS movieId,
                        movieIds_and_ratings.rating AS prediction
                        FROM ALS_recs_temp
                        LATERAL VIEW explode(recommendations) exploded_table
                        AS movieIds_and_ratings")

clean_recs.show()
```

```
+-----+-----+
|userId|movieId|prediction|
+-----+-----+
|  360|  65037|  4.491346|
|  360|  59684|  4.491346|
|  360|  34135|  4.491346|
|  360|    593|  4.453185|
|  360|  67504|  4.389951|
|  360|  83411|  4.389944|
```



```
clean_recs.join(movie_info, ["movieId"], "left").show()
```

```
+-----+-----+-----+
|userId|movieId|prediction|          title|
+-----+-----+-----+
|   360|  65037|  4.491346|    Ben X (2007)|
|   360|  59684|  4.491346| Lake of Fire (2006)|
|   360|  34135|  4.491346|Rory O Shea Was H...|
|   360|    593|  4.453185|Silence of the La...|
|   360|  67504|  4.389951|Land of Silence a...|
|   360|  83411|  4.389944|        Cops (1922)|
|   360|  83318|  4.389938|    Goat, The (1921)|
|   360|  83359|  4.373281| Play House, The(...|
|   360|  76173|  4.190159| Micmacs (Micmacs...|
|   360|   5114|  4.116745|Red and the Beaut...
```

# Filtering recommendations

```
clean_recs.join(movie_ratings, ["userId", "movieId"], "left")
```

```
clean_recs.join(movie_ratings, ["userId", "movieId"], "left").show()
```

```
+-----+-----+-----+
|userId|movieId|prediction|rating|
+-----+-----+-----+
|   173|   318|  4.947126|  null|
|   150|   318|  4.066513|   5.0|
|   369|   318|  4.514297|   5.0|
|    27|   318|  4.523860|  null|
|    42|   318|  4.568357|   5.0|
|   662|   318|  4.242076|   5.0|
|   250|   318|  5.042126|   5.0|
|    94|   318|  4.291757|   5.0|
|   515|   318|  5.165822|  null|
|   100|   318|  4.885314|   5.0|
```

```
clean_recs.join(movie_ratings, ["userId", "movieId"], "left")
              .filter(movie_ratings.rating.isNull()).show()
```

```
+-----+-----+-----+
|userId|movieId|prediction|rating|
+-----+-----+-----+
|   173|    318|  4.947126|  null|
|    27|    318|  4.523860|  null|
|   515|    318|  5.165822|  null|
|   275|    318|  5.171431|  null|
|   503|    318|  4.308533|  null|
|   106|    318|  4.688634|  null|
|   249|    318|  4.759836|  null|
|   368|    318|  3.589334|  null|
|   581|    318|  4.717382|  null|
```

# Let's practice!

**BUILDING RECOMMENDATION ENGINES WITH PYSPARK**