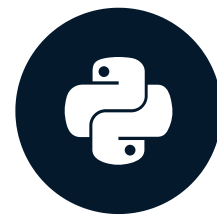


Introduction to the Million Songs Dataset

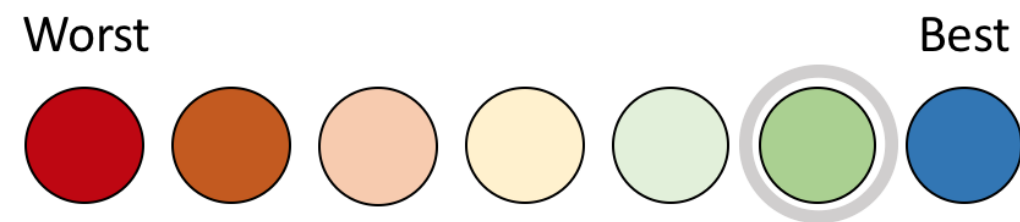
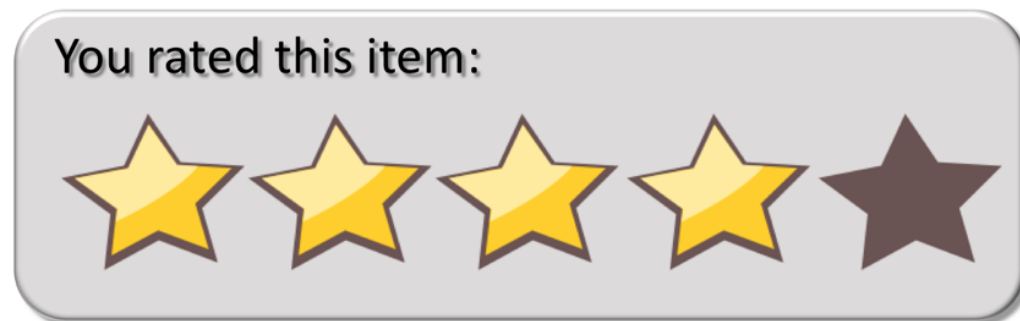
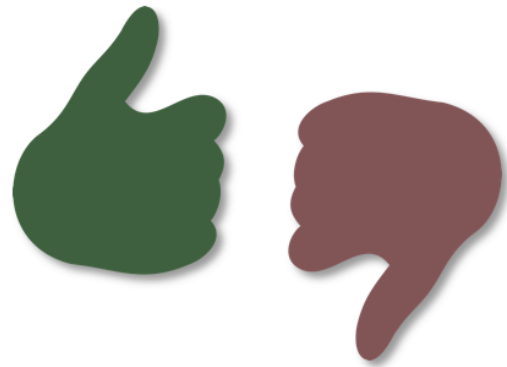
BUILDING RECOMMENDATION ENGINES WITH PYSPARK



Jamen Long
Data Scientist at Nike

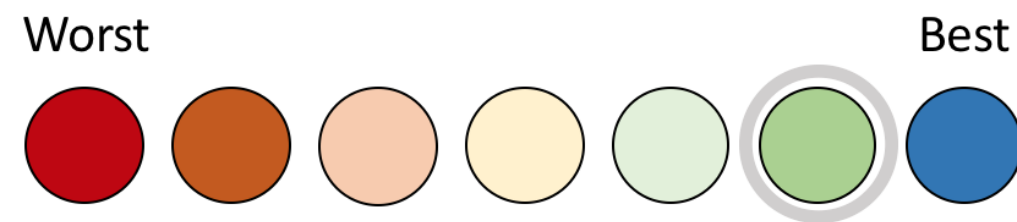
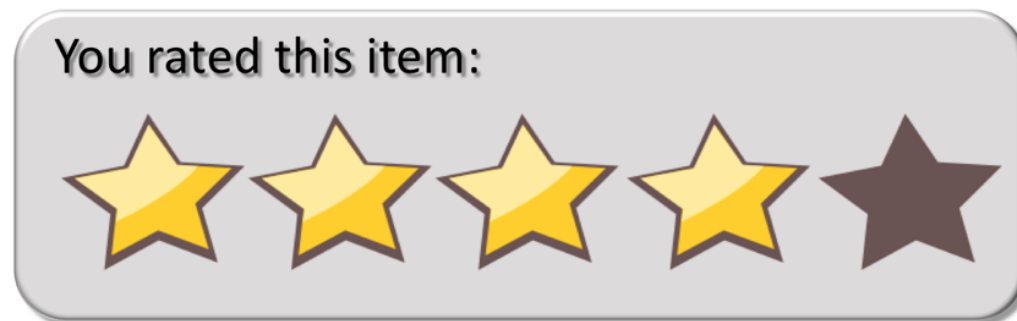
Explicit vs implicit

Explicit Ratings



Explicit vs implicit (cont.)

Explicit Ratings



Implicit Ratings



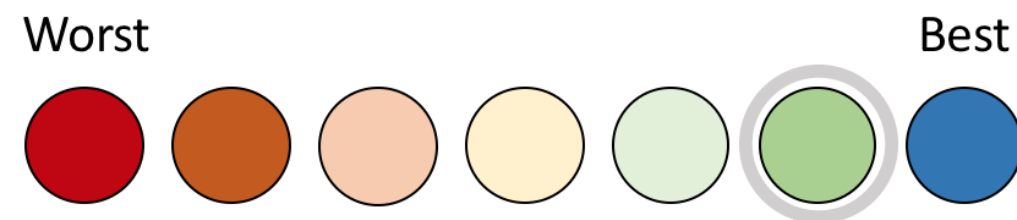
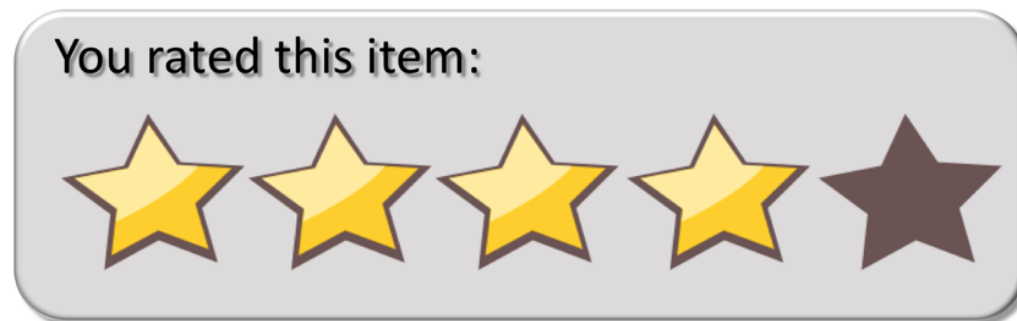
= Low Confidence Rating



= High Confidence Rating

Implicit refresher II

Explicit Ratings



Implicit Ratings



= Low Confidence Rating



= High Confidence Rating

Introduction to the Million Songs Dataset

Thierry Bertin-Mahieux, Daniel P.W. Ellis, Brian Whitman, and Paul Lamere. The Million Song Dataset. In Proceedings of the 12th International Society for Music Information Retrieval Conference (SIMIR 20122), 2011.

Add zeros sample

```
ratings.show()
```

```
+-----+-----+-----+
|userId|songId|num_plays|
+-----+-----+-----+
|    10|    22|        5|
|    38|    99|        1|
|    38|    77|        3|
|    42|    99|        1|
+-----+-----+-----+
```

Cross join intro

```
users = ratings.select("userId").distinct()  
users.show()
```

```
+-----+  
|userId|  
+-----+  
|    10|  
|    38|  
|    42|  
+-----+
```

```
songs = ratings.select("songId").distinct()  
songs.show()
```

```
+-----+  
|songId|  
+-----+  
|    22|  
|    77|  
|    99|  
+-----+
```

Cross join output

```
cross_join = users.crossJoin(songs)
cross_join.show()
```

```
+-----+-----+
|userId|songId|
+-----+-----+
|    10|    22|
|    10|    77|
|    10|    99|
|    38|    22|
|    38|    77|
|    38|    99|
|    42|    22|
|    42|    77|
|    42|    99|
+-----+-----+
```


Joining back original ratings data

```
cross_join = users.crossJoin(songs)
               .join(ratings, ["userId", "songId"], "left")
cross_join.show()
```

```
+-----+-----+-----+
|userId|songId|num_plays|
+-----+-----+-----+
|    10|    22|      5|
|    10|    77|    null|
|    10|    99|    null|
|    38|    22|    null|
|    38|    77|      3|
|    38|    99|      1|
|    42|    22|    null|
|    42|    77|    null|
|    42|    99|      1|
+-----+-----+-----+
```

Filling in with zero

```
cross_join = users.crossJoin(songs)
                .join(ratings, ["userId", "songId"], "left").fillna(0)
cross_join.show()
```

```
+-----+-----+-----+
|userId|songId|num_plays|
+-----+-----+-----+
|    10|    22|        5|
|    10|    77|        0|
|    10|    99|        0|
|    38|    22|        0|
|    38|    77|        3|
|    38|    99|        1|
|    42|    22|        0|
|    42|    77|        0|
|    42|    99|        1|
+-----+-----+-----+
```

Add zeros function

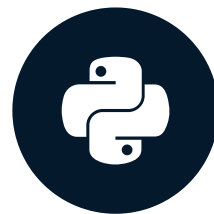
```
def add_zeros(df):  
    # Extracts distinct users  
    users = df.select("userId").distinct()  
  
    # Extracts distinct songs  
    songs = df.select("songId").distinct()  
  
    # Joins users and songs, fills blanks with 0  
    cross_join = users.crossJoin(songs) \  
        .join(df, ["userId", "songId"], "left").fillna(0)  
  
    return cross_join
```

Let's practice!

BUILDING RECOMMENDATION ENGINES WITH PYSPARK

Evaluating implicit ratings models

BUILDING RECOMMENDATION ENGINES WITH PYSPARK



Jamen Long

Data Scientist at Nike

Why RMSE worked before

userId	movieId	rating	explicit rating prediction
1	2112	5	4.88
1	303	3.5	3.96
2	5	3	2.78
2	77	2	2.89
3	913	1.5	2.11
3	44	4	3.56
3	6	4.5	4.67

Predictions reflect actual ratings.
RMSE makes sense here.

Why RMSE doesn't work now

userId	movieId	num_plays	implicit rating prediction
1	2112	16	1.755
1	303	3	.88
2	5	1	.01
2	77	2	.5
3	913	1	.08
3	44	21	1.98
3	6	4	.98

Different metrics.
RMSE doesn't make sense here.

(ROEM) Rank Ordering Error Metric

$$\text{ROEM} = \frac{\sum_{u,i} r_{u,i}^t \text{rank}_{u,i}}{\sum_{u,i} r_{u,i}^t}$$

ROEM bad predictions

```
bad_prediction.show()
```

```
+-----+-----+-----+-----+-----+
|userId |songId|plays|badPreds|percRank|
+-----+-----+-----+-----+-----+
|    111|    22|    3| 0.0001|    1.000|
|    111|     9|    0| 0.999|    0.000|
|    111|   321|    0| 0.08|    0.500|
|    222|    84|    0|0.000003|    1.000|
|    222|   821|    2| 0.88|    0.000|
|    222|    91|    2| 0.73|    0.500|
|    333|  2112|    0| 0.90|    0.000|
|    333|    42|    2| 0.80|    0.500|
|    333|     6|    0| 0.01|    1.000|
+-----+-----+-----+-----+-----+
```

ROEM: PercRank * plays

```
bp = bad_predictions.withColumn("np*rank", col("badPreds")*col("percRank"))
bp.show()
```

```
+-----+-----+-----+-----+-----+-----+
|userId |songId|num_plays|badPreds|percRank|np*rank|
+-----+-----+-----+-----+-----+-----+
|    111|    22|      3| 0.0001|  1.000|   3.00|
|    111|     9|      0| 0.999|  0.000|   0.00|
|    111|   321|      0|  0.08|  0.500|   0.00|
|    222|    84|      0|0.000003|  1.000|   0.00|
|    222|   821|      2|  0.88|  0.000|   0.00|
|    222|    91|      2|  0.73|  0.500|   1.00|
|    333|  2112|      0|  0.90|  0.000|   0.00|
|    333|    42|      2|  0.80|  0.500|   1.00|
|    333|     6|      0|  0.01|  1.000|   0.00|
+-----+-----+-----+-----+-----+-----+
```

ROEM: bad predictions

userId	songId	num_plays	badPreds	percRank	np*rank
111	22	3	0.0001	1.000	3.00
111	9	0	0.999	0.000	0.00
111	321	0	0.08	0.500	0.00
222	84	0	0.000003	1.000	0.00
222	821	2	0.88	0.000	0.00
222	91	2	0.73	0.500	1.00
333	2112	0	0.90	0.000	0.00
333	42	2	0.80	0.500	1.00
333	6	0	0.01	1.000	0.00

```
numerator = bp.groupBy().sum("np*rank").collect()[0][0]
denominator = bp.groupBy().sum("num_plays").collect()[0][0]
print ("ROEM: "), numerator * 1.0/ denominator
```

ROEM: 5.0 / 9 = 0.556

Good predictions

```
gp = good_predictions.withColumn("np*rank", col("goodPreds")*col("percRank"))
gp.show()
```

```
+-----+-----+-----+-----+-----+-----+
|userId |songId|num_plays|goodPreds|percRank|np*rank|
+-----+-----+-----+-----+-----+-----+
|   111|   22|      3|    1.1|  0.000|  0.000|
|   111|   77|      0|    0.01|  0.500|  0.000|
|   111|   99|      0|    0.008| 1.000|  0.000|
|   222|   22|      0| 0.0003| 1.000|  0.000|
|   222|   77|      2|    1.5|  0.000|  0.000|
|   222|   99|      2|    1.4|  0.500|  1.000|
|   333|   22|      0|    0.90|  0.500|  0.000|
|   333|   77|      2|    1.6|  0.000|  0.000|
|   333|   99|      0|    0.01| 1.000|  0.000|
+-----+-----+-----+-----+-----+-----+
```

ROEM: good predictions

userId	songId	num_plays	goodPreds	percRank	np*rank
111	22	3	1.1	0.000	0.000
111	77	0	0.01	0.500	0.000
111	99	0	0.008	1.000	0.000
222	22	0	0.0003	1.000	0.000
222	77	2	1.5	0.000	0.000
222	99	2	1.4	0.500	1.000
333	22	0	0.90	0.500	0.000
333	77	2	1.6	0.000	0.000
333	99	0	0.01	1.000	0.000

```
numerator = gp.groupBy().sum("np*rank").collect()[0][0]
denominator = gp.groupBy().sum("num_plays").collect()[0][0]
print ("ROEM: "), numerator * 1.0/ denominator
```

```
ROEM: 1.0 / 9 = 0.1111
```

ROEM: link to function on GitHub

userId	songId	num_plays	goodPreds	percRank	np*rank
111	22	3	1.1	0.000	0.000
111	77	0	0.01	0.500	0.000
111	99	0	0.008	1.000	0.000
222	22	0	0.0003	1.000	0.000
222	77	2	1.5	0.000	0.000
222	99	2	1.4	0.500	1.000
333	22	0	0.90	0.500	0.000
333	77	2	1.6	0.000	0.000
333	99	0	0.01	1.000	0.000

```
numerator = gp.groupBy().sum("np*rank").collect()[0][0]
denominator = gp.groupBy().sum("num_plays").collect()[0][0]
print ("ROEM: "), numerator * 1.0/ denominator
```

```
ROEM: 1.0 / 9 = 0.1111
```

Building several ROEM models

```
(train, test) = implicit_ratings.randomSplit([.8, .2])
# Empty list to be filled with models
model_list = []

# Complete each of the hyperparameter value lists
ranks = [10, 20, 30, 40]
maxIter = [10, 20, 30, 40]
regParams = [.05, .1, .15]
alphas = [20, 40, 60, 80]

# For loop will automatically create and store ALS models
for r in ranks:
    for mi in maxIter:
        for rp in regParams:
            for a in alphas:
                model_list.append(ALS(userCol= "userId", itemCol= "songId",
                                     ratingCol= "num_plays", rank = r, maxIter = mi, regParam = rp,
                                     alpha = a, coldStartStrategy="drop", nonnegative = True,
                                     implicitPrefs = True))
```

Error output

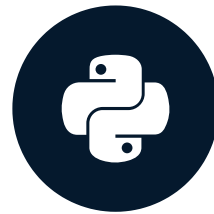
```
for model in model_list:  
    # Fits each model to the training data  
    trained_model = model.fit(train)  
  
    # Generates test predictions  
    predictions = trained_model.transform(test)  
  
    # Evaluates each model's performance  
    ROEM(predictions)
```


Let's practice!

BUILDING RECOMMENDATION ENGINES WITH PYSPARK

Overview of binary, implicit ratings

BUILDING RECOMMENDATION ENGINES WITH PYSPARK



Jamen Long

Data Scientist at Nike

Binary ratings

```
binary_movie_ratings.show()
```

```
+-----+-----+-----+
|userId|movieId|binary_rating|
+-----+-----+-----+
|    26|    474|           0|
|    26|   2529|           1|
|    26|     26|           0|
|    26|   1950|           0|
|    26|   4823|           1|
|    26|  72011|           1|
|    26| 142507|           0|
|    38|   1325|           0|
|    38|   6011|           1|
+-----+-----+-----+
```

Class imbalance

```
getSparsity(binary_ratings)
```

```
Sparsity: .993
```

Item weighting

- **Item Weighting:** Movies with more user views = higher weight

Item weighting and user weighting

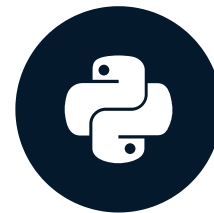
- **Item Weighting:** Movies with more user views = higher weight
- **User Weighting:** Users that have seen more movies will have lower weights applied to unseen movies

Let's practice!

BUILDING RECOMMENDATION ENGINES WITH PYSPARK

Course recap

BUILDING RECOMMENDATION ENGINES WITH PYSPARK



Jamen Long

Data Scientist at Nike

Course summary

Three types of data

- Explicit Ratings
- Implicit Ratings using user behavior counts
- Implicit Ratings using binary user behavior

Things to bear in mind

- The more data the better

Things to bear in mind (cont.)

- The more data the better
- The best model evaluation is whether actual users take your recommendations

Resources

- [McKinsey&Company: "How Retailers Can Keep Up With Consumers"](#)
- [ALS Data Preparation: Wide to Long Function](#)
- [Hu, Koren, Volinsky: "Collaborative Filtering for Implicit Feedback Datasets"](#)
- [GitHub Repo: Cross Validation With Implicit Ratings in Pyspark](#)
- [Pan, Zhou, Cao, Liu, Lukose, Scholz, Yang: "One Class Collaborative Filtering"](#)

Let's practice!

BUILDING RECOMMENDATION ENGINES WITH PYSPARK