BUILDING RECOMMENDATION ENGINES WITH PYSPARK

Introduction to the Million Songs Dataset

Jamen Long
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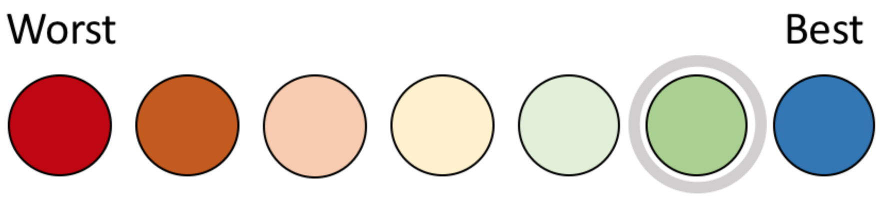
Explicit vs Implicit

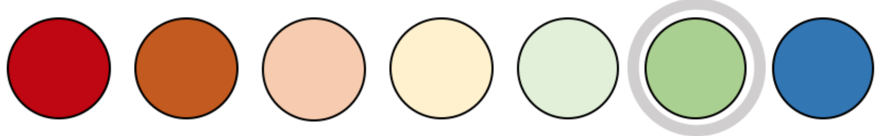
Explicit Ratings



Explicit vs Implicit (cont.)

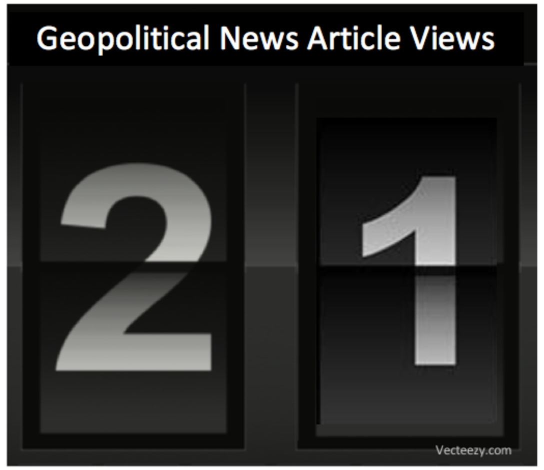
Explicit Ratings

Worst Best



Implicit Ratings

= Low Confidence Rating

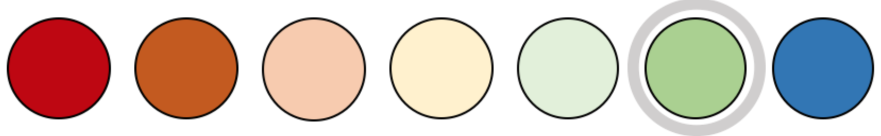


= High Confidence Rating

Implicit Refresher II

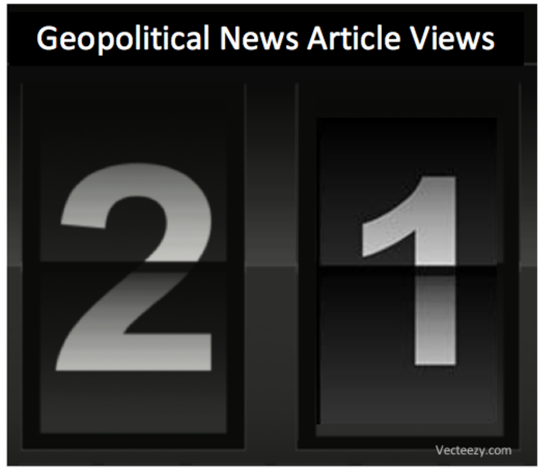
Explicit Ratings

Worst Best



Implicit Ratings

= Low Confidence Rating



= High Confidence Rating

Collaborative Filerting for Implicit Feedback Datasets
Yifan Hu, Yehuda Koren and Chris Volinsky

THE ECHO NEST TASTE PROFILE 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(items) \
            .join(df, ["userId", "songId"], "left").fillna(0)

    return cross_join
```

BUILDING RECOMMENDATION ENGINES WITH PYSPARK

Let's practice!

BUILDING RECOMMENDATION ENGINES WITH PYSPARK

Evaluating Implicit Ratings Models

Jamen Long
Data Scientist

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

$$\mathrm{ROEM} = \frac{\sum_{u,i} r^t_{u,i} \mathrm{rank}_{u,i}}{\sum_{u,i} r^t_{u,i}}$$

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]
maxIters = [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 maxIters:
        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)
```

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Let's practice!

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Overview of binary, implicit ratings

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Data Scientist

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|
|    26|     29|            0|
|    26|   5385|            0|
|    26|   3506|            0|
|    38|   2112|            1|
|    38|     42|            0|
|    38|     17|            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

BUILDING RECOMMENDATION ENGINES WITH PYSPARK

Let's practice!

BUILDING RECOMMENDATION ENGINES WITH PYSPARK

Course Recap

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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

- 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"