

```
In [1]: # Importing standard libraries
import pandas as pd
import numpy as np
import matplotlib
import matplotlib.pyplot as plt
%matplotlib inline
```

```
In [2]: # Importing ratings file
ratings = pd.read_csv('ratings.csv')
ratings.head()
```

Out[2]:

	user_id	movie_id	rating	unix_timestamp
0	196	242	3	881250949
1	186	302	3	891717742
2	22	377	1	878887116
3	244	51	2	880606923
4	166	346	1	886397596

```
In [3]: # Create a number of ratings column to see how many ratings each movie
        # has
ratings_over_fifty = pd.DataFrame(ratings.groupby('movie_id')['rating']
                                   .count())
# Rename the column to number_of_ratings
ratings_over_fifty.columns = ['number_of_ratings']
# Get only the movies that have more than 50 ratings
ratings_over_fifty = ratings_over_fifty[ratings_over_fifty['number_of_r
atings']>50]
# Reset index so that movie_id is not index, put an artificial index va
lue
ratings_over_fifty.reset_index(inplace=True)
```

```
# See the movies with over 50 ratings
ratings_over_fifty.head(20)
```

Out[3]:

	movie_id	number_of_ratings
0	1	452
1	2	131
2	3	90
3	4	209
4	5	86
5	7	392
6	8	219
7	9	299
8	10	89
9	11	236
10	12	267
11	13	184
12	14	183
13	15	293
14	17	92
15	19	69
16	20	72
17	21	84
18	22	297
19	23	182

```
In [4]: # Define function to check if a movie in the main dataset has over 50 ratings or not
def rows_above_under_fifty(row):
    if np.any(row == ratings_over_fifty['movie_id']):
        return True
    return False
```

```
In [5]: # Apply that function on the movies column, assigns the True or False values in a new Series object
series_above_under_fifty = ratings['movie_id'].apply(rows_above_under_fifty)
# It can be seen that the 1st, 2nd movies have over 50 ratings, whereas the 3rd one does not
# 1st corresponds to movie_id 242
# 2nd corresponds to movie_id 302
# 3rd corresponds to movie_id 377
series_above_under_fifty.head()
```

```
Out[5]: 0      True
1      True
2     False
3      True
4      True
Name: movie_id, dtype: bool
```

```
In [6]: # Let's see if that is the case
# Prints out that it has 117 ratings
print(ratings_over_fifty[ratings_over_fifty['movie_id'] == 242])
# Prints out that it has 297 ratings
print(ratings_over_fifty[ratings_over_fifty['movie_id'] == 302])
# Returns empty dataframe => it is not in the ratings_over_fifty list => it does not have over 50 ratings
print(ratings_over_fifty[ratings_over_fifty['movie_id'] == 377])
```

	movie_id	number_of_ratings
209	242	117
	movie_id	number_of_ratings
257	302	297

```
Empty DataFrame
Columns: [movie_id, number_of_ratings]
Index: []
```

```
In [7]: # Filter ratings dataset so that only the movies with above 50 rating remain
ratings_filtered = ratings[series_above_under_fifty]
ratings_filtered.head()
```

Out[7]:

	user_id	movie_id	rating	unix_timestamp
0	196	242	3	881250949
1	186	302	3	891717742
3	244	51	2	880606923
4	166	346	1	886397596
5	298	474	4	884182806

```
In [8]: # Split the ratings dataframe into train and test set
from sklearn.model_selection import train_test_split
# Model with the whole dataset
ratings_train, ratings_test = train_test_split(ratings, test_size=0.15,
random_state=1)
# Model with only the movies that have above 50 rating
#ratings_train, ratings_test = train_test_split(ratings_filtered, test_
size=0.15, random_state=1)
```

```
In [9]: # Turicreate is a high-level machine learning library created by Apple
import turicreate as tc
ratings_train = tc.SFrame(ratings_train)
ratings_test = tc.SFrame(ratings_test)
```

```
/home/vanko/anaconda3/lib/python3.6/site-packages/h5py/__init__.py:36:
FutureWarning: Conversion of the second argument of issubdtype from `fl
oat` to `np.floating` is deprecated. In future, it will be treated as `
```

```
np.float64 == np.dtype(float).type`.
from ._conv import register_converters as _register_converters
```

```
In [10]: # A simple popularity model is trained, which recommends movies based on their popularity
# item_id parameter specifies the column name that will be recommended, namely, movie_id
popularity_model = tc.popularity_recommender.create(ratings_train, user_id='user_id',
                                                    item_id='movie_id', target='rating')
```

Recsys training: model = popularity

Warning: Ignoring columns unix\_timestamp;

To use these columns in scoring predictions, use a model that allows the use of additional features.

Preparing data set.

Data has 85000 observations with 943 users and 1653 items.

Data prepared in: 0.334914s

85000 observations to process; with 1653 unique items.

```
In [11]: # Recommend the top 5 movies to users 1, 2, 3, 4, 5
popularity_recomm = popularity_model.recommend(users=[1,2,3,4,5],k=5)
popularity_recomm.print_rows(num_rows=25)
```

user_id	movie_id	score	rank
1	1189	5.0	1
1	1599	5.0	2
1	1293	5.0	3
1	1643	5.0	4
1	1536	5.0	5
2	1189	5.0	1

2	1599	5.0	2
2	1293	5.0	3
2	1643	5.0	4
2	1536	5.0	5
3	1189	5.0	1
3	1599	5.0	2
3	1293	5.0	3
3	1643	5.0	4
3	1536	5.0	5
4	1189	5.0	1
4	1599	5.0	2
4	1293	5.0	3
4	1643	5.0	4
4	1536	5.0	5
5	1189	5.0	1
5	1599	5.0	2
5	1293	5.0	3
5	1643	5.0	4
5	1536	5.0	5

+-----+-----+-----+-----+

[25 rows x 4 columns]

```
In [12]: # The above was a simple popularity model. Now we will build a collaborative-filtering model.
# Ranking factorization recommender trains a model to predict a rating for
# each possible combination of users and movies. The internal coefficients of the model are
# learned from known ratings of users on movies. Recommendations are then based on these ratings.
# Training the model
item_sim_model = tc.ranking_factorization_recommender.create(ratings_train, user_id='user_id',
                                                             item_id='movie_id', target='rating')
```

Recsys training: model = ranking\_factorization\_recommender

Preparing data set.

Data has 85000 observations with 943 users and 1653 items.

Data prepared in: 0.240837s

Training ranking\_factorization\_recommender for recommendations.

+-----+-----+		
-----+-----+		
Parameter		Description
	Value	
+-----+-----+		
-----+-----+		
num_factors		Factor Dimension
	32	
regularization		L2 Regularization on Factors
	1e-09	
solver		Solver used for training
	adagrad	
linear_regularization		L2 Regularization on Linear Coeffici
ents	1e-09	
ranking_regularization		Rank-based Regularization Weight
	0.25	
max_iterations		Maximum Number of Iterations
	25	
+-----+-----+		
-----+-----+		

Optimizing model using SGD; tuning step size.

Attempt	Initial Step Size	Estimated Objective Value
0	16.6667	Not Viable
1	4.16667	Not Viable
2	1.04167	Not Viable
3	0.260417	Not Viable
4	0.0651042	1.8657
5	0.0325521	1.8702
6	0.016276	1.98718
7	0.00813802	2.12851
Final	0.0651042	1.8657



```

|
+-----+-----+-----+-----+
--+
Starting Optimization.
+-----+-----+-----+-----+
-----+
| Iter.  | Elapsed Time | Approx. Objective | Approx. Training RMSE |
| Step Size |
+-----+-----+-----+-----+
-----+
| Initial | 17.426ms      | 2.48549           | 1.12591                |
|          |               |                   |                         |
+-----+-----+-----+-----+
-----+
| 1       | 828.95ms      | 2.12678           | 1.14161                |
| 0.0651042 |               |                   |                         |
| 2       | 1.50s         | 1.90197           | 1.06083                |
| 0.0651042 |               |                   |                         |
| 3       | 2.17s         | 1.81637           | 1.0283                 |
| 0.0651042 |               |                   |                         |
| 4       | 3.06s         | 1.73893           | 1.00472                |
| 0.0651042 |               |                   |                         |
| 5       | 4.05s         | 1.6847            | 0.987224               |
| 0.0651042 |               |                   |                         |
| 10      | 7.50s         | 1.54326           | 0.940059               |
| 0.0651042 |               |                   |                         |

```

```

| 15      | 10.17s      | 1.46666      | 0.909931      |
0.0651042 |
| 20      | 14.98s      | 1.41824      | 0.883675      |
0.0651042 |
| 25      | 19.04s      | 1.43903      | 0.869355      |
0.0651042 |

+-----+-----+-----+-----+
-----+

```

Optimization Complete: Maximum number of passes through the data reached.

Computing final objective value and training RMSE.

Final objective value: 1.45394

Final training RMSE: 0.852866

In [13]: *# Making recommendations*  
 item\_sim\_recomm = item\_sim\_model.recommend(users=[1,2,3,4,5],k=5)  
 item\_sim\_recomm.print\_rows(num\_rows=25)

```

+-----+-----+-----+-----+
| user_id | movie_id | score          | rank |
+-----+-----+-----+-----+
| 1       | 408      | 4.633140248337915 | 1    |
| 1       | 474      | 4.430625391284158 | 2    |
| 1       | 919      | 4.391392669731905 | 3    |
| 1       | 483      | 4.2822603407298825 | 4    |
| 1       | 238      | 4.257882935086419 | 5    |
| 2       | 269      | 4.561351833025148 | 1    |
| 2       | 258      | 4.416115162054231 | 2    |
| 2       | 283      | 4.395786491314103 | 3    |
| 2       | 127      | 4.348903534094026 | 4    |
| 2       | 124      | 4.308760699907472 | 5    |
| 3       | 50       | 4.862409320751359 | 1    |

```

3	127	4.486713168302705	2
3	98	4.334899989048173	3
3	56	4.300042775551011	4
3	257	4.239566472450425	5
4	302	4.755937409678628	1
4	100	4.604095113555124	2
4	313	4.6038982394134305	3
4	258	4.565941047946145	4
4	127	4.564202514568498	5
5	7	4.349293303767373	1
5	175	4.19093973664396	2
5	408	4.190826487818887	3
5	173	4.131918025294473	4
5	12	4.0241669538413785	5

+-----+-----+-----+-----+

[25 rows x 4 columns]

```
In [14]: # Evaluate RMSE (Root Mean Square Error), the lower it is, the better.
# A lower score means the actual data points
# are closer to the regression line (therefore the regression line's pr
# edicted value is closer to the actual value)
# For visual explanation refer to:
# https://www.khanacademy.org/math/ap-statistics/bivariate-data-ap/asse
# ssing-fit-least-squares-regression/v/standard-dev-residuals
item_sim_model.evaluate_rmse(ratings_test, target='rating')
# For this model, on the testing data, the RMSE is ~1.01, which is not
# too bad. It is also quite close to
# the RMSE of the model on the training data, which is ~0.85.
```

```
Out[14]: {'rmse_by_user': Columns:
      user_id int
      rmse     float
      count    int
```

Rows: 936

Data:

+-----+-----+-----+-----+

user_id	rmse	count
747	1.2981214691745575	45
118	1.0451524006516273	8
153	1.508314253741147	2
660	1.0182323399319324	35
92	0.9108288857742471	47
264	1.3253550391043698	19
690	0.8469186934862357	16
839	1.3639768389329134	7
837	1.0468211086952406	6
208	1.0593900404122296	1

[936 rows x 3 columns]

Note: Only the head of the SFrame is printed.

You can use `print_rows(num_rows=m, num_columns=n)` to print more rows and columns.,

'rmse\_by\_item': Columns:  
 movie\_id int  
 rmse float  
 count int

Rows: 1366

Data:

movie_id	rmse	count
973	0.8836474840855688	1
1270	0.8200935647819125	2
1611	0.3223828077892839	2
747	0.8211008559973578	20
118	0.958870429970247	44
153	1.051357770442147	35
660	0.863244055470406	30
1236	0.14044750002808737	1
92	1.2084345090230597	17
1657	0.6132284969121984	1

```
[1366 rows x 3 columns]
Note: Only the head of the SFrame is printed.
You can use print_rows(num_rows=m, num_columns=n) to print more rows and columns.,
{'rmse_overall': 1.0156485870814331}
```