Recommender Systems with Python

Welcome to the code notebook for Recommender Systems with Python. In this lecture we will develop basic recommendation systems using Python and pandas. There is another notebook: *Advanced Recommender Systems with Python*. That notebook goes into more detail with the same data set.

In this notebook, we will focus on providing a basic recommendation system by suggesting items that are most similar to a particular item, in this case, movies. Keep in mind, this is not a true robust recommendation system, to describe it more accurately,it just tells you what movies/items are most similar to your movie choice.

There is no project for this topic, instead you have the option to work through the advanced lecture version of this notebook (totally optional!).

Let's get started!

Import Libraries

```
import numpy as np
import pandas as pd
```

Get the Data

```
column_names = ['user_id', 'item_id', 'rating', 'timestamp']
df = pd.read_csv('u.data', sep='\t', names=column_names)

df.head()
```

	user_id	item_id	rating	timestamp
0	0	50	5	881250949
1	0	172	5	881250949
2	0	133	1	881250949
3	196	242	3	881250949
4	186	302	3	891717742

Now let's get the movie titles:

```
movie_titles = pd.read_csv("Movie_Id_Titles")
movie_titles.head()
```

	item_id	title
0	1	Toy Story (1995)
1	2	GoldenEye (1995)
2	3	Four Rooms (1995)

```
3         4  Get Shorty (1995)
4         5     Copycat (1995)
```

We can merge them together:

```
df = pd.merge(df,movie_titles,on='item_id')
df.head()

   user_id  item_id  rating  timestamp
title
0        0       50       5  881250949                      Star Wars
(1977)
1        0      172       5  881250949  Empire Strikes Back, The
(1980)
2        0      133       1  881250949        Gone with the Wind
(1939)
3      196      242       3  881250949                          Kolya
(1996)
4      186      302       3  891717742         L.A. Confidential
(1997)
```

EDA

Let's explore the data a bit and get a look at some of the best rated movies.

Visualization Imports

```
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style('white')
%matplotlib inline
```

Let's create a ratings dataframe with average rating and number of ratings:

```
df.groupby('title')
['rating'].mean().sort_values(ascending=False).head()

title
They Made Me a Criminal (1939)                5.0
Marlene Dietrich: Shadow and Light (1996)     5.0
Saint of Fort Washington, The (1993)          5.0
Someone Else's America (1995)                 5.0
Star Kid (1997)                               5.0
Name: rating, dtype: float64

df.groupby('title')
['rating'].count().sort_values(ascending=False).head()
```

```
title
Star Wars (1977)             584
Contact (1997)               509
Fargo (1996)                 508
Return of the Jedi (1983)    507
Liar Liar (1997)             485
Name: rating, dtype: int64
```

```
ratings = pd.DataFrame(df.groupby('title')['rating'].mean())
ratings.head()
```

```
                             rating
title
'Til There Was You (1997)  2.333333
1-900 (1994)               2.600000
101 Dalmatians (1996)      2.908257
12 Angry Men (1957)        4.344000
187 (1997)                 3.024390
```

Now set the number of ratings column:

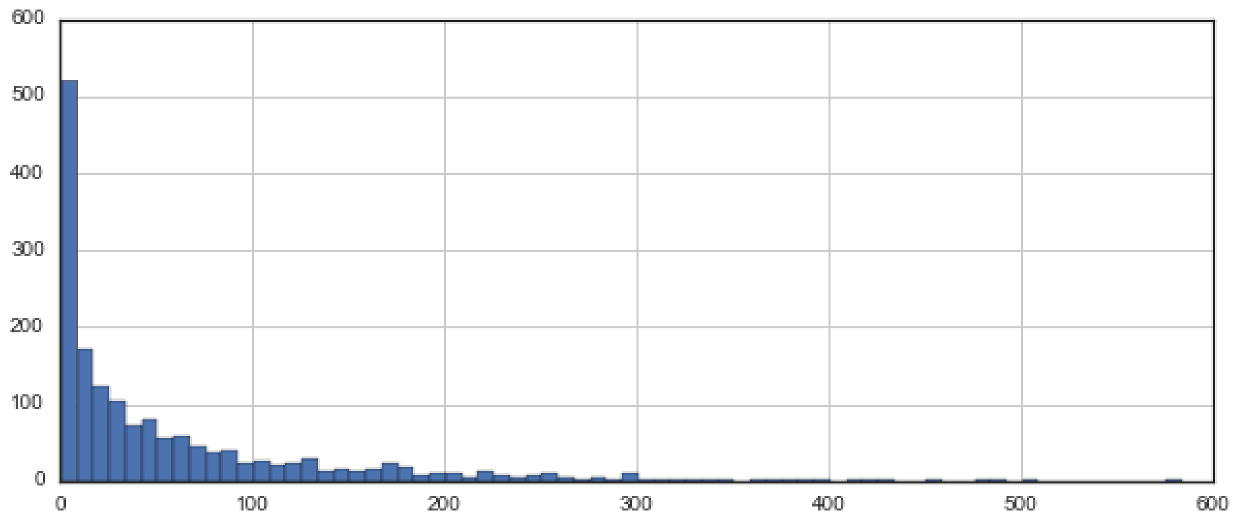
```
ratings['num of ratings'] = pd.DataFrame(df.groupby('title')
['rating'].count())
ratings.head()
```

```
                             rating  num of ratings
title
'Til There Was You (1997)  2.333333               9
1-900 (1994)               2.600000               5
101 Dalmatians (1996)      2.908257             109
12 Angry Men (1957)        4.344000             125
187 (1997)                 3.024390              41
```

Now a few histograms:

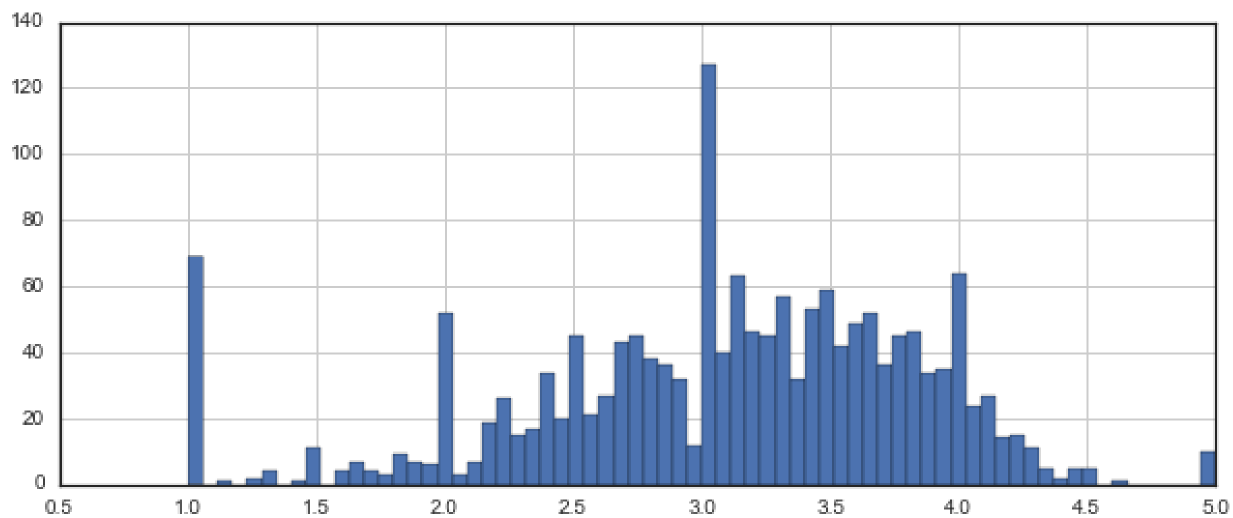
```
plt.figure(figsize=(10,4))
ratings['num of ratings'].hist(bins=70)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x1258f8780>
```



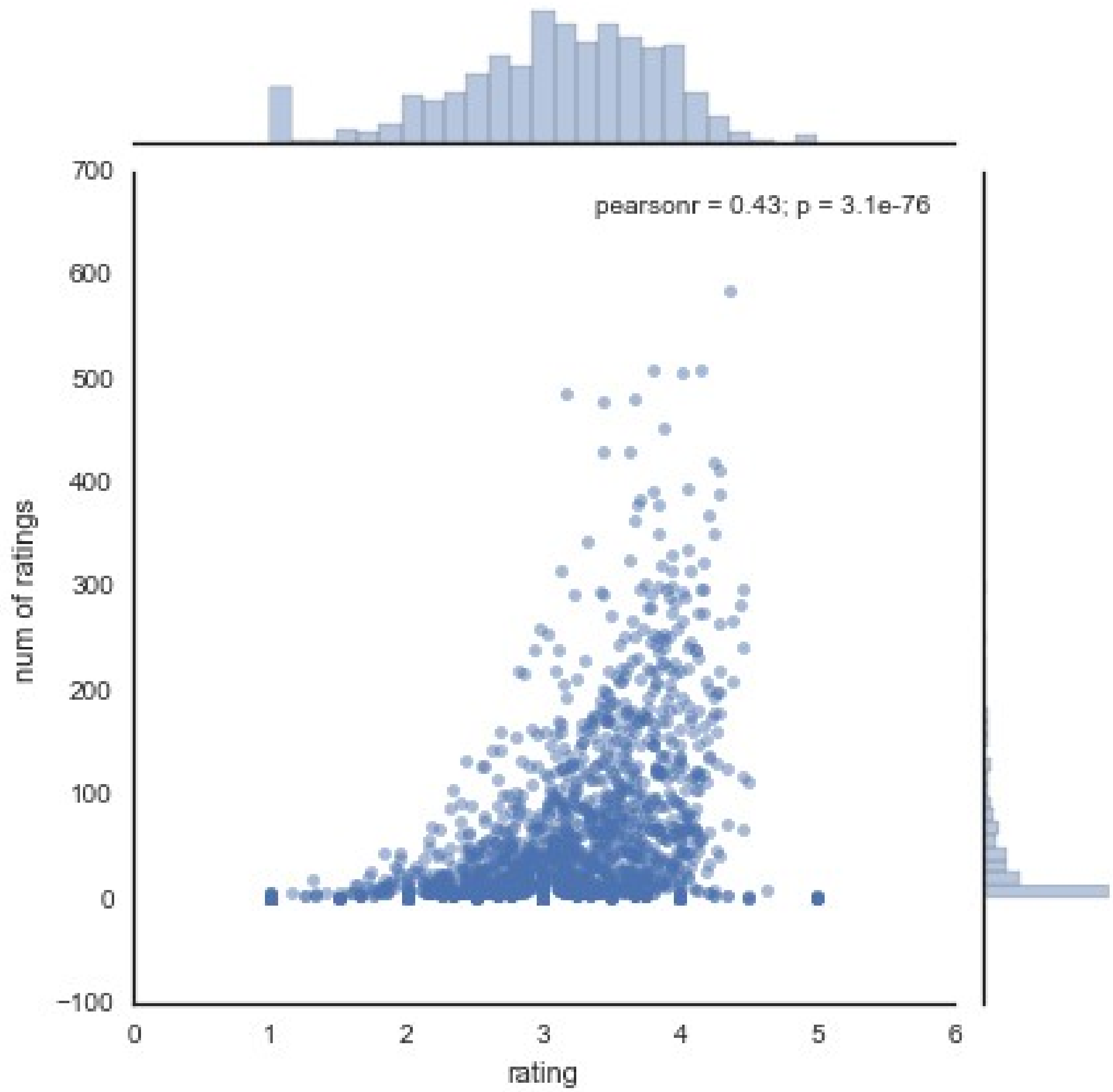

```
plt.figure(figsize=(10,4))
ratings['rating'].hist(bins=70)

<matplotlib.axes._subplots.AxesSubplot at 0x125d12908>
```




```
sns.jointplot(x='rating',y='num of ratings',data=ratings,alpha=0.5)

<seaborn.axisgrid.JointGrid at 0x126005320>
```



Okay! Now that we have a general idea of what the data looks like, let's move on to creating a simple recommendation system:

Recommending Similar Movies

Now let's create a matrix that has the user ids on one access and the movie title on another axis. Each cell will then consist of the rating the user gave to that movie. Note there will be a lot of NaN values, because most people have not seen most of the movies.

```
moviemat =
df.pivot_table(index='user_id',columns='title',values='rating')
moviemat.head()

title    'Til There Was You (1997)  1-900 (1994)  101 Dalmatians
(1996)  \
```

```
user_id

0                                NaN           NaN
NaN
1                                NaN           NaN
2.0
2                                NaN           NaN
NaN
3                                NaN           NaN
NaN
4                                NaN           NaN
NaN

title    12 Angry Men (1957)  187 (1997)  2 Days in the Valley (1996)
\
user_id

0                        NaN         NaN                          NaN

1                        5.0         NaN                          NaN

2                        NaN         NaN                          NaN

3                        NaN         2.0                          NaN

4                        NaN         NaN                          NaN


title    20,000 Leagues Under the Sea (1954)  2001: A Space Odyssey
(1968)  \
user_id

0                                        NaN
NaN
1                                        3.0
4.0
2                                        NaN
NaN
3                                        NaN
NaN
4                                        NaN
NaN

title    3 Ninjas: High Noon At Mega Mountain (1998)  39 Steps, The
(1935)  \
user_id

0                                                NaN
NaN
1                                                NaN
```

```
NaN
2                                                 1.0
NaN
3                                                 NaN
NaN
4                                                 NaN
NaN

title                   ...                 Yankee Zulu (1994)  \
user_id                 ...
0                       ...                                NaN
1                       ...                                NaN
2                       ...                                NaN
3                       ...                                NaN
4                       ...                                NaN

title    Year of the Horse (1997)  You So Crazy (1994)  \
user_id
0                             NaN                  NaN
1                             NaN                  NaN
2                             NaN                  NaN
3                             NaN                  NaN
4                             NaN                  NaN

title    Young Frankenstein (1974)  Young Guns (1988)  Young Guns II
(1990)  \
user_id

0                              NaN                NaN
NaN
1                              5.0                3.0
NaN
2                              NaN                NaN
NaN
3                              NaN                NaN
NaN
4                              NaN                NaN
NaN

title    Young Poisoner's Handbook, The (1995)  Zeus and Roxanne
(1997)  \
user_id

0                                          NaN
NaN
1                                          NaN
NaN
2                                          NaN
NaN
3                                          NaN
```

```
NaN
4                                          NaN
NaN

title    unknown  Á köldum klaka (Cold Fever) (1994)
user_id
0            NaN                                  NaN
1            4.0                                  NaN
2            NaN                                  NaN
3            NaN                                  NaN
4            NaN                                  NaN

[5 rows x 1664 columns]
```

Most rated movie:

```
ratings.sort_values('num of ratings',ascending=False).head(10)
```

```
                                 rating  num of ratings
title
Star Wars (1977)               4.359589             584
Contact (1997)                 3.803536             509
Fargo (1996)                   4.155512             508
Return of the Jedi (1983)      4.007890             507
Liar Liar (1997)               3.156701             485
English Patient, The (1996)    3.656965             481
Scream (1996)                  3.441423             478
Toy Story (1995)               3.878319             452
Air Force One (1997)           3.631090             431
Independence Day (ID4) (1996)  3.438228             429
```

Let's choose two movies: starwars, a sci-fi movie. And Liar Liar, a comedy.

```
ratings.head()
```

```
                             rating  num of ratings
title
'Til There Was You (1997)  2.333333               9
1-900 (1994)               2.600000               5
101 Dalmatians (1996)      2.908257             109
12 Angry Men (1957)        4.344000             125
187 (1997)                 3.024390              41
```

Now let's grab the user ratings for those two movies:

```
starwars_user_ratings = moviemat['Star Wars (1977)']
liarliar_user_ratings = moviemat['Liar Liar (1997)']
starwars_user_ratings.head()
```

```
user_id
0    5.0
1    5.0
2    5.0
3    NaN
4    5.0
Name: Star Wars (1977), dtype: float64
```

We can then use corrwith() method to get correlations between two pandas series:

```
similar_to_starwars = moviemat.corrwith(starwars_user_ratings)
similar_to_liarliar = moviemat.corrwith(liarliar_user_ratings)
```

```
/Users/marci/anaconda/lib/python3.5/site-packages/numpy/lib/
function_base.py:2487: RuntimeWarning: Degrees of freedom <= 0 for
slice
  warnings.warn("Degrees of freedom <= 0 for slice", RuntimeWarning)
```

Let's clean this by removing NaN values and using a DataFrame instead of a series:

```
corr_starwars =
pd.DataFrame(similar_to_starwars,columns=['Correlation'])
corr_starwars.dropna(inplace=True)
corr_starwars.head()
```

```
                           Correlation
title
'Til There Was You (1997)     0.872872
1-900 (1994)                 -0.645497
101 Dalmatians (1996)         0.211132
12 Angry Men (1957)           0.184289
187 (1997)                    0.027398
```

Now if we sort the dataframe by correlation, we should get the most similar movies, however note that we get some results that don't really make sense. This is because there are a lot of movies only watched once by users who also watched star wars (it was the most popular movie).

```
corr_starwars.sort_values('Correlation',ascending=False).head(10)
```

```
                                                   Correlation
title
Commandments (1997)                                        1.0
Cosi (1996)                                                1.0
No Escape (1994)                                           1.0
Stripes (1981)                                             1.0
Man of the Year (1995)                                     1.0
Hollow Reed (1996)                                         1.0
Beans of Egypt, Maine, The (1994)                          1.0
Good Man in Africa, A (1994)                               1.0
```

```
Old Lady Who Walked in the Sea, The (Vieille qu...          1.0
Outlaw, The (1943)                                          1.0
```

Let's fix this by filtering out movies that have less than 100 reviews (this value was chosen based off the histogram from earlier).

```
corr_starwars = corr_starwars.join(ratings['num of ratings'])
corr_starwars.head()

                           Correlation  num of ratings
title
'Til There Was You (1997)     0.872872               9
1-900 (1994)                 -0.645497               5
101 Dalmatians (1996)         0.211132             109
12 Angry Men (1957)           0.184289             125
187 (1997)                    0.027398              41
```

Now sort the values and notice how the titles make a lot more sense:

```
corr_starwars[corr_starwars['num of
ratings']>100].sort_values('Correlation',ascending=False).head()

                                                    Correlation  \
title
Star Wars (1977)                                       1.000000
Empire Strikes Back, The (1980)                        0.748353
Return of the Jedi (1983)                              0.672556
Raiders of the Lost Ark (1981)                         0.536117
Austin Powers: International Man of Mystery (1997)     0.377433

                                                    num of ratings
title
Star Wars (1977)                                               584
Empire Strikes Back, The (1980)                                368
Return of the Jedi (1983)                                      507
Raiders of the Lost Ark (1981)                                 420
Austin Powers: International Man of Mystery (1997)             130
```

Now the same for the comedy Liar Liar:

```
corr_liarliar =
pd.DataFrame(similar_to_liarliar,columns=['Correlation'])
corr_liarliar.dropna(inplace=True)
corr_liarliar = corr_liarliar.join(ratings['num of ratings'])
corr_liarliar[corr_liarliar['num of
ratings']>100].sort_values('Correlation',ascending=False).head()

                       Correlation  num of ratings
title
```

Liar Liar (1997)	1.000000	485
Batman Forever (1995)	0.516968	114
Mask, The (1994)	0.484650	129
Down Periscope (1996)	0.472681	101
Con Air (1997)	0.469828	137

Great Job!

Advanced Recommender Systems with Python

Welcome to the code notebook for creating Advanced Recommender Systems with Python. This is an optional lecture notebook for you to check out. Currently there is no video for this lecture because of the level of mathematics used and the heavy use of SciPy here.

Recommendation Systems usually rely on larger data sets and specifically need to be organized in a particular fashion. Because of this, we won't have a project to go along with this topic, instead we will have a more intensive walkthrough process on creating a recommendation system with Python with the same Movie Lens Data Set.

Note: The actual mathematics behind recommender systems is pretty heavy in Linear Algebra.

Methods Used

Two most common types of recommender systems are **Content-Based** and **Collaborative Filtering (CF)**.

- Collaborative filtering produces recommendations based on the knowledge of users' attitude to items, that is it uses the "wisdom of the crowd" to recommend items.
- Content-based recommender systems focus on the attributes of the items and give you recommendations based on the similarity between them.

Collaborative Filtering

In general, Collaborative filtering (CF) is more commonly used than content-based systems because it usually gives better results and is relatively easy to understand (from an overall implementation perspective). The algorithm has the ability to do feature learning on its own, which means that it can start to learn for itself what features to use.

CF can be divided into **Memory-Based Collaborative Filtering** and **Model-Based Collaborative filtering**.

In this tutorial, we will implement Model-Based CF by using singular value decomposition (SVD) and Memory-Based CF by computing cosine similarity.

The Data

We will use famous MovieLens dataset, which is one of the most common datasets used when implementing and testing recommender engines. It contains 100k movie ratings from 943 users and a selection of 1682 movies.

You can download the dataset here or just use the u.data file that is already included in this folder.

Getting Started

Let's import some libraries we will need:

```
import numpy as np
import pandas as pd
```

We can then read in the **u.data** file, which contains the full dataset. You can read a brief description of the dataset here.

Note how we specify the separator argument for a Tab separated file.

```
column_names = ['user_id', 'item_id', 'rating', 'timestamp']
df = pd.read_csv('u.data', sep='\t', names=column_names)
```

Let's take a quick look at the data.

```
df.head()
```

	user_id	item_id	rating	timestamp
0	0	50	5	881250949
1	0	172	5	881250949
2	0	133	1	881250949
3	196	242	3	881250949
4	186	302	3	891717742

Note how we only have the item_id, not the movie name. We can use the Movie_ID_Titles csv file to grab the movie names and merge it with this dataframe:

```
movie_titles = pd.read_csv("Movie_Id_Titles")
movie_titles.head()
```

	item_id	title
0	1	Toy Story (1995)
1	2	GoldenEye (1995)
2	3	Four Rooms (1995)
3	4	Get Shorty (1995)
4	5	Copycat (1995)

Then merge the dataframes:

```
df = pd.merge(df,movie_titles,on='item_id')
df.head()
```

	user_id	item_id	rating	timestamp	title
0	0	50	5	881250949	Star Wars (1977)
1	290	50	5	880473582	Star Wars (1977)
2	79	50	4	891271545	Star Wars (1977)

```
3          2        50         5   888552084   Star Wars (1977)
4          8        50         5   879362124   Star Wars (1977)
```

Now let's take a quick look at the number of unique users and movies.

```
n_users = df.user_id.nunique()
n_items = df.item_id.nunique()

print('Num. of Users: '+ str(n_users))
print('Num of Movies: '+str(n_items))

Num. of Users: 944
Num of Movies: 1682
```

Train Test Split

Recommendation Systems by their very nature are very difficult to evaluate, but we will still show you how to evaluate them in this tutorial. In order to do this, we'll split our data into two sets. However, we won't do our classic X_train,X_test,y_train,y_test split. Instead we can actually just segement the data into two sets of data:

```
from sklearn.cross_validation import train_test_split
train_data, test_data = train_test_split(df, test_size=0.25)
```

Memory-Based Collaborative Filtering

Memory-Based Collaborative Filtering approaches can be divided into two main sections: **user-item filtering** and **item-item filtering**.

A *user-item filtering* will take a particular user, find users that are similar to that user based on similarity of ratings, and recommend items that those similar users liked.

In contrast, *item-item filtering* will take an item, find users who liked that item, and find other items that those users or similar users also liked. It takes items and outputs other items as recommendations.

- *Item-Item Collaborative Filtering*: "Users who liked this item also liked …"
- *User-Item Collaborative Filtering*: "Users who are similar to you also liked …"

In both cases, you create a user-item matrix which built from the entire dataset.

Since we have split the data into testing and training we will need to create two `[943 x 1682]` matrices (all users by all movies).

The training matrix contains 75% of the ratings and the testing matrix contains 25% of the ratings.

Example of user-item matrix:

After you have built the user-item matrix you calculate the similarity and create a similarity matrix.

The similarity values between items in *Item-Item Collaborative Filtering* are measured by observing all the users who have rated both items.

For *User-Item Collaborative Filtering* the similarity values between users are measured by observing all the items that are rated by both users.

A distance metric commonly used in recommender systems is *cosine similarity*, where the ratings are seen as vectors in `n`-dimensional space and the similarity is calculated based on the angle between these vectors. Cosine similiarity for users *a* and *m* can be calculated using the formula below, where you take dot product of the user vector u_k and the user vector u_a and divide it by multiplication of the Euclidean lengths of the vectors.

To calculate similarity between items *m* and *b* you use the formula:

Your first step will be to create the user-item matrix. Since you have both testing and training data you need to create two matrices.

```
#Create two user-item matrices, one for training and another for
testing
train_data_matrix = np.zeros((n_users, n_items))
for line in train_data.itertuples():
    train_data_matrix[line[1]-1, line[2]-1] = line[3]

test_data_matrix = np.zeros((n_users, n_items))
for line in test_data.itertuples():
    test_data_matrix[line[1]-1, line[2]-1] = line[3]
```

You can use the pairwise_distances function from sklearn to calculate the cosine similarity. Note, the output will range from 0 to 1 since the ratings are all positive.

```
from sklearn.metrics.pairwise import pairwise_distances
user_similarity = pairwise_distances(train_data_matrix,
metric='cosine')
item_similarity = pairwise_distances(train_data_matrix.T,
metric='cosine')
```

Next step is to make predictions. You have already created similarity matrices: `user_similarity` and `item_similarity` and therefore you can make a prediction by applying following formula for user-based CF:

You can look at the similarity between users *k* and *a* as weights that are multiplied by the ratings of a similar user *a* (corrected for the average rating of that user). You will need to normalize it so that the ratings stay between 1 and 5 and, as a final step, sum the average ratings for the user that you are trying to predict.

The idea here is that some users may tend always to give high or low ratings to all movies. The relative difference in the ratings that these users give is more important than the absolute values. To give an example: suppose, user *k* gives 4 stars to his favourite movies and 3 stars to all other good movies. Suppose now that another user *t* rates movies that he/she likes with 5 stars, and the movies he/she fell asleep over with 3 stars. These two users could have a very similar taste but treat the rating system differently.

When making a prediction for item-based CF you don't need to correct for users average rating since query user itself is used to do predictions.

```
def predict(ratings, similarity, type='user'):
    if type == 'user':
        mean_user_rating = ratings.mean(axis=1)
        #You use np.newaxis so that mean_user_rating has same format
as ratings
        ratings_diff = (ratings - mean_user_rating[:, np.newaxis])
        pred = mean_user_rating[:, np.newaxis] +
similarity.dot(ratings_diff) /
np.array([np.abs(similarity).sum(axis=1)]).T
    elif type == 'item':
        pred = ratings.dot(similarity) /
np.array([np.abs(similarity).sum(axis=1)])
    return pred

item_prediction = predict(train_data_matrix, item_similarity,
type='item')
user_prediction = predict(train_data_matrix, user_similarity,
type='user')
```

Evaluation

There are many evaluation metrics but one of the most popular metric used to evaluate accuracy of predicted ratings is *Root Mean Squared Error (RMSE)*.

You can use the mean_square_error (MSE) function from `sklearn`, where the RMSE is just the square root of MSE. To read more about different evaluation metrics you can take a look at this article.

Since you only want to consider predicted ratings that are in the test dataset, you filter out all other elements in the prediction matrix with `prediction[ground_truth.nonzero()]`.

```
from sklearn.metrics import mean_squared_error
from math import sqrt
```

```
def rmse(prediction, ground_truth):
    prediction = prediction[ground_truth.nonzero()].flatten()
    ground_truth = ground_truth[ground_truth.nonzero()].flatten()
    return sqrt(mean_squared_error(prediction, ground_truth))

print('User-based CF RMSE: ' + str(rmse(user_prediction, 
test_data_matrix)))
print('Item-based CF RMSE: ' + str(rmse(item_prediction, 
test_data_matrix)))

User-based CF RMSE: 3.135451660158989
Item-based CF RMSE: 3.4593766647252515
```

Memory-based algorithms are easy to implement and produce reasonable prediction quality. The drawback of memory-based CF is that it doesn't scale to real-world scenarios and doesn't address the well-known cold-start problem, that is when new user or new item enters the system. Model-based CF methods are scalable and can deal with higher sparsity level than memory-based models, but also suffer when new users or items that don't have any ratings enter the system. I would like to thank Ethan Rosenthal for his post about Memory-Based Collaborative Filtering.

Model-based Collaborative Filtering

Model-based Collaborative Filtering is based on **matrix factorization (MF)** which has received greater exposure, mainly as an unsupervised learning method for latent variable decomposition and dimensionality reduction. Matrix factorization is widely used for recommender systems where it can deal better with scalability and sparsity than Memory-based CF. The goal of MF is to learn the latent preferences of users and the latent attributes of items from known ratings (learn features that describe the characteristics of ratings) to then predict the unknown ratings through the dot product of the latent features of users and items. When you have a very sparse matrix, with a lot of dimensions, by doing matrix factorization you can restructure the user-item matrix into low-rank structure, and you can represent the matrix by the multiplication of two low-rank matrices, where the rows contain the latent vector. You fit this matrix to approximate your original matrix, as closely as possible, by multiplying the low-rank matrices together, which fills in the entries missing in the original matrix.

Let's calculate the sparsity level of MovieLens dataset:

```
sparsity=round(1.0-len(df)/float(n_users*n_items),3)
print('The sparsity level of MovieLens100K is ' +  str(sparsity*100) + 
'%')

The sparsity level of MovieLens100K is 93.7%
```

To give an example of the learned latent preferences of the users and items: let's say for the MovieLens dataset you have the following information: *(user id, age, location, gender, movie id, director, actor, language, year, rating)*. By applying matrix factorization the model learns that important user features are *age group (under 10, 10-18, 18-30, 30-90)*, *location* and *gender*, and for movie features it learns that *decade*, *director* and *actor* are most important. Now if you look into the information you have stored, there is no such feature as the *decade*, but the model can learn on its own. The important aspect is that the CF model only uses data (user_id, movie_id, rating) to learn the latent features. If there is little data available model-based CF model will predict poorly, since it will be more difficult to learn the latent features.

Models that use both ratings and content features are called **Hybrid Recommender Systems** where both Collaborative Filtering and Content-based Models are combined. Hybrid recommender systems usually show higher accuracy than Collaborative Filtering or Content-based Models on their own: they are capable to address the cold-start problem better since if you don't have any ratings for a user or an item you could use the metadata from the user or item to make a prediction.

SVD

A well-known matrix factorization method is **Singular value decomposition (SVD)**. Collaborative Filtering can be formulated by approximating a matrix `X` by using singular value decomposition. The winning team at the Netflix Prize competition used SVD matrix factorization models to produce product recommendations, for more information I recommend to read articles: Netflix Recommendations: Beyond the 5 stars and Netflix Prize and SVD. The general equation can be expressed as follows:

Given `m x n` matrix `X`:

- *U* is an `(m x r)` orthogonal matrix
- *S* is an `(r x r)` diagonal matrix with non-negative real numbers on the diagonal
- *V^T* is an `(r x n)` orthogonal matrix

Elements on the diagnoal in `S` are known as *singular values of X*.

Matrix *X* can be factorized to *U*, *S* and *V*. The *U* matrix represents the feature vectors corresponding to the users in the hidden feature space and the *V* matrix represents the feature vectors corresponding to the items in the hidden feature space.

Now you can make a prediction by taking dot product of *U*, *S* and *V^T*.

```
import scipy.sparse as sp
from scipy.sparse.linalg import svds

#get SVD components from train matrix. Choose k.
u, s, vt = svds(train_data_matrix, k = 20)
s_diag_matrix=np.diag(s)
X_pred = np.dot(np.dot(u, s_diag_matrix), vt)
print('User-based CF MSE: ' + str(rmse(X_pred, test_data_matrix)))
```

```
User-based CF MSE: 2.727093975231784
```

Carelessly addressing only the relatively few known entries is highly prone to overfitting. SVD can be very slow and computationally expensive. More recent work minimizes the squared error by applying alternating least square or stochastic gradient descent and uses regularization terms to prevent overfitting. Alternating least square and stochastic gradient descent methods for CF will be covered in the next tutorials.

Review:

- We have covered how to implement simple **Collaborative Filtering** methods, both memory-based CF and model-based CF.
- **Memory-based models** are based on similarity between items or users, where we use cosine-similarity.
- **Model-based CF** is based on matrix factorization where we use SVD to factorize the matrix.
- Building recommender systems that perform well in cold-start scenarios (where little data is available on new users and items) remains a challenge. The standard collaborative filtering method performs poorly is such settings.

Looking for more?

If you want to tackle your own recommendation system analysis, check out these data sets. Note: The files are quite large in most cases, not all the links may stay up to host the data, but the majority of them still work. Or just Google for your own data set!

Movies Recommendation:

MovieLens - Movie Recommendation Data Sets http://www.grouplens.org/node/73

Yahoo! - Movie, Music, and Images Ratings Data Sets
http://webscope.sandbox.yahoo.com/catalog.php?datatype=r

Jester - Movie Ratings Data Sets (Collaborative Filtering Dataset)
http://www.ieor.berkeley.edu/~goldberg/jester-data/

Cornell University - Movie-review data for use in sentiment-analysis experiments
http://www.cs.cornell.edu/people/pabo/movie-review-data/

Music Recommendation:

Last.fm - Music Recommendation Data Sets
http://www.dtic.upf.edu/~ocelma/MusicRecommendationDataset/index.html

Yahoo! - Movie, Music, and Images Ratings Data Sets
http://webscope.sandbox.yahoo.com/catalog.php?datatype=r

Audioscrobbler - Music Recommendation Data Sets
http://www-etud.iro.umontreal.ca/~bergstrj/audioscrobbler_data.html

Amazon - Audio CD recommendations http://131.193.40.52/data/

Books Recommendation:

Institut für Informatik, Universität Freiburg - Book Ratings Data Sets http://www.informatik.uni-freiburg.de/~cziegler/BX/ Food Recommendation:

Chicago Entree - Food Ratings Data Sets http://archive.ics.uci.edu/ml/datasets/Entree+Chicago+Recommendation+Data Merchandise Recommendation:

Healthcare Recommendation:

Nursing Home - Provider Ratings Data Set http://data.medicare.gov/dataset/Nursing-Home-Compare-Provider-Ratings/mufm-vy8d

Hospital Ratings - Survey of Patients Hospital Experiences http://data.medicare.gov/dataset/Survey-of-Patients-Hospital-Experiences-HCAHPS-/rj76-22dk

Dating Recommendation:

www.libimseti.cz - Dating website recommendation (collaborative filtering) http://www.occamslab.com/petricek/data/ Scholarly Paper Recommendation:

National University of Singapore - Scholarly Paper Recommendation http://www.comp.nus.edu.sg/~sugiyama/SchPaperRecData.html

Great Job!