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.

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

In [1]:
```
import numpy as np
import pandas as pd
```

Get the Data

In [2]:
```
column_names = ['user_id', 'item_id', 'rating', 'timestamp']
df = pd.read_csv("u.data", sep='\t', names=column_names)
```

In [3]:
```
df.head()
```

Out[3]:

	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:

In [4]:
```
movie_titles = pd.read_csv("Movie_Id_Titles (1).txt")
movie_titles.head()
```

Out[4]:

	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:

In [5]:
```python
df = pd.merge(df,movie_titles,on='item_id')
df.head()
```

Out[5]:

	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)

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

Visualization Imports

In [6]:
```python
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:

In [7]:
```python
df.groupby('title')['rating'].mean().sort_values(ascending=False).head()
```

Out[7]:
```
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
```

In [8]:
```
df.groupby('title')['rating'].count().sort_values(ascending=False).head()
```

Out[8]:
```
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
```

In [9]:
```
ratings = pd.DataFrame(df.groupby('title')['rating'].mean())
ratings.head()
```

Out[9]:

	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:

In [10]:
```
ratings['num of ratings'] = pd.DataFrame(df.groupby('title')['rating'].count())
ratings.head()
```

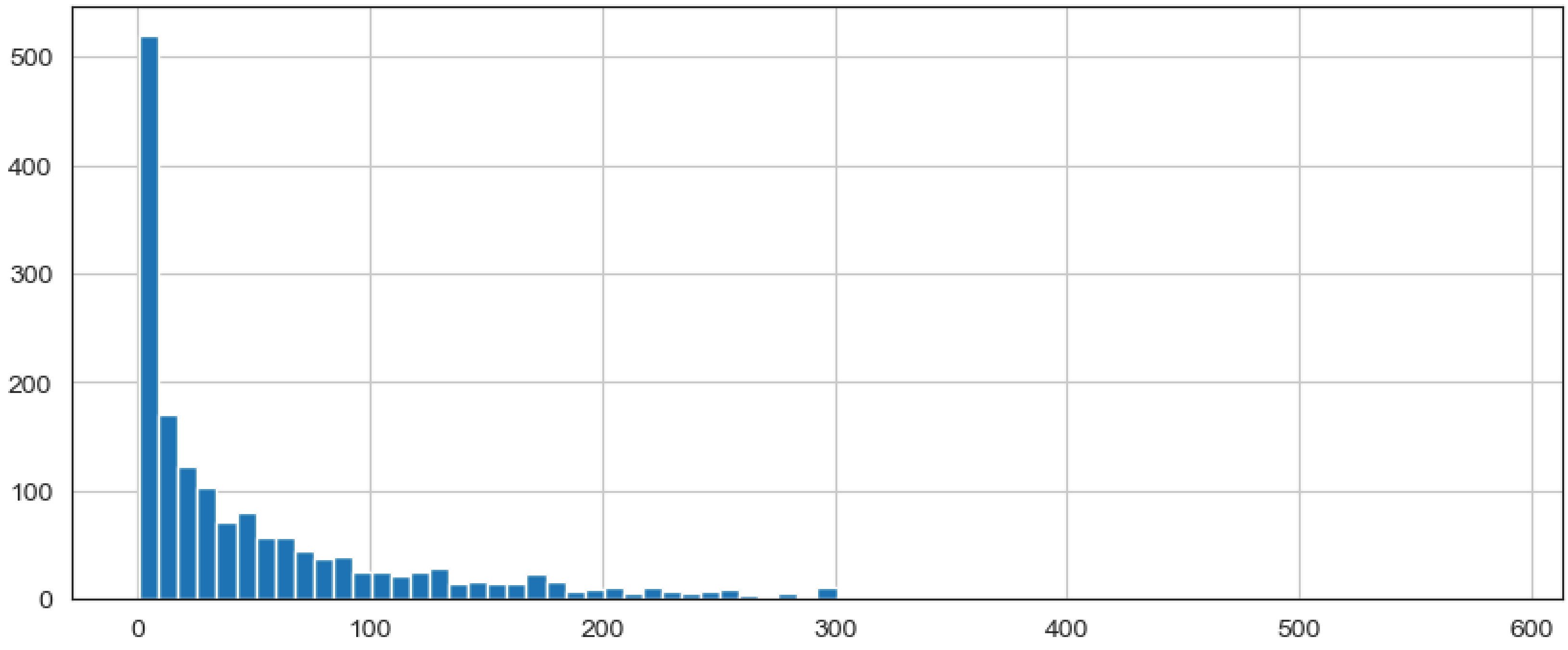
Out[10]:

title	rating	num of ratings
'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:

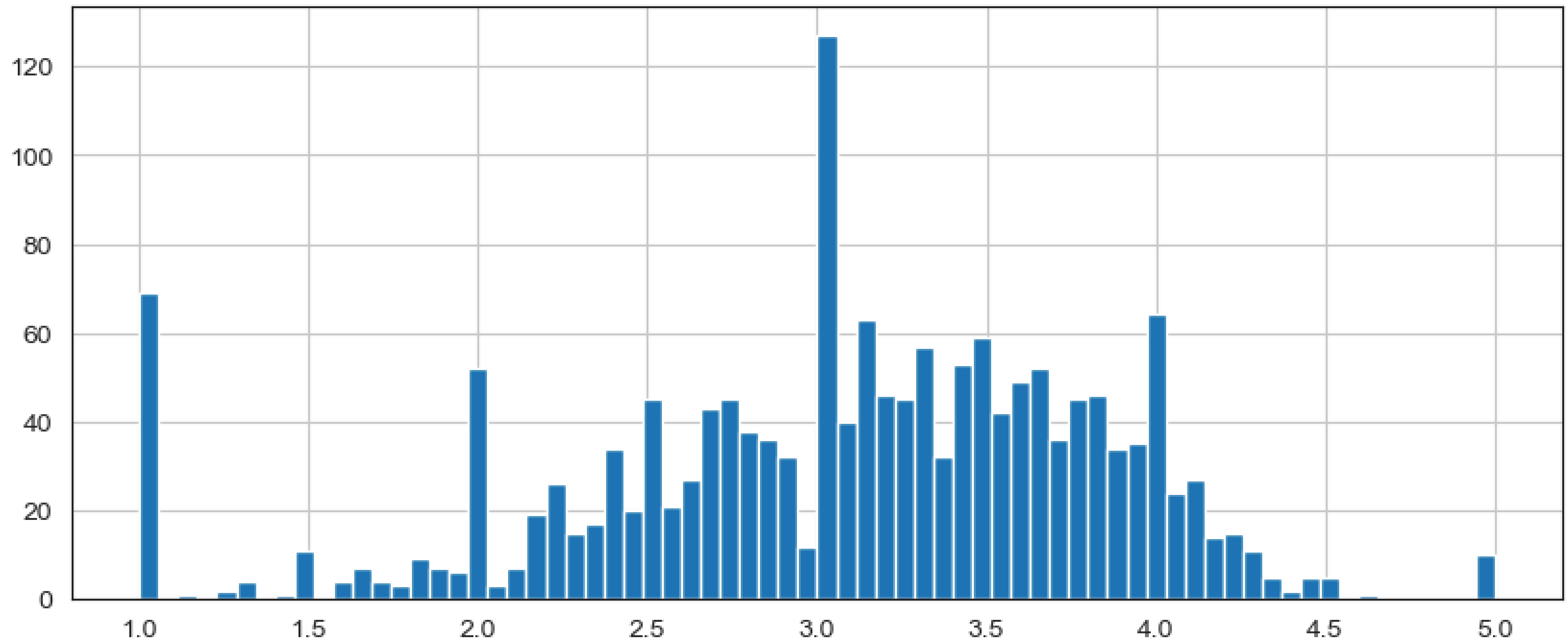
In [11]:
```
plt.figure(figsize=(10,4))
ratings['num of ratings'].hist(bins=70)
```

Out[11]: `<Axes: >`



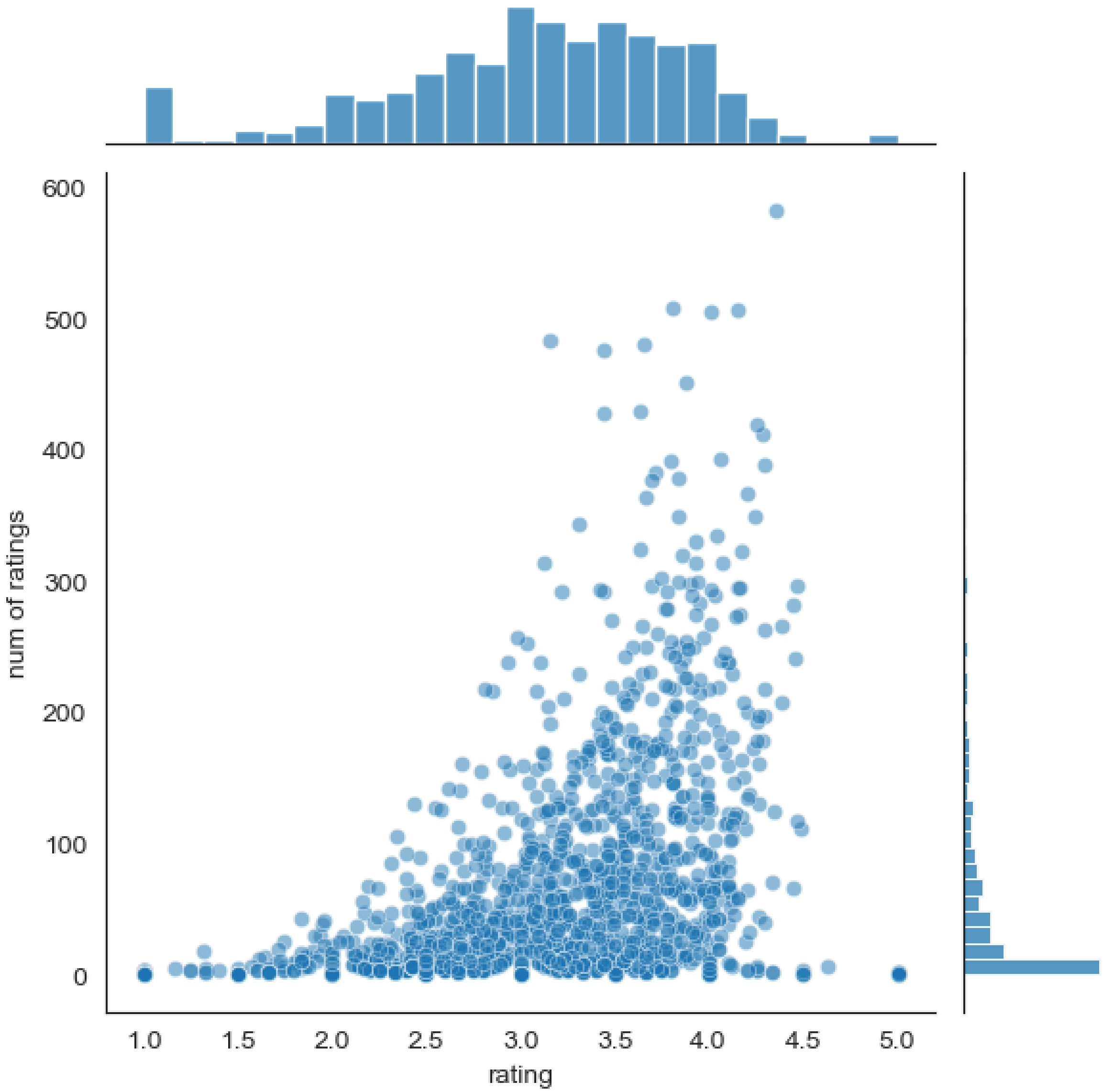
In [12]:
```python
plt.figure(figsize=(10,4))
ratings['rating'].hist(bins=70)
```

Out[12]: <Axes: >



In [13]:
```
sns.jointplot(x='rating',y='num of ratings',data=ratings,alpha=0.5)
```

Out[13]: <seaborn.axisgrid.JointGrid at 0x1ba5d701210>



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.

In [14]:
```
moviemat = df.pivot_table(index='user_id',columns='title',values='rating')
moviemat.head()
```

Out[14]:

title	'Til There Was You (1997)	1-900 (1994)	101 Dalmatians (1996)	12 Angry Men (1957)	187 (1997)	2 Days in the Valley (1996)	20,000 Leagues Under the Sea (1954)	2001: A Space Odyssey (1968)	3 Ninjas: High Noon At Mega Mountain (1998)	39 Steps, The (1935)	...	Yankee Zulu (1994)	Year of the Horse (1997)	You So Crazy (1994)	Young Frankenstei (1974
user_id															
0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN
1	NaN	NaN	2.0	5.0	NaN	NaN	3.0	4.0	NaN	NaN	...	NaN	NaN	NaN	5.(
2	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1.0	NaN	...	NaN	NaN	NaN	NaN
3	NaN	NaN	NaN	NaN	2.0	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN
4	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN

5 rows × 1664 columns

Most rated movie:

In [15]:
```
ratings.sort_values('num of ratings',ascending=False).head(10)
```

Out[15]:

title	rating	num of ratings
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.

In [16]:
```
ratings.head()
```

Out[16]:

title	rating	num of ratings
'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:

In [17]:
```
starwars_user_ratings = moviemat['Star Wars (1977)']
liarliar_user_ratings = moviemat['Liar Liar (1997)']
starwars_user_ratings.head()
```

Out[17]:
```
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:

In [18]:
```
similar_to_starwars = moviemat.corrwith(starwars_user_ratings)
similar_to_liarliar = moviemat.corrwith(liarliar_user_ratings)
```

```
D:\anaconda\Lib\site-packages\numpy\lib\function_base.py:2846: RuntimeWarning: Degrees of freedom <= 0 for sl
ice
  c = cov(x, y, rowvar, dtype=dtype)
D:\anaconda\Lib\site-packages\numpy\lib\function_base.py:2705: RuntimeWarning: divide by zero encountered in
divide
  c *= np.true_divide(1, fact)
```

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

In [19]:
```
corr_starwars = pd.DataFrame(similar_to_starwars,columns=['Correlation'])
corr_starwars.dropna(inplace=True)
corr_starwars.head()
```

Out[19]:

title	Correlation
'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).

In [20]:
```
corr_starwars.sort_values('Correlation',ascending=False).head(10)
```

Out[20]:

	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 qui marchait dans la mer, La) (1991)	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).

In [21]:
```
corr_starwars = corr_starwars.join(ratings['num of ratings'])
corr_starwars.head()
```

Out[21]:

	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:

In [22]:
```
corr_starwars[corr_starwars['num of ratings']>100].sort_values('Correlation',ascending=False).head()
```

Out[22]:

title	Correlation	num of ratings
Star Wars (1977)	1.000000	584
Empire Strikes Back, The (1980)	0.748353	368
Return of the Jedi (1983)	0.672556	507
Raiders of the Lost Ark (1981)	0.536117	420
Austin Powers: International Man of Mystery (1997)	0.377433	130

Now the same for the comedy Liar Liar:

In [23]:
```
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()
```

Out[23]:

title	Correlation	num of ratings
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

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In [ ]: