In [1]:

```
#In this notebook, the focus is on providing a basic recommendation system by suggestin
g items that are most similar
#to a particular item, in this case, movies. This is not a true robust recommendation s
ystem,
#to describe it more accurately,it just tells you what movies/items are most similar to
your movie choice.
```

In [2]:

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

In [3]:

```
col_names=['user_id','item_id','rating','timestamp']
```

In [4]:

```
df=pd.read_csv('u.data',sep='\t',names=col_names)
```

In [6]:

```
df.head()  #The MovieLens dataset
```

Out[6]:

	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

In [7]:

```
movie_titles=pd.read_csv('Movie_Id_Titles')
```

In [8]:

```
movie_titles.head()
```

Out[8]:

	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)

In [9]:

```
df=pd.merge(df,movie_titles,on='item_id') #To have a connection between item id and tit
le
```

In [10]:

```
df.head() #Much better, now the id atleast gives the title of the movie now.
```

Out[10]:

	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)

In [11]:

```
#Lets explore and get a feel of the data
```

In [12]:

```
import matplotlib.pyplot
import seaborn as sns
%matplotlib inline
```

In [13]:

```
sns.set_style('white')
```

In [14]:

```
#Dataframe for average rating and number of ratings
```

In [16]:

```
df.groupby('title')['rating'].mean() #I have the average of mean rating of every movie
```

Out[16]:

```
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
                                            ...
Young Guns II (1990)                      2.772727
Young Poisoner's Handbook, The (1995)     3.341463
Zeus and Roxanne (1997)                   2.166667
unknown                                   3.444444
Á köldum klaka (Cold Fever) (1994)        3.000000
Name: rating, Length: 1664, dtype: float64
```

In [17]:

```
df.groupby('title')['rating'].mean().sort_values(ascending=False).head()  #Gives out th
e top rated movies
```

Out[17]:

```
title
Marlene Dietrich: Shadow and Light (1996)     5.0
Prefontaine (1997)                            5.0
Santa with Muscles (1996)                     5.0
Star Kid (1997)                               5.0
Someone Else's America (1995)                 5.0
Name: rating, dtype: float64
```

In [18]:

```
#Now its possible that only a few people saw it and gave high ratings
```

In [19]:

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

Out[19]:

```
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 [20]:

```
 #So these are rated the most number of times , kinda famous
```

In [22]:

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

In [23]:

```
ratings.head()
```

Out[23]:

	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

In [24]:

```
#BUt we saw that raitng kind of depends on how many people rated it
```

In [25]:

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

In [26]:

```
ratings.head()
```

Out[26]:

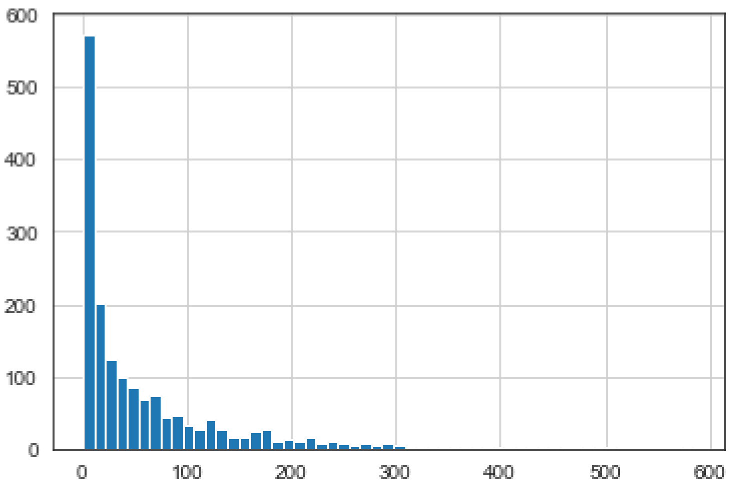
	rating	Count of Ratings
title		
'Til There Was You (1997)	2.333333	9
1-900 (1994)	2.600000	5
101 Dalmatians (1996)	2.908257	109
12 Angry Men (1957)	4.344000	125
187 (1997)	3.024390	41

In [27]:

```
ratings['Count of Ratings'].hist(bins=55)  #Okay so most people dont rate
```

Out[27]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x22e53815d48>
```

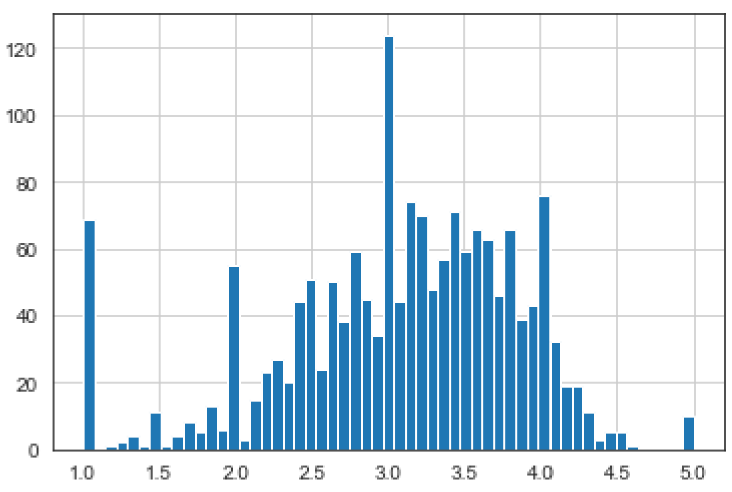


In [28]:

```
ratings['rating'].hist(bins=55) #Okay so ratings are maximum around 3
```

Out[28]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x22e53b3b1c8>
```

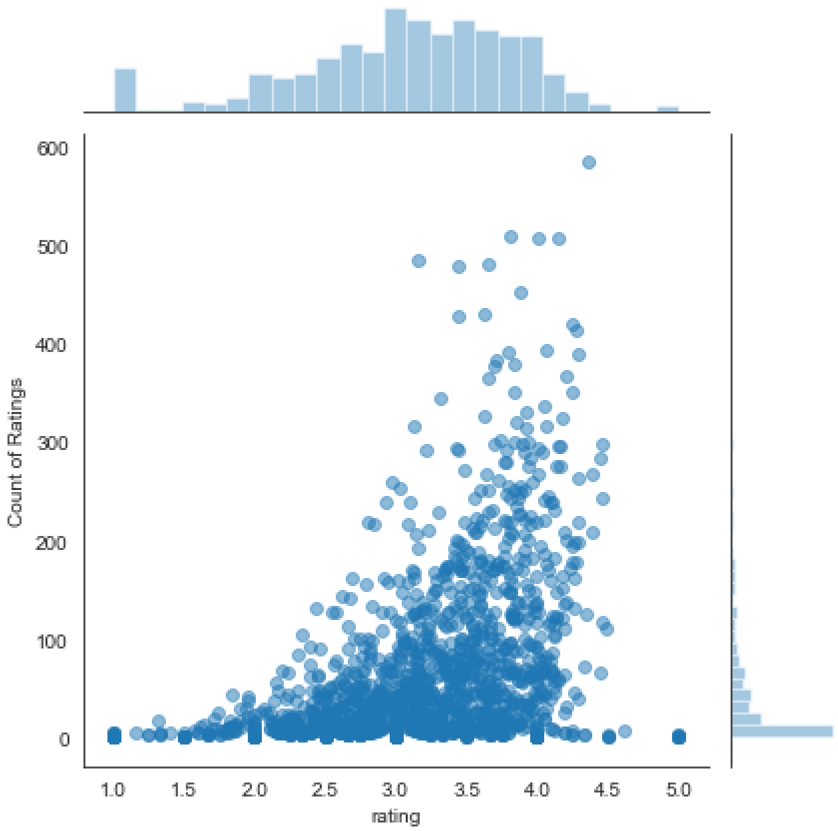


In [29]:

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

Out[29]:

```
<seaborn.axisgrid.JointGrid at 0x22e53a41dc8>
```



In [30]:

```
#So kind of signifies if we have more ratings , more likely to have a higher rating
#kinda makes sense, more people watch better movies and raters
```

In [31]:

```
#Okay so we have a basic idea about the data, Let's look at a simple recommender system
#based of item similarity
```

In [32]:

```
#Matrix for userId of one axis and movie title on other axis, each cell then contains
#the rating the user gave to that movie
```

In [33]:

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

In [34]:

```
moviematrix.head()
```

Out[34]:

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)	Ste T (19
user_id										
0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
1	NaN	NaN	2.0	5.0	NaN	NaN	3.0	4.0	NaN	N
2	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1.0	N
3	NaN	NaN	NaN	NaN	2.0	NaN	NaN	NaN	NaN	N
4	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N

5 rows × 1664 columns

In [35]:

```
#lot of null values make sense as most people have not seen most of the movies
```

In [36]:

```
ratings.sort_values('Count of Ratings',ascending=False)
```

Out[36]:

	rating	Count 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
...	...	...
Great Day in Harlem, A (1994)	5.000000	1
Other Voices, Other Rooms (1997)	3.000000	1
Good Morning (1971)	1.000000	1
Girls Town (1996)	3.000000	1
Á köldum klaka (Cold Fever) (1994)	3.000000	1

1664 rows × 2 columns

In [62]:

```
fargo_user_ratings=moviematrix['Fargo (1996)']
starwars_user_ratings=moviematrix['Star Wars (1977)']
```

In [63]:

```
fargo_user_ratings.head()
```

Out[63]:

```
user_id
0    NaN
1    5.0
2    5.0
3    NaN
4    NaN
Name: Fargo (1996), dtype: float64
```

In [39]:

```
#Using corr with as a method to get a correlation between to pandas series
#Corr with will compute the pair wise correlation between rows and colums of two df obj
ects instead
#of just index or colums of df
```

In [45]:

```
moviematrix.corrwith(fargo_user_ratings)
#I asking for the correlation of every other movie to that specific user behaivor
#on the fargo movie
```

```
C:\Users\anike\anaconda3\lib\site-packages\numpy\lib\function_base.py:252
6: RuntimeWarning: Degrees of freedom <= 0 for slice
  c = cov(x, y, rowvar)
C:\Users\anike\anaconda3\lib\site-packages\numpy\lib\function_base.py:245
5: RuntimeWarning: divide by zero encountered in true_divide
  c *= np.true_divide(1, fact)
```

Out[45]:

```
title
'Til There Was You (1997)             0.100000
1-900 (1994)                          0.866025
101 Dalmatians (1996)                -0.245368
12 Angry Men (1957)                   0.098676
187 (1997)                            0.142509
                                        ...
Young Guns II (1990)                 -0.018688
Young Poisoner's Handbook, The (1995) -0.034345
Zeus and Roxanne (1997)              -0.353553
unknown                              -0.101768
Á köldum klaka (Cold Fever) (1994)         NaN
Length: 1664, dtype: float64
```

In [64]:

```
similar_to_fargo=moviematrix.corrwith(fargo_user_ratings)
similar_to_starwars=moviematrix.corrwith(starwars_user_ratings)
```

```
C:\Users\anike\anaconda3\lib\site-packages\numpy\lib\function_base.py:252
6: RuntimeWarning: Degrees of freedom <= 0 for slice
  c = cov(x, y, rowvar)
C:\Users\anike\anaconda3\lib\site-packages\numpy\lib\function_base.py:245
5: RuntimeWarning: divide by zero encountered in true_divide
  c *= np.true_divide(1, fact)
```

In [48]:

```
#cleaning by removing null values
corr_fargo=pd.DataFrame(similar_to_fargo,columns=['Correlations'])
corr_fargo.dropna(inplace=True)
```

In [51]:

```
corr_fargo.head() #How correlated is the movie ratings of these movies in comparison to fargo
```

Out[51]:

	Correlations
title	
'Til There Was You (1997)	0.100000
1-900 (1994)	0.866025
101 Dalmatians (1996)	-0.245368
12 Angry Men (1957)	0.098676
187 (1997)	0.142509

In [55]:

```
#So basically if we sort it , we will get similar movies
# However some results dont make sense
corr_fargo.sort_values('Correlations',ascending=False).head(10)
```

Out[55]:

	Correlations
title	
Open Season (1996)	1.0
Maya Lin: A Strong Clear Vision (1994)	1.0
Captives (1994)	1.0
City of Industry (1997)	1.0
Convent, The (Convento, O) (1995)	1.0
Fargo (1996)	1.0
Smile Like Yours, A (1997)	1.0
Journey of August King, The (1995)	1.0
King of the Hill (1993)	1.0
Wooden Man's Bride, The (Wu Kui) (1994)	1.0

In [56]:

```
#Funny how smile like yours is perfectly correlated to fargo
#Probably cuz of that one rater who has rated both
#Lets fix this by filtering out movies having less than a certain number of views
```

In [57]:

```
corr_fargo=corr_fargo.join(ratings['Count of Ratings']) #joining the data frame
```

In [58]:

```
corr_fargo.head()
```

Out[58]:

	Correlations	Count of Ratings
title		
'Til There Was You (1997)	0.100000	9
1-900 (1994)	0.866025	5
101 Dalmatians (1996)	-0.245368	109
12 Angry Men (1957)	0.098676	125
187 (1997)	0.142509	41

In [59]:

```
#Join insted of merge as i have title as the index of the data frame
```

In [60]:

```
corr_fargo=corr_fargo[corr_fargo['Count of Ratings']>100].sort_values('Correlations',as
cending=False)
```

In [61]:

```
corr_fargo.head()
```

Out[61]:

title	Correlations	Count of Ratings
Fargo (1996)	1.000000	508
Sling Blade (1996)	0.381159	136
Lone Star (1996)	0.370915	187
Quiz Show (1994)	0.355031	175
Lawrence of Arabia (1962)	0.353408	173

In [66]:

```
corr_starwars=pd.DataFrame(similar_to_starwars,columns=['Correlations'])
```

In [67]:

```
corr_starwars
```

Out[67]:

title	Correlations
'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
...	...
Young Guns II (1990)	0.228615
Young Poisoner's Handbook, The (1995)	-0.007374
Zeus and Roxanne (1997)	0.818182
unknown	0.723123
Á köldum klaka (Cold Fever) (1994)	NaN

1664 rows × 1 columns

In [68]:

```
corr_starwars.dropna(inplace=True)
```

In [69]:

```
corr_starwars=corr_starwars.join(ratings['Count of Ratings'])
```

In [73]:

```
corr_starwars[corr_starwars['Count of Ratings']>150].sort_values('Correlations',ascendi
ng=False).head()
```

Out[73]:

	Correlations	Count of Ratings
title		
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
Sting, The (1973)	0.367538	241

In [74]:

```
#Similar movies to star wars
#Well we were able to filter out some similar movies
#Thank you
```

In [ ]:

```

```