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

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

# Importing users file
users = pd.read_csv('users.csv')

# Importing ratings file
ratings = pd.read_csv('ratings.csv')
```

In [3]:
```python
# Printing the shape of the items dataframe
print(items.shape)
# It shows that there are 1682 rows of different movies, described by 2
3 columns

# Prints the first 5 rows of the dataframe
items.head()
```

```
(1682, 24)
```

Out[3]:

	movie_id	title	release_date	video_release_date	imdb_url	unkn
0	1	Toy Story (1995)	01-Jan-1995	NaN	http://us.imdb.com/M/title-exact?Toy%20Story%2...	0

	movie_id	title	release_date	video_release_date	imdb_url	unkn
1	2	GoldenEye (1995)	01-Jan-1995	NaN	http://us.imdb.com/M/title-exact?GoldenEye%20(...	0
2	3	Four Rooms (1995)	01-Jan-1995	NaN	http://us.imdb.com/M/title-exact? Four%20Rooms%...	0
3	4	Get Shorty (1995)	01-Jan-1995	NaN	http://us.imdb.com/M/title-exact?Get%20Shorty%...	0
4	5	Copycat (1995)	01-Jan-1995	NaN	http://us.imdb.com/M/title-exact? Copycat%20(1995)	0

5 rows × 24 columns

In [4]:

```
# Printing the shape of the users dataframe
print(users.shape)
# It shows that there are 943 rows of unique users, described by 4 colu
mns

# Prints the first 5 rows of the users dataframe
users.head()
```

```
(943, 5)
```

Out[4]:

	user_id	age	sex	occupation	zip_code
0	1	24	M	technician	85711
1	2	53	F	other	94043
2	3	23	M	writer	32067
3	4	24	M	technician	43537

	user_id	age	sex	occupation	zip_code
4	5	33	F	other	15213

In [5]:

```
# Printing the shape of the ratings dataframe
print(ratings.shape)
# It shows that there are 100000 rows of unique ratings, described by 3
 columns. The ratings are all made by the 943 users.

# Prints the first 5 rows of the ratings dataframe
ratings.head()
# Ratings are from 1 to 5. Timestamps are the time when the user left t
he rating. They are unix timestamps, which are expressed
# in seconds after 1970-01-01 00:00:00 UTC
```

```
(100000, 4)
```

Out[5]:

	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 [6]:

```
# items.describe() is not useful in this case, doesn't provide any usef
ul information
# items.describe()
```

In [7]:

```
# Describes the numerical values in the users dataframe, since there is
 only 1 numerical value, namely age, it is the
# only one that is displayed
users.describe()
```

Out[7]:

	user_id	age
count	943.000000	943.000000
mean	472.000000	34.051962
std	272.364951	12.192740
min	1.000000	7.000000
25%	236.500000	25.000000
50%	472.000000	31.000000
75%	707.500000	43.000000
max	943.000000	73.000000

In [8]:

```
# We can see that the lowest rating is 1 and the highest is 5, with an
 average of ~3.5
ratings['rating'].describe()
```

Out[8]:

```
count    100000.000000
mean          3.529860
std           1.125674
min           1.000000
25%           3.000000
50%           4.000000
75%           4.000000
max           5.000000
Name: rating, dtype: float64
```

In [9]:

```
# Merge items (movies) dataframe with ratings dataframe on common colum
n movie_id
movie_ratings = pd.merge(items, ratings, on='movie_id')
movie_ratings.head()
```

Out[9]:

	movie_id	title	release_date	video_release_date	imdb_url	unknown

	movie_id	title	release_date	video_release_date	imdb_url	unknown
0	1	Toy Story (1995)	01-Jan-1995	NaN	http://us.imdb.com/M/title-exact?Toy%20Story%2...	0
1	1	Toy Story (1995)	01-Jan-1995	NaN	http://us.imdb.com/M/title-exact?Toy%20Story%2...	0
2	1	Toy Story (1995)	01-Jan-1995	NaN	http://us.imdb.com/M/title-exact?Toy%20Story%2...	0
3	1	Toy Story (1995)	01-Jan-1995	NaN	http://us.imdb.com/M/title-exact?Toy%20Story%2...	0
4	1	Toy Story (1995)	01-Jan-1995	NaN	http://us.imdb.com/M/title-exact?Toy%20Story%2...	0

5 rows × 27 columns

In [10]:

```
# Create number of ratings column per movie in ratings dataset
ratings_average = pd.DataFrame(movie_ratings.groupby('title')['rating']
.mean())
ratings_average.head()
```

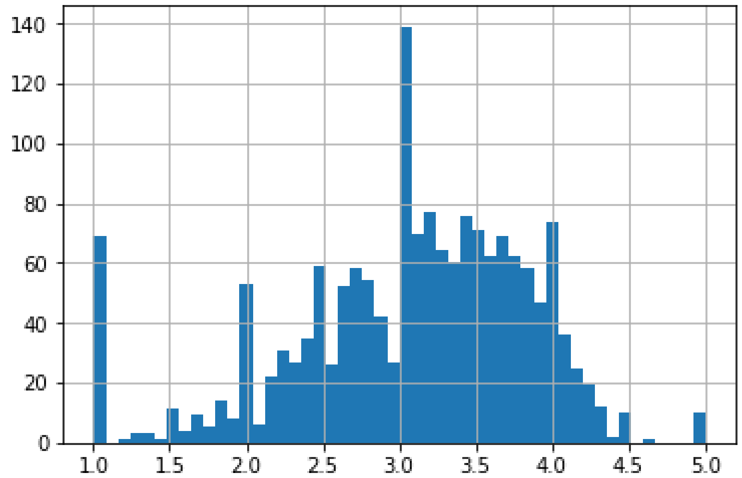
Out[10]:

	rating
title	
'Til There Was You (1997)	2.333333

	rating
title	
1-900 (1994)	2.600000
101 Dalmatians (1996)	2.908257
12 Angry Men (1957)	4.344000
187 (1997)	3.024390

In [11]:
```
# Plot average rating in a histogram
ratings_average['rating'].hist(bins=50)
```

Out[11]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5d77709a20>



In [12]:
```
# Create a number of ratings column to see how many ratings each movie
 has
ratings_average['number_of_ratings'] = movie_ratings.groupby('title')[
'rating'].count()
```

In [13]:
```
# Dataframe after new column
ratings_average.head()
```

Out[13]:

	rating	number_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 [14]:

```
# Display movies with most ratings
ratings_average.sort_values('number_of_ratings', ascending=False).head(
5)
```

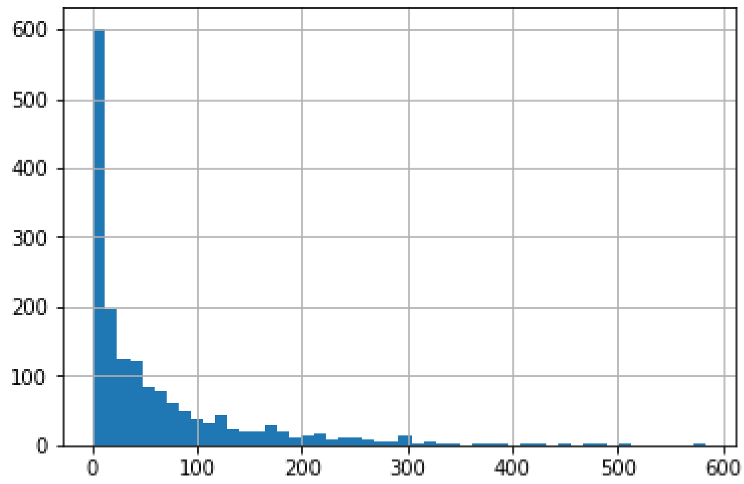
Out[14]:

	rating	number_of_ratings
title		
Star Wars (1977)	4.358491	583
Contact (1997)	3.803536	509
Fargo (1996)	4.155512	508
Return of the Jedi (1983)	4.007890	507
Liar Liar (1997)	3.156701	485

In [15]:

```
# Plot a histogram of the number of ratings to roughly see the distribu
tion of the count of ratings
ratings_average['number_of_ratings'].hist(bins=50)
# It can be seen that most movies have few ratings
```

Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5d77652438>



In [16]:
```
# Is there a correlation between the number of ratings and rating itsel
f?
ratings_average.corr()
# There seems to be quite a big correlation between the 2 variables - 4
3%
```

Out[16]:

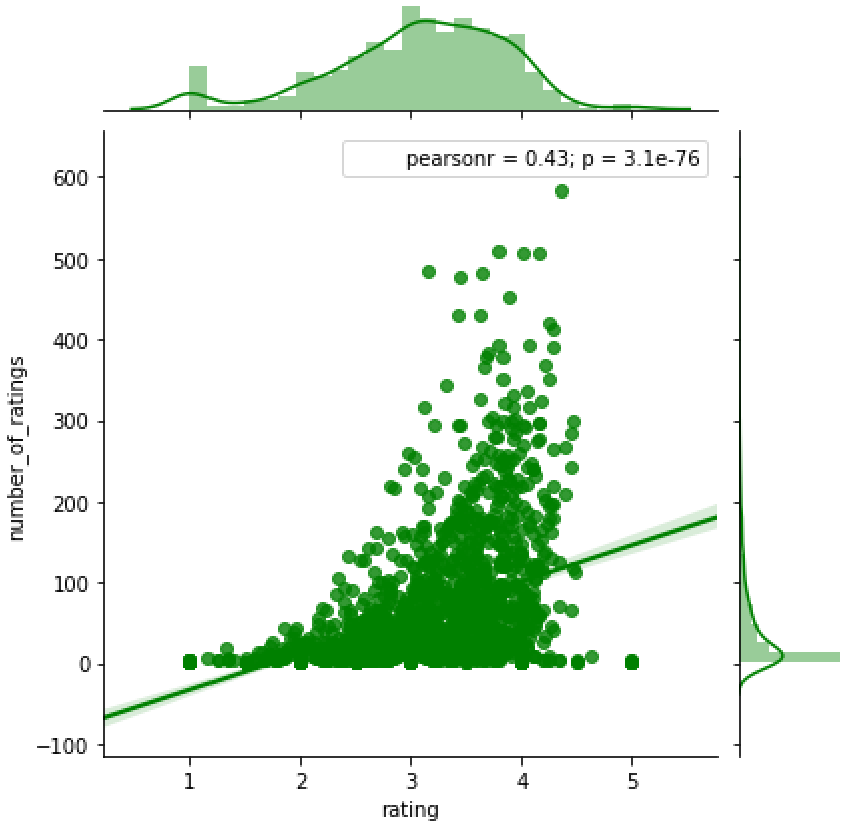
	rating	number_of_ratings
rating	1.000000	0.430998
number_of_ratings	0.430998	1.000000

In [17]:
```
# See the distribution of number of ratings and average ratings
sns.jointplot(x='rating', y='number_of_ratings', data=ratings_average,
kind="reg", color="g")
```

```
/home/vanko/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axe
s.py:6462: UserWarning: The 'normed' kwarg is deprecated, and has been
replaced by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
/home/vanko/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axe
s.py:6462: UserWarning: The 'normed' kwarg is deprecated, and has been
```

```
replaced by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```

Out[17]: `<seaborn.axisgrid.JointGrid at 0x7f5d77525b00>`



Using the correlation between the ratings of movies as a similarity metric

In [18]:
```
# Create a pivot table to display every rating (in table) of each user
 (vertical) for each movie (horizontal)
user_movie_rating = movie_ratings.pivot_table(index='user_id', columns=
```

```
'title', values='rating')
user_movie_rating.head()
```

Out[18]:

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)	(
user_id										
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	NaN	NaN	2.0	NaN	NaN	NaN	NaN	4.0	NaN	N

5 rows × 1664 columns

In [19]:

```
# Select Toy Story movie as an example (displays every rating by each u
ser for Toy Story)
toy_story_ratings = user_movie_rating['Toy Story (1995)']
toy_story_ratings.head()
```

Out[19]:

```
user_id
1    5.0
2    4.0
3    NaN
4    NaN
5    4.0
Name: Toy Story (1995), dtype: float64
```

In [20]:

```
# Find the correlation between Toy Story and every other movie in the d
```

```
ataset
movies_like_toy_story = user_movie_rating.corrwith(toy_story_ratings)
# Create a dataframe out of the correlations
corr_toy_story = pd.DataFrame(movies_like_toy_story, columns=['correlat
ion'])
# Join ratings_average dataframe to see how many ratings each correlate
d movie has
corr_toy_story = corr_toy_story.join(ratings_average['number_of_rating
s'])
# Drop all rows with NaN values
corr_toy_story.dropna(inplace=True)
corr_toy_story.head()
```

```
/home/vanko/anaconda3/lib/python3.6/site-packages/numpy/lib/function_ba
se.py:3175: RuntimeWarning: Degrees of freedom <= 0 for slice
  c = cov(x, y, rowvar)
/home/vanko/anaconda3/lib/python3.6/site-packages/numpy/lib/function_ba
se.py:3109: RuntimeWarning: divide by zero encountered in double_scalar
s
  c *= 1. / np.float64(fact)
```

Out[20]:

	correlation	number_of_ratings
title		
'Til There Was You (1997)	0.534522	9
101 Dalmatians (1996)	0.232118	109
12 Angry Men (1957)	0.334943	125
187 (1997)	0.651857	41
2 Days in the Valley (1996)	0.162728	93

In [21]:

```
# Display 10 most correlated movies
corr_toy_story.sort_values('correlation', ascending=False).head(10)
# It can be seen that all movies that have 100% correlation have a very
 few number of ratings, from which we cannot
# deduce similarity
```

Out[21]:

	correlation	number_of_ratings
title		
Old Lady Who Walked in the Sea, The (Vieille qui marchait dans la mer, La) (1991)	1.0	5
Reckless (1995)	1.0	8
Ladybird Ladybird (1994)	1.0	4
Infinity (1996)	1.0	6
Albino Alligator (1996)	1.0	6
Toy Story (1995)	1.0	452
Guantanamera (1994)	1.0	4
Late Bloomers (1996)	1.0	5
Across the Sea of Time (1995)	1.0	4
Substance of Fire, The (1996)	1.0	4

In [22]:

```
# Therefore we need to put a condition on a minimum number of ratings
corr_toy_story[corr_toy_story['number_of_ratings']>50].sort_values('correlation', ascending=False).head()
```

Out[22]:

	correlation	number_of_ratings
title		
Toy Story (1995)	1.000000	452
Raise the Red Lantern (1991)	0.641535	58
Flubber (1997)	0.558389	53
Jackal, The (1997)	0.557876	87

	correlation	number_of_ratings
title		
Craft, The (1996)	0.549100	104