Exploring the MovieLens 1M Dataset

Extrated (and slightly modified) from *Python for Data Analysis (Wes McKinney)*

This dataset contains 1 million ratings collected from 6000 users on 4000 movies, and it is organized into three tables:

- Ratings
- Users
- Movie information

Each table is available as a separate file, each containing a series of rows where columns are separated by *::*

Download the dataset here

This example illustrates a series of interesting things that we can learn from this dataset. Most operations will be performed using the pandas library. For more details, please refer to *Python for Data Analysis - page 26*.

Code

Let's begin by importing pandas. It is conventional to use *pd* to denote pandas

In [ ]:
```
import pandas as pd
```

Next we will import each of the three tables and assign names to each of the columns:

In [ ]:
```
unames = ['user_id', 'gender', 'age', 'occupation', 'zip']
users = pd.read_table('./ml-1m/users.dat', sep='::', header=None, names=uname
rnames = ['user_id', 'movie_id', 'rating', 'timestamp']
ratings = pd.read_table('./ml-1m/ratings.dat', sep='::', header=None, names=r
mnames = ['movie_id', 'title', 'genres']
movies = pd.read_table('./ml-1m/movies.dat', sep='::', header=None, names=mna
```

Let's take a look at the first 5 rows of each table:

In [ ]:
```
users[:5]
```

Out[ ]:

	user_id	gender	age	occupation	zip
0	1	F	1	10	48067
1	2	M	56	16	70072
2	3	M	25	15	55117
3	4	M	45	7	02460

user_id	gender	age	occupation	zip

In [ ]:
```
ratings[:5]
```

Out[ ]:

	user_id	movie_id	rating	timestamp
0	1	1193	5	978300760
1	1	661	3	978302109
2	1	914	3	978301968
3	1	3408	4	978300275
4	1	2355	5	978824291

In [ ]:
```
movies[:5]
```

Out[ ]:

	movie_id	title	genres
0	1	Toy Story (1995)	Animation|Children's|Comedy
1	2	Jumanji (1995)	Adventure|Children's|Fantasy
2	3	Grumpier Old Men (1995)	Comedy|Romance
3	4	Waiting to Exhale (1995)	Comedy|Drama
4	5	Father of the Bride Part II (1995)	Comedy

Having all information spread across different tables makes it much more dificult to analyse the data. Using pandas's merge function, we first merge ratings with users then we merge that result with the movies data. pandas infers which columns to use as the merge (or join) keys based on overlapping names:

In [ ]:
```
data = pd.merge(pd.merge(ratings, users), movies)
```

Below is the first row in that dataset

In [ ]:
```
data.head()
```

Out[ ]:

	user_id	movie_id	rating	timestamp	gender	age	occupation	zip	title	genres
0	1	1193	5	978300760	F	1	10	48067	One Flew Over the Cuckoo's Nest (1975)	Drama
1	2	1193	5	978298413	M	56	16	70072	One Flew Over the Cuckoo's Nest (1975)	Drama

	user_id	movie_id	rating	timestamp	gender	age	occupation	zip	title	genres
2	12	1193	4	978220179	M	25	12	32793	One Flew Over the Cuckoo's Nest (1975)	Drama
3	15	1193	4	978199279	M	25	7	22903	One Flew Over the Cuckoo's Nest (1975)	Drama
									One Flew Over the	

In this form, aggregating the ratings grouped by one or more user or movie characteristics is straightforward once you build some familiarity with pandas. To get mean movie ratings for each film grouped by gender, we can use the pivot_table method:

In [ ]:
```
mean_ratings = data.pivot_table('rating', index='title', columns='gender', ag
```

In [ ]:
```
mean_ratings[:5]
```

Out[ ]:

gender	F	M
title		
$1,000,000 Duck (1971)	3.375000	2.761905
'Night Mother (1986)	3.388889	3.352941
'Til There Was You (1997)	2.675676	2.733333
'burbs, The (1989)	2.793478	2.962085
...And Justice for All (1979)	3.828571	3.689024

If we wish to only look at movies that received more than a certain number of ratings, we can group them as follows (here using 250 ratings):

In [ ]:
```
ratings_by_title = data.groupby('title').size()
```

In [ ]:
```
ratings_by_title[:5]
```

Out[ ]:
```
title
$1,000,000 Duck (1971)            37
'Night Mother (1986)              70
'Til There Was You (1997)         52
'burbs, The (1989)               303
...And Justice for All (1979)    199
dtype: int64
```

Let's now grab the titles of movies that were rated more than 250 times:

In [ ]:
```
active_titles = ratings_by_title.index[ratings_by_title >= 250]
```

In [ ]:
```
active_titles[:5]
```

Out[ ]:
```
Index([''burbs, The (1989)', '10 Things I Hate About You (1999)',
       '101 Dalmatians (1961)', '101 Dalmatians (1996)',
       '12 Angry Men (1957)'],
      dtype='object', name='title')
```

The index of titles receiving at least 250 ratings can then be used to select rows from mean_ratings above:

In [ ]:
```
mean_ratings = mean_ratings.loc[active_titles]
```

In [ ]:
```
mean_ratings[:5]
```

Out[ ]:

gender	F	M
title		
'burbs, The (1989)	2.793478	2.962085
10 Things I Hate About You (1999)	3.646552	3.311966
101 Dalmatians (1961)	3.791444	3.500000
101 Dalmatians (1996)	3.240000	2.911215
12 Angry Men (1957)	4.184397	4.328421

To see the top films among female viewers, we can sort by the F column in descending order:

In [ ]:
```
top_female_ratings = mean_ratings.sort_values(by='F', ascending=False)
```

In [ ]:
```
top_female_ratings[:10]
```

Out[ ]:

gender	F	M
title		
Close Shave, A (1995)	4.644444	4.473795
Wrong Trousers, The (1993)	4.588235	4.478261
Sunset Blvd. (a.k.a. Sunset Boulevard) (1950)	4.572650	4.464589
Wallace & Gromit: The Best of Aardman Animation (1996)	4.563107	4.385075
Schindler's List (1993)	4.562602	4.491415
Shawshank Redemption, The (1994)	4.539075	4.560625
Grand Day Out, A (1992)	4.537879	4.293255

gender	F	M
title		
To Kill a Mockingbird (1962)	4.536667	4.372611

Likewise, for males:

In [ ]:
```
top_male_ratings = mean_ratings.sort_values(by='M', ascending=False)
```

In [ ]:
```
top_male_ratings[:10]
```

Out[ ]:

gender	F	M
title		
Godfather, The (1972)	4.314700	4.583333
Seven Samurai (The Magnificent Seven) (Shichinin no samurai) (1954)	4.481132	4.576628
Shawshank Redemption, The (1994)	4.539075	4.560625
Raiders of the Lost Ark (1981)	4.332168	4.520597
Usual Suspects, The (1995)	4.513317	4.518248
Star Wars: Episode IV - A New Hope (1977)	4.302937	4.495307
Schindler's List (1993)	4.562602	4.491415
Wrong Trousers, The (1993)	4.588235	4.478261
Close Shave, A (1995)	4.644444	4.473795
Rear Window (1954)	4.484536	4.472991

Suppose you wanted to find the movies that are most divisive between male and female viewers. One way is to add a column to *mean_ratings* containing the difference in means, then sort by that:

In [ ]:
```
mean_ratings['diff'] = mean_ratings['M'] - mean_ratings['F']
```

Sorting by 'diff' gives us the movies with the greatest rating difference and which were preferred by women:

In [ ]:
```
sorted_by_diff = mean_ratings.sort_values(by='diff')
```

In [ ]:
```
sorted_by_diff[:10]
```

Out[ ]:

gender	F	M	diff
title			
Dirty Dancing (1987)	3.790378	2.959596	-0.830782
Jumpin' Jack Flash (1986)	3.254717	2.578358	-0.676359

gender	F	M	diff
title			
Grease (1978)	3.975265	3.367041	-0.608224
Little Women (1994)	3.870588	3.321739	-0.548849
Steel Magnolias (1989)	3.901734	3.365957	-0.535777
Anastasia (1997)	3.800000	3.281609	-0.518391
Rocky Horror Picture Show, The (1975)	3.673016	3.160131	-0.512885
Color Purple, The (1985)	4.158192	3.659341	-0.498851

Reversing the order of the rows and again slicing off the top 10 rows, we get the movies preferred by men that women didn't rate highly:

In [ ]:

```
sorted_by_diff[::-1][:10]
```

Out[ ]:

gender	F	M	diff
title			
Good, The Bad and The Ugly, The (1966)	3.494949	4.221300	0.726351
Kentucky Fried Movie, The (1977)	2.878788	3.555147	0.676359
Dumb & Dumber (1994)	2.697987	3.336595	0.638608
Longest Day, The (1962)	3.411765	4.031447	0.619682
Cable Guy, The (1996)	2.250000	2.863787	0.613787
Evil Dead II (Dead By Dawn) (1987)	3.297297	3.909283	0.611985
Hidden, The (1987)	3.137931	3.745098	0.607167
Rocky III (1982)	2.361702	2.943503	0.581801
Caddyshack (1980)	3.396135	3.969737	0.573602
For a Few Dollars More (1965)	3.409091	3.953795	0.544704

(1) [10 pts] An aggregate on the number of rating done for each particular genre, e.g., (Action, Adventure, Drama, Science Fiction, ...)

In [ ]:

```
import numpy as np
# split the genres up so they are actually seperate not a single string.
data['genres'] = data['genres'].apply(lambda x: x.split('|'))
# Flatten the data so they are a single list of the genres
a = pd.Series(np.concatenate(data.genres))
a.shape
```

Out[ ]:

```
(2101815,)
```

In [ ]:

```
df = a.groupby(a).size().rename_axis('genres').reset_index(name='count')
df
```

Out[ ]:

	genres	count
0	Action	257457
1	Adventure	133953
2	Animation	43293
3	Children's	72186
4	Comedy	356580
5	Crime	79541
6	Documentary	7910
7	Drama	354529
8	Fantasy	36301
9	Film-Noir	18261
10	Horror	76386
11	Musical	41533
12	Mystery	40178
13	Romance	147523
14	Sci-Fi	157294
15	Thriller	189680
16	War	68527
17	Western	20683

(2) [5 pts] The top 5 ranked genres by women on most number of rating

In [ ]:

```
genre_woman = data[['genres','gender']]
genre_woman = genre_woman[genre_woman.gender == 'F']
genre_woman.reset_index(inplace=True)
genre_woman.head()
```

Out[ ]:

	index	genres	gender
0	0	[Drama]	F
1	5	[Drama]	F
2	7	[Drama]	F
3	8	[Drama]	F
4	19	[Drama]	F

In [ ]:

```
genre_f = pd.Series(np.concatenate(genre_woman.genres))
genre_f.shape
```

Out[ ]:

```
(505937,)
```

In [ ]:

```
df_f = genre_f.groupby(genre_f).size().rename_axis('genres').reset_index(name
df_f.sort_values(by='count', ascending=False)[0:5]
```

Out[ ]:

	genres	count
7	Drama	98153
4	Comedy	96271
13	Romance	50297
0	Action	45650
15	Thriller	40308

(3) [5 pts] The top 5 ranked genres by men on most number of rating.

In [ ]:

```
genre_man = data[['genres','gender']]
genre_man = genre_man[genre_man.gender == 'M']
genre_man.reset_index(inplace=True)
genre_man.head()
```

Out[ ]:

	index	genres	gender
0	1	[Drama]	M
1	2	[Drama]	M
2	3	[Drama]	M
3	4	[Drama]	M

index	genres	gender

In [ ]:
```
genre_m = pd.Series(np.concatenate(genre_man.genres))
genre_m.shape
```

Out[ ]:
```
(1595878,)
```

In [ ]:
```
df_m = genre_m.groupby(genre_m).size().rename_axis('genres').reset_index(name
df_m.sort_values(by='count', ascending=False)[0:5]
```

Out[ ]:

	genres	count
4	Comedy	260309
7	Drama	256376
0	Action	211807
15	Thriller	149372
14	Sci-Fi	129894

(4) [30 pts] Pick a genre of your choice and provide average movie's ratings by the following four time intervals during which the movies were released (a) 1970 to 1979 (b) 1980 to 1989 (c) 1990 to 1999 (d) 2000 to 2009. Also, if you observed any issues with data in any of these ranges, please mention it.

The genere I'm chosing is Thriller

In [ ]:
```
import re
data_thriller = data[['Thriller' in x for x in data['genres']]]
thriller_mean_ratings = data_thriller.pivot_table('rating', index='title', ag
thriller_mean_ratings['year'] = [int(re.search(r'\(\d+\)', i)[0][1:-1]) for i
print(f'Total thriller movies {thriller_mean_ratings.shape[0]}')
thriller_mean_ratings.head()
```

```
Total thriller movies 485
```

Out[ ]:

title	rating	year
...And Justice for All (1979)	3.713568	1979
13th Warrior, The (1999)	3.158667	1999
2001: A Space Odyssey (1968)	4.068765	1968

	rating	year
title		

In [ ]:
```
def thrillers_between(lower: int, upper:int):
    thriller_mean_ratings_a = thriller_mean_ratings[thriller_mean_ratings['ye
    print(f'\n \n Number of thriller movies from {lower} to {upper}: {thrille
    print(thriller_mean_ratings_a.head())
```

In [ ]:
```
year_ranges = [(1970, 1979),(1980, 1989),(1990, 1999),(2000, 2009)]
for year_range in year_ranges:
    thrillers_between(year_range[0], year_range[1])
```

```
 Number of thriller movies from 1970 to 1979: 21
                                 rating  year
title
...And Justice for All (1979)  3.713568  1979
Alien (1979)                   4.159585  1979
Assault on Precinct 13 (1976)  3.571429  1976
Boys from Brazil, The (1978)   3.661765  1978
Chinatown (1974)               4.339241  1974


 Number of thriller movies from 1980 to 1989: 54
                      rating  year
title
52 Pick-Up (1986)   3.300000  1986
Abyss, The (1989)   3.683965  1989
Akira (1988)        3.933628  1988
Aliens (1986)       4.125824  1986
Angel Heart (1987)  3.404018  1987


 Number of thriller movies from 1990 to 1999: 317
                            rating  year
title
13th Warrior, The (1999)  3.158667  1999
8MM (1999)                2.863971  1999
Absolute Power (1997)     3.357895  1997
Air Force One (1997)      3.588290  1997
Albino Alligator (1996)   2.851064  1996


 Number of thriller movies from 2000 to 2009: 25
                            rating  year
title
American Psycho (2000)    3.219048  2000
Bless the Child (2000)    2.666667  2000
Cell, The (2000)          3.261398  2000
Contender, The (2000)     3.780928  2000
Final Destination (2000)  3.272331  2000
```

(5) 30 pts] A function that given a genre and a rating_range (i.e. [3.5, 4]), returns all the

movies of that genre and within that rating range sorted by average rating. Using an example, demonstrate that your function works.

In [ ]:

```
def genre_average_rating(genre: str, rating_range: list[float], ascending: bo
    """Returns the movies from a genre with an average rating between the spe

    Args:
        genre (str): the genre
        rating_range (list[float]): a rating range which should be a list of
    """
    # input checking
    if len(rating_range) != 2:
        print('Please make sure you only include a lower and upper rating_ran
        return
    elif rating_range[0] < 1:
        # the readme for the data says the ratings are bouned by whole star s
        print('your lower limit must be greater than or equal to 1')
        return
    elif rating_range[0] > 5:
        print('your lower limit must be lower than or equal to 5')
        return
    elif rating_range[1] > 5:
        print('your upper limit must be lower than or equal to 5')
        return
    elif rating_range[0] > rating_range[1]:
        print('Make sure you putt the lower limit first in the list')
        return

    # seperate data to the specified genre
    data_genre_specific = data[[genre in x for x in data['genres']]]


    if data_genre_specific.shape[0] < 1:
        print('You selected a genre that doesn\'t exist!')
        return

    # aggregate the data and then select between the given range
    gs_mean_ratings = data_thriller.pivot_table('rating', index='title', aggf
    gs_mean_ratings = gs_mean_ratings[gs_mean_ratings['rating'].between(ratin

    return gs_mean_ratings.sort_values(by='rating', ascending=ascending)
```

In [ ]:

```
genre_average_rating('Thriller', [3.8, 3.85])
```

Out[ ]:

title	rating
Born American (1986)	3.800000
I Can't Sleep (J'ai pas sommeil) (1994)	3.800000

	rating
title	
Rosemary's Baby (1968)	3.818820
Saboteur (1942)	3.820225
Dark City (1998)	3.822654
Bound (1996)	3.823427

(6) [20 pts] Present one other statistic, figure, aggregate, or plot that you created using this dataset, along with a short description of what interesting observations you derived from it. This question is meant to give you a freehand to explore and present aspects of the dataset that interests you!

In [ ]:

```
def genre_specifc_mean_ratings_year(genre: str):
    data_gs = data[[genre in x for x in data['genres']]]
    gs_mean_ratings = data_gs.pivot_table('rating', index='title', aggfunc='m
    gs_mean_ratings['year'] = [int(re.search(r'\(\d+\)', i)[0][1:-1]) for i i
    gs_mean_ratings['genre'] = genre
    return gs_mean_ratings.sort_values(by='year').reset_index()[['rating', 'y
```

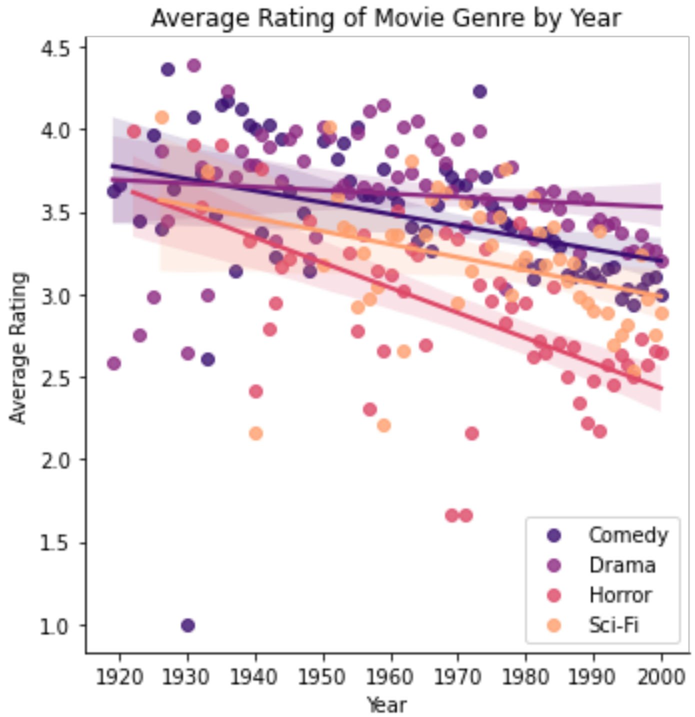
In [ ]:

```
genres = ['Comedy', 'Drama', 'Horror', 'Sci-Fi']
genre_year_avg_rating = pd.concat([genre_specifc_mean_ratings_year(genre) for
genre_df =genre_year_avg_rating.groupby(['year', 'genre']).mean().reset_index
genre_df['genre'] = genre_df['genre'].astype('category')
```

In [ ]:

```
import seaborn as sn
import matplotlib.pyplot as plt
sn.lmplot(data= genre_df, x='year', y='rating', hue='genre', legend=False, pa

plt.title("Average Rating of Movie Genre by Year")
plt.xlabel("Year")
plt.ylabel("Average Rating")
plt.legend(loc='lower right')
plt.show()
```



I was interested in seeing if there was an overarching trend in the average rating of movies over time. It was advantageous to breakdown the data by genre. I selected four genres (Comedy, Drama, Horror, Sci-Fi) to compare but this can be done with any amount. Four genres were chosen to keep clarity within the graphic, these specific genres were chosen arbitrarily. What was interesting is that all genres had a trend down over time. The spread of the data doesn't allow for a completely accurate trend line but this trend still appeared. Furthermore, this is descriptive of the data but does not explain why the trend is there. Exploring the data further may lead to understanding of the trend, if I was to intuit some explanations I would guess that there is something to do with the number of reviews over time. I would predict that as the number of reviews goes up the average rating will go down as it trends towards a 'common' rating.