Final Project Submission

Please fill out:

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- Student pace: **Part time**
- Scheduled project review date/time:
- Instructor name:
- Blog post URL:

Research Questions

1. Which genres are most popular for all-time?
2. Is movie production budget directly related to the popularity/gross revenue?
3. Which cast and crew are associated with the most popular movies?

In [45]:
```
#import required modules
import gzip
import requests
import pandas as pd
import numpy as np
import json
import matplotlib.pyplot as plt
from datetime import datetime
```

In [62]:
```
plt.style.use('seaborn-v0_8')
```

In [2]:
```
#Load tmdb.movies.csv.gz file
with gzip.open('zippedData/tmdb.movies.csv.gz', 'r') as f:
    tmdb_movies = pd.read_csv(f, index_col= 0)
```

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

Out[3]:

	genre_ids	id	original_language	original_title	popularity	release_date	title	vot
0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	Harry Potter and the Deathly Hallows: Part 1	
1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon	
2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	
3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	
4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	

In [4]:
```
#filter to take only movies subset with vote count that is higher t
tmdb_movies = tmdb_movies[tmdb_movies['vote_count'] > tmdb_movies['
```

In [5]:
```
#function for loading api key file that will be used to request tmd
def get_keys(path):
    with open(path) as f:
        return json.load(f)

keys = get_keys('/Users/dave/.secret/tmdb_api.json')
api_key = keys['api_key']
```

In [6]:
```
#Request tmdb for genres ids
url = "https://api.themoviedb.org/3/genre/movie/list?language=en"

headers = {
    "accept": "application/json",
    "Authorization": "Bearer {}".format(api_key)
}

response = requests.get(url, headers=headers)
```

In [7]:
```
#load the json format of the response from the api call into a data
tmdb_genre_ids = pd.DataFrame(response.json()['genres'])
tmdb_genre_ids.head()
```

Out[7]:

	id	name
0	28	Action
1	12	Adventure
2	16	Animation
3	35	Comedy
4	80	Crime

In [8]:
```
#Define a function that processes tmdb_movies['genre_ids'] values,
def process_genre_ids(index):
    ids = list(index.replace("[","").replace("]","").split(','))
    return [int(num.strip()) for num in ids if num.strip()]

# Apply the function to every element in tmdb_movies['genre_ids']
tmdb_movies['genre_ids'] = tmdb_movies['genre_ids'].apply(process_g
```

In [9]:
```
#Create a new column in tmdb.movies that will hold translated value
# Create a function to extract the genre names
def get_genre_names(genre_ids):
    genre_names = []
    for genre_id in genre_ids:
        if genre_id in tmdb_genre_ids['id'].values:
            genre_index = tmdb_genre_ids[tmdb_genre_ids['id'] == ge
            genre_names.append(tmdb_genre_ids.loc[genre_index, 'nam
    return genre_names

# Apply the function to the 'genre_ids' column and assign the resul
tmdb_movies['genre'] = tmdb_movies['genre_ids'].apply(lambda x: get
```

In [10]:
```
tmdb_movies.head()
```

Out[10]:

	genre_ids	id	original_language	original_title	popularity	release_date	title	vot
0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	Harry Potter and the Deathly Hallows: Part 1	
1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon	
2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	
3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	
4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	

In [11]:
```
#Load imdb.title.ratings.csv.gz
with gzip.open('zippedData/imdb.title.ratings.csv.gz', 'r') as f:
    imdb_movies_ratings = pd.read_csv(f)
```

In [12]:
```
imdb_movies_ratings.head()
```

Out[12]:

	tconst	averagerating	numvotes
0	tt10356526	8.3	31
1	tt10384606	8.9	559
2	tt1042974	6.4	20
3	tt1043726	4.2	50352
4	tt1060240	6.5	21

In [13]:
```
#Load imdb.title.basics.csv.gz
with gzip.open('zippedData/imdb.title.basics.csv.gz', 'r') as f:
    imdb_title_basics = pd.read_csv(f)
```

In [14]:
```
imdb_title_basics.head()
```

Out[14]:

	tconst	primary_title	original_title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy

In [15]:
```
#concatenate imdb_title_basics and imdb.title.ratings on the 'tcons
imdb_movies = pd.concat([imdb_title_basics.set_index('tconst'), imd
```

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

Out[16]:

tconst	primary_title	original_title	start_year	runtime_minutes	genres	av
tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	
tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama	
tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama	
tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Drama	
tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy	

In [17]:
```
imdb_movies.shape
```

Out[17]:
```
(146144, 7)
```

In [18]:
```
imdb_movies = imdb_movies[imdb_movies['numvotes'] > imdb_movies['nu
```

In [19]:
```
imdb_movies.shape
```

Out[19]: (4751, 7)

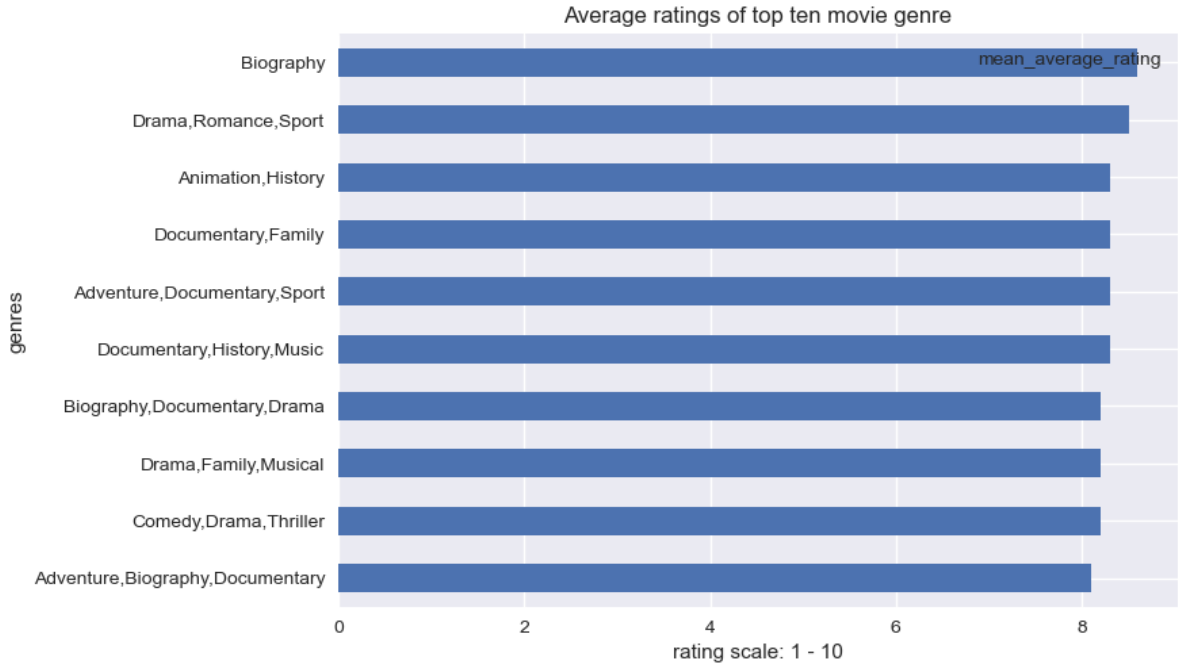
In [20]:
```
#aggregate imdb movies by genre and find the averages of ratings an
imdb_genre_aggregate = imdb_movies[['genres', 'averagerating', 'num
    mean_average_rating=('averagerating', 'mean'),
    mean_num_votes=('numvotes', 'mean')
)
#sort values by average ratings
imdb_genre_aggregate.sort_values(by= imdb_genre_aggregate.columns[0
```

Out[20]:

genres	mean_average_rating	mean_num_votes
Biography	8.6	3879.0
Drama,Romance,Sport	8.5	4098.0
Animation,History	8.3	7451.0
Documentary,Family	8.3	3820.0
Adventure,Documentary,Sport	8.3	7288.0
...	...	...
Action,Adventure,History	4.5	7523.0
Crime,Romance,Thriller	4.3	8782.0
Comedy,Romance,Sci-Fi	4.2	4953.0
Comedy,Family,Sci-Fi	2.6	4552.0
Crime,Mystery	1.5	26723.0

383 rows × 2 columns

In [69]:
```
#plot for the top ten (10) most rated genres on imdb movies
imdb_genre_aggregate.sort_values(by= imdb_genre_aggregate.columns[0
imdb_genre_aggregate[:10].plot(kind= 'barh', y=imdb_genre_aggregate
plt.gca().invert_yaxis()
plt.title('Average ratings of top ten movie genre')
plt.xlabel('rating scale: 1 - 10');
```



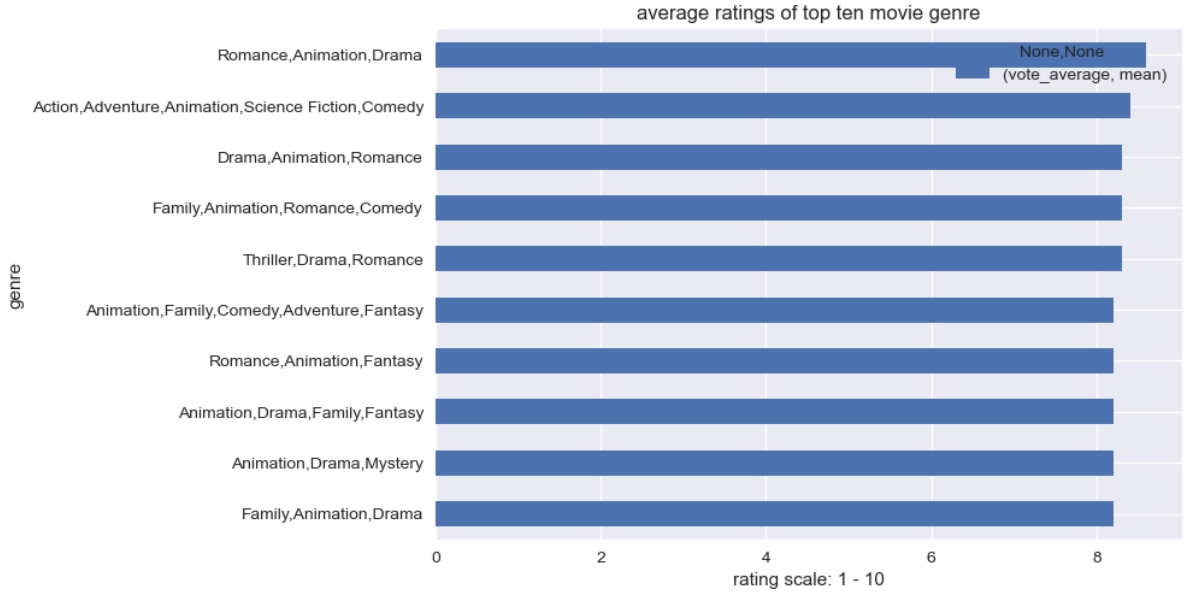
In [22]:
```
#Similarly to tmdb.movies, also aggregate tmdb.movies by genre and
#First convert the values of the tmdb genre column into a string ob
#as that of the imdb.movies genre column
tmdb_movies['genre'] = tmdb_movies['genre'].apply(lambda x: ','.joi

#group by genre
tmdb_genre_aggregate = tmdb_movies[['vote_average','vote_count','ge
    {'vote_average':['mean'],'vote_count':['mean']})
tmdb_genre_aggregate.sort_values(by= tmdb_genre_aggregate.columns[0
```

Out[22]:

	vote_average	vote_count
	mean	mean
genre		
Romance,Animation,Drama	8.6	4161.0
Action,Adventure,Animation,Science Fiction,Comedy	8.4	4048.0
Drama,Animation,Romance	8.3	1034.0
Family,Animation,Romance,Comedy	8.3	684.0
Thriller,Drama,Romance	8.3	1213.0
...	...	...
Action,TV Movie,Science Fiction,Comedy,Adventure	4.3	246.0
Fantasy,Horror,Mystery,Thriller	4.2	2475.0
Action,Horror	4.1	238.0
Mystery,Adventure,Comedy,Crime	4.1	217.0
Science Fiction,TV Movie,Action,Adventure,Comedy	3.8	873.0

822 rows × 2 columns

In [70]:
```
#Similarly as done for the imdb data, also plot for the top ten (10
tmdb_genre_aggregate.sort_values(by= tmdb_genre_aggregate.columns[0
tmdb_genre_aggregate[:10].plot(kind= 'barh', y= tmdb_genre_aggregat
plt.gca().invert_yaxis()
plt.title('average ratings of top ten movie genre')
plt.xlabel('rating scale: 1 - 10');
```



In [28]:
```
#Check to see if there are genres whose ratings have a trend over t
#First group by year of release
imdb_rating_by_year = imdb_movies[['start_year','genres','averagera
imdb_rating_by_year.head()
```

Out[28]:

		averagerating	numvotes
		mean	mean
genres	start_year		
Action	2010	3.850000	8532.000000
	2011	5.500000	7592.000000
	2012	5.650000	38569.000000
	2013	5.333333	6815.666667
	2015	7.200000	21092.000000

In [29]:
```
#The same with tmdb movies
tmdb_movies['release_date'] = pd.to_datetime(tmdb_movies['release_d
tmdb_rating_by_year = tmdb_movies[['release_date','vote_average','v
tmdb_rating_by_year.head()
```

Out[29]:

		vote_average	vote_count
		mean	mean
genre	release_date		
Action	2012-01-01	6.0	713.0
	2012-11-02	5.3	573.0
	2015-02-27	4.7	223.0
	2015-07-14	4.6	213.0
	2015-07-31	7.1	5242.0

In [66]:
```
pivot_imdb = imdb_rating_by_year.pivot_table(index='start_year', co

# Plot the data
pivot_imdb.plot(figsize=(10, 6))
plt.title('Mean Average Rating by Year for Each Genre')
plt.xlabel('Year')
plt.ylabel('Mean Average Rating')
plt.legend(title='Genres', loc='center left', bbox_to_anchor=(1, 0.
plt.show()
```

In [65]:
```
pivot_tmdb = tmdb_rating_by_year.pivot_table(index='release_date',

# Plot the data
pivot_tmdb.plot(figsize=(10, 6))
plt.xlim('2010-01-01','2020-01-01')
plt.title('Mean Average Rating by Year for Each Genre')
plt.xlabel('Year')
plt.ylabel('Mean Average Rating')
plt.legend(title='Genres', loc='center left', bbox_to_anchor=(1, 0.
plt.show()
```

Research Question 2: Is movie production budget directly related to its gross revenue?

In [38]:
```
#load tn.movie budgets
with gzip.open('zippedData/tn.movie_budgets.csv.gz') as f:
    tn_movie_budgets = pd.read_csv(f)
tn_movie_budgets.head()
```

Out[38]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	$425,000,000	$760,507,625	$2,776,345,279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,875
2	3	Jun 7, 2019	Dark Phoenix	$350,000,000	$42,762,350	$149,762,350
3	4	May 1, 2015	Avengers: Age of Ultron	$330,600,000	$459,005,868	$1,403,013,963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	$317,000,000	$620,181,382	$1,316,721,747

In [39]:
```
#load bom.movie gross for movie revenues
with gzip.open('zippedData/bom.movie_gross.csv.gz') as f:
    bom_movies_gross = pd.read_csv(f)
bom_movies_gross.head()
```

Out[39]:

	title	studio	domestic_gross	foreign_gross	year
0	Toy Story 3	BV	415000000.0	652000000	2010
1	Alice in Wonderland (2010)	BV	334200000.0	691300000	2010
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	664300000	2010
3	Inception	WB	292600000.0	535700000	2010
4	Shrek Forever After	P/DW	238700000.0	513900000	2010

In [40]:
```
ovies_budget_and_revenue = pd.merge(tn_movie_budgets, bom_movies_gro
ovies_budget_and_revenue.drop(['domestic_gross_x','title'], axis= 1,
ovies_budget_and_revenue.rename(columns={'domestic_gross_y': 'domest
ovies_budget_and_revenue.head()
```

Out[40]:

	id	release_date	movie	production_budget	worldwide_gross	studio	domestic_gros
0	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$1,045,663,875	BV	241100000.
1	4	May 1, 2015	Avengers: Age of Ultron	$330,600,000	$1,403,013,963	BV	459000000.
2	7	Apr 27, 2018	Avengers: Infinity War	$300,000,000	$2,048,134,200	BV	678800000.
3	9	Nov 17, 2017	Justice League	$300,000,000	$655,945,209	WB	229000000.
4	10	Nov 6, 2015	Spectre	$300,000,000	$879,620,923	Sony	200100000.

In [41]:
```
movies_budget_and_revenue['production_budget'] = movies_budget_and_
movies_budget_and_revenue['worldwide_gross'] = movies_budget_and_re
movies_budget_and_revenue.head()
```

Out[41]:

	id	release_date	movie	production_budget	worldwide_gross	studio	domestic_gros
0	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000	1045663875	BV	241100000.
1	4	May 1, 2015	Avengers: Age of Ultron	330600000	1403013963	BV	459000000.
2	7	Apr 27, 2018	Avengers: Infinity War	300000000	2048134200	BV	678800000.
3	9	Nov 17, 2017	Justice League	300000000	655945209	WB	229000000.
4	10	Nov 6, 2015	Spectre	300000000	879620923	Sony	200100000.

In [43]:
```
movies_budget_and_revenue['production_budget'] = movies_budget_and_
movies_budget_and_revenue['worldwide_gross'] = movies_budget_and_re
movies_budget_and_revenue['year'] = movies_budget_and_revenue['year
```

In [63]:
```
ple_movies = movies_budget_and_revenue.sample(n=100)
.scatter(sample_movies['production_budget'], sample_movies['worldwi

efine the line equation: y = mx + b
b = np.polyfit(sample_movies['production_budget'], sample_movies['w

reate the line
e = m * sample_movies['production_budget'] + b

lot the line
.plot(sample_movies['production_budget'], line, color='red', label=

dd labels and a legend
.xlabel('production_budget')
.ylabel('worldwide_gross revenues')
.title('production_budget vs worldwide_gross revenues')
.legend()

how the plot
.show();
```

Reserch Question 3: Which cast and crew are associated with the most popular movies?

In [51]:
```
#join imdb.title.principles and imdb.name.basics
with gzip.open('zippedData/imdb.title.principals.csv.gz') as f:
    imdb_title_principals = pd.read_csv(f)
with gzip.open('zippedData/imdb.name.basics.csv.gz') as f:
    imdb_name_basics = pd.read_csv(f)
```

In [52]:
```
imdb_title_principals.head()
```

Out[52]:

	tconst	ordering	nconst	category	job	characters
0	tt0111414	1	nm0246005	actor	NaN	["The Man"]
1	tt0111414	2	nm0398271	director	NaN	NaN
2	tt0111414	3	nm3739909	producer	producer	NaN
3	tt0323808	10	nm0059247	editor	NaN	NaN
4	tt0323808	1	nm3579312	actress	NaN	["Beth Boothby"]

In [53]:
```
imdb_name_basics.head()
```

Out[53]:

	nconst	primary_name	birth_year	death_year	primary_
0	nm0061671	Mary Ellen Bauder	NaN	NaN	miscellaneous,production_manage
1	nm0061865	Joseph Bauer	NaN	NaN	composer,music_department,sound_
2	nm0062070	Bruce Baum	NaN	NaN	miscellaneous,
3	nm0062195	Axel Baumann	NaN	NaN	camera_department,cinematographer,art_
4	nm0062798	Pete Baxter	NaN	NaN	production_designer,art_department,set

In [54]:
```
#merge imdb.title.principals and imdb_name_basics on the nconst col
movie_principals = pd.merge(imdb_title_principals, imdb_name_basics
movie_principals.head()
```

Out[54]:

	tconst	ordering	nconst	category	job	characters	primary_name	birth_yea
0	tt0111414	1	nm0246005	actor	NaN	["The Man"]	Tommy Dysart	Na
1	tt0111414	2	nm0398271	director	NaN	NaN	Frank Howson	1952.
2	tt5573596	5	nm0398271	director	NaN	NaN	Frank Howson	1952.
3	tt0111414	3	nm3739909	producer	producer	NaN	Barry Porter-Robinson	Na
4	tt0323808	10	nm0059247	editor	NaN	NaN	Sean Barton	1944.

In [55]:
```
#load imdb.title.akas
with gzip.open('zippedData/imdb.title.akas.csv.gz') as f:
    imdb_title_akas = pd.read_csv(f)
imdb_title_akas.head()
```

Out[55]:

	title_id	ordering	title	region	language	types	attributes	is_original_titl
0	tt0369610	10	Джурасик свят	BG	bg	NaN	NaN	0.
1	tt0369610	11	Jurashikku warudo	JP	NaN	imdbDisplay	NaN	0.
2	tt0369610	12	Jurassic World: O Mundo dos Dinossauros	BR	NaN	imdbDisplay	NaN	0.
3	tt0369610	13	O Mundo dos Dinossauros	BR	NaN	NaN	short title	0.
4	tt0369610	14	Jurassic World	FR	NaN	imdbDisplay	NaN	0.

In [56]:
```
#include imdb.title.akas in the merge
movie_principals = pd.merge(movie_principals,imdb_title_akas, left_
movie_principals = movie_principals[['tconst', 'nconst', 'primary_n
movie_principals.head()
```

Out[56]:

	tconst	nconst	primary_name	primary_profession	
0	tt0111414	nm0246005	Tommy Dysart	actor	tt0093120,tt0076974,tt(
1	tt0111414	nm0398271	Frank Howson	actor,writer,producer	tt0104271,tt0094789,tt(
2	tt0111414	nm3739909	Barry Porter-Robinson	producer,art_department	tt0290884,tt0101374,tt(
3	tt5573596	nm0398271	Frank Howson	actor,writer,producer	tt0104271,tt0094789,tt(
4	tt5573596	nm0000476	Sally Kirkland	actress,producer,miscellaneous	tt0315327,tt0092569,tt3

In [57]:
```
#check out a sample of the ultimate table
tmdb_movies.sample(n=10)
```

Out[57]:

	genre_ids	id	original_language	original_title	popularity	release_date	
17512	[28, 16]	379291	en	Justice League vs. Teen Titans	11.817	2016-03-29	Ju Leagu Teen T
11172	[9648, 53, 28]	241848	en	The Guest	10.101	2014-09-17	The (
5222	[18]	84892	en	The Perks of Being a Wallflower	15.148	2012-09-21	The Pe Be Wallf
14782	[35, 18, 10402, 10749]	206296	en	The Last Five Years	5.079	2015-02-13	The Las
20747	[18]	393457	en	Fences	12.753	2016-12-16	Fe
11394	[27]	254194	en	Starry Eyes	7.145	2014-11-14	Starry
17433	[14, 28, 12, 878]	274854	en	The Last Witch Hunter	16.685	2015-10-23	The Witch H
14386	[35, 18, 10749]	306952	en	Naomi and Ely's No Kiss List	8.794	2015-09-18	Naom Ely's Nc
8070	[18, 80]	96936	en	The Bling Ring	8.935	2013-06-21	The
14206	[12, 27, 35]	257445	en	Goosebumps	18.957	2015-10-16	Gooseb

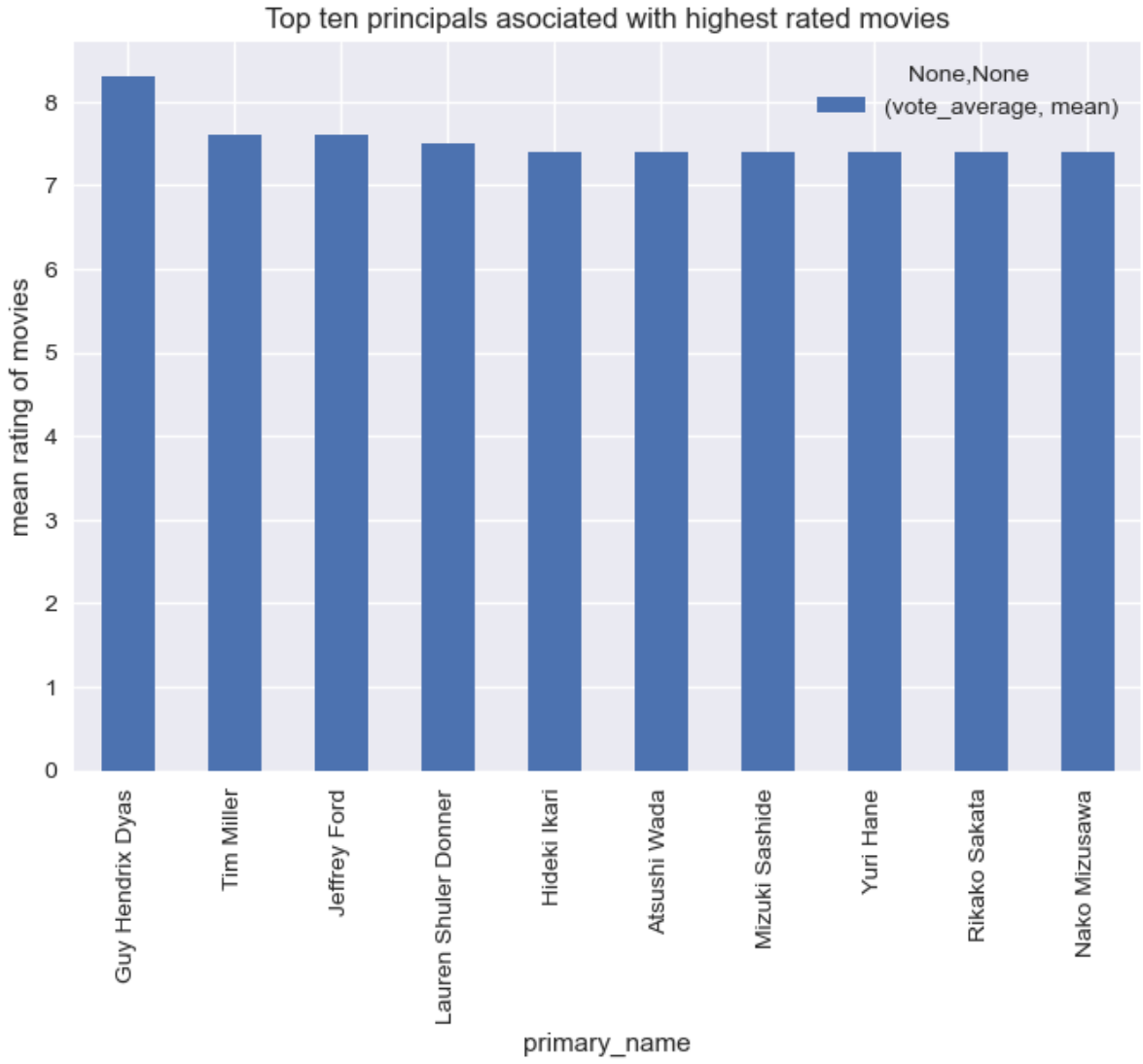
In [58]:
```
#merge some columns of tmdb.movies and select some columns from the
movie_principals = pd.merge(movie_principals,tmdb_movies[['title','
movie_principals.head()
```

Out[58]:

	tconst	nconst	primary_name	primary_profession	
0	tt1639075	nm0532721	Luis Machín	actor,cinematographer	tt1085786,tt3
1	tt1639075	nm0079065	Mariela Besuievsky	producer,actress,executive	tt1816608,tt6
2	tt1639075	nm0324409	Bárbara Goenaga	actress	tt0374164,tt0
3	tt1639075	nm0324184	Lucio Godoy	composer,music_department,soundtrack	tt0319769,tt0
4	tt1639075	nm0380547	Gerardo Herrero	producer,director,writer	tt0120311,tt1

In [59]:
```
#aggregate using primary names of the movie principals
movie_principals_grouped = movie_principals.groupby(by='primary_nam
movie_principals_grouped.sort_values(by=movie_principals_grouped.co
```

In [72]:
```
#Plot the top ten principals asociated with highest rated movies
movie_principals_grouped.iloc[:10].plot(kind='bar', y=movie_princip
plt.title('Top ten principals asociated with highest rated movies')
plt.ylabel('mean rating of movies');
```



Reccomendations

1. Based on the analysis, Microsoft should source more movies with a bias for Romance, Drama, and Animation genres for their new movie studio.
2. Microsoft new movie studio should make block buster films (i.e. high budget movies) since there is a direct relationship between production budget and gross revenues raked in by such movies
3. The movies should star top movie principals especialy: Guy Hendric Dyas Tim Miller Jeffrey Ford Lauren Shuler Donner Hideki Ikari Atsushi Wada Mizuki Sashide Yuri Hane Rikako Sakata Nako Mizusawa