TMDb movie data

July 26, 2020

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[46]:
```
#import modules
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

[47]:
```
#display visuals in notebook
%matplotlib inline
```

[48]:
```
#set theme for visualisations
sns.set_style('darkgrid')
```

1.1 Data Wrangling

1.1.1 General Properties

[49]:
```
# read in the dataset
df_movie = pd.read_csv(r"C:\Users\noama\tmdb-movies.csv")
```

[50]:
```
#visually inspect first 3 rows
df_movie.head(3)
```

[50]:
```
       id    imdb_id  popularity     budget     revenue      original_title  \
0  135397  tt0369610   32.985763  150000000  1513528810      Jurassic World
1   76341  tt1392190   28.419936  150000000   378436354  Mad Max: Fury Road
2  262500  tt2908446   13.112507  110000000   295238201           Insurgent
```

```
                                                cast  \
0  Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi…
1  Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic…
2  Shailene Woodley|Theo James|Kate Winslet|Ansel…

                                         homepage          director  \
0                   http://www.jurassicworld.com/   Colin Trevorrow
1                     http://www.madmaxmovie.com/     George Miller
2  http://www.thedivergentseries.movie/#insurgent  Robert Schwentke

                  tagline  …  \
0           The park is open.  …
1          What a Lovely Day.  …
2  One Choice Can Destroy You  …

                                         overview runtime  \
0  Twenty-two years after the events of Jurassic …     124
1  An apocalyptic story set in the furthest reach…     120
2  Beatrice Prior must confront her inner demons …     119

                                    genres  \
0  Action|Adventure|Science Fiction|Thriller
1  Action|Adventure|Science Fiction|Thriller
2         Adventure|Science Fiction|Thriller

                              production_companies release_date vote_count  \
0  Universal Studios|Amblin Entertainment|Legenda…       6/9/15       5562
1  Village Roadshow Pictures|Kennedy Miller Produ…      5/13/15       6185
2  Summit Entertainment|Mandeville Films|Red Wago…      3/18/15       2480

   vote_average  release_year    budget_adj   revenue_adj
0           6.5          2015  1.379999e+08  1.392446e+09
1           7.1          2015  1.379999e+08  3.481613e+08
2           6.3          2015  1.012000e+08  2.716190e+08

[3 rows x 21 columns]
```

[51]:
```python
#display number of columns and rows in the dataset
print("This dataset has " + str(df_movie.shape[0]) + " observations and " +␣
 ↪str(df_movie.shape[1]) + " columns")
```

```
This dataset has 10866 observations and 21 columns
```

[52]:
```python
#display column names, data types and number of missing values
df_movie.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10866 entries, 0 to 10865
```

```
Data columns (total 21 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   id                    10866 non-null  int64
 1   imdb_id               10856 non-null  object
 2   popularity            10866 non-null  float64
 3   budget                10866 non-null  int64
 4   revenue               10866 non-null  int64
 5   original_title        10866 non-null  object
 6   cast                  10790 non-null  object
 7   homepage              2936 non-null   object
 8   director              10822 non-null  object
 9   tagline               8042 non-null   object
 10  keywords              9373 non-null   object
 11  overview              10862 non-null  object
 12  runtime               10866 non-null  int64
 13  genres                10843 non-null  object
 14  production_companies  9836 non-null   object
 15  release_date          10866 non-null  object
 16  vote_count            10866 non-null  int64
 17  vote_average          10866 non-null  float64
 18  release_year          10866 non-null  int64
 19  budget_adj            10866 non-null  float64
 20  revenue_adj           10866 non-null  float64
dtypes: float64(4), int64(6), object(11)
memory usage: 1.7+ MB
```

[53]:
```
#statistical summary of numerical variables
df_movie.describe()
```

[53]:

	id	popularity	budget	revenue	runtime
count	10866.000000	10866.000000	1.086600e+04	1.086600e+04	10866.000000
mean	66064.177434	0.646441	1.462570e+07	3.982332e+07	102.070863
std	92130.136561	1.000185	3.091321e+07	1.170035e+08	31.381405
min	5.000000	0.000065	0.000000e+00	0.000000e+00	0.000000
25%	10596.250000	0.207583	0.000000e+00	0.000000e+00	90.000000
50%	20669.000000	0.383856	0.000000e+00	0.000000e+00	99.000000
75%	75610.000000	0.713817	1.500000e+07	2.400000e+07	111.000000
max	417859.000000	32.985763	4.250000e+08	2.781506e+09	900.000000

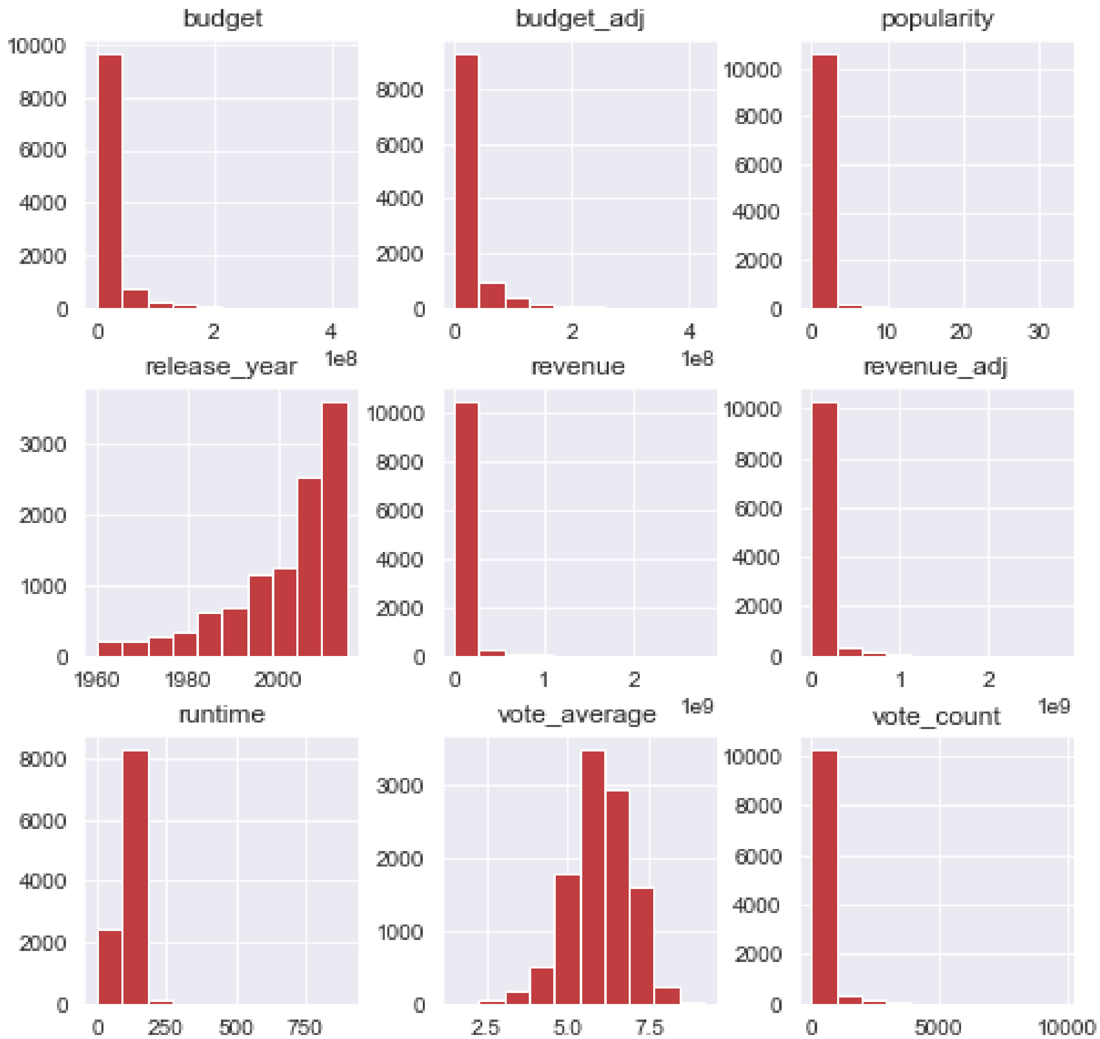
	vote_count	vote_average	release_year	budget_adj	revenue_adj
count	10866.000000	10866.000000	10866.000000	1.086600e+04	1.086600e+04
mean	217.389748	5.974922	2001.322658	1.755104e+07	5.136436e+07
std	575.619058	0.935142	12.812941	3.430616e+07	1.446325e+08
min	10.000000	1.500000	1960.000000	0.000000e+00	0.000000e+00
25%	17.000000	5.400000	1995.000000	0.000000e+00	0.000000e+00
50%	38.000000	6.000000	2006.000000	0.000000e+00	0.000000e+00

```
75%      145.750000      6.600000   2011.000000  2.085325e+07  3.369710e+07
max     9767.000000      9.200000   2015.000000  4.250000e+08  2.827124e+09
```

1.1.2 Univariate Exploration

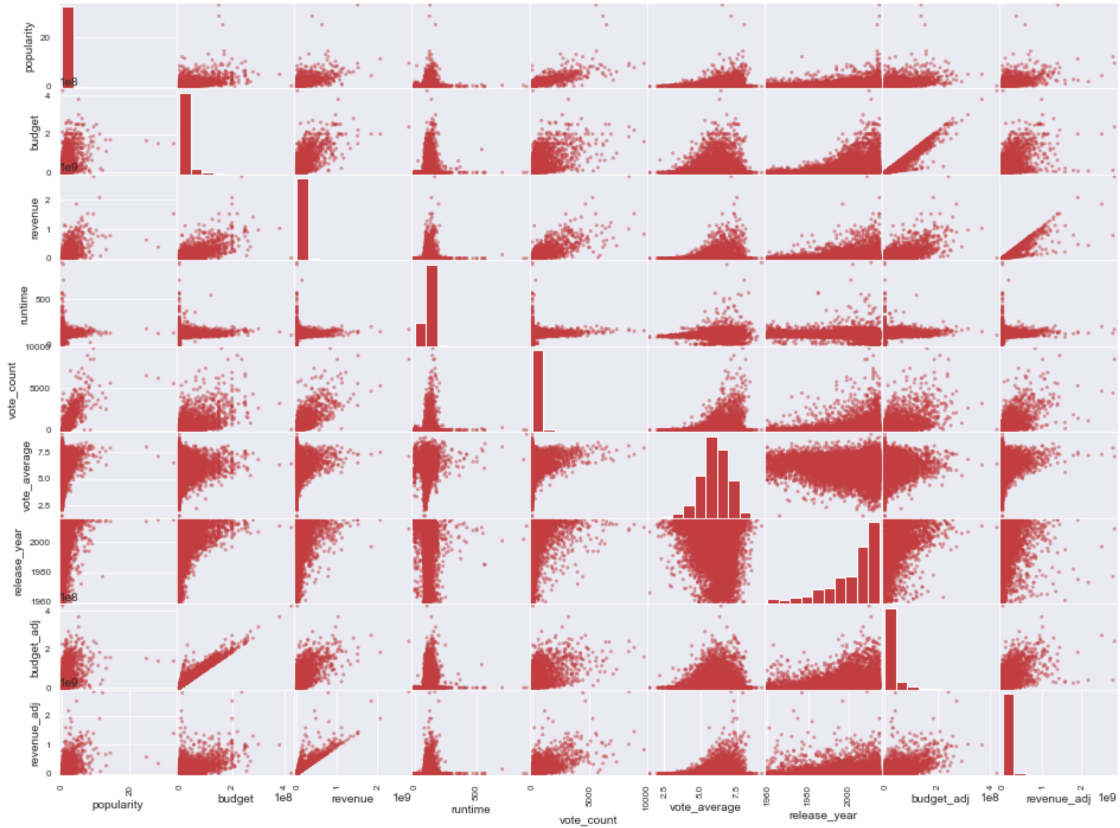
[54]:
```
# create histograms for analysis
df_movie.drop(['id'], axis=1).hist(figsize=(8,8));
```

```
C:\Users\noama\anaconda3\lib\site-
packages\pandas\plotting\_matplotlib\tools.py:298: MatplotlibDeprecationWarning:
The rowNum attribute was deprecated in Matplotlib 3.2 and will be removed two
minor releases later. Use ax.get_subplotspec().rowspan.start instead.
  layout[ax.rowNum, ax.colNum] = ax.get_visible()
C:\Users\noama\anaconda3\lib\site-
packages\pandas\plotting\_matplotlib\tools.py:298: MatplotlibDeprecationWarning:
The colNum attribute was deprecated in Matplotlib 3.2 and will be removed two
minor releases later. Use ax.get_subplotspec().colspan.start instead.
  layout[ax.rowNum, ax.colNum] = ax.get_visible()
C:\Users\noama\anaconda3\lib\site-
packages\pandas\plotting\_matplotlib\tools.py:304: MatplotlibDeprecationWarning:
The rowNum attribute was deprecated in Matplotlib 3.2 and will be removed two
minor releases later. Use ax.get_subplotspec().rowspan.start instead.
  if not layout[ax.rowNum + 1, ax.colNum]:
C:\Users\noama\anaconda3\lib\site-
packages\pandas\plotting\_matplotlib\tools.py:304: MatplotlibDeprecationWarning:
The colNum attribute was deprecated in Matplotlib 3.2 and will be removed two
minor releases later. Use ax.get_subplotspec().colspan.start instead.
  if not layout[ax.rowNum + 1, ax.colNum]:
```



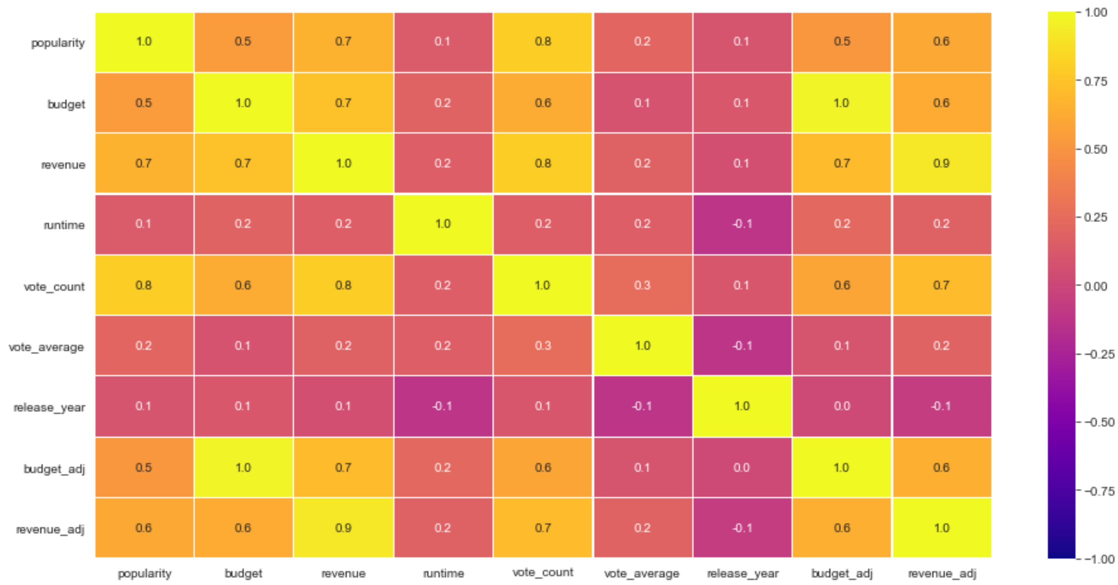
1.1.3 Bivariate Exploration

[55]:
```
#create scatter plots between each of the variables in the dataset
pd.plotting.scatter_matrix(df_movie.drop(['id'], axis=1), figsize=(16,12));
```



[56]:
```
#calculate correlation matrix
df_corr = df_movie.drop(['id'], axis=1).corr()
```

[57]:
```
#draw heapmap of correlation matrix
f, ax= plt.subplots(figsize=(16,8))
sns.heatmap(df_corr, annot=True, linewidths=.3, cmap="plasma", fmt='.1f',␣
↪ax=ax, vmin=-1, vmax=1);
```



1.2 Data Assessment

1.2.1 Missing Data

[58]:
```
#user defined function to calculate number missing values
def missing_values(df):
    '''
    Function that aggregates missing values values and creates an output table␣
↪with two columns
    one with the count and the other a percentage of total values for that␣
↪column.
    '''
    miss_val = df.isnull().sum()
    miss_val_perc = (df.isnull().sum() / len(df)) * 100
    miss_val_table = pd.concat([miss_val, miss_val_perc], axis=1)
    miss_val_table_ren_columns = miss_val_table.rename(
    columns = {0 : 'Missing Values', 1 : '% of Total Values'})
    miss_val_table_ren_columns =␣
↪miss_val_table_ren_columns[miss_val_table_ren_columns.iloc[:,1] != 0].
↪sort_values(
        '% of Total Values', ascending=False).round(1)
    print ("The selected dataframe has a total of " + str(df.shape[1]) + "␣
↪columns, of which " + str(miss_val_table_ren_columns.shape[0]) + " contain␣
↪missing values.")
    return miss_val_table_ren_columns
```

[59]:
```
#apply data to user defined function
missing_values(df_movie)
```

```
The selected dataframe has a total of 21 columns, of which 9 contain missing
values.
```

[59]:

	Missing Values	% of Total Values
homepage	7930	73.0
tagline	2824	26.0
keywords	1493	13.7
production_companies	1030	9.5
cast	76	0.7
director	44	0.4
genres	23	0.2
imdb_id	10	0.1
overview	4	0.0

1.2.2 Outliers

[60]:
```
#calculate number of values recorded as a zero
(df_movie == 0).sum()
```

[60]:
```
id                         0
imdb_id                    0
popularity                 0
budget                  5696
revenue                 6016
original_title             0
cast                       0
homepage                   0
director                   0
tagline                    0
keywords                   0
overview                   0
runtime                   31
genres                     0
production_companies       0
release_date               0
vote_count                 0
vote_average               0
release_year               0
budget_adj              5696
revenue_adj             6016
dtype: int64
```

1.2.3 Duplicates

[61]:
```
#count number of duplicated records
sum(df_movie.duplicated())
```

[61]:
```
1
```

1.3 Data Cleaning

[62]:
```
# Drop extraneous columns
columns = ['imdb_id', 'homepage', 'tagline', 'overview']
df_movie.drop(columns, axis=1, inplace=True)
```

[63]:
```
#drop the null values in cast, director, genres columns
columns = ['cast', 'director', 'genres']
df_movie.dropna(subset = columns, how='any', inplace=True)
```

[64]:
```
#replace the value 0 with null value label
df_movie['budget'] = df_movie['budget'].replace(0, np.NaN)
df_movie['revenue'] = df_movie['revenue'].replace(0, np.NaN)
df_movie['budget_adj'] = df_movie['budget_adj'].replace(0, np.NaN)
df_movie['revenue_adj'] = df_movie['revenue_adj'].replace(0, np.NaN)
```

[65]:
```
# remove movies with 0 minutes as runtime
df_movie = df_movie.query('runtime != 0')
```

1.4 Results

[66]:
```
#display number of columns and rows in the dataset
print("This dataset has " + str(df_movie.shape[0]) + " observations and " +␣
 ↪str(df_movie.shape[1]) + " columns")
```

```
This dataset has 10704 observations and 17 columns
```

[67]:
```
#display column names, data types and number of missing values
df_movie.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10704 entries, 0 to 10865
Data columns (total 17 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   id                    10704 non-null  int64
 1   popularity            10704 non-null  float64
 2   budget                5151 non-null   float64
 3   revenue               4844 non-null   float64
 4   original_title        10704 non-null  object
```

```
 5   cast                  10704 non-null  object
 6   director              10704 non-null  object
 7   keywords              9294 non-null   object
 8   runtime               10704 non-null  int64
 9   genres                10704 non-null  object
 10  production_companies  9760 non-null   object
 11  release_date          10704 non-null  object
 12  vote_count            10704 non-null  int64
 13  vote_average          10704 non-null  float64
 14  release_year          10704 non-null  int64
 15  budget_adj            5151 non-null   float64
 16  revenue_adj           4844 non-null   float64
dtypes: float64(6), int64(4), object(7)
memory usage: 1.5+ MB
```

[68]:
```
#statistical summary of numerical variables
df_movie.describe()
```

[68]:
```
                  id    popularity        budget       revenue       runtime  \
count   10704.000000  10704.000000  5.151000e+03  4.844000e+03  10704.000000
mean    64902.866592      0.653813  3.084385e+07  8.932157e+07    102.735893
std     91158.001799      1.005641  3.893405e+07  1.621428e+08     30.078104
min         5.000000      0.000188  1.000000e+00  2.000000e+00      3.000000
25%     10538.750000      0.211545  6.000000e+06  7.769608e+06     90.000000
50%     20235.500000      0.388068  1.750000e+07  3.190530e+07     99.000000
75%     73612.500000      0.722425  4.000000e+07  1.000000e+08    112.000000
max    417859.000000     32.985763  4.250000e+08  2.781506e+09    900.000000

         vote_count  vote_average  release_year    budget_adj   revenue_adj
count  10704.000000  10704.000000  10704.000000  5.151000e+03  4.844000e+03
mean     220.322870      5.966022   2001.236173  3.701358e+07  1.152105e+08
std      579.455879      0.930158     12.825600  4.198277e+07  1.989286e+08
min       10.000000      1.500000   1960.000000  9.210911e-01  2.370705e+00
25%       17.000000      5.400000   1995.000000  8.233996e+06  1.047632e+07
50%       39.000000      6.000000   2006.000000  2.299019e+07  4.402312e+07
75%      149.000000      6.600000   2011.000000  5.024535e+07  1.317125e+08
max     9767.000000      9.200000   2015.000000  4.250000e+08  2.827124e+09
```

1.5 Exploratory Data Analysis

Question 1: How has the success of genres changed over time (Revenue/Rating)?

[69]:
```
#display genre names
df_movie.genres.unique()
```

[69]:
```
array(['Action|Adventure|Science Fiction|Thriller',
       'Adventure|Science Fiction|Thriller',
       'Action|Adventure|Science Fiction|Fantasy', …,
```

```
'Adventure|Drama|Action|Family|Foreign',
'Comedy|Family|Mystery|Romance',
'Mystery|Science Fiction|Thriller|Drama'], dtype=object)
```

Observations:

-Some of the columns contain multiple entries delimitted by '|'. Use split function to seperate the rows

[70]:
```
#rename orignal dataframe
df_movie_genre = df_movie

# columns to split by "|"
df_movie_genre['genres'] = df_movie['genres'].apply(lambda x: x.split("|")[0])
```

[71]:
```
# Confirm the action worked and split by genre
df_movie_genre.genres.unique()
```

[71]:
```
array(['Action', 'Adventure', 'Western', 'Science Fiction', 'Drama',
       'Family', 'Comedy', 'Crime', 'Romance', 'War', 'Mystery',
       'Thriller', 'Fantasy', 'History', 'Animation', 'Horror', 'Music',
       'Documentary', 'TV Movie', 'Foreign'], dtype=object)
```

Question 1.1: How many movies of a particular genre have been released?

[72]:
```
#count number of releases by year and genre
df_genres_year = df_movie_genre.groupby(['release_year', 'genres']).
 ↪count()['id'].unstack()
df_genres_year.head(5)
```

[72]:
```
genres        Action  Adventure  Animation  Comedy  Crime  Documentary  Drama  \
release_year
1960             8.0        2.0        NaN     7.0    1.0          NaN    5.0
1961             3.0        2.0        NaN     8.0    NaN          NaN    7.0
1962             5.0        4.0        NaN     2.0    3.0          NaN   11.0
1963             3.0        5.0        1.0     9.0    NaN          NaN    7.0
1964             2.0        5.0        2.0    10.0    5.0          NaN   10.0

genres        Family  Fantasy  Foreign  History  Horror  Music  Mystery  \
release_year
1960             NaN      NaN      NaN      NaN     6.0    NaN      NaN
1961             NaN      2.0      NaN      NaN     3.0    1.0      NaN
1962             NaN      1.0      NaN      NaN     2.0    NaN      1.0
1963             NaN      NaN      NaN      NaN     6.0    NaN      2.0
1964             NaN      1.0      NaN      NaN     3.0    1.0      NaN

genres        Romance  Science Fiction  TV Movie  Thriller  War  Western
release_year
```

```
1960               NaN               NaN        NaN        3.0  NaN        NaN
1961               1.0               1.0        NaN        NaN  NaN        3.0
1962               NaN               NaN        NaN        1.0  NaN        2.0
1963               1.0               NaN        NaN        NaN  NaN        NaN
1964               NaN               NaN        NaN        2.0  NaN        1.0
```

[73]:
```
#sort number of releases by genre in descending order
df_movie_genre.groupby(['genres']).count()['id'].sort_values(ascending=False)
```

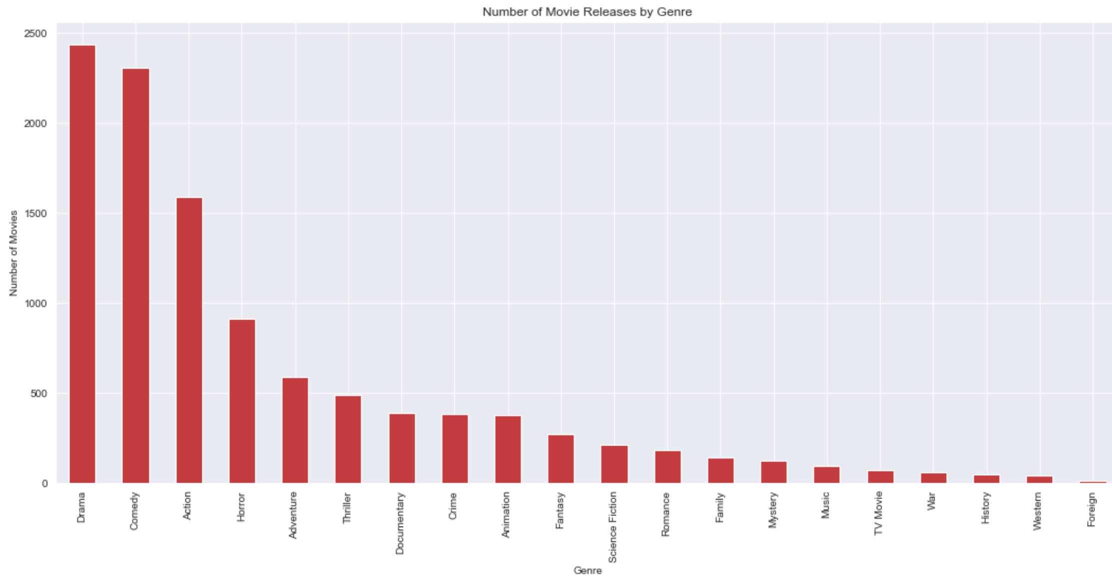
[73]:
```
genres
Drama              2439
Comedy             2307
Action             1586
Horror              909
Adventure           585
Thriller            489
Documentary         385
Crime               381
Animation           375
Fantasy             270
Science Fiction     211
Romance             182
Family              141
Mystery             125
Music                95
TV Movie             72
War                  58
History              44
Western              42
Foreign               8
Name: id, dtype: int64
```

[74]:
```
# plot data
fig, ax = plt.subplots(figsize=(18,8))

sns.set_palette("Set1", 20, .65)

# use unstack()
df_movie_genre.groupby(['genres']).count()['id'].sort_values(ascending=False).
 ↪plot(kind="bar",  ax=ax);
ax.set(xlabel='Genre', ylabel='Number of Movies', title = 'Number of Movie␣
 ↪Releases by Genre')
```

[74]:
```
[Text(0, 0.5, 'Number of Movies'),
 Text(0.5, 0, 'Genre'),
 Text(0.5, 1.0, 'Number of Movie Releases by Genre')]
```



Observations:

-Drama is the most frequent genre, followed by comedy and action.

Question 1.2: How have the fortunes of genres compared over time?

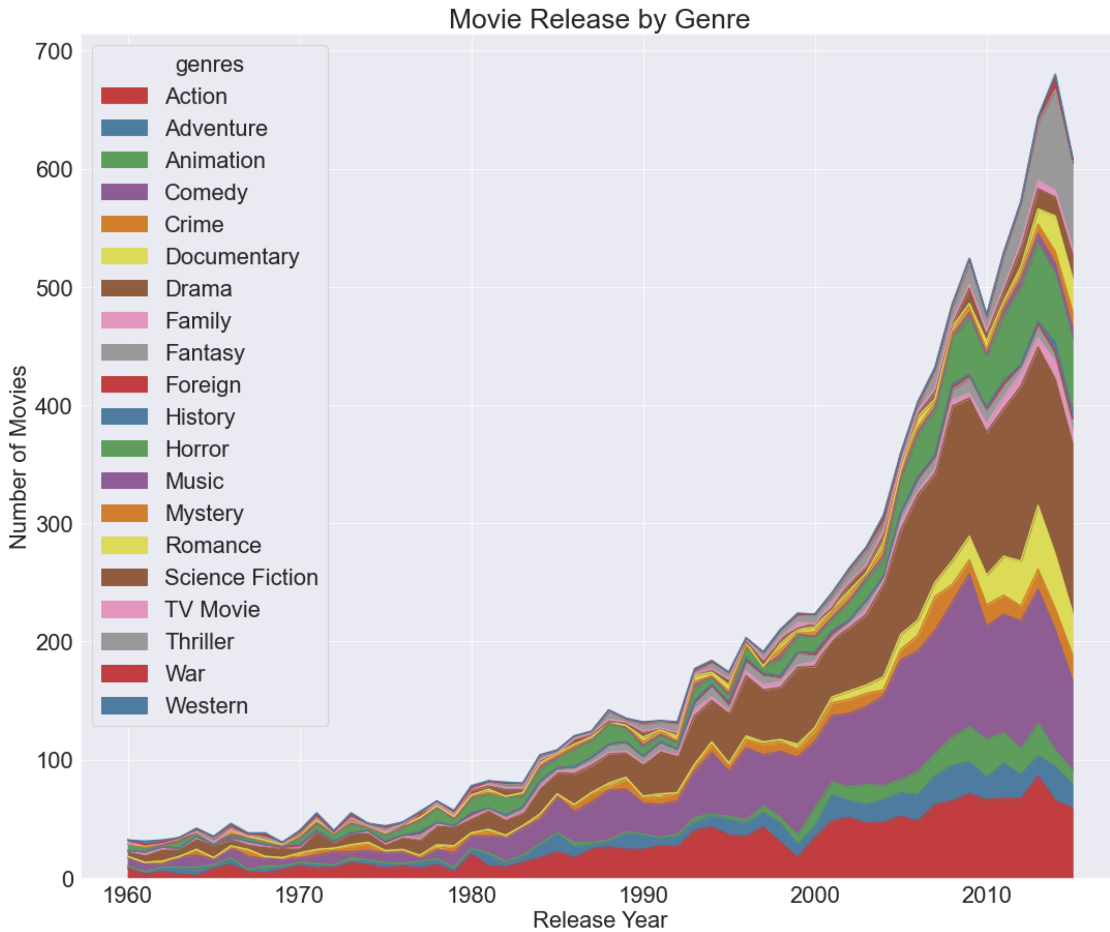
[75]:
```
#Set global font size
plt.rcParams.update({'font.size': 22})

# plot data
fig, ax = plt.subplots(figsize=(18,15))

sns.set_palette("Set1", 20, .65)

# use unstack()
df_movie_genre.groupby(['release_year', 'genres']).count()['id'].unstack().plot.
↪area(ax=ax);
ax.set(xlabel='Release Year', ylabel='Number of Movies', title = 'Movie Release␣
↪by Genre')
```

[75]:
```
[Text(0, 0.5, 'Number of Movies'),
 Text(0.5, 0, 'Release Year'),
 Text(0.5, 1.0, 'Movie Release by Genre')]
```



Observations:

The number of movie releases has generally grown over time. Picking out specific genres, Drama, Thriller, Comedy and Action movies seem to be the predominant themes.

[76]:
```
#calculate mean by genre and year
genre_year = df_movie_genre.groupby(['genres', 'release_year']).mean().
 ↪sort_index()
genre_year.head(5)
```

[76]:
```
                                id  popularity      budget     revenue  \
genres release_year
Action 1960            7602.250000    0.590724   7000000.0  32452500.0
       1961           15514.000000    0.540904   6000000.0  28900000.0
       1962           24739.000000    0.299207  10000000.0         NaN
       1963           17721.333333    1.008599   9750000.0  44449382.5
       1964           18975.500000    0.254216         NaN         NaN

                      runtime  vote_count  vote_average    budget_adj  \
```

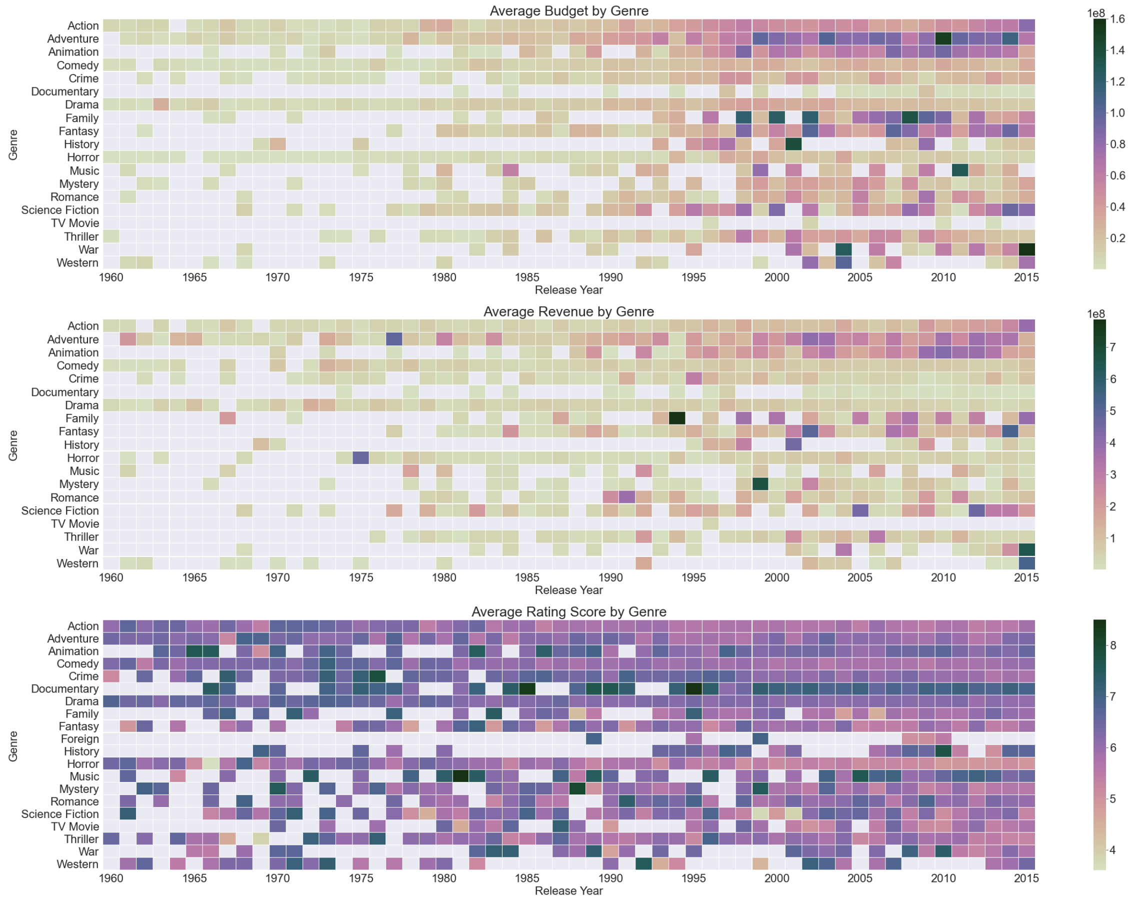
```
genres release_year
Action 1960              137.0    65.875000      6.050000  5.161077e+07
       1961              147.0    43.333333      6.633333  4.376917e+07
       1962              123.4    38.000000      6.140000  7.208449e+07
       1963              127.0   166.666667      6.433333  6.942175e+07
       1964              128.0    40.000000      6.500000           NaN

                      revenue_adj
genres release_year
Action 1960          2.392712e+08
       1961          2.108215e+08
       1962                   NaN
       1963          3.164876e+08
       1964                   NaN
```

Let's plot these into a time series heat map to guage the change over time per genre.

[77]:
```
#create multiple heatmaps to display trends over time
df_gyBudget = genre_year.pivot_table(index=['genres'],␣
↪columns=['release_year'], values='budget', aggfunc=np.mean)
df_gyGross = genre_year.pivot_table(index=['genres'], columns=['release_year'],␣
↪values='revenue', aggfunc=np.mean)
df_gyVote = genre_year.pivot_table(index=['genres'], columns=['release_year'],␣
↪values='vote_average', aggfunc=np.mean)
f, [axA, axB, axC] = plt.subplots(figsize=(40, 30), nrows=3)
cmap = sns.cubehelix_palette(start=1.3, rot=1.3, as_cmap=True)
sns.heatmap(df_gyBudget, xticklabels=5, cmap=cmap, linewidths=0.05, ax=axA)
sns.heatmap(df_gyGross, xticklabels=5, cmap=cmap, linewidths=0.05, ax=axB)
sns.heatmap(df_gyVote, xticklabels=5, cmap=cmap, linewidths=0.05, ax=axC)
axA.set_title('Average Budget by Genre')
axB.set_title('Average Revenue by Genre')
axC.set_title('Average Rating Score by Genre')
axA.set_xlabel('Release Year')
axA.set_ylabel('Genre')
axB.set_xlabel('Release Year')
axB.set_ylabel('Genre')
axC.set_xlabel('Release Year')
axC.set_ylabel('Genre')
```

[77]:
```
Text(328.90625, 0.5, 'Genre')
```



Observations: Revenues and budgets have generally grown over time. This makes sense as more films are released.

That doesn't necessarily mean average ratings are increasing though. In particular the average ratings of Horror movies has declined over time, while the quality of Dramas has increased.

Question 2: How succesful are different genres (Revenue/Rating)?

Success can be measured in two ways; return on investment (ROI) or user rating.

[78]:
```
#calculate mean values for selcted measures of interest
df_movie[['genres', 'revenue', 'budget', 'popularity', 'vote_average']].
↪groupby(['genres']).mean()
```

[78]:

genres	revenue	budget	popularity	vote_average
Action	1.170983e+08	4.231958e+07	0.838266	5.751009
Adventure	2.071020e+08	6.477152e+07	1.219834	6.049744
Animation	2.399754e+08	6.229486e+07	0.853208	6.401867
Comedy	6.471663e+07	2.320338e+07	0.539358	5.880971
Crime	6.138535e+07	2.274751e+07	0.693807	6.214436

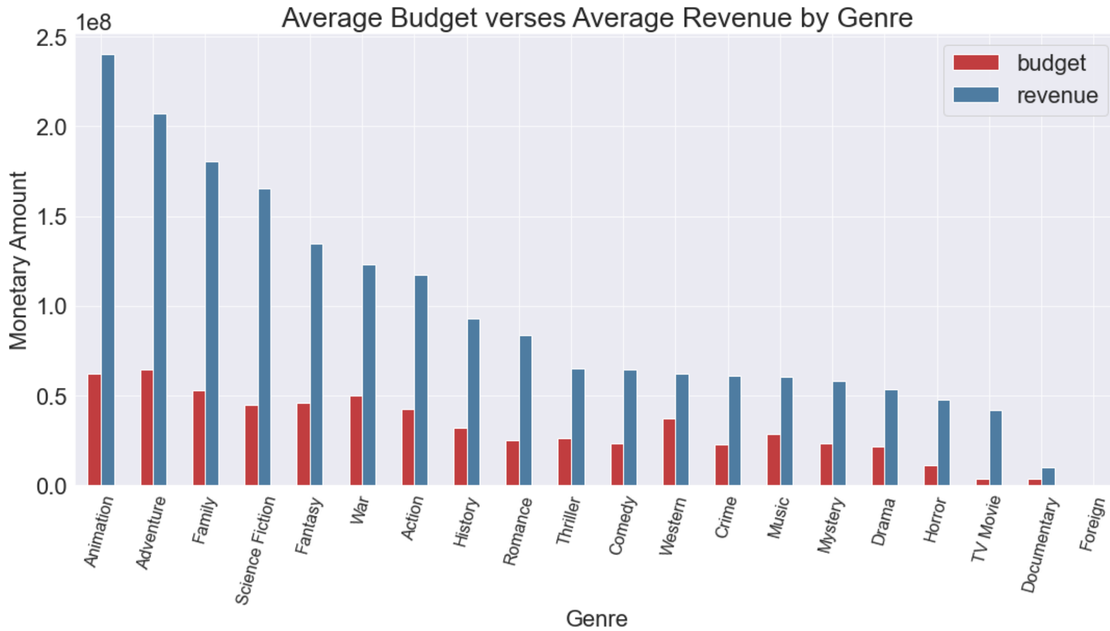
```
Documentary      9.839752e+06  3.690254e+06    0.184708      6.916623
Drama            5.334542e+07  2.149751e+07    0.554855      6.198524
Family           1.807031e+08  5.275776e+07    0.744438      5.941844
Fantasy          1.345879e+08  4.588527e+07    0.864781      5.789630
Foreign                   NaN           NaN    0.178917      5.687500
History          9.294606e+07  3.186905e+07    0.764636      6.381818
Horror           4.763156e+07  1.137138e+07    0.470718      5.320902
Music            6.064779e+07  2.843784e+07    0.465062      6.568421
Mystery          5.807465e+07  2.339429e+07    0.596896      5.900800
Romance          8.389153e+07  2.494572e+07    0.717200      6.151099
Science Fiction  1.654990e+08  4.478218e+07    1.087261      5.938389
TV Movie         4.200000e+07  3.900000e+06    0.248304      5.722222
Thriller         6.534306e+07  2.645800e+07    0.675204      5.641718
War              1.231160e+08  4.989667e+07    0.777887      6.187931
Western          6.218189e+07  3.725972e+07    0.690646      6.080952
```

Question 2.1: Which genres have the largest revenue and largest budgets?

[79]:
```
#create figure and axis
f,ax=plt.subplots(figsize=(18, 8))

# calculate and plot average budget and revenue by genre
df_movie[['genres', 'budget', 'revenue']].groupby(['genres']).mean().
 ↪sort_values(["revenue","budget"], ascending=False).plot(kind="bar",  ax=ax);
ax.set(xlabel = 'Genre', ylabel = 'Monetary Amount', title = 'Average Budget␣
 ↪verses Average Revenue by Genre')
plt.xticks(rotation=75,fontsize=16)
```

[79]:
```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
        17, 18, 19]),
 <a list of 20 Text major ticklabel objects>)
```



Observations

Animation as a genre has the highest revenue, followed by the genre Adventure - but it's budget is slightly higher. At the opposite end of the spectrum foreign movies, documentaries and TV Movies bring in the least revenue.

[80]:
```
# Create new dataframe to work on RoI
df_movie_roi = df_movie[['genres', 'revenue', 'budget', 'popularity',␣
↪'vote_average']].groupby(['genres']).mean()
df_movie_roi.head(2)
```

[80]:

	revenue	budget	popularity	vote_average
genres				
Action	1.170983e+08	4.231958e+07	0.838266	5.751009
Adventure	2.071020e+08	6.477152e+07	1.219834	6.049744

[81]:
```
# calculate RoI and add to dataframe
df_movie_roi['RoI'] = df_movie_roi['revenue'] / df_movie_roi['budget']
df_movie_roi.head(2)
```

[81]:

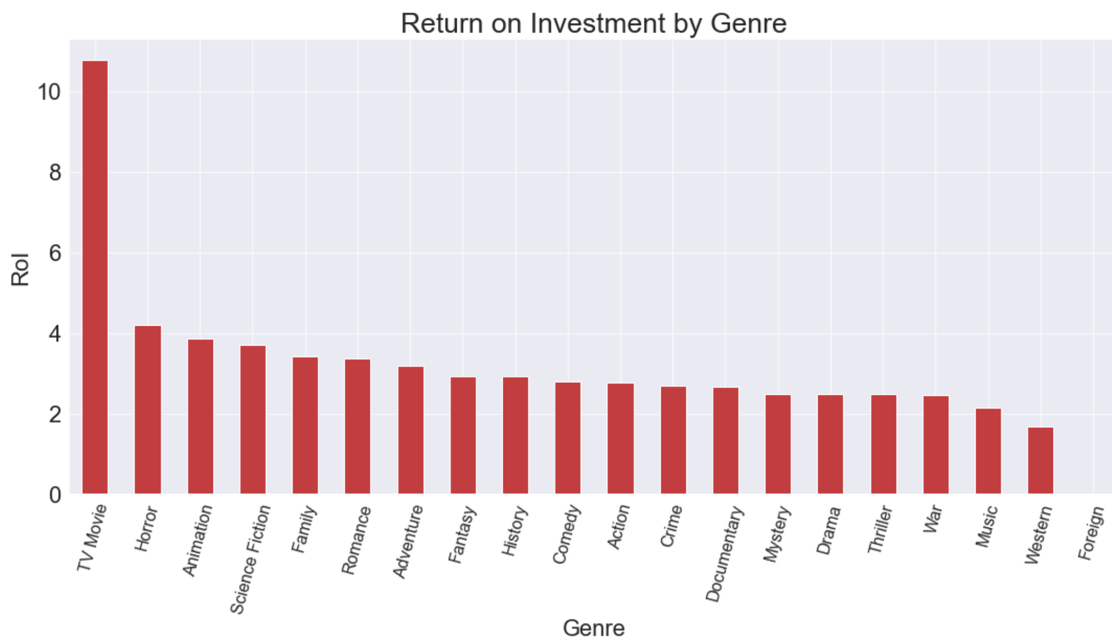
	revenue	budget	popularity	vote_average	RoI
genres					
Action	1.170983e+08	4.231958e+07	0.838266	5.751009	2.767000
Adventure	2.071020e+08	6.477152e+07	1.219834	6.049744	3.197424

[82]:
```
#create figure object and axis
f,ax=plt.subplots(figsize=(18, 8))
```

```
# RoI of each genres' movies
df_movie_roi['RoI'].sort_values(ascending=False).plot(kind="bar",  ax=ax);

ax.set(xlabel = 'Genre', ylabel = 'RoI', title = 'Return on Investment by␣
↪Genre')
plt.xticks(rotation=75,fontsize=16)
```

[82]:
```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
        17, 18, 19]),
 <a list of 20 Text major ticklabel objects>)
```



Observations

TV Movies takes the number 1 spot for RoI. This makes sense as it has comparable revenue to other genres, but it's budget is tiny in comparison.

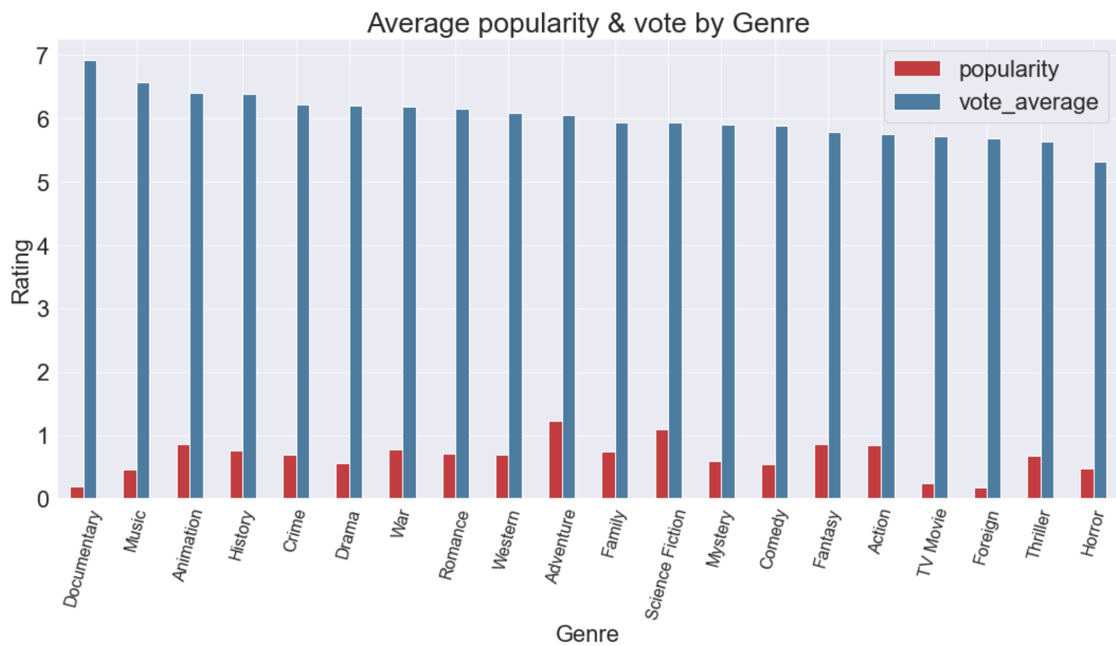
Question 2.3: Which genres are the most popular?

[84]:
```
#create figure object and axis
f,ax=plt.subplots(figsize=(18, 8))


# Avergae popularity by genre
df_movie[['genres', 'popularity', 'vote_average']].groupby(['genres']).mean().
↪sort_values(["vote_average"], ascending=False).plot(kind="bar",  ax=ax);
```

```
ax.set(xlabel = 'Genre', ylabel = 'Rating', title = 'Average popularity & vote␣
↪by Genre')
plt.xticks(rotation=75,fontsize=16)
```

[84]:
```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
        17, 18, 19]),
 <a list of 20 Text major ticklabel objects>)
```



Observations

Documentaries are consistantly highly rated, but have a very low popularity score indicating that while they are not frequently watched, they are intensly enjoyed by those who do.

Question 3: Which Directors are the most successful (Revenue/Rating)?

[85]:
```
#Create new dataframe
df_director_movies = df_movie

#split out the director field
df_director_movies['director'] = df_director_movies['director'].apply(lambda x:␣
↪x.split("|")[0])
```

[86]:
```
#Create new dataframe with the sum of revenue for directors by year
df_director_revenue = df_director_movies.groupby(['director', 'release_year']).
↪sum()['revenue']#.nlargest(10)
df_director_revenue = pd.DataFrame(df_director_revenue)
df_director_revenue.head(10)
```

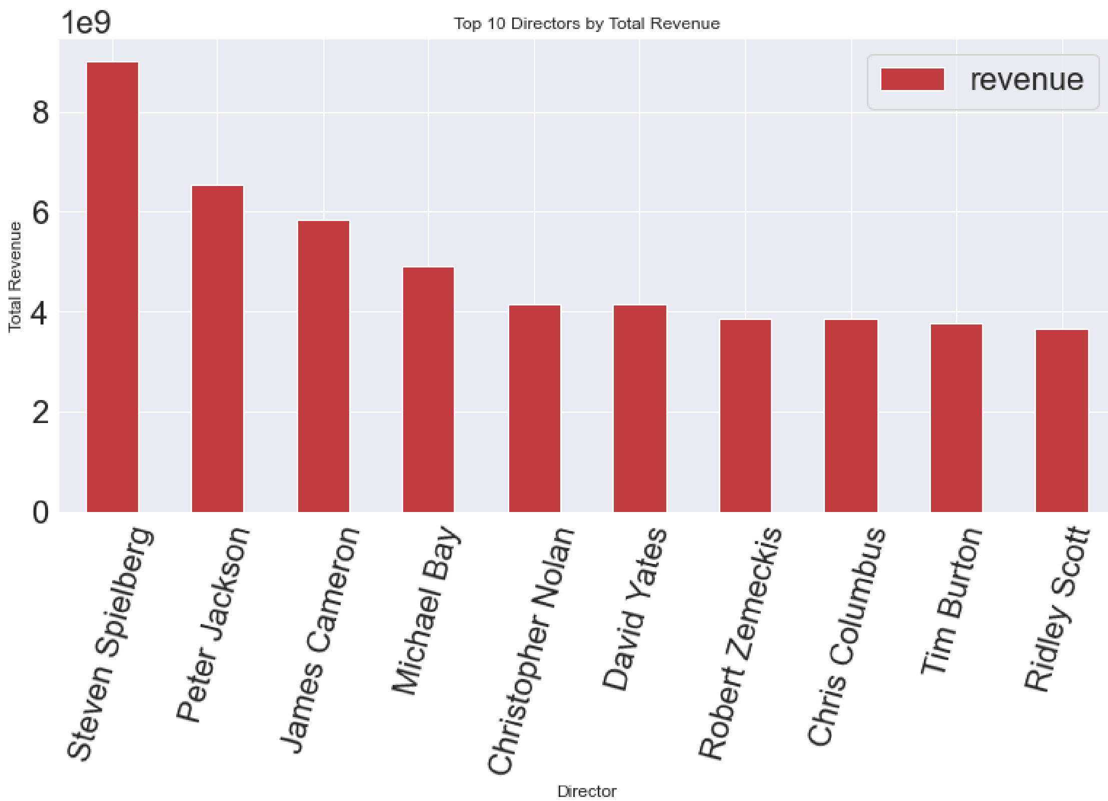
[86]:
```
                                          revenue
director             release_year
 FrÃ©dÃ©ric Jardin 2011                3358.0
A.R. Murugadoss     2008            76000000.0
Aaron Aites         2008                   0.0
Aaron Blaise        2003                 250.0
Aaron Hann          2015                   0.0
Aaron Harvey        2011                   0.0
Aaron Katz          2014                   0.0
Aaron Keeling       2015                   0.0
Aaron Moorhead      2015               49970.0
Aaron Norris        1988             6193901.0
```

[87]:
```
#Create new data frame for the total sumation of revenue for directors
df_director_revenue_total = df_director_revenue.groupby(['director']).sum()
df_director_revenue_total = pd.DataFrame(df_director_revenue_total)
df_director_revenue_total = df_director_revenue_total.sort_values(by =␣
 ↪['revenue'], ascending = False)
df_director_revenue_total.head(10)
```

[87]:
```
                         revenue
director
Steven Spielberg    9.018564e+09
Peter Jackson       6.523245e+09
James Cameron       5.841895e+09
Michael Bay         4.917208e+09
Christopher Nolan   4.167549e+09
David Yates         4.154296e+09
Robert Zemeckis     3.869691e+09
Chris Columbus      3.851492e+09
Tim Burton          3.782610e+09
Ridley Scott        3.649996e+09
```

[88]:
```
#plot a bar graph
df_director_revenue_total[:10].plot(kind = 'bar', figsize=(13,6))

#setup the title and the labels
plt.title("Top 10 Directors by Total Revenue",fontsize=12)
plt.xticks(rotation=75)
plt.xlabel("Director",fontsize= 12)
plt.ylabel("Total Revenue",fontsize= 12)
sns.set_style("whitegrid")
```



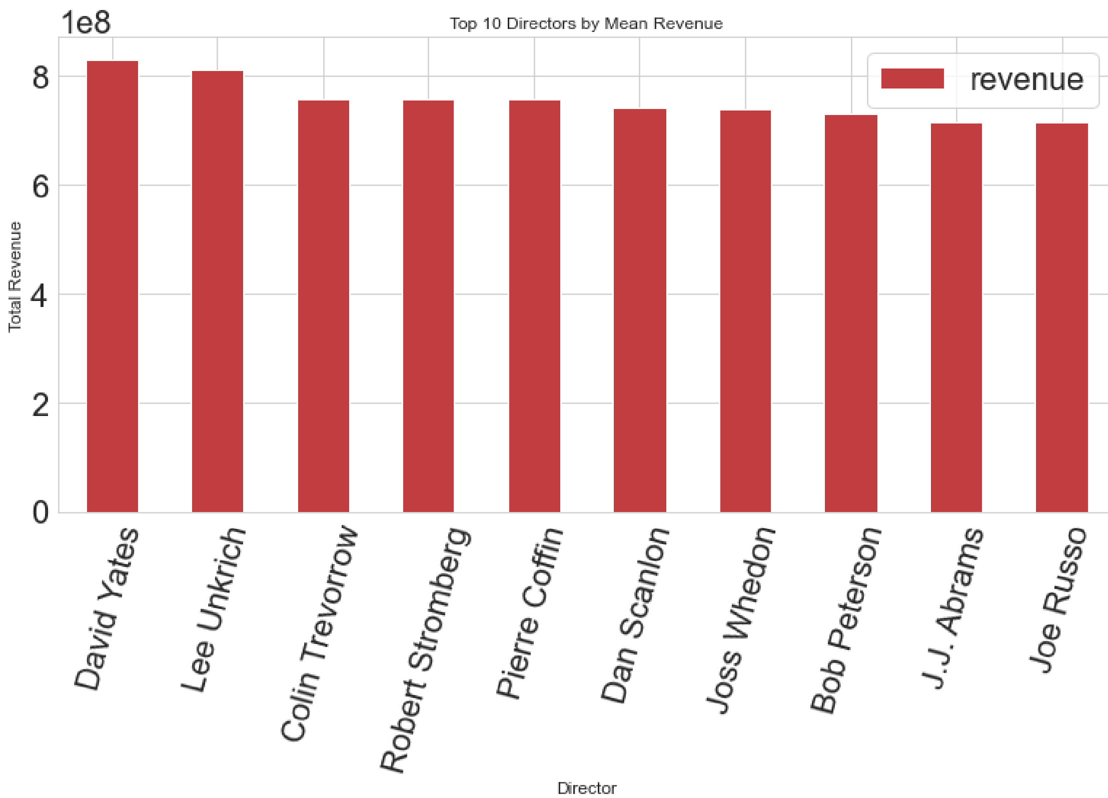
Observations

However, this skews our data toward those directors who have released more movies over their career. An apples-to-apple comparison could use the mean revenue of each film.

[89]:
```
#Create new data frame for the mean of revenue for directors
df_director_revenue_mean = df_director_revenue.groupby(['director']).mean()
df_director_revenue_mean = pd.DataFrame(df_director_revenue_mean)
df_director_revenue_mean = df_director_revenue_mean.sort_values(by =␣
↪['revenue'], ascending = False)
```

[90]:
```
#plot a bar graph
df_director_revenue_mean[:10].plot(kind = 'bar', figsize=(13,6))

#setup the title and the labels
plt.title("Top 10 Directors by Mean Revenue",fontsize=12)
plt.xticks(rotation=75)
plt.xlabel("Director",fontsize= 12)
plt.ylabel("Total Revenue",fontsize= 12)
sns.set_style("whitegrid")
```



Observations

David Yates is the most succesfull in terms of average revenue.

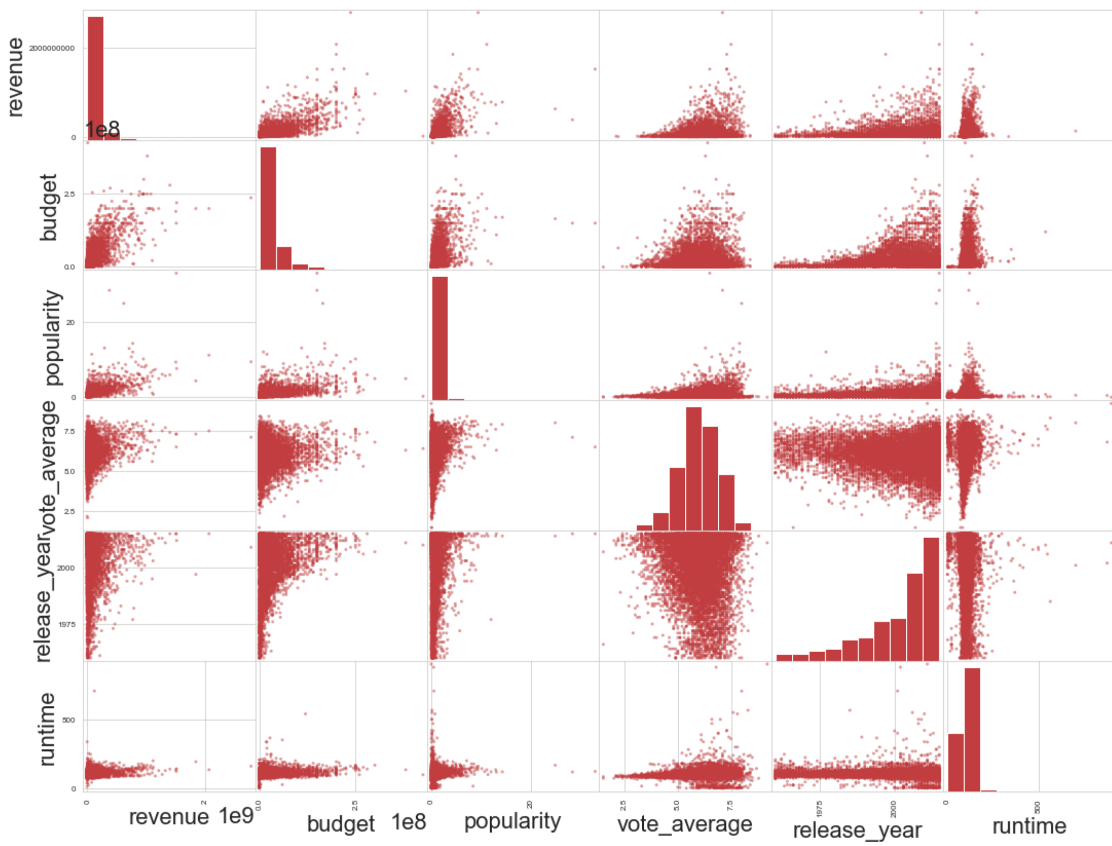
Question 4: Which attributes indicate a movie's chances of success (Revenue/Rating)?

[91]:
```
#subset data for columns of interest
aux_df = df_movie[['revenue', 'budget', 'popularity', 'vote_average',␣
↪'release_year', 'runtime']]

#create scatter matrix
pd.plotting.scatter_matrix(aux_df, figsize=(18,14));
```

```
C:\Users\noama\anaconda3\lib\site-
packages\pandas\plotting\_matplotlib\tools.py:298: MatplotlibDeprecationWarning:
The rowNum attribute was deprecated in Matplotlib 3.2 and will be removed two
minor releases later. Use ax.get_subplotspec().rowspan.start instead.
  layout[ax.rowNum, ax.colNum] = ax.get_visible()
C:\Users\noama\anaconda3\lib\site-
packages\pandas\plotting\_matplotlib\tools.py:298: MatplotlibDeprecationWarning:
The colNum attribute was deprecated in Matplotlib 3.2 and will be removed two
minor releases later. Use ax.get_subplotspec().colspan.start instead.
  layout[ax.rowNum, ax.colNum] = ax.get_visible()
```

```
C:\Users\noama\anaconda3\lib\site-
packages\pandas\plotting\_matplotlib\tools.py:304: MatplotlibDeprecationWarning:
The rowNum attribute was deprecated in Matplotlib 3.2 and will be removed two
minor releases later. Use ax.get_subplotspec().rowspan.start instead.
  if not layout[ax.rowNum + 1, ax.colNum]:
C:\Users\noama\anaconda3\lib\site-
packages\pandas\plotting\_matplotlib\tools.py:304: MatplotlibDeprecationWarning:
The colNum attribute was deprecated in Matplotlib 3.2 and will be removed two
minor releases later. Use ax.get_subplotspec().colspan.start instead.
  if not layout[ax.rowNum + 1, ax.colNum]:
```



Observations

There is a positive correlation between budget and revenue, and a slightly positive correlation with release year and budget. With average rating only slightly positive influenced by budget.

1.6 Conclusion

Question 1: How has the success of genres changed over time (Revenue/Rating)?

Drama, comedy and action were the 3 top most frequent type of movies. The popularity of movie releases has generally grown over time. Heatmaps confirmed these trends.

Question 2: How succesful are different genres (Revenue/Rating)?

The success of genres was first analysed by evaluating revenues. The genre animation is the largest earner, followed by adventure. At the other end of the spectrum it appears foreign movies, documentaries and TV Movies rank at the bottom in terms of revenue. If return on investment (RoI) is calculated however, TV Movies moved to the top of the RoI ranking,meaning it earned the most per budget spent.

Question 3: Which Directors are the most successful (Revenue/Rating)?

By looking at the total revenue generated by directors, Stevn Spielberg appeared to be the most succesfull director, followed by Peter Jackson. However, this favours directors with long careers, and thus more the opportunity to create more movies. To account for this, the average revenue per movie wwas calculted, resulting in David Yates being the most successful director.

Question 4: Which attributes indicate a movie's chances of success (Revenue/Rating)?

We skimmed the surface of what attributes helped define a movies chance of success. We can tentatively say there appears to be a positive correlation between budget and revenue. This would confirm the intuition that higher budgets are indeed likely to result in higher revenues.

Limitations and Assumptions

Original budget and revenue figures used, ignoring figures adjusted for inflation.

Voter average can be skewed by the total number of votes for each category.

Director analysis based on the sum of revenue. We could also have looked at our definition of success and incorporated average rating for each director.