

# Investigate\_a\_Dataset

September 15, 2020

## 1 Project: TMDb Movie Data Analysis

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## Introduction

I choose **TMDb Movie Data** for this project.

There's a description of this dataset from Kaggle:

*"What can we say about the success of a movie before it is released? Are there certain companies (Pixar?) that have found a consistent formula? Given that major films costing over \">\$100 million to produce can still flop, this question is more important than ever to the industry. Film aficionados might have different interests. Can we predict which films will be highly rated, whether or not they are a commercial success? This is a great place to start digging in to those questions, with data on the plot, cast, crew, budget, and revenues of several thousand films.*

**The following questions could be answered using these data:** 1. Which genres are most popular from year to year?

2. How sharp is the divide between major film studios and the independents?

3. What kinds of properties are associated with movies that have high revenues?

4. Other questions which will arise during Data Cleaning.

Link to data:

[https://www.google.com/url?q=https://d17h27t6h515a5.cloudfront.net/topher/2017/October/59dd1c4c\\_tmdb-movies/tmdb-movies.csv&sa=D&ust=1532469042115000](https://www.google.com/url?q=https://d17h27t6h515a5.cloudfront.net/topher/2017/October/59dd1c4c_tmdb-movies/tmdb-movies.csv&sa=D&ust=1532469042115000)

```
In [1]: # Import statements for all of the packages that will be used.
```

```
# + 'magic word' so that visualizations are plotted
# inline with the notebook. See this page for more:
# http://ipython.readthedocs.io/en/stable/interactive/magics.html
```

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
% matplotlib inline

pd.set_option('display.max_columns', 100)
```

## Data Wrangling

### 1.1.1 General Properties

This data set contains information about 10,000 movies collected from The Movie Database (TMDb), including user ratings and revenue.

```
In [2]: # Load your data and print out a few lines. Perform operations to inspect data
#        types and look for instances of missing or possibly errant data.

df = pd.read_csv('tmdb-movies.csv', parse_dates=['release_date'])
# release_date is date type column, so, when load data parse_dates was used to nterpret
df.head(3)
```

```
Out[2]:
```

	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	<a href="http://www.jurassicworld.com/">http://www.jurassicworld.com/</a>	Colin Trevorrow
1	<a href="http://www.madmaxmovie.com/">http://www.madmaxmovie.com/</a>	George Miller
2	<a href="http://www.thedivergentseries.movie/#insurgent">http://www.thedivergentseries.movie/#insurgent</a>	Robert Schwentke

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

	keywords \
0	monster dna tyrannosaurus rex velociraptor island
1	future chase post-apocalyptic dystopia australia
2	based on novel revolution dystopia sequel dyst...

	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...  2015-06-09         5562
1 Village Roadshow Pictures|Kennedy Miller Produ...  2015-05-13         6185
2 Summit Entertainment|Mandeville Films|Red Wago...  2015-03-18         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

```

There are 21 columns and 10866 movies in dataset.

```
In [3]: df.shape
```

```
Out[3]: (10866, 21)
```

Some column types are correct (like popularity or director, and probably "id" column type isn't correct (should be string).

```
In [4]: df.dtypes
```

```

Out[4]: id                                int64
imdb_id                                object
popularity                            float64
budget                                int64
revenue                              int64
original_title                        object
cast                                 object
homepage                             object
director                             object
tagline                              object
keywords                             object
overview                             object
runtime                              int64
genres                               object
production_companies                  object
release_date                          datetime64[ns]
vote_count                            int64
vote_average                          float64
release_year                          int64
budget_adj                            float64
revenue_adj                           float64
dtype: object

```

Descriptive statistics of all numeric columns is shown below.

```
In [5]: df.describe()
```

```
Out[5]:
```

	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

Most of columns don't have missing values. And only cast, homepage, director, and other string columns which describe movies have some missings. However, numeric columns "budget", "revenue", "runtime", "budget\_adj", and "revenue\_adj" have no missing data. So, zeros will be interpreted as missing data.

```
In [6]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10866 entries, 0 to 10865
Data columns (total 21 columns):
id                10866 non-null int64
imdb_id           10856 non-null object
popularity        10866 non-null float64
budget            10866 non-null int64
revenue           10866 non-null int64
original_title    10866 non-null object
cast              10790 non-null object
homepage          2936 non-null object
director          10822 non-null object
tagline           8042 non-null object
keywords          9373 non-null object
overview          10862 non-null object
runtime           10866 non-null int64
genres            10843 non-null object
production_companies 9836 non-null object
release_date      10866 non-null datetime64[ns]
vote_count        10866 non-null int64
```

```

vote_average          10866 non-null float64
release_year          10866 non-null int64
budget_adj            10866 non-null float64
revenue_adj           10866 non-null float64
dtypes: datetime64[ns](1), float64(4), int64(6), object(10)
memory usage: 1.7+ MB

```

### 1.1.2 Data Cleaning

From Kaggle:

Certain columns, like "cast" and "genres", contain multiple values separated by pipe (|) characters. There are some odd characters in the "cast" column. Don't worry about cleaning them. You can leave them as is.

The final two columns ending with "\_adj" show the budget and revenue of the associated movie in terms of 2010 dollars, accounting for inflation over time.

In the IMDb version it was necessary to treat values of zero in the budget field as missing. ... (It's probably a good idea to keep treating zeros as missing, with the caveat that missing budgets much more likely to have been from small budget films in the first place).

In [7]: *# Check are column release\_year and year in release\_date differ*

```

df['different_years'] = df.release_date.dt.year - df.release_year
print('Columns with different years in release_date and release_year columns')
print(df['different_years'].sum())
df.sort_values('different_years', ascending=False).head(3)

```

Columns with different years in release\_date and release\_year columns  
36200

```

Out[7]:
      id  imdb_id  popularity  budget  revenue  \
10865  22293  tt0060666    0.035919   19000      0
10155  43040  tt0054292    0.269428      0      0
10153  23439  tt0053925    0.323180  270000      0

      original_title  \
10865  Manos: The Hands of Fate
10155      Sergeant Rutledge
10153      House of Usher

      cast homepage  \
10865  Harold P. Warren|Tom Neyman|John Reynolds|Dian...   NaN
10155  Jeffrey Hunter|Woody Strode|Constance Towers|B...   NaN
10153  Vincent Price|Mark Damon|Myrna Fahey|Harry Ell...   NaN

      director  tagline  \
10865  Harold P. Warren  It's Shocking! It's Beyond Your Imagination!
10155      John Ford  Forget all the suspense you have ever seen! Fo...

```

```
10153      Roger Corman  Edgar Allan Poe's demonic tale of The Ungodly...
```

```

                                keywords \
10865  fire|gun|drive|sacrifice|flashlight
10155                                rape|court martial
10153  curse|new england|edgar allan poe

```

```

                                overview  runtime \
10865  A family gets lost on the road and stumbles up...      74
10155  Respected black cavalry Sergeant Brax Rutledge...    111
10153  After a long journey, Philip arrives at the Us...      79

```

```

                                genres  production_companies  release_date  vote_count \
10865                                Horror                Norm-Iris    2066-11-15        15
10155  Crime|Western      John Ford Productions    2060-05-18        12
10153  Horror|Thriller    Alta Vista Productions    2060-06-21        28

```

```

                                vote_average  release_year  budget_adj  revenue_adj  different_years
10865                1.5            1966  1.276423e+05         0.0            100
10155                5.2            1960  0.000000e+00         0.0            100
10153                5.9            1960  1.990701e+06         0.0            100

```

```

In [8]: # Create new release_date where year is replaced with release_year
df['release_date_corrected'] = pd.to_datetime(df.release_year.astype(str) + '-' + df.release_year.dt.month.astype(str) + '-' + df.release_year.dt.day.astype(str))

# Drop useless columns
df.drop(['release_year', 'release_date', 'different_years'], axis=1, inplace=True)

# Rename release_date_corrected
df.rename(columns={'release_date_corrected': 'release_date'}, inplace=True)

df.head(3)

```

```

Out[8]:      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

keywords \
0      monster|dna|tyrannosaurus rex|velociraptor|island
1      future|chase|post-apocalyptic|dystopia|australia
2      based on novel|revolution|dystopia|sequel|dyst...

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 vote_count \
0      Universal Studios|Amblin Entertainment|Legenda...      5562
1      Village Roadshow Pictures|Kennedy Miller Produ...      6185
2      Summit Entertainment|Mandeville Films|Red Wago...      2480

vote_average budget_adj revenue_adj release_date
0      6.5  1.379999e+08  1.392446e+09  2015-06-09
1      7.1  1.379999e+08  3.481613e+08  2015-05-13
2      6.3  1.012000e+08  2.716190e+08  2015-03-18

```

In [9]: # Check duplicated rows

```
df[df.duplicated()]
```

```

Out[9]:
      id  imdb_id  popularity  budget  revenue  original_title \
2090  42194  tt0411951    0.59643  30000000    967000      TEKKEN

cast homepage \
2090  Jon Foo|Kelly Overton|Cary-Hiroyuki Tagawa|Ian...      NaN

director tagline \
2090  Dwight H. Little  Survival is no game

keywords \
2090  martial arts|dystopia|based on video game|mart...

overview runtime \

```

```
2090 In the year of 2039, after World Wars destroy ... 92
```

```

                                genres    production_companies \
2090 Crime|Drama|Action|Thriller|Science Fiction Namco|Light Song Films

```

```

        vote_count  vote_average  budget_adj  revenue_adj  release_date
2090           110           5.0  30000000.0    967000.0    2010-03-20

```

```
In [10]: df[df.id == 42194]
```

```

Out[10]:      id  imdb_id  popularity    budget  revenue  original_title \
2089  42194  tt0411951    0.59643  30000000    967000          TEKKEN
2090  42194  tt0411951    0.59643  30000000    967000          TEKKEN

```

```

                                cast homepage \
2089 Jon Foo|Kelly Overton|Cary-Hiroiyuki Tagawa|Ian...      NaN
2090 Jon Foo|Kelly Overton|Cary-Hiroiyuki Tagawa|Ian...      NaN

```

```

        director    tagline \
2089 Dwight H. Little  Survival is no game
2090 Dwight H. Little  Survival is no game

```

```

                                keywords \
2089 martial arts|dystopia|based on video game|mart...
2090 martial arts|dystopia|based on video game|mart...

```

```

                                overview  runtime \
2089 In the year of 2039, after World Wars destroy ...    92
2090 In the year of 2039, after World Wars destroy ...    92

```

```

                                genres    production_companies \
2089 Crime|Drama|Action|Thriller|Science Fiction Namco|Light Song Films
2090 Crime|Drama|Action|Thriller|Science Fiction Namco|Light Song Films

```

```

        vote_count  vote_average  budget_adj  revenue_adj  release_date
2089           110           5.0  30000000.0    967000.0    2010-03-20
2090           110           5.0  30000000.0    967000.0    2010-03-20

```

From 10866 movies, "TEKKEN" is met twice. So, duplicated row will be deleted.

```
In [11]: df = df[~df.duplicated()]
df.shape
```

```
Out[11]: (10865, 20)
```

```

In [12]: # Check which columns has only unique values, or don't include importnat information

        # "id" columns is a unique identifier
        print(df.id.unique().shape[0] == df.shape[0])

```



```

# imdb_id has 9 missing values and all other ids are also unique for movies
imdb_id_null = df[df.imdb_id.duplicated() & df.imdb_id.isnull()].shape[0]
print(df.imdb_id.unique().shape[0] + imdb_id_null == df.shape[0])

```

True

True

```

In [13]: print(df[(df.budget == 0) & (df.budget_adj != 0)].shape)
print(df[(df.revenue == 0) & (df.revenue_adj != 0)].shape)

df['budget_check'] = df.budget / df.budget_adj
df['revenue_check'] = df.revenue / df.revenue_adj
df_agg = df.groupby(df.release_date.dt.year).agg({'revenue_check': ['min', 'max'], 'bud
df_agg.columns = map('_', df_agg.columns)

# We don't need 'budget_check' and 'revenue_check' columns anymore
df.drop(['budget_check', 'revenue_check'], axis=1, inplace=True)

print(int((df_agg.revenue_check_max - df_agg.revenue_check_min).sum()))
print(int((df_agg.budget_check_max - df_agg.budget_check_min).sum()))
df_agg.head()

```

(0, 20)

(0, 20)

0

0

```

Out[13]:
      revenue_check_min  revenue_check_max  budget_check_min \
release_date
1960                0.135631            0.135631            0.135631
1961                0.137083            0.137083            0.137083
1962                0.138726            0.138726            0.138726
1963                0.140446            0.140446            0.140446
1964                0.142242            0.142242            0.142242

      budget_check_max
release_date
1960                0.135631
1961                0.137083
1962                0.138726
1963                0.140446
1964                0.142242

```

Columns "revenue" and "budget" could be deleted since corresponding adjusted columns are calculated correctly. Moreover, it's inconvenient to compare financial indicators across years and don't take into account inflation.

There're 5068 directors in this dataset. This means, on average, one person made 2 movies.

```
In [14]: df['director'].unique().shape
```

```
Out[14]: (5068,)
```

```
In [15]: directors_df = df['director'].value_counts()  
directors_df.head(15)
```

```
Out[15]: Woody Allen          45  
         Clint Eastwood       34  
         Martin Scorsese       29  
         Steven Spielberg      29  
         Ridley Scott          23  
         Steven Soderbergh     22  
         Ron Howard            22  
         Joel Schumacher       21  
         Brian De Palma        20  
         Tim Burton            19  
         Barry Levinson        19  
         Wes Craven            19  
         John Carpenter        18  
         Rob Reiner            18  
         David Cronenberg      18  
         Name: director, dtype: int64
```

Top-8 directors made more than 20 movies. Whether their movies are also popular or profitable than movies of the other directors? It will be discussed in Data Analysis part.

```
In [16]: # Drop columns which won't be used in analysis
```

```
df.drop(['id', 'imdb_id', 'budget', 'revenue', 'homepage', 'tagline', 'overview'], axis=1)  
df.head(3)
```

```
Out[16]:   popularity  original_title \  
0    32.985763      Jurassic World  
1    28.419936  Mad Max: Fury Road  
2    13.112507      Insurgent
```

```
         cast          director \  
0  Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...  Colin Trevorrow  
1  Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...   George Miller  
2  Shailene Woodley|Theo James|Kate Winslet|Ansel...  Robert Schwentke
```

```
         keywords  runtime \  
0  monster|dna|tyrannosaurus rex|velociraptor|island    124  
1  future|chase|post-apocalyptic|dystopia|australia    120  
2  based on novel|revolution|dystopia|sequel|dyst...    119
```

```
         genres \  
0  Action|Adventure|Science Fiction|Thriller
```

```

1 Action|Adventure|Science Fiction|Thriller
2 Adventure|Science Fiction|Thriller

production_companies vote_count \
0 Universal Studios|Amblin Entertainment|Legenda... 5562
1 Village Roadshow Pictures|Kennedy Miller Produ... 6185
2 Summit Entertainment|Mandeville Films|Red Wago... 2480

vote_average budget_adj revenue_adj release_date
0 6.5 1.379999e+08 1.392446e+09 2015-06-09
1 7.1 1.379999e+08 3.481613e+08 2015-05-13
2 6.3 1.012000e+08 2.716190e+08 2015-03-18

```

Replace zeros in numeric columns without missing values with NaN. The logic was explained above.

```

In [17]: col_numeric = ['runtime', 'budget_adj', 'revenue_adj']

for col in col_numeric:
    df[col] = df[col].replace(0, np.nan)

df.describe()

```

```

Out[17]:
      popularity      runtime  vote_count  vote_average  budget_adj \
count  10865.000000  10834.000000  10865.000000  10865.000000  5.169000e+03
mean     0.646446    102.363855    217.399632     5.975012  3.688907e+07
std     1.000231     30.948225    575.644627     0.935138  4.196096e+07
min     0.000065     2.000000     10.000000     1.500000  9.210911e-01
25%     0.207575     90.000000     17.000000     5.400000  8.102293e+06
50%     0.383831     99.000000     38.000000     6.000000  2.271505e+07
75%     0.713857    112.000000    146.000000     6.600000  5.008384e+07
max     32.985763    900.000000   9767.000000     9.200000  4.250000e+08

      revenue_adj
count  4.849000e+03
mean   1.151009e+08
std    1.988557e+08
min    2.370705e+00
25%    1.046585e+07
50%    4.395666e+07
75%    1.316482e+08
max    2.827124e+09

```

### 1.1.3 Split columns with different values in each row

Let's look at "cast", "keywords", "genres", "production\_companies" columns. Values in this columns are stored as multiple values separated by pipe (|) characters.

cast

```
In [18]: crew_df = df['cast'].str.split('|').apply(pd.Series).stack().value_counts()
print('Shape', crew_df.shape)
crew_df[crew_df > 40].head(15)
#crew_df.head()
```

Shape (19026,)

```
Out[18]: Robert De Niro      72
         Samuel L. Jackson   71
         Bruce Willis       62
         Nicolas Cage       61
         Michael Caine      53
         Robin Williams     51
         John Cusack        50
         Morgan Freeman     49
         John Goodman       49
         Liam Neeson       48
         Susan Sarandon     48
         Julianne Moore     47
         Alec Baldwin       47
         Gene Hackman       46
         Johnny Depp        46
dtype: int64
```

Since, there's a lot of actresses and actors in this data, columns called "Robert\_De\_Niro" and "Samuel\_L\_Jackson" will be added, they'll indicate whether these super enduring men were starred in the movie or not. In future, this analysis could be extended by analysing more actors from the list above.

```
In [19]: df['Robert_De_Niro'] = np.where(df['cast'].str.contains('Robert De Niro')).replace(np.nan, 0)
         df['Samuel_L_Jackson'] = np.where(df['cast'].str.contains('Samuel L. Jackson')).replace(np.nan, 0)

         df.drop('cast', axis=1, inplace=True)

         print('Share of movies with Robert De Niro and Samuel L. Jackson')
         print(df[['Robert_De_Niro', 'Samuel_L_Jackson']].mean())

         df.head(3)
```

```
Share of movies with Robert De Niro and Samuel L. Jackson
Robert_De_Niro      0.006627
Samuel_L_Jackson    0.006535
dtype: float64
```

```
Out[19]:   popularity   original_title   director \
0    32.985763    Jurassic World    Colin Trevorrow
```

1	28.419936	Mad Max: Fury Road	George Miller
2	13.112507	Insurgent	Robert Schwentke

	keywords	runtime	\
0	monster dna tyrannosaurus rex velociraptor island	124.0	
1	future chase post-apocalyptic dystopia australia	120.0	
2	based on novel revolution dystopia sequel dyst...	119.0	

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

	production_companies	vote_count	\
0	Universal Studios Amblin Entertainment Legenda...	5562	
1	Village Roadshow Pictures Kennedy Miller Produ...	6185	
2	Summit Entertainment Mandeville Films Red Wago...	2480	

	vote_average	budget_adj	revenue_adj	release_date	Robert_De_Niro	\
0	6.5	1.379999e+08	1.392446e+09	2015-06-09	0	
1	7.1	1.379999e+08	3.481613e+08	2015-05-13	0	
2	6.3	1.012000e+08	2.716190e+08	2015-03-18	0	

	Samuel_L_Jackson
0	0
1	0
2	0

## keywords

```
In [20]: keywords_df = df['keywords'].str.split('|').apply(pd.Series).stack().value_counts()
print('Shape', keywords_df.shape)
keywords_df.head()
```

Shape (7878,)

```
Out[20]: woman director      413
independent film           396
based on novel             278
sex                        272
sport                      216
dtype: int64
```

There're 7878 different keywords. So, only for Top-2, columns calles "woman\_director" and "independent\_film" will be added, they'll indicate wheter the director of movie was woman or man, and whether the movie is independent film or not. In future, this analysis could also be extend by analysing more keywords from the list above.

```
In [21]: df['woman_director'] = np.where(df['keywords'].str.contains('woman director').replace(n
df['independent_film'] = np.where(df['keywords'].str.contains('independent film').repla

df.drop('keywords', axis=1, inplace=True)

print('Share of movies with woman director and independent films')
print(df[['woman_director', 'independent_film']].mean())

df.head(3)
```

```
Share of movies with woman director and independent films
woman_director      0.038012
independent_film    0.036539
dtype: float64
```

```
Out[21]:
```

	popularity	original_title	director	runtime	\
0	32.985763	Jurassic World	Colin Trevorrow	124.0	
1	28.419936	Mad Max: Fury Road	George Miller	120.0	
2	13.112507	Insurgent	Robert Schwentke	119.0	

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

	production_companies	vote_count	\
0	Universal Studios Amblin Entertainment Legenda...	5562	
1	Village Roadshow Pictures Kennedy Miller Produ...	6185	
2	Summit Entertainment Mandeville Films Red Wago...	2480	

	vote_average	budget_adj	revenue_adj	release_date	Robert_De_Niro	\
0	6.5	1.379999e+08	1.392446e+09	2015-06-09	0	
1	7.1	1.379999e+08	3.481613e+08	2015-05-13	0	
2	6.3	1.012000e+08	2.716190e+08	2015-03-18	0	

	Samuel_L_Jackson	woman_director	independent_film
0	0	0	0
1	0	0	0
2	0	0	0

genres

```
In [22]: genres_df = df['genres'].str.split('|').apply(pd.Series).stack().value_counts()
print('Shape', genres_df.shape)
genres_df
```

```
Shape (20,)
```

```
Out[22]: Drama          4760
         Comedy         3793
         Thriller       2907
         Action         2384
         Romance        1712
         Horror         1637
         Adventure      1471
         Crime          1354
         Family         1231
         Science Fiction 1229
         Fantasy         916
         Mystery        810
         Animation      699
         Documentary    520
         Music          408
         History        334
         War            270
         Foreign        188
         TV Movie       167
         Western        165
         dtype: int64
```

For every genre will be created dummy variable which will indicate what genre the film belongs to.

```
In [23]: genre_unique = genres_df.index.tolist()

         for genre in genre_unique:
             df[genre] = np.where(df['genres'].str.contains(genre).replace(np.nan, False), 1, 0)

         df.drop('genres', axis=1, inplace=True)

         print('New shape', df.shape)
         df.head(3)
```

New shape (10865, 34)

```
Out[23]: popularity    original_title    director    runtime \
0    32.985763    Jurassic World    Colin Trevorrow    124.0
1    28.419936    Mad Max: Fury Road    George Miller    120.0
2    13.112507    Insurgent    Robert Schwentke    119.0

                                production_companies    vote_count \
0    Universal Studios|Amblin Entertainment|Legenda...    5562
1    Village Roadshow Pictures|Kennedy Miller Produ...    6185
2    Summit Entertainment|Mandeville Films|Red Wago...    2480

    vote_average    budget_adj    revenue_adj    release_date    Robert_De_Niro \
```

0	6.5	1.379999e+08	1.392446e+09	2015-06-09	0
1	7.1	1.379999e+08	3.481613e+08	2015-05-13	0
2	6.3	1.012000e+08	2.716190e+08	2015-03-18	0

	Samuel_L_Jackson	woman_director	independent_film	Drama	Comedy	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	

	Thriller	Action	Romance	Horror	Adventure	Crime	Family	\
0	1	1	0	0	1	0	0	
1	1	1	0	0	1	0	0	
2	1	0	0	0	1	0	0	

	Science Fiction	Fantasy	Mystery	Animation	Documentary	Music	History	\
0	1	0	0	0	0	0	0	
1	1	0	0	0	0	0	0	
2	1	0	0	0	0	0	0	

	War	Foreign	TV Movie	Western
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0

### production\_companies

```
In [24]: production_companies_df = df['production_companies'].str.split('|').apply(pd.Series).stack()
print('Shape', production_companies_df.shape)
production_companies_df.head(10)
```

Shape (7879,)

```
Out[24]: Universal Pictures      522
Warner Bros.                    509
Paramount Pictures              431
Twentieth Century Fox Film Corporation  282
Columbia Pictures               272
New Line Cinema                 219
Metro-Goldwyn-Mayer (MGM)       218
Walt Disney Pictures            214
Touchstone Pictures             178
Columbia Pictures Corporation    160
dtype: int64
```

Top-3 production companies are used among list of 7879 different firms: \* Universal Pictures  
 \* Warner Bros.  
 \* Paramount Pictures.



```

In [25]: df['Universal_Pictures'] = (np.where(df['production_companies'].str.contains('Universal
                                                .replace(np.nan, False), 1, 0))
df['Warner_Bros'] = np.where(df['production_companies'].str.contains('Warner Bros.').re
df['Paramount_Pictures'] = (np.where(df['production_companies'].str.contains('Paramount
                                                .replace(np.nan, False), 1, 0))

df.drop('production_companies', axis=1, inplace=True)

print('Share of movies of Universal Pictures, Warner Bros., and Paramount Pictures')
print(df[['Universal_Pictures', 'Warner_Bros', 'Paramount_Pictures']].mean() * 100)

df.head(3)

```

```

Share of movies of Universal Pictures, Warner Bros., and Paramount Pictures
Universal_Pictures    4.878049
Warner_Bros           5.715601
Paramount_Pictures    3.985274
dtype: float64

```

```

Out[25]:
popularity    original_title    director    runtime    vote_count  \
0    32.985763    Jurassic World    Colin Trevorrow    124.0    5562
1    28.419936    Mad Max: Fury Road    George Miller    120.0    6185
2    13.112507    Insurgent    Robert Schwentke    119.0    2480

vote_average    budget_adj    revenue_adj    release_date    Robert_De_Niro  \
0            6.5    1.379999e+08    1.392446e+09    2015-06-09    0
1            7.1    1.379999e+08    3.481613e+08    2015-05-13    0
2            6.3    1.012000e+08    2.716190e+08    2015-03-18    0

Samuel_L_Jackson    woman_director    independent_film    Drama    Comedy  \
0            0            0            0            0            0
1            0            0            0            0            0
2            0            0            0            0            0

Thriller    Action    Romance    Horror    Adventure    Crime    Family  \
0            1            1            0            0            1            0            0
1            1            1            0            0            1            0            0
2            1            0            0            0            1            0            0

Science Fiction    Fantasy    Mystery    Animation    Documentary    Music    History  \
0            1            0            0            0            0            0            0
1            1            0            0            0            0            0            0
2            1            0            0            0            0            0            0

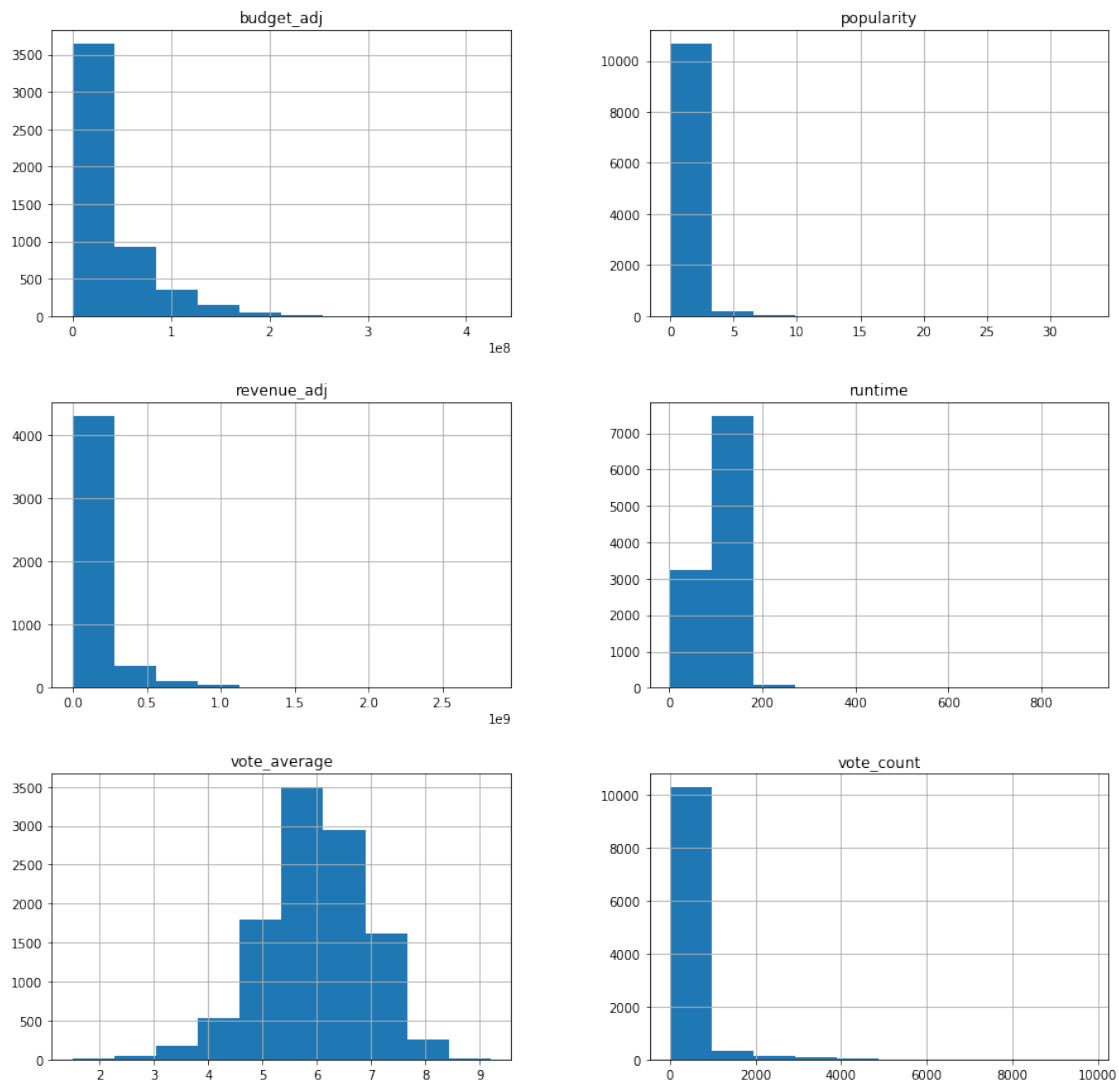
War    Foreign    TV Movie    Western    Universal_Pictures    Warner_Bros  \
0    0            0            0            0            0            0
1    0            0            0            0            0            0

```

2	0	0	0	0	0	0
Paramount_Pictures						
0						0
1						0
2						0

### 1.1.4 Visualize results

```
In [26]: df[['popularity', 'runtime', 'vote_count', 'vote_average', 'budget_adj', 'revenue_adj']]
plt.show()
```



```
In [27]: df_nulls = df.isnull().sum().sort_values(ascending=False)
```

```
print('Share of missing values')
df_nulls[df_nulls > 0] / df.shape[0]
```

Share of missing values

```
Out[27]: revenue_adj    0.553705
        budget_adj     0.524252
        director       0.004050
        runtime        0.002853
        dtype: float64
```

Missing values in "director" column isn't significant, and it's equal 0.41%. So we'll only look at non-missing data. The same could be applied to "runtime" column, and share of NaN is equal 0.29%. here we'll also look at non-missing data. More than 50% of missing values in revenues and budget will significantly distort results. Replace a half of missing values with any measure of center won't produce accurate results. So, one way is somehow impute NaN. The other way is to analyse only data with valid not-zero numbers. And some other scenarios. In the following analyses will be used only not-zero budgets and revenues.

```
In [28]: df = df[(df.director.notnull()) & (df.runtime.notnull())]
```

```
In [29]: print('Final shape', df.shape)
        df.head()
```

Final shape (10792, 36)

```
Out[29]: popularity          original_title    director  runtime \
0    32.985763          Jurassic World    Colin Trevorrow    124.0
1    28.419936      Mad Max: Fury Road    George Miller    120.0
2    13.112507          Insurgent    Robert Schwentke    119.0
3    11.173104  Star Wars: The Force Awakens    J.J. Abrams    136.0
4     9.335014          Furious 7    James Wan    137.0

        vote_count  vote_average  budget_adj  revenue_adj  release_date \
0           5562           6.5  1.379999e+08  1.392446e+09  2015-06-09
1           6185           7.1  1.379999e+08  3.481613e+08  2015-05-13
2           2480           6.3  1.012000e+08  2.716190e+08  2015-03-18
3           5292           7.5  1.839999e+08  1.902723e+09  2015-12-15
4           2947           7.3  1.747999e+08  1.385749e+09  2015-04-01

        Robert_De_Niro  Samuel_L_Jackson  woman_director  independent_film  Drama \
0                0                0                0                0                0
1                0                0                0                0                0
2                0                0                0                0                0
3                0                0                0                0                0
4                0                0                0                0                0
```

	Comedy	Thriller	Action	Romance	Horror	Adventure	Crime	Family	\
0	0	1	1	0	0	1	0	0	
1	0	1	1	0	0	1	0	0	
2	0	1	0	0	0	1	0	0	
3	0	0	1	0	0	1	0	0	
4	0	1	1	0	0	0	1	0	

	Science Fiction	Fantasy	Mystery	Animation	Documentary	Music	History	\
0		1	0	0		0	0	0
1		1	0	0		0	0	0
2		1	0	0		0	0	0
3		1	1	0		0	0	0
4		0	0	0		0	0	0

	War	Foreign	TV Movie	Western	Universal_Pictures	Warner_Bros	\
0	0	0	0	0		0	
1	0	0	0	0		0	
2	0	0	0	0		0	
3	0	0	0	0		0	
4	0	0	0	0	1	0	

	Paramount_Pictures
0	0
1	0
2	0
3	0
4	0

## Exploratory Data Analysis

- Research questions:**
1. Which genres are most popular from year to year?
  2. How sharp is the divide between major film studios and the independents?
  3. What kinds of properties are associated with movies that have high revenues?
  4. Top-8 directors made more than 20 movies. Whether their movies are also popular or profitable than movies of the other directors?

### 1.1.5 Research Question 1: Which genres are most popular from year to year?

```
In [30]: df.popularity.describe()
```

```
Out[30]: count      10792.000000
         mean         0.649765
         std         1.002611
         min         0.000188
         25%         0.209737
         50%         0.385598
         75%         0.717722
         max         32.985763
         Name: popularity, dtype: float64
```

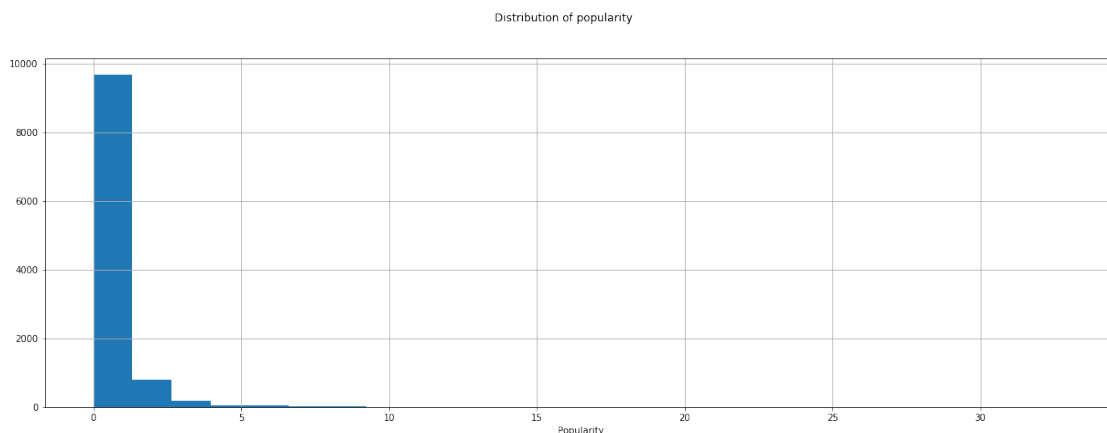
```
In [31]: df[df.popularity == df.popularity.max()]
```

```
Out[31]:
```

	popularity	original_title	director	runtime	vote_count	\		
0	32.985763	Jurassic World	Colin Trevorrow	124.0	5562			
	vote_average	budget_adj	revenue_adj	release_date	Robert_De_Niro	\		
0	6.5	1.379999e+08	1.392446e+09	2015-06-09	0			
	Samuel_L_Jackson	woman_director	independent_film	Drama	Comedy	\		
0	0	0	0	0	0			
	Thriller	Action	Romance	Horror	Adventure	Crime	Family	\
0	1	1	0	0	1	0	0	
	Science Fiction	Fantasy	Mystery	Animation	Documentary	Music	History	\
0	0	1	0	0	0	0	0	
	War	Foreign	TV Movie	Western	Universal_Pictures	Warner_Bros	\	
0	0	0	0	0	0	0		
	Paramount_Pictures							
0	0	0						

Most of the popularity ratings are less than 1. The distribution of popularity is right skewed with maximum rating 32.99 of movie "Jurassic World" (2015).

```
In [32]: df.popularity.hist(figsize=(21,7), bins=25)
plt.xlabel('Popularity')
plt.suptitle('Distribution of popularity')
plt.show()
```

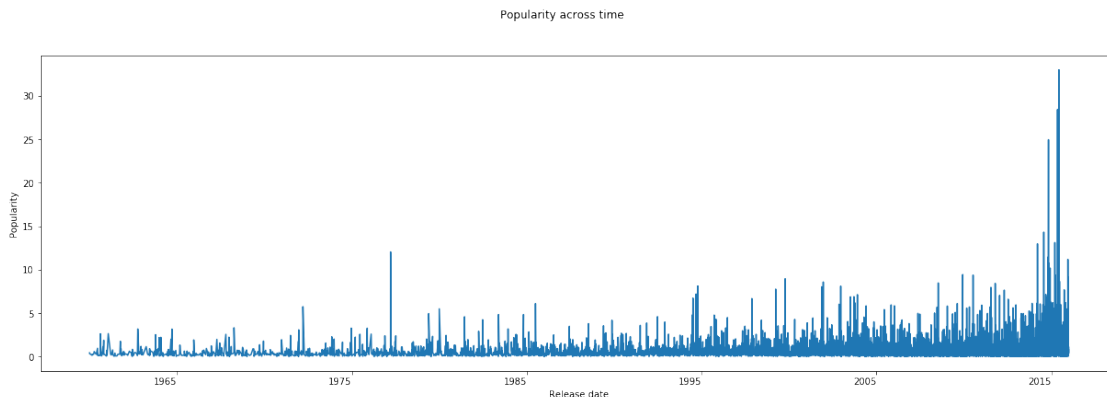


From 1960 to 2015 the number of movies increased with the corresponding increase of average opularity rate. However, some movies became popular since 20 century. For example, "The Godfather" (1972) has 5.74 popularity rate.

```
In [33]: df[(df.release_date >= '1972-01-01') & (df.release_date <= '1974-01-01')].sort_values('
                                                ascending=False).iloc[0, :9
```

```
Out[33]: popularity                5.73803
original_title          The Godfather
director          Francis Ford Coppola
runtime                175
vote_count              3970
vote_average            8.3
budget_adj          3.12874e+07
revenue_adj          1.27791e+09
release_date    1972-03-15 00:00:00
Name: 7269, dtype: object
```

```
In [34]: fig, ax = plt.subplots(nrows=1, ncols=1, figsize=(21,7))
df.plot(x='release_date', y='popularity', rot=0, legend=False, kind='line', ax=ax)
plt.xlabel('Release date')
plt.ylabel('Popularity')
plt.suptitle('Popularity across time')
# ax.set_yscale('log')
plt.show()
```

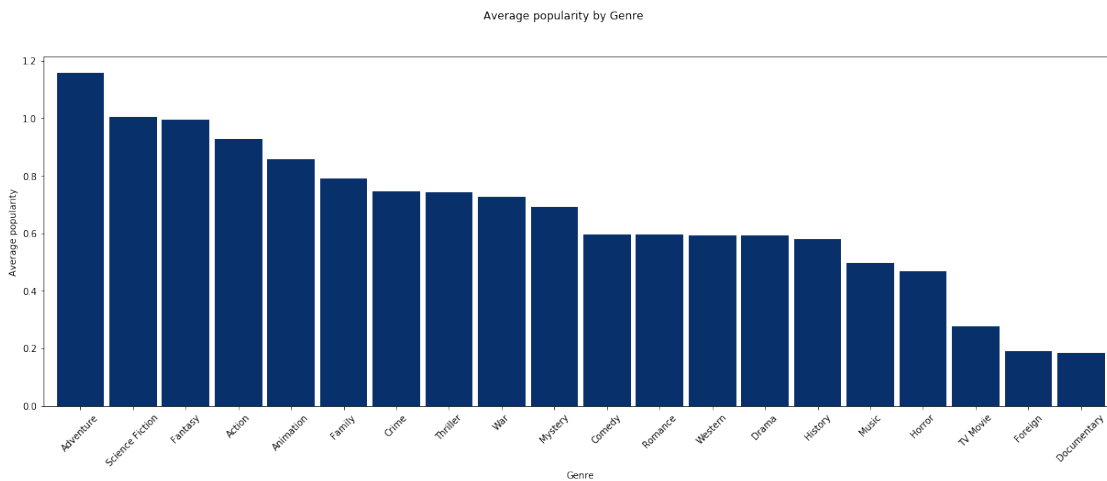


Among all 10 thousand movies, Adventure is the most popular genre with average popularity about 1.2.

```
In [35]: temp_lst = []
for col in genre_unique:
    temp_lst.append(df[df[col] == 1].popularity.mean())

popularity_by_genre = pd.DataFrame({'Genre': genre_unique, 'Mean popularity': temp_lst})
popularity_by_genre.sort_values(by='Mean popularity', ascending=False, inplace=True)
popularity_by_genre.plot(x='Genre', y='Mean popularity', rot=45, legend=False, kind='bar',
                        figsize=(21,7), cmap='Blues_r', width=.9)
plt.xlabel('Genre')
```

```
plt.ylabel('Average popularity')
plt.suptitle('Average popularity by Genre')
plt.show()
```



Now, that we have average popularity separately by release date and by genres, let's look at the most popular genres over time.

In [36]: # Reshape dataset such that genre became one row and create popularity\_by\_genre dataset

```
popularity_by_genre = df[df[genre_unique[0]] == 1].groupby(df.release_date.dt.year)['popularity']
popularity_by_genre['genre'] = genre_unique[0]
years = df.release_date.dt.year.tolist()
for col in genre_unique[1:]:
    temp = df[df[col] == 1].groupby(df.release_date.dt.year)['popularity'].mean().reset_index()
    temp['genre'] = col
    popularity_by_genre = popularity_by_genre.append(temp)

print('Genres\n', popularity_by_genre.genre.unique())
print('Average popularity\n', popularity_by_genre.popularity.mean())
popularity_by_genre.head()
```

Genres

```
['Drama' 'Comedy' 'Thriller' 'Action' 'Romance' 'Horror' 'Adventure'
 'Crime' 'Family' 'Science Fiction' 'Fantasy' 'Mystery' 'Animation'
 'Documentary' 'Music' 'History' 'War' 'Foreign' 'TV Movie' 'Western']
```

Average popularity

```
0.586307521846
```

```
Out[36]:   release_date  popularity  genre
0         1960     0.566305  Drama
1         1961     0.432233  Drama
```

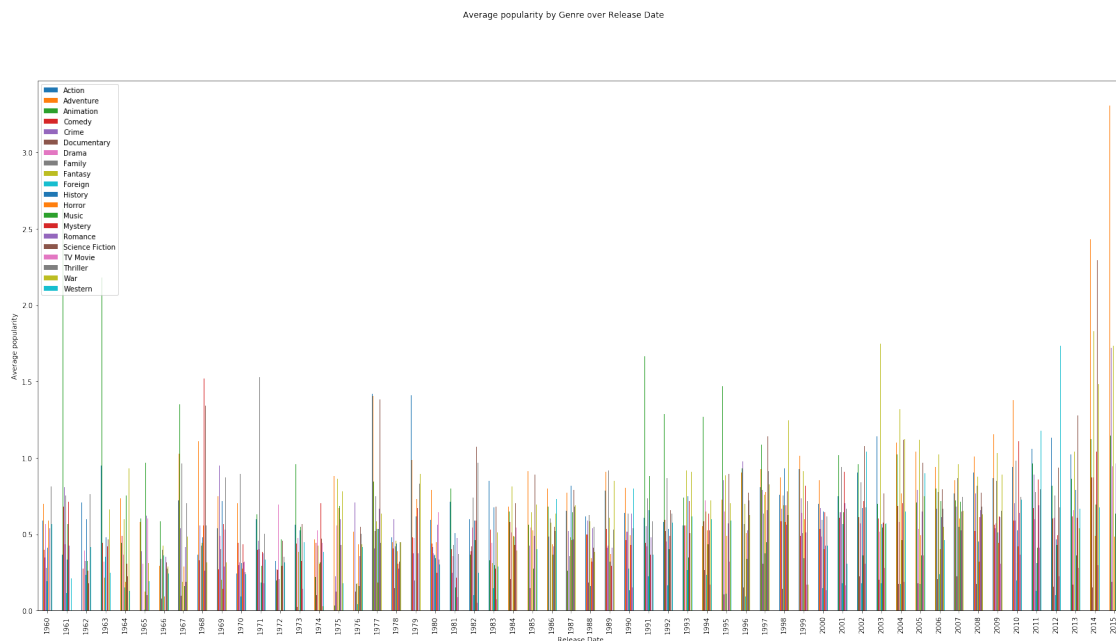
2	1962	0.392000	Drama
3	1963	0.322448	Drama
4	1964	0.364818	Drama

In [37]: # Create dataset with popularity means to make visuals

```
df_plot = popularity_by_genre.groupby(['release_date', 'genre']).popularity.mean()
```

It's not a good idea to use all the genres for the last 55 years. Let's fix this in the following figure.

```
In [38]: df_plot.sort_index(level='release_date', ascending=True).unstack().plot(
        kind='bar', figsize=(28,14))
plt.legend(loc='upper left')
plt.xlabel('Release Date')
plt.ylabel('Average popularity')
plt.suptitle('Average popularity by Genre over Release Date')
plt.show()
```



Get only top-5 genres from each year, so we could distinguish their popularity rates.

```
In [39]: df_plot_top5 = df_plot.reset_index().sort_values(by=['release_date', 'genre'],
        ascending=[True, False]).groupby('release_date').head(5)
df_plot_top5.set_index(['release_date', 'genre'], inplace=True)
df_plot_top5.head(10)
```

```
Out[39]:
```

	popularity
release_date genre	



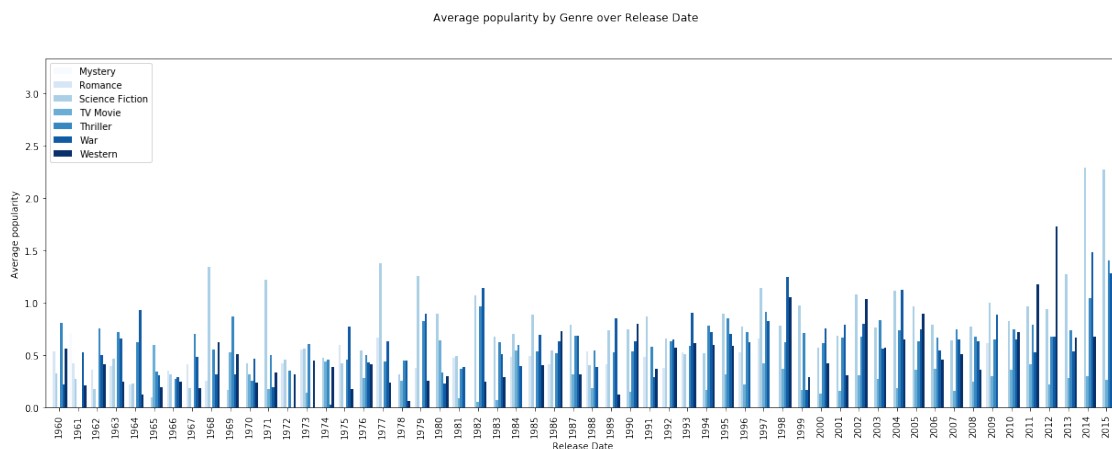
1960	Western	0.567759
	War	0.225863
	Thriller	0.811910
	Science Fiction	0.327905
	Romance	0.541227
1961	Western	0.210021
	War	0.531184
	Science Fiction	0.274103
	Romance	0.426036
	Mystery	0.712793

```
In [40]: df_plot_top5.groupby('genre').popularity.mean().sort_values()
```

```
Out[40]: genre
TV Movie      0.285852
Romance       0.464334
Mystery       0.501919
Western       0.537787
War           0.626728
Thriller      0.645515
Science Fiction 0.763493
Name: popularity, dtype: float64
```

The most popular genres by popularity rate during the whole period is Science Fiction, Thriller, and Wars. Moreover, during the 20 century Romance and TV movies were also as popular as Science Fiction genre. In the 21st century Western genre has reached leading positions.

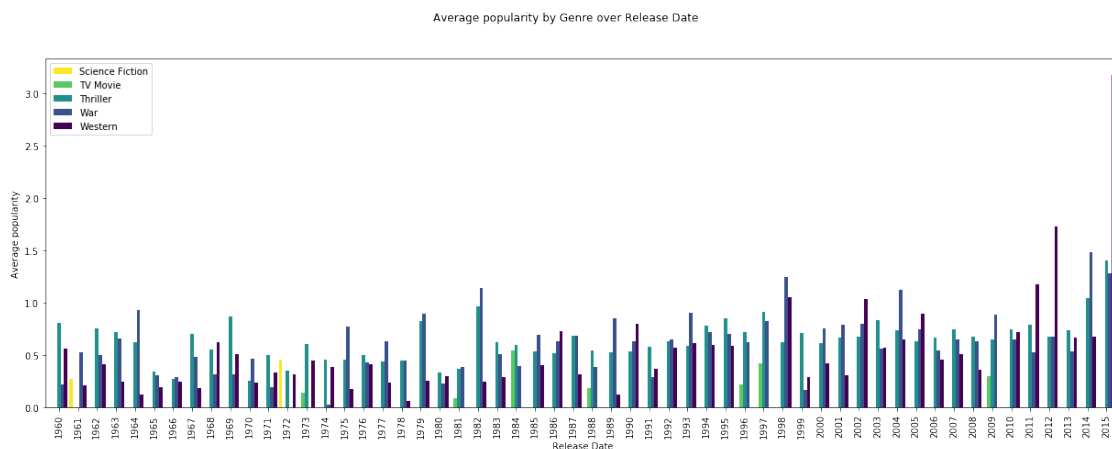
```
In [41]: df_plot_top5.sort_values(['release_date', 'popularity'], ascending=[True, False]).unstack()
plt.legend(['Western', 'War', 'Thriller', 'TV Movie', 'Science Fiction', 'Romance', 'Mystery'],
           loc='upper left')
plt.xlabel('Release Date')
plt.ylabel('Average popularity')
plt.suptitle('Average popularity by Genre over Release Date')
plt.show()
```



If we look only on top-3 genres of each year, Thriller and war genres begin to compete for first place with each other from year to year.

```
In [42]: df_plot_top3 = df_plot.reset_index().sort_values(by=['release_date', 'genre'],
                                                         ascending=[True, False]).groupby('release_date')
df_plot_top3.set_index(['release_date', 'genre'], inplace=True)

df_plot_top3.unstack().plot(kind='bar', width=.9, figsize=(21,7), cmap='viridis_r')
plt.legend(['Western', 'War', 'Thriller', 'TV Movie', 'Science Fiction'][::-1], loc='upper left')
plt.xlabel('Release Date')
plt.ylabel('Average popularity')
plt.suptitle('Average popularity by Genre over Release Date')
plt.show()
```



### 1.1.6 Research Question 2: How sharp is the divide between major film studios and the independents?

Top-2 production companies are:

1. Universal Pictures (produced 522 movies),
2. Warner Bros. (produced 509 movies).

Let's look at difference between major film studios and the independents using this production companies data.

```
In [43]: df.groupby(['independent_film', 'Universal_Pictures']).mean()[['popularity', 'runtime', 'vote_count', 'budget_adj', 'revenue_adj']]
```

```
Out[43]:
```

	independent_film	Universal_Pictures	popularity	runtime	vote_count	\
0	0	0	0.646776	102.220736	215.945171	
		1	0.962337	108.499055	407.565217	

1	0	0.306643	98.840506	36.240506
	1	0.327996	102.000000	23.000000

		vote_average	budget_adj	revenue_adj
independent_film	Universal_Pictures			
0	0	5.968410	3.657895e+07	1.138762e+08
	1	6.073535	5.267046e+07	1.660731e+08
1	0	5.951646	9.054178e+06	5.819831e+06
	1	5.800000	4.577416e+06	NaN

```
In [44]: pd.crosstab(df.independent_film, df.Universal_Pictures)
```

```
Out[44]: Universal_Pictures    0    1
independent_film
0           9867  529
1           395    1
```

```
In [45]: df.groupby(['independent_film', 'Warner_Bros']).mean()[['popularity', 'runtime', 'vote_
'budget_adj', 'revenue_adj']]
```

```
Out[45]:
```

		popularity	runtime	vote_count	\
independent_film	Warner_Bros				
0	0	0.638903	102.101156	210.486550	
	1	1.040808	109.474960	465.922456	
1	0	0.305501	98.829949	36.269036	
	1	0.542260	102.500000	24.000000	

		vote_average	budget_adj	revenue_adj
independent_film	Warner_Bros			
0	0	5.960949	3.546243e+07	1.125606e+08
	1	6.176090	6.425075e+07	1.769029e+08
1	0	5.951269	8.617312e+06	5.754943e+06
	1	5.950000	6.792302e+07	1.432024e+07

```
In [46]: 210.486550 / 36.269036, 465.922456 / 24.000000
```

```
Out[46]: (5.803477930871942, 19.413435666666667)
```

```
In [47]: pd.crosstab(df.independent_film, df.Warner_Bros)
```

```
Out[47]: Warner_Bros    0    1
independent_film
0           9777  619
1           394    2
```

Universal Pictures made only 1 independent film (it's about 0.19% of all movies made by the company), and Warner Bros. made 2 independent films (it's about 0.32% of all movies made by the company). In comparison, 393 movies of the other companies were independent (it's about 3.67% of all movies).

So, why major film studios don't made independent?

Popularity rates of independent movies are twice lower (0.65 vs. 0.31, or 0.96 vs. 0.33) than not-independent ones.

If we don't take into account missing data in revenue and budget columns, the result for independent movies is more than twice worse. Despite average votes for independent and not-independent movies are approximately the same (6 points), number of votes for independent movies is more than 5 times smaller (200-500 vs. 20-40).

So, producing companies don't make independent movies because revenues from them are lower, or revenues from independent movies are lower because producing companies don't make them? It's really interesting question for the further investigation and analysis.

### 1.1.7 Research Question 3: What kinds of properties are associated with movies that have high revenues?

To answer this question, only numeric columns were considered.

```
In [48]: revenue_df = df[df.revenue_adj.notnull()].sort_values(by='revenue_adj', ascending=False)
revenue_df.head()
```

```
Out[48]:
```

	popularity	original_title	director	runtime	vote_count	\
1386	9.432768	Avatar	James Cameron	162.0	8458	
1329	12.037933	Star Wars	George Lucas	121.0	4428	
5231	4.355219	Titanic	James Cameron	194.0	4654	
10594	2.010733	The Exorcist	William Friedkin	122.0	1113	
9806	2.563191	Jaws	Steven Spielberg	124.0	1415	

	vote_average	budget_adj	revenue_adj	release_date	Robert_De_Niro	\
1386	7.1	2.408869e+08	2.827124e+09	2009-12-10	0	
1329	7.9	3.957559e+07	2.789712e+09	1977-03-20	0	
5231	7.3	2.716921e+08	2.506406e+09	1997-11-18	0	
10594	7.2	3.928928e+07	2.167325e+09	1973-12-26	0	
9806	7.3	2.836275e+07	1.907006e+09	1975-06-18	0	

	Samuel_L_Jackson	woman_director	independent_film	Drama	Comedy	\
1386	0	0	0	0	0	
1329	0	0	0	0	0	
5231	0	0	0	1	0	
10594	0	0	0	1	0	
9806	0	0	0	0	0	

	Thriller	Action	Romance	Horror	Adventure	Crime	Family	\
1386	0	1	0	0	1	0	0	
1329	0	1	0	0	1	0	0	
5231	1	0	1	0	0	0	0	
10594	1	0	0	1	0	0	0	
9806	1	0	0	1	1	0	0	

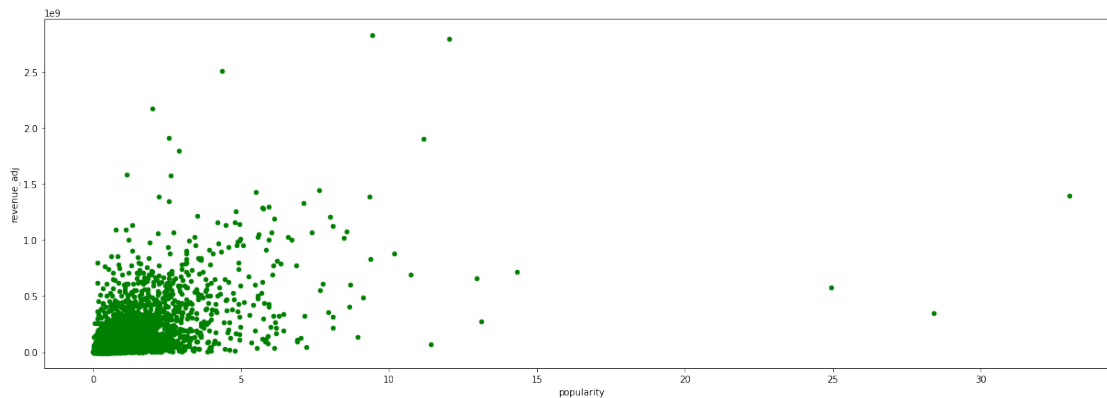
	Science Fiction	Fantasy	Mystery	Animation	Documentary	Music	\
1386	1	1	0	0	0	0	

1329	1	0	0	0	0	0
5231	0	0	0	0	0	0
10594	0	0	0	0	0	0
9806	0	0	0	0	0	0

	History	War	Foreign	TV Movie	Western	Universal_Pictures	\
1386	0	0	0	0	0		0
1329	0	0	0	0	0		0
5231	0	0	0	0	0		0
10594	0	0	0	0	0		0
9806	0	0	0	0	0		1

	Warner_Bros	Paramount_Pictures
1386	0	0
1329	0	0
5231	0	1
10594	1	0
9806	0	0

```
In [49]: revenue_df[['popularity', 'revenue_adj']].plot(kind='scatter', x='popularity', y='revenue_adj', color='green')
plt.show()
```



```
In [50]: print('Average Revenue', revenue_df[revenue_df.popularity > 20].revenue_adj.mean())
revenue_df[revenue_df.popularity > 20]
```

Average Revenue 771099276.712

```
Out[50]:
```

	popularity	original_title	director	runtime	vote_count	\
0	32.985763	Jurassic World	Colin Trevorrow	124.0	5562	
629	24.949134	Interstellar	Christopher Nolan	169.0	6498	
1	28.419936	Mad Max: Fury Road	George Miller	120.0	6185	

	vote_average	budget_adj	revenue_adj	release_date	Robert_De_Niro	\
0	6.5	1.379999e+08	1.392446e+09	2015-06-09	0	
629	8.0	1.519800e+08	5.726906e+08	2014-11-05	0	
1	7.1	1.379999e+08	3.481613e+08	2015-05-13	0	

	Samuel_L_Jackson	woman_director	independent_film	Drama	Comedy	\
0	0	0	0	0	0	
629	0	0	0	1	0	
1	0	0	0	0	0	

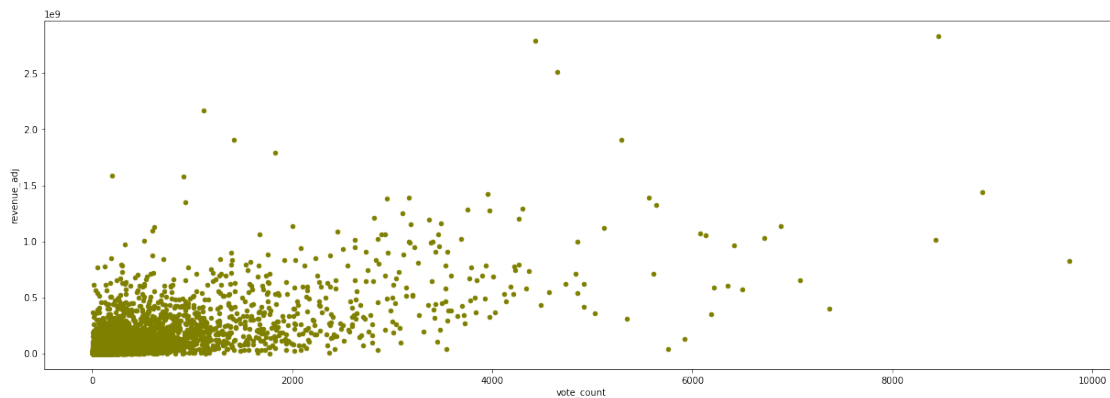
	Thriller	Action	Romance	Horror	Adventure	Crime	Family	\
0	1	1	0	0	1	0	0	
629	0	0	0	0	1	0	0	
1	1	1	0	0	1	0	0	

	Science Fiction	Fantasy	Mystery	Animation	Documentary	Music	\
0	1	0	0	0	0	0	
629	1	0	0	0	0	0	
1	1	0	0	0	0	0	

	History	War	Foreign	TV Movie	Western	Universal_Pictures	\
0	0	0	0	0	0	0	
629	0	0	0	0	0	0	
1	0	0	0	0	0	0	

	Warner_Bros	Paramount_Pictures
0	0	0
629	1	1
1	0	0

```
In [51]: revenue_df[['vote_count', 'revenue_adj']].plot(kind='scatter', x='vote_count', y='revenue_adj', color='olive')
plt.show()
```



```
In [52]: print('Average Revenue', revenue_df[revenue_df.vote_count > 8000].revenue_adj.mean())
         revenue_df[revenue_df.vote_count > 8000]
```

Average Revenue 1527637054.52

```
Out[52]:
```

	popularity	original_title	director	runtime	vote_count	\
1386	9.432768	Avatar	James Cameron	162.0	8458	
4361	7.637767	The Avengers	Joss Whedon	143.0	8903	
2875	8.466668	The Dark Knight	Christopher Nolan	152.0	8432	
1919	9.363643	Inception	Christopher Nolan	148.0	9767	

	vote_average	budget_adj	revenue_adj	release_date	Robert_De_Niro	\
1386	7.1	2.408869e+08	2.827124e+09	2009-12-10	0	
4361	7.3	2.089437e+08	1.443191e+09	2012-04-25	0	
2875	8.1	1.873655e+08	1.014733e+09	2008-07-16	0	
1919	7.9	1.600000e+08	8.255000e+08	2010-07-14	0	

	Samuel_L_Jackson	woman_director	independent_film	Drama	Comedy	\
1386	0	0	0	0	0	
4361	0	0	0	0	0	
2875	0	0	0	1	0	
1919	0	0	0	0	0	

	Thriller	Action	Romance	Horror	Adventure	Crime	Family	\
1386	0	1	0	0	1	0	0	
4361	0	1	0	0	1	0	0	
2875	1	1	0	0	0	1	0	
1919	1	1	0	0	1	0	0	

	Science Fiction	Fantasy	Mystery	Animation	Documentary	Music	\
1386	1	1	0	0	0	0	
4361	1	0	0	0	0	0	
2875	0	0	0	0	0	0	
1919	1	0	1	0	0	0	

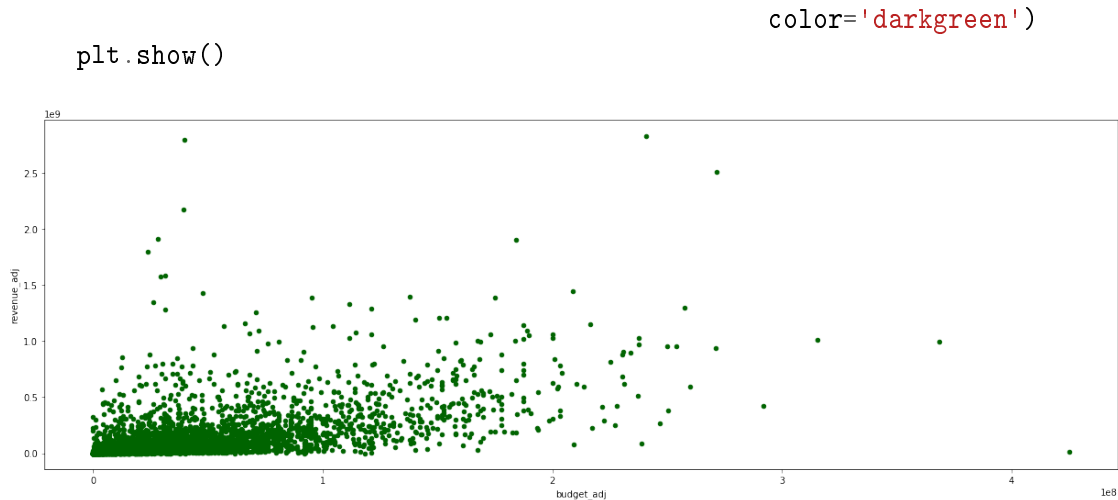
  

	History	War	Foreign	TV Movie	Western	Universal_Pictures	\
1386	0	0	0	0	0	0	
4361	0	0	0	0	0	0	
2875	0	0	0	0	0	0	
1919	0	0	0	0	0	0	

	Warner_Bros	Paramount_Pictures
1386	0	0
4361	0	0
2875	1	0
1919	1	0

```
In [53]: revenue_df[['budget_adj', 'revenue_adj']].plot(kind='scatter', x='budget_adj', y='revenue_adj')
```



```
In [54]: print('Average Revenue', revenue_df[revenue_df.budget_adj > 300000000].revenue_adj.mean()
revenue_df[revenue_df.budget_adj > 300000000]
```

Average Revenue 670719525.753

```
Out[54]:
```

	popularity	original_title	director	\
7387	4.965391	Pirates of the Caribbean: At World's End	Gore Verbinski	
3375	4.955130	Pirates of the Caribbean: On Stranger Tides	Rob Marshall	
2244	0.250540	The Warrior's Way	Sngmoo Lee	

	runtime	vote_count	vote_average	budget_adj	revenue_adj	\
7387	169.0	2626	6.8	3.155006e+08	1.010654e+09	
3375	136.0	3180	6.3	3.683713e+08	9.904175e+08	
2244	100.0	74	6.4	4.250000e+08	1.108757e+07	

	release_date	Robert_De_Niro	Samuel_L_Jackson	woman_director	\
7387	2007-05-19	0	0	0	
3375	2011-05-11	0	0	0	
2244	2010-12-02	0	0	0	

	independent_film	Drama	Comedy	Thriller	Action	Romance	Horror	\
7387	0	0	0	0	1	0	0	
3375	0	0	0	0	1	0	0	
2244	0	0	0	1	1	0	0	

	Adventure	Crime	Family	Science Fiction	Fantasy	Mystery	Animation	\
7387	1	0	0	0	1	0	0	
3375	1	0	0	0	1	0	0	
2244	1	0	0	0	1	0	0	



	Documentary	Music	History	War	Foreign	TV Movie	Western	\
7387	0	0	0	0	0	0	0	
3375	0	0	0	0	0	0	0	
2244	0	0	0	0	0	0	1	

	Universal_Pictures	Warner_Bros	Paramount_Pictures
7387	0	0	0
3375	0	0	0
2244	0	0	0

The relationship between revenue and popularity, revenue and number of votes, revenue and budget is positive.

Some outliers are present in the dataset, so:

\* 3 movies with the highest popularity made on average \$771099276.71 (Jurassic World (2015), Interstellar (2014), Mad Max: Fury Road (2015)),

\* 4 movies with the number of votes higher than 8000 gathered on average, \$1527637054.52 (Avatar (2009), The Avengers (2012), The Dark Knight (2008), Inception (2010)),

\* 3 movies with the highest budget made on average \$670719525.753 (Pirates of the Caribbean: At World's End (2001), Pirates of the Caribbean: On Stranger Tides (2011), The Warrior's Way (2010)).

#### 1.1.8 Research Question 4: Top-8 directors made more than 20 movies.

Whether their movies are also popular or profitable than movies of the other directors?

```
In [55]: directors = directors_df.iloc[:8].index.tolist()
top8_directors = df[df.director.isin(directors)]
print('Shape', top8_directors.shape)
top8_directors.head()
```

Shape (225, 36)

```
Out[55]:
```

	popularity	original_title	director	runtime	\
7	7.667400	The Martian	Ridley Scott	141.0	
33	3.648210	Bridge of Spies	Steven Spielberg	141.0	
66	2.345821	In the Heart of the Sea	Ron Howard	122.0	
155	1.007054	Irrational Man	Woody Allen	95.0	
572	0.082569	The Audition	Martin Scorsese	16.0	

	vote_count	vote_average	budget_adj	revenue_adj	release_date	\
7	4572	7.6	9.935996e+07	5.477497e+08	2015-09-30	
33	1638	7.1	3.679998e+07	1.496016e+08	2015-10-15	
66	805	6.4	9.199996e+07	8.631506e+07	2015-11-20	
155	319	6.1	1.012000e+07	2.519979e+07	2015-07-17	
572	10	6.1	NaN	NaN	2015-10-27	

	Robert_De_Niro	Samuel_L_Jackson	woman_director	independent_film	\
7	0	0	0	0	

33	0	0	0	0
66	0	0	0	0
155	0	0	0	0
572	1	0	0	0

	Drama	Comedy	Thriller	Action	Romance	Horror	Adventure	Crime	\
7	1	0	0	0	0	0	1	0	
33	1	0	1	0	0	0	0	0	
66	1	0	1	1	0	0	1	0	
155	1	0	0	0	0	0	0	0	
572	0	1	0	0	0	0	0	0	

	Family	Science Fiction	Fantasy	Mystery	Animation	Documentary	Music	\
7	0	1	0	0	0	0	0	
33	0	0	0	0	0	0	0	
66	0	0	0	0	0	0	0	
155	0	0	0	1	0	0	0	
572	0	0	0	0	0	0	0	

	History	War	Foreign	TV Movie	Western	Universal_Pictures	\
7	0	0	0	0	0	0	
33	0	0	0	0	0	0	
66	1	0	0	0	0	0	
155	0	0	0	0	0	0	
572	0	0	0	0	0	0	

	Warner_Bros	Paramount_Pictures
7	0	0
33	0	0
66	1	0
155	0	0
572	0	0

```
In [56]: means_ = top8_directors.groupby('director')[['popularity', 'vote_average', 'budget_adj',
+ genre_unique].mean().sort_values('popularity', ascending=False)

means_
```

```
Out[56]:
```

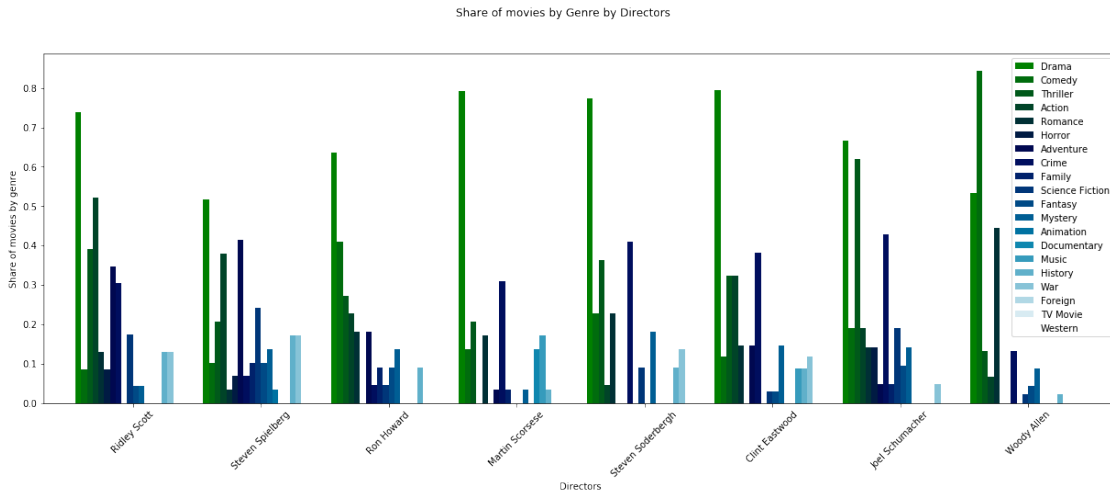
director	popularity	vote_average	budget_adj	revenue_adj	\
Ridley Scott	2.009294	6.478261	7.909806e+07	1.917985e+08	
Steven Spielberg	1.875138	6.824138	7.419896e+07	5.630536e+08	
Ron Howard	1.295499	6.377273	8.682048e+07	2.515053e+08	
Martin Scorsese	1.128548	6.958621	5.473410e+07	1.348079e+08	
Steven Soderbergh	0.945138	6.172727	4.068058e+07	1.456043e+08	
Clint Eastwood	0.830037	6.508824	4.264728e+07	1.407573e+08	
Joel Schumacher	0.768102	5.971429	5.768043e+07	1.309330e+08	
Woody Allen	0.563424	6.444444	1.848060e+07	5.882820e+07	

	Drama	Comedy	Thriller	Action	Romance	Horror	\
director							
Ridley Scott	0.739130	0.086957	0.391304	0.521739	0.130435	0.086957	
Steven Spielberg	0.517241	0.103448	0.206897	0.379310	0.034483	0.068966	
Ron Howard	0.636364	0.409091	0.272727	0.227273	0.181818	0.000000	
Martin Scorsese	0.793103	0.137931	0.206897	0.000000	0.172414	0.000000	
Steven Soderbergh	0.772727	0.227273	0.363636	0.045455	0.227273	0.000000	
Clint Eastwood	0.794118	0.117647	0.323529	0.323529	0.147059	0.000000	
Joel Schumacher	0.666667	0.190476	0.619048	0.190476	0.142857	0.142857	
Woody Allen	0.533333	0.844444	0.133333	0.066667	0.444444	0.000000	
	Adventure	Crime	Family	Science Fiction	Fantasy	\	
director							
Ridley Scott	0.347826	0.304348	0.000000		0.173913	0.043478	
Steven Spielberg	0.413793	0.068966	0.103448		0.241379	0.103448	
Ron Howard	0.181818	0.045455	0.090909		0.045455	0.090909	
Martin Scorsese	0.034483	0.310345	0.034483		0.000000	0.000000	
Steven Soderbergh	0.000000	0.409091	0.000000		0.090909	0.000000	
Clint Eastwood	0.147059	0.382353	0.000000		0.029412	0.029412	
Joel Schumacher	0.047619	0.428571	0.047619		0.190476	0.095238	
Woody Allen	0.000000	0.133333	0.000000		0.022222	0.044444	
	Mystery	Animation	Documentary	Music	History	\	
director							
Ridley Scott	0.043478	0.000000	0.000000	0.000000	0.130435		
Steven Spielberg	0.137931	0.034483	0.000000	0.000000	0.172414		
Ron Howard	0.136364	0.000000	0.000000	0.000000	0.090909		
Martin Scorsese	0.034483	0.000000	0.137931	0.172414	0.034483		
Steven Soderbergh	0.181818	0.000000	0.000000	0.000000	0.090909		
Clint Eastwood	0.147059	0.000000	0.000000	0.088235	0.088235		
Joel Schumacher	0.142857	0.000000	0.000000	0.000000	0.000000		
Woody Allen	0.088889	0.000000	0.000000	0.000000	0.022222		
	War	Foreign	TV Movie	Western			
director							
Ridley Scott	0.130435	0.0	0.0	0.000000			
Steven Spielberg	0.172414	0.0	0.0	0.000000			
Ron Howard	0.000000	0.0	0.0	0.090909			
Martin Scorsese	0.000000	0.0	0.0	0.000000			
Steven Soderbergh	0.136364	0.0	0.0	0.000000			
Clint Eastwood	0.117647	0.0	0.0	0.176471			
Joel Schumacher	0.047619	0.0	0.0	0.000000			
Woody Allen	0.000000	0.0	0.0	0.000000			

The most popular genres are Drama, Action, and Crime.

```
In [57]: means_[genre_unique].plot(kind='bar', width=.9, rot=45, figsize=(21,7), cmap='ocean')
plt.legend(loc='best')
```

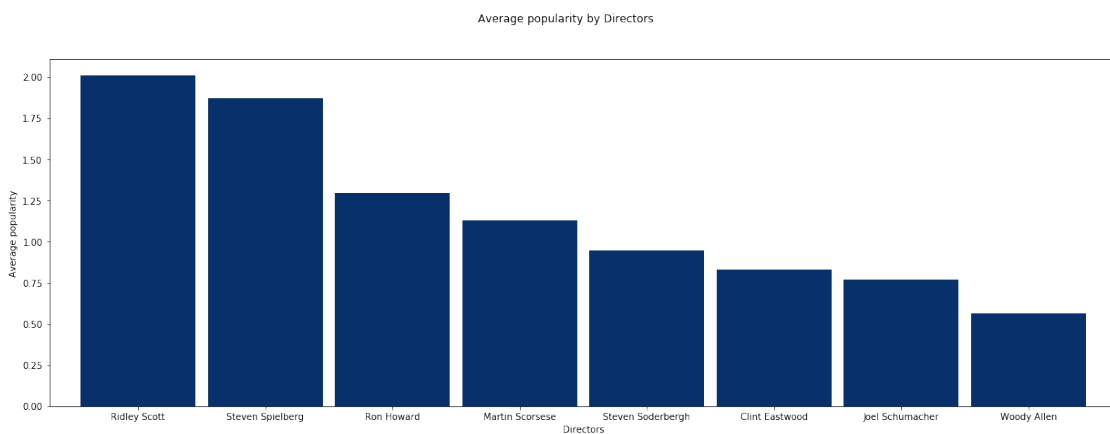
```
plt.xlabel('Directors')
plt.ylabel('Share of movies by genre')
plt.suptitle('Share of movies by Genre by Directors')
plt.show()
```



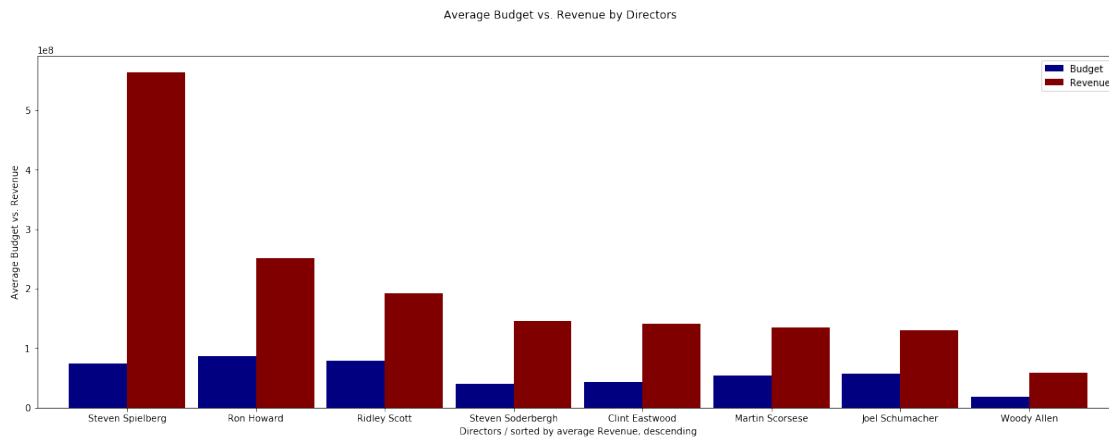
Movies of Ridley Scott have the highest average popularity rate (2.01), compared to the next Steven Spielberg's movies with average popularity rate equals 1.88.

```
In [58]: means_['popularity'].sort_values(ascending=False).plot(kind='bar', width=.9, rot=0, fig
                                                cmap='Blues_r', legend=False)

plt.xlabel('Directors')
plt.ylabel('Average popularity')
plt.suptitle('Average popularity by Directors')
plt.show()
```



```
In [59]: means_[['budget_adj', 'revenue_adj']].sort_values('revenue_adj', ascending=False).plot(
                                                width=.9, rot=0, figsize=(21,7), cmap='jet')
plt.legend(['Budget', 'Revenue'], loc='best')
plt.xlabel('Directors / sorted by average Revenue, descending')
plt.ylabel('Average Budget vs. Revenue')
plt.suptitle('Average Budget vs. Revenue by Directors')
plt.show()
```



```
In [60]: roi = ((means_['revenue_adj'] - means_['budget_adj']) / means_['budget_adj'] * 100).sort(
print('Average ROI', roi.mean())
roi
```

Average ROI 246.324639484

```
Out[60]: director
Steven Spielberg      658.842923
Steven Soderbergh    257.920973
Clint Eastwood        230.049812
Woody Allen           218.324059
Ron Howard            189.684298
Martin Scorsese       146.295994
Ridley Scott          142.481863
Joel Schumacher       126.997194
dtype: float64
```

Finally, average ROI of movies of directors from these group is 246%. Moreover, ROI of movies directed by Steven Spielberg equals 658%.

## Conclusions

In this project TMDb Movie Data was analyzed. This dataset contains information about 10,000 movies, including user ratings and revenue.

There're 2 main parts in this Jupyter notebook:

1. Data Wrangling,
2. Exploratory Data Analysis.

First part consists of the following blocks:

- \* General Properties,
- \* Data Cleaning,
- \* Data visualization.

In the second part the following research questions were considered:

1. Which genres are most popular from year to year? Most of the popularity ratings are less than 1. The distribution of popularity is right skewed with maximum rating 32.99 of movie "Jurassic World" (2015).

From 1960 to 2015 the number of movies increased with the corresponding increase of average popularity rate. However, some movies became popular since 20 century. For example, "The Godfather" (1972) has 5.74 popularity rate.

Among all 10 thousand movies, Adventure is the most popular genre with average popularity about 1.2.

The most popular genres by popularity rate during the whole period is Science Fiction, Thriller, and Wars. Moreover, during the 20 century Romance and TV movies were also as popular as Science Fiction genre. In the 21st century Western genre has reached leading positions.

If we look only on top-3 genres of each year, Thriller and war genres begin to compete for first place with each other from year to year.

- 
2. How sharp is the divide between major film studios and the independents?

Top-2 production companies are:

- > Universal Pictures (produced 522 movies),
- > Warner Bros. (produced 509 movies).

Universal Pictures made only 1 independent film (it's about 0.19% of all movies made by the company), and Warner Bros. made 2 independent films (it's about 0.32% of all movies made by the company). In comparison, 393 movies of the other companies were independent (it's about 3.67% of all movies).

So, why major film studios don't make independent?

Popularity rates of independent movies are twice lower (0.65 vs. 0.31, or 0.96 vs. 0.33) than not-independent ones.

If we don't take into account missing data in revenue and budget columns, the result for independent movies is more than twice worse. Despite average votes for independent and not-independent movies are approximately the same (6 points), number of votes for independent movies is more than 5 times smaller (200-500 vs. 20-40).

So, producing companies don't make independent movies because revenues from them are lower, or revenues from independent movies are lower because producing companies don't make them? It's really interesting question for the further investigation and analysis.

- 
3. What kinds of properties are associated with movies that have high revenues?

To answer this question, only numeric columns were considered.

The relationship between revenue and popularity, revenue and number of votes, revenue and budget is positive.

Some outliers are present in the dataset, so:

~ 3 movies with the highest popularity made on average \$771099276.71 (Jurassic World (2015), Interstellar (2014), Mad Max: Fury Road (2015)),

~ 4 movies with the number of votes higher than 8000 gathered on average, \(\$1527637054.52 (Avatar (2009), The Avengers (2012), The Dark Knight (2008), Inception (2010)),  
~ 3 movies with the highest budget made on average \(\$670719525.753 (Pirates of the Caribbean: At World's End (2001), Pirates of the Caribbean: On Stranger Tides (2011), The Warrior's Way (2010)).

---

4. Top-8 directors made more than 20 movies. Whether their movies are also popular or profitable than movies of the other directors?

Movies of Ridley Scott have the highest average popularity rate (2.01), compared to the next Steven Spielberg's movies with average popularity rate equals 1.88.

The most popular genres are Drama, Action, and Crime.

Finally, average ROI of movies of directors from these group is 246%. Moreover, ROI of movies directed by Steven Spielberg equals 658%. \_\_\_\_\_

```
In [61]: from subprocess import call
         call(['python', '-m', 'nbconvert', 'Investigate_a_Dataset.ipynb'])
```

```
Out[61]: 0
```