Project: Investigate a Dataset - [tmdb-movies]

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Introduction

Dataset Description

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

The features in the data set cinclude : id, imdb_id, popularity, budget, revenue, original_title, cast, homepage, director, tagline, keywords, overview, runtime, genres, production_companies, release_date, vote_count, vote_average, release_year, budget_adj, revenue_adj

Example of Data Analysis Questions

Question one: Which genres are most popular from year to year?

Identify movies which are most popular (higly rated movies) from year to year

Question one: What kinds of properties are associated with movies that have high revenues?

Identifying correlates that influence (correlated/ related with) revenues

In [128…

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

Loading the dataset

In [18]:

```
df=pd.read_csv('tmdb-movies.csv')
```

Vieing and exploring the dataset

In [19]:

```
df.head(3)
```

Out[19]:

	id	imdb_id	popularity	budget	revenue	original_title	cast	
0	135397	tt0369610	32.985763	150000000	1513528810	Jurassic World	Chris Pratt|Bryce Dallas	ht

							Howard|Irrfan Khan|Vi...	
1	76341	tt1392190	28.419936	150000000	378436354	Mad Max: Fury Road	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...	htt
2	262500	tt2908446	13.112507	110000000	295238201	Insurgent	Shailene Woodley|Theo James|Kate Winslet|Ansel...	http://www.thediver

3 rows × 21 columns

Viewing number of rows, columns and datatypes

In [20]:
```
df.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
```

In [21]:
```
df.shape
```

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

The dataset contain 10866 rows and 21 columns, the number of rows for each column are not uniform showing that there could be missing values.

Some features are continous (float), discrete (integers) (numeric variables) while others are string (objects)

Data Wrangling

Checking Data Quality issues and Data Cleaning

Checking and Handling Missing Vlues

In [22]:
```
def missings_(df):
    miss      = df.isnull().sum()
    miss_pct  = 100 * df.isnull().sum()/len(df)

    miss_pct      = pd.concat([miss,miss_pct], axis=1)
    missings_cols = miss_pct.rename(columns = {0:'Missings values', 1: 'Missing percenta
    missings_cols = missings_cols[missings_cols.iloc[:,1]!=0].sort_values('Missing perce

    return missings_cols

missings = missings_(df)
missings
```

Out[22]:

	Missings values	Missing percentage
homepage	7930	72.98
tagline	2824	25.99
keywords	1493	13.74
production_companies	1030	9.48
cast	76	0.70
director	44	0.40
genres	23	0.21
imdb_id	10	0.09
overview	4	0.04

The variables with missing values are homepage', 'tagline', 'keywords', 'production_companies', 'cast,director,genres,imdb_id,overview. However homepage has the highest missing value of about 73% thus feature should be dropped moreover the feature is not much useful to movie rating or revenue.

The missing values other features are below 30% and may be imputed with either mode or median however tagline and keyword may not be useful and may be eliminated to make the data more streamlined and focused

In [23]:
```
#make a copy of dataframe
dfc=df.copy()
```

Droping homepage column with 72.98% missing values

In [24]:
```
dfc.drop('homepage', axis=1, inplace=True)
```

Imputing missing values for string (object) whose percentage is less than 30% with mode

Mode is better approach to impute missing values for categorical variables or strings (objects) Although a number of columns will be dropped since they are not useful in our analysis will just impute first with mode

In [25]:
```
dfc[['tagline', 'keywords', 'production_companies', 'cast',
       'director', 'genres', 'imdb_id', 'overview']].info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10866 entries, 0 to 10865
Data columns (total 8 columns):
 #   Column                Non-Null Count  Dtype 
---  ------                --------------  ----- 
 0   tagline               8042 non-null   object
 1   keywords              9373 non-null   object
 2   production_companies  9836 non-null   object
 3   cast                  10790 non-null  object
 4   director              10822 non-null  object
 5   genres                10843 non-null  object
 6   imdb_id               10856 non-null  object
 7   overview              10862 non-null  object
dtypes: object(8)
memory usage: 679.2+ KB
```

In [26]:
```
dfc.isna().sum()
```

Out[26]:
```
id                         0
imdb_id                   10
popularity                 0
budget                     0
revenue                    0
original_title             0
cast                      76
director                  44
tagline                 2824
keywords                1493
overview                   4
runtime                    0
genres                    23
production_companies    1030
release_date               0
vote_count                 0
vote_average               0
release_year               0
budget_adj                 0
revenue_adj                0
dtype: int64
```

In [27]:
```
lc=['tagline', 'keywords', 'production_companies', 'cast',
       'director', 'genres', 'imdb_id', 'overview']
dfc[lc]=dfc[lc].fillna(dfc[lc].mode().iloc[0])
dfc.isna().sum()
```

Out[27]:
```
id                      0
imdb_id                 0
popularity              0
budget                  0
revenue                 0
original_title          0
cast                    0
director                0
tagline                 0
keywords                0
overview                0
runtime                 0
genres                  0
production_companies    0
release_date            0
vote_count              0
vote_average            0
release_year            0
```

```
budget_adj              0
revenue_adj             0
dtype: int64
```

Handling the duplicates

Now that we dont have missing values in the data we can check the duplicates and drop if they exist

before dealing with nan values, lets check duplicates and remove them

In [28]:
```
dfc.duplicated().sum()
```

Out[28]:
```
1
```

In [29]:
```
dfc[dfc.duplicated()]
```

Out[29]:

	id	imdb_id	popularity	budget	revenue	original_title	cast	director	tagline	
2090	42194	tt0411951	0.59643	30000000	967000	TEKKEN	Jon Foo|Kelly Overton|Cary-Hiroyuki Tagawa|Ian...	Dwight H. Little	Survival is no game	arts

We can try to doublecheck presence of identical rows

In [30]:
```
dfc[dfc.id==42194]
```

Out[30]:

	id	imdb_id	popularity	budget	revenue	original_title	cast	director	tagline	
2089	42194	tt0411951	0.59643	30000000	967000	TEKKEN	Jon Foo|Kelly Overton|Cary-Hiroyuki Tagawa|Ian...	Dwight H. Little	Survival is no game	arts
2090	42194	tt0411951	0.59643	30000000	967000	TEKKEN	Jon Foo|Kelly Overton|Cary-Hiroyuki Tagawa|Ian...	Dwight H. Little	Survival is no game	arts

Dropr the dupicates

In [31]:
```
dfc.drop_duplicates(inplace=True)
```

lets see how many null values

Remove the unnecessary Features from the dataset

The unnecessary columns will be removed from dataset.

It's important to delete columns they will not be used in analysis

In [33]:
```
dfc.nunique()
```

Out[33]:
```
id                      10865
imdb_id                 10855
popularity              10814
budget                    557
revenue                  4702
original_title          10571
cast                    10719
director                 5067
tagline                  7997
keywords                 8804
overview                10847
runtime                   247
genres                   2039
production_companies     7445
release_date             5909
vote_count               1289
vote_average               72
release_year               56
budget_adj               2614
revenue_adj              4840
dtype: int64
```

In [34]:
```
dfc.overview.value_counts()
```

Out[34]:
```
No overview found.


                           17
Wilbur the pig is scared of the end of the season, because he knows that come that time, 
he will end up on the dinner table. He hatches a plan with Charlotte, a spider that live
s in his pen, to ensure that this will never happen.
                           2
1960. The thrilling battles waged by a band of kids from two rival villages in the south
ern French countryside.

                            2
Zenon Kar a teenager living on a space station in the year 2054 competes in the first ev
er Galactic Teen Supreme contest.

                            1
A drug kingpin's return home touches off a turf war.



                            1




                           ..
During the Bosnian War, Danijel, a soldier fighting for the Serbs, re-encounters Ajla, a
Bosnian who's now a captive in his camp he oversees. Their once promising connection has
become ambiguous as their motives have changed.
                         1
Perry's worst fear comes true when Phineas and Ferb finds out that he is in fact Secret 
Agent P, but that soon pales in comparison during a trip to the 2nd dimension where Perr
y finds out that Dr. Doofenshmirtz is truly evil and successful.
                            1
A wedding at her parents' Annapolis estate hurls high-strung Lynn into the center of tou
chy family dynamics.

                            1
Troubled divorcee Mary Kee is tormented by a series of sinister phone calls from a myste
```

```
rious woman. When the stranger reveals she's calling from the past, Mary tries to break
off contact. But the caller doesn't like being ignored, and looks for revenge in a uniqu
e and terrifying way...     1
A family gets lost on the road and stumbles upon a hidden, underground, devil-worshiping
cult led by the fearsome Master and his servant Torgo.


                           1
Name: overview, Length: 10847, dtype: int64
```

In [35]:
```python
# this column will not be neccessary for my analysis
dfc.drop(['id','overview', 'keywords', 'tagline', 'imdb_id'], axis=1, inplace=True)
```

Checking the Inconsistencies

● 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 [36]:
```python
dfc.genres.value_counts()
```

Out[36]:
```
Comedy                                        735
Drama                                         712
Documentary                                   312
Drama|Romance                                 289
Comedy|Drama                                  280
                                             ...
Adventure|Animation|Romance                     1
Family|Animation|Drama                          1
Action|Adventure|Animation|Comedy|Family        1
Action|Adventure|Animation|Fantasy              1
Mystery|Science Fiction|Thriller|Drama          1
Name: genres, Length: 2039, dtype: int64
```

In [37]:
```python
dfc.cast.value_counts()
```

Out[37]:
```
Louis C.K.                                                                      82
William Shatner|Leonard Nimoy|DeForest Kelley|James Doohan|George Takei          5
Bill Burr                                                                        4
Pierre Coffin                                                                    3
Chris Wedge                                                                      3
                                                                                ..
Ray Stevenson|Vincent D'Onofrio|Val Kilmer|Christopher Walken|Linda Cardellini   1
Freida Pinto|Riz Ahmed|Roshan Seth|Kalki Koechlin|Anurag Kashyap                 1
William Hurt|Paul Giamatti|James Woods|Billy Crudup|Topher Grace                 1
Dennis Quaid|Tony Oller|Aimee Teegarden|Stephen Lunsford|Devon Werkheiser        1
Harold P. Warren|Tom Neyman|John Reynolds|Diane Mahree|Stephanie Nielson         1
Name: cast, Length: 10719, dtype: int64
```

It is evident that features such as ‘cast’and ‘genres’, contain multiple values separated by pipe (|) characters.

We're going to take each hybrid row and split them into new rows - one with values for the first genres amd cast type (values before the "|"), and the other with values for the second genres amd cast type (values after the "|").

In [38]:
```python
dfc.shape
```

Out[38]: (10865, 15)

In [39]:
```
ds = dfc[dfc['genres'].str.contains('|')]
ds[['genres','cast']].head()
```

Out[39]:

	genres	cast
0	Action|Adventure|Science Fiction|Thriller	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...
1	Action|Adventure|Science Fiction|Thriller	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...
2	Adventure|Science Fiction|Thriller	Shailene Woodley|Theo James|Kate Winslet|Ansel...
3	Action|Adventure|Science Fiction|Fantasy	Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...
4	Action|Crime|Thriller	Vin Diesel|Paul Walker|Jason Statham|Michelle ...

In [40]:
```
ds.shape
```

Out[40]: (10865, 15)

This means all the rows in genres column contains |

In [41]:
```
ds.cast.value_counts()
```

Out[41]:
```
Louis C.K.                                                               82
William Shatner|Leonard Nimoy|DeForest Kelley|James Doohan|George Takei   5
Bill Burr                                                                 4
Pierre Coffin                                                             3
Chris Wedge                                                               3
                                                                         ..
Ray Stevenson|Vincent D'Onofrio|Val Kilmer|Christopher Walken|Linda Cardellini   1
Freida Pinto|Riz Ahmed|Roshan Seth|Kalki Koechlin|Anurag Kashyap          1
William Hurt|Paul Giamatti|James Woods|Billy Crudup|Topher Grace          1
Dennis Quaid|Tony Oller|Aimee Teegarden|Stephen Lunsford|Devon Werkheiser  1
Harold P. Warren|Tom Neyman|John Reynolds|Diane Mahree|Stephanie Nielson  1
Name: cast, Length: 10719, dtype: int64
```

In [ ]:

In [42]:
```
for s in ds.select_dtypes(include='object').columns:
    print(ds[s][ds[s].str.contains('|')].unique())
```

```
['Jurassic World' 'Mad Max: Fury Road' 'Insurgent' ...
 'Beregis Avtomobilya' "What's Up, Tiger Lily?" 'Manos: The Hands of Fate']
["Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vincent D'Onofrio|Nick Robinson"
 'Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nicholas Hoult|Josh Helman'
 'Shailene Woodley|Theo James|Kate Winslet|Ansel Elgort|Miles Teller' ...
 'Innokentiy Smoktunovskiy|Oleg Efremov|Georgi Zhzhyonov|Olga Aroseva|Lyubov Dobrzhanska
ya'
 'Tatsuya Mihashi|Akiko Wakabayashi|Mie Hama|John Sebastian|Tadao Nakamaru'
 'Harold P. Warren|Tom Neyman|John Reynolds|Diane Mahree|Stephanie Nielson']
['Colin Trevorrow' 'George Miller' 'Robert Schwentke' ... 'Alan Rafkin'
 'Bruce Brown' 'Harold P. Warren']
['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']
['Universal Studios|Amblin Entertainment|Legendary Pictures|Fuji Television Network|Dent
su'
 'Village Roadshow Pictures|Kennedy Miller Productions'
 'Summit Entertainment|Mandeville Films|Red Wagon Entertainment|NeoReel'
```

```
 ... 'Cherokee Productions|Joel Productions|Douglas & Lewis Productions'
 'Benedict Pictures Corp.' 'Norm-Iris']
['6/9/15' '5/13/15' '3/18/15' ... '12/21/66' '11/2/66' '11/15/66']
```

In [43]:
```
ds.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10865 entries, 0 to 10865
Data columns (total 15 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   popularity            10865 non-null  float64
 1   budget                10865 non-null  int64  
 2   revenue               10865 non-null  int64  
 3   original_title        10865 non-null  object 
 4   cast                  10865 non-null  object 
 5   director              10865 non-null  object 
 6   runtime               10865 non-null  int64  
 7   genres                10865 non-null  object 
 8   production_companies  10865 non-null  object 
 9   release_date          10865 non-null  object 
 10  vote_count            10865 non-null  int64  
 11  vote_average          10865 non-null  float64
 12  release_year          10865 non-null  int64  
 13  budget_adj            10865 non-null  float64
 14  revenue_adj           10865 non-null  float64
dtypes: float64(4), int64(5), object(6)
memory usage: 1.3+ MB
```

In [46]:
```
#since we have multiple questions answers being similar in logic and code, we will give

#function which will take any column as argument from which data is need to be extracted
def extract_data(column_name):
    #will take a column, and separate the string by '|'
    all_data = dfc[column_name].str.cat(sep = '|')

    #giving pandas series and storing the values separately
    all_data = pd.Series(all_data.split('|'))

    #this will us value in descending order
    count = all_data.value_counts(ascending = False)

    return count
```

In [47]:
```
split_cols=['genres','cast','production_companies']
```

In [48]:
```
def explode_values(df,col):
    """ This Function Take dataframe 'df' and column 'col' with multiple values and retu
    # split column values into lists
    df[col] = df[col].str.split('|')
    # return exploded dataframe
    return df.explode(col, ignore_index=True)
```

In [49]:
```
# explode 'genre' values
movie_df = explode_values(dfc, 'genres')
```

The genres feature has been exploded, similar apprach can be applied to cast column

In [50]:
```
movie_df.shape
```

Out[50]:
```
(26978, 15)
```

In [51]:
```
movie_df.head(3)
```

Out[51]:

	popularity	budget	revenue	original_title	cast	director	runtime	genres	producti
0	32.985763	150000000	1513528810	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	Colin Trevorrow	124	Action	Universal Entertainr
1	32.985763	150000000	1513528810	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	Colin Trevorrow	124	Adventure	Universal Entertainr
2	32.985763	150000000	1513528810	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	Colin Trevorrow	124	Science Fiction	Universal Entertainr

Parsing Date

The release_date columns appears as string yet it should be in datetime hence should be converted to datetime

In [68]:

```
dfc['release_date']=pd.DatetimeIndex(dfc['release_date'])
dfc.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10865 entries, 0 to 10865
Data columns (total 15 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   popularity            10865 non-null  float64
 1   budget                10865 non-null  int64
 2   revenue               10865 non-null  int64
 3   original_title        10865 non-null  object
 4   cast                  10865 non-null  object
 5   director              10865 non-null  object
 6   runtime               10865 non-null  int64
 7   genres                10865 non-null  object
 8   production_companies  10865 non-null  object
 9   release_date          10865 non-null  datetime64[ns]
 10  vote_count            10865 non-null  int64
 11  vote_average          10865 non-null  float64
 12  release_year          10865 non-null  int64
 13  budget_adj            10865 non-null  float64
 14  revenue_adj           10865 non-null  float64
dtypes: datetime64[ns](1), float64(4), int64(5), object(5)
memory usage: 1.3+ MB
```

Since the dataset has been cleaned the next step is to explore the dataset

Exploratory Data Analysis

Exploratory data analysis is a technique used to understand and summarize the characteristics of a dataset.

It is an Imperative step in the data analysis process since it aid in identifying patterns, trends, and relationships in the data that can be used to inform subsequent analysis.

It involves visualizing the data using graphs and plots, as well as summarizing the main characteristics of the data

Checking the correlation and multicollinearity

In [52]:
```
corr = movie_df.corr()
corr.style.background_gradient(cmap='coolwarm')
```

Out[52]:

	popularity	budget	revenue	runtime	vote_count	vote_average	release_year	budget_
popularity	1.000000	0.541850	0.665842	0.142636	0.794904	0.232962	0.109962	0.507
budget	0.541850	1.000000	0.729464	0.201225	0.641793	0.100735	0.147667	0.968
revenue	0.665842	0.729464	1.000000	0.171713	0.798671	0.194966	0.081055	0.700
runtime	0.142636	0.201225	0.171713	1.000000	0.174389	0.158019	-0.134953	0.235
vote_count	0.794904	0.641793	0.798671	0.174389	1.000000	0.278908	0.131224	0.594
vote_average	0.232962	0.100735	0.194966	0.158019	0.278908	1.000000	-0.124385	0.113
release_year	0.109962	0.147667	0.081055	-0.134953	0.131224	-0.124385	1.000000	0.042
budget_adj	0.507593	0.968086	0.700055	0.235356	0.594014	0.113723	0.042380	1.000
revenue_adj	0.610355	0.620325	0.920886	0.187006	0.715034	0.216350	-0.047509	0.643

Multicollinearity

Multicollinearity is a statistical phenomenon in which two or more predictor variables in a multiple regression model are highly correlated.

This can lead to unstable and unpredictable model coefficients, and can make it difficult to interpret the results of the model.

It is evident that theere is high multicollinearity between budget_adj vs budget (0.96) and revenue_adj vs revunue (0.92) therefore we can drop revenue and budget.

Droping unadjusted revenues

Since budget_adj and revenue_adj are adjusted budget and revunue respectively to capture inflation over time we may used them and this back up our reason even more drop unadjusted budget and revunue

(We can as well add a profit column that is equal to revenuee minus budget though not neccessary at momment

movie_df['profit']=movie_df['revenue']-movie_df['budget'])

In [53]:
```
movie_df.drop(['budget','revenue'], axis=1, inplace=True)
```

In [56]:
```
movie_df.describe()
```

Out[56]:

	popularity	runtime	vote_count	vote_average	release_year	budget_adj	revenue
count	26978.000000	26978.000000	26978.000000	26978.000000	26978.000000	2.697800e+04	2.697800
mean	0.705653	102.773000	249.801579	5.956932	2000.701794	2.102152e+07	6.083795
std	1.114621	30.411297	637.784544	0.912318	12.764426	3.818896e+07	1.614714

min	0.000065	0.000000	10.000000	1.500000	1960.000000	0.000000e+00	0.000000
25%	0.224439	90.000000	18.000000	5.400000	1994.000000	0.000000e+00	0.000000
50%	0.410850	99.000000	44.000000	6.000000	2005.000000	1.039001e+02	0.000000
75%	0.774231	112.000000	173.000000	6.600000	2011.000000	2.704173e+07	4.359754
max	32.985763	900.000000	9767.000000	9.200000	2015.000000	4.250000e+08	2.827124

We can see that there is high disparity in some features such as djusted budget and revenue, vote_count and runtime

There are some strange values where movie runtime is 0 and yet the Maximum runtime is 900 minutes.

Thre are movies whose adjusted budget and revenue is 0

Investigating movies whose runtime is equal to zero

In [61]:

```
movie_df[movie_df['runtime']==0]
```

Out[61]:

	popularity	original_title	cast	director	runtime	genres	production_compa
256	1.876037	Mythica: The Necromancer	Melanie Stone|Adam Johnson|Kevin Sorbo|Nicola ...	A. Todd Smith	0	Fantasy	Arrowst Entertainment|Camera Productio
257	1.876037	Mythica: The Necromancer	Melanie Stone|Adam Johnson|Kevin Sorbo|Nicola ...	A. Todd Smith	0	Action	Arrowst Entertainment|Camera Productio
258	1.876037	Mythica: The Necromancer	Melanie Stone|Adam Johnson|Kevin Sorbo|Nicola ...	A. Todd Smith	0	Adventure	Arrowst Entertainment|Camera Productio
803	0.357654	Ronaldo	Cristiano Ronaldo	Anthony Wonke	0	Documentary	On The Corner Films Came, We Saw Conq
961	0.097514	Anarchy Parlor	Robert LaSardo|Jordan James Smith|Sara Fabel|T...	Kenny Gage|Devon Downs	0	Horror	Paramount Pict
...	...	...	...	...	...	...	
15704	0.006440	Quatre Ã©toiles	JosÃ© Garcia|Isabelle CarrÃ©|RenÃ©e Le Calm|Fr...	Christian Vincent	0	Comedy	Paramount Pict
16694	0.071872	Jean-Philippe	Fabrice Luchini|Johnny Hallyday|Jackie Berroye...	Laurent Tuel	0	Comedy	FidÃ©li Productions|StudioCanal Films
21740	0.069903	Mission Kashmir	Sanjay Dutt|Hrithik Roshan|Preity Zinta|Jackie...	Vidhu Vinod Chopra	0	Action	Paramount Pict
21741	0.069903	Mission Kashmir	Sanjay Dutt|Hrithik	Vidhu Vinod Chopra	0	Drama	Paramount Pict

			Roshan|Preity Zinta|Jackie...				
21742	0.069903	Mission Kashmir	Sanjay Dutt|Hrithik Roshan|Preity Zinta|Jackie...	Vidhu Vinod Chopra	0	Foreign	Paramount Pict

62 rows × 13 columns

In [62]:
```
movie_df.query('runtime==0').count()
```

Out[62]:
```
popularity              62
original_title          62
cast                    62
director                62
runtime                 62
genres                  62
production_companies    62
release_date            62
vote_count              62
vote_average            62
release_year            62
budget_adj              62
revenue_adj             62
dtype: int64
```

Droping movies whose runtime is equal to zero

It may not be informative to have movies whose runtime is zero also most of such movies their buget and zero revunues is zero as well, thus will consider drop them out

In [64]:
```
movie_df.drop(movie_df[movie_df.runtime==0].index, inplace=True)
movie_df.query('runtime==0').count().sum()
```

Out[64]:
```
0
```

In [65]:
```
movie_df.describe()
```

Out[65]:

	popularity	runtime	vote_count	vote_average	release_year	budget_adj	revenue_
count	26916.000000	26916.000000	26916.000000	26916.000000	26916.000000	2.691600e+04	2.691600e
mean	0.706791	103.009734	250.333445	5.958021	2000.678333	2.106917e+07	6.097809e
std	1.115493	30.043147	638.422052	0.912031	12.767995	3.821996e+07	1.616308e
min	0.000065	2.000000	10.000000	1.500000	1960.000000	0.000000e+00	0.000000e
25%	0.225197	90.000000	18.000000	5.400000	1994.000000	0.000000e+00	0.000000e
50%	0.411816	100.000000	44.000000	6.000000	2005.000000	7.020250e+02	0.000000e
75%	0.776305	112.000000	174.000000	6.600000	2011.000000	2.709274e+07	4.389831e
max	32.985763	900.000000	9767.000000	9.200000	2015.000000	4.250000e+08	2.827124e

In [ ]:
```

```

Question one: Which genres are most popular from year to year?

Identify movies which are most popular (higly rated movies) from year to year

In [96]:
```
# check movies genres popularity over years
# year to year best genres from 2000 to 2015
sorted_genres = movie_df[["release_year","popularity" ,"genres"]].sort_values(["release_
each_year_sorted_genres = pd.DataFrame(sorted_genres.groupby(["release_year"]).genres.ma
each_year_sorted_genres.tail(16)
```

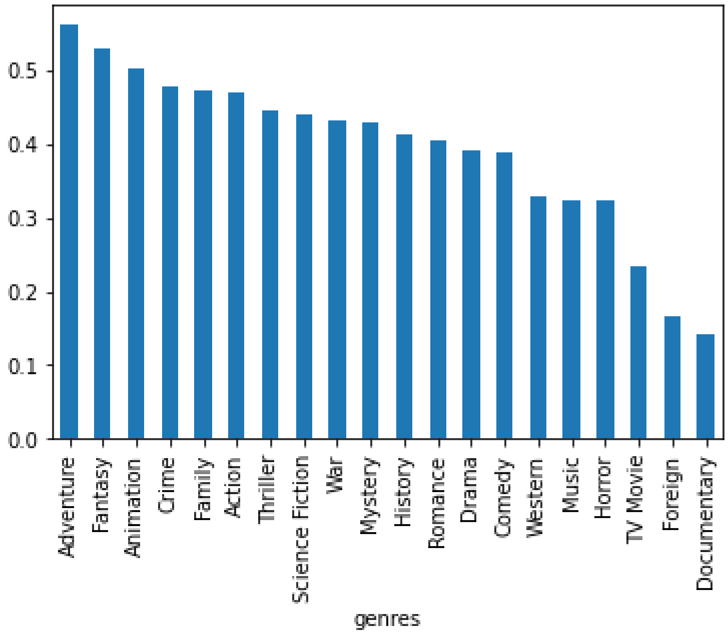
Out[96]:

release_year	genres
2000	Western
2001	Western
2002	Western
2003	Western
2004	Western
2005	Western
2006	Western
2007	Western
2008	Western
2009	War
2010	Western
2011	Western
2012	Western
2013	Western
2014	Western
2015	Western

In [78]:
```
movie_df.groupby("genres").popularity.median().sort_values(ascending=False)
```

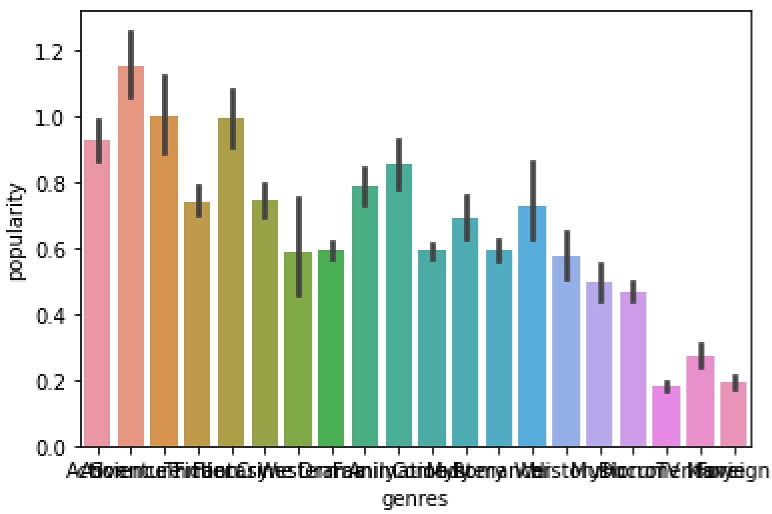
Out[78]:
```
genres
Adventure          0.560689
Fantasy            0.529881
Animation          0.501163
Crime              0.476687
Family             0.471104
Action             0.469825
Thriller           0.444439
Science Fiction    0.440049
War                0.432470
Mystery            0.428949
History            0.412770
Romance            0.405537
Drama              0.389778
Comedy             0.387712
Western            0.328263
Music              0.323933
Horror             0.322620
TV Movie           0.233227
Foreign            0.166284
Documentary        0.142518
Name: popularity, dtype: float64
```

In [80]:
```
movie_df.groupby("genres").popularity.median().sort_values(ascending=False).plot(kind="b
```

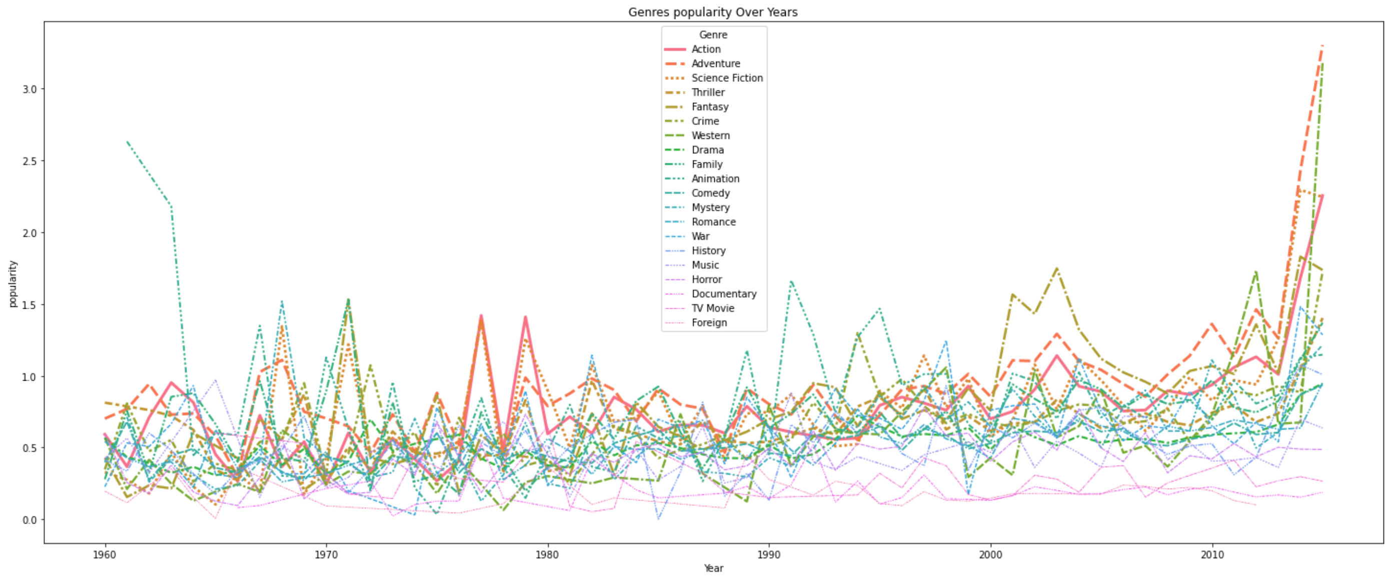


In [81]:
```
sns.barplot(x="genres", y="popularity", data=movie_df);
```

Out[81]: <AxesSubplot:xlabel='genres', ylabel='popularity'>



In [84]:
```
plt.figure(figsize=(25,10))
sns.lineplot(x='release_year', y='popularity', data=movie_df, hue='genres', style='genre
plt.legend(title='Genre')
plt.title("Genres popularity Over Years")
plt.xlabel("Year")
plt.ylabel("popularity")
plt.show()
```



In [103…
```
movie_df.groupby(['release_year', 'genres'])['popularity'].median().head(40)
```

Out[103]:
```
release_year  genres
1960          Action             0.288758
              Adventure          0.465879
              Comedy             0.307729
              Crime              0.346479
              Drama              0.271858
              Family             0.254124
              Fantasy            0.428247
              Foreign            0.194948
              History            0.256779
              Horror             0.323180
              Music              0.423531
              Romance            0.551315
              Science Fiction    0.144106
              Thriller           0.496477
              War                0.225863
              Western            0.289913
1961          Action             0.307820
              Adventure          0.473274
              Animation          2.631987
              Comedy             0.297034
              Crime              0.806519
              Drama              0.286475
              Family             0.303783
              Fantasy            0.154073
              Foreign            0.113651
              History            0.307820
              Horror             0.249542
              Music              0.564748
              Mystery            0.712793
              Romance            0.242244
              Science Fiction    0.226185
              War                0.531184
              Western            0.173731
1962          Action             0.400881
              Adventure          0.526108
              Comedy             0.235542
              Crime              0.341718
              Drama              0.275157
              Family             0.323463
              Fantasy            0.235542
Name: popularity, dtype: float64
```

In [100…
```
movie_df.groupby(['release_year', 'genres'])['popularity'].median().tail(60)
```

```
Out[100]: release_year  genres
2012          Thriller           0.419030
              War                0.574793
              Western            0.390865
2013          Action             0.534902
              Adventure          0.661187
              Animation          0.467773
              Comedy             0.349655
              Crime              0.732866
              Documentary        0.141918
              Drama              0.422634
              Family             0.463994
              Fantasy            0.470131
              History            0.423209
              Horror             0.291471
              Music              0.288878
              Mystery            0.355905
              Romance            0.393664
              Science Fiction    0.471044
              TV Movie           0.176388
              Thriller           0.474132
              War                0.249031
              Western            0.393664
2014          Action             0.560295
              Adventure          0.495840
              Animation          0.612052
              Comedy             0.430708
              Crime              0.444337
              Documentary        0.114728
              Drama              0.434350
              Family             0.518405
              Fantasy            0.647224
              History            0.252762
              Horror             0.337256
              Music              0.352727
              Mystery            0.472703
              Romance            0.363776
              Science Fiction    0.501539
              TV Movie           0.297395
              Thriller           0.492028
              War                0.299103
              Western            0.690200
2015          Action             0.816055
              Adventure          1.552516
              Animation          0.542568
              Comedy             0.439598
              Crime              1.225325
              Documentary        0.136423
              Drama              0.438492
              Family             0.676520
              Fantasy            0.836226
              History            0.526642
              Horror             0.311991
              Music              0.435582
              Mystery            0.489171
              Romance            0.390188
              Science Fiction    0.374991
              TV Movie           0.298628
              Thriller           0.433073
              War                0.689579
              Western            1.201526
Name: popularity, dtype: float64
```

At around 1960s Romance and Animation was popular movies however their pooularity decline as adventure, action and western movies gain popularity . By 2015 the most popular movies are

Adventure, Crime, Western and Action

Question one: What kinds of properties are associated with movies that have high revenues?

Identifying correlates that influence (correlated/ related with) revenues

Renaming columns ending with adj

First let rename adjusted budgets and revenues

In [105…
```
movie_df.rename({'budget_adj':'budget', 'revenue_adj':'revenue'}, axis=1, inplace=True)
```

In [106…
```
corr = movie_df.corr()
corr.style.background_gradient(cmap='coolwarm')
```

Out[106]:

	popularity	runtime	vote_count	vote_average	release_year	budget	revenue
popularity	1.000000	0.141105	0.794947	0.232899	0.110858	0.507398	0.610295
runtime	0.141105	1.000000	0.173899	0.156277	-0.130583	0.234320	0.186574
vote_count	0.794947	0.173899	1.000000	0.278918	0.132023	0.593853	0.714945
vote_average	0.232899	0.156277	0.278918	1.000000	-0.123443	0.113301	0.216252
release_year	0.110858	-0.130583	0.132023	-0.123443	1.000000	0.043433	-0.046865
budget	0.507398	0.234320	0.593853	0.113301	0.043433	1.000000	0.643404
revenue	0.610295	0.186574	0.714945	0.216252	-0.046865	0.643404	1.000000

Correlation between revenues and Popularity is 0.61, which is strong Positive Correlation.

Correlation between revenues and Runtime is 0.187, which is a Weak Positive Correlation.

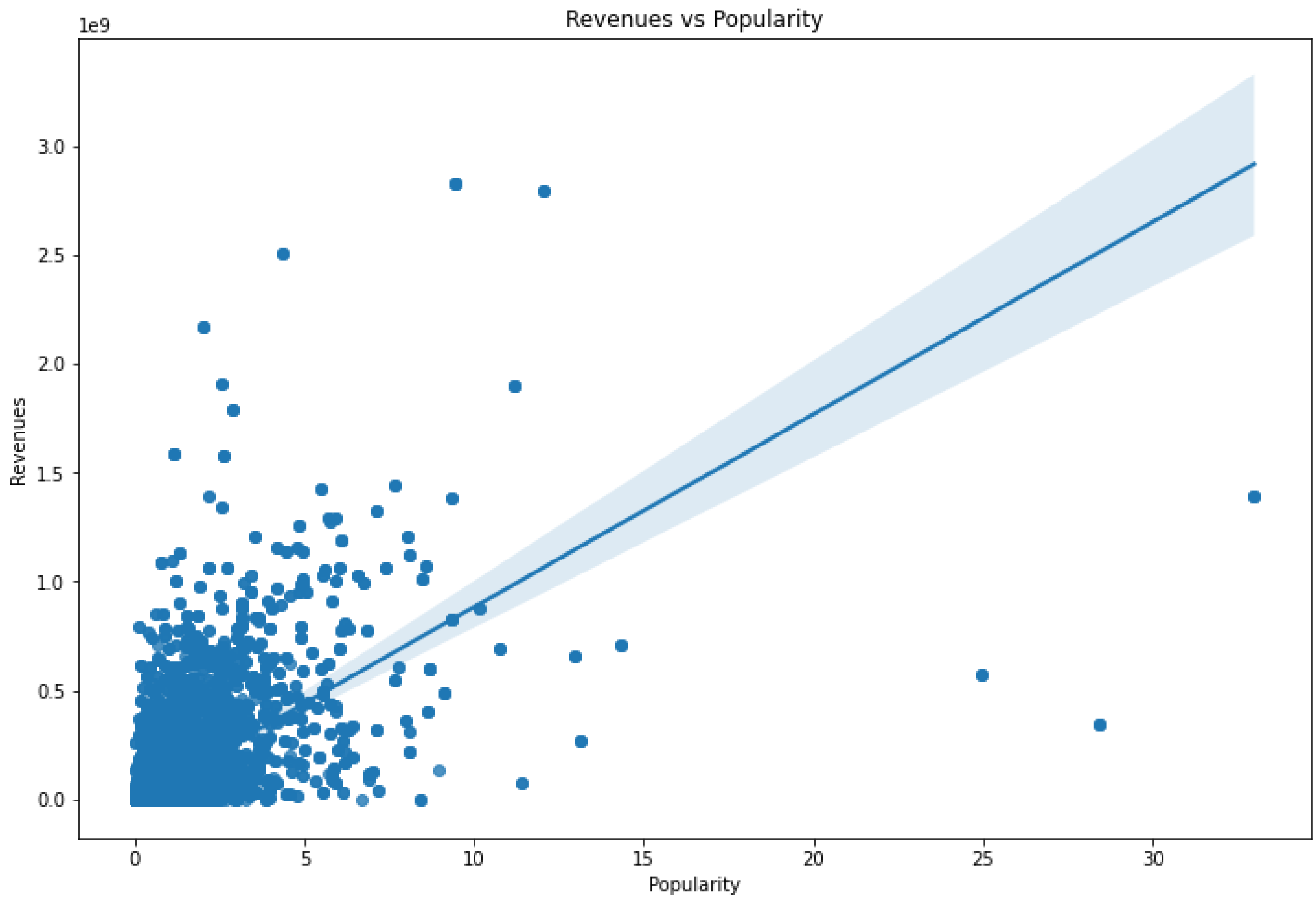
Correlation between revenues and vote_count is 0.715, which is a strong Positive Correlation.

Correlation between revenues and vote_average is 0.216, which is Weak Positive Correlation.

Correlation between revenues and release year is -0.047, which is a Weak Negative Correlation.

Correlation between revenues and budget is 0.643, which is a strong Positive Correlation.

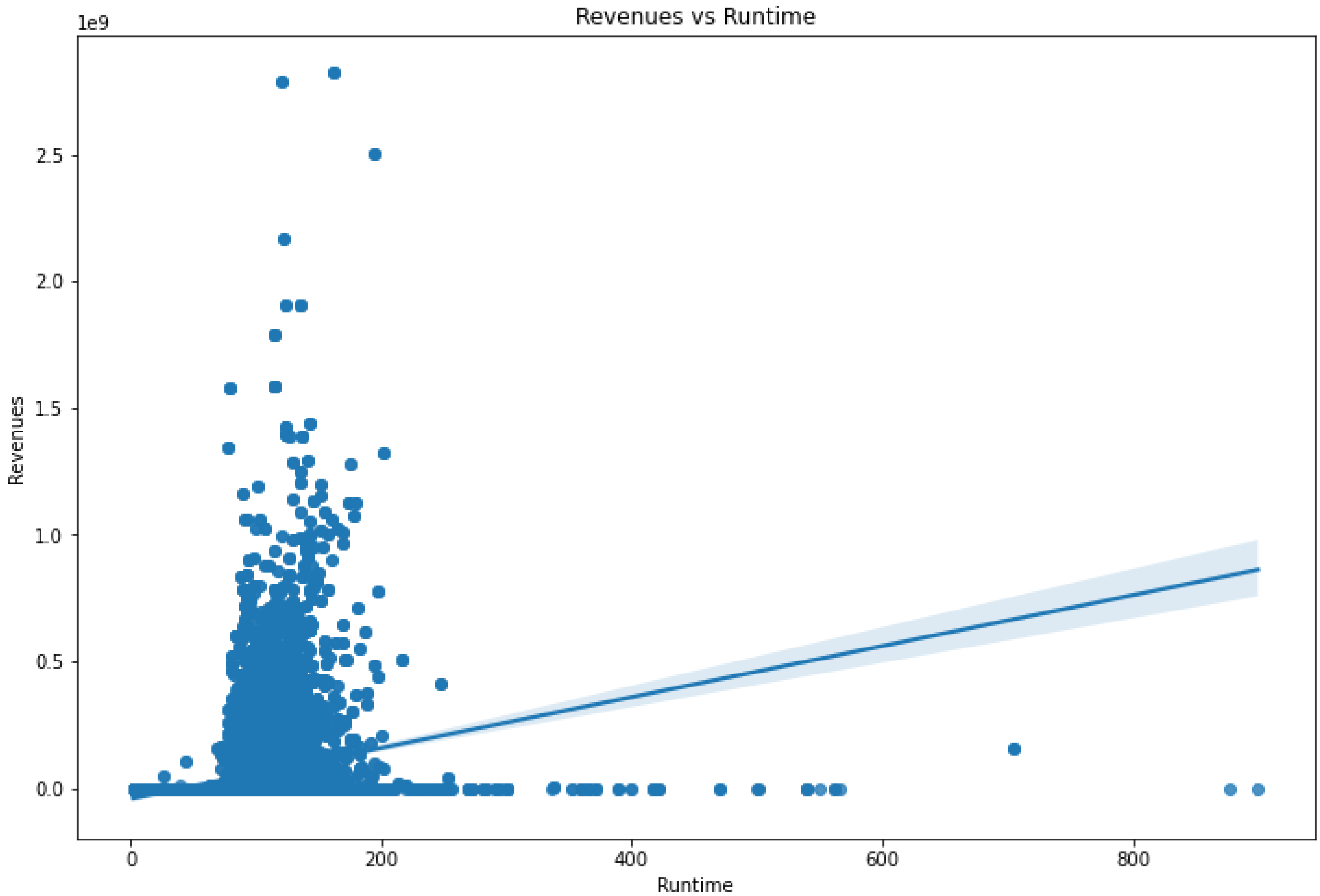
In [116…
```
# visualize the correlation between Popularity and revenues
plt.figure(figsize=(12,8))
sns.regplot(x='popularity', y='revenue', data=movie_df)
plt.title("Revenues vs Popularity")
plt.xlabel("Popularity")
plt.ylabel("Revenues")
plt.show()
```



Correlation between revenues and Popularity is 0.61, which is strong Positive Correlation. However from the observation of the scatter plot the revenue increases Popularity upto certain point(where popularity is around 13.

In [117…

```
# visualize the correlation between Runtime and revenues
plt.figure(figsize=(12,8))
sns.regplot(x='runtime', y='revenue', data=movie_df)
plt.title("Revenues vs Runtime")
plt.xlabel("Runtime")
plt.ylabel("Revenues")
plt.show()
```

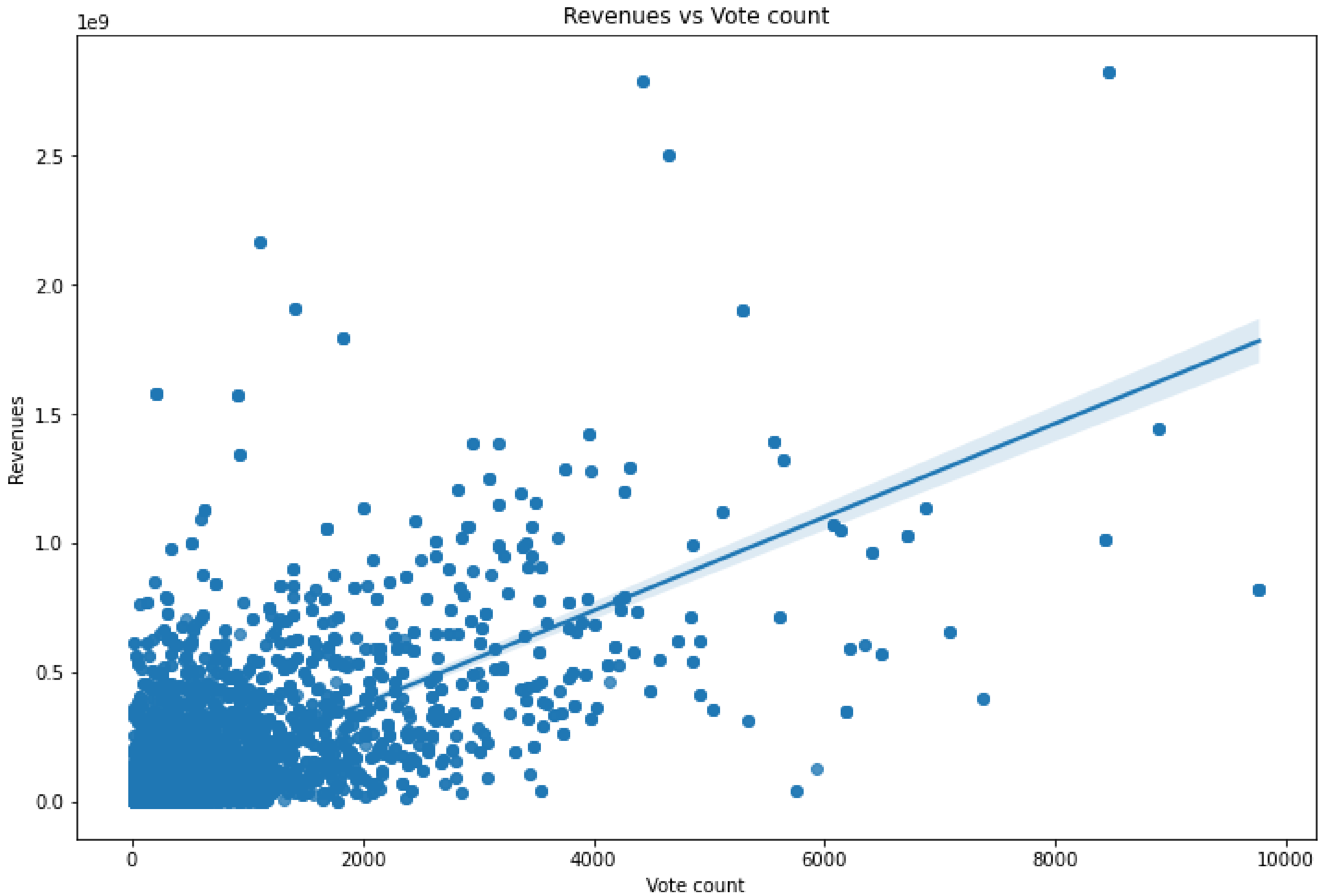


Correlation between revenues and Runtime is 0.187, which is a Weak Positive Correlation.

The revenue is high when Runtime is between 50 and 200

In [118…

```
# visualize the correlation between vote count and revenues
plt.figure(figsize=(12,8))
sns.regplot(x='vote_count', y='revenue', data=movie_df)
plt.title("Revenues vs Vote count")
plt.xlabel("Vote count")
plt.ylabel("Revenues")
plt.show()
```

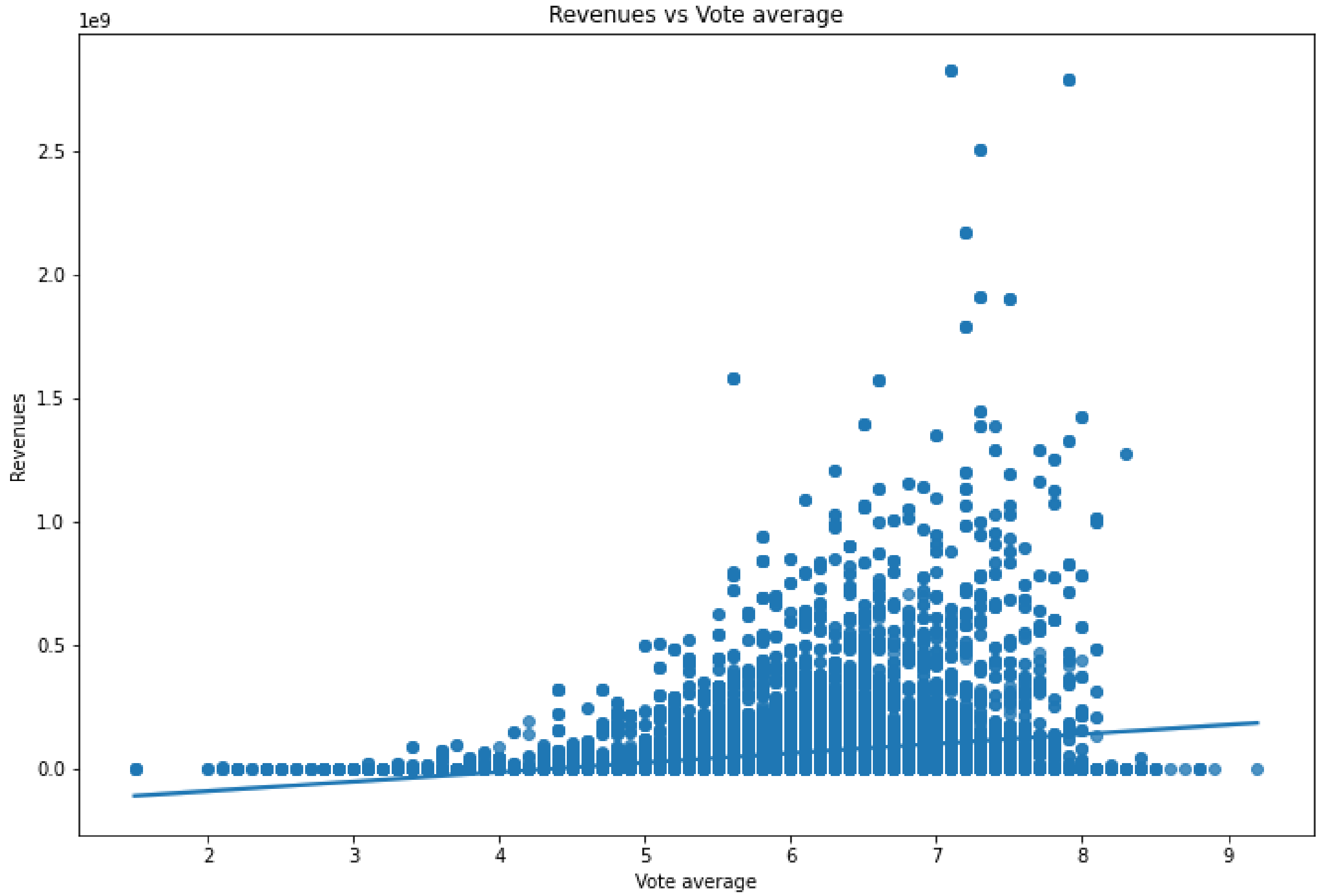


Correlation between revenues and vote_count is 0.715, which is a strong Positive Correlation.

From the observation of the scatter plot the revenue increases vote_count

In [119…

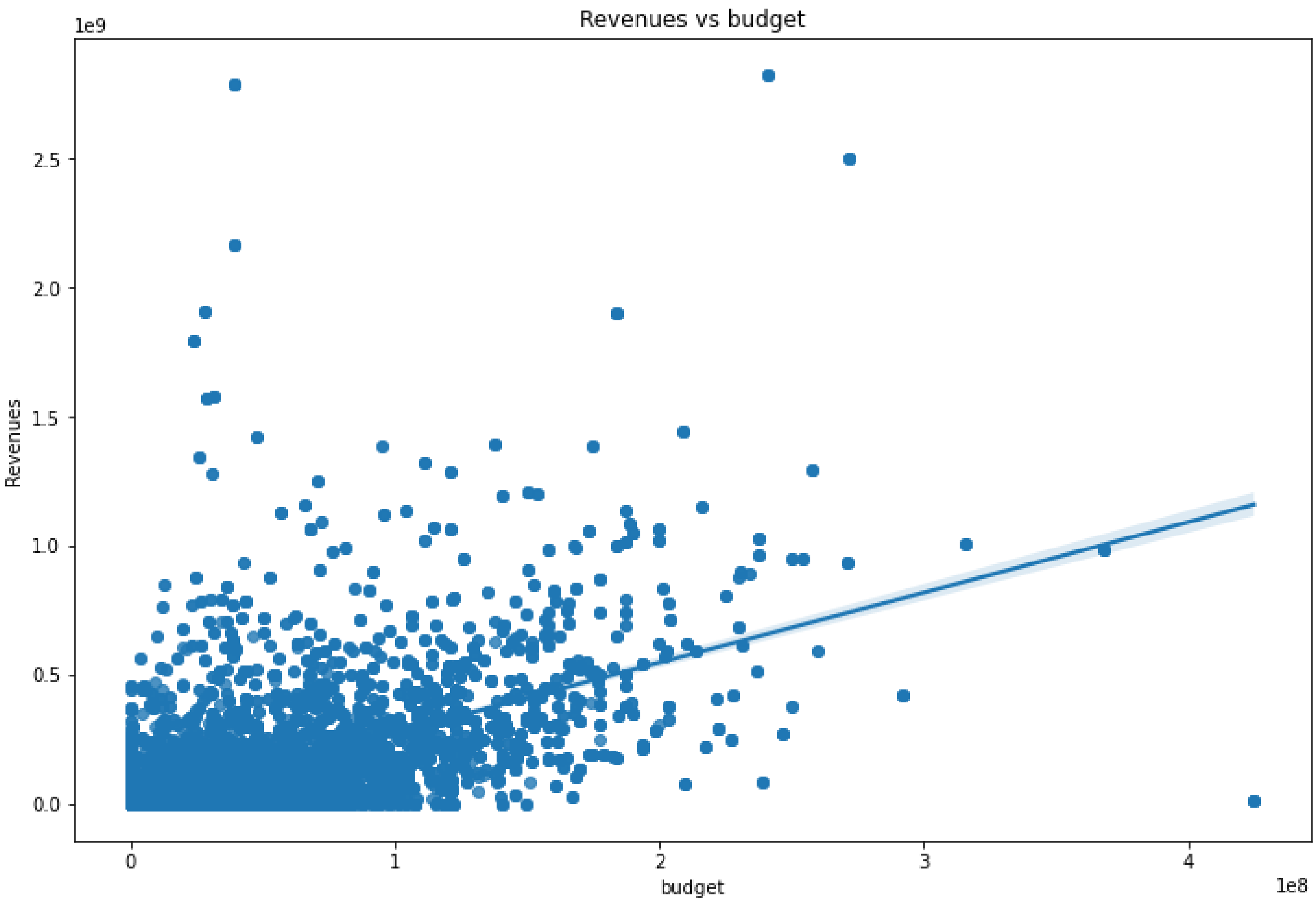
```
# visualize the correlation between Vote average and revenues
plt.figure(figsize=(12,8))
sns.regplot(x='vote_average', y='revenue', data=movie_df)
plt.title("Revenues vs Vote average")
plt.xlabel("Vote average")
plt.ylabel("Revenues")
plt.show()
```



Correlation between revenues and vote_average is 0.216, which is Weak Positive Correlation.

In [113…

```
# visualize the correlation between Popularity and revenues
plt.figure(figsize=(12,8))
sns.regplot(x='budget', y='revenue', data=movie_df)
plt.title("Revenues vs budget")
plt.xlabel("budget")
plt.ylabel("Revenues")
plt.show()
```



Correlation between revenues and budget is 0.643, which is a slightly strong Positive Correlation.

In [122…

```
movie_df.groupby("genres").revenue.median().sort_values(ascending=False)
```

Out[122]:

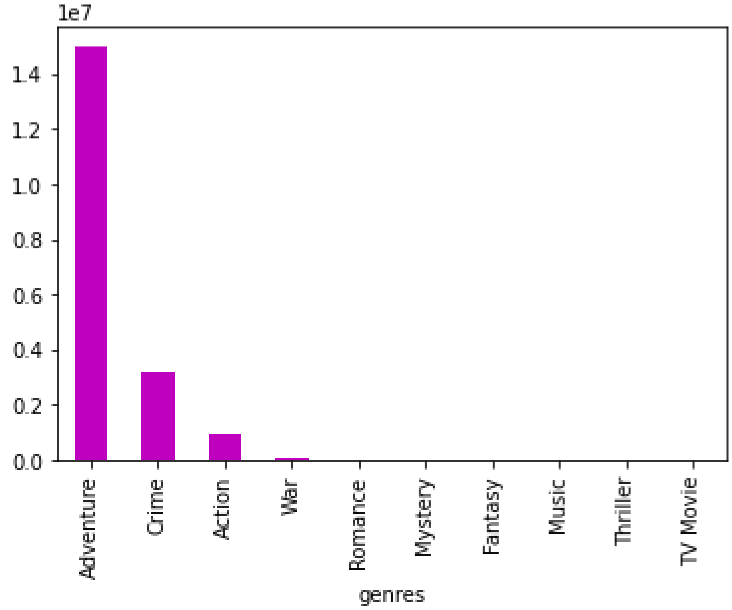
```
genres
Adventure          1.500831e+07
Crime              3.177156e+06
Action             9.135486e+05
War                5.044519e+04
Romance            1.800000e+04
Mystery            7.722911e+03
Fantasy            6.339774e+01
Music              0.000000e+00
Thriller           0.000000e+00
TV Movie           0.000000e+00
Science Fiction    0.000000e+00
History            0.000000e+00
Horror             0.000000e+00
Foreign            0.000000e+00
Family             0.000000e+00
Drama              0.000000e+00
Documentary        0.000000e+00
Comedy             0.000000e+00
Animation          0.000000e+00
Western            0.000000e+00
Name: revenue, dtype: float64
```

In [127…

```
movie_df.groupby("genres").revenue.median().sort_values(ascending=False).head(10).plot.b
```

Out[127]:

```
<AxesSubplot:xlabel='genres'>
```



The movie genre that contribute the highest revenue is Adventure movies followed by crime

In [ ]:

Conclusions

so, after processing this data set we can conclude the following :

The most popular genres over time are adventure and western movies

The movies features such vote_count, Popularity,and budget are strong positively correlated with revenues

Adventure contributes the highest revenue is followed by crime

Limitation

There were movies with zero(0) minutes runtime though they were dropped still the challenge was losing more data Also budget and revenue had zero(0) values. Removinng this zero data would have reduced the number of data as well

Referncės:

Github links

```
https://github.com/franciskip/Data-Cleaning-and-Data-Wrangling-Preprocessing-
https://github.com/PacktPublishing/Practical-Data-Wrangling
https://github.com/franciskip/Business-Success-prediction
https://github.com/franciskip/Data-Visualiaztion
```

Jiang, S., & Kahn, J. (2020). Data wrangling practices and collaborative interactions with aggregated data. International Journal of Computer-Supported Collaborative Learning, 15(3), 257-281.

Royston, P. (2004). Multiple imputation of missing values. The Stata Journal, 4(3), 227-241.

Chen, C. H., Härdle, W. K., & Unwin, A. (Eds.). (2007). Handbook of data visualization. Springer Science & Business Media.

In [ ]: