Investigate_a_Dataset

October 26, 2021

1 Project: Investigating Movie revenue trends & genres through the years

1.1 Table of Contents

Introduction

The Dataset under analysis is set containing with their relevant information, the main attribute under investigation is the Revenues of these movies.This analysis will try to answer some questions such as :
1) how the season in which the movie is released in affects its profit ?
2) do some genres generate more profit than the others ?
3) does the runtime affects the movie profits or not ? 4) what is the relation between average movie votes and the movie profit ? 5) does a higher budget yields a higher profit ?

In [1]:
```
# Use this cell to set up import statements for all of the packages that you
#   plan to use.

# Remember to include a 'magic word' so that your 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 sn
%matplotlib inline
```

In [2]:
```
df = pd.read_csv('tmdb-movies.csv')
```

Data Wrangling

1.1.1 General Properties

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

Out[3]:
```
       id    imdb_id  popularity     budget     revenue  \
0  135397  tt0369610   32.985763  150000000  1513528810
1   76341  tt1392190   28.419936  150000000   378436354
2  262500  tt2908446   13.112507  110000000   295238201
3  140607  tt2488496   11.173104  200000000  2068178225
4  168259  tt2820852    9.335014  190000000  1506249360

                 original_title  \
0                Jurassic World
1            Mad Max: Fury Road
2                     Insurgent
3  Star Wars: The Force Awakens
4                     Furious 7

                                                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...
3  Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...
4  Vin Diesel|Paul Walker|Jason Statham|Michelle ...

                                            homepage          director  \
0                      http://www.jurassicworld.com/   Colin Trevorrow
1                        http://www.madmaxmovie.com/     George Miller
2     http://www.thedivergentseries.movie/#insurgent  Robert Schwentke
3  http://www.starwars.com/films/star-wars-episod...       J.J. Abrams
4                           http://www.furious7.com/         James Wan

                      tagline      ...       \
0            The park is open.      ...
1           What a Lovely Day.      ...
2     One Choice Can Destroy You      ...
3  Every generation has a story.      ...
4            Vengeance Hits Home      ...

                                            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
3  Thirty years after defeating the Galactic Empi...     136
4  Deckard Shaw seeks revenge against Dominic Tor...     137

                                      genres  \
```

```
0  Action|Adventure|Science Fiction|Thriller
1  Action|Adventure|Science Fiction|Thriller
2         Adventure|Science Fiction|Thriller
3   Action|Adventure|Science Fiction|Fantasy
4                      Action|Crime|Thriller

                              production_companies release_date vote_count  \
0  Universal Studios|Amblin Entertainment|Legenda...       6/9/15       5562
1  Village Roadshow Pictures|Kennedy Miller Produ...      5/13/15       6185
2  Summit Entertainment|Mandeville Films|Red Wago...      3/18/15       2480
3          Lucasfilm|Truenorth Productions|Bad Robot     12/15/15       5292
4  Universal Pictures|Original Film|Media Rights ...       4/1/15       2947

   vote_average  release_year    budget_adj   revenue_adj
0           6.5          2015  1.379999e+08  1.392446e+09
1           7.1          2015  1.379999e+08  3.481613e+08
2           6.3          2015  1.012000e+08  2.716190e+08
3           7.5          2015  1.839999e+08  1.902723e+09
4           7.3          2015  1.747999e+08  1.385749e+09

[5 rows x 21 columns]
```

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

Out[4]:
```
(10866, 21)
```

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
```

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 object
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: float64(4), int64(6), object(11)
memory usage: 1.7+ MB
```

We will now drop columns that will not be of use to us such as non adjusted budget and revenue , homepage,tagline,keywords,etc since they will not be of value while investigating the profits

```
In [7]: df.drop(['budget','revenue','homepage','imdb_id','tagline','keywords','overview','produc
```

```
In [8]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10866 entries, 0 to 10865
Data columns (total 12 columns):
id                10866 non-null int64
popularity        10866 non-null float64
original_title    10866 non-null object
cast              10790 non-null object
director          10822 non-null object
runtime           10866 non-null int64
genres            10843 non-null object
release_date      10866 non-null object
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: float64(4), int64(3), object(5)
memory usage: 1018.8+ KB
```

1.1.2 Data Cleaning :

Step 1, investigate null values :

1) Cast

In [9]:
```
df[df.cast.isnull()].head()
```

Out[9]:
```
         id  popularity                             original_title cast  \
371  345637    0.422901                         Sanjay's Super Team  NaN
441  355020    0.220751  Winter on Fire: Ukraine's Fight for Freedom  NaN
465  321109    0.201696                                 Bitter Lake  NaN
536  333350    0.122543                              A Faster Horse  NaN
538  224972    0.114264                         The Mask You Live In  NaN

                  director  runtime       genres release_date  vote_average  \
371           Sanjay Patel        7    Animation     11/25/15           6.9
441      Evgeny Afineevsky       98  Documentary      10/9/15           8.2
465            Adam Curtis      135  Documentary      1/24/15           7.8
536             David Gelb       90  Documentary      10/8/15           8.0
538  Jennifer Siebel Newsom       88  Documentary       1/1/15           8.9

     release_year  budget_adj  revenue_adj
371          2015         0.0          0.0
441          2015         0.0          0.0
465          2015         0.0          0.0
536          2015         0.0          0.0
538          2015         0.0          0.0
```

Most of the movies without their cast listed are documentries or animation films which do not have any information about their budgets or revenue so we will drop them

In [10]:
```
df.dropna(subset=['cast'],inplace = True)
```

2) director:

In [11]:
```
df[df.director.isnull()].head()
```

Out[11]:
```
          id  popularity                      original_title  \
532   320996    0.126594       Iliza Shlesinger: Freezing Hot
548   355131    0.108072            Sense8: Creating the World
556   321160    0.100910                      With This Ring
1032  259910    0.291253  Marvel Studios: Assembling a Universe
```

```
1054  253675    0.269468                     Unlocking Sherlock

                                                  cast director  runtime  \
532                                    Iliza Shlesinger      NaN       71
548   Tuppence Middleton|Bae Doona |Brian J. Smith|A...      NaN       25
556   Regina Hall|Jill Scott|Eve|Brooklyn Sudano|Dei...      NaN      105
1032  Robert Downey Jr.|Chris Hemsworth|Chris Evans|...      NaN       43
1054  Benedict Cumberbatch|Martin Freeman|Steven Mof...      NaN       60

                         genres release_date  vote_average  release_year  \
532                      Comedy      1/23/15           6.6          2015
548   Documentary|Science Fiction      8/10/15           7.5          2015
556              Comedy|Romance      1/24/15           6.5          2015
1032         TV Movie|Documentary      3/18/14           6.3          2014
1054         TV Movie|Documentary      1/19/14           7.2          2014

      budget_adj  revenue_adj
532          0.0          0.0
548          0.0          0.0
556          0.0          0.0
1032         0.0          0.0
1054         0.0          0.0
```

1.1.3 Most of these movies are under the feature film length therefore they can be dropped without having an effect on our dataset

```
In [12]: df.dropna(subset=['director'],inplace = True )
```

3) genres and feature length cleaning:

```
In [13]: df[df.genres.isnull()].head()
```

```
Out[13]:           id  popularity                      original_title  \
        424   363869    0.244648                       Belli di papÃă
        997   287663    0.330431   Star Wars Rebels: Spark of Rebellion
        1712   21634    0.302095                     Prayers for Bobby
        1897   40534    0.020701  Jonas Brothers: The Concert Experience
        2370  127717    0.081892                        Freshman Father

                                                           cast  \
        424   Diego Abatantuono|Matilde Gioli|Andrea Pisani|...
        997   Freddie Prinze Jr.|Vanessa Marshall|Steve Blum...
        1712  Ryan Kelley|Sigourney Weaver|Henry Czerny|Dan ...
        1897  Nick Jonas|Joe Jonas|Kevin Jonas|John Lloyd Ta...
        2370  Britt Irvin|Merrilyn Gann|Barbara Tyson|Anthon...

                              director  runtime genres release_date  vote_average  \
        424               Guido Chiesa      100    NaN     10/29/15           6.1
        997   Steward Lee|Steven G. Lee       44    NaN      10/3/14           6.8
```

```
1712             Russell Mulcahy       88     NaN       2/27/09              7.4
1897             Bruce Hendricks       76     NaN       2/27/09              7.0
2370               Michael Scott        0     NaN        6/5/10              5.8

      release_year  budget_adj  revenue_adj
424           2015         0.0          0.0
997           2014         0.0          0.0
1712          2009         0.0          0.0
1897          2009         0.0          0.0
2370          2010         0.0          0.0
```

1.1.4 The same condition as the above two cleaning condition applies Here , so We will drop them also we will drop movies which have runtime less than feature film which is 70 minutes according to Screen Actors Guild and more than 210. Movies released before 2000 will also be dropped to keep our analysis relevant to modern movies , Moreover we will remove movies that did not generate any income

In [14]:
```python
df.dropna(subset=['genres'],inplace = True)
df = df[df['runtime']>70]
df = df[df['runtime']<210]
df = df[df['release_year']>2000]
df = df[df['revenue_adj']>0]
df.head()
```

Out[14]:
```
       id  popularity                original_title  \
0  135397   32.985763                Jurassic World
1   76341   28.419936            Mad Max: Fury Road
2  262500   13.112507                     Insurgent
3  140607   11.173104  Star Wars: The Force Awakens
4  168259    9.335014                     Furious 7

                                                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
3  Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...       J.J. Abrams
4  Vin Diesel|Paul Walker|Jason Statham|Michelle ...         James Wan

   runtime                                     genres release_date  \
0      124  Action|Adventure|Science Fiction|Thriller       6/9/15
1      120  Action|Adventure|Science Fiction|Thriller      5/13/15
2      119         Adventure|Science Fiction|Thriller      3/18/15
3      136   Action|Adventure|Science Fiction|Fantasy     12/15/15
4      137                      Action|Crime|Thriller       4/1/15

   vote_average  release_year    budget_adj   revenue_adj
0           6.5          2015  1.379999e+08  1.392446e+09
1           7.1          2015  1.379999e+08  3.481613e+08
```

```
2             6.3          2015  1.012000e+08  2.716190e+08
3             7.5          2015  1.839999e+08  1.902723e+09
4             7.3          2015  1.747999e+08  1.385749e+09
```

1.1.5 We will now add a few things to our dataset that will be of use :

1) we will add a season column to know the season in which the movie was released. (1:Winter , 2:Spring, 3:Summer, 4:Autumn)

2) get the most the significant genre of the movie (i.e the first one before the '|' character).

3) get the most the significant Cast of the movie (i.e the first one before the '|' character)

4) get the most the significant Director of the movie (i.e the first one before the '|' character)

5) get the net proift (revenue - budget).

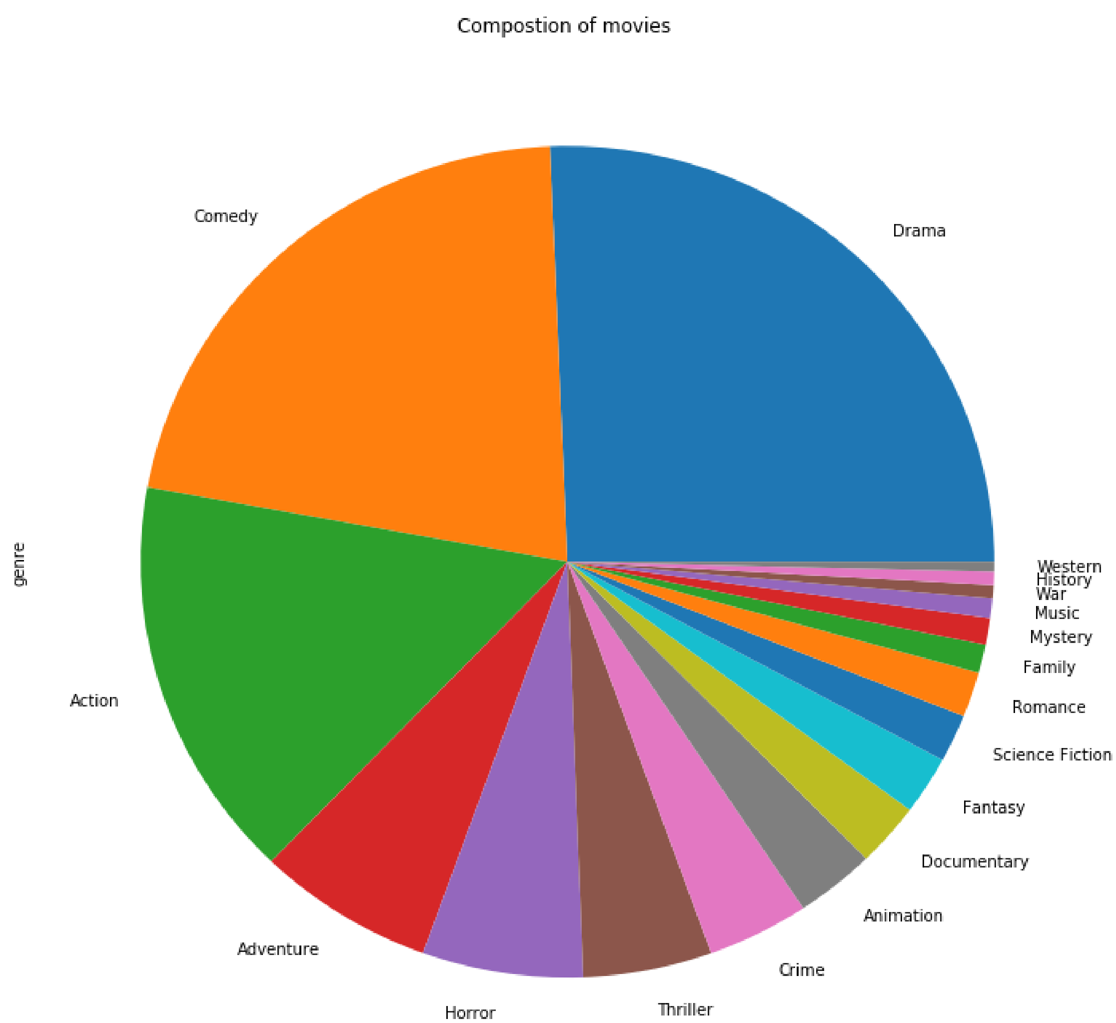
```
In [15]: # After discussing the structure of the data and any problems that need to be
         #   cleaned, perform those cleaning steps in the second part of this section.
         #df ['new_date'] = pd.to_datetime(df.release_date.str[:-3])

         df['season'] =  pd.to_datetime(df['release_date']).dt.month%12 // 3 + 1
         df['release_date'] = pd.to_datetime(df['release_date'])
         df['genre'] = df.genres.str.split('|').apply(lambda x : x[0])
         df['leadingRole'] = df.cast.str.split('|').apply(lambda x : x[0])
         df['leadingDirector'] = df.director.str.split('|').apply(lambda x : x[0])
         df['profit'] = df['revenue_adj']-df['budget_adj']
         #grpbydf = df.groupby('genres')['vote_average'].mean()


         #df['Season'] = pd.cut(df['release_date'],bins = ['1/3','1/6','1/11'])
         #df.head()
         #grpbydf
```

Exploratory Data Analysis

1.1.6 We will now explore some of the Data :

firstly, what is the composition of genres in the dataset ?

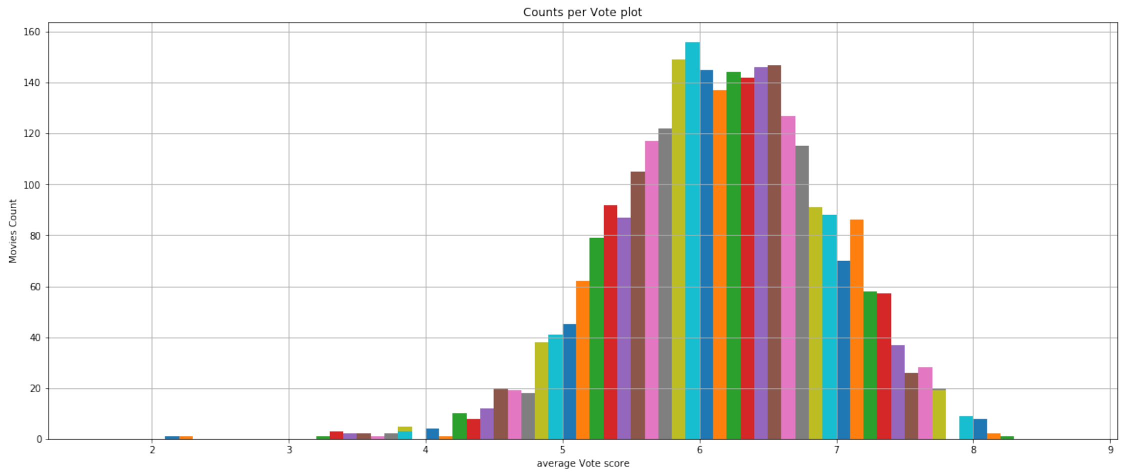
```
In [16]: df['genre'].value_counts().plot(kind = 'pie',figsize=(12,12));


         plt.title('Compostion of movies ');
```



1.1.7 We will recogninze the 5 major genres are Drama , Comedy , Action , Adventure , Horror

1.1.8 We will now see the distribution of our vote average ratings , we will group by the vote_average and plot a histogram

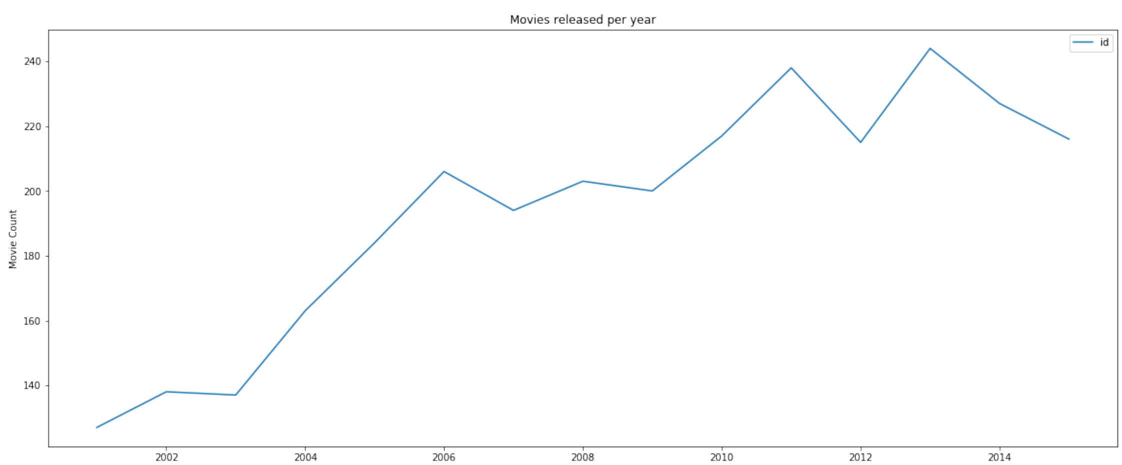
```
In [17]: rating_df = df.groupby('vote_average')
         I = rating_df['vote_average'].hist( figsize=(20,8));

         plt.ylabel('Movies Count');
         plt.xlabel('average Vote score');
         plt.title('Counts per Vote plot');
```



1.1.9 The figure above shows that most of the movies have an average vote score of 6

1.1.10 The number of movies released per year :

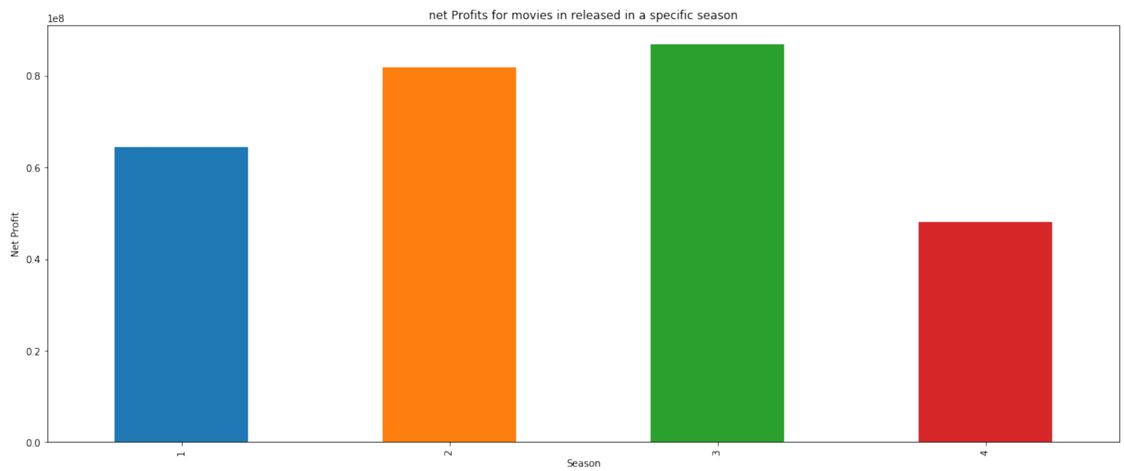
```
In [18]: release_df = df.groupby('release_year').count()
         release_df = release_df.reset_index()
         #release_df.plot (x = 'release_year' , kind = 'line')
         release_df.plot(y = 'id', x = 'release_year', kind = 'line' , figsize=(20,8) );

         plt.ylabel('Movie Count');
         plt.xlabel('Movie runtime category');
         plt.title('Movies released per year');
```



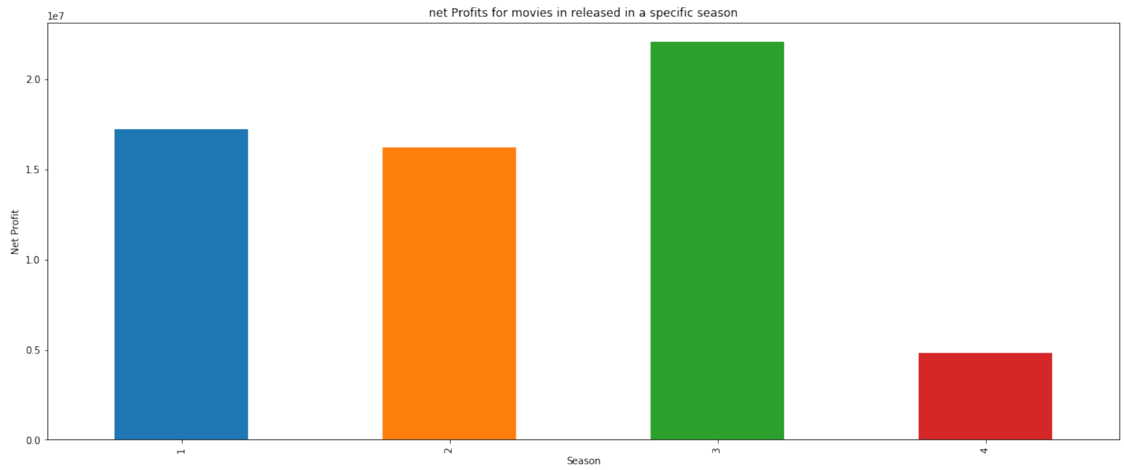
1.2 We Will start now with explorations of Data that relates to profits.

1.2.1 How does the season in which a movie is released affects its revenue while taking into consideration the budget ?

In [19]:
```
# Use this, and more code cells, to explore your data. Don't forget to add
#   Markdown cells to document your observations and findings.
season_df = df.groupby('season')['profit'].mean()
season_df.plot(x='season' , y = ['profit'] , kind = 'bar' , figsize=(20,8));


plt.ylabel('Net Profit');
plt.xlabel('Season');
plt.title('net Profits for movies in released in a specific season');
```



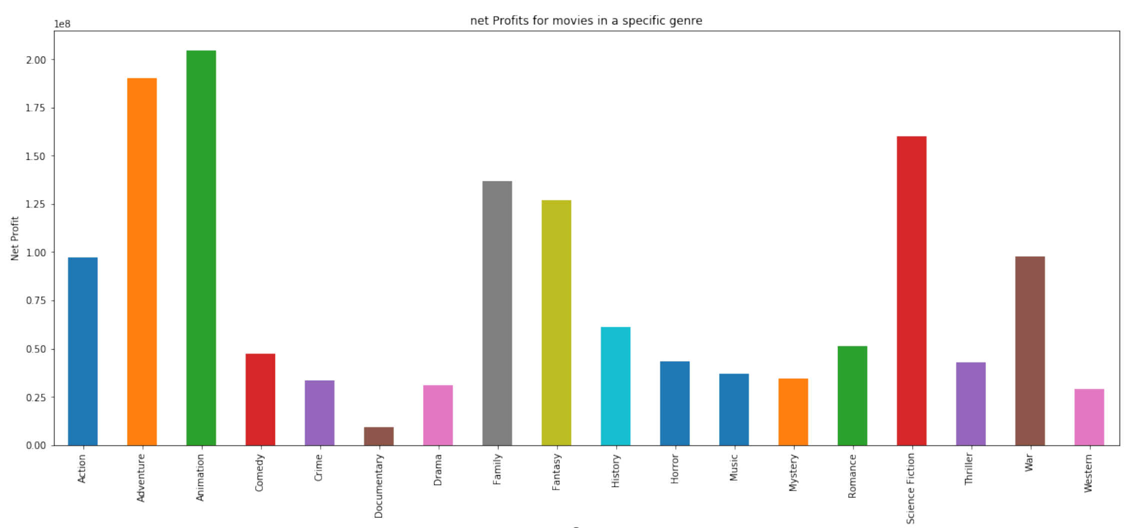
In [20]:
```
season_df = df.groupby('season')['profit'].median()
season_df.plot(x='season' , y = ['profit'] , kind = 'bar' , figsize=(20,8));

plt.ylabel('Net Profit');
plt.xlabel('Season');
plt.title('net Profits for movies in released in a specific season');
```



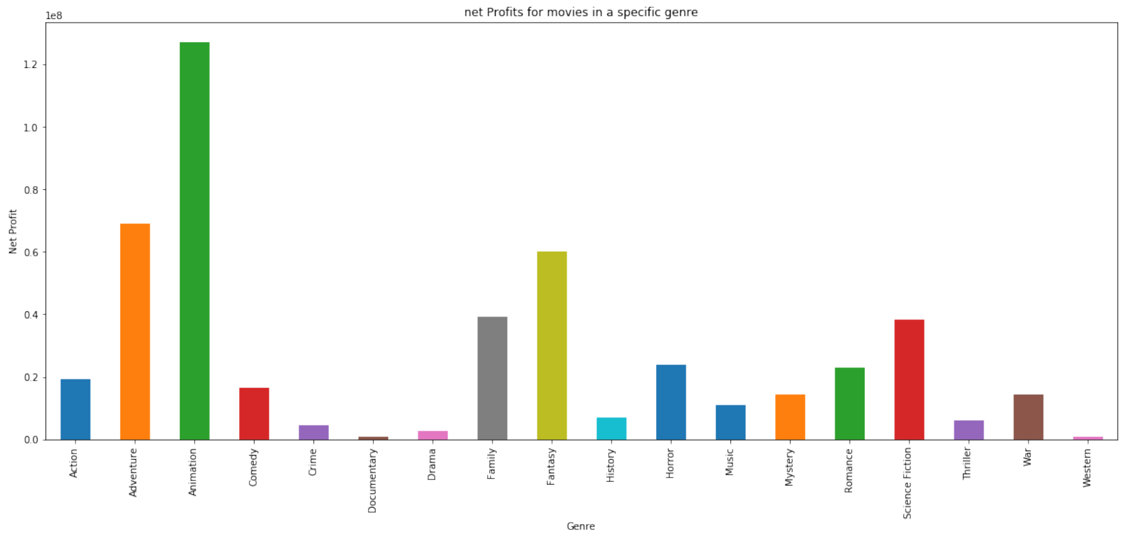
Finding number 1 : movies released in the summer generate higher Profit on average compared to other movies released in other seasons

1.2.2 Which genre generated the most Profit ?

In [21]:
```
genre_df = df.groupby('genre')['profit'].mean()
genre_df.plot(x='genre' , y = 'profit' , kind = 'bar' , figsize=(20,8));


plt.ylabel('Net Profit');
plt.xlabel('Genre');
plt.title('net Profits for movies in a specific genre');
```



In [22]:
```
genre_df = df.groupby('genre')['profit'].median()
genre_df.plot(x='genre' , y = 'profit' , kind = 'bar' , figsize=(20,8));


plt.ylabel('Net Profit');
plt.xlabel('Genre');
plt.title('net Profits for movies in a specific genre');
```

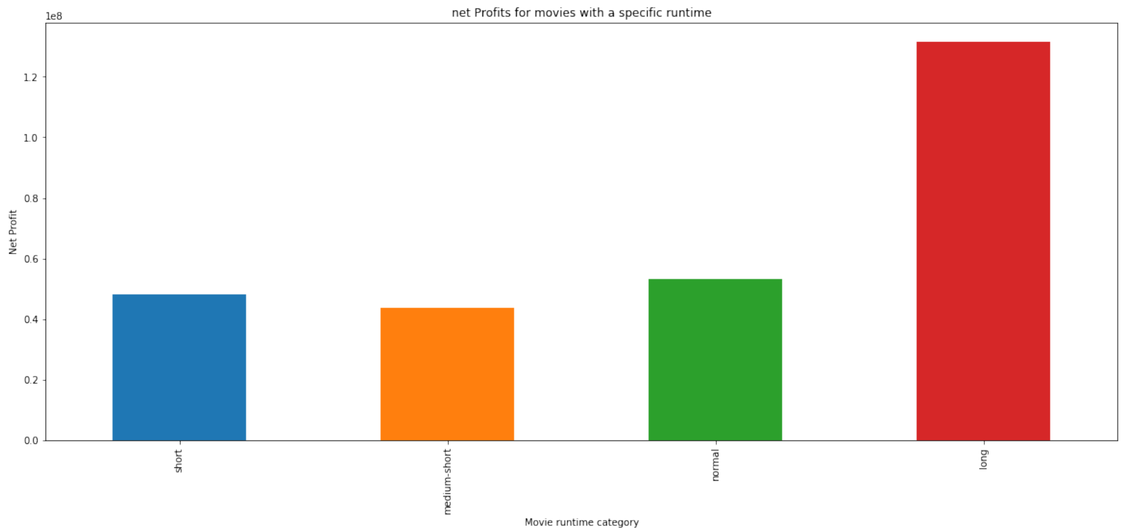


Finding number 2: Animation movies generate the most net profit on average while documentaries generate the less net profit

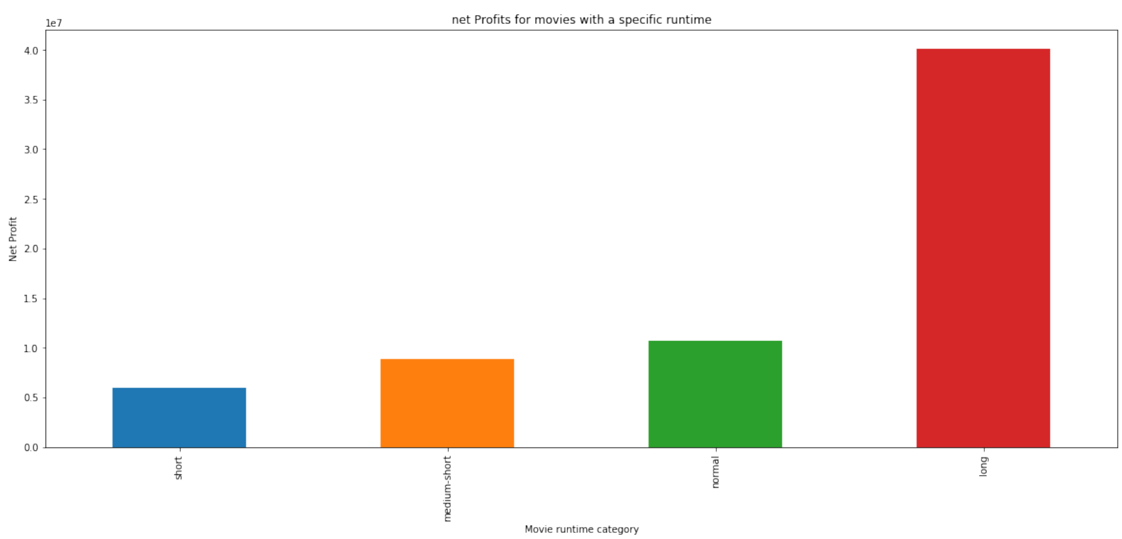
1.2.3 Does runtime affect a movie revenue ?

we will cut the runtime into categories using the min , 25% , 50%,75%,Max quartiles

In [23]:
```
df['runtime_desc'] = pd.cut(df['runtime'],[72,94,104,116,201],labels = ["short","medium

runtime_dfmean = df.groupby('runtime_desc')['profit'].mean()

runtime_dfmean.plot(x='runtime_desc' , y = 'profit' , kind = 'bar' , figsize=(20,8));

plt.ylabel('Net Profit');
plt.xlabel('Movie runtime category');
plt.title('net Profits for movies with a specific runtime');
#runtime_dfmedian.plot(x='runtime_desc' , y = 'profit' , kind = 'bar' );
```



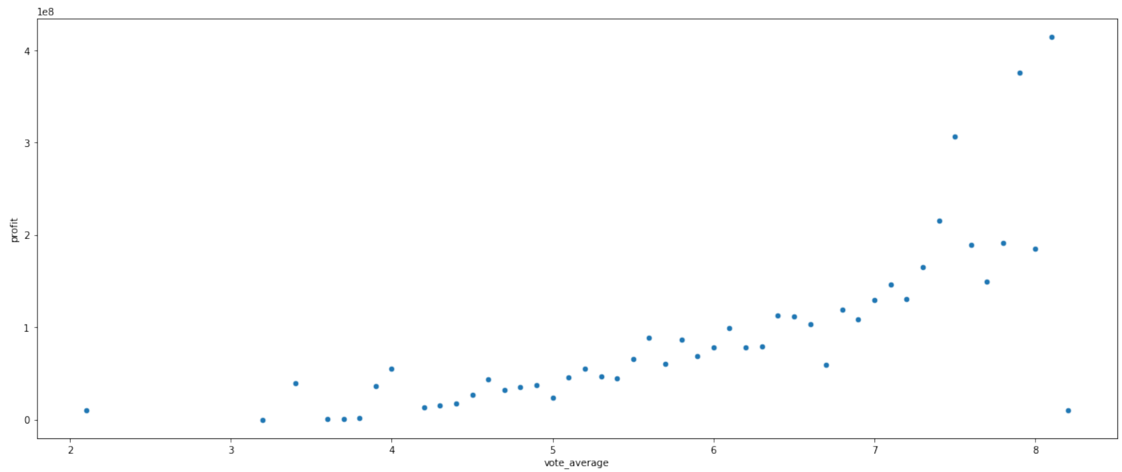

```
In [24]: runtime_dfmedian = df.groupby('runtime_desc')['profit'].median()
         runtime_dfmedian.plot(x='runtime_desc' , y = 'profit' , kind = 'bar' ,  figsize=(20,8))

         plt.ylabel('Net Profit');
         plt.xlabel('Movie runtime category');
         plt.title('net Profits for movies with a specific runtime');
```



Finding number 3: Movies which have a run time between 116 and 201 generate the most profit on average

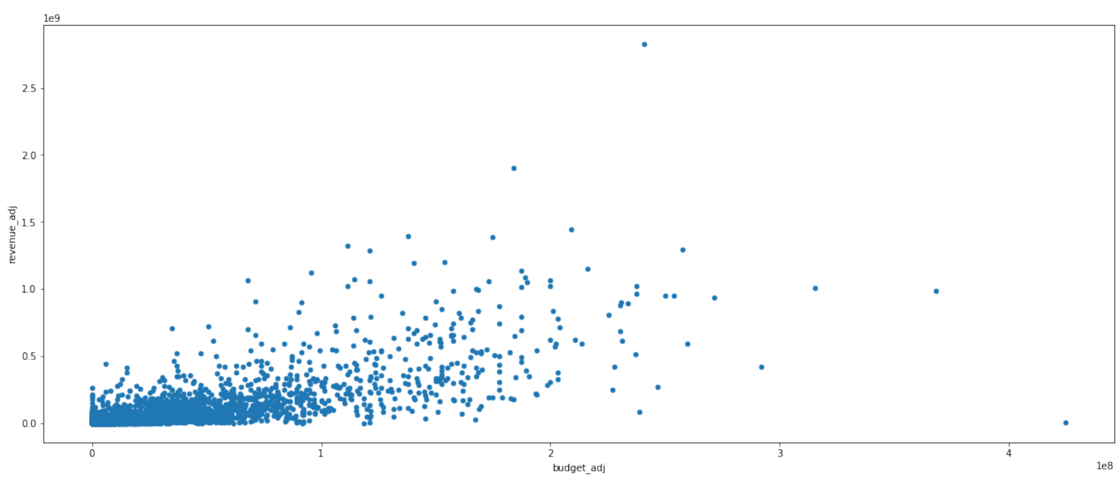
1.2.4 We will now investigate the relation between the average vote and the profit of the movie using a scatter plot:

```
In [25]: above_zero = df[df['profit']>0]
         above_zero=above_zero.groupby('vote_average').mean().reset_index()
         above_zero.head()
         above_zero.plot(kind = 'scatter' , x = 'vote_average' , y = 'profit' , figsize=(20,8));
```



1.2.5 Now we will investigate profit against the movie budget popularity (basically the question here does a higher budget increases the chance of a higher profit?) :

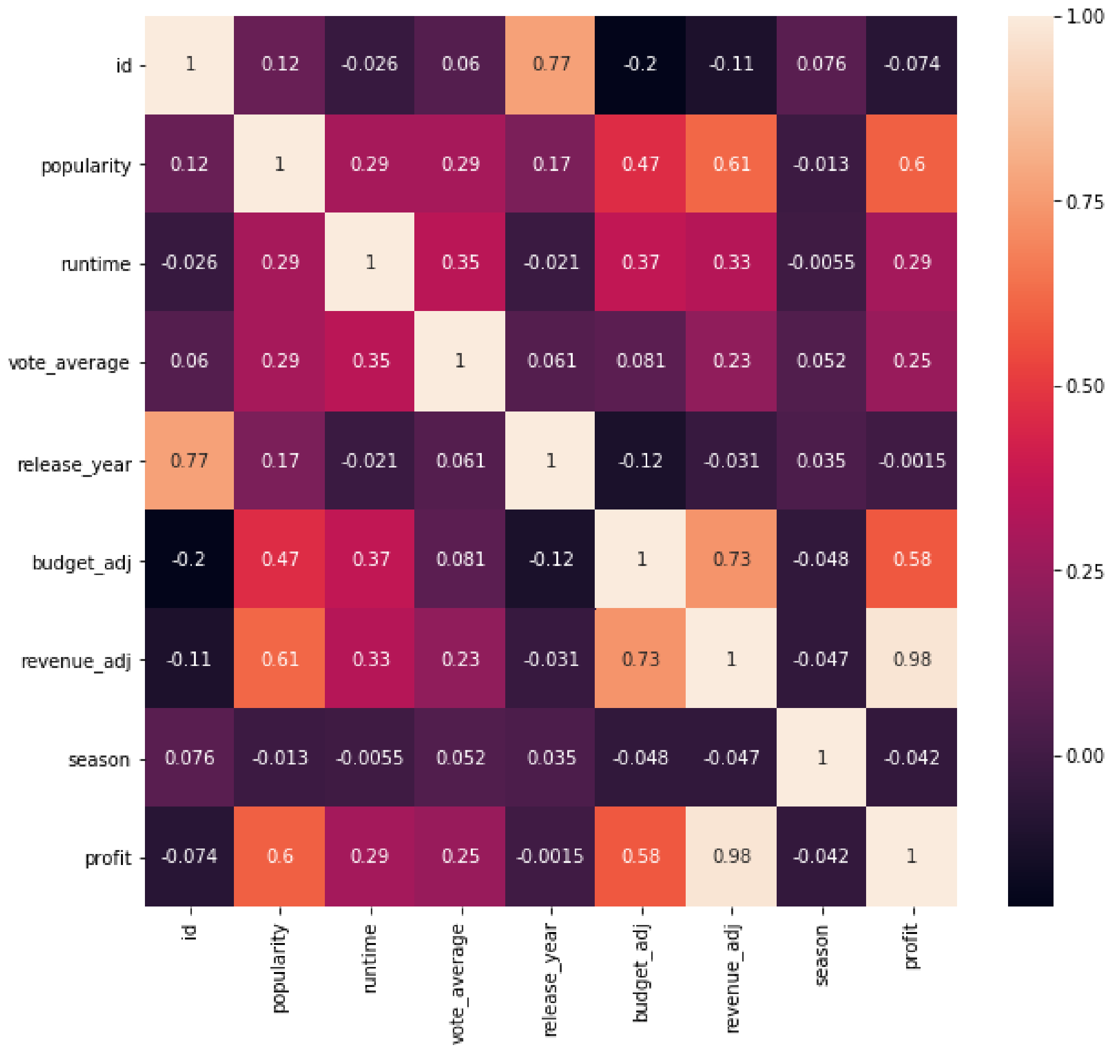
```
In [26]: df.plot(kind = 'scatter' , x = 'budget_adj' , y = 'revenue_adj' , figsize=(20,8));
```



We can detect a rising trend we can confirm it using a correlation matrix

1.2.6 Now we will draw a correlation matrix to see if they support findings above :

```
In [27]: corrMt = df.corr()
         plt.figure(figsize = (10,9))
         sn.heatmap(corrMt, annot=True )
         plt.show()
```



Conclusions > The findings above have a number of constraints as stated above ; most of the analysis are done on commercial movies other movies are ignored however the purpose of the analysis is to find attributes of high grossing movies therefore the imposed constraints and cleaning done are justified and helps in with dealing with a lot of values

1.2.7 Findings :

Movies released in the summer tend to generate more profits thant other movies

Movies of the animation genre generate more profits than other movies while they are not one of the 5 movie genres that make up 3/4 of the movies (refer to pie chart above)

Movies with runtime between 116 and 201 minutes generates the more profit compared to other movies with runtimes less than 116 minutes

Movies with higher vote_averages tend to earn more profit by average

there is a somewhat strong positive co-relation between budget and profit indicated by the coefficient of 0.58

1.2.8 Limitations :

some movies like the "Avatar - james Cameron" generated a lot of revenue which can lead to some anamolies while using the mean function therefore the mean and the median were used to verify that those figures are true and not actual anomalies

When cleaning the data I removed other genres and left the first one which could lead that some movies were categorised wrongly

```
In [28]: from subprocess import call
         call(['python', '-m', 'nbconvert', 'Investigate_a_Dataset.ipynb'])

Out[28]: 0
```