🐼 The killer Panda's Capstone Project 🐼

In this notebok you can find all our work, how we manipulate all data and how we made the data analysis and their statistics

Business Understanding

Our team is currently tasked with generating valuable insights as computer vision ventures into the film industry:

- The movies who have the higher earnings and its categories
- The best categories to develop a movie in
- The most likely successful directors within these categories to make a successful movie
- Find out if the duration of a movie has an influence in the earnings and engagement

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Data Understanding and Analysis

The data that we used is from pages about movies such as the moviedb.org and rotten tomatoes. We used them due to their records where we got info such as movie ratings, genres, directors, etc. We used data sets with more than 140,000 entries and using statistical measures such as mean or standard deviation to understand the behavior of data The conclusions and graphs we're getting from the information of the datasets, such as the graph of the most popular genres in movies using columns from im.db dataset. We had to adjust our analysis due to limitations with some datasets that weren´t up to date and other ones had missing data Description of data

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💸💲Budget/Gross/Profit 💸💲

Computer vision wants to make projects with big earning and that's why we started studying the movies with highest earnings, if we identified them, we could find common points such as genres, directors, and another interesting data. We started with dataset `tn.movie_budget.csv` we cleaned to converting the data in integers, then we get the values `Earnings` subtracting values `Budget` from values `Gross`. We ordered the data in descent way, and we get the first 10 movies to graph.

First we load all the libraries:

In [1]:
```
import pandas as pd
import sqlite3
import matplotlib.pyplot as plt
import seaborn
import numpy as np
from scipy import stats
import math
```

The first dataset we work was the from `tn.movie_budgets.csv`, let's import all the libraries we will need

In [2]:
```
tn_budgets = pd.read_csv('data/tn.movie_budgets.csv', index_col=0)

#We can make a checkout of the dataset, know their columns and kind of values
#Also is useful if we check the information of our dataset
#If think you may need see this information, plese uncomment the code below

#tn_budgets.info()
#tn_budgets.head(10)
```

We can see we do not have missing values, all the type of data is object and we have four columns. As you can see, `production_budget`, `domestic_gross`, `worldwide_gross` are columns for money so we need them in type int, let's make a cleaning delenting the `$` and `,`

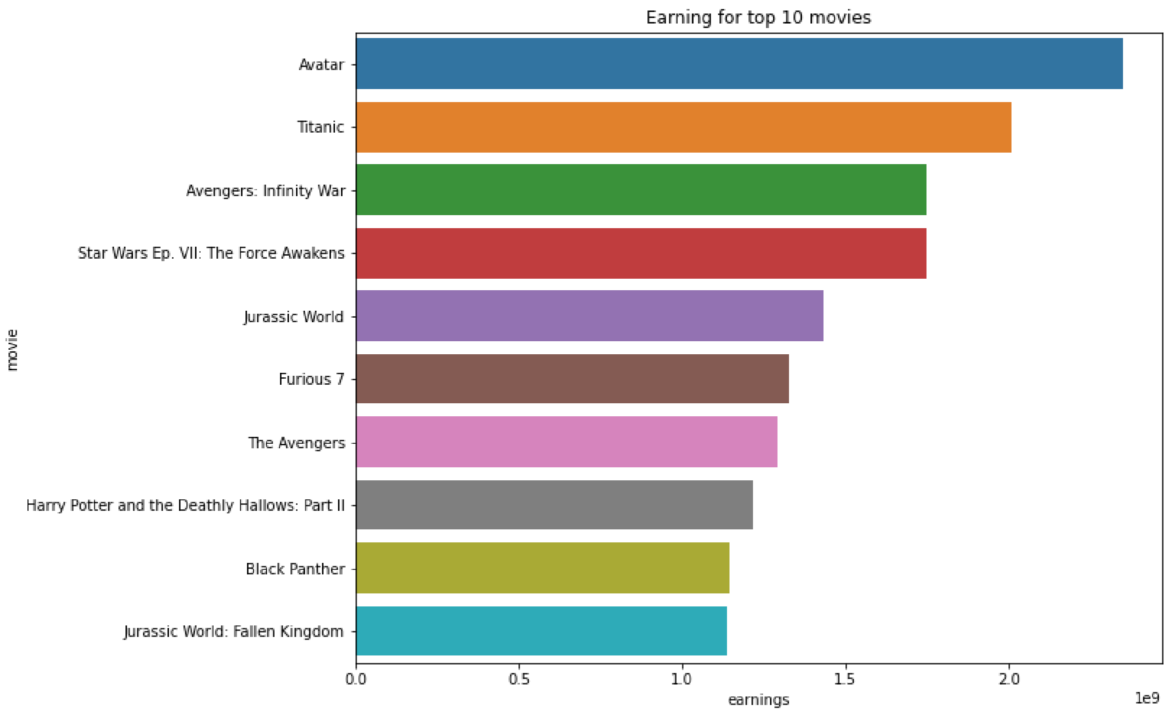
In [3]:
```
'''
We made this funtion to clear all the columns just calling it, in order to re
we also set as argument a list call columns, if we had another data ser we co
the funtion and specify the columns we want to transform
'''
def cleaning(columns):
    for x in columns:
        # This part clean the symbols $ and , by replacing them with "nothing
        tn_budgets[x]=tn_budgets[x].apply(lambda x: x.replace(",","").replace
        # ecause of the type of this rows and columns and in order we
        # want to make some calculation it is needed to transform them to num
        tn_budgets[x]=pd.to_numeric(tn_budgets[x])

#The columns we want to clean are save them in a list
columns =  ['production_budget', 'domestic_gross','worldwide_gross']

#Call the funtion, and now all the columns are in good formart! :D
cleaning(columns)

#Now we want to add a column call "earnings"
tn_budgets["earnings"]=tn_budgets["worldwide_gross"]-tn_budgets["production_b

#As well as a column called "Profit"
tn_budgets["Profit"]=(tn_budgets["earnings"]/tn_budgets["worldwide_gross"])*1
```

Ploting with seaborn

We have the new columns and the cleaning have been applied to all the data, but for a preview we only want to see the top ten movie sorted with more earnings

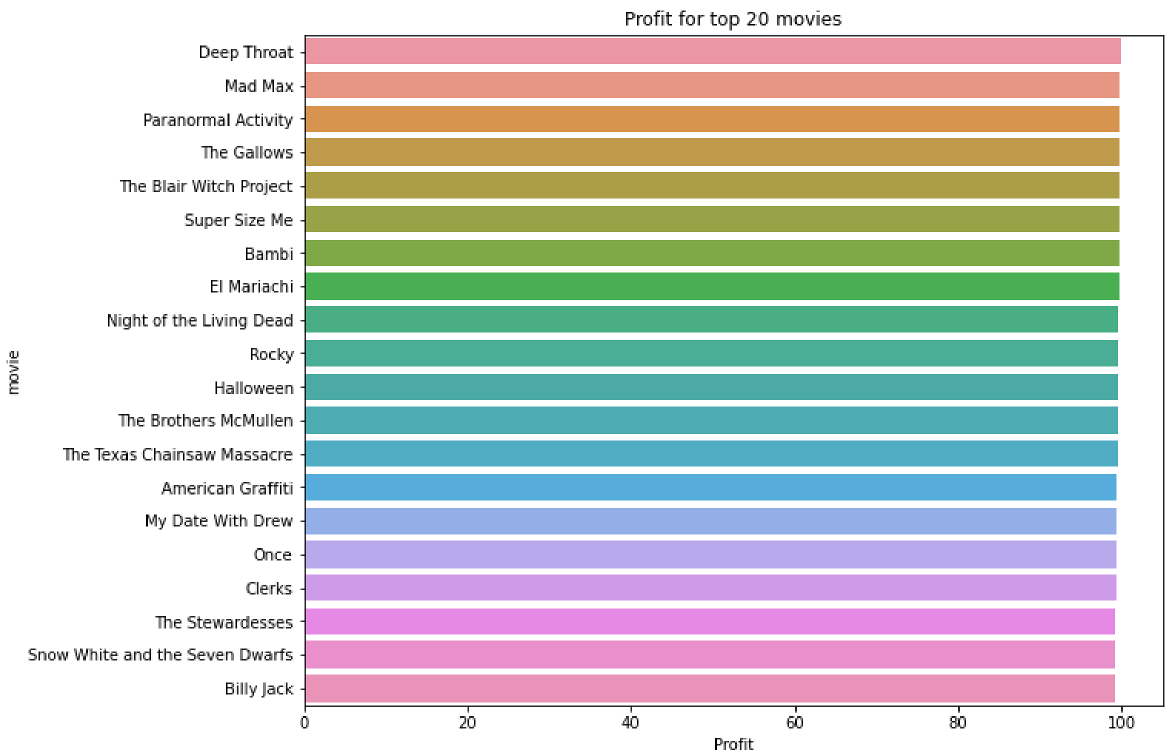
Earning

In [4]:
```
# Making a copy with the first 10 movies, you can use more than only 10 elemn
tp1=tn_budgets.sort_values(by="earnings", ascending=False).head(10).copy()

#Making a new dataframe with only the required columns
topten1 = tp1.loc[:,["movie", "earnings"]]

fig= plt.subplots(figsize=(10, 8))

##We decide to use seaborn and the bar kind
seaborn.barplot(x ="earnings", y ="movie", data = topten1)
plt.title("Earning for top 10 movies")
plt.show()
```



Profit

In [5]:
```
#We also want to see how it sees ploting the profit vs the movie
tptw=tn_budgets.sort_values(by="Profit", ascending=False).head(20).copy()

#Repeat the process for new columns
toptw = tptw.loc[:,["movie", "Profit"]]


fig= plt.subplots(figsize=(10, 8))
seaborn.barplot(x ="Profit", y ="movie", data = toptw)
plt.title("Profit for top 20 movies")
plt.show()
```

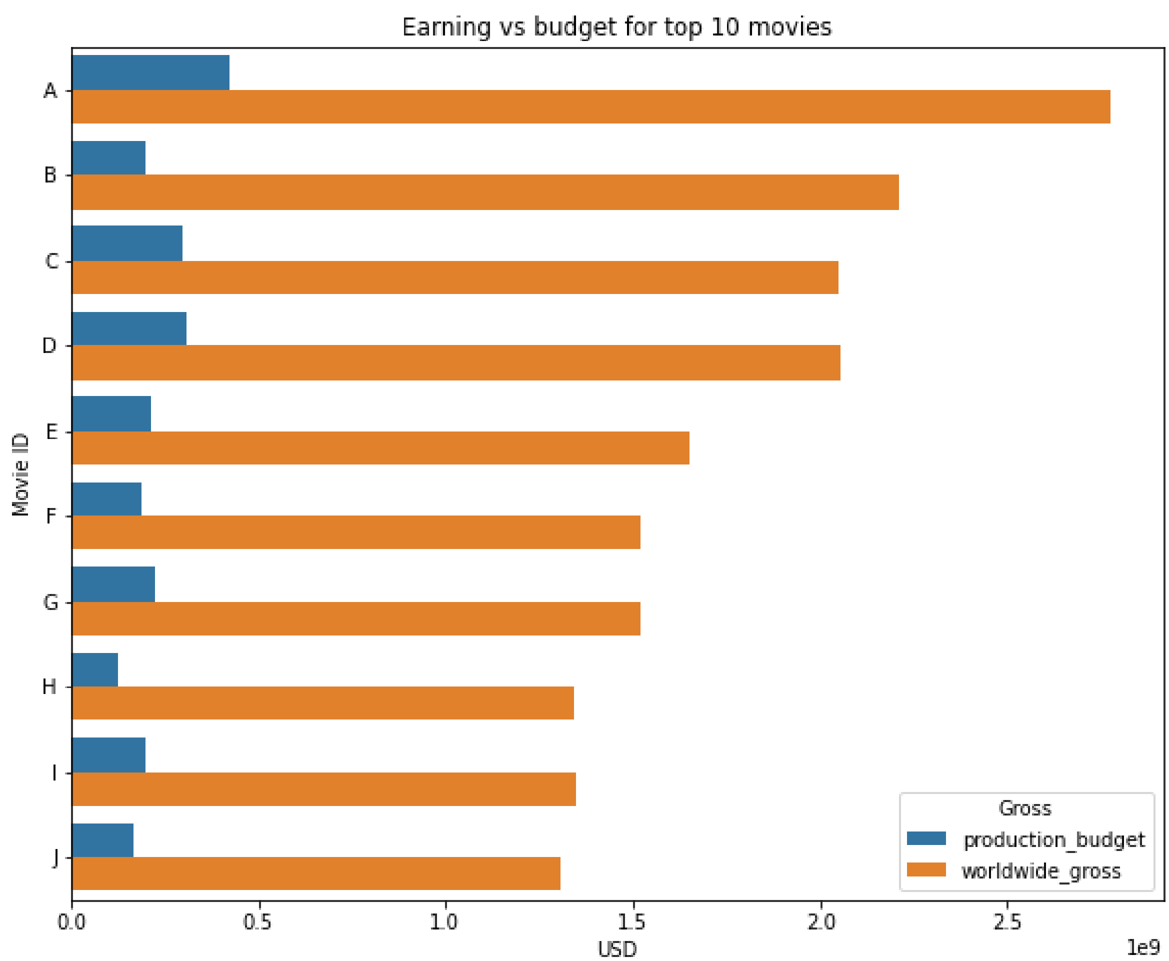


Earning and budget

Exploring other options for the plotting. The movie's name are large, let's try to use an ID, crating a list with the IDs.

- How to use the method stack and how it works for seaborn by [Stefan (https://stackoverflow.com/users/1494637/stefan)](https://stackoverflow.com/users/1494637/stefan) on [Stack**overflow** (https://stackoverflow.com/questions/37174715/using-seaborn-barplot-to-plot-wide-form-dataframes)](https://stackoverflow.com/questions/37174715/using-seaborn-barplot-to-plot-wide-form-dataframes)

In [6]:
```
MovieID = ["A","B","C","D","E","F","G","H","I","J"]
tp2 = tp1

#adding the IDs to the dataframe
tp2["Movie ID"]= MovieID
topten2 = tp2.loc[:,["Movie ID","production_budget", "worldwide_gross"]]

#For this plot we want to plot two values for each movie, so in order to do th
#In this expression the two values join

#First let's set the ID columns as the index
topten2 = topten2.set_index("Movie ID")

#In order to use "hue" we need to chage the structure of the datafram with .st
stopten = topten2.stack().reset_index()

#Settin the columns to the new structured dataframe
stopten.columns = ['Movie ID', 'Gross', 'USD']

fig= plt.subplots(figsize=(10, 8))
seaborn.barplot(y ="Movie ID", x="USD", hue="Gross", data = stopten)
plt.title("Earning vs budget for top 10 movies")
plt.show()
```



Genres of the movies

For the plot above we have the graph but we do not know what is A or B, etc, let's make a new DataFarame which include the name of the movie as well as the director and their categorie, this information was gathered from the `im.db`

Then we got a data frame of the top ten movies with highest earnings and added the genres of each movie, in this way we could find more useful information about those genres.

In [7]:
```
# DataFrame to explain what is A, B, C etc
#First a list with the genres and then the list for directors
genres_tp=["Action, Adventure, Sci-fi, Fantasy",
           "Drama",  "Action, Sci-fi",
           "Action, Sci-fi-, Adventure, Fantasy",
           "Action, Sci-fi-, Thriller, Adventure",
           "Action, Adventure",
           "Action, Fantasy, Adventure, Sci-fi",
           "Adventure, Fantasy, Mystery, Drama",
           "Action, Fantasy, Adventure, Sci-fi",
           "Action, Adventure, Sci-Fi"]

director_tp=["James Cameron", "James Cameron",
             "Anthony Russo, Joe Russo",
             "J.J. Abrams", "Colin Trevorrow",
             "James Wan", "Joss Whedon", "David Yates",
             "Ryan Coogler", "J.A. Bayona"]

#Gather the movie's name list from the previos Df
title = list(tp2["movie"])

#Creating the new Df using .zip()
ID_df=pd.DataFrame(zip(MovieID,title,genres_tp, director_tp),
                   columns = ["MovieID", "Title", "Genre", "Director"])
ID_df.set_index("MovieID")
```

Out[7]:

	Title	Genre	Director
MovieID			
A	Avatar	Action, Adventure, Sci-fi, Fantasy	James Cameron
B	Titanic	Drama	James Cameron
C	Avengers: Infinity War	Action, Sci-fi	Anthony Russo, Joe Russo
D	Star Wars Ep. VII: The Force Awakens	Action, Sci-fi-, Adventure, Fantasy	J.J. Abrams
E	Jurassic World	Action, Sci-fi-, Thriller, Adventure	Colin Trevorrow
F	Furious 7	Action, Adventure	James Wan
G	The Avengers	Action, Fantasy, Adventure, Sci-fi	Joss Whedon
H	Harry Potter and the Deathly Hallows: Part II	Adventure, Fantasy, Mystery, Drama	David Yates
I	Black Panther	Action, Fantasy, Adventure, Sci-fi	Ryan Coogler
J	Jurassic World: Fallen Kingdom	Action, Adventure, Sci-Fi	J.A. Bayona

Now a new table for only the MovieID and the Genre

In [8]:
```
AB_df=pd.DataFrame(zip(MovieID,genres_tp), columns = ["MovieID", "Genre"])
AB_df.set_index("MovieID")
```

Out[8]:

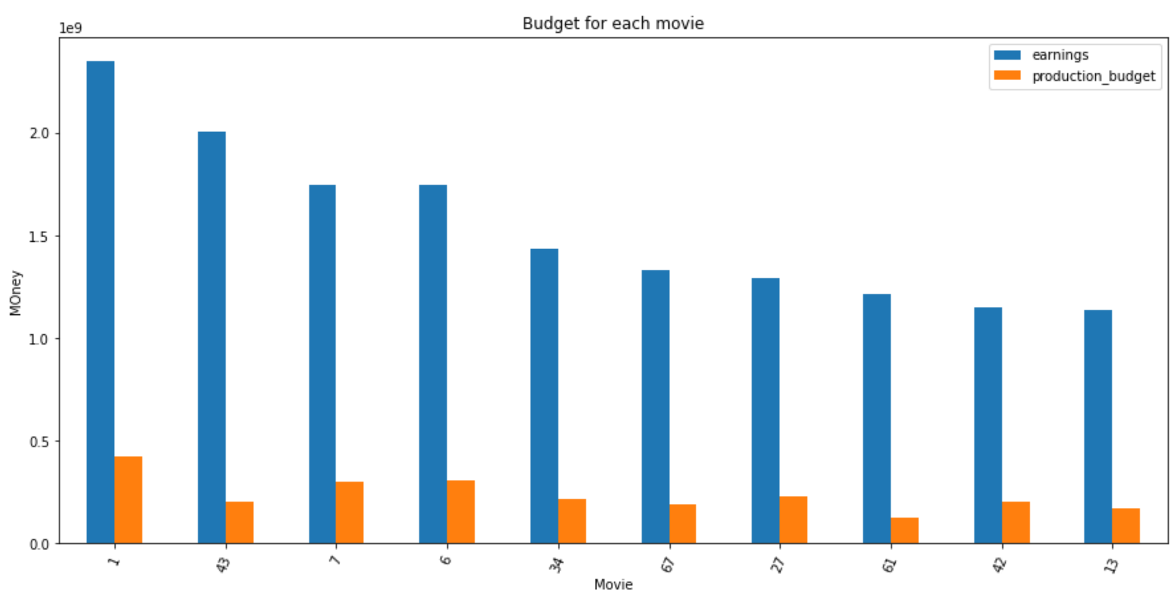
MovieID	Genre
A	Action, Adventure, Sci-fi, Fantasy
B	Drama
C	Action, Sci-fi
D	Action, Sci-fi-, Adventure, Fantasy
E	Action, Sci-fi-, Thriller, Adventure
F	Action, Adventure
G	Action, Fantasy, Adventure, Sci-fi
H	Adventure, Fantasy, Mystery, Drama
I	Action, Fantasy, Adventure, Sci-fi
J	Action, Adventure, Sci-Fi

Plotting whit matplotlib

We also want to see how it sees the plot in matplotlib

In [9]:
```
topten = tp1.loc[:,["movie", "earnings", "production_budget"]]
topten.plot.bar(figsize=(15,7))
plt.xticks(rotation=67)
plt.xlabel('Movie')
plt.ylabel('MOney')
plt.title('Budget for each movie')
```

Out[9]: `Text(0.5, 1.0, 'Budget for each movie')`



🎥🎟 Data Analysis of Categories 🎟 🎥

Why is this data relevant?

- Is important because depends in how much rating and number of votes you can see wich category is more succesful
- With this we can assume wich category is most relevant on these days

Here we can see the average rating of the category with the highest number of votes. The main reason to filter this way is to show that not always the best rated categories are the one who have more votes

In [10]:
```
#Doing the connection
conn = sqlite3.connect('data/im.db')
```

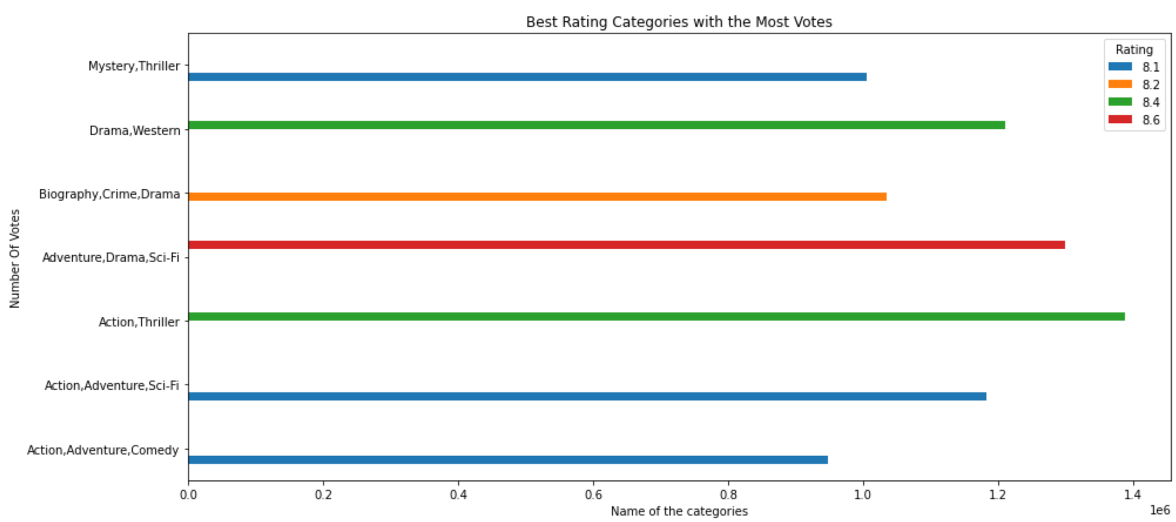
In [11]:
```
pd.read_sql("""
SELECT
    mb.genres AS Category,
    mr.averagerating AS Rating,
    mr.numvotes as NumberVotes
FROM
    movie_basics mb
INNER JOIN
    movie_ratings mr
ON
    mb.movie_id = mr.movie_id
WHERE
    mr.numvotes >= 900000
AND
    mr.averagerating >= 8.1
GROUP BY
    mb.genres
ORDER BY Rating  DESC
;""", conn)
```

Out[11]:

	Category	Rating	NumberVotes
0	Adventure,Drama,Sci-Fi	8.6	1299334
1	Drama,Western	8.4	1211405
2	Action,Thriller	8.4	1387769
3	Biography,Crime,Drama	8.2	1035358
4	Mystery,Thriller	8.1	1005960
5	Action,Adventure,Sci-Fi	8.1	1183655
6	Action,Adventure,Comedy	8.1	948394

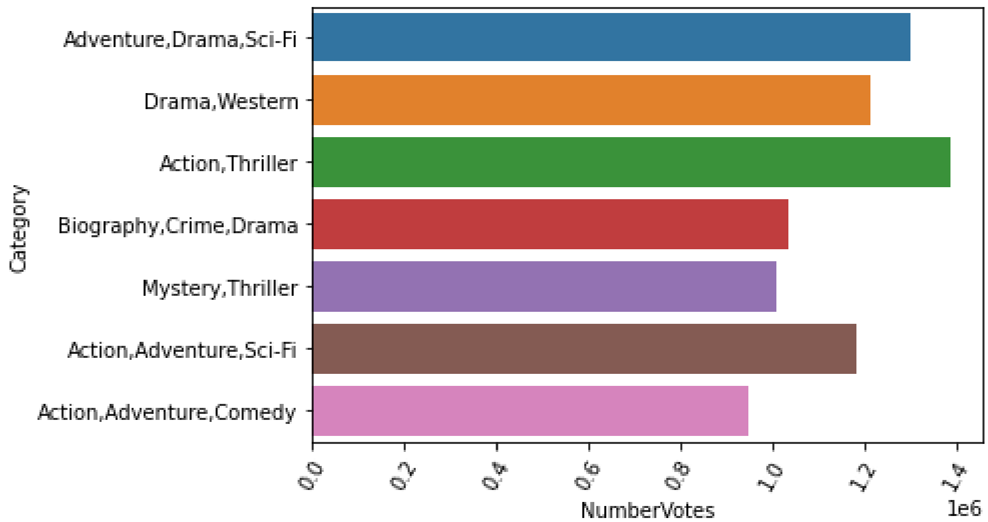
In the next graphic we can see that the best rating category is not the one that have the most votes.With that in mind we need to hear more to the audience to see what is the best option. Here I prefered to use matplotib only to show you the 3 main values and see the difference between them

In [12]:
```
q= """
SELECT
    mb.genres AS Category,
    mr.averagerating AS Rating,
    mr.numvotes as NumberVotes
FROM
    movie_basics mb
INNER JOIN
    movie_ratings mr
ON
    mb.movie_id = mr.movie_id
WHERE
    mr.numvotes >= 900000
AND
    mr.averagerating >= 8.1
GROUP BY
    mb.genres
ORDER BY
    Rating  DESC
;
"""
df=pd.read_sql(q, conn)
df.pivot(index='Category',columns='Rating',values='NumberVotes').plot(kind='b
plt.xlabel('Name of the categories')
plt.ylabel('Number Of Votes')
plt.title('Best Rating Categories with the Most Votes')
plt.show()
```



Now that we can see that not always the best rating category have the most votes so with that in mind we will see in the next graphic that only ***Action and Thriller are the two with the most votes but they are together****, What if we only want to see the best categories with the most votes? We will see it after that!*

In [13]:
```
seaborn.barplot(data=df, x="NumberVotes", y="Category")
plt.xticks(rotation=60)
plt.show()
```



First we need to filter the data between 900000 votes (the main reason we use this value is because the highest number of votes are 1800000)

In [14]:
```
df4=pd.read_sql("""
SELECT
    mb.genres AS Category,
    mr.averagerating AS Rating
FROM
    movie_basics mb
INNER JOIN
    movie_ratings mr
ON
    mb.movie_id = mr.movie_id
WHERE
    mr.numvotes >= 900000 AND mr.averagerating >= 8.1
""", conn)
df4
```

Out[14]:

	Category	Rating
0	Mystery,Thriller	8.1
1	Action,Thriller	8.4
2	Adventure,Drama,Sci-Fi	8.6
3	Action,Adventure,Comedy	8.1
4	Drama,Western	8.4
5	Biography,Crime,Drama	8.2
6	Action,Adventure,Sci-Fi	8.1
7	Action,Adventure,Sci-Fi	8.8

Then we are going to make the split of the values just to count the most voted ones!

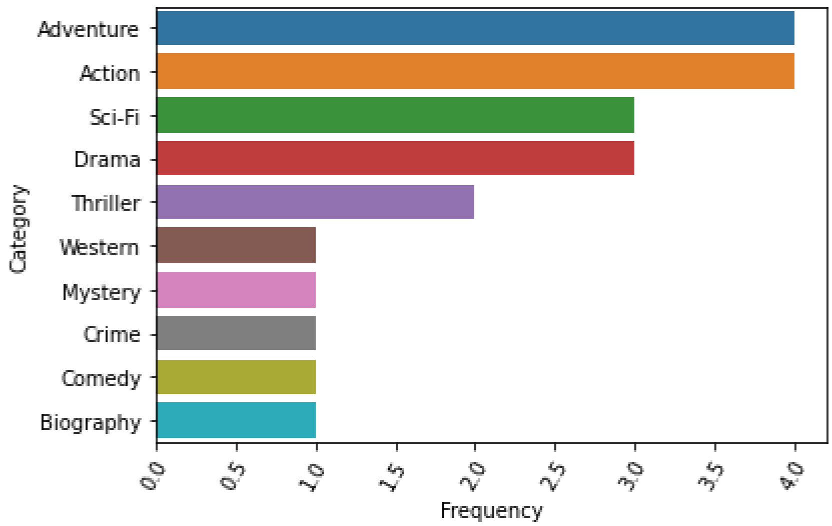
In [15]:
```
#We separete the values with the methon split by the commas
categories_cols = df4['Category'].str.split(',',expand=True)

#Adding the columns in wich the genre will split
categories_cols.columns = ['genre1','genre2','genre3']

#for each category we need to sum each time the same appear
counts1=categories_cols['genre1'].value_counts()
counts2=categories_cols['genre2'].value_counts()
counts3=categories_cols['genre3'].value_counts()

total_counts = counts1.add(counts2, fill_value=0).add(counts3, fill_value=0)

#Gathering the count in a dataframe and sorting them
one_category = total_counts.sort_values(ascending=False)
one_category.index

#Now we can create the dataframe with the frecuency of each category
dfone=pd.DataFrame(list(zip(one_category.values, one_category.index)),
                   columns = ["Frequency", "Category"])
dfone.head(5)
```

Out[15]:

	Frequency	Category
0	4.0	Adventure
1	4.0	Action
2	3.0	Sci-Fi
3	3.0	Drama
4	2.0	Thriller

In the next graphic we will show you the top 5 of the most voted categories!

In [16]:
```
seaborn.barplot(data=dfone, x="Frequency", y="Category")
plt.xticks(rotation=60)
plt.show()
```

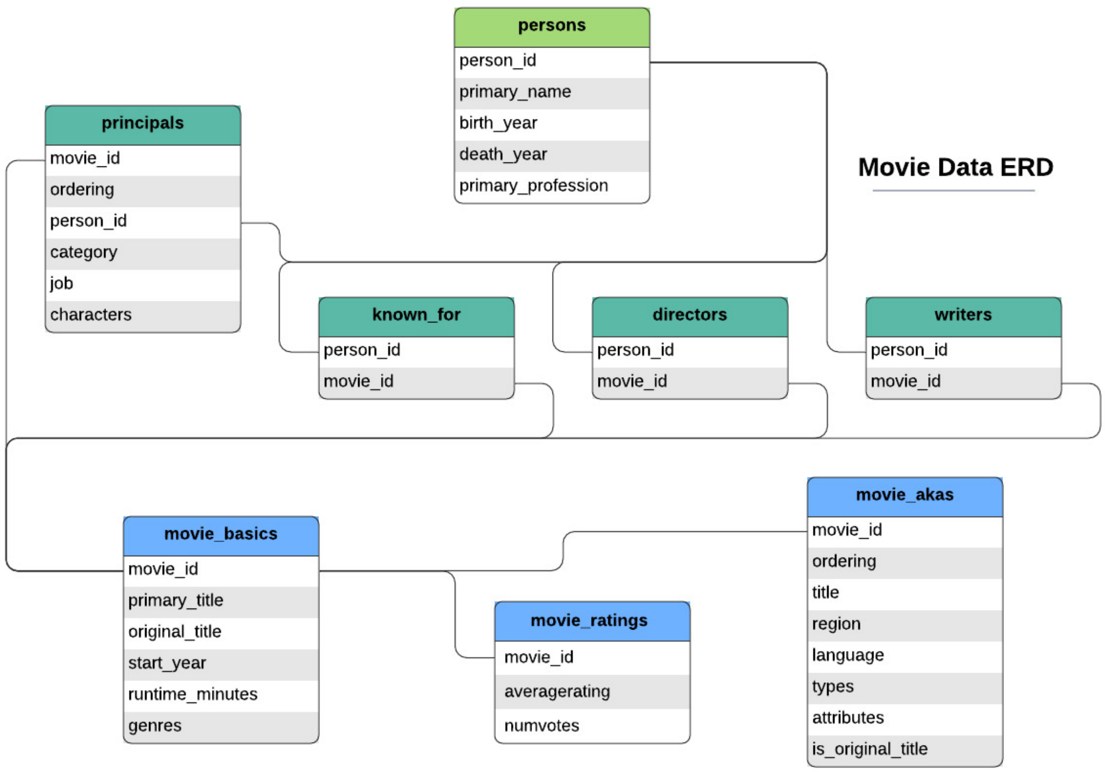


Our main value is the number of votes because this votes are provided by the community and the rating are provided by movie critics or people that is related with producers and movies.So if you want to be in this trend, you should make with our top 5!

🎬 👨 Data Analysis Directors 👩 🎬

We filtered the im.db database to only select directors that have a 7 or higher average rating for their body of work and over 400,000 votes on their films then limited the query to the top 20 in order of highest rating. On the next graph you will see that we worked on getting the Categories and film names for those top 20 directors. but the categories are grouped together i.e "action,adventure,drama".

In reference to:



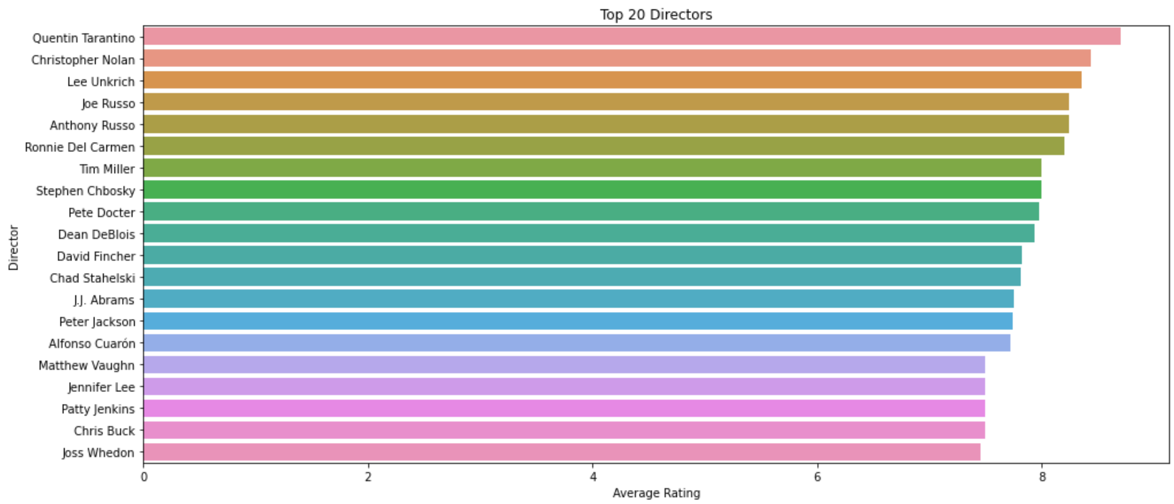
In [17]:
```
avg_rating = """
SELECT
    person_id ,
    primary_name as Director ,
    COUNT(DISTINCT directors.movie_id) as "MoviesMade",
SUM
    (movie_ratings.averagerating) /
COUNT
    (movie_ratings.averagerating) as "Average Rating",
    movie_ratings.numvotes as numvotes
FROM
    persons
    JOIN
        directors
    USING
        (person_id)
        JOIN
            movie_basics
        USING
            (movie_id)
            JOIN
                movie_ratings
            USING
                (movie_id)
GROUP BY
    person_id
HAVING
    "Average Rating" >= 7.0
AND
    numvotes >= 400000
ORDER BY
    "Average Rating" DESC
LIMIT 20

;
"""
pd.read_sql(avg_rating, conn)
```

Out[17]:

	person_id	Director	MoviesMade	Average Rating	numvotes
0	nm0000233	Quentin Tarantino	4	8.700000	1211405
1	nm0634240	Christopher Nolan	4	8.437500	1299334
2	nm0881279	Lee Unkrich	2	8.350000	682218
3	nm0751648	Joe Russo	4	8.246667	666252
4	nm0751577	Anthony Russo	4	8.246667	666252
5	nm0215455	Ronnie Del Carmen	1	8.200000	536181
6	nm1783265	Tim Miller	1	8.000000	820847
7	nm0154716	Stephen Chbosky	2	8.000000	422671
8	nm0230032	Pete Docter	2	7.977778	536181
9	nm0213450	Dean DeBlois	3	7.940000	611299
10	nm0000399	David Fincher	3	7.820000	568578
11	nm0821432	Chad Stahelski	3	7.816667	449942
12	nm0009190	J.J. Abrams	3	7.755556	445535
13	nm0001392	Peter Jackson	4	7.743750	719629
14	nm0190859	Alfonso Cuarón	2	7.725000	710018
15	nm0891216	Matthew Vaughn	4	7.500000	497363
16	nm1601644	Jennifer Lee	1	7.500000	516998
17	nm0420941	Patty Jenkins	1	7.500000	487527
18	nm0118333	Chris Buck	1	7.500000	516998
19	nm0923736	Joss Whedon	3	7.455556	1183655

Here is the graph with the top 20 directors with their average ratings. In the following function we ran a query to see what directors have a overall high average rating about 7 as well as a high number of votes to eliminate high rating but low voting outliers. We organized it into a top 20 by average rating of their movies made in descending order from highest to lowest.

In [18]:
```
top_20_directors = pd.read_sql(avg_rating , conn)
fig = plt.subplots(figsize = (16,7))
seaborn.barplot(data=top_20_directors,
            x="Average Rating" , y= "Director", orient="h")

plt.title("Top 20 Directors")

plt.show()
```



Query for top 20 Director in terms of votes and the categories of the films

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In the following function we ran a query for the top 20 directors in term of number of votes and the catergories of the films they have directed. In order to see the patterns of categories for these directors.

In [19]:
```
df4=pd.read_sql("""
SELECT
    mb.genres AS Category,
    mr.averagerating AS Rating ,
    mb.movie_id,
    p.primary_name AS Directors,
    mb.primary_title
FROM
    movie_basics mb
INNER JOIN
    movie_ratings mr
ON mb.movie_id = mr.movie_id
    INNER JOIN
        directors d
    ON mb.movie_id = d.movie_id
        INNER JOIN
            persons p
        ON d.person_id = p.person_id
WHERE
    mr.numvotes >= 600000
GROUP BY
    mb.movie_id
ORDER BY
    p.primary_name
LIMIT 20
""", conn)
df4
```

Out[19]:

	Category	Rating	movie_id	Directors	primary_title
0	Action,Adventure,Biography	8.0	tt1663202	Alejandro G. Iñárritu	The Revenant
1	Drama,Sci-Fi,Thriller	7.7	tt1454468	Alfonso Cuarón	Gravity
2	Action,Adventure,Sci-Fi	7.8	tt1843866	Anthony Russo	Captain America: The Winter Soldier
3	Action,Adventure,Sci-Fi	8.5	tt4154756	Anthony Russo	Avengers: Infinity War
4	Action,Adventure,Sci-Fi	8.0	tt1877832	Bryan Singer	X-Men: Days of Future Past
5	Adventure,Drama,Sci-Fi	8.6	tt0816692	Christopher Nolan	Interstellar
6	Action,Thriller	8.4	tt1345836	Christopher Nolan	The Dark Knight Rises
7	Action,Adventure,Sci-Fi	8.8	tt1375666	Christopher Nolan	Inception
8	Drama,Music	8.5	tt2582802	Damien Chazelle	Whiplash
9	Drama,Thriller	8.0	tt0947798	Darren Aronofsky	Black Swan
10	Drama,Mystery,Thriller	8.1	tt2267998	David Fincher	Gone Girl
11	Comedy,Drama,Romance	7.7	tt1045658	David O. Russell	Silver Linings Playbook
12	Adventure,Drama,Fantasy	8.1	tt1201607	David Yates	Harry Potter and the Deathly Hallows: Part 2
13	Action,Adventure,Animation	8.1	tt0892769	Dean DeBlois	How to Train Your Dragon
14	Action,Adventure,Sci-Fi	7.2	tt1392170	Gary Ross	The Hunger Games
15	Action,Adventure,Sci-Fi	8.1	tt1392190	George Miller	Mad Max: Fury Road
16	Action,Adventure,Fantasy	8.0	tt2488496	J.J. Abrams	Star Wars: Episode VII - The Force Awakens
17	Action,Adventure,Comedy	8.1	tt2015381	James Gunn	Guardians of the Galaxy
18	Action,Adventure,Sci-Fi	6.9	tt0458339	Joe Johnston	Captain America: The First Avenger
19	Action,Adventure,Sci-Fi	7.0	tt1228705	Jon Favreau	Iron Man 2

Organizing splitting categories

In the following section we split up the categories section of the dataframe to seperate the categories into individual rows and seeing the frequency.

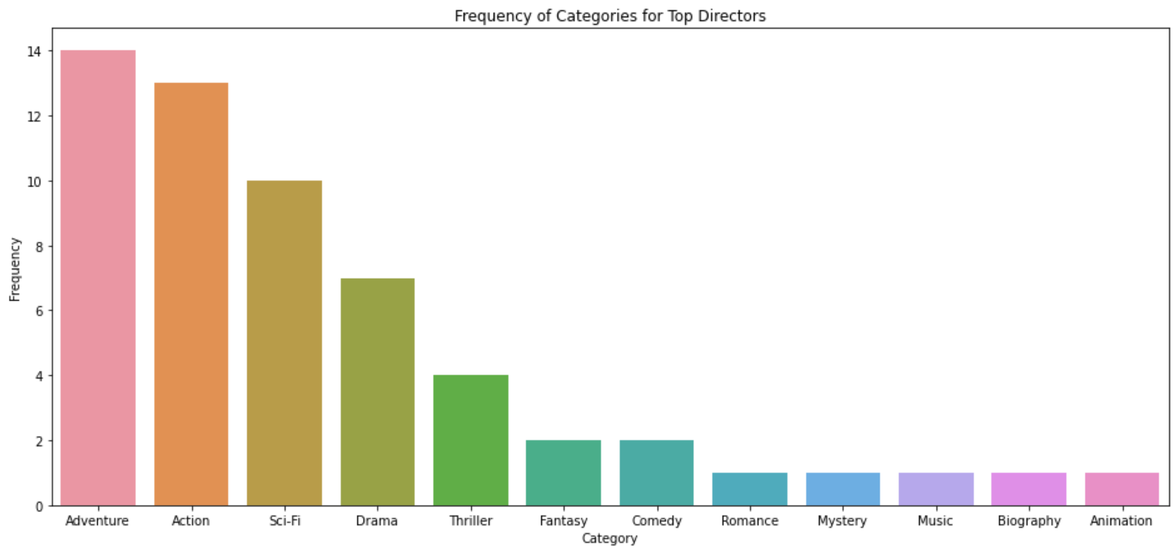
In [20]:
```
#splitting the category string into individual categories
genres_cols = df4['Category'].str.split(',',expand=True)

#Here we are going to do te same process as we did for the frecuency for each
genres_cols.columns = ['genre1','genre2','genre3']
counts1=genres_cols['genre1'].value_counts()
counts2=genres_cols['genre2'].value_counts()
counts3=genres_cols['genre3'].value_counts()

total_counts = counts1.add(counts2, fill_value=0).add(counts3, fill_value=0)
one_category = total_counts.sort_values(ascending=False)
one_category.index

# making a list of the zip with two columns of frequency and category
cat_freq=pd.DataFrame(list(zip(one_category.values, one_category.index)),
                      columns = ["Frequency", "Category"])
cat_freq
```

Out[20]:

	Frequency	Category
0	14.0	Adventure
1	13.0	Action
2	10.0	Sci-Fi
3	7.0	Drama
4	4.0	Thriller
5	2.0	Fantasy
6	2.0	Comedy
7	1.0	Romance
8	1.0	Mystery
9	1.0	Music
10	1.0	Biography
11	1.0	Animation

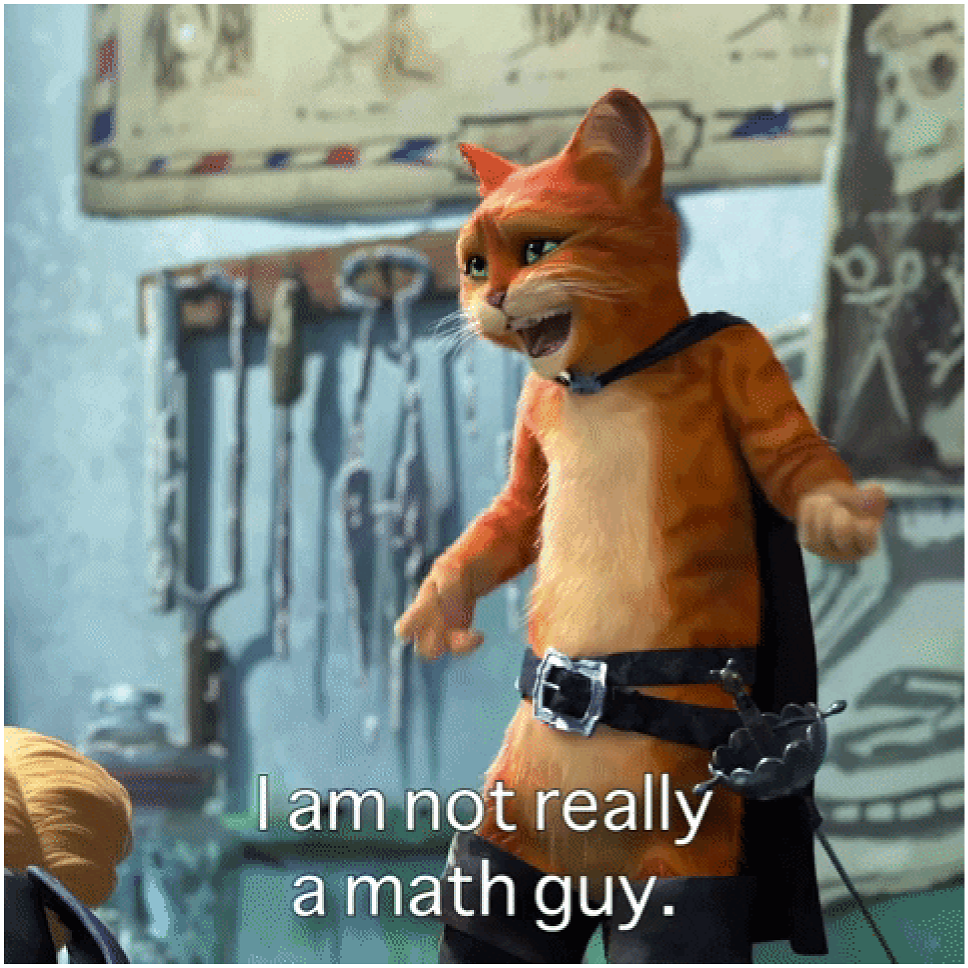
So, in the next graph we then seperated those categories into individual strings and also listed the frequency showing that Adventure, Action, and Sci-fi were the top three most highly voted and rated categories for these directors.

In [21]:
```
fig = plt.subplots(figsize = (16,7))
seaborn.barplot(data=cat_freq, x="Category" , y= "Frequency")

plt.title("Frequency of Categories for Top Directors")

plt.show()
```



We filtered and sorted the data from the im.db database to extract various queries. We would recommend the client select a director such as one of the 20 we showed in the graph above due to their history of highly rated movies with a high number of votes in the category of either Adventure, Action , or Sci-Fi showing that it is popular amongst the population.

📈 Statistical insights📈



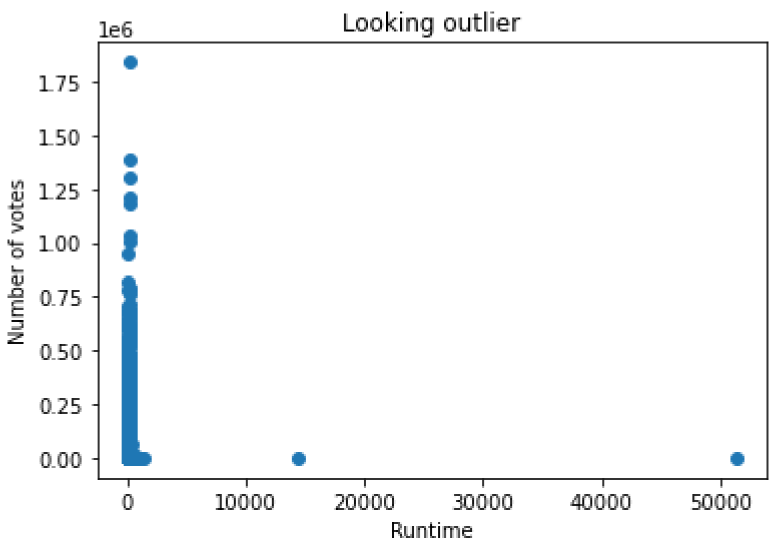
Our first query is for the poblation, so we do not want null values, lets exclude them. In reference to the previous ERD we could know what table join and what is the key

In [22]:
```
prueba= pd.read_sql("""
SELECT
    mb.runtime_minutes, mr.numvotes,
    mr.averagerating,  mb.original_title, mb.genres
  FROM
      movie_basics mb
  JOIN
      movie_ratings mr USING(movie_id)
  WHERE
      mb.runtime_minutes AND mb.genres IS NOT Null
  ;
""", conn)
#prueba.info()
```

Ok, now we are sure we have no null values in the columns of our interest, also we can confirm by putting `prueba.info()` because it load as a dataframe, but maybe we have outlier, so in order to check that we can see the sactter between the `numvotes` and `runtime`

In [23]:
```
#In order to see the correlation we need the columns of runtime and votes as
prueba_run=list(prueba["runtime_minutes"])
prueba_numv=list(prueba["numvotes"])


fig, ax = plt.subplots()
#We use the method scatter
ax.scatter(prueba_run, prueba_numv)

#Setting labels and title
ax.set_title("Looking outlier")
ax.set_xlabel("Runtime")
ax.set_ylabel("Number of votes")
```

Out[23]:
```
Text(0, 0.5, 'Number of votes')
```



We can see there is outliers in our data in runtime as well as in Number of votes, according to `prueba.info()` we have 65720 rows, so we actually do not need this data, let's exclude them in our query, in the chart below we can have and idea of this limits.

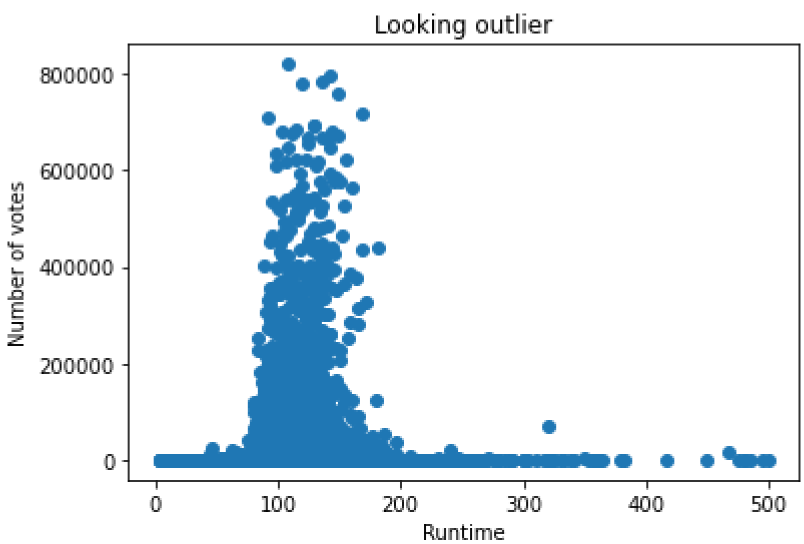
Poblation

In [24]:
```
poblation= pd.read_sql("""
SELECT
    mb.runtime_minutes, mr.numvotes,
    mr.averagerating,  mb.original_title, mb.genres
  FROM
      movie_basics mb
  JOIN
      movie_ratings mr USING(movie_id)
  WHERE
      mb.runtime_minutes AND mb.genres IS NOT Null
  AND
      mr.numvotes < 948394
  AND
      mb.runtime_minutes < 600
  ORDER
      BY mr.numvotes DESC
  ;""", conn)
```

Let's confirm we do not have outliers anymore

In [25]:
```
sc_p_run=list(poblation["runtime_minutes"])
sc_p_nv=list(poblation["numvotes"])


fig, ax = plt.subplots()
#We use the method scatter
ax.scatter(sc_p_run, sc_p_nv)

#Setting labels and title
ax.set_title("Looking outlier")
ax.set_xlabel("Runtime")
ax.set_ylabel("Number of votes")
```

Out[25]:
```
Text(0, 0.5, 'Number of votes')
```



Ok, this data is cotinuos now :D, let's set our sample:

Sample

For this query we want to set the proposed interval of time 90-130 minutes

In [26]:
```
condition= pd.read_sql("""
SELECT
    mb.runtime_minutes,
    mr.numvotes, mr.averagerating
FROM
    movie_basics mb
JOIN
    movie_ratings mr USING(movie_id)
WHERE
    mb.runtime_minutes
AND
    mb.genres IS NOT Null
AND
    mb.runtime_minutes < 130
AND
    mb.runtime_minutes > 90
AND
    mr.numvotes < 948394
ORDER BY
    mb.runtime_minutes DESC
  ;
""", conn)
```

But this is not our actual sample because in order to be a sample we need to choose random data from `condition`

In [27]:
```
sample1=condition.sample(650)
```

In [28]:
```
sample_1=sample1.copy()
```

Ok, now let's set our hypothesis:

- H_a : The mean of the number of votes when a movie has a runtime between 90 and 130 is significantly bigger than the mean of all the movies in our dataset.
- H_0 : There is no significantly difference between the sample mean and the poblation mean.
- α = 0.05.

Z-score

We can know the mean and standard desviation of our poblation and sample, let's get them

In [29]:
```
#In advance we can see the basics for our sample and poblation
poblation.describe(), sample_1.describe()
```

Out[29]:
```
(       runtime_minutes       numvotes  averagerating
 count     65702.000000   65702.000000   65702.000000
 mean         93.635064    3804.866427       6.320407
 std          23.713557   28903.896286       1.458682
 min           3.000000       5.000000       1.000000
 25%          81.000000      16.000000       5.500000
 50%          91.000000      62.000000       6.500000
 75%         104.000000     352.000000       7.300000
 max         500.000000  820847.000000      10.000000,
        runtime_minutes       numvotes  averagerating
 count      650.000000     650.000000     650.000000
 mean       103.107692    6165.038462       6.322000
 std          9.923316   34433.896394       1.275993
 min         91.000000       5.000000       1.700000
 25%         95.000000      26.000000       5.500000
 50%        100.000000     114.000000       6.400000
 75%        110.000000     738.000000       7.200000
 max        129.000000  452036.000000       9.600000)
```

In [30]:
```
#For the pupulation
p_mean=poblation["numvotes"].mean()
p_std=poblation["numvotes"].std()

#For the sample
s_mean=sample_1["numvotes"].mean()
s_std=sample_1["numvotes"].std()

#Z equation
z = (s_mean - p_mean)/(p_std/np.sqrt(650))

#P-value:
#Positive z
p_value=1 - stats.norm.cdf(z)

#Negative z
#p_value=1 - stats.norm.cdf(z)

print("Z is equal to: " + str(z) + "\n And p-value: " +str(p_value) )
```

```
Z is equal to: 2.0818236993844654
 And p-value: 0.018679288093761737
```

With this P-value we was able to reject the Null Hypothesis and we can conclude if the movie has a runtime between 90 and 130 minutes will get bigger number of votes.

In [ ]:
```

```