Project 01: Analysis of the tmdb database

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Introduction

Dataset Description

> This data set contains information about 10866 movies collected between years 1960 and 2015 from The Movie Database (TMDb).It contains 21 columns with informations about genre, budget,revenue, cast, popularity rating, average vote, vote count, keyword, tagline etc of each movie. this analysis will be looking at the general characteristics of profitable and unprofitable movies (which may also be reffered to as loss movies for the most part) over the decades focusing on budget and popularity rating.

Question(s) that can be answered with the dataset

> what percentage of the movies made profit or loss
>
> how does movies profit changes across release seasons
>
> relationship between popularity and profit
>
> which production companies are most successful what genres made the most profit

In [1]:
```
#importing packages  planned to use.
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import seaborn
% matplotlib inline
```

In [2]:
```
# Upgrade pandas to use dataframe.explode() function.
#!pip install --upgrade pandas==0.25.0
```

Data Wrangling

In [3]:
```
# Loading dataset and inspecting properties
df_movies = pd.read_csv('tmdb-movies.csv')
df_movies.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
```

Data Cleaning

> based on observations of the dataset and intended exploration, these following cleaning steps will be taken on the dataset
>
> ***1 drop unwanted columns***
>
> the following columns will be dropped from the datasset since they don't contain any variable I intend to explore based on the questions above :

column name	drop reason
tmdb_id	we already have an id column
budget	hasn't been corrected for inflation
revenue	hasn't been corrected for inflation
homepage	not relevant for the analysis
tagline	not relevant for the analysis
keyword	not relevant for the analysis
overview	not relevant for the analysis
id	not relevant for the analysis

fix null rows

> the null cells are only present in 'cast', 'director' and 'production_company' columns and they will be filled with 'unknown' since they are not the main variables for this analysis. every other column with null rows will have been dropped

fix data type

> change 'release_date' columns type from strng to date and format numbers columns as int

create a profits and profit rank column

> subracting budget_adj from revenue_adj to get a profits column as main variable a profit rank columnn will be created for easy referencing

In [4]:
```
# 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.
# dropping unwanted columns
df_movies.drop(['imdb_id', 'budget', 'revenue', 'homepage', 'keywords', 'tagline', 'overview','id'], axis = 1, inplace = True)
df_movies.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10866 entries, 0 to 10865
Data columns (total 13 columns):
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
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(3), object(6)
memory usage: 1.1+ MB
```

In [5]:
```
#fixing null rows
#filling null rows with 'unknown' in columns 'cast', 'director','genres'and 'production_companies'
df_movies['cast'].fillna('unknown', inplace = True)
df_movies['director'].fillna('unknown', inplace = True)
df_movies['genres'].fillna('unknown', inplace = True)
df_movies['production_companies'].fillna('unknown', inplace = True)
#confirming for null values
df_movies.isnull().sum().any()
```

Out[5]:
```
False
```

In [6]:
```
#adding a profits column
df_movies['profits']= df_movies.revenue_adj-df_movies.budget_adj
```

In [7]:
```
#adding a profit rank column
df_movies.sort_values(by='profits',ascending=False,inplace=True)
df_movies['profit_rank']= df_movies.profits.reset_index().index +1
df_movies.head(5)
```

Out[7]:

	popularity	original_title	cast	director	runtime	g
1329	12.037933	Star Wars	Mark Hamill|Harrison Ford|Carrie Fisher|Peter ...	George Lucas	121	Adventure|Action|Science
1386	9.432768	Avatar	Sam Worthington|Zoe Saldana|Sigourney Weaver|S...	James Cameron	162	Action|Adventure|Fantasy|S
5231	4.355219	Titanic	Kate Winslet|Leonardo DiCaprio|Frances Fisher|...	James Cameron	194	Drama|Romance|
10594	2.010733	The Exorcist	Linda Blair|Max von Sydow|Ellen Burstyn|Jason ...	William Friedkin	122	Drama|Horror|
9806	2.563191	Jaws	Roy Scheider|Robert Shaw|Richard Dreyfuss|Lorr...	Steven Spielberg	124	Horror|Thriller|Adv

In [8]:
```
#changing release_date column's data type to date
df_movies.release_date =df_movies.release_date.astype('datetime64')
df_movies.profits =df_movies.profits.astype('int64')
df_movies.budget_adj =df_movies.budget_adj.round(0).astype('int64')
df_movies.revenue_adj =df_movies.revenue_adj.round(0).astype('int64')
#confirming changes
#df_movies.dtypes[['release_date','profits','budget_adj','revenue_adj']]
df_movies.head()
```

Out[8]:

	popularity	original_title	cast	director	runtime	g
1329	12.037933	Star Wars	Mark Hamill|Harrison Ford|Carrie Fisher|Peter ...	George Lucas	121	Adventure|Action|Science
1386	9.432768	Avatar	Sam Worthington|Zoe Saldana|Sigourney Weaver|S...	James Cameron	162	Action|Adventure|Fantasy|S
5231	4.355219	Titanic	Kate Winslet|Leonardo DiCaprio|Frances Fisher|...	James Cameron	194	Drama|Romance|
10594	2.010733	The Exorcist	Linda Blair|Max von Sydow|Ellen Burstyn|Jason ...	William Friedkin	122	Drama|Horror|
9806	2.563191	Jaws	Roy Scheider|Robert Shaw|Richard Dreyfuss|Lorr...	Steven Spielberg	124	Horror|Thriller|Adv

Exploratory Data Analysis

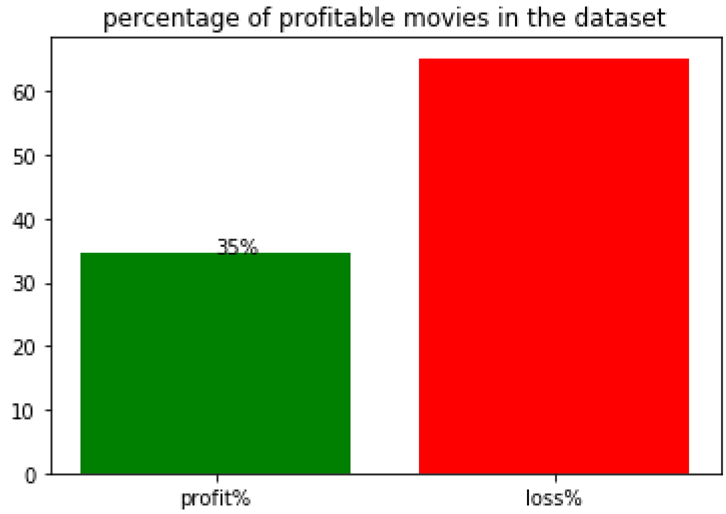
Research Questions

Question 1

How has movie finance changed throughout the dataset

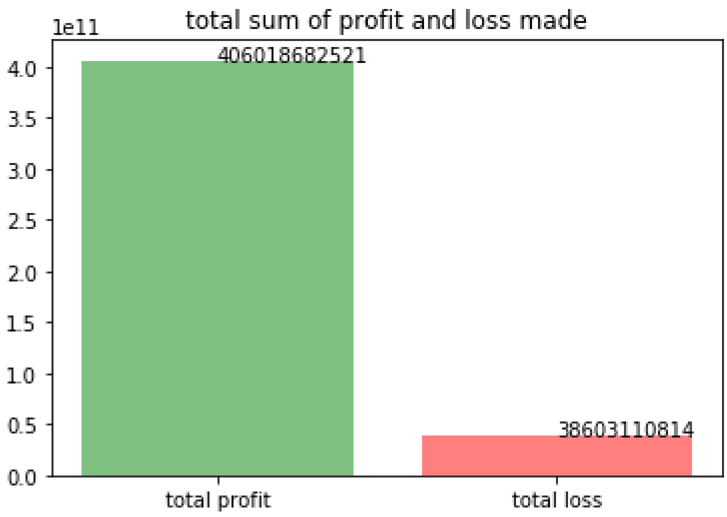
In [9]:
```
#the dataset will eventually be segmented into decades for easier analysis
#           QUESTION 1.1
#what percentage of movies in the dataset made a profit
profit = df_movies.profits>=1
loss = df_movies.profits< 1
p= (df_movies[profit].shape[0]/df_movies.shape[0])*100
l= (df_movies[loss].shape[0]/df_movies.shape[0])*100
plt.bar([1,2],[p,l],tick_label=['profit%','loss%'],color=['green','red'])
plt.title('percentage of profitable movies in the dataset')
plt.text(1,p,str(round(p))+'%')
```

Out[9]:
```
Text(1,34.7138,'35%')
```



In [10]:
```
#       Question1.2
# how much is the total profit and loss madecfor all movies in the dataset
height1 = [df_movies[profit].sum().profits, -1*(df_movies[loss].sum().profi
ts)]
plt.bar([1,2], height1 ,color=['green','red'],tick_label=['total profit','t
otal loss'],alpha =.5)
plt.text(1,height1[0],str(height1[0]))
plt.text(2,height1[1],str(height1[1]))
plt.title('total sum of profit and loss made')
```

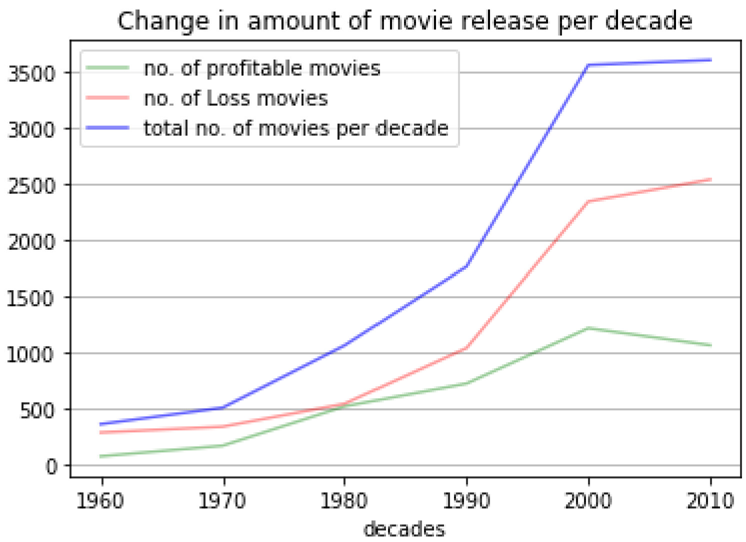
Out[10]:
```
Text(0.5,1,'total sum of profit and loss made')
```



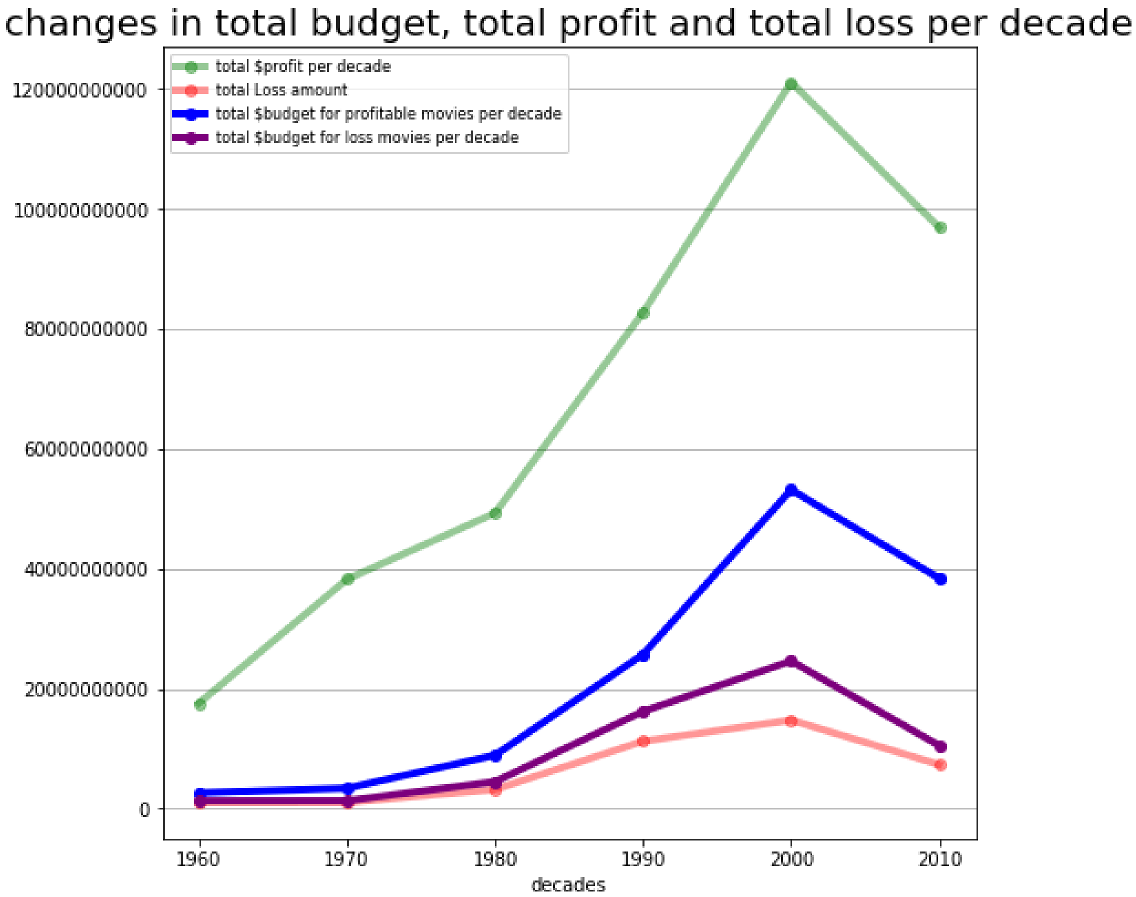
In [11]:
```
#total profit to total loss ratio
r = height1[0]/height1[1]
r
```

Out[11]:
```
10.517771080090032
```

In [12]:
```
#       QUESTION 1.4
# Which decade has the highest number of profitable movies?
# NUMBER OF MOVIES THAT MADE PROFIT OR LOSS PER RELEASE DECADE
# we'll have to create a decade's column from the release_year
list1= [np.arange(1960,1970,1),np.arange(1970,1980,1),np.arange(1980,1990,
1),np.arange(1990,2000,1),np.arange(2000,2010,1),np.arange(2010,2020,1)]
def decade(d) :
    if d in list1[0]:
        return 1960
    elif d in list1[1]:
        return 1970
    elif d in list1[2]:
        return 1980
    elif d in list1[3]:
        return 1990
    elif d in list1[4]:
        return 2000
    elif d in list1[5]:
        return 2010
    else:
        return 2020
df_movies['decades'] = df_movies.release_year.apply(lambda x: decade(x))
df_movies[profit].groupby('decades')['original_title'].count().plot(kind='l
ine',color='green',label='no. of profitable movies',alpha=.4);
df_movies[loss].groupby("decades")['original_title'].count().plot(kind='lin
e',color='red',alpha=.4,label='no. of Loss movies');
df_movies.groupby('decades').original_title.count().plot(kind='line',color
='blue',alpha=.6,label='total no. of movies per decade');
plt.legend()
plt.title('Change in amount of movie release per decade')
plt.grid(axis='y')
```



In [13]:
```
#            QUESTION 1.5:
# How has the total profit, loss and budget changed per decade
plt.figure(figsize=(8,8))
#plotting for total profit pre decade
prof_perdec = df_movies[profit].groupby('decades')['profits'].sum()
prof_perdec.plot(kind='line',marker='o',color='green',label='total $profit
per decade',alpha=.4,linewidth=4);

#total loss will be converted to positive values so that they can be on the
same axis on the chart
pos_loss= df_movies[loss].groupby('decades')['profits'].sum()
pos_loss= pos_loss* -1
pos_loss.plot(kind='line',marker ='o',color='red',alpha=.4,label='total Los
s amount',linewidth=4);

#plotting budget for profitable movies per decade
profbudg_perdec=df_movies[profit].groupby('decades')['budget_adj'].sum()
profbudg_perdec.plot(kind='line',marker='o',color='blue',label='total $budg
et for profitable movies per decade',linewidth=4)

# plotting budget for loss movies per decade
lossbudg_perdec=df_movies[loss].groupby('decades')['budget_adj'].sum()
lossbudg_perdec.plot(kind='line',marker='o',color='purple',label='total $bu
dget for loss movies per decade',linewidth=4)
plt.title('changes in total budget, total profit and total loss per decad
e',fontsize=20)
plt.legend(fontsize=8)
plt.ticklabel_format(style='plain')
plt.grid(axis='y')


#I tried adding value to each point on the plot, ended up with this code bl
ock but still failed :

#adding values to the line plot for better understanding
# the series used in plotting will be converted to lists first
####     a=prof_perdec.tolist()
####     b=pos_loss.tolist()
####     c=profbudg_perdec.tolist()
####     d=lossbudg_perdec.tolist()
####     plotlist =[a,b,c,d]
####     for i in plotlist :
####         for j,p in enumerate(i):
####             plt.text(j,p,str(p))
```



Answer to q1 how has movie finance changed

Only 34.7% of all movies released turned a profit. Despite this fact the Total profit made from these profitable movies each decade is always twice as much as their budget and 3 times the loss from other unprofitable movies for each decade. Generally the total profit to total loss ratio is 1:1051, while only ~35% of the total movies released was profitable. we saw a general correlation between budget and profit/loss

QUESTION 2

which production companies have been most successful throughout the decade

In [14]:
```
#checking out the production company column
df_movies.production_companies.head()
#production companies might be abbreviated as pc when creating related vari
ables throughout this section for easy reference
```

Out[14]:
```
1329      Lucasfilm|Twentieth Century Fox Film Corporation
1386     Ingenious Film Partners|Twentieth Century Fox ...
5231     Paramount Pictures|Twentieth Century Fox Film ...
10594                         Warner Bros.|Hoya Productions
9806            Universal Pictures|Zanuck/Brown Productions
Name: production_companies, dtype: object
```

In [15]:
```
#           Question 2.1
#  which set of production companies column produced the most movies in the
dataset

df_movies.production_companies.value_counts()[1:6]
```

Out[15]:
```
Paramount Pictures           156
Universal Pictures           133
Warner Bros.                  84
Walt Disney Pictures          76
Metro-Goldwyn-Mayer (MGM)     72
Name: production_companies, dtype: int64
```

Quick notice

for this question, some movies were co produced by multiple companies . This will not be Split into individual companies because every collaboration represents a unique effort and by splitting, some companies might end up taking all the credit for a movie they contributed the least to.

In [16]:
```
# creating decade selection variable
d1960 = df_movies.decades == 1960
d1970 = df_movies.decades == 1970
d1980 = df_movies.decades == 1980
d1990 = df_movies.decades == 1990
d2000 = df_movies.decades == 2000
d2010 = df_movies.decades == 2010
#top production companies for all decades
list1960=(df_movies[d1960].production_companies.value_counts()[1:6].index).
tolist()
list1970=(df_movies[d1970].production_companies.value_counts().head().inde
x).tolist()
list1980=(df_movies[d1980].production_companies.value_counts()[1:6].index).
tolist()
list1990=(df_movies[d1990].production_companies.value_counts()[1:6].index).
tolist()
list2000=(df_movies[d2000].production_companies.value_counts()[1:6].index).
tolist()
list2010=(df_movies[d2010].production_companies.value_counts()[1:6].index).
tolist()
#adding them into a dataframe
df_topcompanies= pd.DataFrame({'1960':list1960,'1970':list1970,'1980':list1
980,'1990':list1990,'2000':list2000,'2010':list2010})
df_topcompanies
```

Out[16]:

	1960	1970	1980	1990	2000	2010
0	Metro-Goldwyn-Mayer (MGM)	Universal Pictures	Paramount Pictures	Paramount Pictures	Walt Disney Pictures	The Asylum
1	Universal Pictures	Paramount Pictures	Universal Pictures	Universal Pictures	New Line Cinema	DreamWorks Animation
2	Walt Disney Productions	Warner Bros.	Orion Pictures	Touchstone Pictures	Universal Pictures	Marvel Studios
3	Twentieth Century Fox Film Corporation	unknown	Warner Bros.	Columbia Pictures	Metro-Goldwyn-Mayer (MGM)	Pixar Animation Studios
4	Warner Bros.	Walt Disney Productions	TriStar Pictures	Walt Disney Pictures	Dimension Films	WWE Studios

In [17]:
```
#       Question 2.2
# what production companies made the most profit in each decade
# the final result will  be polluted in a dataframe created with the follow
ing dictionary
dict_top_earners= {}

dic_keys=['1960 top earners','1970 top earners','1980 top earners','1990 to
p earners','2000 top earners','2010 top earners']
#the following is a list holding the names of production companies with the
highest profits per decade

top_list = [(df_movies[profit][d1960].groupby('production_companies')['prof
its'].sum().head().index).tolist(),
     (df_movies[profit][d1970].groupby('production_companies')['profits'].s
um().head().index).tolist(),
     (df_movies[profit][d1980].groupby('production_companies')['profits'].s
um().head().index).tolist(),
     (df_movies[profit][d1990].groupby('production_companies')['profits'].s
um().head().index).tolist(),
     (df_movies[profit][d2000].groupby('production_companies')['profits'].s
um().head().index).tolist(),
     (df_movies[profit][d2010].groupby('production_companies')['profits'].s
um().head().index).tolist()]
for x in top_list:
    dict_top_earners.update({dic_keys[0]:x})
    dic_keys.pop(0)
```

```
/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:9: UserWarnin
g: Boolean Series key will be reindexed to match DataFrame index.
  if __name__ == '__main__':
/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:10: UserWarni
ng: Boolean Series key will be reindexed to match DataFrame index.
  # Remove the CWD from sys.path while we load stuff.
/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:11: UserWarni
ng: Boolean Series key will be reindexed to match DataFrame index.
  # This is added back by InteractiveShellApp.init_path()
/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:12: UserWarni
ng: Boolean Series key will be reindexed to match DataFrame index.
  if sys.path[0] == '':
/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:13: UserWarni
ng: Boolean Series key will be reindexed to match DataFrame index.
  del sys.path[0]
/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:14: UserWarni
ng: Boolean Series key will be reindexed to match DataFrame index.
```

In [18]:
```
df_top_earners =pd.DataFrame(dict_top_earners)
df_top_earners
```

Out[18]:

	1960 top earners	1970 top earners	1980 top earners	1990 top earners	2000 top earners	2010 top
0	Alfred J. Hitchcock Productions	20th Century Fox	1818|Lone Wolf McQuade Associates|Topkick Prod...	20th Century Fox	1492 Pictures|Warner Bros.|Heyday Films	120dB Filn Films Productio
1	Alta Vista Productions	ABC Pictures	20th Century Fox	20th Century Fox|Baltimore Pictures	1492 Pictures|Warner Bros.|Heyday Films|MIRACL...	1492 Pictur Entertainn 20(
2	American International Pictures (AIP)|Santa Cl...	AVCO Embassy Pictures	20th Century Fox|American Entertainment Partne...	20th Century Fox|Egg Pictures	1492 Pictures|Warner Bros.|Heyday Films|P of A...	20th Cen
3	Batjac Productions	Algonquin	20th Century Fox|Davis Entertainment	20th Century Fox|Gruskoff/Venture Films	20th Century Fox	20th Fox Entertainment
4	Bryna Productions	American Film Institute (AFI)|Libra Films	20th Century Fox|Gladden Entertainment	20th Century Fox|Largo Entertainment|JVC Enter...	20th Century Fox|Figment Films	20th Fox|Double Films|Apr

Answer to Question 2

Production companies that produced the most movies aren't necessarily the ones to make the most profit. For the highest number of movies released we saw a lot of big names dominating the top 5 from their solo productions, with companies like Walt Disney, paramount pictures, Universal pictures and Warner bros appearing for multiple decades.

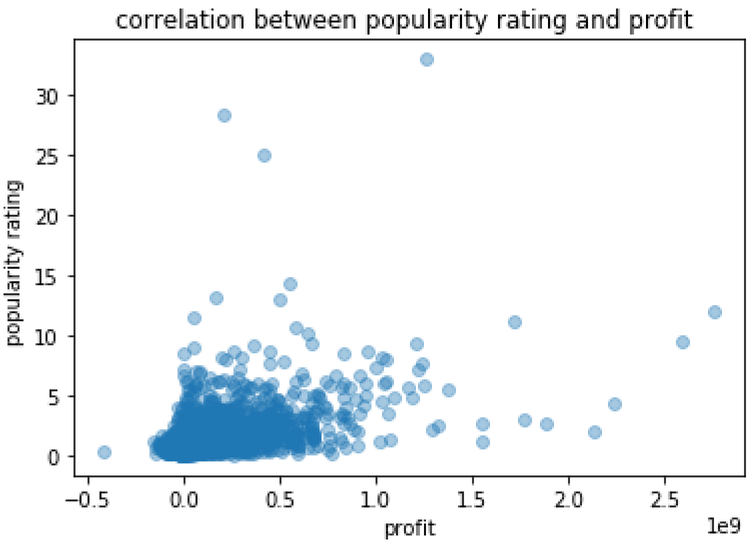
But for the most profitable set of production companies we saw a lot of multi-production-companies team at the top 5s especially since the 80s.

Question 3

how does popularity rating affect a movies profit and how has it changes over the decades

In [19]:
```
#        Question 3.1
# what Is the correlation between a movie's popularity rating and its profi
t
# for this we will be creating a scatter plot
y= df_movies.popularity
x= df_movies.profits
colors =['y','g']

plt.scatter(x,y,alpha=.4)
plt.title('correlation between popularity rating and profit ')
plt.ylabel('popularity rating ')
plt.xlabel('profit')
```

Out[19]: Text(0.5,0,'profit')



In [20]:
```
#        QUESTION 3.2
#   HOW HAS THE AVERAGE POPULARITY RATING CHANGEd COMPARED TO AVERAGE PROFI
T AND  LOSS TGROUGh THE DECADES
plt.figure(figsize =(10,8,))
#plotting average popularity rating for profitable movies
df_movies[profit].groupby('decades')['popularity'].mean().plot(kind='line',
color='g',marker='o',label ='average popularity rating for profitable movie
s')
#plotting average popularity rating for loss movies per decade
df_movies[loss].groupby('decades')['popularity'].mean().plot(kind='line',co
lor='y',marker='o',label ='average popularity rating for loss movies')
plt.legend()
plt.title('changes in average popularity rating for profitable and loss mov
ies')
```

Out[20]:
```
Text(0.5,1,'changes in average popularity rating for profitable and loss m
ovies')
```

Answer for question 3

popularity rating has a positive correlation with profit as we saw in the chart where unprofitable movies generally has low popularity rating and the only time it ever increases was in the 1990s which of course was a due to an increase in number of released movie for that decade.

profitable movies generally have a high popularity rating...

In [ ]:

In [21]:
```
#relationship between a movies budget and popularity
```

Conclusions

The number of profitable movies released in a year has always been less than number of unprofitable movies but still the profit amonut made from these few profitable movies has always been in multitudes of the budget of all released movies put together. The most profitable movies have a few things in common, like they have higher budgets, are most co-produced by top production companies and they always end up with higher popularity ratings. top genres feature in these movies includes Adventure, Action and Drama.

Limitations

1. the production companies were difficult to analyze as a group(for coproduced movies), and at thesame time could not be separated as that might lead to a bias and will not give us the truth about the efficiency and success of coproduced movies.
2. the dataset stops at 2016 so the 2010 decade is only halfway recorded yet
3. this analyst is a rookie and this is actually his first ever analysis so he might be leaving out a lot, forgive him :)

In [22]:
```
#from subprocess import call
#call(['python', '-m', 'nbconvert', 'Investigate_a_Dataset.ipynb'])
```