Investigate a Dataset of TMDb Movies

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Introduction

> TMDb Movies Dataset contains ofer 10 tousand movies which include for example revenues, user raitings. This database was cleaned and taken from Kaggle. In total there are 21 columns with various needed informations.
>
> For example in cast or genres values are separated by pipe "|" but we will not look into that in following data analys. On top of that, some strange chars can be found in cast columns, however we will skip them also.
>
> Revenue and budget were counted for 2010 USD accounting inflation.

Questions:

Some important questions I will focus on in this analysis:

```
- Correlation between runtime to raiting
- Mean budget per year
- Mean revenue per year
- Correlation between movie budgets and raiting
- Correlation between movie revenues and raiting
- Length of the movies between years
- Number of movies released over time
```

In [1]:

```
# Use this cell to set up import statements for all of the packages that you
#   plan to use.
import pandas as pd
import numpy as np
import seaborn as sns
from datetime import datetime
import matplotlib.pyplot as plt

# 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
%matplotlib inline
```

Data Wrangling

To load and explore dataset we will use Pandas. This library contains plenty of useful functions and can give us quick overview of dataset.

General Properties

In [2]:

```
# Loading data.
df = pd.read_csv('tmdb-movies.csv')
# Printing out a few first lines
df.head(3)
```

Out[2]:

	id	imdb_id	popularity	budget	revenue	original_title	cast	
0	135397	tt0369610	32.985763	150000000	1513528810	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	
1	76341	tt1392190	28.419936	150000000	378436354	Mad Max: Fury Road	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...	
2	262500	tt2908446	13.112507	110000000	295238201	Insurgent	Shailene Woodley|Theo James|Kate Winslet|Ansel...	http://v

3 rows × 21 columns

In [3]:

```
# Printing out a few last lines
df.tail(3)
```

Out[3]:

	id	imdb_id	popularity	budget	revenue	original_title	cast	home
10863	39768	tt0060161	0.065141	0	0	Beregis Avtomobilya	Innokentiy Smoktunovskiy|Oleg Efremov|Georgi Z...	
10864	21449	tt0061177	0.064317	0	0	What's Up, Tiger Lily?	Tatsuya Mihashi|Akiko Wakabayashi|Mie Hama|Joh...	
10865	22293	tt0060666	0.035919	19000	0	Manos: The Hands of Fate	Harold P. Warren|Tom Neyman|John Reynolds|Dian...	

3 rows × 21 columns

In [4]:

```
#lets see what we are working with
df.columns
```

Out[4]:

```
Index(['id', 'imdb_id', 'popularity', 'budget', 'revenue', 'original_titl
e',
       'cast', 'homepage', 'director', 'tagline', 'keywords', 'overview',
       'runtime', 'genres', 'production_companies', 'release_date',
       'vote_count', 'vote_average', 'release_year', 'budget_adj',
       'revenue_adj'],
      dtype='object')
```

Data Cleaning

Finding what data looks like

In [5]:

```
df.shape
```

Out[5]:

```
(10866, 21)
```

There is 10866 movies and each of them has 21 properties (columns)

In [6]:

```
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
```

There is few rows in genres column with NaN values, we will drop them later of for simplicity.

Let's delete columns we will not use

In [7]:

```
to_delete = [ 'id', 'imdb_id', 'popularity', 'budget', 'revenue', 'cast', 'homepage',
'director', 'tagline',
             'keywords', 'overview', 'production_companies', 'vote_count']

df = df.drop(to_delete, axis = 1)
```

Taking a look at changed dataset and it looks more pleasant, there is still some work to be done though.

In [8]:

```
df.head()
```

Out[8]:

	original_title	runtime	genres	release_date	vote_average	release_year	
0	Jurassic World	124	Action|Adventure|Science Fiction|Thriller	6/9/15	6.5	2015	1
1	Mad Max: Fury Road	120	Action|Adventure|Science Fiction|Thriller	5/13/15	7.1	2015	1
2	Insurgent	119	Adventure|Science Fiction|Thriller	3/18/15	6.3	2015	1
3	Star Wars: The Force Awakens	136	Action|Adventure|Science Fiction|Fantasy	12/15/15	7.5	2015	1
4	Furious 7	137	Action|Crime|Thriller	4/1/15	7.3	2015	1

For rest of the columns, as revenue, budget, vote_average, runtime we have to check if any of them are equal to 0 and drop them also.

In [9]:

```
#for revenue and  budget in 2010 USD we have to use revenue_adj budget_adj instead of r
evenue and  budget
print(' Revenue minimum:' , min(df['revenue_adj']))
print(' Budget minimum:' , min(df['budget_adj']))
print(' Runtime minimum:' , min(df['runtime']))
print(' Vote average minimum:' , min(df['vote_average']))
```

```
 Revenue minimum: 0.0
 Budget minimum: 0.0
 Runtime minimum: 0
 Vote average minimum: 1.5
```

Ok, we know we have some incostistent data in our data base, firstly we will find out how many of them we shall delete.

Vote Average seems possible, altough 1.5 is very low and this movie shouldn't exists, we will still keep it.

In [10]:

```
print(' Revenue "0" count', df.revenue_adj.isin([0]).sum())
print(' Budget "0" count', df.budget_adj.isin([0]).sum())
print(' Runtime "0" count', df.runtime.isin([0]).sum())
```

```
 Revenue "0" count 6016
 Budget "0" count 5696
 Runtime "0" count 31
```

Dropping rows containing "0"

In [11]:

```
to_change = ['revenue_adj', 'budget_adj', 'runtime']
df[to_change] = df[to_change].replace(0, np.NAN)
```

Checking if it worked

In [12]:

```
print(' Revenue minimum:' , min(df['revenue_adj']))
print(' Budget minimum:' , min(df['budget_adj']))
print(' Runtime minimum:' , min(df['runtime']))
```

```
 Revenue minimum: 2.37070528956505
 Budget minimum: 0.921091050771459
 Runtime minimum: 2.0
```

Dropping those NaN's from our dataset

In [13]:

```
df.dropna(subset = to_change, inplace = True)
```

Checking if it worked

In [14]:

```
df.shape
```

Out[14]:

```
(3855, 8)
```

Chaning budget_adj and revenue_adj to more human readible format:

In [15]:

```
df['budget_adj'] = df['budget_adj'].astype(float)
df['revenue_adj'] = df['revenue_adj'].astype(float)
```

In [16]:

```
df.head()
```

Out[16]:

	original_title	runtime	genres	release_date	vote_average	release_year	
0	Jurassic World	124.0	Action|Adventure|Science Fiction|Thriller	6/9/15	6.5	2015	1
1	Mad Max: Fury Road	120.0	Action|Adventure|Science Fiction|Thriller	5/13/15	7.1	2015	1
2	Insurgent	119.0	Adventure|Science Fiction|Thriller	3/18/15	6.3	2015	1
3	Star Wars: The Force Awakens	136.0	Action|Adventure|Science Fiction|Fantasy	12/15/15	7.5	2015	1
4	Furious 7	137.0	Action|Crime|Thriller	4/1/15	7.3	2015	1

After cleaning of our data we had to drop A LOT of movies. Most of them were dropped for revenue and budget analysis. We will reload file once again to make comparasions for runtime

Quick overview of our cleaned dataset:

In [17]:

```
df.describe()
```

Out[17]:

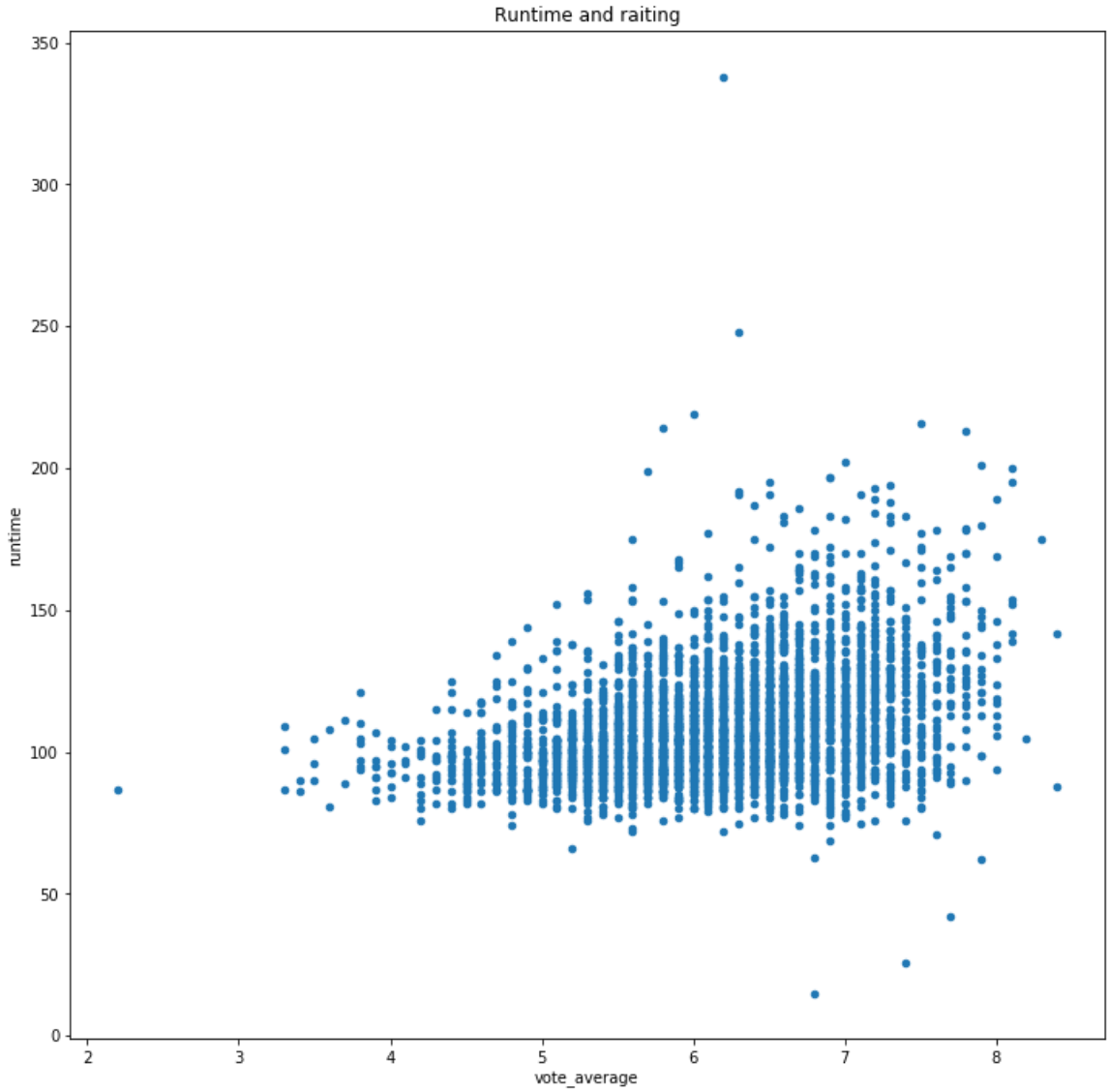
	runtime	vote_average	release_year	budget_adj	revenue_adj
count	3855.000000	3855.00000	3855.000000	3.855000e+03	3.855000e+03
mean	109.215824	6.16786	2001.263294	4.423630e+07	1.370294e+08
std	19.922166	0.79504	11.281989	4.480403e+07	2.160944e+08
min	15.000000	2.20000	1960.000000	9.693980e-01	2.370705e+00
25%	95.000000	5.70000	1995.000000	1.309053e+07	1.834123e+07
50%	106.000000	6.20000	2004.000000	3.001558e+07	6.171861e+07
75%	119.000000	6.70000	2010.000000	6.061307e+07	1.632401e+08
max	338.000000	8.40000	2015.000000	4.250000e+08	2.827124e+09

Exploratory Data Analysis

Research Question: Runtime compared to raiting

In [18]:

```
df.plot( x='vote_average', y = 'runtime', kind = 'scatter', figsize=(12,12));
plt.title('Runtime and raiting');
```

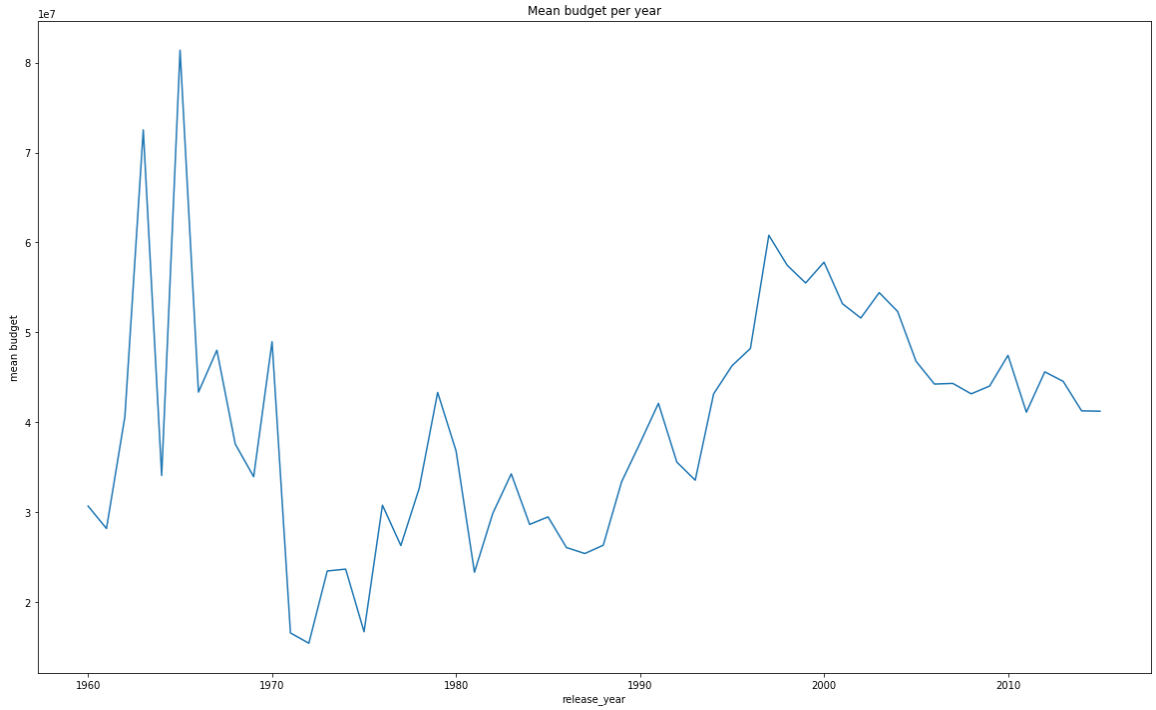


Except seeing that most of the movies are about 110 minues long there is no strong connection to raitings as they are all over the place. Movies with runtime lower than 50 might get better raiting, but there is too litle data to say it for sure.

Research Question: Mean budget per year

In [19]:

```
df.groupby('release_year').mean().budget_adj.plot(figsize=(20,12))
plt.title('Mean budget per year')
plt.ylabel('mean budget')
plt.show()
```

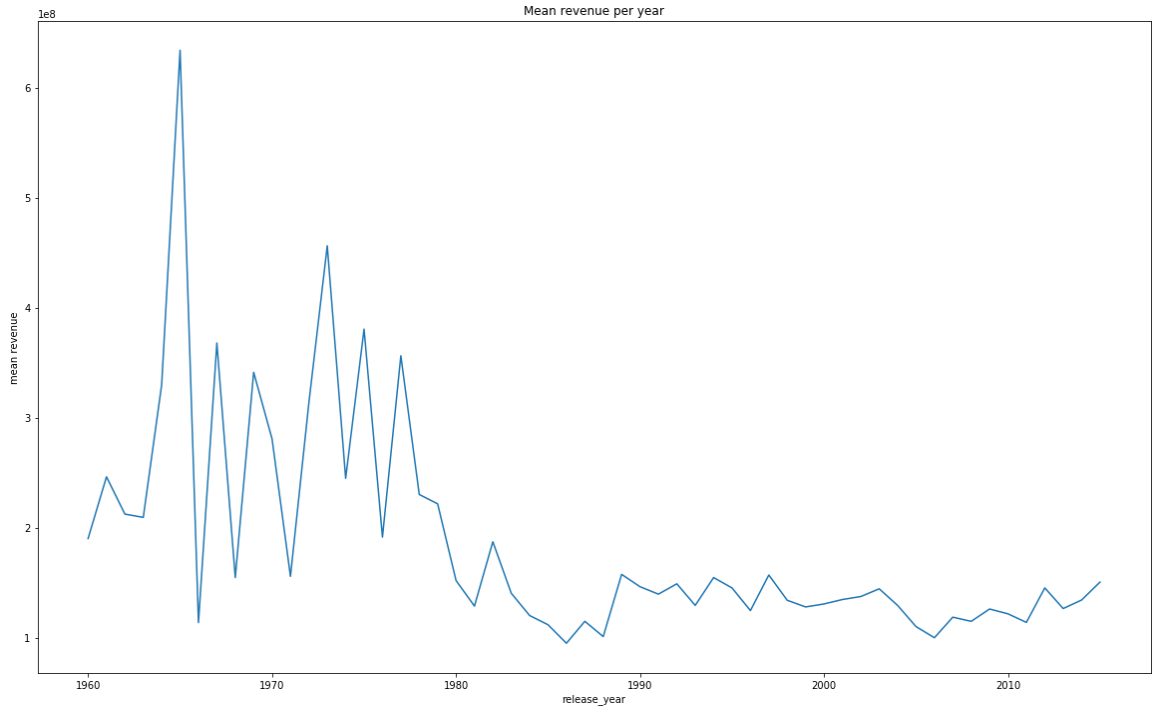


There is small correlation betweend earlier years, where movies were expensive and recent (past 1995). Back in 1960s movie companies were just starting to go into the main stream, nowadays budgets are getting bigger because of growing number of releasing movies.

Research Question: Mean revenue per year

In [20]:

```
df.groupby('release_year').mean().revenue_adj.plot(figsize=(20,12))
plt.title('Mean revenue per year')
plt.ylabel('mean revenue')
plt.show()
```

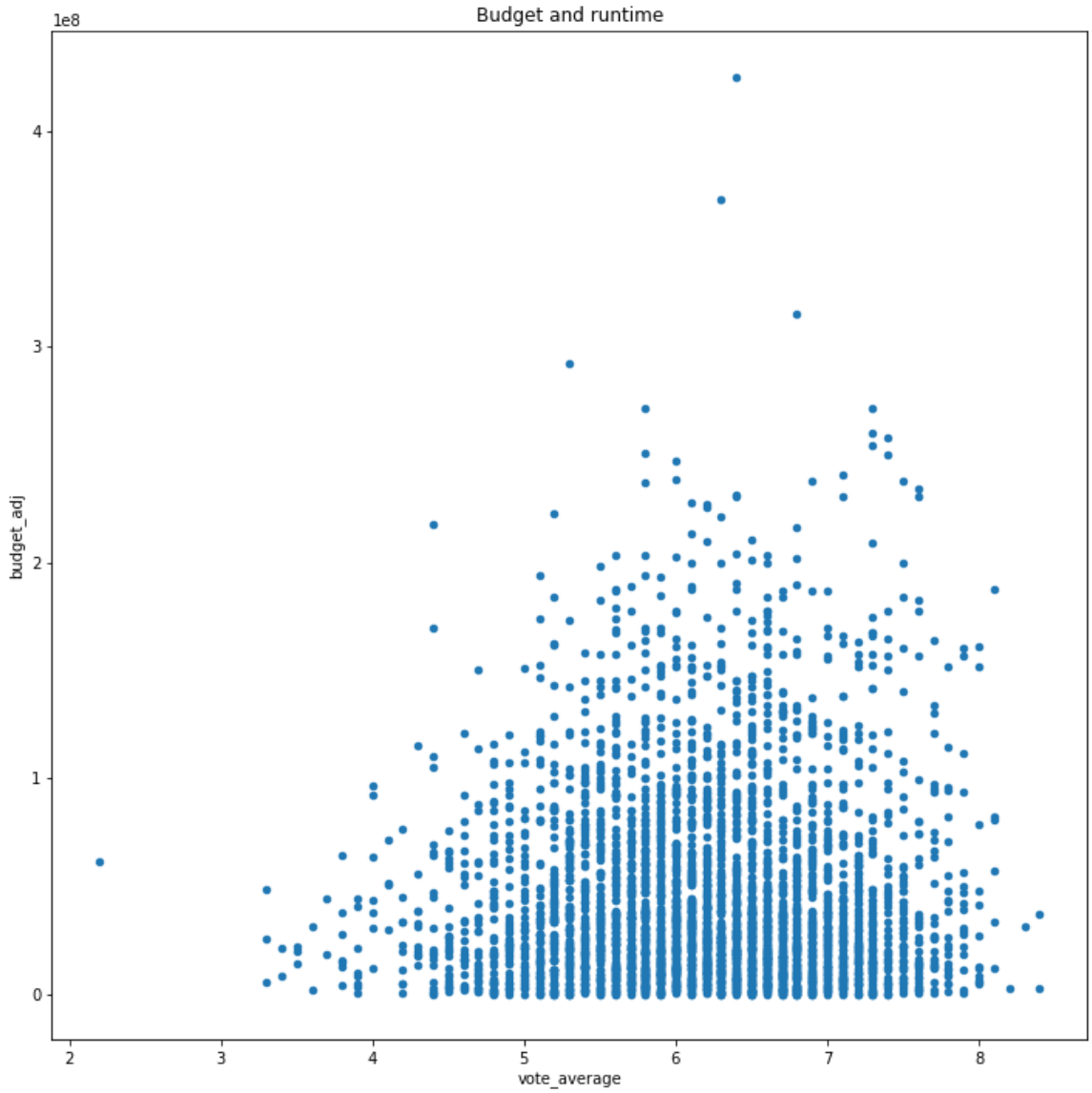


We can clearly see that it has been harder and harder to make decent revenue with each year

Research Question: Correlation between movie budgets and ongoing time

In [21]:

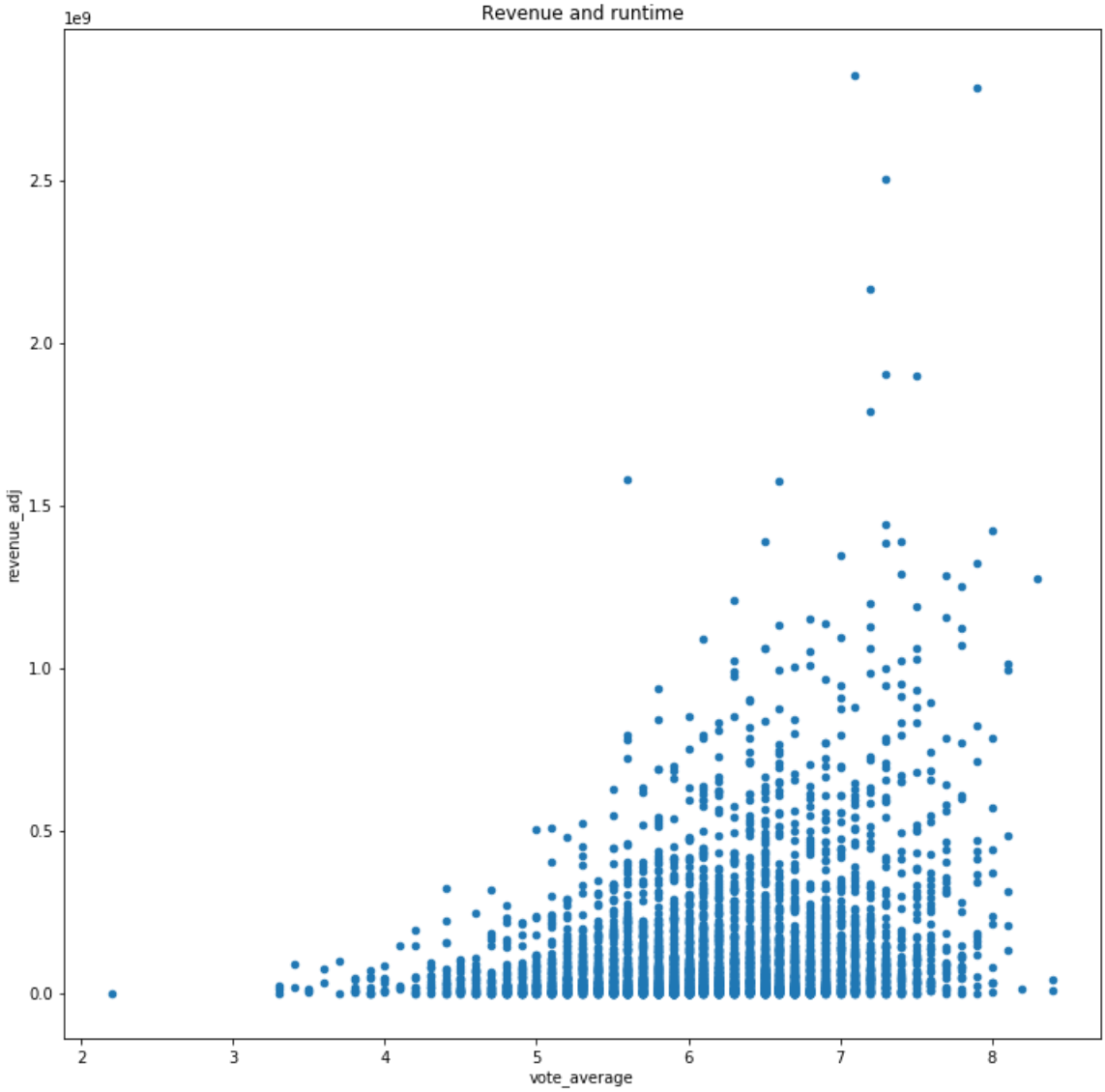
```
df.plot( y='budget_adj', x = 'vote_average', kind = 'scatter', figsize=(12,12))
plt.title('Budget and runtime');
```



Research Question: Correlation between movie revenues and ongoing time

In [22]:

```
df.plot( y='revenue_adj', x = 'vote_average', kind = 'scatter', figsize=(12,12))
plt.title('Revenue and runtime');
```



With higher raiting creators can expect higher revenues. There is few outliers on higher vote average, but because there is so few of them they can be skipped in overlooking of the results

Now creating new data frame to answer more general questions

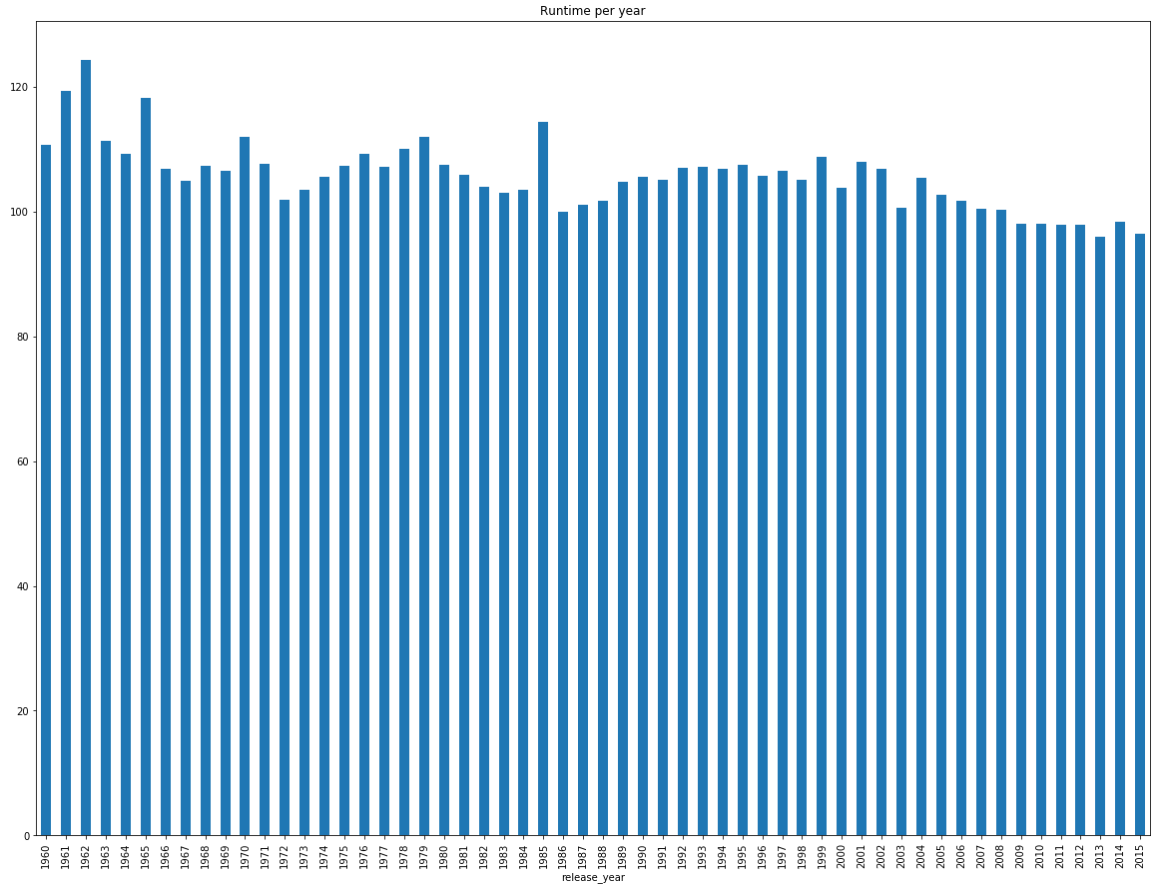
In [23]:

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

Research Question: Length of the movies between years

In [24]:

```
df_2 =  df_clean.groupby('release_year')
df_2.runtime.mean().plot.bar(figsize=(20, 15))
plt.title('Runtime per year')
plt.show()
```

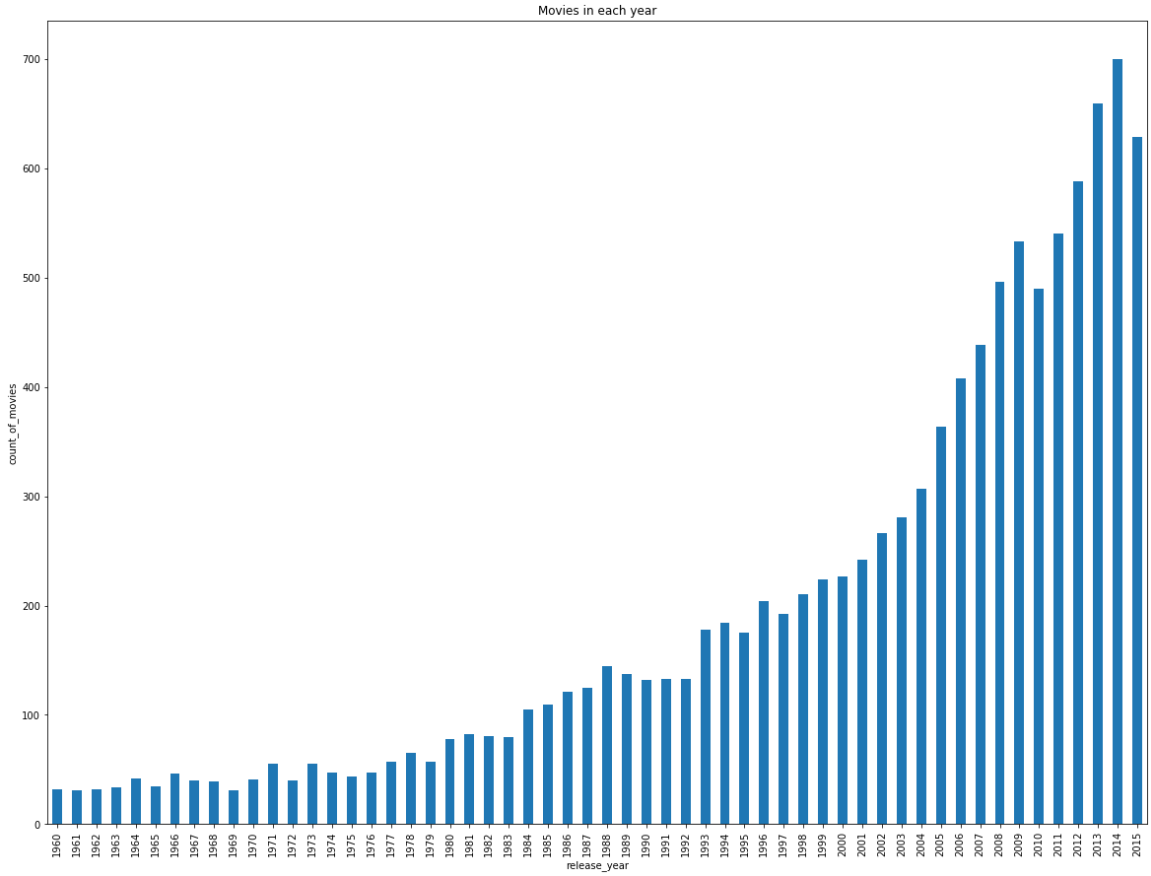


On first look, as with progress we have less and less time people tend to choose shorter movies, but changes are not consistent and cannot be taken for granted.

Research Question: Number of movies released over time

In [25]:

```
df_clean.groupby('release_year')['id'].count().plot.bar(figsize=(20, 15))
plt.ylabel('count_of_movies')
plt.title('Movies in each year')
plt.show()
```



With each year there is more and more movies.

Conclusions

There was only ~40% of the data viable for most of our testing, some of them still have had inconsistent data, it could've been definetelly handled better.

Key observations:

```
 -With each year there is more movies and each of them is, on average, shorter.
 -It is suginificantly cheaper to create movies comparing to begginings of the d
ataset
 -Even though its cheaper and there is more movies, revenues are falling and has
been on the same average level for past 10 years
 -With higher budgets you can expect higher raitings and revenues, but there is
 no strict rule for that. Apparently there are other factors which should be tak
en into consideration to answer this question. Moreover, we have data only up to
2015, and it doesnt includes data about world trends in generes, top actors etc.
 -With over 10800 movies you could watch new movie a day for the next 30 years
 (and in 2050 you would catch up with all of 2015 movies)
```

In [ ]: