# Project 2 TMDb movie data

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# 1 Project: TMDb movie data

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## Introduction

I will investigate and analyze the TMDb movies dataset (cleaned from original data on Kaggle) on different properties of 10,000 movie samples.

I will answer these questions in my analysis process:

To start investigating these questions, first I have to import all the package that I will use in this project.

```
In [1]: import pandas as pd
    import numpy as np
    import matplotlib.pyplot as plt
    import seaborn as sns
    %matplotlib inline
```

## Data Wrangling

Then, I will load the dataset and assess it to identify any problems and make sure it is cleaned and in a great quality for the analysis process.

#### 1.1.1 General Properties

```
In [2]: df = pd.read_csv('tmdb-movies.csv');
        df.head()
Out[2]:
               id
                      imdb_id
                               popularity
                                               budget
                                                           revenue
        0
           135397
                   tt0369610
                                32.985763
                                            150000000
                                                        1513528810
        1
            76341
                   tt1392190
                                28.419936
                                            150000000
                                                         378436354
                   tt2908446
           262500
                                13.112507
                                            110000000
                                                         295238201
        3
          140607
                   tt2488496
                                11.173104
                                            200000000
                                                       2068178225
           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 \
           Chris Pratt | Bryce Dallas Howard | Irrfan Khan | Vi...
           Tom Hardy | Charlize Theron | Hugh Keays-Byrne | Nic...
           Shailene Woodley | Theo James | Kate Winslet | Ansel...
        3 Harrison Ford | Mark Hamill | Carrie Fisher | Adam D...
           Vin Diesel | Paul Walker | Jason Statham | Michelle ...
                                                      homepage
                                                                         director
                                http://www.jurassicworld.com/
        0
                                                                  Colin Trevorrow
        1
                                  http://www.madmaxmovie.com/
                                                                    George Miller
        2
              http://www.thedivergentseries.movie/#insurgent
                                                                 Robert Schwentke
           http://www.starwars.com/films/star-wars-episod...
        3
                                                                      J.J. Abrams
        4
                                     http://www.furious7.com/
                                                                        James Wan
                                  tagline
        0
                        The park is open.
        1
                       What a Lovely Day.
              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
           An apocalyptic story set in the furthest reach...
                                                                    120
           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
           Action | Adventure | Science Fiction | Thriller
```

```
Action | Adventure | Science Fiction | Thriller
1
2
          Adventure | Science Fiction | Thriller
3
    Action | Adventure | Science Fiction | Fantasy
4
                        Action|Crime|Thriller
                                 production_companies release_date vote_count
  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...
                                                                           2480
                                                             3/18/15
           Lucasfilm|Truenorth Productions|Bad Robot
3
                                                            12/15/15
                                                                           5292
  Universal Pictures | Original Film | Media Rights ...
                                                              4/1/15
                                                                           2947
   vote_average release_year
                                                revenue_adj
                                  budget_adj
0
            6.5
                          2015 1.379999e+08 1.392446e+09
            7.1
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
            7.3
4
                          2015 1.747999e+08 1.385749e+09
```

#### [5 rows x 21 columns]

#### **Attribute Information**

```
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 (show the budget of the associated movie in terms of 2010 dollars, accounting for inflation over time.)

revenue\_adj (show the revenue of the associated movie in terms of 2010 dollars, accounting for inflation over time.)

```
In [3]: df.shape
```

# Out[3]: (10866, 21)

In [4]: df.describe()

Out[4]:		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	0.00000e+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 [5]: df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10866 entries, 0 to 10865
Data columns (total 21 columns):

10866 non-null int64  $imdb_id$ 10856 non-null object 10866 non-null float64 popularity budget 10866 non-null int64 revenue 10866 non-null int64 10866 non-null object original\_title 10790 non-null object cast 2936 non-null object homepage 10822 non-null object director tagline 8042 non-null object 9373 non-null object keywords overview 10862 non-null object 10866 non-null int64 runtime 10843 non-null object genres production\_companies 9836 non-null object 10866 non-null object release\_date 10866 non-null int64 vote\_count 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
```

## In the previous code cells I used three functions (.shape, .describe and .info).

shape

As the output of the shape function, I found there are 10866 movies (rows) in this dataset and 21 columns.

describe

The output of this function shows the statistical summary of the dataset.

When observing the output some of the numbers does not make sense. For that I can identify the changes I will make to clean the data

info

In this function I can find a summary of the data in the columns, how many data are there, the missing data and the data type.

### 1.1.2 Data Cleaning

In this section I will clean the dataset to insure it is in high quality as I need in my analysis process. I will use drop function to remove the columns that I won't use.

The columns are: id, imdb\_id, budget, revenue, popularity, cast, homepage, director, tagline, keywords, overview, production\_companies, release\_date, vote\_count, budget\_adj and revenue\_adj.

**Reasons of removing:** 1. For both IDs colummns, cast, homepage, director, tagline, keywords, overview and production\_companies these data are specific to the movies. 2. For released\_date I will be contented with the released\_year instead of the date. 3. For the budget, revenue, budget\_adj and revenue\_adj, (I looked at my dataset in excel sheet, and I found that there are more than 6000 movies with '0' value in these 4 columns).

```
In [6]: df.drop(['id','imdb_id', 'budget','revenue','popularity','cast','homepage','director','t
In [7]: df.head()
Out [7]:
                          original_title runtime
        0
                          Jurassic World
                                               124
        1
                     Mad Max: Fury Road
                                               120
                               Insurgent
                                               119
        3 Star Wars: The Force Awakens
                                               136
                               Furious 7
        4
                                               137
                                                genres vote_average release_year
           Action | Adventure | Science Fiction | Thriller
                                                                   6.5
                                                                                2015
           Action | Adventure | Science Fiction | Thriller
                                                                   7.1
                                                                                2015
        1
        2
                   Adventure | Science Fiction | Thriller
                                                                   6.3
                                                                                2015
        3
            Action | Adventure | Science Fiction | Fantasy
                                                                   7.5
                                                                                2015
        4
                                Action|Crime|Thriller
                                                                   7.3
                                                                                2015
```

Based on the above output, I will need to do more of cleaning. This time I will clean some rows since there are some missing data.

```
In [9]: df[df.genres.isnull()]
```

997

1712

1897

6.8

7.4

7.0

### Belli di papăă 100 NaN 620 All Hallows' Eve 2 90 NaN 997 Star Wars Rebels: Spark of Rebellion 44 NaN 1712 Prayers for Bobby 88 NaN 1897 Jonas Brothers: The Concert Experience 76 NaN 2370 Freshman Father 0 NaN 2376 Doctor Who: A Christmas Carol 62 NaN 2853 Vizontele 110 NaN 3279 Goldeneye 105 NaN 4797 Doctor Who: The Snowmen 60 NaN 4797 Doctor Who: The Snowmen 60 NaN 4890 Cousin Ben Troop Screening 2 NaN 5830 Doctor Who: The Time of the Doctor 60 NaN 5934 Prada: Candy 3 NaN 6043 Bombay Talkies 127 NaN 6530 Saw Rebirth 6 NaN 8234 Viaggi di nozze 103 NaN 8614 T2 3-D: Battle Across Time 12 NaN 8878 Mom's Got a Date With a Vampire 85 NaN 9307 Goldeneye 105 NaN 7999 The Party at Kitty and Stud's 71 NaN vote_average release_year 424 6.1 2015 620 5.0 2015	Out[9]:		original_title	runtime	genres	\
997 Star Wars Rebels: Spark of Rebellion 44 NaN 1712 Prayers for Bobby 88 NaN 1897 Jonas Brothers: The Concert Experience 76 NaN 2370 Freshman Father 0 NaN 2376 Doctor Who: A Christmas Carol 62 NaN 2853 Vizontele 110 NaN 3279 6 NaN 4547 London 2012 Olympic Opening Ceremony: Isles of 220 NaN 4732 The Scapegoat 100 NaN 4797 Doctor Who: The Snowmen 60 NaN 4890 Cousin Ben Troop Screening 2 NaN 5830 Doctor Who: The Time of the Doctor 60 NaN 5934 Prada: Candy 3 NaN 6043 Bombay Talkies 127 NaN 6530 Saw Rebirth 6 NaN 8234 Viaggi di nozze 103 NaN 8234 Talkies 127 NaN 6530 Saw Rebirth 6 NaN 8234 Talkies 127 NaN 6530 Saw Rebirth 6 NaN 8234 Talkies 127 NaN 6530 Saw Rebirth 6 NaN 8234 Talkies 127 NaN 6530 Saw Rebirth 6 NaN 8234 Talkies 127 NaN 6530 Saw Rebirth 6 NaN 8234 Talkies 127 NaN 6530 Talkies 127 N		424	Belli di papÃă	100	NaN	
1712		620	All Hallows' Eve 2	90	NaN	
1897		997	Star Wars Rebels: Spark of Rebellion	44	${\tt NaN}$	
2370   Freshman Father   O NaN		1712	Prayers for Bobby	88	${\tt NaN}$	
2376		1897	Jonas Brothers: The Concert Experience	76	${\tt NaN}$	
Vizontele   110		2370	Freshman Father	0	NaN	
3279       îêÿřî ë       96       NaN         4547       London 2012 Olympic Opening Ceremony: Isles of       220       NaN         4732       The Scapegoat       100       NaN         4797       Doctor Who: The Snowmen       60       NaN         4890       Cousin Ben Troop Screening       2       NaN         5830       Doctor Who: The Time of the Doctor       60       NaN         5934       Prada: Candy       3       NaN         6043       Bombay Talkies       127       NaN         6530       Saw Rebirth       6       NaN         8234       Viaggi di nozze       103       NaN         8614       T2 3-D: Battle Across Time       12       NaN         8878       Mom's Got a Date With a Vampire       85       NaN         9307       Goldeneye       105       NaN         9799       The Amputee       5       NaN         10659       The Party at Kitty and Stud's       71       NaN         vote_average       release_year         424       6.1       2015		2376	Doctor Who: A Christmas Carol	62	${\tt NaN}$	
4547 London 2012 Olympic Opening Ceremony: Isles of 220 NaN 4732 The Scapegoat 100 NaN 4797 Doctor Who: The Snowmen 60 NaN 4890 Cousin Ben Troop Screening 2 NaN 5830 Doctor Who: The Time of the Doctor 60 NaN 5934 Prada: Candy 3 NaN 6043 Bombay Talkies 127 NaN 6530 Saw Rebirth 6 NaN 8234 Viaggi di nozze 103 NaN 8614 T2 3-D: Battle Across Time 12 NaN 8878 Mom's Got a Date With a Vampire 85 NaN 9307 Goldeneye 105 NaN 9799 The Amputee 5 NaN 10659 The Party at Kitty and Stud's 71 NaN  vote_average release_year 424 6.1 2015		2853	Vizontele	110	${\tt NaN}$	
4732       The Scapegoat       100       NaN         4797       Doctor Who: The Snowmen       60       NaN         4890       Cousin Ben Troop Screening       2       NaN         5830       Doctor Who: The Time of the Doctor       60       NaN         5934       Prada: Candy       3       NaN         6043       Bombay Talkies       127       NaN         6530       Saw Rebirth       6       NaN         8234       Viaggi di nozze       103       NaN         8614       T2 3-D: Battle Across Time       12       NaN         8878       Mom's Got a Date With a Vampire       85       NaN         9307       Goldeneye       105       NaN         9799       The Amputee       5       NaN         10659       The Party at Kitty and Stud's       71       NaN         vote_average       release_year         424       6.1       2015		3279	ìêÿřì ë	96 NaN	ſ	
4797         Doctor Who: The Snowmen         60         NaN           4890         Cousin Ben Troop Screening         2         NaN           5830         Doctor Who: The Time of the Doctor         60         NaN           5934         Prada: Candy         3         NaN           6043         Bombay Talkies         127         NaN           6530         Saw Rebirth         6         NaN           8234         Viaggi di nozze         103         NaN           8614         T2 3-D: Battle Across Time         12         NaN           8878         Mom's Got a Date With a Vampire         85         NaN           9307         Goldeneye         105         NaN           9799         The Amputee         5         NaN           10659         The Party at Kitty and Stud's         71         NaN           vote_average         release_year           424         6.1         2015		4547	London 2012 Olympic Opening Ceremony: Isles of	220	NaN	
4890       Cousin Ben Troop Screening       2       NaN         5830       Doctor Who: The Time of the Doctor       60       NaN         5934       Prada: Candy       3       NaN         6043       Bombay Talkies       127       NaN         6530       Saw Rebirth       6       NaN         8234       Viaggi di nozze       103       NaN         8614       T2 3-D: Battle Across Time       12       NaN         8878       Mom's Got a Date With a Vampire       85       NaN         9307       Goldeneye       105       NaN         9799       The Amputee       5       NaN         10659       The Party at Kitty and Stud's       71       NaN         vote_average       release_year         424       6.1       2015		4732	The Scapegoat	100	${\tt NaN}$	
5830         Doctor Who: The Time of the Doctor         60         NaN           5934         Prada: Candy         3         NaN           6043         Bombay Talkies         127         NaN           6530         Saw Rebirth         6         NaN           8234         Viaggi di nozze         103         NaN           8614         T2 3-D: Battle Across Time         12         NaN           8878         Mom's Got a Date With a Vampire         85         NaN           9307         Goldeneye         105         NaN           9799         The Amputee         5         NaN           10659         The Party at Kitty and Stud's         71         NaN           vote_average         release_year           424         6.1         2015		4797	Doctor Who: The Snowmen	60	NaN	
5934       Prada: Candy       3       NaN         6043       Bombay Talkies       127       NaN         6530       Saw Rebirth       6       NaN         8234       Viaggi di nozze       103       NaN         8614       T2 3-D: Battle Across Time       12       NaN         8878       Mom's Got a Date With a Vampire       85       NaN         9307       Goldeneye       105       NaN         9799       The Amputee       5       NaN         10659       The Party at Kitty and Stud's       71       NaN         vote_average       release_year         424       6.1       2015		4890	Cousin Ben Troop Screening	2	${\tt NaN}$	
6043       Bombay Talkies       127       NaN         6530       Saw Rebirth       6       NaN         8234       Viaggi di nozze       103       NaN         8614       T2 3-D: Battle Across Time       12       NaN         8878       Mom's Got a Date With a Vampire       85       NaN         9307       Goldeneye       105       NaN         9799       The Amputee       5       NaN         10659       The Party at Kitty and Stud's       71       NaN         vote_average       release_year         424       6.1       2015		5830	Doctor Who: The Time of the Doctor	60	NaN	
6530         Saw Rebirth         6 NaN           8234         Viaggi di nozze         103 NaN           8614         T2 3-D: Battle Across Time         12 NaN           8878         Mom's Got a Date With a Vampire         85 NaN           9307         Goldeneye         105 NaN           9799         The Amputee         5 NaN           10659         The Party at Kitty and Stud's         71 NaN   vote_average release_year 424 6.1 2015		5934	Prada: Candy	3	NaN	
8234       Viaggi di nozze       103       NaN         8614       T2 3-D: Battle Across Time       12       NaN         8878       Mom's Got a Date With a Vampire       85       NaN         9307       Goldeneye       105       NaN         9799       The Amputee       5       NaN         10659       The Party at Kitty and Stud's       71       NaN         vote_average       release_year         424       6.1       2015		6043	Bombay Talkies	127	${\tt NaN}$	
8614 T2 3-D: Battle Across Time 12 NaN 8878 Mom's Got a Date With a Vampire 85 NaN 9307 Goldeneye 105 NaN 9799 The Amputee 5 NaN 10659 The Party at Kitty and Stud's 71 NaN  vote_average release_year 424 6.1 2015		6530	Saw Rebirth	6	NaN	
Mom's Got a Date With a Vampire 85 NaN Goldeneye 105 NaN Goldeneye 5 NaN The Amputee 5 NaN 10659 The Party at Kitty and Stud's 71 NaN vote_average release_year 424 6.1 2015		8234	Viaggi di nozze	103	${\tt NaN}$	
9307 Goldeneye 105 NaN 9799 The Amputee 5 NaN 10659 The Party at Kitty and Stud's 71 NaN  vote_average release_year 424 6.1 2015		8614	T2 3-D: Battle Across Time	12	${\tt NaN}$	
9799 The Amputee 5 NaN 10659 The Party at Kitty and Stud's 71 NaN vote_average release_year 424 6.1 2015		8878	Mom's Got a Date With a Vampire	85	NaN	
10659 The Party at Kitty and Stud's 71 NaN  vote_average release_year 424 6.1 2015		9307	Goldeneye	105	${\tt NaN}$	
vote_average release_year 424 6.1 2015		9799	The Amputee	5	NaN	
424 6.1 2015		10659	The Party at Kitty and Stud's	71	NaN	
424 6.1 2015			vote_average release_year			
620 5.0 2015		424	-			
		620	5.0 2015			

2014

2009

2009

2370	5.8	2010
2376	7.7	2010
2853	7.2	2001
3279	6.1	2008
4547	8.3	2012
4732	6.2	2012
4797	7.8	2012
4890	7.0	2012
5830	8.5	2013
5934	6.9	2013
6043	5.9	2013
6530	5.9	2005
8234	6.7	1995
8614	6.7	1996
8878	5.4	2000
9307	5.3	1989
9799	5.0	1974
10659	3.0	1970

There are 23 rows with missing data in genres columns, I will drop these rows.

```
In [10]: df.dropna(inplace=True)
         df.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10843 entries, 0 to 10865
Data columns (total 5 columns):
                  10843 non-null object
original_title
runtime
                  10843 non-null int64
                  10843 non-null object
genres
                  10843 non-null float64
vote_average
                  10843 non-null int64
release_year
dtypes: float64(1), int64(2), object(2)
memory usage: 508.3+ KB
In [11]: df.loc[df['runtime'] == 0 ]
```

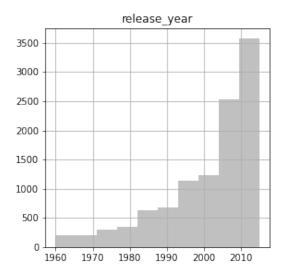
# I noticed in the output of the describe function the minmmum of runtime is 0, which of this code will show me the movies with 0 runtime. For cleaning the data I'll remove to

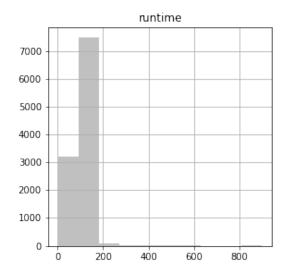
```
Out[11]:
                               original_title runtime
                                                                                    genres
                                                                 Fantasy|Action|Adventure
         92
                     Mythica: The Necromancer
         334
                                       Ronaldo
                                                       0
                                                                               Documentary
         410
                               Anarchy Parlor
                                                      0
                                                                                    Horror
         445
               The Exorcism of Molly Hartley
                                                                                    Horror
                                                       0
         486
                           If There Be Thorns
                                                      0
                                                                            TV MovielDrama
         595
                                     Deep Dark
                                                      0
                                                                                    Horror
                                 The Outfield
                                                      0
                                                                              Drama | Comedy
         616
```

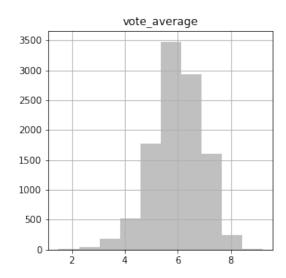
Romance Music Comedy	0	Dance-Off	1241
Thriller Horror Mystery	0	Treehouse	1289
${ t Documentary}     { t Drama}     { t Music}$	0	Tim Maia	1293
Drama Music	0	Spectacular!	1849
Drama Music Romance	0	Listen to Your Heart	2315
Family	0	Grande, grosso e Verdone	3329
${ t Music} \mid { t Romance}$	0	Toi, moi, les autres	3794
Horror	0	Cell 213	3857
Romance	0	eCupid	3884
Comedy	0	Madea's Family Reunion	4063
Drama Music	0	A Time for Dancing	4138
TV Movie Comedy Drama	0	Rags	4829
Comedy Romance TV Movie	0	How to Fall in Love	4944
Comedy Music	0	Madea's Class Reunion	5216
Thriller Horror Science Fiction	0	Skinwalker Ranch	5695
Romance Comedy	0	The Food Guide to Love	5920
Comedy Horror	0	Go Goa Gone	5938
Romance Crime Comedy	0	Amiche da morire	5992
Horror Documentary Mystery	0	The Vatican Exorcisms	6040
${\tt Drama} {\sf Family}$	0	The 12 Dogs of Christmas	6383
Comedy	0	Quatre Ãľtoiles	6552
Comedy	0	Jean-Philippe	6934
Action Drama Foreign	0	Mission Kashmir	8874
		+	

	vote_average	release_year
92	5.4	2015
334	6.5	2015
410	5.6	2015
445	5.0	2015
486	5.4	2015
595	4.6	2015
616	6.6	2015
1241	5.7	2014
1289	3.4	2014
1293	6.0	2014
1849	5.2	2009
2315	7.3	2010
3329	5.3	2008
3794	5.2	2011
3857	5.2	2011
3884	4.6	2011
4063	5.9	2002
4138	7.5	2002
4829	5.7	2012
4944	4.7	2012
5216	6.9	2003
5695	4.3	2013
5920	5.6	2013

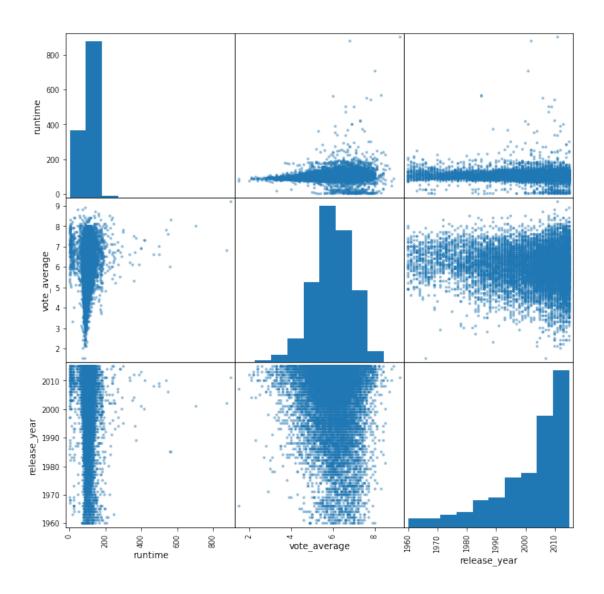
```
5.3
         5938
                                      2013
         5992
                        5.5
                                      2013
         6040
                        4.7
                                      2013
         6383
                        4.7
                                      2005
                        5.9
         6552
                                      2005
         6934
                        5.6
                                      2006
         8874
                        5.7
                                      2000
In [12]: df = df[df.runtime != 0]
         # I used this code based on this site (https://stackoverflow.com/questions/18172851/del
         # To delet all the movies with the runtime = 0
In [13]: sum(df.duplicated())
         # I used .duplicated function to find if there is any duplicated row
Out[13]: 1
In [14]: df.drop_duplicates(inplace=True)
         print(df.shape)
         #Here I removed the duplicated row
(10812, 5)
In [15]: df.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10812 entries, 0 to 10865
Data columns (total 5 columns):
original_title
                  10812 non-null object
runtime
                  10812 non-null int64
                  10812 non-null object
genres
vote_average
                  10812 non-null float64
release_year
                  10812 non-null int64
dtypes: float64(1), int64(2), object(2)
memory usage: 506.8+ KB
   My dataset is cleaned, I will start next step. I ended up with 10812 rows and 5 columns.
   ## Exploratory Data Analysis
In [16]: df.hist(figsize=(10,10), color='silver');
```







In [17]: pd.plotting.scatter\_matrix(df, figsize=(10,10));



### 1.1.3 Question 1: What is the most common movie genre produced in this dataset?

For this question, have split the genres columns sinces it has followed values the cell. the steps this same I of document:(https://static1.squarespace.com/static/55bfa8e4e4b007976149574e/t/5b998f398a922d8eaecaefd2/15 dataset-movies.pdf), to get a copy of my dataframe and then split the genres column into several rows (to show each genre indviually) then remove the genres column with the multiple values.

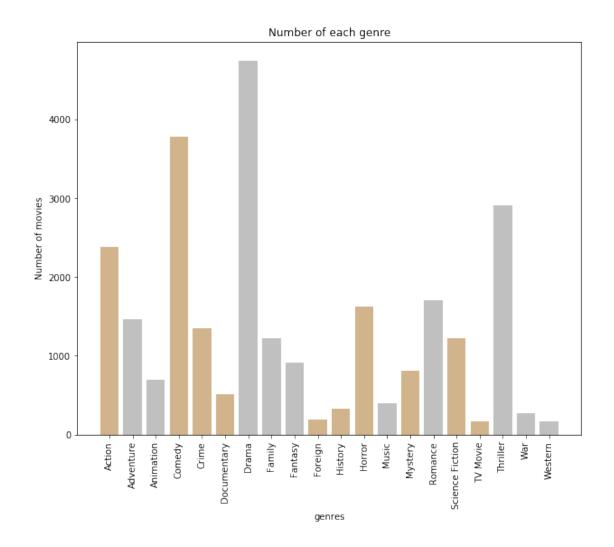
```
In [20]: df_genre.head()
Out [20]:
                 original_title
                                 runtime
                                          vote_average release_year
                                                                                    genre
                 Jurassic World
         0
                                      124
                                                                   2015
                                                                                   Action
         0
                 Jurassic World
                                      124
                                                     6.5
                                                                   2015
                                                                                Adventure
         0
                 Jurassic World
                                      124
                                                     6.5
                                                                   2015
                                                                        Science Fiction
         0
                 Jurassic World
                                      124
                                                     6.5
                                                                   2015
                                                                                 Thriller
                                      120
                                                     7.1
                                                                   2015
            Mad Max: Fury Road
                                                                                   Action
```

in the previous code cells, after splitting the genres and dropping the genres with multiple values, I saved the new dataframe. As the output of the head function shows that, one movie has the same index number with multiple rows for different value in the genre column.

In [21]: df\_genre['genre'].value\_counts()

```
Out[21]: Drama
                              4751
         Comedy
                              3782
         Thriller
                              2905
         Action
                              2382
         Romance
                              1705
         Horror
                              1629
         Adventure
                              1470
         Crime
                              1353
         Family
                              1229
         Science Fiction
                              1228
         Fantasy
                               915
         Mystery
                               808
         Animation
                               699
         Documentary
                               517
         Music
                               401
                               334
         History
         War
                               270
         Foreign
                               187
         Western
                               165
         TV Movie
                               164
         Name: genre, dtype: int64
In [22]: x = ['Drama', 'Comedy', 'Thriller', 'Action', 'Romance', 'Horror', 'Adventure', 'Crime', 'Famil
         y = [4751, 3782, 2905, 2382, 1705, 1629, 1470, 1353, 1229, 1228, 915, 808, 699, 517, 401, 334, 270, 187,
         plt.figure(figsize=(10,8))
         plt.xticks(rotation=90)
         plt.bar(x, y,color=['silver','tan'])
         plt.title('Number of each genre')
         plt.xlabel('genres')
```

plt.ylabel('Number of movies');

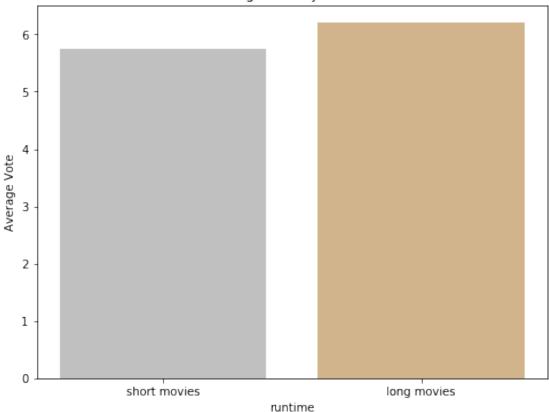


From the bar chart, I found that the most common movie genre produced in this dataset is **Drama genre**.

### 1.1.4 Question 2: Do movies with longger runtime receive better rating?

```
plt.title('Average vote by runtime')
plt.xlabel('runtime')
plt.ylabel('Average Vote');
```

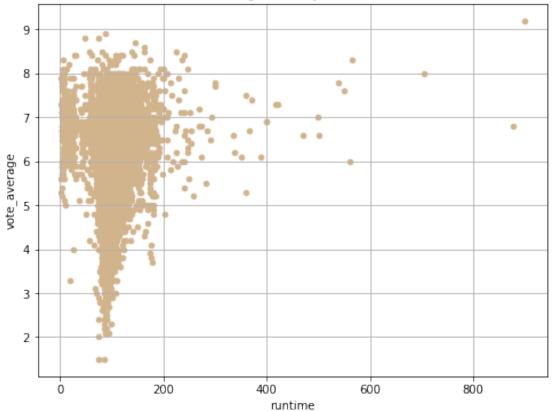
# Average vote by runtime



The bar chart above shows that the movies with longger runtime receive higher rating, I followed the same steps in the first case study (19.Plotting with Matplotlib). by using query to group the two types of movies runtime as (short runtime and long runtime) through the median, then compare it to the mean of the 'vote\_average'.

```
In [25]: df.plot(x='runtime', y='vote_average', kind='scatter',figsize=(8,6), color='tan', grid=
```

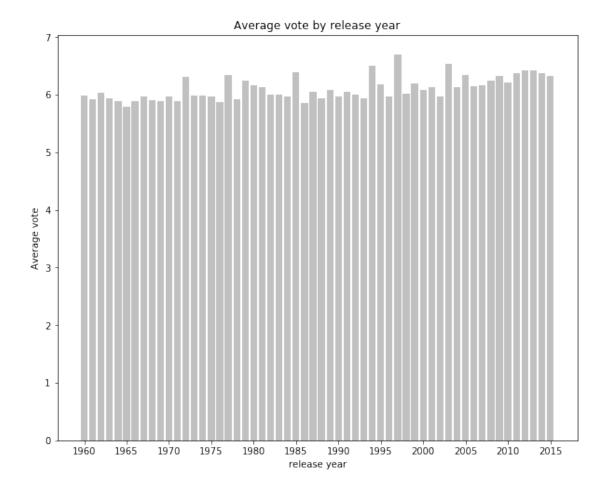




**I also applied another kind of plots (scatter),** it appears that the longest movie reciecved the highest rating overall.

## 1.1.5 Question 3: Which year is associated with the higher rating?

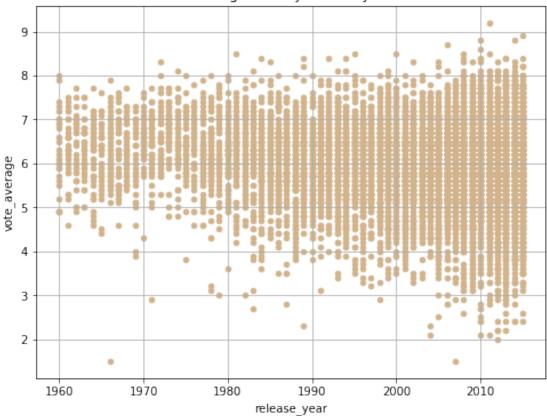
```
In [26]: years_vote_means = df.groupby('release_year').vote_average.mean()
    x = df.release_year.unique()
    y = years_vote_means
    plt.figure(figsize=(10,8))
    plt.xticks([1960,1965,1970,1975,1980,1985,1990,1995,2000,2005,2010,2015])
    plt.bar(x, y,color=['silver'])
    plt.title('Average vote by release year')
    plt.xlabel('release year')
    plt.ylabel('Average vote');
```



The bar chart above shows that, the higher average vote movies released in year 1997, I followed the same steps in the first case study (19.Plotting with Matplotlib). by using the groupby function. I changed the size of the figure and customized the ticks.

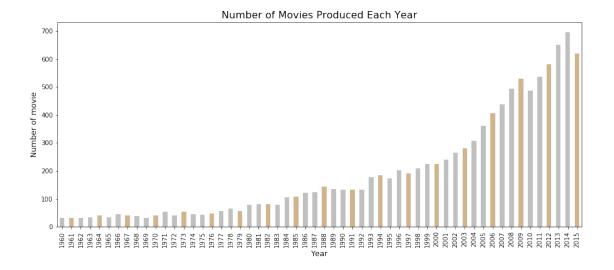
In [27]: df.plot(x='release\_year', y='vote\_average', kind='scatter',figsize=(8,6), color='tan',

# Average vote by release year



**I also applied another kind of plots (scatter),** it appears that the highest rate movie produced in 2011.

## 1.1.6 Question 4: How many movies produced in each year?



In the above bar chart, it shows the number of movies produced each year. So, the year with the highest number of movies produced is **2014**. Overall, it shows that the production of movies is getting increased over time.

## Conclusions

I investigated and analyzed a dataset of approximatly 10,000 movies, from the TMDb from the Kaggle.

#### 1. Data Wrangling

I observe the dataset from the excel sheet (csv) and found in the (budget, revenue, budget\_a

Also, the info() function showed the missing data. So, I cleand the data, and based on the questions I posed, I dropped the columns that I did not need in my analysis process.

Moreover, there were some rows with NaN value in genres column, some with 0 value in runtime column and a duplicated row. So I removed those rows.

### 2. Exploratory Data Analysis

The most common movie genre produced in this dataset is Drama genre. on the other hand, the

I used the median function for the runtime and the mean function for the vote\_average and by using the bar chart, it showed that the movies with longger runtime in this dataset receive higher rating.

By using the scatter chart, I found that the highest vote average was for a movie with long runtime.

I used the mean function for the vote average for the movies in this dataset groupby the release year. The bar chart showed that, 1997 got the highest vote\_average (by using the mean).

By using the scatter chart, I found that the highest vote average of movies as indviuiual was produced in 2011.

The year with the highest number of movies produced is 2014 as the bar chart shown **References** 

<a herf='https://stackoverflow.com/questions/18172851/deleting-dataframe-row-in-pandas-based
<li><a herf='https://static1.squarespace.com/static/55bfa8e4e4b007976149574e/t/5b998f398a922d8ea
<li><a herf='https://classroom.udacity.com/nanodegrees/nd002-connect/parts/9c4fa82f-b4cb-40fe-91
</ul>