FinalProject_DavidSchmid

October 11, 2021

[ ]:
```
import numpy as np
import pandas as pd
```

This is a template for your final project.

[ ]:
```
full_dataset = pd.read_csv('IMDb movies.csv')
full_dataset.head(3)
```

[ ]:
```
  imdb_title_id                       title              original_title  \
0     tt0000574  The Story of the Kelly Gang  The Story of the Kelly Gang
1     tt0001892              Den sorte drøm              Den sorte drøm
2     tt0002101                   Cleopatra                   Cleopatra

   year date_published                      genre  duration          country  \
0  1906     1906-12-26  Biography, Crime, Drama        70        Australia
1  1911     1911-08-19                     Drama        53  Germany, Denmark
2  1912     1912-11-13            Drama, History       100              USA

  language             director  …  \
0      NaN         Charles Tait  …
1      NaN            Urban Gad  …
2  English  Charles L. Gaskill  …

                                              actors  \
0  Elizabeth Tait, John Tait, Norman Campbell, Be…
1  Asta Nielsen, Valdemar Psilander, Gunnar Helse…
2  Helen Gardner, Pearl Sindelar, Miss Fielding, …

                                         description avg_vote votes   budget  \
0  True story of notorious Australian outlaw Ned …      6.1   537   $ 2250
1  Two men of high rank are both wooing the beaut…      5.9   171      NaN
2  The fabled queen of Egypt's affair with Roman …      5.2   420  $ 45000

   usa_gross_income worlwide_gross_income metascore reviews_from_users  \
0               NaN                   NaN       NaN                7.0
1               NaN                   NaN       NaN                4.0
2               NaN                   NaN       NaN               24.0
```

```
   reviews_from_critics
0                   7.0
1                   2.0
2                   3.0

[3 rows x 22 columns]
```

0.0.1 Part 1.

Task formalization and Evaluation criteria

1.1 Select your target variable, explain your choice. Separate target variable from the feature matrix.

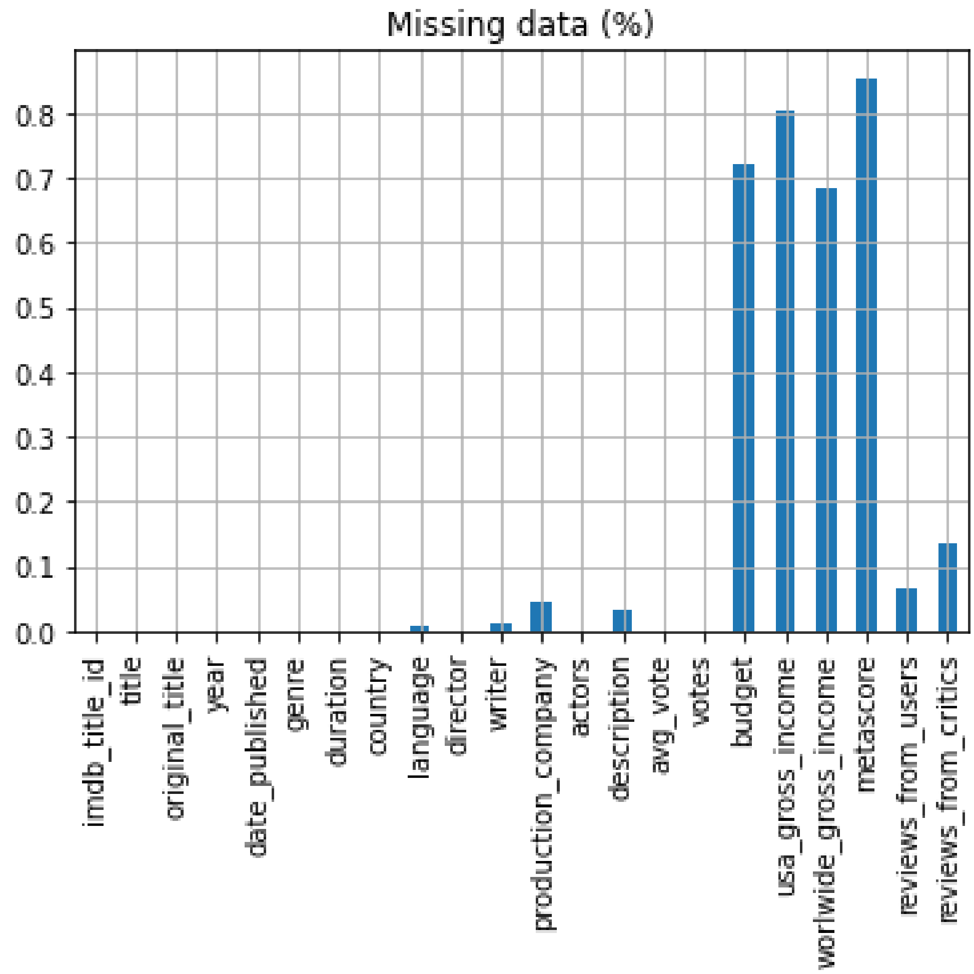
I select as target variable "avg_votes". See reasoning below.

What is success? Intuitively I would say, that ideally the target variable should be the worldwide_gross_income. The gross income can be classified equally as success. #### What are the problems with world_wide_gross_income? - The date range is too big, the currency valuation is very unstable and noisy through the whole period, so that worldwide_gross_income cannot be taken (Obvious) - There are too many missing values in worldwide_gross_income. (appr. 70%), so that alone this fact makes it not usable as a target variable (See cell below)

We have to reject worldwide_gross_income as a good target measure.

```
[ ]: num_rows = full_dataset.shape[0]
     (full_dataset.isna().sum() / num_rows).plot(kind="bar", title="Missing data␣
      ↪(%)", grid=True)
```

```
[ ]: <AxesSubplot:title={'center':'Missing data (%)'}>
```



0.0.2 What alternative targets exist?

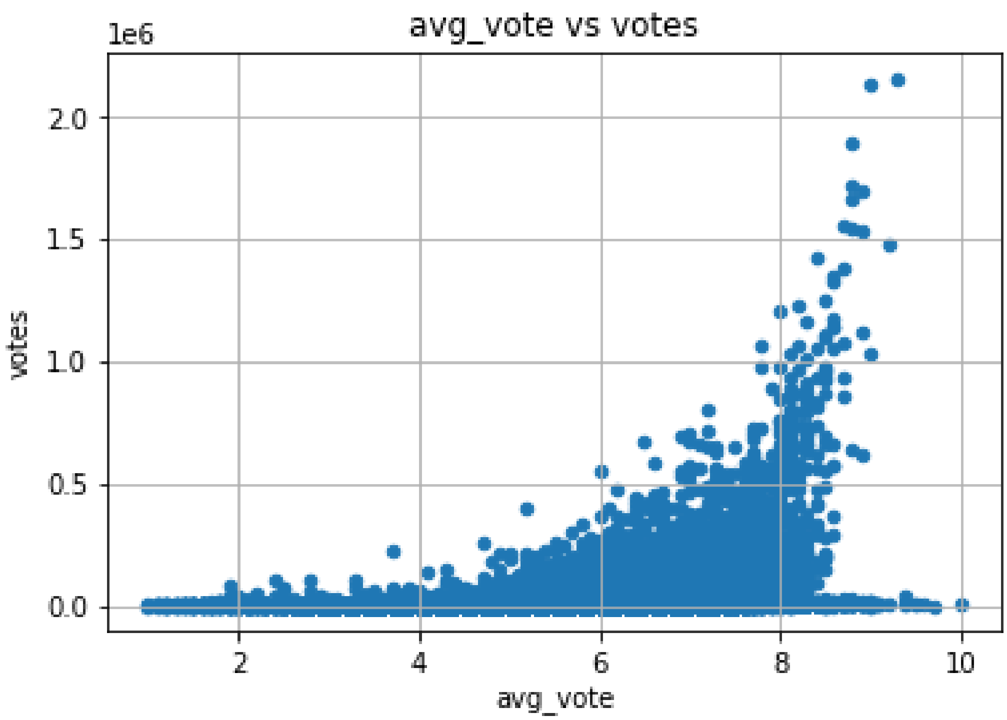
- Number of Votes and Avg_votes seem to be another good quantitative measure of success. Number of votes represents the popularity of a movie (therefore many people vote), while Avg_votes repesents the quality of a movie. One would expect that this goes hand in hand and is strongly correlated.
- Which one is better? By observing some samples of data, it seems that the early year movies generally don't have much votes. Moreover the movies of countries outside of USA & Europe seem to have generally fewer votes.
- We see a correlation, but because of the mentioned reasons, the number of votes seems to be biased by year and country. If this biased would be removed an even stronger correlation could be expected.
- "avg_votes" has a nice distribution, which approixmates a Gaussian normal distribution. This improves the quality of prediction.

0.0.3 Conclusion:

I select as target variable "avg_votes".

```
[ ]: pd.concat([full_dataset['avg_vote'], full_dataset['votes']], axis=1).plot.
     ↪scatter(x='avg_vote', y='votes', title='avg_vote vs votes', grid=True)
```

```
[ ]: <AxesSubplot:title={'center':'avg_vote vs votes'}, xlabel='avg_vote',
     ylabel='votes'>
```



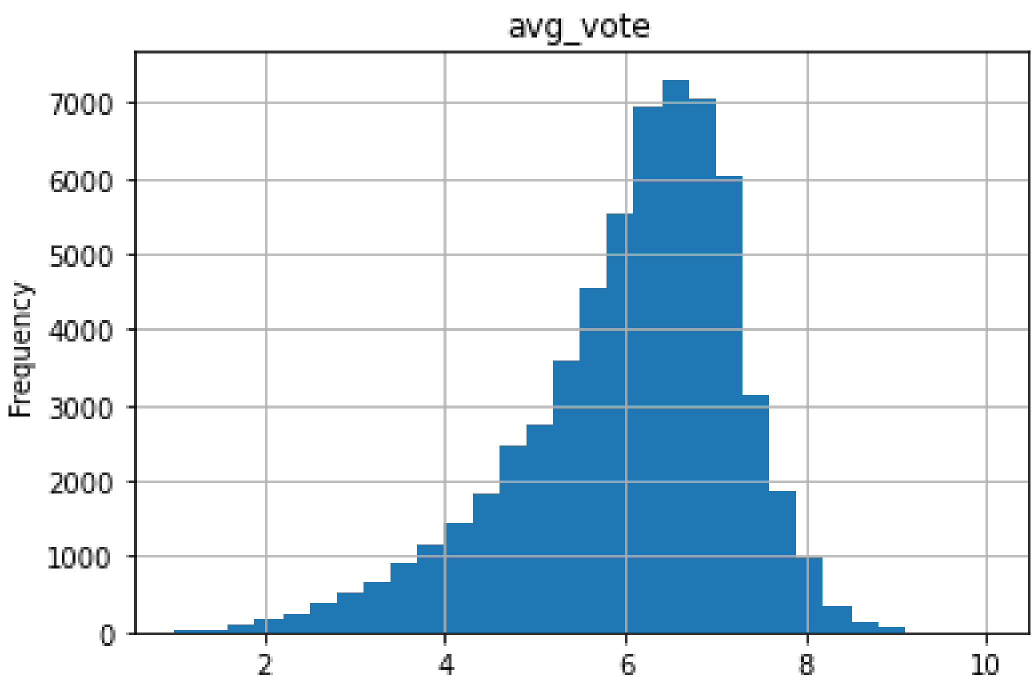

```
[ ]: partial_dataset = pd.concat([full_dataset['avg_vote'],␣
     ↪full_dataset['votes'],full_dataset['year'],full_dataset['country']], axis=1)

     partial_dataset[(partial_dataset['avg_vote']>8)&(partial_dataset['votes']<200000)]
```

```
[ ]:        avg_vote   votes  year  country
     155         8.1   51644  1920  Germany
     238         8.3  101619  1921      USA
     239         8.1    9322  1921   Sweden
     320         8.1   16798  1923      USA
     357         8.1   11361  1924  Germany
     …            …       …     …        …
     59934       8.4    1206  2010      USA
     60017       8.1   53242  2012    India
```

```
60031        8.1    3712  2011    India
60081        8.2    3815  2011    Egypt
60134        8.2    1600  2011    India

[704 rows x 4 columns]
```

[ ]:
```
full_dataset['avg_vote'].plot.hist(bins=30, grid=True, title="avg_vote")
```

[ ]:
```
<AxesSubplot:title={'center':'avg_vote'}, ylabel='Frequency'>
```



[ ]:
```
# Seperating target variable from the feature matrix.
full_dataset.rename({'avg_vote': 'target'}, axis=1)
```

[ ]:
```
      imdb_title_id                                          title  \
0         tt0000574                    The Story of the Kelly Gang
1         tt0001892                                 Den sorte drøm
2         tt0002101                                      Cleopatra
3         tt0002130                                      L'Inferno
4         tt0002199  From the Manger to the Cross; or, Jesus of Naz…
…               …                                              …
60193     tt1836907                                    Sài Gòn Yo!
60194     tt1836912                                        Shaitan
60195     tt1836918                                    Slow Action
60196     tt1836926                             Stealing Las Vegas
```

```
60197    tt1836944                              The Baytown Outlaws   

                                          original_title  year date_published  \
0                          The Story of the Kelly Gang  1906     1906-12-26   
1                                       Den sorte drøm  1911     1911-08-19   
2                                            Cleopatra  1912     1912-11-13   
3                                            L'Inferno  1911     1911-03-06   
4      From the Manger to the Cross; or, Jesus of Naz…  1912           1913   
…                                                  …   …            …   
60193                                      Sài Gòn Yo!  2011     2011-04-22   
60194                                          Shaitan  2011     2011-06-10   
60195                                      Slow Action  2011     2011-01-28   
60196                               Stealing Las Vegas  2012     2012-09-11   
60197                              The Baytown Outlaws  2012     2013-06-15   

                            genre  duration           country        language  \
0         Biography, Crime, Drama        70         Australia             NaN   
1                           Drama        53  Germany, Denmark             NaN   
2                  Drama, History       100               USA         English   
3       Adventure, Drama, Fantasy        68             Italy         Italian   
4                Biography, Drama        60               USA         English   
…                             …       …               …             …   
60193                       Drama       106           Vietnam      Vietnamese   
60194         Action, Crime, Drama       121             India  Hindi, English   
60195                      Sci-Fi        45                UK         English   
60196             Crime, Thriller        87               USA         English   
60197        Action, Comedy, Crime        98               USA         English   

                                  director  …  \
0                             Charles Tait  …   
1                               Urban Gad  …   
2                        Charles L. Gaskill  …   
3       Francesco Bertolini, Adolfo Padovan  …   
4                            Sidney Olcott  …   
…                                      …  …   
60193                      Stephane Gauger  …   
60194                        Bejoy Nambiar  …   
60195                           Ben Rivers  …   
60196                   Francisco Menéndez  …   
60197                        Barry Battles  …   

                                                   actors  \
0       Elizabeth Tait, John Tait, Norman Campbell, Be…   
1       Asta Nielsen, Valdemar Psilander, Gunnar Helse…   
2       Helen Gardner, Pearl Sindelar, Miss Fielding, …   
3       Salvatore Papa, Arturo Pirovano, Giuseppe de L…   
4       R. Henderson Bland, Percy Dyer, Gene Gauntier,…   
```

```
…                                                  …
60193  Quynh Hoa, Khuong Ngoc, Elly Nguyen, Phan Tan …
60194  Kalki Koechlin, Shiv Panditt, Gulshan Devaiah,…
60195                                                NaN
60196  Eric Roberts, Antonio Fargas, Ethan Landry, An…
60197  Clayne Crawford, Travis Fimmel, Daniel Cudmore…

                                             description target  votes  \
0      True story of notorious Australian outlaw Ned …    6.1    537
1      Two men of high rank are both wooing the beaut…    5.9    171
2      The fabled queen of Egypt's affair with Roman …    5.2    420
3      Loosely adapted from Dante's Divine Comedy and…    7.0   2019
4      An account of the life of Jesus Christ, based …    5.7    438
…                                                  …     …     …
60193  Mai, a ribbon dancer from the countryside arri…    6.8    106
60194  Five substance-abusing friends decide to fake …    7.2   7615
60195                                                NaN    6.8    107
60196  When a greedy Las Vegas casino owner threatens…    3.9    354
60197  When three redneck brothers agree to help a wo…    6.4  13182

          budget  usa_gross_income worlwide_gross_income metascore  \
0         $ 2250               NaN                   NaN       NaN
1            NaN               NaN                   NaN       NaN
2        $ 45000               NaN                   NaN       NaN
3            NaN               NaN                   NaN       NaN
4            NaN               NaN                   NaN       NaN
…              …                 …                     …         …
60193   $ 500000               NaN                   NaN       NaN
60194        NaN               NaN                   NaN       NaN
60195  GBP 30000               NaN                   NaN       NaN
60196        NaN               NaN                   NaN       NaN
60197  $ 4000000               NaN               $ 37470      33.0

      reviews_from_users  reviews_from_critics
0                    7.0                   7.0
1                    4.0                   2.0
2                   24.0                   3.0
3                   28.0                  14.0
4                   12.0                   5.0
…                      …                     …
60193                3.0                   4.0
60194               42.0                  15.0
60195                4.0                   6.0
60196               10.0                   4.0
60197               64.0                   6.0

[60198 rows x 22 columns]
```

1.2 Explain which task are you going to solve (is it a regression, classification or something else)?

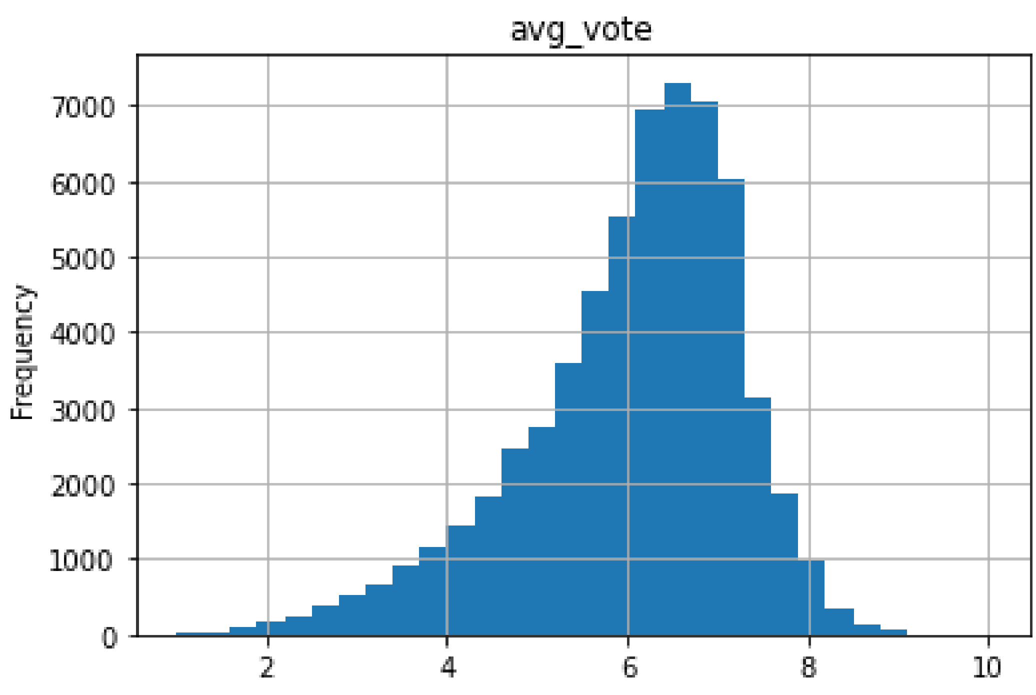
- I think the nature of the question is "binary", either True or False. Therefore it is a classification task.
- Moreover, we have a target variable avg_vote, therefore it is supervised.

See below the preparation of the target variable to be either 1 = successful or 0 = not successful. The question is; what is the best threshold of either 0 and 1.

[ ]:
```
# Defining success threshold
# When observing the target dsitribution, a quantile of 0.75 makes absolutely␣
↪sense,
# it is where, the marjority of movies are rated, but cuts off the lower and␣
↪longer end of "unsuccessful movies".
success_threshold = full_dataset['avg_vote'].quantile(0.75)
print(f"Success Threshhold : {success_threshold}")
full_dataset['avg_vote'].plot.hist(bins=30, grid=True, title="avg_vote")
```

```
Success Threshhold : 6.8
```

[ ]:
```
<AxesSubplot:title={'center':'avg_vote'}, ylabel='Frequency'>
```



[ ]:
```
#Formatting the target variable
full_dataset['target'] = full_dataset['avg_vote'].apply(lambda x: 1 if x >=␣
↪success_threshold else 0)
```

```
#Target distribution (absolute)
print(f"Target distribution (absolute):\n{full_dataset['target'].
↪value_counts()}")

#Target distribution (relative)
print(f"Target distribution (relative):\n{full_dataset['target'].value_counts()/
↪full_dataset['target'].shape[0]}")

# One would expect that 0.75 Quantile is exactly explit 75% - 25%. However,␣
↪there is a deviation by the low granularity of ratings,
# which only measure avg_votes rounded to 1 decimal position.
```

```
Target distribution (absolute):
0    43013
1    17185
Name: target, dtype: int64
Target distribution (relative):
0    0.714525
1    0.285475
Name: target, dtype: float64
```

1.3 Select a metric. Is it already implemented in sklearn? If yes, import it. If not, it is time to write a function which will calculate it.

- The F1 score is the harmonic mean of the precision and recall
- It is a measure of accuracy; exactly what we want.
- The greater the F1-Score, the better is the performance of our model
- Best value at 1 and worst score at 0
- Formula F1-Score -> F1 = 2 * (precision * recall) / (precision + recall)
- In sklearn.metrics f1_score is already in-built

[ ]:
```
from sklearn.metrics import f1_score
```

0.0.4 Part 2.

Explore and preprocess the data

2.1 Split data into train and test

[ ]:
```
from sklearn.model_selection import train_test_split

# Splitting between 0.4-0.2 in test seems approriate. I chose the lower bound␣
↪of test sets
train, test = train_test_split(full_dataset, test_size=0.2, random_state=42)␣
↪#Choosing a random state, that test results can be compared & reproduced
X_train, y_train, X_test, y_test = train.drop(['target'], axis=1), train.
↪target, test.drop(['target'], axis=1), test.target # Splitting
```

2.2 Explore you data: make plots, print tables. Make sure to write your observations. Do not forget to fill-in missing values, define relevant columns transformatios.

[ ]:
```
full_dataset.dtypes #Datset Types Overview, what is numeric, what is a String
```

[ ]:
```
imdb_title_id              object
title                      object
original_title             object
year                        int64
date_published             object
genre                      object
duration                    int64
country                    object
language                   object
director                   object
writer                     object
production_company         object
actors                     object
description                object
avg_vote                  float64
votes                       int64
budget                     object
usa_gross_income           object
worlwide_gross_income      object
metascore                 float64
reviews_from_users        float64
reviews_from_critics      float64
target                      int64
dtype: object
```

[ ]:
```
full_dataset.isna().sum() # How many missing values?
```

[ ]:
```
imdb_title_id                0
title                        0
original_title               0
year                         0
date_published               0
genre                        0
duration                     0
country                      5
language                   439
director                    24
writer                     808
production_company        2744
actors                      30
description               1993
avg_vote                     0
votes                        0
budget                   43379
usa_gross_income         48306
```

```
worlwide_gross_income    41062
metascore                51386
reviews_from_users        4069
reviews_from_critics      8229
target                       0
dtype: int64
```

imdb__title__id imdb__title_id is simply a sequential id, every id is unique. It has to be dropped.

```
[ ]: # imdb_title_id
print(full_dataset.imdb_title_id.describe())
full_dataset.drop(['imdb_title_id'], axis=1, inplace=True)
```

```
count         60198
unique        60198
top       tt1126618
freq              1
Name: imdb_title_id, dtype: object
```

title There is no quantitative value in title, there are 57'284 uniqze values out of 60'198. It has to be dropped.

```
[ ]: print(full_dataset.title.describe())
full_dataset.drop(['title'], axis=1, inplace=True)
```

```
count                     60198
unique                    57284
top       The Three Musketeers
freq                          8
Name: title, dtype: object
```

original title This is the same/equivalent to title. It has to be dropped.

```
[ ]: print(full_dataset.original_title.describe())
full_dataset.drop(['original_title'], axis=1, inplace=True)
```

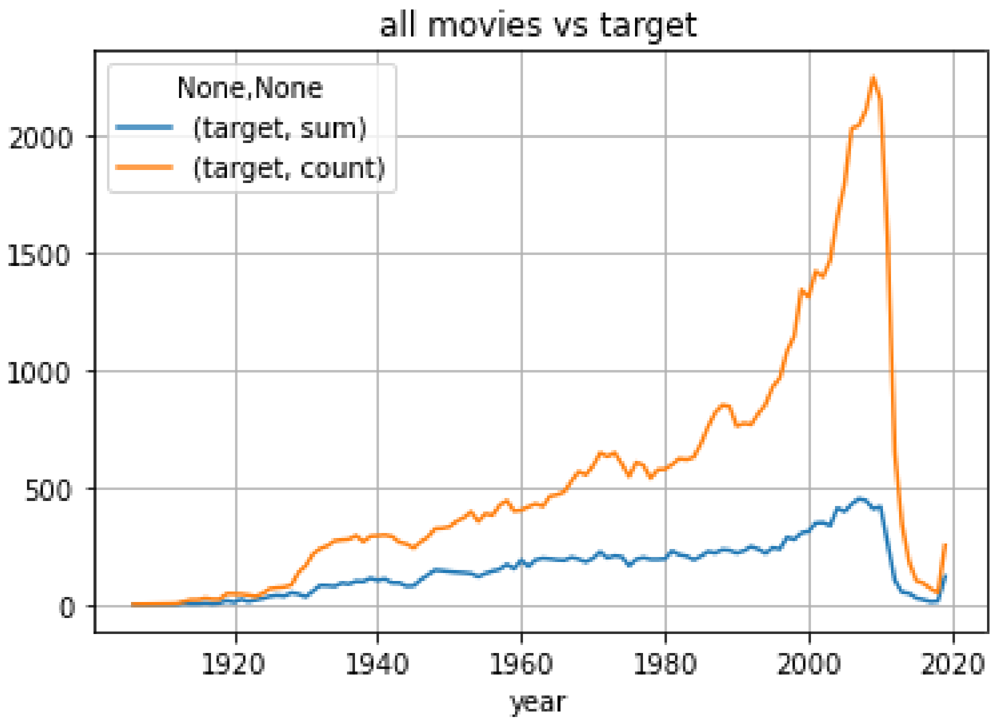
```
count                     60198
unique                    57290
top       The Three Musketeers
freq                          8
Name: original_title, dtype: object
```

year

- We see that the correlation between the number of movies and successful movies is not linear.
- The year is an important feature to identify the success; there is kind of a nonlinear relationship.

[ ]:
```
print(full_dataset[['target', 'year']].groupby(['year']).agg(['sum', 'count']).
↪plot.line(grid=True, title="all movies vs target"))
```

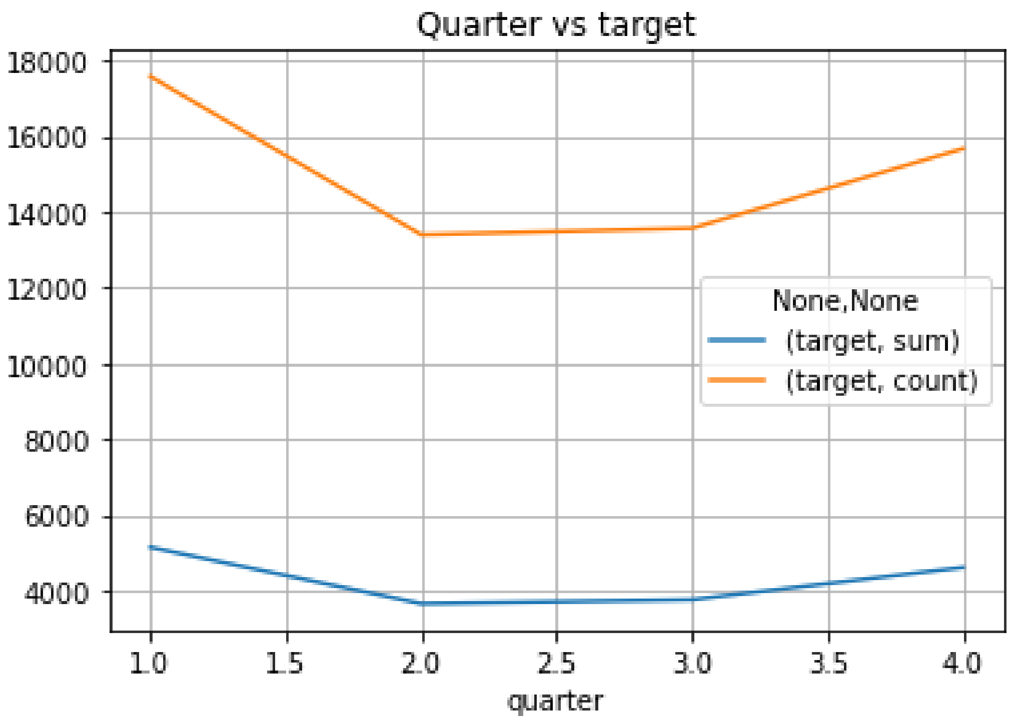
```
AxesSubplot(0.125,0.125;0.775x0.755)
```



date_published The only value of date_published could be if it during a weekend or workday or a special quarter. Below there is seen the investigation by season. There is a strong correlation between not successful and successful values, so that there is no additional value. I drop the feature.

[ ]:
```
full_dataset['quarter'] = pd.to_datetime(full_dataset['date_published']).
↪apply(lambda x: x.quarter)

print(full_dataset[['target', 'quarter']].groupby(['quarter']).agg(['sum',␣
↪'count']).plot.line(grid=True, title="Quarter vs target"))

full_dataset.drop(['date_published','quarter'], axis=1, inplace=True)
```

```
AxesSubplot(0.125,0.125;0.775x0.755)
```



imdb_title_id is simply a sequential id, every id is unique,

genre

[ ]:
```
print(full_dataset["genre"].value_counts())
```

```
Drama                            8498
Comedy                           5420
Comedy, Drama                    2654
Drama, Romance                   2529
Comedy, Romance                  1777
                                 …
Action, Thriller, Sci-Fi            1
Crime, Romance, Sci-Fi              1
Comedy, Film-Noir, Mystery          1
Drama, Mystery, Sport               1
Animation, Comedy, Western          1
Name: genre, Length: 1202, dtype: int64
```

- We see that there is a general problem, that there are more than one category.
- Potentially we could split all genres, if more than one. But this would give a bias between one-category-genres and many-categories genres.
- I assume that the first genre is always the main genre, therefore let's only keep the main genre.

[ ]:
```
full_dataset["genre"] = full_dataset["genre"].str.split(', ').apply(lambda␣
↪main_genre: main_genre[0])

print(full_dataset["genre"])

genre_vals = full_dataset[['target', 'genre']].groupby(['genre']).agg(['sum',␣
↪'count'])

print(pd.concat([genre_vals.target["sum"], genre_vals.
↪target["count"],genre_vals.target["sum"]/genre_vals.target["count"]],␣
↪axis=1))
```

```
0        Biography
1            Drama
2            Drama
3        Adventure
4        Biography
           …
60193        Drama
60194       Action
60195       Sci-Fi
60196        Crime
60197       Action
Name: genre, Length: 60198, dtype: object
              sum  count         0
genre
Action       1670   8360  0.199761
Adult           0      2  0.000000
Adventure     712   2797  0.254558
Animation     603   1284  0.469626
Biography     698   1400  0.498571
Comedy       4466  17350  0.257406
Crime        1370   4228  0.324030
Documentary     2      2  1.000000
Drama        6809  17565  0.387646
Family         88    453  0.194260
Fantasy        64    342  0.187135
Film-Noir      13     34  0.382353
History        17     52  0.326923
Horror        158   3215  0.049145
Music          18     54  0.333333
Musical        79    293  0.269625
Mystery        71    426  0.166667
Romance       127    531  0.239171
Sci-Fi         21    302  0.069536
Sport           1      4  0.250000
Thriller       81    811  0.099877
War            34     93  0.365591
```

```
Western         83     600  0.138333
```

- We see that there are some very small categories, however they don't disturb since the category number is not that big
- Otherwise the genre data look very promising; there is a lot of success cariance between the categories, which will allow a strong categorical feature

[ ]:
```
genre_vals = full_dataset[['target', 'genre']].groupby(['genre']).agg(['sum',␣
↪'count'])

print(pd.concat([genre_vals.target["sum"], genre_vals.
↪target["count"],genre_vals.target["sum"]/genre_vals.target["count"]],␣
↪axis=1))
```

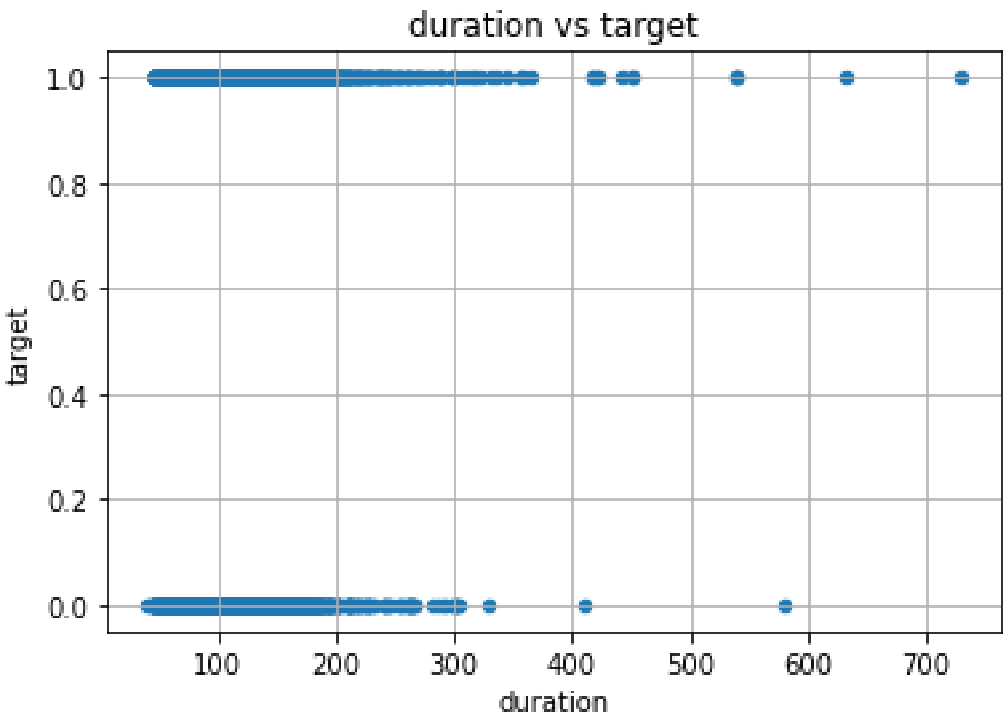
```
              sum  count         0
genre
Action       1670   8360  0.199761
Adult           0      2  0.000000
Adventure     712   2797  0.254558
Animation     603   1284  0.469626
Biography     698   1400  0.498571
Comedy       4466  17350  0.257406
Crime        1370   4228  0.324030
Documentary     2      2  1.000000
Drama        6809  17565  0.387646
Family         88    453  0.194260
Fantasy        64    342  0.187135
Film-Noir      13     34  0.382353
History        17     52  0.326923
Horror        158   3215  0.049145
Music          18     54  0.333333
Musical        79    293  0.269625
Mystery        71    426  0.166667
Romance       127    531  0.239171
Sci-Fi         21    302  0.069536
Sport           1      4  0.250000
Thriller       81    811  0.099877
War            34     93  0.365591
Western        83    600  0.138333
```

duration

- We see generally longer films are more successful, there is a difference, therefore it is a valid feature.

[ ]:
```
pd.concat([full_dataset['target'], full_dataset['duration']], axis=1).plot.
↪scatter(x='duration', y='target', title='duration vs target', grid=True)
```

```
[ ]: <AxesSubplot:title={'center':'duration vs target'}, xlabel='duration',
ylabel='target'>
```



country

- Only first country is chosen, assuming this to be the main country
- The success rates by country are very diverse, that will be good for a strong feature.
- I don't want to have a prediction of countries, which do have less than 2 movies (Not representative)

```
[ ]: full_dataset['country'].value_counts()

full_dataset['country'] = full_dataset['country'].str.split(', ').apply(lambda main_country: main_country[0] if main_country is not np.nan else "missing_value")

print(full_dataset['country'].value_counts())

country_vals = full_dataset[['target', 'country']].groupby(['country']).agg(['sum', 'count'])

country_vals_other = country_vals.target[(country_vals.target["count"]>2)]
```

```
country_vals_other = set(country_vals_other["count"].index.tolist())

full_dataset['country'] = full_dataset['country'].apply(lambda ctry: "Other" if␣
↪ctry not in country_vals_other else ctry)

print(full_dataset['country'].value_counts())

country_vals = full_dataset[['target', 'country']].groupby(['country']).
↪agg(['sum', 'count'])

print(pd.concat([country_vals.target["sum"], country_vals.
↪target["count"],country_vals.target["sum"]/country_vals.target["count"]],␣
↪axis=1))
```

```
USA         23832
UK           4365
France       3910
India        3102
Italy        3012
            …
Kenya           1
Moldova         1
Suriname        1
Belarus         1
Zambia          1
Name: country, Length: 140, dtype: int64
USA                 23832
UK                   4365
France               3910
India                3102
Italy                3012
                    …
Greenland               3
Liechtenstein           3
Panama                  3
Nepal                   3
Guatemala               3
Name: country, Length: 110, dtype: int64
               sum  count         0
country
Afghanistan      3      3  1.000000
Albania          5      9  0.555556
Algeria          5     10  0.500000
Angola           1      4  0.250000
Argentina      149    407  0.366093
…             …    …        …
Venezuela        8     21  0.380952
```

```
Vietnam          12      17  0.705882
West Germany    161     583  0.276158
Yugoslavia      211     288  0.732639
missing_value     1       5  0.200000

[110 rows x 3 columns]
```

director

- There are many different unique directors, however they are very divcerse and make a strong feature
- There are a lot of difference between a successful and a not successful director.
- I only take the first Director as main director
- In a previous version I had tested it with category "Other" and OneHotEncoding. The outcome was quite poor.
- I put together the average success rate of every director in one single column,. By doing this I get a very good result

[ ]:
```
feature = "director"

full_dataset[feature] = full_dataset[feature].str.split(', ').apply(lambda␣
↪value: value[0] if value is not np.nan else "missing_value")

values = full_dataset[['target', feature]].groupby([feature]).agg(['sum',␣
↪'count'])
success_rate = values.target["sum"]/values.target["count"]
full_dataset[feature] = full_dataset[feature].apply(lambda row: success_rate.
↪loc[row] if row in success_rate.index else 0)

print(success_rate)
```

```
director
'Evil' Ted Smith            0.000000
'Philthy' Phil Phillips     0.000000
A. Bhimsingh                0.875000
A. Dean Bell                0.000000
A. Edward Sutherland        0.217391
                              …
Ümit Elçi                   0.000000
Ümit Ünal                   0.200000
Þorsteinn Gunnar Bjarnason  0.000000
Þráinn Bertelsson           0.750000
Þórhildur Þorleifsdóttir    1.000000
Length: 21052, dtype: float64
```

language

- There are quite some different language, which success rate on tgarget ist quite different.

- In a previous version I had tested it with category “Other” and OneHotEncoding. The outcome was quite poor.
- I put together the average success rate of every director in one single column. By doing this I get a very good result

[ ]:
```
feature = "language"

full_dataset[feature] = full_dataset[feature].str.split(', ').apply(lambda␣
↪value: value[0] if value is not np.nan else "missing_value")

values = full_dataset[['target', feature]].groupby([feature]).agg(['sum',␣
↪'count'])
success_rate = values.target["sum"]/values.target["count"]
full_dataset[feature] = full_dataset[feature].apply(lambda row: success_rate.
↪loc[row] if row in success_rate.index else 0)

print(success_rate)
```

```
language
Aboriginal                  0.666667
Afrikaans                   0.727273
Akan                        1.000000
Albanian                    0.555556
American Sign Language      0.000000
                              …
Xhosa                       0.000000
Yiddish                     0.400000
Yoruba                      1.000000
Zulu                        0.666667
missing_value               0.318907
Length: 145, dtype: float64
```

Writer

- Too many uniue values, writer is not the director, and a director doesn’t always choose the same writers, therefore a disturbing feature.
- I will drop this feature

[ ]:
```
print(full_dataset['writer'].value_counts())
print(full_dataset['writer'].describe())

full_dataset.drop(['writer'], axis=1, inplace=True)
```

```
Jing Wong                                 70
Kuang Ni                                  44
Woody Allen                               33
Cheh Chang, Kuang Ni                      32
Leonardo Benvenuti, Piero De Bernardi     32
                                          ..
```

```
Hideo Oguni, Ryûzô Kikushima             1
Manoj Mitra, Tapan Sinha                 1
Christopher Folino                       1
Rob Lieber, Rob Lieber                   1
Georgiy Grebner, Karel Capek             1
Name: writer, Length: 47546, dtype: int64
count          59390
unique         47546
top        Jing Wong
freq              70
Name: writer, dtype: object
```

production_company

- There are many different production companies, who do have a big impact on success ratge.
- In a previous version I had tested it with category "Other" and OneHotEncoding. The outcome was quite poor.
- I put together the average success rate of every director in one single column. By doing this I get a very good result

[ ]:
```python
feature = "production_company"

full_dataset[feature] = full_dataset[feature].str.split(', ').apply(lambda␣
↪value: value[0] if value is not np.nan else "missing_value")

values = full_dataset[['target', feature]].groupby([feature]).agg(['sum',␣
↪'count'])
success_rate = values.target["sum"]/values.target["count"]
full_dataset[feature] = full_dataset[feature].apply(lambda row: success_rate.
↪loc[row] if row in success_rate.index else 0)


print(success_rate)
```

```
production_company
"DIA" Productions GmbH & Co. KG    0.000000
"DumBeast" Partners                0.000000
"G" P.C. S.A.                      0.000000
"Mi" Production Studio             0.000000
"Ulitka" Studio                    0.000000
                                      …
Österreichisches Filminstitut      0.000000
Özen Film                          0.500000
Özer Film                          0.000000
Új Budapest Filmstudió             0.333333
Új Dialóg Stúdió                   0.000000
Length: 21437, dtype: float64
```

actors

- The actors feature is very extensive and we need to simply it, by only taking the firt actor (main actor). Surely there are more than 1 main actor, but the first one is the most important.
- In a previous version I had tested it with category "Other" and OneHotEncoding. The outcome was quite poor.
- I put together the average success rate of every director in one single column,. By doing this I get a very good result

[ ]:
```
feature = "actors"

full_dataset[feature] = full_dataset[feature].str.split(', ').apply(lambda␣
↪value: value[0] if value is not np.nan else "missing_value")

values = full_dataset[['target', feature]].groupby([feature]).agg(['sum',␣
↪'count'])
success_rate = values.target["sum"]/values.target["count"]
full_dataset[feature] = full_dataset[feature].apply(lambda row: success_rate.
↪loc[row] if row in success_rate.index else 0)

print(success_rate)
```

```
actors
'Lee' George Quinones     1.0
'Weird Al' Yankovic       1.0
2Mex                      0.0
50 Cent                   0.0
A Martinez                1.0
                          …
Ümit Acar                 0.0
Ümit Kantarcilar          0.0
Þröstur Leó Gunnarsson    0.0
Þórhallur Sigurðsson      0.0
Þórhallur Sverrisson      1.0
Length: 25082, dtype: float64
```

description

- Description is a custom text, all values are quite unique. One can think to extract words count the words, but this would be an overkill for this final project and the success is not guaranteed.
- The feature has to be dropped

[ ]:
```
print(full_dataset['description'])
print(full_dataset['description'].describe())

full_dataset.drop(['description'], axis=1, inplace=True)
```

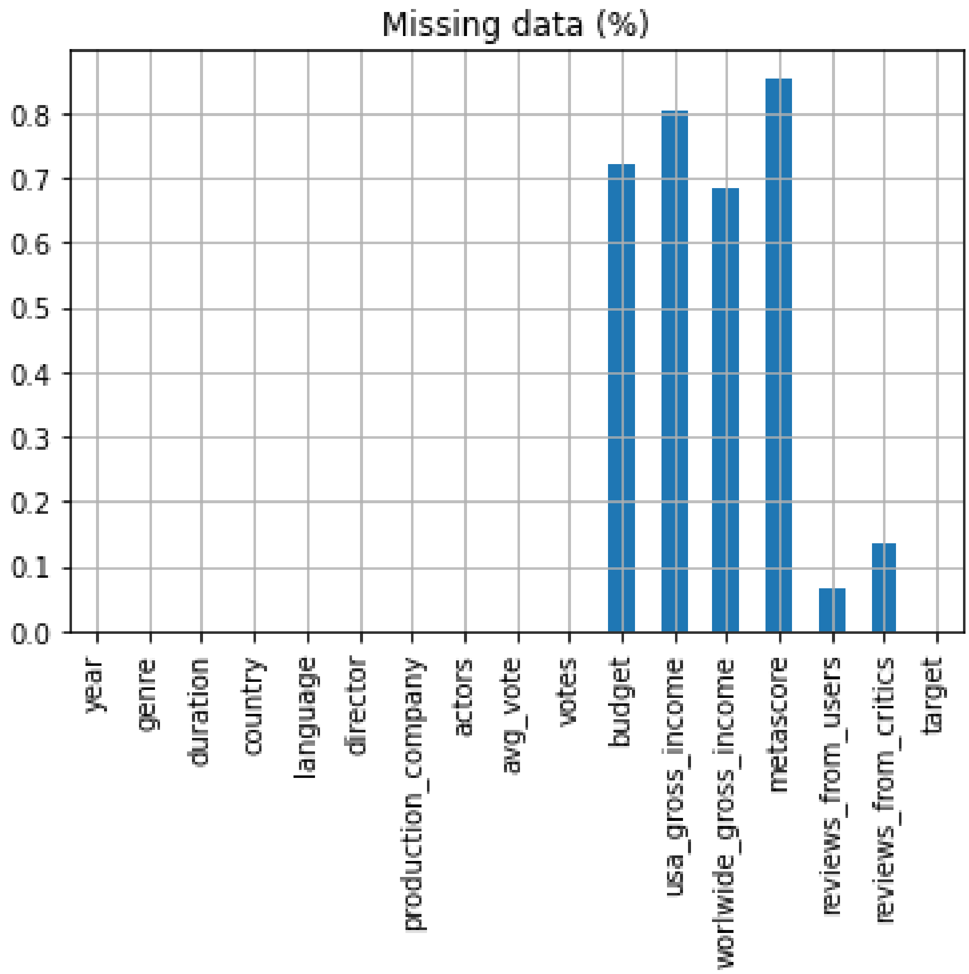
```
0        True story of notorious Australian outlaw Ned …
```

```
1        Two men of high rank are both wooing the beaut…
2        The fabled queen of Egypt's affair with Roman …
3        Loosely adapted from Dante's Divine Comedy and…
4        An account of the life of Jesus Christ, based …
                              …
60193    Mai, a ribbon dancer from the countryside arri…
60194    Five substance-abusing friends decide to fake …
60195                                                 NaN
60196    When a greedy Las Vegas casino owner threatens…
60197    When three redneck brothers agree to help a wo…
Name: description, Length: 60198, dtype: object
count     58205
unique    58126
top        Mail
freq          7
Name: description, dtype: object
```

Columns with too many missing values have to be dropped

- budget, usa_gross_income, worldwide_gross_income, metascore have too many missing values, all over 65%, therefore it is not representative and has to be dropped

```
[ ]: (full_dataset.isna().sum() / num_rows).plot(kind="bar", title="Missing data␣
     ↪(%)", grid=True)

     full_dataset.
     ↪drop(['budget','usa_gross_income','worlwide_gross_income','metascore'],␣
     ↪axis=1, inplace=True)
```

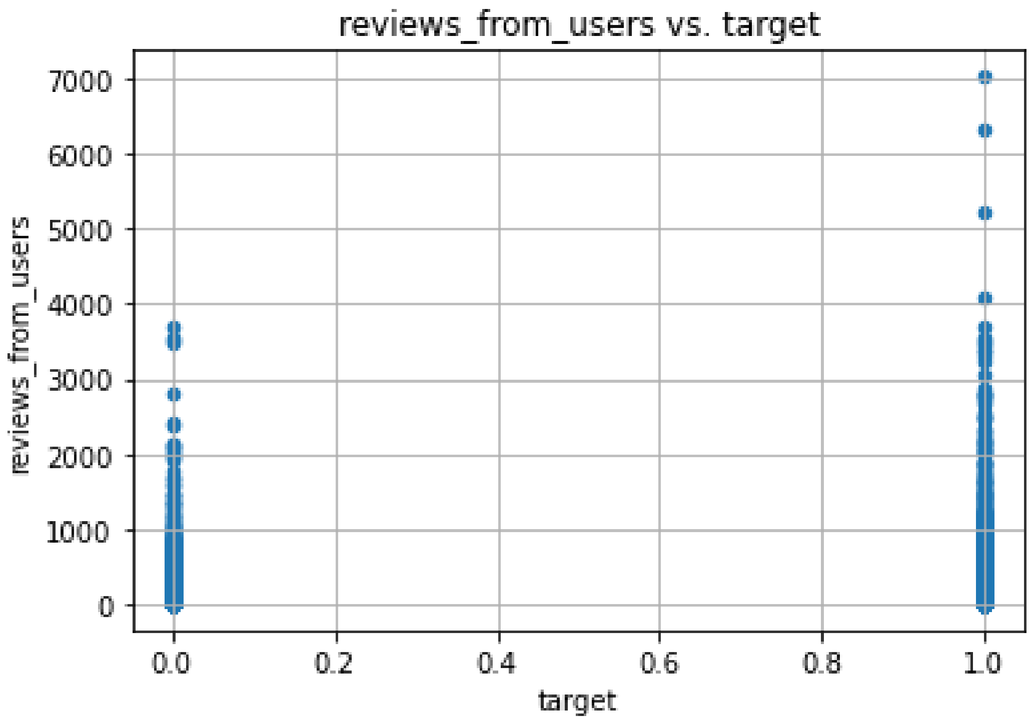


reviews__from__users

- The number of reviews is not randomly distributed to successful & not successful movies. There is a tendency that sucessful movies get more reviews.
- The feature is useful, no transformation required
- NA values ares filled by 0

[ ]:
```
print(pd.concat([full_dataset['reviews_from_users'], full_dataset['target']],␣
↪axis=1).plot.scatter(x='target', y='reviews_from_users',␣
↪title='reviews_from_users vs. target', grid=True))

full_dataset['reviews_from_users'] = full_dataset['reviews_from_users'].
↪fillna(0)
```

```
AxesSubplot(0.125,0.125;0.775x0.755)
```

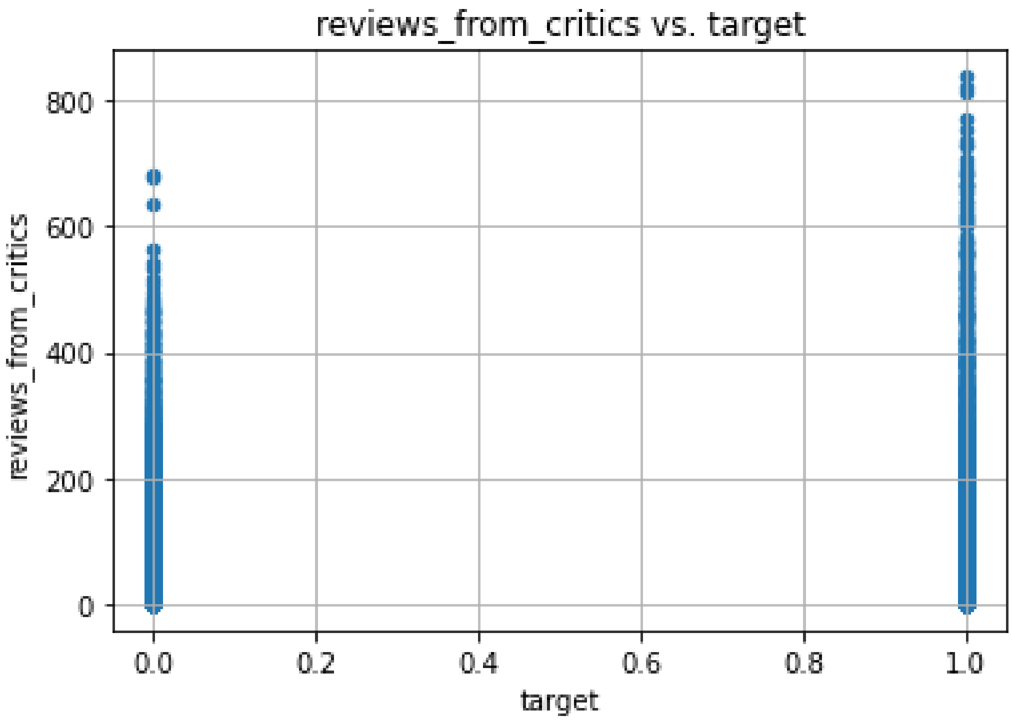


reviews__from__critics

- The number of reviews is not randomly distributed to successful & not successful movies. There is a tendency that sucessful movies get more reviews.
- The feature is useful, no transformation required
- NA values ares filled by 0

[ ]:
```
print(pd.concat([full_dataset['reviews_from_critics'], full_dataset['target']],␣
↪axis=1).plot.scatter(x='target', y='reviews_from_critics',␣
↪title='reviews_from_critics vs. target', grid=True))

full_dataset['reviews_from_critics'] = full_dataset['reviews_from_critics'].
↪fillna(0)
```

```
AxesSubplot(0.125,0.125;0.775x0.755)
```

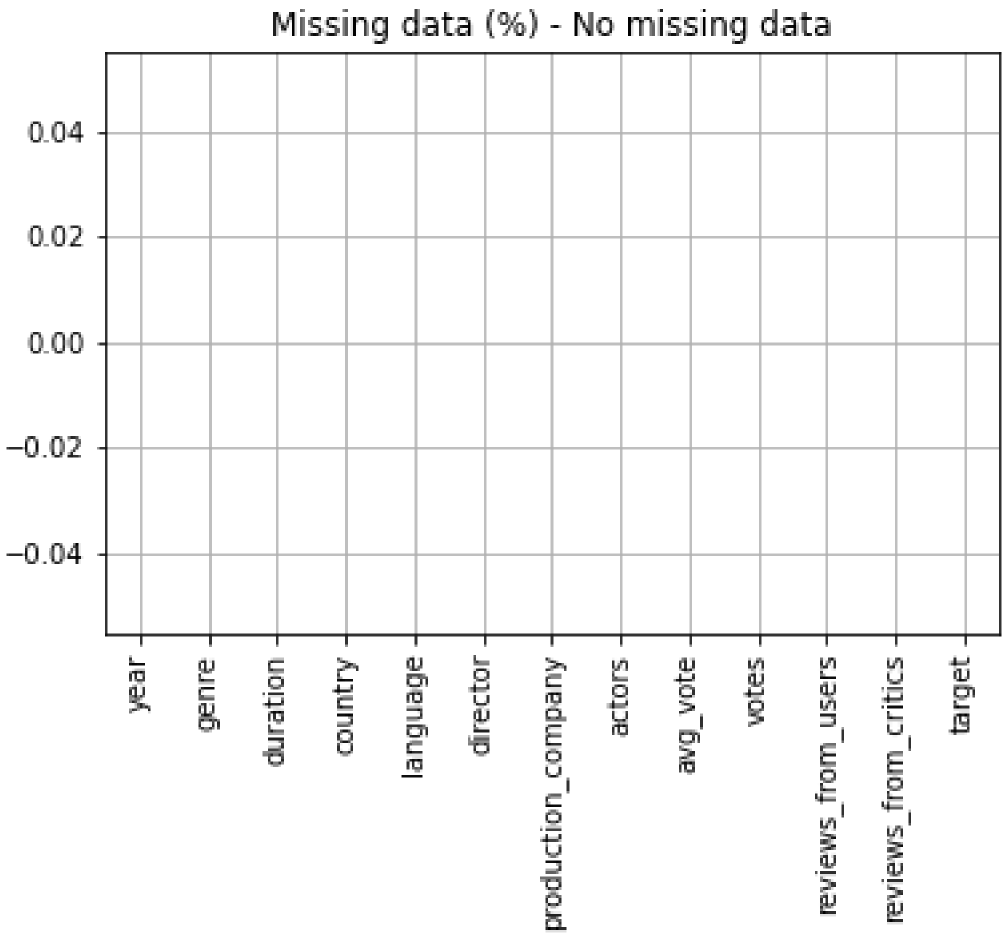


0.0.5 RECAP & PIPELINE

[ ]:
```
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.impute import SimpleImputer
from sklearn.pipeline import make_pipeline

#Missing values -> No missing values anymore
print((full_dataset.isna().sum() / num_rows).plot(kind="bar", title="Missing␣
↪data (%) - No missing data", grid=True))

#Drop avg_vote, because it is the target
full_dataset.drop(['avg_vote'], axis=1, inplace=True)

#Num_cols
num_cols = full_dataset.select_dtypes(exclude="object").columns.to_list()
num_cols.remove("target")
print(f"num_cols: {num_cols}")

#Cat_cols
cat_cols = full_dataset.select_dtypes("object").columns.to_list()
print(f"cat_cols: {cat_cols}")
```

```python
#Columntransformer
num_pipe = make_pipeline(
    SimpleImputer(missing_values=np.nan,strategy='constant'),
    StandardScaler()
    )

cat_pipe = make_pipeline(
    SimpleImputer(missing_values=np.nan,strategy='constant'),
    OneHotEncoder(handle_unknown="ignore")
    )

column_transformer = ColumnTransformer([
 ('num', num_pipe, num_cols),
 ('cat', cat_pipe, cat_cols)
 ],
 remainder='passthrough'
)
```

```
AxesSubplot(0.125,0.125;0.775x0.755)
num_cols: ['year', 'duration', 'language', 'director', 'production_company',
'actors', 'votes', 'reviews_from_users', 'reviews_from_critics']
cat_cols: ['genre', 'country']
```



0.0.6 Part 3.

Train and compare the models

3.1. Select models, you are going to train, select hyperparameters that have to be tunes.

[ ]:
```
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.impute import SimpleImputer
from sklearn.pipeline import make_pipeline
from sklearn.pipeline import Pipeline
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import BaggingClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import f1_score

train, test = train_test_split(full_dataset, test_size=0.2, random_state=42)
```

```
X_train, y_train, X_test, y_test = train.drop(['target'], axis=1), train.
↪target, test.drop(['target'], axis=1), test.target

param_grid = [
    {'cf' : [BaggingClassifier()],
            'cf__n_estimators': [5, 10],
            'cf__max_samples': [5, 10],
            'cf__n_jobs': [10, 50]
    },
    {'cf' : [RandomForestClassifier()],
         'cf__n_estimators': [100, 1000],
         'cf__criterion': ['entropy', 'gini'],
         'cf__max_depth': [100,500,1000],
    },
    {'cf' : [GradientBoostingClassifier()],
         'cf__n_estimators': [100,150,200],
         'cf__learning_rate': [0.1,0.15,0.2],
         'cf__max_depth': [3,4,5]
    }
]
```

3.2 Use cross-validation to compare models and select best set of hyperparameters

F1_Score:

- The GradientBoostingClassifier won the compeition in param_grid. The best parameters were {'max_depth': 5, 'n_estimators': 200}
- F-1 Score: 0.90 (compared to 0.45 in ones dataset). I estimate this value as quite high and good.
- There was not much difference in the F-1 Score between training and test data set, even quite identical (R1-Score: 0.8971 vs. 0.9002)

[ ]:
```
pipe = Pipeline([
    ('ct', column_transformer),
    ('cf' , RandomForestClassifier())
])
```

[ ]:
```
grid_pipe = GridSearchCV(pipe, param_grid = param_grid, cv=3,␣
↪scoring='f1',n_jobs=-1)
grid_pipe.fit(X_train, y_train)
```

[ ]:
```
GridSearchCV(cv=3,
             estimator=Pipeline(steps=[('ct',
ColumnTransformer(remainder='passthrough',
                                                         transformers=[('num',
Pipeline(steps=[('simpleimputer',
          SimpleImputer(strategy='constant')),
         ('standardscaler',
```

```
          StandardScaler())]),
['year',
'duration',
'language',
'director',
'production_company',
'actors',
'votes',
'reviews_from_users',
'reviews_from_critics']),
                                                                        ('cat…
                          'cf__n_estimators': [5, 10], 'cf__n_jobs': [10, 50]},
                         {'cf': [RandomForestClassifier()],
                          'cf__criterion': ['entropy', 'gini'],
                          'cf__max_depth': [100, 500, 1000],
                          'cf__n_estimators': [100, 1000]},
                         {'cf': [GradientBoostingClassifier(max_depth=5,
                                                             n_estimators=200)],
                          'cf__learning_rate': [0.1, 0.15, 0.2],
                          'cf__max_depth': [3, 4, 5],
                          'cf__n_estimators': [100, 150, 200]}],
             scoring='f1')
```

[ ]:
```
print(grid_pipe.best_score_)
print(f1_score(y_test, grid_pipe.predict(X_test)))

print(grid_pipe.best_estimator_.steps[1][1])
```

```
0.8970738000835361
0.9002326934264108
GradientBoostingClassifier(max_depth=5, n_estimators=200)
```

[ ]:
```
print(grid_pipe.best_estimator_.steps[1][1])
```

```
GradientBoostingClassifier(max_depth=5, n_estimators=200)
```

[ ]:
```
# ones
print(f1_score(y_test, np.ones(y_test.size)))
```

```
0.44815363794547913
```

3.3 Which model and setup is the best? How does it perform on the test dataset? If you were to present this model to the client, how would you describe it?

Conclusion:

- Unfortunately it was very hard to find a good measure of success. Finally I decided >0.75 (Top 25% is a success) quantile of average_votes seems to be a good target.
- On the other side, we consider the quality of the movies (high rating) and it has a diret correlation with the number of votes, even if not perfect.

- Finally the number of votes are a strong indicator of financial success. But because we lack the control variable of revenue (too many missing values), it is hard to determine a good Threshold of success. Therefore average_votes was the right measure.
- I consider the high predictability of 90% a veray good ML-model to predict success of a movie.