eda

May 11, 2022

[ ]:
```
import sqlite3
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from bs4 import BeautifulSoup
import requests
import os
import datetime

sns.set_theme(style="dark")
%matplotlib inline
```

[ ]:
```
os.chdir("../")
```

1 Data processing

[ ]:
```
conn = sqlite3.connect("im.db")
cursor = conn.cursor()
```

[ ]:
```
query = """
-- SQLite
with mov as (
    select
        movies.*,
        cast(strftime('%Y', date(opening_date)) as int) opening_year,
        cast(strftime('%Y', date(release_date)) as int) release_year
    from movies
),

new_cpi as (
    select *, (select avg_annual_cpi from cpi where year = 2022) current_cpi
    from cpi
    ),

af_filtered as (
```

```
    select distinct a.*
    from actor_filmo a
    left join actor_movie b on a.crew_url = b.actor_url
    left join mov on b.movie_id = mov.movie_id
    where 1=1
    and a.movie_id not in (select movie_id from movies)
    and a.year < mov.release_year
),

af_adj as (
    select
        af.*,
        revenue_world * avg_annual_cpi / current_cpi revenue_world_adj
    from af_filtered af
    left join new_cpi on af.year = new_cpi.year
    where 1=1
    and is_star = 'True'
),

df_filtered as (
    select distinct a.*
    from director_filmo a
    left join director_movie b on a.crew_url = b.director_url
    left join mov on b.movie_id = mov.movie_id
    where 1=1
    and a.movie_id not in (select movie_id from movies)
    and a.year < mov.release_year
),

df_adj as (
    select
        df.*,
        revenue_world * avg_annual_cpi / current_cpi revenue_world_adj
    from df_filtered df
    left join new_cpi on df.year = new_cpi.year
    where 1=1
),

wf_filtered as (
    select distinct a.*
    from writer_filmo a
    left join writer_movie b on a.crew_url = b.writer_url
    left join mov on b.movie_id = mov.movie_id
    where 1=1
    and a.movie_id not in (select movie_id from movies)
    and a.year < mov.release_year
),
```

```
wf_adj as (
    select
        wf.*,
        revenue_world * avg_annual_cpi / current_cpi revenue_world_adj
    from wf_filtered wf
    left join new_cpi on wf.year = new_cpi.year
    where movie_id not in (select movie_id from movies)
),

actor_profile as (
    select
        af.crew_url actor_id,
        a.name,
        -- avg(rating) avg_actor_movie_rating,
        -- avg(rating_count) avg_actor_movie_rating_count,
        -- avg(revenue_world_adj) avg_actor_movie_revenue_world_adj,

        -- avg(case when is_star = 'True' then rating end)␣
 ↪avg_star_actor_movie_rating,
        -- avg(case when is_star = 'True' then rating_count end)␣
 ↪avg_star_actor_movie_rating_count,
        -- avg(case when is_star = 'True' then revenue_world_adj end)␣
 ↪avg_star_actor_movie_revenue_world_adj,

        -- max(case when is_star = 'True' then rating end)␣
 ↪max_star_actor_movie_rating,
        -- max(case when is_star = 'True' then rating_count end)␣
 ↪max_star_actor_movie_rating_count,
        -- max(case when is_star = 'True' then revenue_world_adj end)␣
 ↪max_star_actor_movie_revenue_world_adj,

        -- min(case when is_star = 'True' then rating end)␣
 ↪min_star_actor_movie_rating,
        -- min(case when is_star = 'True' then rating_count end)␣
 ↪min_star_actor_movie_rating_count,
        -- min(case when is_star = 'True' then revenue_world_adj end)␣
 ↪min_star_actor_movie_revenue_world_adj,

        -- avg(case when is_star = 'False' then rating end)␣
 ↪avg_non_star_actor_movie_rating,
        -- avg(case when is_star = 'False' then rating_count end)␣
 ↪avg_non_star_actor_movie_rating_count,
        -- avg(case when is_star = 'False' then revenue_world_adj end)␣
 ↪avg_non_star_actor_movie_revenue_world_adj,
```

```
        sum(rating) sum_star_actor_movie_rating,
        sum(rating_count) sum_star_actor_movie_rating_count,
        sum(revenue_world_adj) sum_star_actor_movie_revenue_world_adj,

        count(crew_url) cnt_star_actor_movie

    from af_adj af
    left join actors a on af.crew_url = a.actor_id
    group by
        af.crew_url,
        a.name
),

director_profile as (
    select
        df.crew_url director_id,
        d.name,
        avg(rating) avg_director_movie_rating,
        avg(rating_count) avg_director_movie_rating_count,
        avg(revenue_world_adj) avg_director_movie_revenue_world_adj,

        max(rating) max_director_movie_rating,
        max(rating_count) max_director_movie_rating_count,
        max(revenue_world_adj) max_director_movie_revenue_world_adj,

        min(rating) min_director_movie_rating,
        min(rating_count) min_director_movie_rating_count,
        min(revenue_world_adj) min_director_movie_revenue_world_adj,

        sum(rating) sum_director_movie_rating,
        sum(rating_count) sum_director_movie_rating_count,
        sum(revenue_world_adj) sum_director_movie_revenue_world_adj,

        count(crew_url) cnt_director_movie
    from df_adj df
    left join directors d on df.crew_url = d.director_id
    group by
        df.crew_url,
        d.name
),

writer_profile as (
    select
        wf.crew_url writer_id,
        w.name,
        avg(rating) avg_writer_movie_rating,
        avg(rating_count) avg_writer_movie_rating_count,
```

```
        avg(revenue_world_adj) avg_writer_movie_revenue_world_adj,

        max(rating) max_writer_movie_rating,
        max(rating_count) max_writer_movie_rating_count,
        max(revenue_world_adj) max_writer_movie_revenue_world_adj,

        min(rating) min_writer_movie_rating,
        min(rating_count) min_writer_movie_rating_count,
        min(revenue_world_adj) min_writer_movie_revenue_world_adj,

        sum(rating) sum_writer_movie_rating,
        sum(rating_count) sum_writer_movie_rating_count,
        sum(revenue_world_adj) sum_writer_movie_revenue_world_adj,

        count(crew_url) cnt_writer_movie
    from wf_adj wf
    left join writers w on wf.crew_url = w.writer_id
    group by
        wf.crew_url,
        w.name
),

movie_af as (
    select
        am.movie_id,
        sum(sum_star_actor_movie_rating) / sum(cnt_star_actor_movie)
 ↪avg_movie_rating_by_star_actor,
        sum(sum_star_actor_movie_rating_count) / sum(cnt_star_actor_movie)
 ↪avg_movie_rating_count_by_star_actor,
        sum(sum_star_actor_movie_revenue_world_adj) / sum(cnt_star_actor_movie)
 ↪avg_movie_revenue_world_adj_by_star_actor
    from actor_movie am
    left join actor_profile ap on am.actor_url = ap.actor_id
    where is_star = 'True'
    group by am.movie_id
),

movie_df as (
    select
        dm.movie_id,
        sum(sum_director_movie_rating) / sum(cnt_director_movie)
 ↪avg_movie_rating_by_director,
        sum(sum_director_movie_rating_count) / sum(cnt_director_movie)
 ↪avg_movie_rating_count_by_director,
        sum(sum_director_movie_revenue_world_adj) / sum(cnt_director_movie)
 ↪avg_movie_revenue_world_adj_by_director
```

```
    from director_movie dm
    left join director_profile dp on dm.director_url = dp.director_id
    group by dm.movie_id
),

movie_wf as (
    select
        wm.movie_id,
        sum(sum_writer_movie_rating) / sum(cnt_writer_movie)␣
 ↪avg_movie_rating_by_writer,
        sum(sum_writer_movie_rating_count) / sum(cnt_writer_movie)␣
 ↪avg_movie_rating_count_by_writer,
        sum(sum_writer_movie_revenue_world_adj) / sum(cnt_writer_movie)␣
 ↪avg_movie_revenue_world_adj_by_writer
    from writer_movie wm
    left join writer_profile wp on wm.writer_url = wp.writer_id
    group by wm.movie_id
),

total_rating as (
select
    movie_id,
    sum(vote_count) rating_count
    from rating_dist
    group by movie_id
),

mov_adj as (
    select
        mov.movie_rank,
        mov.movie_id,
        mov.name,
        mov.popularity,
        mov.rating,
        tr.rating_count,
        -- mov.user_review_count,
        mov.critic_review_count,
        mov.runtime,
        mov.release_date,
        mov.release_year,

        ma.avg_movie_rating_by_star_actor,
        ma.avg_movie_rating_count_by_star_actor,
        ma.avg_movie_revenue_world_adj_by_star_actor / 10E6␣
 ↪avg_movie_revenue_world_adj_by_star_actor,

        md.avg_movie_rating_by_director,
```

```
        md.avg_movie_rating_count_by_director,
        md.avg_movie_revenue_world_adj_by_director / 10E6␣
 ↪avg_movie_revenue_world_adj_by_director,

        mw.avg_movie_rating_by_writer,
        mw.avg_movie_rating_count_by_writer,
        mw.avg_movie_revenue_world_adj_by_writer / 10E6␣
 ↪avg_movie_revenue_world_adj_by_writer,

        revenue_world * avg_annual_cpi / current_cpi / 10E6 revenue_world_adj,
        revenue_usa * avg_annual_cpi / current_cpi / 10E6 revenue_usa_adj,
        budget * avg_annual_cpi / current_cpi / 10E6 budget_adj

    from mov
    left join new_cpi on mov.release_year = new_cpi.year
    left join movie_af ma on mov.movie_id = ma.movie_id
    left join movie_df md on mov.movie_id = md.movie_id
    left join movie_wf mw on mov.movie_id = mw.movie_id
    left join total_rating tr on mov.movie_id =tr.movie_id
)

select * from mov_adj
"""
movies = pd.read_sql(query, conn)
movies['release_date'] = pd.to_datetime(movies['release_date'],␣
 ↪format="%Y-%m-%d")
```

[ ]:
```
movies.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 250 entries, 0 to 249
Data columns (total 22 columns):
 #   Column                                   Non-Null Count  Dtype
---  ------                                   --------------  -----
 0   movie_rank                               250 non-null    int64
 1   movie_id                                 250 non-null    object
 2   name                                     207 non-null    object
 3   popularity                               228 non-null    float64
 4   rating                                   250 non-null    float64
 5   rating_count                             250 non-null    int64
 6   critic_review_count                      250 non-null    int64
 7   runtime                                  244 non-null    float64
 8   release_date                             250 non-null    datetime64[ns]
 9   release_year                             250 non-null    int64
 10  avg_movie_rating_by_star_actor           241 non-null    float64
 11  avg_movie_rating_count_by_star_actor     241 non-null    float64
 12  avg_movie_revenue_world_adj_by_star_actor  212 non-null    float64
```

```
 13  avg_movie_rating_by_director            227 non-null    float64
 14  avg_movie_rating_count_by_director      227 non-null    float64
 15  avg_movie_revenue_world_adj_by_director  207 non-null    float64
 16  avg_movie_rating_by_writer              231 non-null    float64
 17  avg_movie_rating_count_by_writer        231 non-null    float64
 18  avg_movie_revenue_world_adj_by_writer   194 non-null    float64
 19  revenue_world_adj                       243 non-null    float64
 20  revenue_usa_adj                         221 non-null    float64
 21  budget_adj                              209 non-null    float64
dtypes: datetime64[ns](1), float64(15), int64(4), object(2)
memory usage: 43.1+ KB
```

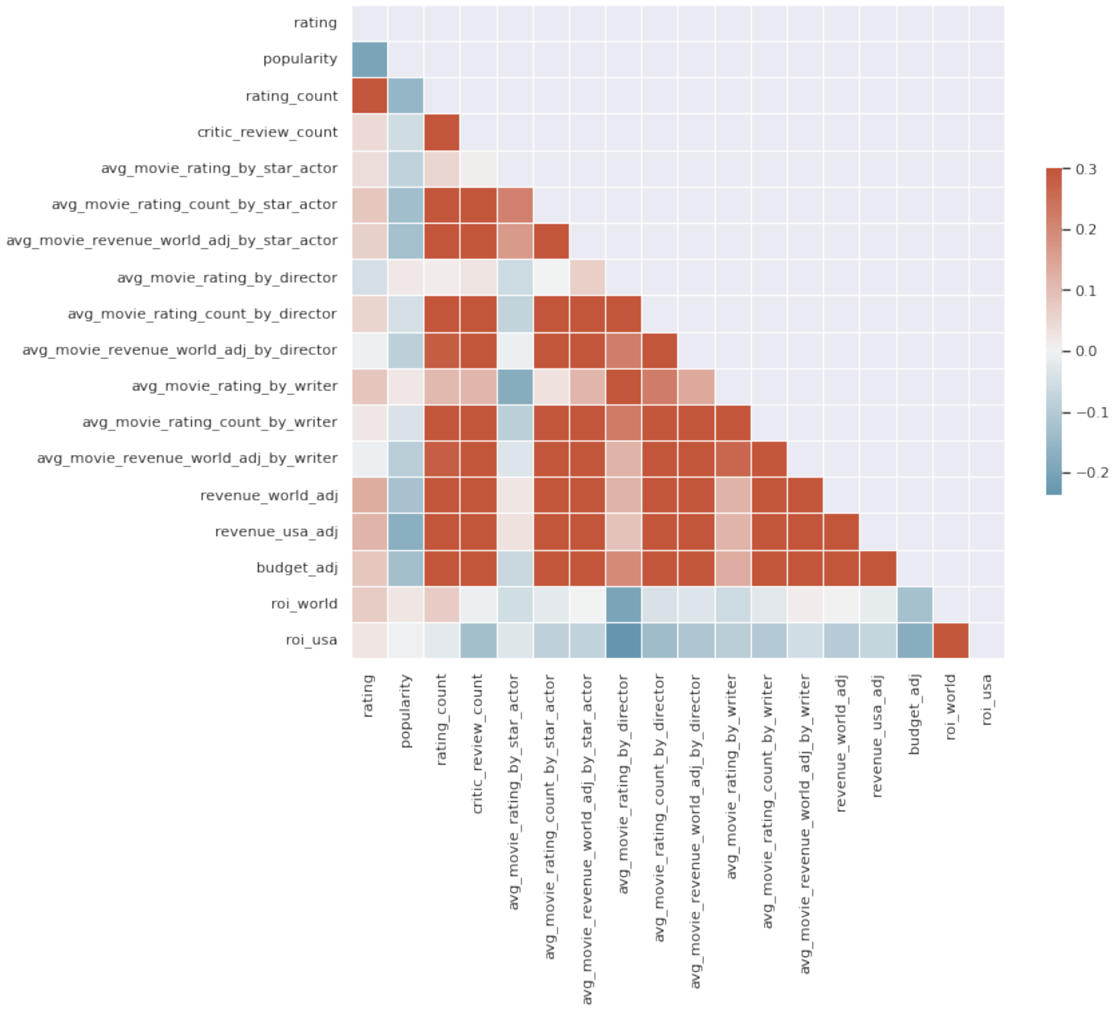
2 Analysis

2.1 Correlation matrix

[ ]:
```
movies['roi_world'] = (movies['revenue_world_adj'] - movies['budget_adj'])/
 ↪movies['budget_adj']
movies['roi_usa'] = (movies['revenue_usa_adj'] - movies['budget_adj'])/
 ↪movies['budget_adj']

movies['days_since_release'] = (pd.to_datetime(datetime.date.today()) -␣
 ↪movies['release_date']).dt.days
```

[ ]:
```
numerical_cols = [
    'rating', 'popularity', 'rating_count',
    # 'days_since_release',
    'critic_review_count',
    'avg_movie_rating_by_star_actor',
    'avg_movie_rating_count_by_star_actor',
    'avg_movie_revenue_world_adj_by_star_actor',
    'avg_movie_rating_by_director',
    'avg_movie_rating_count_by_director',
    'avg_movie_revenue_world_adj_by_director',
    'avg_movie_rating_by_writer',
    'avg_movie_rating_count_by_writer',
    'avg_movie_revenue_world_adj_by_writer',
    'revenue_world_adj',
    'revenue_usa_adj',
    'budget_adj',
    'roi_world',
    'roi_usa'
    ]

def corr_matrix(df, num_cols):

    corr = df[num_cols].corr()
```

```
    mask = np.triu(np.ones_like(corr, dtype=bool))

    f, ax = plt.subplots(figsize=(11, 9))
    cmap = sns.diverging_palette(230, 20, as_cmap=True)

    sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0,
                square=True, linewidths=.5, cbar_kws={"shrink": .5})

corr_matrix(movies, numerical_cols)
```



[ ]:
```
import statsmodels.api as sm
from sklearn.model_selection import train_test_split
from sklearn import tree
from sklearn.metrics import r2_score
```

[ ]:
```python
def linear_regression(df, x_cols, y_col):
    new_data = df[x_cols + [y_col]].dropna()

    X = [list(row.values) for _, row in new_data[x_cols].iterrows()]
    X_OLS = sm.add_constant(X)
    y = new_data[y_col].values


    model = sm.OLS(y, X_OLS)
    model.data.xnames = ['const'] + x_cols
    results = model.fit()

    return results
```

2.2 Commercial Success

2.2.1 Revenue worldwide

[ ]:
```python
x_cols = [
    # 'rating',
    # 'popularity',
    # 'rating_count',
    # 'revenue_world_adj',
    # 'revenue_usa_adj',
    # 'roi_usa',
    # 'roi_world',
    'critic_review_count',
    'avg_movie_rating_by_star_actor',
    'avg_movie_rating_count_by_star_actor',
    'avg_movie_revenue_world_adj_by_star_actor',
    'avg_movie_rating_by_director',
    'avg_movie_rating_count_by_director',
    'avg_movie_revenue_world_adj_by_director',
    'avg_movie_rating_by_writer',
    'avg_movie_rating_count_by_writer',
    'avg_movie_revenue_world_adj_by_writer',
    'budget_adj',
    ]

y_col = 'revenue_world_adj'

res = linear_regression(movies, x_cols, y_col)
res.summary()
```

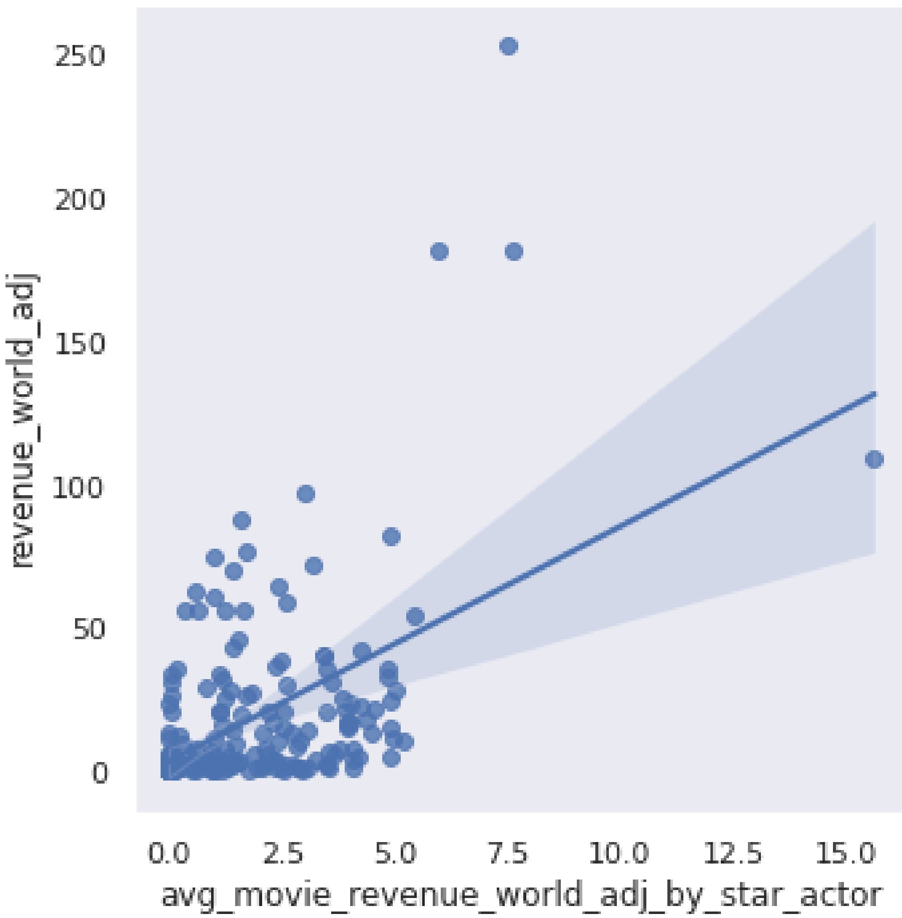
[ ]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
```

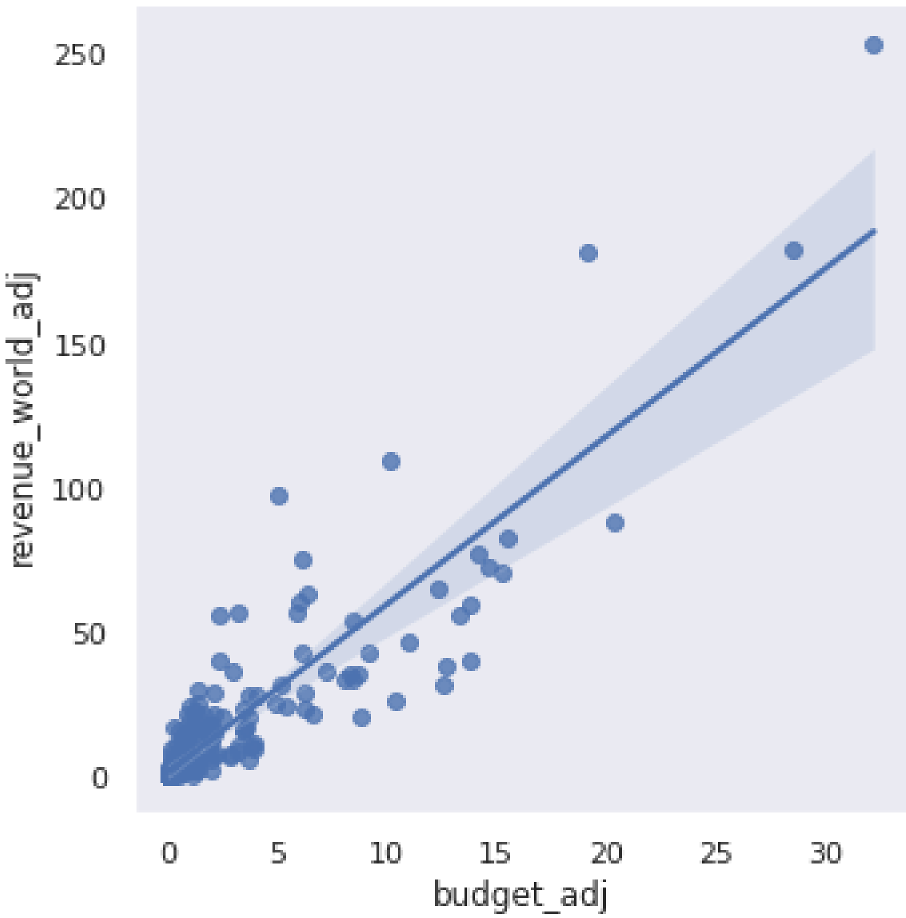
```
==============================================================================
Dep. Variable:                      y   R-squared:                       0.854
Model:                            OLS   Adj. R-squared:                  0.842
Method:                 Least Squares   F-statistic:                     69.14
Date:                Wed, 11 May 2022   Prob (F-statistic):           7.87e-49
Time:                        06:58:20   Log-Likelihood:                -571.26
No. Observations:                 142   AIC:                             1167.
Df Residuals:                     130   BIC:                             1202.
Df Model:                          11
Covariance Type:            nonrobust
================================================================================
=============================
                                                coef    std err          t
P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
-----------------------------
const                                        -3.1852     34.147     -0.093
0.926     -70.741      64.370
critic_review_count                           0.0049      0.010      0.481
0.631      -0.015       0.025
avg_movie_rating_by_star_actor                8.2627      4.687      1.763
0.080      -1.010      17.535
avg_movie_rating_count_by_star_actor         -0.0002   5.91e-05     -2.845
0.005      -0.000   -5.12e-05
avg_movie_revenue_world_adj_by_star_actor     6.7974      2.156      3.152
0.002       2.531      11.063
avg_movie_rating_by_director                 -7.2592      2.914     -2.491
0.014     -13.025      -1.494
avg_movie_rating_count_by_director         4.476e-05   2.64e-05      1.696
0.092   -7.47e-06     9.7e-05
avg_movie_revenue_world_adj_by_director       0.0195      1.008      0.019
0.985      -1.975       2.015
avg_movie_rating_by_writer                   -0.3324      2.376     -0.140
0.889      -5.034       4.369
avg_movie_rating_count_by_writer          -5.829e-05   3.47e-05     -1.679
0.096      -0.000    1.04e-05
avg_movie_revenue_world_adj_by_writer         1.9586      1.144      1.712
0.089      -0.305       4.222
budget_adj                                    5.1917      0.413     12.569
0.000       4.375       6.009
==============================================================================
Omnibus:                       39.147   Durbin-Watson:                   1.912
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              167.239
Skew:                           0.882   Prob(JB):                     4.84e-37
Kurtosis:                       8.015   Cond. No.                     6.59e+06
==============================================================================
```

```
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 6.59e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

[ ]:
```
sns.lmplot(x='avg_movie_revenue_world_adj_by_star_actor', y=y_col, data=movies,
scatter=True, fit_reg=True)

sns.lmplot(x='budget_adj', y=y_col, data=movies,
scatter=True, fit_reg=True)
```

[ ]: <seaborn.axisgrid.FacetGrid at 0x7f8597037e80>





2.2.2 Return on Investment

[ ]:
```
x_cols = [
    # 'rating',
    # 'popularity',
    # 'rating_count',
    # 'revenue_world_adj',
    # 'revenue_usa_adj',
    # 'roi_usa',
    # 'roi_world',
    'critic_review_count',
    'avg_movie_rating_by_star_actor',
    'avg_movie_rating_count_by_star_actor',
    'avg_movie_revenue_world_adj_by_star_actor',
    'avg_movie_rating_by_director',
    'avg_movie_rating_count_by_director',
    'avg_movie_revenue_world_adj_by_director',
    'avg_movie_rating_by_writer',
```

```
    'avg_movie_rating_count_by_writer',
    'avg_movie_revenue_world_adj_by_writer',
    'budget_adj',
    ]

y_col = 'roi_world'

res = linear_regression(movies, x_cols, y_col)
res.summary()
```

[ ]:

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.158
Model:                            OLS   Adj. R-squared:                  0.087
Method:                 Least Squares   F-statistic:                     2.218
Date:                Wed, 11 May 2022   Prob (F-statistic):             0.0170
Time:                        06:58:20   Log-Likelihood:                -579.47
No. Observations:                 142   AIC:                             1183.
Df Residuals:                     130   BIC:                             1218.
Df Model:                          11
Covariance Type:            nonrobust
================================================================================
=============================
                                             coef    std err          t
P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
-----------------------------
const                                    113.0149     36.179      3.124
0.002      41.438     184.592
critic_review_count                       -0.0014      0.011     -0.130
0.897      -0.023       0.020
avg_movie_rating_by_star_actor            -3.7163      4.966     -0.748
0.456     -13.541       6.108
avg_movie_rating_count_by_star_actor   -7.932e-05   6.26e-05     -1.266
0.208      -0.000    4.46e-05
avg_movie_revenue_world_adj_by_star_actor  3.3996      2.285      1.488
0.139      -1.120       7.919
avg_movie_rating_by_director             -10.3829      3.088     -3.363
0.001     -16.492      -4.274
avg_movie_rating_count_by_director      3.995e-05    2.8e-05      1.428
0.156   -1.54e-05    9.53e-05
avg_movie_revenue_world_adj_by_director   -1.6381      1.068     -1.533
0.128      -3.752       0.476
avg_movie_rating_by_writer                -1.3312      2.518     -0.529
0.598      -6.313       3.650
```

```
avg_movie_rating_count_by_writer          -2.768e-05   3.68e-05     -0.752
0.453      -0.000    4.51e-05
avg_movie_revenue_world_adj_by_writer         1.6782      1.212      1.384
0.169      -0.720       4.077
budget_adj                                   -0.4630      0.438     -1.058
0.292      -1.329       0.403
==============================================================================
Omnibus:                      153.980   Durbin-Watson:                   2.035
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             3266.802
Skew:                           4.006   Prob(JB):                         0.00
Kurtosis:                      25.089   Cond. No.                     6.59e+06
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 6.59e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

2.3 Popularity

Popularity can be determined with 2 metrics:

- `popularity` ranking on IMDB. This is the current popularity of the movie.
- `voting_count`, i.e. the number of votes that make up the rating. This can be understood as the popularity overtime of a title.

2.3.1 Popularity overtime

[ ]:
```
x_cols = [
    'avg_movie_rating_by_star_actor',
    'avg_movie_rating_count_by_star_actor',
    'avg_movie_revenue_world_adj_by_star_actor',
    'avg_movie_rating_by_director',
    'avg_movie_rating_count_by_director',
    'avg_movie_revenue_world_adj_by_director',
    'avg_movie_rating_by_writer',
    'avg_movie_rating_count_by_writer',
    'avg_movie_revenue_world_adj_by_writer',
    'budget_adj',
    'critic_review_count',
    'revenue_world_adj',
    'revenue_usa_adj',
    # 'rating',
    # 'popularity',
    # 'rating_count',
    # 'roi_usa',
```

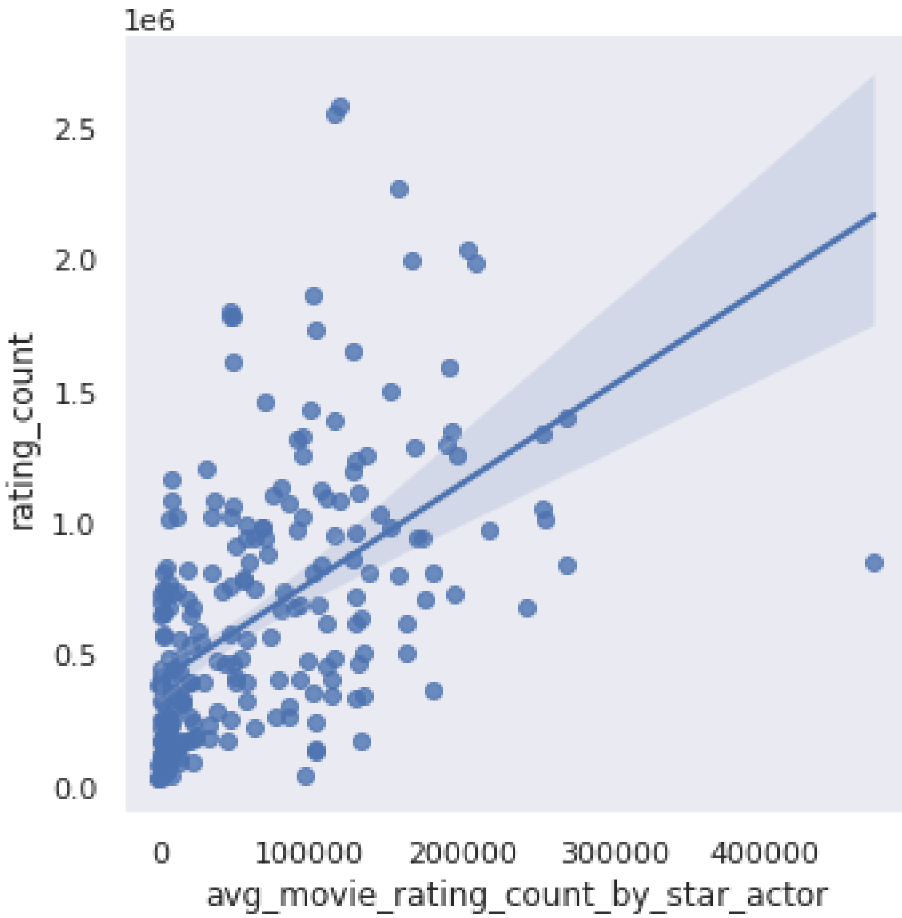
```
    # 'roi_world',
    ]

y_col = 'rating_count'

res = linear_regression(movies, x_cols, y_col)
res.summary()
```

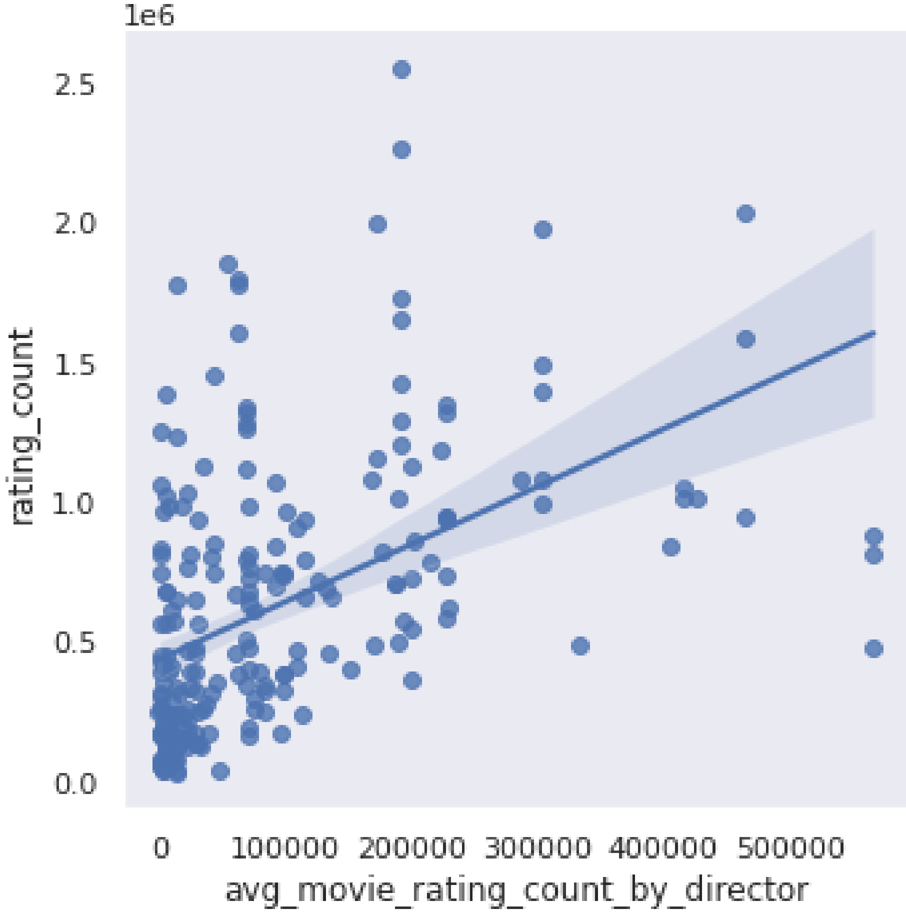
[ ]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.465
Model:                            OLS   Adj. R-squared:                  0.406
Method:                 Least Squares   F-statistic:                     7.885
Date:                Wed, 11 May 2022   Prob (F-statistic):           4.02e-11
Time:                        06:58:20   Log-Likelihood:                -1876.8
No. Observations:                 132   AIC:                             3782.
Df Residuals:                     118   BIC:                             3822.
Df Model:                          13
Covariance Type:            nonrobust
================================================================================
==============================
                                                 coef    std err          t
P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
------------------------------
const                                       2.143e+06   9.94e+05      2.156
0.033    1.75e+05    4.11e+06
avg_movie_rating_by_star_actor             -1.497e+05   1.34e+05     -1.114
0.268   -4.16e+05    1.16e+05
avg_movie_rating_count_by_star_actor           2.1956      1.671      1.314
0.191      -1.114       5.505
avg_movie_revenue_world_adj_by_star_actor -1.035e+04   6.13e+04     -0.169
0.866   -1.32e+05    1.11e+05
avg_movie_rating_by_director               -1.497e+05   8.23e+04     -1.818
0.072   -3.13e+05    1.33e+04
avg_movie_rating_count_by_director             2.4466      0.728      3.361
0.001       1.005       3.888
avg_movie_revenue_world_adj_by_director    -1.117e+05   2.74e+04     -4.074
0.000   -1.66e+05   -5.74e+04
avg_movie_rating_by_writer                   3.38e+04   6.75e+04      0.501
0.617   -9.99e+04    1.67e+05
avg_movie_rating_count_by_writer               0.5118      0.957      0.535
0.594      -1.383       2.407
avg_movie_revenue_world_adj_by_writer      -1.188e+04    3.2e+04     -0.371
0.711   -7.52e+04    5.15e+04
```

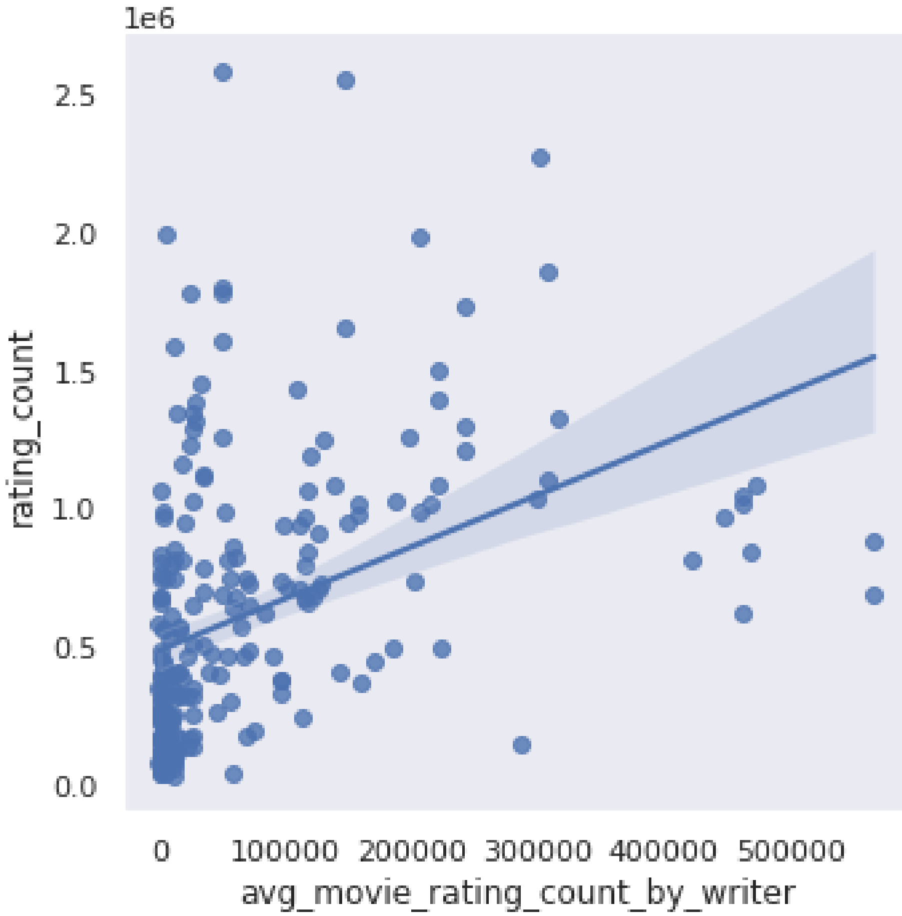
```
budget_adj                                   9945.1514   1.68e+04      0.591
0.556   -2.34e+04    4.33e+04
critic_review_count                            44.5276    282.783      0.157
0.875    -515.459     604.514
revenue_world_adj                           -9043.6084   4819.111     -1.877
0.063   -1.86e+04     499.544
revenue_usa_adj                              4.241e+04   1.34e+04      3.173
0.002    1.59e+04    6.89e+04
==============================================================================
Omnibus:                        5.870   Durbin-Watson:                   1.105
Prob(Omnibus):                  0.053   Jarque-Bera (JB):                5.411
Skew:                           0.422   Prob(JB):                       0.0668
Kurtosis:                       3.520   Cond. No.                     7.07e+06
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 7.07e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

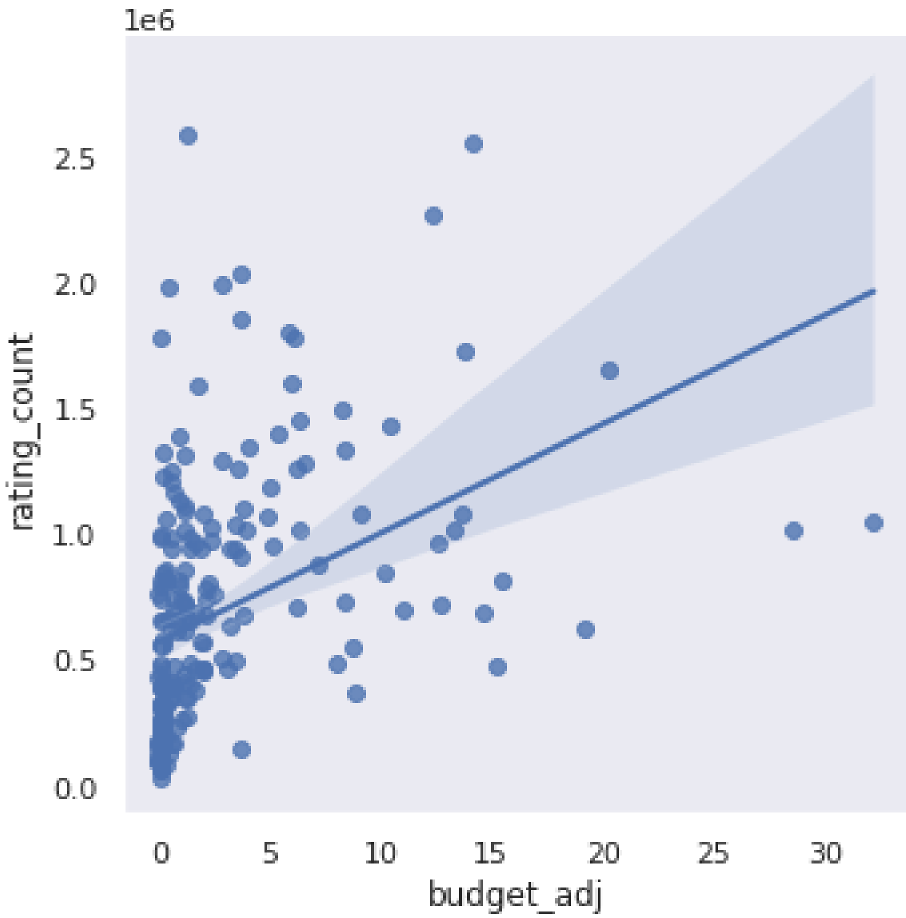
[ ]:
```
sns.lmplot(x='avg_movie_rating_count_by_star_actor', y=y_col, data=movies,
scatter=True, fit_reg=True)

sns.lmplot(x='avg_movie_rating_count_by_director', y=y_col, data=movies,
scatter=True, fit_reg=True)

sns.lmplot(x='avg_movie_rating_count_by_writer', y=y_col, data=movies,
scatter=True, fit_reg=True)

sns.lmplot(x='budget_adj', y=y_col, data=movies,
scatter=True, fit_reg=True)
```

[ ]:
```
<seaborn.axisgrid.FacetGrid at 0x7f8596ebe850>
```


1e6
2.5
2.0
1.5
1.0
0.5
0.0
rating_count
0
100000
200000
300000
400000
avg_movie_rating_count_by_star_actor


1e6
2.5
2.0
1.5
1.0
0.5
0.0
rating_count
0
100000
200000
300000
400000
500000
avg_movie_rating_count_by_director


1e6
2.5
2.0
1.5
1.0
0.5
0.0
rating_count
0
100000
200000
300000
400000
500000
avg_movie_rating_count_by_writer



2.3.2 Current Popularity

[ ]:
```
x_cols = [
    'avg_movie_rating_by_star_actor',
    'avg_movie_rating_count_by_star_actor',
    'avg_movie_revenue_world_adj_by_star_actor',
    'avg_movie_rating_by_director',
    'avg_movie_rating_count_by_director',
    'avg_movie_revenue_world_adj_by_director',
    'avg_movie_rating_by_writer',
    'avg_movie_rating_count_by_writer',
    'avg_movie_revenue_world_adj_by_writer',
    'budget_adj',
    'critic_review_count',
    'revenue_world_adj',
    'revenue_usa_adj',
    'days_since_release',
    'rating',
```

```python
    # 'popularity',
    'rating_count',
    # 'roi_usa',
    # 'roi_world',
    ]

y_col = 'popularity'

res = linear_regression(movies, x_cols, y_col)
res.summary()
```

[ ]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.179
Model:                            OLS   Adj. R-squared:                  0.063
Method:                 Least Squares   F-statistic:                     1.549
Date:                Wed, 11 May 2022   Prob (F-statistic):             0.0948
Time:                        06:58:22   Log-Likelihood:                -1207.4
No. Observations:                 131   AIC:                             2449.
Df Residuals:                     114   BIC:                             2498.
Df Model:                          16
Covariance Type:            nonrobust
================================================================================
=============================
                                               coef    std err          t
P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
-----------------------------
const                                     2.602e+04   1.37e+04      1.899
0.060   -1124.454    5.32e+04
avg_movie_rating_by_star_actor            -745.3913   1024.630     -0.727
0.468   -2775.176    1284.393
avg_movie_rating_count_by_star_actor        -0.0071      0.012     -0.572
0.569      -0.032       0.018
avg_movie_revenue_world_adj_by_star_actor  146.8500    429.881      0.342
0.733    -704.742     998.442
avg_movie_rating_by_director               285.1306    587.113      0.486
0.628    -877.936    1448.198
avg_movie_rating_count_by_director           0.0006      0.005      0.117
0.907      -0.010       0.011
avg_movie_revenue_world_adj_by_director      0.3713    202.271      0.002
0.999    -400.326     401.069
avg_movie_rating_by_writer                -674.1673    525.610     -1.283
0.202   -1715.396     367.061
avg_movie_rating_count_by_writer             0.0038      0.007      0.545
```

```
0.587      -0.010       0.018
avg_movie_revenue_world_adj_by_writer      -197.5639    225.258     -0.877
0.382    -643.798     248.670
budget_adj                                  -44.3858    115.679     -0.384
0.702    -273.545     184.773
critic_review_count                          -1.4474      2.176     -0.665
0.507      -5.758       2.863
revenue_world_adj                            28.4949     34.165      0.834
0.406     -39.186      96.175
revenue_usa_adj                             -76.1972     96.980     -0.786
0.434    -268.314     115.920
days_since_release                           -0.0390      0.048     -0.818
0.415      -0.134       0.056
rating                                    -1572.7200   1660.585     -0.947
0.346   -4862.327    1716.887
rating_count                                 -0.0007      0.001     -0.631
0.529      -0.003       0.001
==============================================================================
Omnibus:                        6.750   Durbin-Watson:                   2.076
Prob(Omnibus):                  0.034   Jarque-Bera (JB):                6.052
Skew:                           0.452   Prob(JB):                       0.0485
Kurtosis:                       2.460   Cond. No.                     5.82e+07
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 5.82e+07. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

2.4 Genres

[ ]:

```
mg_query = """
with mov as (
    select
        movies.*,
        cast(strftime('%Y', date(opening_date)) as int) opening_year,
        cast(strftime('%Y', date(release_date)) as int) release_year
    from movies
),

mov_adj as (
    select
        mov.*,
        revenue_world * avg_annual_cpi / current_cpi revenue_world_adj,
        revenue_usa * avg_annual_cpi / current_cpi revenue_usa_adj,
```

```
        revenue_usa_opening * avg_annual_cpi / current_cpi␣
 ↪revenue_usa_opening_adj,
        budget * avg_annual_cpi / current_cpi budget_adj
    from mov
    left join new_cpi on mov.release_year = new_cpi.year
),

base as (select distinct
    gm.genre,
    m.*
from genre_movie gm
inner join mov_adj m
on gm.movie_id = m.movie_id
),



new_cpi as (
    select *, (select avg_annual_cpi from cpi where year = 2022) current_cpi
    from cpi
    ),


total_rating as (
select
    movie_id,
    sum(vote_count) rating_count
    from rating_dist
    group by movie_id
)

select
    genre,
    movie_rank,
    base.movie_id,
    name,
    popularity,
    rating,
    tr.rating_count,
    critic_review_count,
    budget_adj / 10E6 budget_adj,
    revenue_usa_adj / 10E6 revenue_usa_adj,
    revenue_usa_opening_adj / 10E6 revenue_usa_opening_adj,
    revenue_world_adj / 10E6 revenue_world_adj,
    runtime,
    opening_date,
    release_date
```

```
from base
left join total_rating tr
on base.movie_id =tr.movie_id
"""
movie_genre = pd.read_sql(mg_query, conn)
```

[ ]:
```
movie_genre.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 729 entries, 0 to 728
Data columns (total 15 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   genre                   729 non-null    object
 1   movie_rank              729 non-null    int64
 2   movie_id                729 non-null    object
 3   name                    600 non-null    object
 4   popularity              674 non-null    float64
 5   rating                  729 non-null    float64
 6   rating_count            729 non-null    int64
 7   critic_review_count     729 non-null    int64
 8   budget_adj              617 non-null    float64
 9   revenue_usa_adj         643 non-null    float64
 10  revenue_usa_opening_adj 594 non-null    float64
 11  revenue_world_adj       707 non-null    float64
 12  runtime                 710 non-null    float64
 13  opening_date            594 non-null    object
 14  release_date            729 non-null    object
dtypes: float64(7), int64(3), object(5)
memory usage: 85.6+ KB
```

[ ]:
```
movie_genre['roi_world'] = (movie_genre['revenue_world_adj'] -␣
 ↪movie_genre['budget_adj'])/movie_genre['budget_adj']
movie_genre['roi_usa'] = (movie_genre['revenue_usa_adj'] -␣
 ↪movie_genre['budget_adj'])/movie_genre['budget_adj']

movie_genre['release_date'] = pd.to_datetime(movie_genre['release_date'],␣
 ↪format="%Y-%m-%d")
movie_genre['days_since_release'] = (pd.to_datetime(datetime.date.today()) -␣
 ↪movie_genre['release_date']).dt.days
```

[ ]:
```
genre_summary = movie_genre.groupby('genre').agg({
    'rating':['count','mean', 'median', 'max', 'min' ,'std'],
    'rating_count':['count','mean', 'median', 'max', 'min' ,'std'],
    'critic_review_count':['count','mean', 'median', 'max', 'min' ,'std'],
    'revenue_usa_adj':['count','mean', 'median', 'max', 'min' ,'std'],
    'revenue_usa_opening_adj':['count','mean', 'median', 'max', 'min' ,'std'],
```

```
    'revenue_world_adj':['count','mean', 'median', 'max', 'min' ,'std'],
    'roi_world':['count','mean', 'median', 'max', 'min' ,'std'],
    'roi_usa':['count','mean', 'median', 'max', 'min' ,'std']
})
```

[ ]:
```
genre_summary['rating']
```

[ ]:

genre	count	mean	median	max	min	std
Action	48	8.370833	8.30	9.0	8.0	0.260080
Adventure	60	8.315000	8.25	9.0	8.0	0.239225
Animation	23	8.247826	8.20	8.6	8.0	0.178044
Biography	29	8.251724	8.20	9.0	8.1	0.211492
Comedy	49	8.253061	8.20	8.8	8.0	0.167210
Crime	51	8.350980	8.30	9.2	8.1	0.276675
Drama	181	8.317127	8.30	9.3	8.0	0.237778
Family	27	8.229630	8.20	8.6	8.0	0.170553
Fantasy	32	8.343750	8.30	9.0	8.0	0.277009
Film-Noir	4	8.225000	8.20	8.4	8.1	0.150000
History	11	8.272727	8.20	9.0	8.1	0.264919
Horror	5	8.340000	8.40	8.5	8.1	0.181659
Music	6	8.366667	8.40	8.5	8.2	0.136626
Musical	7	8.200000	8.10	8.5	8.0	0.200000
Mystery	35	8.328571	8.30	8.6	8.1	0.161921
Romance	30	8.270000	8.20	8.8	8.0	0.200258
Sci-Fi	27	8.396296	8.40	8.8	8.1	0.212098
Sport	8	8.162500	8.15	8.3	8.1	0.074402
Thriller	55	8.287273	8.20	9.0	8.1	0.196313
War	33	8.290909	8.30	8.6	8.1	0.154846
Western	8	8.312500	8.20	8.8	8.0	0.247487

[ ]:
```
genre_summary['rating_count']
```

[ ]:

genre	count	mean	median	max	min	std
Action	48	885113.250000	794858.5	2553989	35745	582379.930693
Adventure	60	752262.283333	714357.0	2267580	28215	495517.379020
Animation	23	611903.652174	687100.0	1082998	141720	298397.405377
Biography	29	518746.034483	393269.0	1339753	28215	369797.988957
Comedy	49	501369.591837	476243.0	1339753	35745	336277.994121
Crime	51	774990.725490	763159.0	2553989	33862	563984.594955
Drama	181	591119.541436	403845.0	2583883	28215	527989.348074
Family	27	548538.222222	476243.0	1082998	73464	320942.754359
Fantasy	32	752173.875000	671476.5	1797269	35745	446690.486925
Film-Noir	4	169019.750000	161771.5	217509	135027	35244.835928
History	11	467791.454545	350082.0	1315250	53502	392739.127965
Horror	5	658176.600000	652711.0	984210	391754	263304.364526

Music	6	534508.500000	469807.5	807609	262054	223659.014651
Musical	7	401038.000000	389594.0	1023312	86806	301466.403328
Mystery	35	547704.428571	434042.0	1585235	42718	421758.130582
Romance	30	390411.300000	255709.0	1993497	35961	390989.729504
Sci-Fi	27	957855.444444	968315.0	2267580	35745	474140.515566
Sport	8	391767.250000	414678.0	675028	73464	195387.717910
Thriller	55	666189.490909	582498.0	2553989	33862	549174.175874
War	33	413203.333333	310014.0	1393103	35961	346865.805548
Western	8	463303.625000	291413.5	1493824	109675	461365.415288

[ ]:
```
genre_summary['critic_review_count']
```

[ ]:

genre	count	mean	median	max	min	std
Action	48	290.083333	241.0	835	64	165.727902
Adventure	60	267.783333	220.5	835	54	164.544167
Animation	23	255.652174	227.0	593	116	125.052574
Biography	29	216.172414	156.0	512	54	141.870935
Comedy	49	231.285714	164.0	601	57	149.243090
Crime	51	242.862745	182.0	695	63	150.794565
Drama	181	231.441989	178.0	695	7	145.029281
Family	27	222.185185	194.0	593	7	138.382424
Fantasy	32	259.156250	212.0	593	115	123.769585
Film-Noir	4	192.750000	201.0	212	157	24.878036
History	11	204.000000	149.0	488	104	140.232664
Horror	5	306.400000	321.0	373	230	62.648224
Music	6	320.000000	321.5	588	126	184.266112
Musical	7	165.142857	160.0	227	104	41.762936
Mystery	35	255.257143	213.0	628	78	129.468221
Romance	30	177.900000	163.5	347	78	64.216417
Sci-Fi	27	349.000000	278.0	835	164	174.158858
Sport	8	229.250000	225.5	422	59	135.207512
Thriller	55	280.090909	219.0	835	87	170.924423
War	33	192.212121	149.0	515	83	114.320754
Western	8	188.375000	131.5	657	91	190.660459

[ ]:
```
genre_summary['revenue_world_adj']
```

[ ]:

genre	count	mean	median	max	min	std
Action	46	36.881289	22.968594	253.229378	1.627664e-04	51.420290
Adventure	58	36.704776	21.794816	253.229378	1.038006e-05	48.281356
Animation	22	35.541579	34.869840	82.377134	2.165357e-02	23.862929
Biography	28	10.625234	6.906823	33.975043	1.324555e-04	10.717244
Comedy	45	17.415492	5.094559	82.377134	1.667764e-04	22.548948
Crime	50	11.025812	2.581570	97.258658	7.923323e-07	21.090855
Drama	177	11.749915	2.029055	253.229378	7.923323e-07	25.570093

```
Family         26  28.828322  23.672455   82.377134  2.659345e-04  26.154791
Fantasy        32  35.323171  21.794816  181.580925  2.874660e-03  38.738520
Film-Noir       4   0.003336   0.001459    0.010338  8.842624e-05   0.004797
History        10   7.076229   4.254175   16.904705  1.324555e-04   7.059538
Horror          5   2.411252   1.379970    6.937597  3.358122e-01   2.692164
Music           6  18.737084   5.894347   70.109733  2.010063e-03  27.227020
Musical         6  17.210953  11.135881   55.810698  1.804765e-02  21.852473
Mystery        35  10.709939   0.989904  109.122829  7.871902e-05  22.510678
Romance        28   6.071463   0.805603   35.588429  1.445036e-04  10.132092
Sci-Fi         27  40.902079  16.637321  253.229378  8.315266e-03  63.565488
Sport           8   9.270735   5.180790   25.810035  5.307339e-02   9.952980
Thriller       54  12.223386   2.616579   97.258658  1.038006e-05  21.235635
War            32   5.177315   0.669022   35.272693  5.225371e-05   8.946776
Western         8   7.906041   0.228502   35.143683  1.667764e-04  13.000243
```

[ ]:
```python
genre_summary['roi_world']
```

[ ]:
```
           count       mean     median         max       min        std
genre
Action        37   8.001193   4.438391   69.490728 -0.637888  11.954854
Adventure     54   9.750093   5.700610   69.490728 -0.996380  13.345872
Animation     19   7.629055   4.334854   22.635818 -0.860281   6.505476
Biography     24   4.197722   2.604519   18.442479 -0.996380   4.680864
Comedy        37   6.449569   4.040937   27.363636 -0.970839   7.005041
Crime         41   5.960837   2.890261   40.723636 -0.999979   8.948122
Drama        146   7.383795   3.226735  121.135835 -0.999979  14.916078
Family        24   7.446246   4.261685   22.635818 -0.832160   6.483714
Fantasy       28  10.257483   7.747780   69.490728  0.926207  13.197326
Film-Noir      3  -0.919103  -0.943886   -0.828725 -0.984697   0.080885
History        8  16.454848   3.738303  100.177318 -0.942955  34.141612
Horror         5  17.657382   8.662320   39.118740  0.308804  19.665885
Music          6   5.660825   3.023374   13.968711 -0.932351   6.245177
Musical        6  13.677997  16.500249   22.635818 -0.242961   8.280417
Mystery       30   7.221229   2.787666   38.707603 -0.997436  11.451419
Romance       24  10.876931   4.386431  100.177318 -0.966387  20.361661
Sci-Fi        24  10.188026   5.733818   69.490728  0.308804  14.251363
Sport          7  19.235001   1.552184  121.135835 -0.067655  44.989842
Thriller      43   8.908931   4.064864   66.344471 -0.997436  13.458238
War           28   6.606561   2.159702  100.177318 -0.995940  18.978301
Western        8   9.428581   6.657032   24.000000 -0.970839  10.099188
```

[ ]:
```python
genre_summary_flat = genre_summary.copy(deep=True)
```

[ ]:
```python
genre_summary_flat.columns = genre_summary_flat.columns.map('_'.join)
```

[ ]:
```python
genre_summary_flat.reset_index(inplace=True)
```

[ ]:
```
genre_summary_flat
```

[ ]:

	genre	rating_count	rating_mean	rating_median	rating_max
0	Action	48	8.370833	8.30	9.0
1	Adventure	60	8.315000	8.25	9.0
2	Animation	23	8.247826	8.20	8.6
3	Biography	29	8.251724	8.20	9.0
4	Comedy	49	8.253061	8.20	8.8
5	Crime	51	8.350980	8.30	9.2
6	Drama	181	8.317127	8.30	9.3
7	Family	27	8.229630	8.20	8.6
8	Fantasy	32	8.343750	8.30	9.0
9	Film-Noir	4	8.225000	8.20	8.4
10	History	11	8.272727	8.20	9.0
11	Horror	5	8.340000	8.40	8.5
12	Music	6	8.366667	8.40	8.5
13	Musical	7	8.200000	8.10	8.5
14	Mystery	35	8.328571	8.30	8.6
15	Romance	30	8.270000	8.20	8.8
16	Sci-Fi	27	8.396296	8.40	8.8
17	Sport	8	8.162500	8.15	8.3
18	Thriller	55	8.287273	8.20	9.0
19	War	33	8.290909	8.30	8.6
20	Western	8	8.312500	8.20	8.8

\

	rating_min	rating_std	rating_count_count	rating_count_mean
0	8.0	0.260080	48	885113.250000
1	8.0	0.239225	60	752262.283333
2	8.0	0.178044	23	611903.652174
3	8.1	0.211492	29	518746.034483
4	8.0	0.167210	49	501369.591837
5	8.1	0.276675	51	774990.725490
6	8.0	0.237778	181	591119.541436
7	8.0	0.170553	27	548538.222222
8	8.0	0.277009	32	752173.875000
9	8.1	0.150000	4	169019.750000
10	8.1	0.264919	11	467791.454545
11	8.1	0.181659	5	658176.600000
12	8.2	0.136626	6	534508.500000
13	8.0	0.200000	7	401038.000000
14	8.1	0.161921	35	547704.428571
15	8.0	0.200258	30	390411.300000
16	8.1	0.212098	27	957855.444444
17	8.1	0.074402	8	391767.250000
18	8.1	0.196313	55	666189.490909
19	8.1	0.154846	33	413203.333333
20	8.0	0.247487	8	463303.625000

\

	rating_count_median	…	roi_world_median	roi_world_max	roi_world_min	\
0	794858.5	…	4.438391	69.490728	-0.637888	
1	714357.0	…	5.700610	69.490728	-0.996380	
2	687100.0	…	4.334854	22.635818	-0.860281	
3	393269.0	…	2.604519	18.442479	-0.996380	
4	476243.0	…	4.040937	27.363636	-0.970839	
5	763159.0	…	2.890261	40.723636	-0.999979	
6	403845.0	…	3.226735	121.135835	-0.999979	
7	476243.0	…	4.261685	22.635818	-0.832160	
8	671476.5	…	7.747780	69.490728	0.926207	
9	161771.5	…	-0.943886	-0.828725	-0.984697	
10	350082.0	…	3.738303	100.177318	-0.942955	
11	652711.0	…	8.662320	39.118740	0.308804	
12	469807.5	…	3.023374	13.968711	-0.932351	
13	389594.0	…	16.500249	22.635818	-0.242961	
14	434042.0	…	2.787666	38.707603	-0.997436	
15	255709.0	…	4.386431	100.177318	-0.966387	
16	968315.0	…	5.733818	69.490728	0.308804	
17	414678.0	…	1.552184	121.135835	-0.067655	
18	582498.0	…	4.064864	66.344471	-0.997436	
19	310014.0	…	2.159702	100.177318	-0.995940	
20	291413.5	…	6.657032	24.000000	-0.970839	

	roi_world_std	roi_usa_count	roi_usa_mean	roi_usa_median	roi_usa_max	\
0	11.954854	37	3.351164	1.332753	40.908955	
1	13.345872	50	4.951126	2.036005	40.908955	
2	6.505476	19	2.027658	1.039553	8.395195	
3	4.680864	22	2.029636	1.091658	18.425310	
4	7.005041	33	2.876256	1.372053	27.363636	
5	8.948122	37	3.547012	1.280023	27.363636	
6	14.916078	131	4.301569	1.360024	121.119945	
7	6.483714	22	3.131666	1.094408	18.425310	
8	13.197326	27	4.341716	1.527324	40.908955	
9	0.080885	1	-0.828970	-0.828970	-0.828970	
10	34.141612	7	8.540894	1.833600	49.510986	
11	19.665885	5	13.398785	6.445496	38.655640	
12	6.245177	5	1.537415	1.887391	2.967273	
13	8.280417	6	8.161106	7.820956	18.425310	
14	11.451419	27	3.929381	1.280023	38.655640	
15	20.361661	22	6.047031	2.259134	49.510986	
16	14.251363	24	5.158756	1.571270	40.908955	
17	44.989842	7	18.202559	0.299110	121.119945	
18	13.458238	39	4.518155	1.838319	38.655640	
19	18.978301	23	4.754910	0.981388	49.510986	
20	10.099188	7	8.382718	6.025542	24.000000	

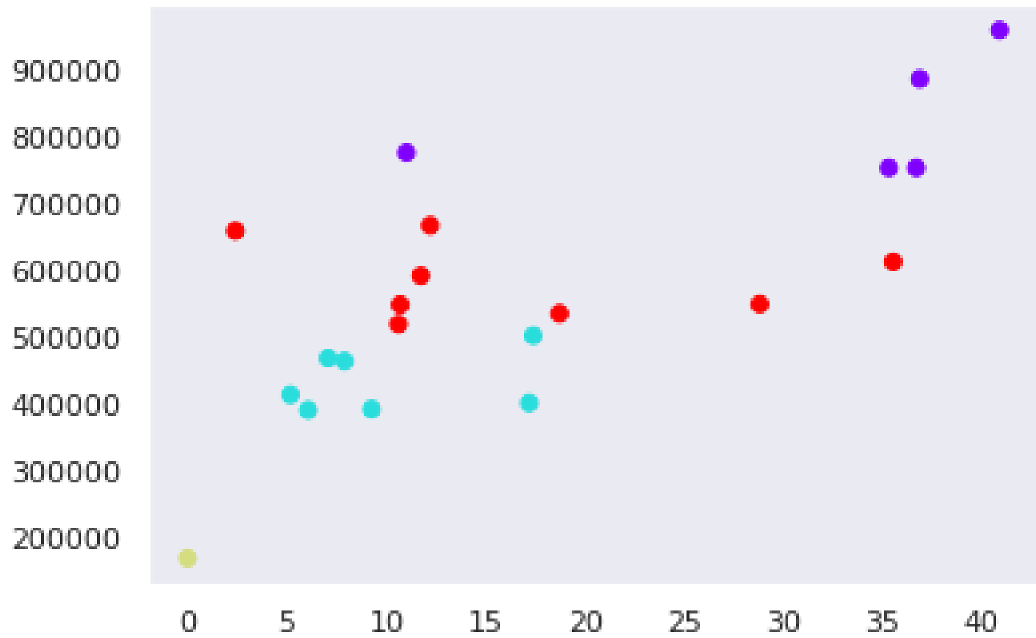
```
    roi_usa_min  roi_usa_std
0     -0.764173     7.194877
1     -0.978482     8.150259
2     -0.860281     2.987448
3     -0.290852     3.847800
4     -0.987213     5.079211
5     -0.994515     6.640125
6     -0.994515    12.372763
7     -0.986164     4.589925
8     -0.986164     8.184877
9     -0.828970          NaN
10     0.050138    18.128914
11     0.308651    16.182958
12    -0.069355     1.403562
13    -0.258290     5.974783
14    -0.994515     9.758557
15    -0.987213    10.840869
16     0.027394     8.631773
17    -0.453715    45.413280
18    -0.994515     9.658098
19    -0.860281    10.962360
20     0.064302     9.766468

[21 rows x 49 columns]
```

[ ]:
```
from sklearn.cluster import KMeans
```

[ ]:
```
X = genre_summary_flat[["revenue_world_adj_mean","rating_count_mean"]]

kmeans = KMeans(n_clusters=4, random_state=1)
kmeans.fit(X)

identified_clusters = kmeans.fit_predict(X)

# genre_clusters = genre_summary_flat.copy()
genre_summary_flat['clusters'] = identified_clusters
```

[ ]:
```
plt.
 ↪scatter(genre_summary_flat['revenue_world_adj_mean'],genre_summary_flat['rating_count_mean']
```

[ ]:
```
<matplotlib.collections.PathCollection at 0x7f858f3a53d0>
```




```
[ ]: genre_summary_flat[['genre','clusters']].sort_values(by='clusters')
```

[ ]:

	genre	clusters
0	Action	0
1	Adventure	0
16	Sci-Fi	0
5	Crime	0
8	Fantasy	0
17	Sport	1
15	Romance	1
13	Musical	1
19	War	1
10	History	1
4	Comedy	1
20	Western	1
9	Film-Noir	2
7	Family	3
11	Horror	3
12	Music	3
6	Drama	3
14	Mystery	3
3	Biography	3
2	Animation	3
18	Thriller	3

[ ]:
```
movie_genre['cluster'] = movie_genre.
 ↪merge(genre_summary_flat[['genre','clusters']], how='left',␣
 ↪on='genre')['clusters']
```

[ ]:
```
movie_genre.groupby('cluster').agg({'rating_count':'mean', 'revenue_world_adj':
 ↪'sum'})
```

[ ]:
```
           rating_count  revenue_world_adj
cluster
0         812281.472477        6611.404509
1         443210.260274        1430.814403
2         169019.750000           0.013345
3         590660.939058        5068.082029
```

[ ]:
```
movie_genre['cluster_label'] = movie_genre['cluster'].replace(
    {
        0: 4,
        3: 3,
        1: 2,
        2: 1
    }
)
```

[ ]:
```
movie_cluster = movie_genre.groupby('movie_id').agg({'cluster_label':
 ↪['max','min']})
movie_cluster.columns = movie_cluster.columns.map('_'.join)
movie_cluster.reset_index(inplace=True)
```

[ ]:
```
movies[['cluster_max','cluster_min']] = movies.merge(movie_cluster, how='left',␣
 ↪on='movie_id')[['cluster_label_max','cluster_label_min']]
```

[ ]:
```
movies.groupby(['cluster_max','cluster_min']).agg({
    'rating':['median','mean'],
    'rating_count':['median','mean'],
    'critic_review_count':['median','mean'],
    'revenue_world_adj':['median','mean'],
    'roi_world':['median','mean'],
})
```

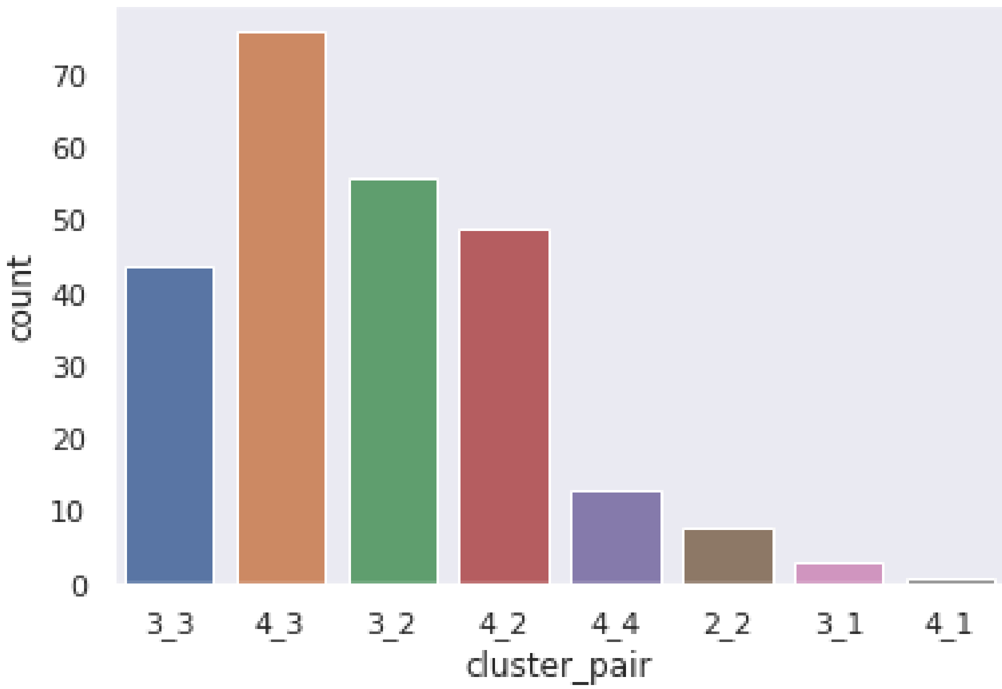
[ ]:
```
                        rating           rating_count               \
                        median      mean       median          mean
cluster_max cluster_min
2           2             8.25  8.250000     287245.0  3.206424e+05
3           1             8.10  8.200000     169348.0  1.739613e+05
            2             8.25  8.296429     321722.5  4.517375e+05
            3             8.30  8.304545     401045.5  5.863058e+05
4           1             8.30  8.300000     154195.0  1.541950e+05
```

```
            2             8.20  8.234694     476243.0  5.364490e+05
            3             8.30  8.365789     729861.5  7.898803e+05
            4             8.40  8.384615    1011382.0  1.016257e+06

                         critic_review_count             revenue_world_adj  \
                                      median        mean            median
cluster_max cluster_min
2           2                          135.0  140.625000          0.104530
3           1                          207.0  204.666667          0.002561
            2                          154.5  202.071429          1.864602
            3                          195.0  237.681818          1.825915
4           1                          157.0  157.000000          0.000088
            2                          168.0  245.102041         11.123991
            3                          213.0  258.500000          4.159909
            4                          244.0  275.461538         20.818216

                                   roi_world
                              mean    median       mean
cluster_max cluster_min
2           2             1.690669  4.238623   8.122179
3           1             0.004419 -0.886306  -0.886306
            2             6.736256  3.458030  10.201842
            3             5.744949  3.870989  10.628665
4           1             0.000088 -0.984697  -0.984697
            2            19.466601  3.604178   6.420585
            3            19.961109  3.780023   6.533993
            4            43.279388  8.878579  15.122367
```

[ ]:
```
movies['cluster_pair'] = movies['cluster_max'].astype(str) + "_" +
movies['cluster_min'].astype(str)
```

[ ]:
```
sns.countplot(x=movies['cluster_pair'])
```

[ ]:
```
<AxesSubplot:xlabel='cluster_pair', ylabel='count'>
```



[ ]:
```
sns.countplot(x=movies['cluster_pair'])
```