movie-recommendation-final-notebook

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1 Movie Recommendation

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1.1 Import Libraries

[ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from matplotlib import __version__ as mpv
import seaborn as sns
from sklearn.base import BaseEstimator, TransformerMixin
import scipy.sparse as sparse
from surprise.model_selection import train_test_split

from surprise import SVD
from surprise import accuracy
from surprise import KNNWithMeans
from surprise import Dataset
from surprise.model_selection import cross_validate, GridSearchCV
from surprise import Reader
from collections import defaultdict
from ast import literal_eval
from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer
from sklearn.metrics.pairwise import linear_kernel, cosine_similarity
```

1.2 Configurations

[ ]:
```
%matplotlib inline
plt.style.use("seaborn-darkgrid")
random_state = 17
np.random.seed(random_state)
import warnings
warnings.filterwarnings('ignore')
```

1.3 Load Datasets

[ ]:
```python
rating=pd.read_csv("dataset/ratings.csv")
link=pd.read_csv("dataset/links.csv")
movies=pd.read_csv("dataset/movies.csv")

tags=pd.read_csv("dataset/tags.csv")
genome_scores=pd.read_csv("dataset/genome-scores.csv")
genome_tags=pd.read_csv("dataset/genome-tags.csv")

metadata = pd.read_csv("dataset/movies_metadata.csv")
```

1.3.1 Movies dataset

[ ]:
```python
movies.head(5)
```

[ ]:
```
   movieId                               title  \
0        1                    Toy Story (1995)
1        2                      Jumanji (1995)
2        3             Grumpier Old Men (1995)
3        4            Waiting to Exhale (1995)
4        5  Father of the Bride Part II (1995)

                                        genres
0  Adventure|Animation|Children|Comedy|Fantasy
1                   Adventure|Children|Fantasy
2                               Comedy|Romance
3                         Comedy|Drama|Romance
4                                       Comedy
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 62423 entries, 0 to 62422
Data columns (total 3 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   movieId  62423 non-null  int64
 1   title    62423 non-null  object
 2   genres   62423 non-null  object
dtypes: int64(1), object(2)
memory usage: 1.4+ MB
```

1.3.2 Link dataset holding relational keys to IMDb and TMDB datasets

[ ]:
```python
link.head(5)
```

[ ]:

	movieId	imdbId	tmdbId
0	1	114709	862.0
1	2	113497	8844.0
2	3	113228	15602.0
3	4	114885	31357.0
4	5	113041	11862.0

[ ]:

```
link.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 62423 entries, 0 to 62422
Data columns (total 3 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   movieId  62423 non-null  int64  
 1   imdbId   62423 non-null  int64  
 2   tmdbId   62316 non-null  float64
dtypes: float64(1), int64(2)
memory usage: 1.4 MB
```

1.3.3 Rating dataset

[ ]:

```
rating.head(5)
```

[ ]:

	userId	movieId	rating	timestamp
0	1	296	5.0	1147880044
1	1	306	3.5	1147868817
2	1	307	5.0	1147868828
3	1	665	5.0	1147878820
4	1	899	3.5	1147868510

[ ]:

```
rating.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 25000095 entries, 0 to 25000094
Data columns (total 4 columns):
 #   Column     Dtype  
---  ------     -----  
 0   userId     int64  
 1   movieId    int64  
 2   rating     float64
 3   timestamp  int64  
dtypes: float64(1), int64(3)
memory usage: 762.9 MB
```

1.3.4 Scoring dataset

[ ]:
```
genome_scores.head(5)
```

[ ]:
```
   movieId  tagId  relevance
0        1      1    0.02875
1        1      2    0.02375
2        1      3    0.06250
3        1      4    0.07575
4        1      5    0.14075
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15584448 entries, 0 to 15584447
Data columns (total 3 columns):
 #   Column     Dtype
---  ------     -----
 0   movieId    int64
 1   tagId      int64
 2   relevance  float64
dtypes: float64(1), int64(2)
memory usage: 356.7 MB
```

1.3.5 Tags dataset

[ ]:
```
genome_tags.head(5)
```

[ ]:
```
   tagId           tag
0      1           007
1      2  007 (series)
2      3  18th century
3      4         1920s
4      5         1930s
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1128 entries, 0 to 1127
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   tagId   1128 non-null   int64
 1   tag     1128 non-null   object
dtypes: int64(1), object(1)
memory usage: 17.8+ KB
```

1.3.6 Metadata dataset

[ ]:
```
metadata.head(5)
```

[ ]:
```
   adult                              belongs_to_collection    budget  \
0  False  {'id': 10194, 'name': 'Toy Story Collection', …  30000000
1  False                                                NaN  65000000
2  False  {'id': 119050, 'name': 'Grumpy Old Men Collect…         0
3  False                                                NaN  16000000
4  False  {'id': 96871, 'name': 'Father of the Bride Col…         0

                                              genres  \
0  [{'id': 16, 'name': 'Animation'}, {'id': 35, '…
1  [{'id': 12, 'name': 'Adventure'}, {'id': 14, '…
2  [{'id': 10749, 'name': 'Romance'}, {'id': 35, …
3  [{'id': 35, 'name': 'Comedy'}, {'id': 18, 'nam…
4                     [{'id': 35, 'name': 'Comedy'}]

                               homepage     id    imdb_id original_language  \
0  http://toystory.disney.com/toy-story    862  tt0114709                en
1                                   NaN   8844  tt0113497                en
2                                   NaN  15602  tt0113228                en
3                                   NaN  31357  tt0114885                en
4                                   NaN  11862  tt0113041                en

                original_title  \
0                    Toy Story
1                      Jumanji
2             Grumpier Old Men
3            Waiting to Exhale
4  Father of the Bride Part II

                                            overview  … release_date  \
0  Led by Woody, Andy's toys live happily in his …  …   1995-10-30
1  When siblings Judy and Peter discover an encha…  …   1995-12-15
2  A family wedding reignites the ancient feud be…  …   1995-12-22
3  Cheated on, mistreated and stepped on, the wom…  …   1995-12-22
4  Just when George Banks has recovered from his …  …   1995-02-10

       revenue runtime                                   spoken_languages  \
0  373554033.0    81.0           [{'iso_639_1': 'en', 'name': 'English'}]
1  262797249.0   104.0  [{'iso_639_1': 'en', 'name': 'English'}, {'iso…
2          0.0   101.0           [{'iso_639_1': 'en', 'name': 'English'}]
3   81452156.0   127.0           [{'iso_639_1': 'en', 'name': 'English'}]
4   76578911.0   106.0           [{'iso_639_1': 'en', 'name': 'English'}]

     status                                            tagline  \
0  Released                                                NaN
```

```
1  Released         Roll the dice and unleash the excitement!
2  Released  Still Yelling. Still Fighting. Still Ready for…
3  Released  Friends are the people who let you be yourself…
4  Released  Just When His World Is Back To Normal… He's …

                         title  video vote_average vote_count
0                    Toy Story  False          7.7     5415.0
1                      Jumanji  False          6.9     2413.0
2             Grumpier Old Men  False          6.5       92.0
3            Waiting to Exhale  False          6.1       34.0
4  Father of the Bride Part II  False          5.7      173.0

[5 rows x 24 columns]
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45466 entries, 0 to 45465
Data columns (total 24 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   adult                  45466 non-null  object
 1   belongs_to_collection  4494 non-null   object
 2   budget                 45466 non-null  object
 3   genres                 45466 non-null  object
 4   homepage               7782 non-null   object
 5   id                     45466 non-null  object
 6   imdb_id                45449 non-null  object
 7   original_language      45455 non-null  object
 8   original_title         45466 non-null  object
 9   overview               44512 non-null  object
 10  popularity             45461 non-null  object
 11  poster_path            45080 non-null  object
 12  production_companies   45463 non-null  object
 13  production_countries   45463 non-null  object
 14  release_date           45379 non-null  object
 15  revenue                45460 non-null  float64
 16  runtime                45203 non-null  float64
 17  spoken_languages       45460 non-null  object
 18  status                 45379 non-null  object
 19  tagline                20412 non-null  object
 20  title                  45460 non-null  object
 21  video                  45460 non-null  object
 22  vote_average           45460 non-null  float64
 23  vote_count             45460 non-null  float64
dtypes: float64(4), object(20)
memory usage: 8.3+ MB
```

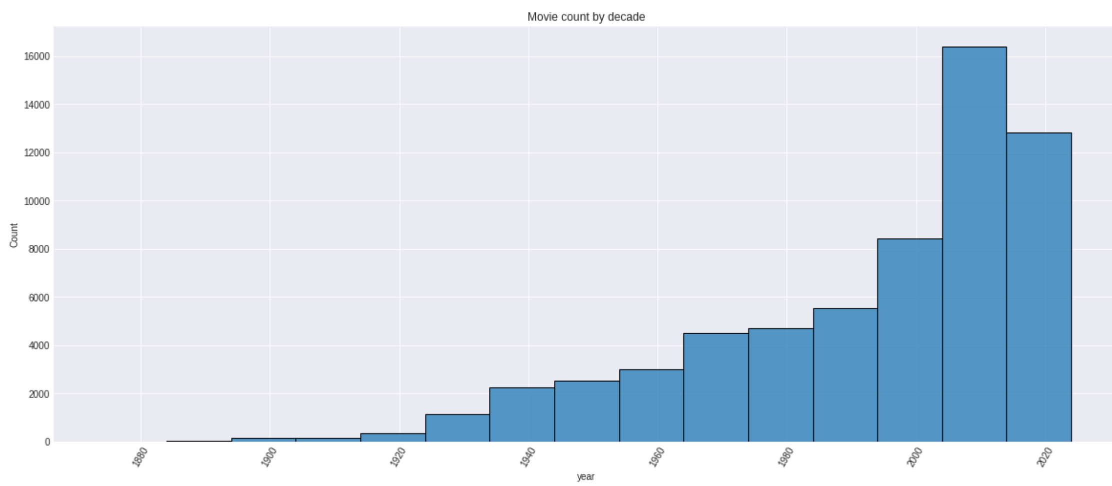
1.4 EDA

1.4.1 Extract Movie Year from Title

[ ]:
```
movies["year"] = movies.title.str.extract('(\(\d{4}\))')
movies.year = movies.year.str.extract('(\d+)')
movies.year = pd.to_numeric(movies.year)
```

1.4.2 Movies by Decade

[ ]:
```
fig, ax = plt.subplots(figsize=(20, 8))
p1=sns.histplot(data=movies, x='year', ax=ax, binwidth=10)
plt.title('Movie count by decade')
plt.xticks(rotation=60)
plt.show()
```



1.4.3 Split genre column to dummy columns

[ ]:
```
genres = movies.genres.str.get_dummies().add_prefix('g_')
movies = pd.concat([movies, genres], axis=1)
```

[ ]:
```
movies.head(5)
```

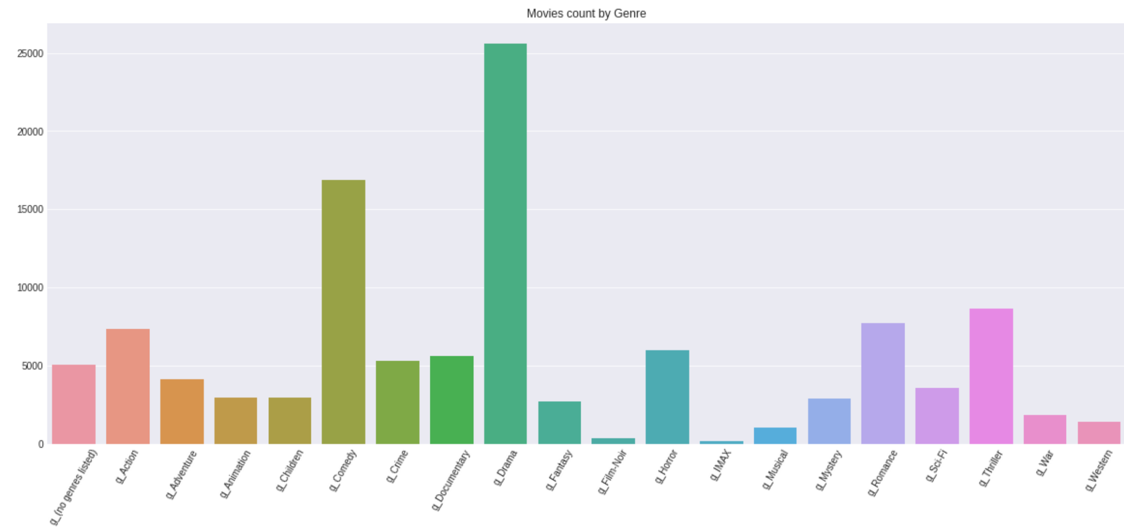
[ ]:
```
   movieId                               title  \
0        1                    Toy Story (1995)
1        2                      Jumanji (1995)
2        3             Grumpier Old Men (1995)
3        4            Waiting to Exhale (1995)
4        5  Father of the Bride Part II (1995)

                                        genres    year  g_(no genres listed)  \
```

```
0  Adventure|Animation|Children|Comedy|Fantasy  1995.0                 0
1                  Adventure|Children|Fantasy  1995.0                 0
2                              Comedy|Romance  1995.0                 0
3                        Comedy|Drama|Romance  1995.0                 0
4                                      Comedy  1995.0                 0

   g_Action  g_Adventure  g_Animation  g_Children  g_Comedy  …  g_Film-Noir  \
0         0            1            1           1         1  …            0
1         0            1            0           1         0  …            0
2         0            0            0           0         1  …            0
3         0            0            0           0         1  …            0
4         0            0            0           0         1  …            0

   g_Horror  g_IMAX  g_Musical  g_Mystery  g_Romance  g_Sci-Fi  g_Thriller  \
0         0       0          0          0          0         0           0
1         0       0          0          0          0         0           0
2         0       0          0          0          1         0           0
3         0       0          0          0          1         0           0
4         0       0          0          0          0         0           0

   g_War  g_Western
0      0          0
1      0          0
2      0          0
3      0          0
4      0          0

[5 rows x 24 columns]
```

1.4.4 Movies by genre

[ ]:
```
g_cols = [ col for col in movies.columns if col.startswith("g_")]
```

[ ]:
```
fig, ax = plt.subplots(figsize=(20, 8))
p1=sns.barplot(x=g_cols, y=movies[g_cols].sum(), ax=ax)
plt.title('Movies count by Genre')
plt.xticks(rotation=60)
plt.show()
```



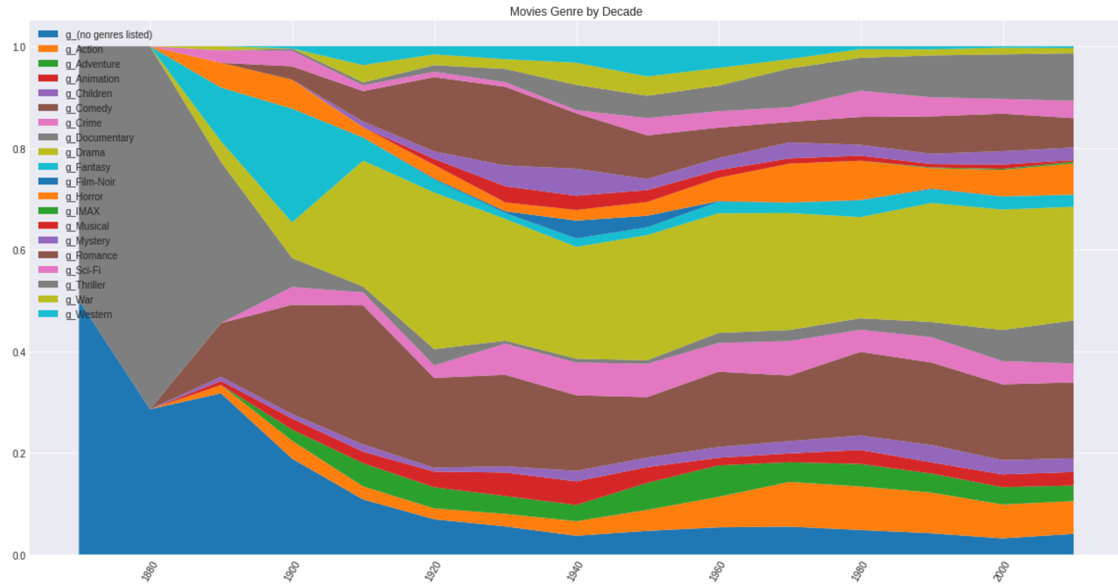
1.4.5 Movies by decade and genre

[ ]:
```
by_decade_genres= movies[g_cols].groupby(np.floor(movies.year/10)*10).sum()
by_decade_genres = by_decade_genres.transpose()
for col in by_decade_genres.columns:
    by_decade_genres[col] = by_decade_genres[col]/by_decade_genres[col].sum()

by_decade_genres
```

[ ]:
```
year                  1870.0    1880.0    1890.0    1900.0    1910.0  \
g_(no genres listed)     0.5  0.285714  0.317073  0.188596  0.108262
g_Action                 0.0  0.000000  0.016260  0.035088  0.025641
g_Adventure              0.0  0.000000  0.000000  0.021930  0.045584
g_Animation              0.0  0.000000  0.008130  0.021930  0.022792
g_Children               0.0  0.000000  0.008130  0.008772  0.014245
g_Comedy                 0.0  0.000000  0.105691  0.214912  0.273504
g_Crime                  0.0  0.000000  0.000000  0.035088  0.025641
g_Documentary            0.5  0.714286  0.317073  0.057018  0.011396
g_Drama                  0.0  0.000000  0.040650  0.070175  0.247863
g_Fantasy                0.0  0.000000  0.105691  0.223684  0.045584
g_Film-Noir              0.0  0.000000  0.000000  0.000000  0.000000
g_Horror                 0.0  0.000000  0.048780  0.057018  0.019943
g_IMAX                   0.0  0.000000  0.000000  0.000000  0.000000
g_Musical                0.0  0.000000  0.000000  0.000000  0.000000
g_Mystery                0.0  0.000000  0.000000  0.000000  0.011396
g_Romance                0.0  0.000000  0.000000  0.026316  0.059829
g_Sci-Fi                 0.0  0.000000  0.024390  0.030702  0.011396
g_Thriller               0.0  0.000000  0.000000  0.004386  0.005698
g_War                    0.0  0.000000  0.008130  0.000000  0.034188
```

```
g_Western                0.0  0.000000  0.000000  0.004386  0.037037

year                  1920.0    1930.0    1940.0    1950.0    1960.0  \
g_(no genres listed)  0.069296  0.055246  0.036784  0.046450  0.053372
g_Action              0.021322  0.024701  0.028634  0.041352  0.059923
g_Adventure           0.041578  0.035060  0.031938  0.053059  0.061841
g_Animation           0.030917  0.046215  0.046476  0.030967  0.015021
g_Children            0.007463  0.012218  0.020705  0.018693  0.021253
g_Comedy              0.176972  0.180080  0.148678  0.119147  0.148130
g_Crime               0.024520  0.061355  0.064537  0.065521  0.056568
g_Documentary         0.031983  0.005843  0.007489  0.006986  0.019815
g_Drama               0.308102  0.239575  0.220044  0.246224  0.235379
g_Fantasy             0.025586  0.011687  0.016520  0.015483  0.022691
g_Film-Noir           0.002132  0.003453  0.035022  0.022659  0.001278
g_Horror              0.026652  0.017264  0.020925  0.027002  0.045702
g_IMAX                0.000000  0.000000  0.000000  0.000000  0.000000
g_Musical             0.011727  0.031873  0.028194  0.023414  0.015181
g_Mystery             0.014925  0.040903  0.053084  0.021903  0.023650
g_Romance             0.146055  0.154847  0.109031  0.085725  0.060083
g_Sci-Fi              0.010661  0.009031  0.006167  0.034177  0.032279
g_Thriller            0.012793  0.026029  0.049780  0.043807  0.050336
g_War                 0.021322  0.019124  0.043612  0.037953  0.034835
g_Western             0.015991  0.025498  0.032379  0.059479  0.042665

year                  1970.0    1980.0    1990.0    2000.0    2010.0
g_(no genres listed)  0.054807  0.048158  0.041693  0.031572  0.040628
g_Action              0.087920  0.085627  0.080099  0.066805  0.064451
g_Adventure           0.038822  0.044242  0.037444  0.033972  0.030556
g_Animation           0.017356  0.027625  0.022049  0.025184  0.026648
g_Children            0.024092  0.028366  0.034076  0.028154  0.027019
g_Comedy              0.129139  0.164691  0.162284  0.148989  0.149387
g_Crime               0.067710  0.043395  0.049792  0.045852  0.037033
g_Documentary         0.021809  0.022756  0.029907  0.061150  0.084736
g_Drama               0.230190  0.198984  0.234285  0.236950  0.223738
g_Fantasy             0.020096  0.032917  0.026780  0.025510  0.023652
g_Film-Noir           0.000571  0.000741  0.001443  0.000610  0.000171
g_Horror              0.076501  0.077053  0.040170  0.051751  0.061598
g_IMAX                0.000000  0.000212  0.001604  0.002197  0.003395
g_Musical             0.010276  0.010055  0.006575  0.008503  0.002825
g_Mystery             0.031628  0.021169  0.020125  0.026364  0.024765
g_Romance             0.040078  0.054932  0.073765  0.073844  0.057946
g_Sci-Fi              0.029002  0.051545  0.037364  0.029009  0.034066
g_Thriller            0.076273  0.064670  0.082505  0.087636  0.093666
g_War                 0.018497  0.017146  0.011947  0.013141  0.010157
g_Western             0.025234  0.005715  0.006094  0.002807  0.003566
```

```
[ ]: fig, ax = plt.subplots(figsize=(20, 10))
     p1=plt.stackplot(by_decade_genres.columns, by_decade_genres,␣
      ↪labels=by_decade_genres.index)
     plt.title('Movies Genre by Decade')
     plt.xticks(rotation=60)
     plt.legend(loc="upper left")
     plt.show()
```



1.4.6 Add year column to metadata from release data

```
[ ]: metadata['year'] = pd.to_datetime(metadata['release_date'], errors='coerce').
      ↪apply(
         lambda x: str(x).split('-')[0] if x != np.nan else np.nan)
```

1.4.7 Utility functions

```
[ ]: def to_int(x):
         try:
             return int(x)
         except:
             return np.nan

     def get_first_index(idx):
         if isinstance(idx, list) or isinstance(idx, pd.Series):
             idx = idx[0]
         return idx
```

1.4.8 Convert Id column to int from object to connect with links

```
[ ]: metadata['id'] = metadata['id'].apply(to_int)
```

1.5 Model Creation

1.5.1 Simple Recommendation model using weighted-rating

Function to return sorted list of movies by weighted rating Following formula is used to calculated weighted rating Weighted Rating (WR) = $(\frac{v}{v+m}.R) + (\frac{m}{v+m}.C)$

```
[ ]: def get_top_weighted_rating(df, number_of_records=200, percentile=0.85):
         non_null_vote_counts = df[df['vote_count'].notnull()]['vote_count']
         non_null_vote_avgs = df[df['vote_average'].notnull()]['vote_average']
         mean_votes = non_null_vote_avgs.mean()
         min_votes_req = non_null_vote_counts.quantile(percentile)

         selected = df[(df['vote_count'] >= min_votes_req) & (
             df['vote_count'].notnull()) & (df['vote_average'].notnull())]
         selected = selected[['title', 'year',
                              'vote_count', 'vote_average', 'popularity', 'id']]
         selected['weighted_rating'] = selected.apply(lambda x: (
             x.vote_count / (x.vote_count + min_votes_req) * x['vote_average']) +␣
      ↪(min_votes_req/(min_votes_req + x.vote_count) * mean_votes), axis=1)

         selected = selected.sort_values(
             'weighted_rating', ascending=False).head(number_of_records)
         return selected
```

Function to create top movie charts for all movies and by genre

```
[ ]: def build_top_movie_chart(dataframe, genre=None, percentile=0.85,␣
      ↪no_of_movies=200):
         if genre is None:
             df = dataframe
         else:
             df = stack_df_by_genre(dataframe)
             df = df[df['genre'] == genre]
         selected = get_top_weighted_rating(df, no_of_movies, percentile)
         return selected

     def stack_df_by_genre(dataframe):
         metadata_temp = dataframe.copy()
         metadata_temp['genres'] = metadata_temp['genres'].fillna('[]').
      ↪apply(literal_eval).apply(
             lambda x: [i['name'] for i in x] if isinstance(x, list) else [])
         df = metadata_temp.apply(lambda x: pd.Series(
             x['genres']), axis=1).stack().reset_index(level=1, drop=True)
         df.name = 'genre'
```

```
    df = metadata_temp.drop('genres', axis=1).join(df)
    return df

def replace_genre_json_with_list(dataframe, fieldName):
    metadata_temp = dataframe.copy()
    metadata_temp[fieldName] = metadata_temp[fieldName].fillna('[]').
 ↪apply(literal_eval).apply(
        lambda x: [i['name'] for i in x] if isinstance(x, list) else [])
    metadata_temp[fieldName] = metadata_temp[fieldName].apply(lambda x: ','.
 ↪join(map(str, x)))
    return metadata_temp
```

Top 10 movies by weighted rating

[ ]:
```
build_top_movie_chart(metadata, percentile=0.95, no_of_movies=10)
```

[ ]:
```
                           title  year  vote_count  vote_average  popularity  \
314     The Shawshank Redemption  1994      8358.0           8.5   51.645403
834                The Godfather  1972      6024.0           8.5   41.109264
12481            The Dark Knight  2008     12269.0           8.3  123.167259
2843                  Fight Club  1999      9678.0           8.3   63.869599
292                 Pulp Fiction  1994      8670.0           8.3  140.950236
351                 Forrest Gump  1994      8147.0           8.2   48.307194
522             Schindler's List  1993      4436.0           8.3   41.725123
23673                   Whiplash  2014      4376.0           8.3    64.29999
5481               Spirited Away  2001      3968.0           8.3   41.048867
1154     The Empire Strikes Back  1980      5998.0           8.2   19.470959

             id  weighted_rating
314       278.0         8.357746
834       238.0         8.306334
12481     155.0         8.208376
2843      550.0         8.184899
292       680.0         8.172155
351        13.0         8.069421
522       424.0         8.061007
23673  244786.0         8.058025
5481      129.0         8.035598
1154     1891.0         8.025793
```

Top 10 Crime movies

[ ]:
```
build_top_movie_chart(metadata, genre="Crime", percentile=0.90, no_of_movies=10)
```

[ ]:
```
                           title  year  vote_count  vote_average  popularity  \
314     The Shawshank Redemption  1994      8358.0           8.5   51.645403
834                The Godfather  1972      6024.0           8.5   41.109264
12481            The Dark Knight  2008     12269.0           8.3  123.167259
292                 Pulp Fiction  1994      8670.0           8.3  140.950236
```

```
1178     The Godfather: Part II  1974      3418.0            8.3   36.629307
289      Leon: The Professional  1994      4293.0            8.2   20.477329
3030             The Green Mile  1999      4166.0            8.2    19.96678
46                        Se7en  1995      5915.0            8.1    18.45743
1170                 GoodFellas  1990      3211.0            8.2   15.424092
586    The Silence of the Lambs  1991      4549.0            8.1    4.307222

          id  weighted_rating
314    278.0         8.389613
834    238.0         8.349302
12481  155.0         8.229593
292    680.0         8.201554
1178   240.0         8.064967
289    101.0         8.016979
3030   497.0         8.011851
46     807.0         7.970079
1170   769.0         7.961638
586    274.0         7.933982
```

Top 10 Drama movies

[ ]:
```python
build_top_movie_chart(metadata, genre="Drama", percentile=0.90, no_of_movies=10)
```

[ ]:
```
                                title  year  vote_count  vote_average  \
10309      Dilwale Dulhania Le Jayenge  1995       661.0           9.1
314           The Shawshank Redemption  1994      8358.0           8.5
834                      The Godfather  1972      6024.0           8.5
12481                  The Dark Knight  2008     12269.0           8.3
2843                        Fight Club  1999      9678.0           8.3
522                   Schindler's List  1993      4436.0           8.3
23673                         Whiplash  2014      4376.0           8.3
2211                Life Is Beautiful  1997      3643.0           8.3
1178            The Godfather: Part II  1974      3418.0           8.3
1152   One Flew Over the Cuckoo's Nest  1975      3001.0           8.3

       popularity        id  weighted_rating
10309   34.457024   19404.0         8.493149
314     51.645403     278.0         8.452756
834     41.109264     238.0         8.434910
12481  123.167259     155.0         8.270123
2843    63.869599     550.0         8.262251
522     41.725123     424.0         8.219148
23673    64.29999  244786.0         8.218078
2211     39.39497     637.0         8.202267
1178    36.629307     240.0         8.196112
1152    35.529554     510.0         8.182386
```

1.5.2 Content Based Recommendation

I will be using genres, spoken_languages, tagline, and overview from metadata dataset to create Content based recommendation

Create new column desc by concatenating 4 column contents spoken_languages, tagline, and overview from metadata dataset

[ ]:
```
metadata_for_cont = metadata.copy()
metadata_for_cont = replace_genre_json_with_list(
    metadata_for_cont, "genres")
metadata_for_cont = replace_genre_json_with_list(
    metadata_for_cont, "spoken_languages")

metadata_for_cont["genres"] = metadata_for_cont.genres.fillna("")
metadata_for_cont["spoken_languages"] = metadata_for_cont.spoken_languages.
 ↪fillna(
    "")
metadata_for_cont["tagline"] = metadata_for_cont.tagline.fillna("")
metadata_for_cont["desc"] = metadata_for_cont.genres + \
    metadata_for_cont.spoken_languages + \
    metadata_for_cont.overview + metadata_for_cont.tagline
metadata_for_cont["desc"] = metadata_for_cont.desc.fillna("")

metadata_for_cont = metadata_for_cont[metadata_for_cont.id.isin(link.tmdbId)]
```

Content that will be used for Content-Based recommendation

[ ]:
```
metadata_for_cont.desc
```

[ ]:
```
0        Animation,Comedy,FamilyEnglishLed by Woody, An…
1        Adventure,Fantasy,FamilyEnglish,FrançaisWhen s…
2        Romance,ComedyEnglishA family wedding reignite…
3        Comedy,Drama,RomanceEnglishCheated on, mistrea…
4        ComedyEnglishJust when George Banks has recove…
                                 …
45461    Drama,Family   Rising and falling between a …
45462    DramaAn artist struggles to finish his work wh…
45463    Action,Drama,ThrillerEnglishWhen one of her hi…
45464    In a small town live two brothers, one a minis…
45465    English50 years after decriminalisation of hom…
Name: desc, Length: 42848, dtype: object
```

Create n-gram and vectorize for each movie

[ ]:
```
tf = TfidfVectorizer(analyzer='word', ngram_range=(1, 2),
                     min_df=0, stop_words='english')
metadata_transformed = tf.fit_transform(metadata_for_cont.desc)
```

[ ]:
```
metadata_transformed.shape
```

[ ]: (42848, 1113576)

Calculate cosine simalirity between all movies by using words from desc column

[ ]:
```
cosine_sim = linear_kernel(metadata_transformed, metadata_transformed)
```

[ ]:
```
metadata_for_cont = metadata_for_cont.reset_index()
titles = metadata_for_cont['title']
indices = pd.Series(metadata_for_cont.index, index=metadata_for_cont['title'])
```

Function to sort movies by simalarity and return(default 30) similar movies of the movie passed as parameter

[ ]:
```
def get_recommendations(title, no_of_movies=30):
    idx = get_first_index(indices[title])
    sim_scores = list(enumerate(cosine_sim[idx]))
    sim_scores = sorted(sim_scores, key=lambda x: x[1], reverse=True)
    sim_scores = sim_scores[1:no_of_movies+1]
    movie_indices = [i[0] for i in sim_scores]
    return titles.iloc[movie_indices]
```

Similar movies to "The Apartment" movie

[ ]:
```
get_recommendations('The Apartment', 10)
```

[ ]:
```
17658              Miss Nobody
8943                  LadyBugs
32824        Unlocking the Cage
2298          Nothing in Common
29887           Company Limited
14094                 Birdsong
7443      Shadow of the Thin Man
8697          The Holy Mountain
8352         The Shopworn Angel
21390           Black Nativity
Name: title, dtype: object
```

1.5.3 Hybrid model combining weighted rating + content-based model

Function to calculate Similarity by considering simalarity scores from cosine similarity followed by weighted ratings

[ ]:
```
def cosine_sim_plus_weighted_rating(title, no_of_movies, quantile=0.60):
    idx = get_first_index(indices[title])
    sim_scores = list(enumerate(cosine_sim[idx]))
    sim_scores = sorted(sim_scores, key=lambda x: x[1], reverse=True)
    sim_scores = sim_scores[1:no_of_movies+20]
    movie_indices = [i[0] for i in sim_scores]

    movs = metadata_for_cont.iloc[movie_indices][[
        'title', 'vote_count', 'vote_average', 'year', 'popularity', 'id']]
```

```
    selected = get_top_weighted_rating(movs, no_of_movies, 0.60)
    return selected
```

Similar movies to "The Family" movie by cosine similarity and weighted rating

```
[ ]: cosine_sim_plus_weighted_rating('The Family', 10, 0.80)
```

```
[ ]:                                             title  year  vote_count  \
1186                                  Harold and Maude  1971       266.0
11131                        All the Invisible Children  2005        14.0
5358                                     The Last Kiss  2001        84.0
42714                                   The Olive Tree  2016        38.0
20489  Those Daring Young Men in Their Jaunty Jalopies  1969        10.0
34492                                   Violent Summer  1959        10.0
16581                                      Monte Carlo  2011       611.0
9230                              Remember Me, My Love  2003        47.0
32177                                  Felix and Meira  2015        12.0
5839                                         Pinocchio  2002       144.0

       vote_average popularity        id  weighted_rating
1186            7.7  10.878112     343.0         7.625912
11131           7.3   2.271382   24553.0         6.614655
5358            6.5    5.50323   12308.0         6.410125
42714           6.5   2.541633  366505.0         6.323994
20489           6.8   4.336514   38792.0         6.227586
34492           6.7   0.906731   88395.0         6.177586
16581           6.0    8.34835   59860.0         5.994447
9230            5.8   4.996071   38970.0         5.774592
32177           5.6   0.776885  285848.0         5.625078
5839            5.6   6.463613   10599.0         5.603583
```

Similar movies to "The Apartment" movie by cosine similarity and weighted rating

```
[ ]: cosine_sim_plus_weighted_rating('The Apartment', 10)
```

```
[ ]:                                     title  year  vote_count  \
8697                         The Holy Mountain  1973       143.0
7642                             Safety Last!  1923        76.0
1203             The Day the Earth Stood Still  1951       323.0
80     Things to Do in Denver When You're Dead  1995        87.0
4908                                  48 Hrs.  1982       364.0
10068                               Baby Face  1933        30.0
2337                           Running Scared  1986        58.0
3888                        The House of Mirth  2000        25.0
29506                           Chloe and Theo  2015        24.0
2298                        Nothing in Common  1986        30.0

       vote_average popularity        id  weighted_rating
8697            7.7   4.190266    8327.0         7.447292
```

```
7642             7.7   4.394823   22596.0          7.276613
1203             7.3   9.360003     828.0          7.205488
80               6.7   4.486179     400.0          6.529401
4908             6.5  15.297121     150.0          6.463430
10068            6.9   3.363332   27449.0          6.459398
2337             6.4   4.819467   15698.0          6.254187
3888             6.4   2.492547   25520.0          6.154357
29506            6.4   2.775514  300686.0          6.149153
2298             6.1   8.750517   29968.0          6.008271
```

1.5.4 Collaborative filtering model by using user ratings and finding similar users

Movies wathced by User with id 5

[ ]:
```
def user_watched(user):
    watched_movies = rating[rating.userId == user]
    return pd.DataFrame({"title": movies.title.iloc[watched_movies.movieId],␣
 ↪"genres": movies.genres.iloc[watched_movies.movieId], "rating":␣
 ↪watched_movies.rating.values})


user_watched(5)
```

[ ]:
```
                                title                            genres  \
1                      Jumanji (1995)        Adventure|Children|Fantasy
19                 Money Train (1995)  Action|Comedy|Crime|Drama|Thriller
32             Wings of Courage (1995)            Adventure|Romance|IMAX
36      Across the Sea of Time (1995)                  Documentary|IMAX
39    Cry, the Beloved Country (1995)                             Drama
…                                   …                                 …
1344                    Grease (1978)            Comedy|Musical|Romance
1357               Jerry Maguire (1996)                     Drama|Romance
1380                  Walkabout (1971)                   Adventure|Drama
1407                 Gridlock'd (1997)                             Crime
1409        Waiting for Guffman (1996)                            Comedy

      rating
1        4.0
19       4.0
32       5.0
36       5.0
39       2.0
…        …
1344     3.0
1357     5.0
1380     4.0
1407     5.0
1409     4.0
```

[101 rows x 3 columns]

Prepare dataset for rating model

Conver ratings to int8 from float

[ ]:
```
rating["rating"] = rating.rating.astype("int8")
```

[ ]:
```
reader = Reader(rating_scale=(1, 5))
train_set_for_grid_search = rating[:100000]
train_set_for_grid_search = Dataset.
 ↪load_from_df(train_set_for_grid_search[['userId', 'movieId', 'rating']],␣
 ↪reader)
```

Grid search to fine-tune hyperparameters and model selection

[ ]:
```
param_grid = {'n_epochs': [5, 10], 'lr_all': [0.002, 0.005],
              'reg_all': [0.4, 0.6]}
gs = GridSearchCV(SVD, param_grid, measures=['rmse', 'mae'], cv=3, n_jobs=10,␣
 ↪joblib_verbose=2 )

gs.fit(train_set_for_grid_search)

print("Model Name", "SVD")
print(gs.best_score['rmse'])
print(gs.best_params['rmse'])


param_grid = {'n_epochs': [5, 10], 'lr_all': [0.002, 0.005],
              'reg_all': [0.4, 0.6], 'k': [50, 100, 200]}
gs = GridSearchCV(KNNWithMeans, param_grid, measures=['rmse', 'mae'], cv=3,␣
 ↪n_jobs=10, joblib_verbose=2 )

gs.fit(train_set_for_grid_search)


print("Model Name", "KNN")
print(gs.best_score['rmse'])
print(gs.best_params['rmse'])
```

```
[Parallel(n_jobs=10)]: Using backend LokyBackend with 10 concurrent workers.
[Parallel(n_jobs=10)]: Done  18 out of  24 | elapsed:   16.3s remaining:    5.4s
[Parallel(n_jobs=10)]: Done  24 out of  24 | elapsed:   20.9s finished
```

```
Model Name SVD
0.935093115053419
{'n_epochs': 10, 'lr_all': 0.005, 'reg_all': 0.4}
```

```
[Parallel(n_jobs=10)]: Using backend LokyBackend with 10 concurrent workers.
[Parallel(n_jobs=10)]: Done  21 tasks      | elapsed:   17.6s
```

```
Model Name KNN
0.9494451125698792
{'n_epochs': 5, 'lr_all': 0.002, 'reg_all': 0.4, 'k': 50}
```

```
[Parallel(n_jobs=10)]: Done  72 out of  72 | elapsed:   56.8s finished
```

build model with full dataset Though the Knn model is better as per grid search reasults I am going with SVD as my hardware is not supporting KNN

prepare dataset for surprise models and split into train and test dataset

[ ]:
```
data = Dataset.load_from_df(rating[['userId', 'movieId', 'rating']], reader)
trainset, testset = train_test_split(data, test_size=.25)
```

[ ]:
```
#knn = KNNWithMeans(k=50, measures=['rmse', 'mae'],
#                    cv=3, n_jobs=10, joblib_verbose=2, pre_dispatch=1)
#knn.fit(trainset)
```

Train SVD model on training dataset to calculate accuracy

[ ]:
```
svd = SVD(verbose=True, n_epochs=10,  lr_all=0.005, reg_all=0.4)
svd.fit(trainset)
```

```
Processing epoch 0
Processing epoch 1
Processing epoch 2
Processing epoch 3
Processing epoch 4
Processing epoch 5
Processing epoch 6
Processing epoch 7
Processing epoch 8
Processing epoch 9
```

[ ]:
```
<surprise.prediction_algorithms.matrix_factorization.SVD at 0x7fc617844450>
```

Accuracy on test dataset

[ ]:
```
predictions = svd.test(testset)
# Compute and print Root Mean Squared Error
accuracy.rmse(predictions, verbose=True)
```

```
RMSE: 0.9275
```

[ ]:
```
0.9275297885294524
```

[ ]:
```
svd.fit(data.build_full_trainset())
```

```
Processing epoch 0
Processing epoch 1
Processing epoch 2
Processing epoch 3
Processing epoch 4
Processing epoch 5
Processing epoch 6
Processing epoch 7
Processing epoch 8
Processing epoch 9
```

[ ]: <surprise.prediction_algorithms.matrix_factorization.SVD at 0x7fc617844450>

[ ]:
```
svd.predict(uid=5, iid=100)
```

[ ]:
```
Prediction(uid=5, iid=100, r_ui=None, est=3.433044024923659,
details={'was_impossible': False})
```

1.5.5 Hybrid model combining weighted rating+content-based cosine simalarity+user based rating based collaborative filtering type

Combine movie dataset with tmdb dataset

[ ]:
```
movieId_tmdbId = link.copy()
movieId_tmdbId = movieId_tmdbId[["movieId", "tmdbId"]]
movieId_tmdbId.columns = ['movieId', 'id']
movieId_tmdbId = movieId_tmdbId.merge(metadata_for_cont[['title', 'id']],␣
 ↪on='id').set_index('title')
movieId_tmdbId
```

[ ]:

title	movieId	id
Toy Story	1	862.0
Jumanji	2	8844.0
Grumpier Old Men	3	15602.0
Waiting to Exhale	4	31357.0
Father of the Bride Part II	5	11862.0
…	…	…
Betrayal	176273	67758.0
Satan Triumphant	176275	227506.0
Queerama	176279	461257.0
Dragon Ball Z: Broly - Second Coming	206323	44251.0
Michael Jackson's Thriller	207145	92060.0

[43224 rows x 2 columns]

function to create Hybrid model

1. Find similar movies by cosine similarity(Content-Based filtering)
2. Filter similar movies having smaller weighted ratings

3. Predict the estimated ratings by using collaborative filtering for all movies from step 2 and sort the list by and return

[ ]:
```
tmdbId_index_movie = movieId_tmdbId.set_index('id')

def hybrid_model_cosine_weighted_rate_svd(userId, title,␣
↪filter_on_weighted_rate=True):
    idx = get_first_index(indices[title])
    tmdbId = movieId_tmdbId.loc[title]['id']
    #print(idx)
    movie_id = movieId_tmdbId.loc[title]['movieId']

    sim_scores = list(enumerate(cosine_sim[int(idx)]))
    sim_scores = sorted(sim_scores, key=lambda x: x[1], reverse=True)
    sim_scores = sim_scores[1:40]
    movie_indices = [i[0] for i in sim_scores]

    mov = metadata_for_cont.iloc[movie_indices][['title', 'vote_count',␣
↪'vote_average', 'year', 'id', 'popularity']]
    if filter_on_weighted_rate:
        mov = get_top_weighted_rating(mov, 200, 0.30)

    mov['est'] = mov['id'].apply(lambda x: svd.predict(userId,␣
↪tmdbId_index_movie.loc[x]['movieId']).est)
    mov = mov.sort_values('est', ascending=False)

    return mov.head(10)
```

Recommended movies for user 5, who watched movie Jumanji and filter_on_weighted_rate=False

[ ]:
```
hybrid_model_cosine_weighted_rate_svd(5, 'Jumanji',␣
↪filter_on_weighted_rate=False)
```

[ ]:
```
                           title  vote_count  vote_average  year        id  \
21577  Guardians of the Galaxy     10014.0           7.9  2014  118340.0
9592               The Phone Box        23.0           6.7  1972   52943.0
9358                   Word Wars         7.0           6.1  2004   28105.0
14863            Le Pont du Nord         6.0           7.7  1982   59484.0
14115        The Spousals of God         4.0           8.8  1999  101342.0
18563             Wreck-It Ralph      4656.0           7.1  2012   82690.0
38987               Snowed Under         0.0           0.0  1936  217672.0
9019                     Nirvana        57.0           6.6  1997    8765.0
16401             The Dark Angel         1.0           7.0  1935  120977.0
8048                      Masques         6.0           5.9  1987   60760.0

       popularity       est
21577   53.291601  3.887143
```

```
9592     1.487562  3.846220
9358     0.549944  3.804895
14863    0.019669  3.786413
14115    0.503167  3.737727
18563   13.697597  3.669460
38987    0.001754  3.662513
9019     3.376578  3.603538
16401     0.11704  3.594286
8048     0.807687  3.591593
```

Recommended movies for user 5, who watched movie Jumanji and filter_on_weighted_rate=True

[ ]:
```
hybrid_model_cosine_weighted_rate_svd(5, 'Jumanji',
 filter_on_weighted_rate=True)
```

[ ]:
```
                           title  year  vote_count  vote_average popularity  \
21577  Guardians of the Galaxy  2014     10014.0           7.9   53.291601
9592                The Phone Box  1972        23.0           6.7    1.487562
9358                    Word Wars  2004         7.0           6.1    0.549944
14863            Le Pont du Nord  1982         6.0           7.7    0.019669
18563             Wreck-It Ralph  2012      4656.0           7.1   13.697597
9019                      Nirvana  1997        57.0           6.6    3.376578
8048                      Masques  1987         6.0           5.9    0.807687
42636                        Quiz  2012        11.0           5.5    1.031617
41766           Liar Game: Reborn  2012         6.0           5.8    0.605467
14744               The Wild Hunt  2009        20.0           6.2    1.847803

             id  weighted_rating       est
21577  118340.0         7.898630  3.887143
9592    52943.0         6.475066  3.846220
9358    28105.0         5.875148  3.804895
14863   59484.0         6.656410  3.786413
18563   82690.0         7.098086  3.669460
9019     8765.0         6.505983  3.603538
8048    60760.0         5.756410  3.591593
42636   96823.0         5.539819  3.570156
41766  133977.0         5.706410  3.565825
14744   44680.0         6.064497  3.564569
```

Recommended movies for user 5, who watched movie Kung Fu Panda and filter_on_weighted_rate=False

[ ]:
```
hybrid_model_cosine_weighted_rate_svd(5, 'Kung Fu Panda',
 filter_on_weighted_rate=False)
```

[ ]:
```
                                       title  vote_count  vote_average  year  \
37898                   Over the Garden Wall        52.0           8.2  2014
41513  Vovka in the Kingdom of Far Far Away         7.0           4.9  1965
```

```
2801                         Drunken Master     178.0           7.2  1978
9577                         Kung Fu Hustle     841.0           7.2  2004
27628                            Kung Fury     762.0           7.6  2015
35435                               Yasmine       0.0           0.0  2014
25916                         Bare Knuckles       0.0           0.0  1977
26287             Big and Little Wong Tin Bar       3.0           6.2  1962
32333               Ten Tigers of Kwangtung       4.0           5.9  1979
36636                      Brigada criminal       1.0           5.0  1950

             id popularity       est
37898  409696.0   2.802111  4.244387
41513  160046.0   1.139555  3.910658
2801    11230.0   7.404755  3.862300
9577     9470.0   8.636632  3.840581
27628  251516.0   7.741143  3.824732
35435  277690.0   0.479662  3.693061
25916   86603.0   0.000157  3.689201
26287   45197.0   0.812949  3.678035
32333   59405.0   0.435576  3.662513
36636  401895.0   0.036471  3.651727
```

Recommended movies for user 5, who watched movie Kung Fu Panda and filter_on_weighted_rate=True

[ ]:
```
hybrid_model_cosine_weighted_rate_svd(5, 'Kung Fu Panda',
    filter_on_weighted_rate=True)
```

[ ]:
```
                                     title  year  vote_count  vote_average  \
37898                  Over the Garden Wall  2014        52.0           8.2
41513    Vovka in the Kingdom of Far Far Away  1965         7.0           4.9
2801                         Drunken Master  1978       178.0           7.2
9577                         Kung Fu Hustle  2004       841.0           7.2
27628                            Kung Fury  2015       762.0           7.6
31560  Films of Fury: The Kung Fu Movie Movie  2011         6.0           5.9
24673                        Shaolin Mantis  1978         6.0           5.0
18702                      New Fist of Fury  1976        17.0           5.4
32873                       Kung Fu Panda 3  2016      1630.0           6.7
16392                       Kung Fu Panda 2  2011      1925.0           6.7

      popularity        id  weighted_rating       est
37898   2.802111  409696.0         7.979198  4.244387
41513   1.139555  160046.0         5.179531  3.910658
2801    7.404755   11230.0         7.157650  3.862300
9577    8.636632    9470.0         7.190847  3.840581
27628   7.741143  251516.0         7.587400  3.824732
31560   0.220443  129175.0         5.760969  3.651060
24673   0.521963   59402.0         5.260969  3.642366
18702    2.29062   18666.0         5.441214  3.633743
```

```
32873  14.696548  140300.0         6.696733  3.632551
16392  11.481921   49444.0         6.697232  3.615541
```

Recommended movies for user 555, who watched movie Kung Fu Panda and filter_on_weighted_rate=False

[ ]:
```
hybrid_model_cosine_weighted_rate_svd(555, 'Kung Fu Panda',␣
↪filter_on_weighted_rate=False)
```

[ ]:
```
                                     title  vote_count  vote_average  year  \
37898                  Over the Garden Wall        52.0           8.2  2014
41513  Vovka in the Kingdom of Far Far Away         7.0           4.9  1965
2801                         Drunken Master       178.0           7.2  1978
9577                         Kung Fu Hustle       841.0           7.2  2004
27628                            Kung Fury       762.0           7.6  2015
26287            Big and Little Wong Tin Bar         3.0           6.2  1962
25916                         Bare Knuckles         0.0           0.0  1977
18754                     Looking for Jackie        17.0           4.4  2009
32333                 Ten Tigers of Kwangtung         4.0           5.9  1979
24673                         Shaolin Mantis         6.0           5.0  1978

             id popularity       est
37898  409696.0   2.802111  4.081172
41513  160046.0   1.139555  3.745631
2801    11230.0   7.404755  3.699606
9577     9470.0   8.636632  3.678205
27628  251516.0   7.741143  3.662128
26287   45197.0   0.812949  3.572198
25916   86603.0   0.000157  3.546032
18754   45682.0   4.625697  3.519797
32333   59405.0   0.435576  3.499436
24673   59402.0   0.521963  3.497826
```

Recommended movies for user 555, who watched movie Kung Fu Panda and filter_on_weighted_rate=True

[ ]:
```
hybrid_model_cosine_weighted_rate_svd(555, 'Kung Fu Panda',␣
↪filter_on_weighted_rate=True)
```

[ ]:
```
                                       title  year  vote_count  vote_average  \
37898                   Over the Garden Wall  2014        52.0           8.2
41513   Vovka in the Kingdom of Far Far Away  1965         7.0           4.9
2801                          Drunken Master  1978       178.0           7.2
9577                          Kung Fu Hustle  2004       841.0           7.2
27628                              Kung Fury  2015       762.0           7.6
18754                     Looking for Jackie  2009        17.0           4.4
24673                         Shaolin Mantis  1978         6.0           5.0
18702                       New Fist of Fury  1976        17.0           5.4
31560  Films of Fury: The Kung Fu Movie Movie  2011         6.0           5.9
```

32873	Kung Fu Panda 3	2016	1630.0	6.7

	popularity	id	weighted_rating	est
37898	2.802111	409696.0	7.979198	4.081172
41513	1.139555	160046.0	5.179531	3.745631
2801	7.404755	11230.0	7.157650	3.699606
9577	8.636632	9470.0	7.190847	3.678205
27628	7.741143	251516.0	7.587400	3.662128
18754	4.625697	45682.0	4.661397	3.519797
24673	0.521963	59402.0	5.260969	3.497826
18702	2.29062	18666.0	5.441214	3.493219
31560	0.220443	129175.0	5.760969	3.477715
32873	14.696548	140300.0	6.696733	3.469336