NETFLIX MOVIE RECOMMENDATION SYSTEM

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1. Business Problem

1.1 Problem Description: Netflix is all about connecting people to the movies they love. To help customers find those movies, they developed world-class movie recommendation system: CinematchSM. Its job is to predict whether someone will enjoy a movie based on how much they liked or disliked other movies. Netflix use those predictions to make personal movie recommendations based on each customer's unique tastes. And while Cinematch is doing pretty well, it can always be made better.

Now there are a lot of interesting alternative approaches to how Cinematch works that netflix haven't tried. Some are described in the literature, some aren't. We're curious whether any of these can beat Cinematch by making better predictions. Because, frankly, if there is a much better approach it could make a big difference to our customers and our business.

1.2 Problem Statement:

Netflix provided a lot of rating data from which a recommendation system is built. Given different details about users and movies problem is to predict movies that would be best rated by a user

1.3 Sources : Data: https://www.kaggle.com/rounakbanik/the-movies-dataset (https://www.kaggle.com/rounakbanik/the-movies-dataset) surprise library: http://surpriselib.com/ (http://surpriselib.com/) surprise library doc: http://surprise.readthedocs.io/en/stable/getting_started.html (http://surprise.readthedocs.io/en/stable/getting_started.html) (we use many models from this library) installing surprise: https://github.com/NicolasHug/Surprise#installation (https://github.com/NicolasHug/Surprise#installation) Research paper: http://courses.ischool.berkeley.edu/i290-dm/s11/SECURE/a1-koren.pdf (http://courses.ischool.berkeley.edu/i290-dm/s11/SECURE/a1-koren.pdf) (most of our work was inspired by this paper) Best Algorithm(SVD):https://github.com/nishantml/NETFLIX-MOVIE-RECOMMENDATION-SYSTEM/blob/master/Netflix_Movie.ipynb (https://github.com/nishantml/NETFLIX-MOVIE-RECOMMENDATION-SYSTEM/blob/master/Netflix_Movie.ipynb)

1.4 Real world/Business Objectives and constraints:

Objectives:

Predict the rating that a user would give to a movie that he has not yet rated. Minimize the difference between predicted and actual rating (RMSE and MAPE)

Constraints:

Some form of interpretability.

2. Machine Learning Problem

2.1 Data 2.1.1 Data Overview Get the data from : [https://www.kaggle.com/rounakbanik/the-movies-dataset (https://www.kaggle.com/rounakbanik/the-movies-dataset)](https://www.kaggle.com/rounakbanik/the-movies-dataset) Data files : credits.csv keywords.csv links.csv links_small.csv movies_metadata.csv ratings.csv ratings_small.csv

*credits file contains cast and crew details of every movie. *keywords file contains Cast and Crew Information for all movies in the movies_metadata.csv file. *links file contains IMDB and TMDB IDs of all movies featured in the ratings.csv file (About 45,000 movies). *links_small file contains IMDB and TMDB IDs of all movies featured in the ratings_small.csv file (About 9000 movies). *movies_metadata has 24 columns representing information about every movie like genres,id,production company,voting,run time,budget and so on. *ratings file contains ratings given by users to movies. *ratings_small file contains 100 ratings from 700 users on 9,000 +91 88708 42439. Is a subset of the ratings available in the Full MovieLens dataset.

2.2 Mapping the real world problem to a Machine Learning Problem:

2.2.1 Type of Machine Learning Problem For a given movie and user we need to predict the similar movies for which highest ratings would be given by him/her to the movie. The given problem is a Recommendation problem It can also seen as a Regression problem

2.2.2 Performance metric Mean Absolute Percentage Error: [https://en.wikipedia.org/wiki/Mean_absolute_percentage_error (https://en.wikipedia.org/wiki/Mean_absolute_percentage_error)](https://en.wikipedia.org/wiki/Mean_absolute_percentage_error) Root Mean Square Error: [https://en.wikipedia.org/wiki/Root-mean-square_deviation (https://en.wikipedia.org/wiki/Root-mean-square_deviation)](https://en.wikipedia.org/wiki/Root-mean-square_deviation)

2.2.3 Machine Learning Objective and Constraints Minimize RMSE. Try to provide some interpretability.

3. Exploratory Data Analysis

3.1 Preprocessing

In [1]:
```
from mpl_toolkits.mplot3d import Axes3D
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt # plotting
import numpy as np # linear algebra
import os # accessing directory structure
import pandas as pd
```

In [2]:
```
# Distribution graphs (histogram/bar graph) of column data
def plotPerColumnDistribution(df, nGraphShown, nGraphPerRow):
    nunique = df.nunique()
    df = df[[col for col in df if nunique[col] > 1 and nunique[col] < 50]] # For
    nRow, nCol = df.shape
    columnNames = list(df)
    nGraphRow = (nCol + nGraphPerRow - 1) / nGraphPerRow
    plt.figure(num = None, figsize = (6 * nGraphPerRow, 8 * nGraphRow), dpi = 80
    for i in range(min(nCol, nGraphShown)):
        plt.subplot(nGraphRow, nGraphPerRow, i + 1)
        columnDf = df.iloc[:, i]
        if (not np.issubdtype(type(columnDf.iloc[0]), np.number)):
            valueCounts = columnDf.value_counts()
            valueCounts.plot.bar()
        else:
            columnDf.hist()
        plt.ylabel('counts')
        plt.xticks(rotation = 90)
        plt.title(f'{columnNames[i]} (column {i})')
    plt.tight_layout(pad = 1.0, w_pad = 1.0, h_pad = 1.0)
    plt.show()
```

In [3]:
```
# Correlation matrix
def plotCorrelationMatrix(df, graphWidth):
    filename = df.dataframeName
    df = df.dropna('columns') # drop columns with NaN
    df = df[[col for col in df if df[col].nunique() > 1]] # keep columns where th
    if df.shape[1] < 2:
        print(f'No correlation plots shown: The number of non-NaN or constant col
        return
    corr = df.corr()
    plt.figure(num=None, figsize=(graphWidth, graphWidth), dpi=80, facecolor='w',
    corrMat = plt.matshow(corr, fignum = 1)
    plt.xticks(range(len(corr.columns)), corr.columns, rotation=90)
    plt.yticks(range(len(corr.columns)), corr.columns)
    plt.gca().xaxis.tick_bottom()
    plt.colorbar(corrMat)
    plt.title(f'Correlation Matrix for {filename}', fontsize=15)
    plt.show()
```

In [4]:
```
# Scatter and density plots
def plotScatterMatrix(df, plotSize, textSize):
    df = df.select_dtypes(include =[np.number]) # keep only numerical columns
    # Remove rows and columns that would lead to df being singular
    df = df.dropna('columns')
    df = df[[col for col in df if df[col].nunique() > 1]] # keep columns where th
    columnNames = list(df)
    if len(columnNames) > 10: # reduce the number of columns for matrix inversion
        columnNames = columnNames[:10]
    df = df[columnNames]
    ax = pd.plotting.scatter_matrix(df, alpha=0.75, figsize=[plotSize, plotSize]
    corrs = df.corr().values
    for i, j in zip(*plt.np.triu_indices_from(ax, k = 1)):
        ax[i, j].annotate('Corr. coef = %.3f' % corrs[i, j], (0.8, 0.2), xycoords
    plt.suptitle('Scatter and Density Plot')
    plt.show()
```

Reading credits.csv file

In [5]:
```
nRowsRead = 1000 # specify 'None' if want to read whole file
# credits.csv has 45476 rows in reality, but we are only loading/previewing the f
df1 = pd.read_csv('C:\\Users\\YAKSHITHA DONTHI\\Downloads\\archive\\credits.csv'
df1.dataframeName = 'credits.csv'
nRow, nCol = df1.shape
print(f'There are {nRow} rows and {nCol} columns')
```

```
There are 1000 rows and 3 columns
```

In [6]:
```
df1.head(5)
```

Out[6]:

	cast	crew	id
0	[{'cast_id': 14, 'character': 'Woody (voice)',...	[{'credit_id': '52fe4284c3a36847f8024f49', 'de...	862
1	[{'cast_id': 1, 'character': 'Alan Parrish', '...	[{'credit_id': '52fe44bfc3a36847f80a7cd1', 'de...	8844
2	[{'cast_id': 2, 'character': 'Max Goldman', 'c...	[{'credit_id': '52fe466a9251416c75077a89', 'de...	15602
3	[{'cast_id': 1, 'character': "Savannah 'Vannah...	[{'credit_id': '52fe44779251416c91011acb', 'de...	31357
4	[{'cast_id': 1, 'character': 'George Banks', '...	[{'credit_id': '52fe44959251416c75039ed7', 'de...	11862

In [7]:
```
plotPerColumnDistribution(df1, 10, 5)
```

```
<Figure size 2400x512 with 0 Axes>
```

Reading keywords.csv file

In [9]:
```
nRowsRead = 1000 # specify 'None' if want to read whole file
# keywords.csv has 46419 rows in reality, but we are only loading/previewing the
df2 = pd.read_csv('C:\\Users\\YAKSHITHA DONTHI\\Downloads\\archive\\keywords.csv
df2.dataframeName = 'keywords.csv'
nRow, nCol = df2.shape
print(f'There are {nRow} rows and {nCol} columns')
```

There are 1000 rows and 2 columns

In [10]:
```
df2.head(5)
```

Out[10]:

	id	keywords
0	862	[{'id': 931, 'name': 'jealousy'}, {'id': 4290,...
1	8844	[{'id': 10090, 'name': 'board game'}, {'id': 1...
2	15602	[{'id': 1495, 'name': 'fishing'}, {'id': 12392...
3	31357	[{'id': 818, 'name': 'based on novel'}, {'id':...
4	11862	[{'id': 1009, 'name': 'baby'}, {'id': 1599, 'n...

In [11]:
```
plotPerColumnDistribution(df2, 10, 5)
```

<Figure size 2400x512 with 0 Axes>

In [ ]:
```
Reading links.csv file
```

In [12]:
```
nRowsRead = 1000 # specify 'None' if want to read whole file
# links_small.csv has 9125 rows in reality, but we are only loading/previewing th
df3 = pd.read_csv('C:\\Users\\YAKSHITHA DONTHI\\Downloads\\archive\\links_small.
df3.dataframeName = 'links_small.csv'
nRow, nCol = df3.shape
print(f'There are {nRow} rows and {nCol} columns')
```

There are 1000 rows and 3 columns

In [13]:
```
df3.head(5)
```

Out[13]:

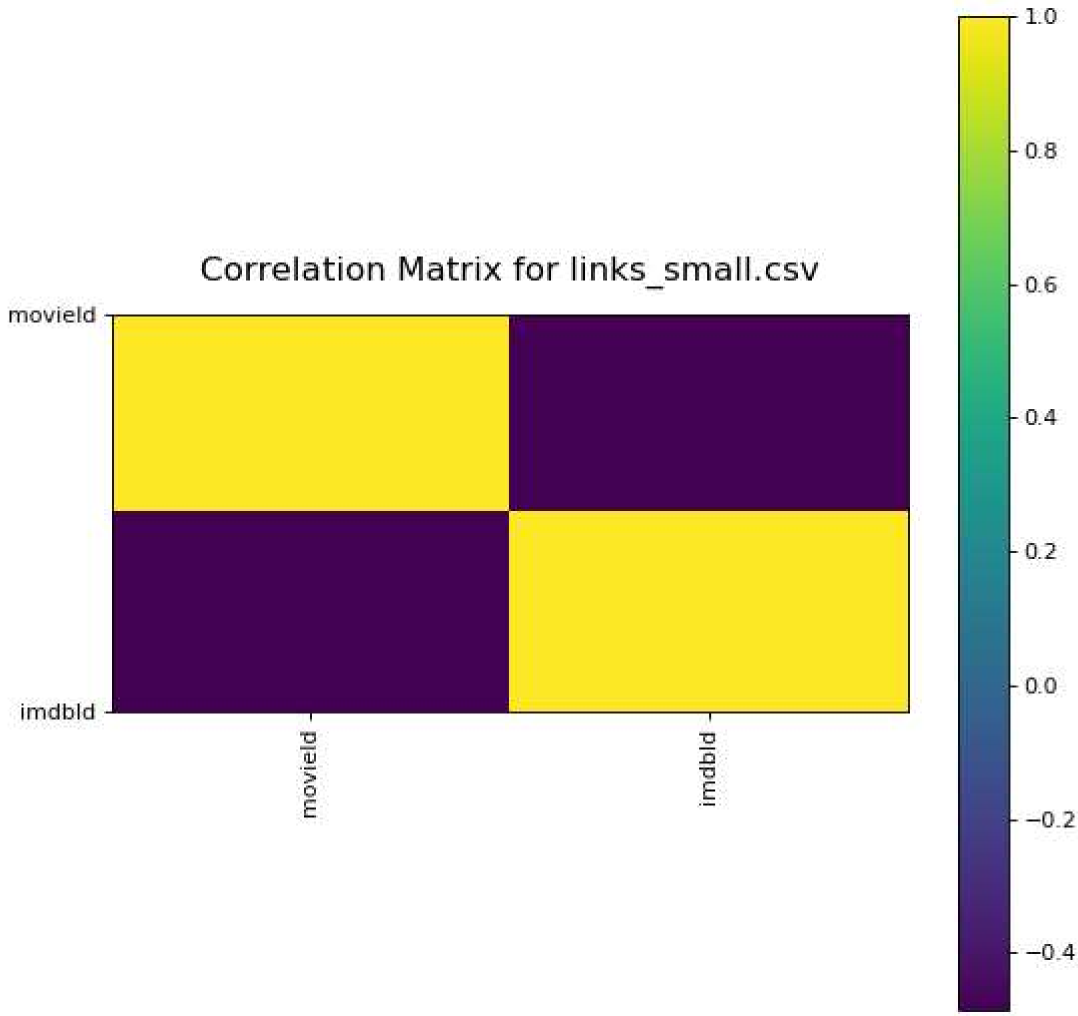
	movieId	imdbId	tmdbId
0	1	114709	862.0
1	2	113497	8844.0
2	3	113228	15602.0
3	4	114885	31357.0
4	5	113041	11862.0

In [14]:
```
plotPerColumnDistribution(df3, 10, 5)
```

```
<Figure size 2400x512 with 0 Axes>
```

Plotting heatmap between movieid and imdbid values

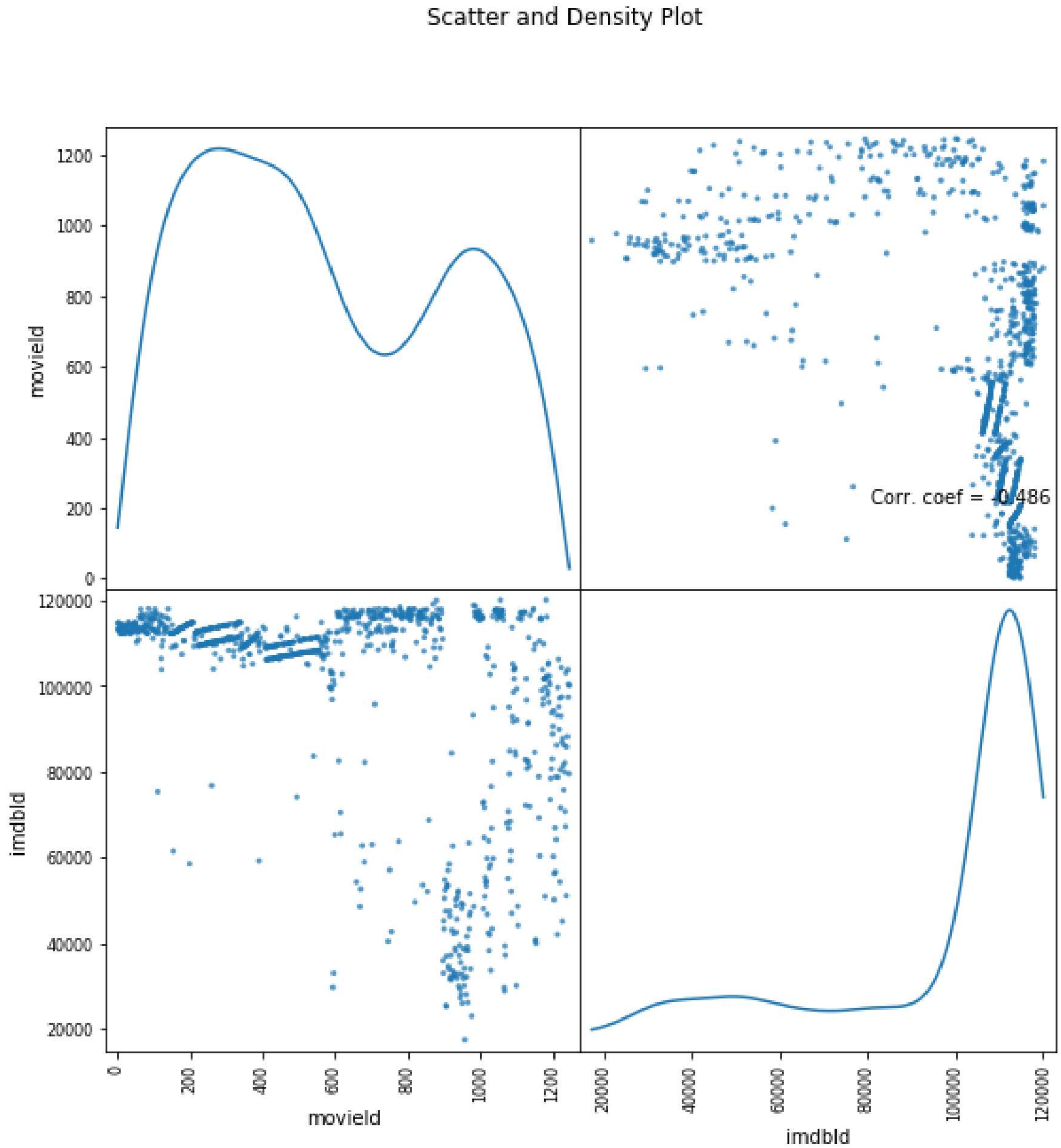
In [16]:
```
plotCorrelationMatrix(df3, 8)
```



conclusion: movie id and imbdb id are not correlated

Scatter and density plots for movie and imdb id

In [17]:
```
plotScatterMatrix(df3, 9, 10)
```



In [20]:
```
%matplotlib inline
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
from ast import literal_eval
from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer
from sklearn.metrics.pairwise import linear_kernel, cosine_similarity
from nltk.stem.snowball import SnowballStemmer
from nltk.stem.wordnet import WordNetLemmatizer
from nltk.corpus import wordnet
from surprise import Reader, Dataset, SVD
from surprise.model_selection import cross_validate
import warnings; warnings.simplefilter('ignore')
```

Reading movies_metadata.csv file

In [21]:
```
md = pd. read_csv('C:\\Users\\YAKSHITHA DONTHI\\Downloads\\archive\\movies_metada
md.head()
```

Out[21]:

	adult	belongs_to_collection	budget	genres	homepage	id	imdb_id
0	False	{'id': 10194, 'name': 'Toy Story Collection', ...	30000000	[{'id': 16, 'name': 'Animation'}, {'id': 35, '...	http://toystory.disney.com/toy-story	862	tt0114709
1	False	NaN	65000000	[{'id': 12, 'name': 'Adventure'}, {'id': 14, '...	NaN	8844	tt0113497
2	False	{'id': 119050, 'name': 'Grumpy Old Men Collect...	0	[{'id': 10749, 'name': 'Romance'}, {'id': 35, ...	NaN	15602	tt0113228
3	False	NaN	16000000	[{'id': 35, 'name': 'Comedy'}, {'id': 18, 'nam...	NaN	31357	tt0114885
4	False	{'id': 96871, 'name': 'Father of the Bride Col...	0	[{'id': 35, 'name': 'Comedy'}]	NaN	11862	tt0113041

5 rows × 24 columns

In [22]:
```
md['genres'] = md['genres'].fillna('[]').apply(literal_eval).apply(lambda x: [i[
md['year'] = pd.to_datetime(md['release_date'], errors='coerce').apply(lambda x:
```

In [23]:
```
C = md['vote_average'].mean()
m= md['vote_count'].quantile(0.95)
print("C is %f, and m is %d"%(C,m))
```

```
C is 5.618207, and m is 434
```

In [24]:
```
qualified = md[(md['vote_count'] >= m) & (md['vote_count'].notnull()) & (md['vote
qualified.shape
```

Out[24]:
```
(2274, 25)
```

In [25]:
```
def weighted_rating(x):
    v = x['vote_count']
    R = x['vote_average']
    return (v/(v+m) * R) + (m/(m+v) * C)
qualified = qualified[['title', 'year', 'vote_count', 'vote_average', 'popularity
qualified['score'] = qualified.apply(weighted_rating, axis=1)
qualified = qualified.sort_values('score', ascending=False)
qualified.head(10)
```

Out[25]:

	title	year	vote_count	vote_average	popularity	genres	score
314	The Shawshank Redemption	1994	8358.0	8.5	51.6454	[Drama, Crime]	8.357746
834	The Godfather	1972	6024.0	8.5	41.1093	[Drama, Crime]	8.306334
12481	The Dark Knight	2008	12269.0	8.3	123.167	[Drama, Action, Crime, Thriller]	8.208376
2843	Fight Club	1999	9678.0	8.3	63.8696	[Drama]	8.184899
292	Pulp Fiction	1994	8670.0	8.3	140.95	[Thriller, Crime]	8.172155
351	Forrest Gump	1994	8147.0	8.2	48.3072	[Comedy, Drama, Romance]	8.069421
522	Schindler's List	1993	4436.0	8.3	41.7251	[Drama, History, War]	8.061007
23673	Whiplash	2014	4376.0	8.3	64.3	[Drama]	8.058025
5481	Spirited Away	2001	3968.0	8.3	41.0489	[Fantasy, Adventure, Animation, Family]	8.035598
1154	The Empire Strikes Back	1980	5998.0	8.2	19.471	[Adventure, Action, Science Fiction]	8.025793

Checking for rows containing NaN values

In [27]:
```
links = pd.read_csv('C:\\Users\\YAKSHITHA DONTHI\\Downloads\\archive\\links_smal
links = links[links['tmdbId'].notnull()]['tmdbId'].astype('int')
print (md[pd.to_numeric(md['id'], errors='coerce').isnull()])
```

```
                                                 adult  \
19730                                 - Written by Ørnås
29503   Rune Balot goes to a casino connected to the ...
35587   Avalanche Sharks tells the story of a bikini ...

      belongs_to_collection                            budget  \
19730              0.065736  /ff9qCepilowshEtG2GYWwzt2bs4.jpg
29503              1.931659  /zV8bHuSL6WXoD6FWogP9j4x80bL.jpg
35587              2.185485  /zaSf5OG7V8X8gqFvly88zDdRm46.jpg

                                                genres  \
19730  [Carousel Productions, Vision View Entertainme...
29503  [Aniplex, GoHands, BROSTA TV, Mardock Scramble...
35587  [Odyssey Media, Pulser Productions, Rogue Stat...

                                              homepage          id imdb_id  \
19730  [{'iso_3166_1': 'CA', 'name': 'Canada'}, {'iso...  1997-08-20       0
29503  [{'iso_3166_1': 'US', 'name': 'United States o...  2012-09-29       0
35587           [{'iso_3166_1': 'CA', 'name': 'Canada'}]  2014-01-01       0

      original_language                            original_title  overview  \
19730             104.0  [{'iso_639_1': 'en', 'name': 'English'}]  Released
29503              68.0      [{'iso_639_1': 'ja', 'name': '日本語'}]  Released
35587              82.0  [{'iso_639_1': 'en', 'name': 'English'}]  Released

       ... revenue runtime spoken_languages status tagline  title  video  \
19730  ...     NaN     NaN              NaN    NaN     NaN    NaN    NaN
29503  ...     NaN     NaN              NaN    NaN     NaN    NaN    NaN
35587  ...     NaN     NaN              NaN    NaN     NaN    NaN    NaN

      vote_average vote_count year
19730          NaN        NaN  NaT
29503          NaN        NaN  NaT
35587          NaN        NaN  NaT

[3 rows x 25 columns]
```

In [28]:
```
md = md.drop([19730, 29503, 35587])
md['id'] = md['id'].astype('int')
```

Getting recommandations based on a movie

In [29]:
```
def get_recommendations(title, cosine_sim):
    idx = 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[1:31]
    movie_indices = [i[0] for i in sim_scores]
    return titles.iloc[movie_indices]
```

Merging credits and keywords file

In [31]:
```
credits = pd.read_csv('C:\\Users\\YAKSHITHA DONTHI\\Downloads\\archive\\credits.
keywords = pd.read_csv('C:\\Users\\YAKSHITHA DONTHI\\Downloads\\archive\\keyword
keywords['id'] = keywords['id'].astype('int')
credits['id'] = credits['id'].astype('int')
md = md.merge(credits, on='id')
md = md.merge(keywords, on='id')
smd1 = md[md['id'].isin(links)]

features = ['cast', 'crew', 'keywords']
for feature in features:
    smd1[feature] = smd1[feature].apply(literal_eval)
```

In [32]:
```
def get_director(x):
    for i in x:
        if i['job'] == 'Director':
            return i['name']
    return np.nan
smd1['director'] = smd1['crew'].apply(get_director)
smd1.head()
```

Out[32]:

overview	...	tagline	title	video	vote_average	vote_count	year	cast	
Led by Woody, Andy's toys live happily in his ...	...	NaN	Toy Story	False	7.7	5415.0	1995	[{'cast_id': 14, 'character': 'Woody (voice)',...	'52fe4284c3a3
When siblings Judy and Peter discover an encha...	...	Roll the dice and unleash the excitement!	Jumanji	False	6.9	2413.0	1995	[{'cast_id': 1, 'character': 'Alan Parrish', '...	'52fe44bfc3a3(
A family wedding reignites the ancient feud be...	...	Still Yelling. Still Fighting. Still Ready for...	Grumpier Old Men	False	6.5	92.0	1995	[{'cast_id': 2, 'character': 'Max Goldman', 'c...	'52fe466a92514
Cheated on, mistreated and stepped on, the wom...	...	Friends are the people who let you be yourself...	Waiting to Exhale	False	6.1	34.0	1995	[{'cast_id': 1, 'character': 'Savannah 'Vannah...	'52fe447792514
Just when George Banks has recovered from his ...	...	Just When His World Is Back To Normal... He's ...	Father of the Bride Part II	False	5.7	173.0	1995	[{'cast_id': 1, 'character': 'George Banks', '...	'52fe449592514

In [33]:
```
def get_list(x):
    if isinstance(x, list):
        names = [i['name'] for i in x]
        #Check if more than 3 elements exist. If yes, return only first three. I
        if len(names) > 3:
            names = names[:3]
        return names
    return []
features = ['cast', 'keywords']
for feature in features:
    smd1[feature] = smd1[feature].apply(get_list)
smd1[['title', 'cast', 'director', 'keywords', 'genres']].head(3)
```

Out[33]:

	title	cast	director	keywords	genres
0	Toy Story	[Tom Hanks, Tim Allen, Don Rickles]	John Lasseter	[jealousy, toy, boy]	[Animation, Comedy, Family]
1	Jumanji	[Robin Williams, Jonathan Hyde, Kirsten Dunst]	Joe Johnston	[board game, disappearance, based on children'...	[Adventure, Fantasy, Family]
2	Grumpier Old Men	[Walter Matthau, Jack Lemmon, Ann-Margret]	Howard Deutch	[fishing, best friend, duringcreditsstinger]	[Romance, Comedy]

In [34]:
```
def clean_data(x):
    if isinstance(x, list):
        return [str.lower(i.replace(" ", "")) for i in x]
    else:
        #Check if director exists. If not, return empty string
        if isinstance(x, str):
            return str.lower(x.replace(" ", ""))
        else:
            return ''
# Apply clean_data function to your features.
features = ['cast', 'keywords', 'director', 'genres']

for feature in features:
    smd1[feature] = smd1[feature].apply(clean_data)
smd1['director'] = smd1['director'].apply(lambda x: [x,x, x])
smd1.head(3)
```

Out[34]:

	adult	belongs_to_collection	budget	genres	homepage	id	imdb_id
0	False	{'id': 10194, 'name': 'Toy Story Collection', ...	30000000	[animation, comedy, family]	http://toystory.disney.com/toy-story	862	tt0114709
1	False	NaN	65000000	[adventure, fantasy, family]	NaN	8844	tt0113497
2	False	{'id': 119050, 'name': 'Grumpy Old Men Collect...	0	[romance, comedy]	NaN	15602	tt0113228

3 rows × 29 columns

In [35]:
```
def create_soup(x):
    return ' '.join(x['keywords']) + ' ' + ' '.join(x['cast'])  + ' '.join(x['di
smd1['soup'] = smd1.apply(create_soup, axis=1)
smd1[['title', 'cast', 'director', 'keywords', 'genres', 'soup']].head(3)
```

Out[35]:

	title	cast	director	keywords	genres	soup
0	Toy Story	[tomhanks, timallen, donrickles]	[johnlasseter, johnlasseter, johnlasseter]	[jealousy, toy, boy]	[animation, comedy, family]	jealousy toy boy tomhanks timallen donricklesj...
1	Jumanji	[robinwilliams, jonathanhyde, kirstendunst]	[joejohnston, joejohnston, joejohnston]	[boardgame, disappearance, basedonchildren'sbook]	[adventure, fantasy, family]	boardgame disappearance basedonchildren'sbook ...
2	Grumpier Old Men	[waltermatthau, jacklemmon, ann-margret]	[howarddeutch, howarddeutch, howarddeutch]	[fishing, bestfriend, duringcreditsstinger]	[romance, comedy]	fishing bestfriend duringcreditsstinger walter...

4. Machine Learning Model

4.1 Using countvectorizer and cosine similarity to get the similar movies that would be liked by user

In [57]:
```
count = CountVectorizer(analyzer='word',ngram_range=(1, 2),min_df=0, stop_words=
count_matrix = count.fit_transform(smd1['soup'])

cosine_sim = cosine_similarity(count_matrix, count_matrix)

smd1 = smd1.reset_index()
titles = smd1['title']
indices = pd.Series(smd1.index, index=smd1['title'])

indices.head()
```

Out[57]:
```
title
Toy Story                      0
Jumanji                        1
Grumpier Old Men               2
Waiting to Exhale              3
Father of the Bride Part II    4
dtype: int64
```

Getting similar movies to "Toy Story" with cosine similarity

In [37]:
```
get_recommendations('Toy Story',cosine_sim)
```

Out[37]:
```
2522                                          Toy Story 2
7629                                          Toy Story 3
8519                                  Toy Story of Terror!
6496                                                 Cars
7914                                               Cars 2
6386                                            Luxo Jr.
283                                      The Santa Clause
320                                       The Flintstones
6534                                        Monster House
1883                                         A Bug's Life
246                                     Man of the House
1432                                     Meet the Deedles
1593                                        Freaky Friday
2751                                     Creature Comforts
4341            The Looney, Looney, Looney Bugs Bunny Movie
7355                                   Aliens in the Attic
584                                    Operation Dumbo Drop
933                                     The Wrong Trousers
1633                                    Hot Lead & Cold Feet
3333                                          See Spot Run
5287     Bon Voyage, Charlie Brown (and Don't Come Back!)
7541                                     The Spy Next Door
8040                                        We Bought a Zoo
3019                   The Adventures of Rocky & Bullwinkle
749                                    The Little Princess
2194                                       Inspector Gadget
4246                                           Captain Ron
9017                                         Freaky Friday
81                                     Dunston Checks In
137                                                Casper
Name: title, dtype: object
```

In [39]:
```
reader = Reader()
ratings = pd.read_csv('C:\\Users\\YAKSHITHA DONTHI\\Downloads\\archive\\ratings_s
ratings.head()
```

Out[39]:

	userId	movieId	rating	timestamp
0	1	31	2.5	1260759144
1	1	1029	3.0	1260759179
2	1	1061	3.0	1260759182
3	1	1129	2.0	1260759185
4	1	1172	4.0	1260759205

5. Cross Validation (Performance meaurement RMSE and MAE)

In [41]:
```
from surprise.model_selection import KFold
data = Dataset.load_from_df(ratings[['userId', 'movieId', 'rating']], reader)
kf=KFold(n_splits=5)
kf.split(data)
svd = SVD()
cross_validate(svd, data, measures=['RMSE', 'MAE'])
```

Out[41]:
```
{'test_rmse': array([0.90161518, 0.90036053, 0.89069071, 0.90108111, 0.8939474
]),
 'test_mae': array([0.6944839 , 0.69020138, 0.6867198 , 0.69153325, 0.6908901
4]),
 'fit_time': (3.2475314140319824,
  3.219769239425659,
  3.2632484436035156,
  3.2235045433044434,
  3.2367424964904785),
 'test_time': (0.19293832778930664,
  0.08161067962646484,
  0.1631002426147461,
  0.08220863342285156,
  0.08162975311279297)}
```

rmse and mae values for 5 splits cross validation

In [42]:
```
from surprise import accuracy
from surprise.model_selection import train_test_split
trainset = data.build_full_trainset()
algo=SVD()
algo.fit(trainset)
ratings[ratings['userId'] == 1]
```

Out[42]:

	userId	movieId	rating	timestamp
0	1	31	2.5	1260759144
1	1	1029	3.0	1260759179
2	1	1061	3.0	1260759182
3	1	1129	2.0	1260759185
4	1	1172	4.0	1260759205
5	1	1263	2.0	1260759151
6	1	1287	2.0	1260759187
7	1	1293	2.0	1260759148
8	1	1339	3.5	1260759125
9	1	1343	2.0	1260759131
10	1	1371	2.5	1260759135
11	1	1405	1.0	1260759203
12	1	1953	4.0	1260759191
13	1	2105	4.0	1260759139
14	1	2150	3.0	1260759194
15	1	2193	2.0	1260759198
16	1	2294	2.0	1260759108
17	1	2455	2.5	1260759113
18	1	2968	1.0	1260759200
19	1	3671	3.0	1260759117

List of user id 1 ratings

In [43]:
```
svd.predict(1, 302)
```

Out[43]:
```
Prediction(uid=1, iid=302, r_ui=None, est=3.0539590474992013, details={'was_imp
ossible': False})
```

It says user id 1 would give 3.05 as rating to movie id 302

In [50]:
```
def convert_int(x):
    try:
        return int(x)
    except:
        return np.nan

id_map = pd.read_csv('C:\\Users\\YAKSHITHA DONTHI\\Downloads\\archive\\links_smal
id_map['tmdbId'] = id_map['tmdbId'].apply(convert_int)
id_map.columns = ['movieId', 'id']
id_map = id_map.merge(smd1[['title', 'id']], on='id').set_index('title')
indices_map = id_map.set_index('id')
```

6. Hybrid Model

6.1 Making a hybrid model to predict the user rating. Cosine similarity gets similar movies to passed movie and SVD will predict ratings given by the user to those similar movies and recommends top 10 movies to the user!!!

And it's done.....That's recommendation system!

In [63]:
```
def hybrid(userId, title):
    idx = indices[title]
    tmdbId = id_map.loc[title]['id']
    #print(idx)
    movie_id = id_map.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[1:26]
    movie_indices = [i[0] for i in sim_scores]
    movies = smd1.iloc[movie_indices][['title', 'vote_count', 'vote_average', 'y
    movies['est'] = movies['id'].apply(lambda x: svd.predict(userId, indices_map
    movies = movies.sort_values('est', ascending=False)
    return movies.head(10)
hybrid(1, 'Avatar')
#hybrid(500, 'Avatar')
```

Out[63]:

	title	vote_count	vote_average	year	id	est
1011	The Terminator	4208.0	7.4	1984	218	3.360299
522	Terminator 2: Judgment Day	4274.0	7.7	1991	280	3.026912
8658	X-Men: Days of Future Past	6155.0	7.5	2014	127585	2.998357
9004	Suicide Squad	7717.0	5.9	2016	297761	2.983292
3181	The Time Machine	217.0	7.5	1960	2134	2.970603
2131	Superman	1042.0	6.9	1978	1924	2.966292
3060	Sinbad and the Eye of the Tiger	39.0	6.3	1977	11940	2.952807
5310	Frank Herbert's Dune	114.0	6.7	2000	876	2.927986
2396	Time Bandits	255.0	6.6	1981	36819	2.918542
5559	Slaughterhouse-Five	47.0	6.3	1972	24559	2.898039

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