Importing Libraries

+ Code + Text

```
# importing necessary libraries
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style('whitegrid')

import warnings
warnings.filterwarnings('ignore')

from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import cosine_similarity
```

Importing Data

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
path = "/content/drive/MyDrive/Project/ml-latest-small/movies.csv"
movies = pd.read_csv(path)
movies.head()
```

	movieId	title	genres
0	1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
1	2	Jumanji (1995)	Adventure|Children|Fantasy
2	3	Grumpier Old Men (1995)	Comedy|Romance
3	4	Waiting to Exhale (1995)	Comedy|Drama|Romance
4	5	Father of the Bride Part II (1995)	Comedy

```
path = "/content/drive/MyDrive/Project/ml-latest-small/ratings.csv"
ratings = pd.read_csv(path)
ratings.head()
```

	userId	movieId	rating	timestamp
0	1	1	4.0	964982703
1	1	3	4.0	964981247
2	1	6	4.0	964982224
3	1	47	5.0	964983815
4	1	50	5.0	964982931

```
ratings['movieId'].isna().sum()
```

```
0
```

```
rated_movie = ratings.groupby('movieId').userId.count().rename('rated_movie')
mean_rating = ratings.groupby('movieId').rating.mean().rename('mean_rating')

df_ = pd.merge(movies, rated_movie, how='left', on='movieId')
df_ = pd.merge(df_, mean_rating, how='left', on='movieId')

df_['rated_movie'].fillna(0, inplace=True)
df_['mean_rating'].fillna(0, inplace=True)

df_['rated_movie'] = df_['rated_movie'].astype(int)
```

```
df_[['title','mean_rating','rated_movie']]
```

	title	mean_rating	rated_movie
0	Toy Story (1995)	3.920930	215
1	Jumanji (1995)	3.431818	110
2	Grumpier Old Men (1995)	3.259615	52
3	Waiting to Exhale (1995)	2.357143	7
4	Father of the Bride Part II (1995)	3.071429	49
...	...	...	...
9737	Black Butler: Book of the Atlantic (2017)	4.000000	1
9738	No Game No Life: Zero (2017)	3.500000	1
9739	Flint (2017)	3.500000	1
9740	Bungo Stray Dogs: Dead Apple (2018)	3.500000	1
9741	Andrew Dice Clay: Dice Rules (1991)	4.000000	1

9742 rows × 3 columns

```
df = pd.merge(ratings,df_, how='left', on = 'movieId')
df.drop(columns = 'timestamp' , inplace = True)
df
```

	userId	movieId	rating	title	genres	rated_movie	mean_rating
0	1	1	4.0	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy	215	3.920930
1	1	3	4.0	Grumpier Old Men (1995)	Comedy|Romance	52	3.259615
2	1	6	4.0	Heat (1995)	Action|Crime|Thriller	102	3.946078
3	1	47	5.0	Seven (a.k.a. Se7en) (1995)	Mystery|Thriller	203	3.975369
4	1	50	5.0	Usual Suspects, The (1995)	Crime|Mystery|Thriller	204	4.237745
...	...	...	...	...	...	...	...
100831	610	166534	4.0	Split (2017)	Drama|Horror|Thriller	6	3.333333
100832	610	168248	5.0	John Wick: Chapter Two (2017)	Action|Crime|Thriller	7	4.142857
100833	610	168250	5.0	Get Out (2017)	Horror	15	3.633333
100834	610	168252	5.0	Logan (2017)	Action|Sci-Fi	25	4.280000
100835	610	170875	3.0	The Fate of the Furious (2017)	Action|Crime|Drama|Thriller	3	2.333333

100836 rows × 7 columns

Content Based Filtering

Content based recommenders will use data exclusively about the items. For this we need to have a minimal understanding of the users' preferences, so that we can then recommend new items with similar tags/keywords to those specified (or inferred) by the user.

Recommendations based on **Popularity** to a New User

```
#We can consider the movies which have more than 200 ratings as POPULAR
pop_movies = df_[df_['rated_movie'] >200].sort_values(by= ['mean_rating','rated_movie'], ascending = [False,False]).head(10)
pop_movies[['title','mean_rating']]
```

	title	mean_rating
277	Shawshank Redemption, The (1994)	4.429022
2226	Fight Club (1999)	4.272936
46	Usual Suspects, The (1995)	4.237745
224	Star Wars: Episode IV - A New Hope (1977)	4.231076
461	Schindler's List (1993)	4.225000
898	Star Wars: Episode V - The Empire Strikes Back	4.215640
510	Silence of the Lambs, The (1991)	4.161290

- These are the most popular movies which can be recommended to a new user. **Recommendations based on Popularity**

Recommendations based on **Movie Genre** to a New User

```
genre_popularity = (movies.genres.str.split('|')
                      .explode()
                      .value_counts()
                      .sort_values(ascending=False))
genre_popularity.head(10)
```

```
Drama        4361
Comedy       3756
Thriller     1894
Action       1828
Romance      1596
Adventure    1263
Crime        1199
Sci-Fi        980
Horror        978
Fantasy       779
Name: genres, dtype: int64
```

The genres alone can be used to provide a reasonably good content based recommendation. But before that, I need to analyse some important aspects.

Most popular genres will be a relevant aspect to take into account when building the content based recommender. We want to understand which genres really are relevant when it comes to defining a user’s taste. A reasonable assumption is that it is precisely the unpopular genres that will be more relevant in characterising the user’s taste.

I will be building a fairly simple recommender, based on the movie genres. A fairly common approach is to use a tf-idf vectorizer.

While this approach is more commonly used on a text corpus, it possesses some interesting properties that will be useful in order to obtain a vector representation of the data.

tf-idf will help capture the important genres of each movie by giving a higher weight to the less frequent genres

```
from itertools import combinations

# Define a TF-IDF Vectorizer Object.
tfidf_genres = TfidfVectorizer(analyzer=lambda s: (c for i in range(1,4)
                                             for c in combinations(s.split('|'), r=i)))

#Construct the required TF-IDF matrix by fitting and transforming the data
tfidf_matrix = tfidf_genres.fit_transform(movies['genres'])

print(tfidf_matrix.shape)
```

```
(9742, 783)
```

```
# I've encoded each movie's genre into its tf-idf representation (only a subset of the columns and rows is sampled)
pd.DataFrame(tfidf_matrix.todense(), columns=tfidf_genres.get_feature_names(), index=movies.title).sample(5, axis=1).sample(10, ax
```

	(Film-Noir, Mystery, Western)	(Action, Animation, Comedy)	(Comedy, Film-Noir, Thriller)	(Action, Crime, Mystery)	(Action, Animation, Musical)
title					
Reversal of Fortune (1990)	0.0	0.0	0.0	0.0	0.0
Campus Man (1987)	0.0	0.0	0.0	0.0	0.0
Rose Red (2002)	0.0	0.0	0.0	0.0	0.0
Babylon 5: The Legend of the					

```
# Compute the cosine similarity matrix
cosine_sim_movies = cosine_similarity(tfidf_matrix)

cosine_sim_df = pd.DataFrame(cosine_sim_movies, index=movies['title'], columns=movies['title'])
print('Shape:', cosine_sim_df.shape)
cosine_sim_df.sample(5, axis=1).round(2)
```

```
Shape: (9742, 9742)
```

title	The Square (2017)	The Man in the Moon (1991)	No Man's Land (2001)	Half a Loaf of Kung Fu (Dian zhi gong fu gan chian chan) (1980)	Intermission (2003)
title					
Toy Story (1995)	0.00	0.00	0.00	0.03	0.02
Jumanji (1995)	0.00	0.00	0.00	0.00	0.00
Grumpier Old Men (1995)	0.00	0.35	0.00	0.15	0.08
Waiting to Exhale (1995)	0.22	0.58	0.06	0.09	0.23
Father of the Bride Part II (1995)	0.00	0.00	0.00	0.37	0.20
...	...	...	...	...	...
Black Butler: Book of the Atlantic (2017)	0.00	0.00	0.00	0.29	0.02
No Game No Life: Zero (2017)	0.00	0.00	0.00	0.06	0.03

```
def get_recommendations_based_on_genres(movie_title, cosine_sim_movies=cosine_sim_movies):
    """
    Calculates top 10 movies to recommend based on given movie titles genres.
    :param movie_title: title of movie to be taken for base of recommendation
    :param cosine_sim_movies: cosine similarity between movies
    :return: Titles of movies recommended to user
    """
    # Get the index of the movie that matches the title
    idx_movie = movies.loc[movies['title'].isin([movie_title])]
    idx_movie = idx_movie.index

    # Get the cosine similarity scores of all movies with that movie
    sim_scores_movies = list(enumerate(cosine_sim_movies[idx_movie][0]))

    # Sort the movies based on the similarity scores
    sim_scores_movies = sorted(sim_scores_movies, key=lambda x: x[1], reverse=True)

    # Get the scores of the 10 most similar movies
    sim_scores_movies = sim_scores_movies[1:11]

    # Get the movie indices
    movie_indices = [i[0] for i in sim_scores_movies]
```

```
    # Return the top 10 most similar movies
```

```
movies[movies.title.eq('Pulp Fiction (1994)')]
```

	movieId	title	genres
257	296	Pulp Fiction (1994)	Comedy|Crime|Drama|Thriller

```
get_recommendations_based_on_genres('Pulp Fiction (1994)')
```

	title	genres
520	Fargo (1996)	Comedy|Crime|Drama|Thriller
791	Freeway (1996)	Comedy|Crime|Drama|Thriller
2453	Man Bites Dog (C'est arrivé près de chez vous)...	Comedy|Crime|Drama|Thriller
3155	Beautiful Creatures (2000)	Comedy|Crime|Drama|Thriller
4169	Confessions of a Dangerous Mind (2002)	Comedy|Crime|Drama|Thriller
4523	Party Monster (2003)	Comedy|Crime|Drama|Thriller
6676	In Bruges (2008)	Comedy|Crime|Drama|Thriller
7129	Informant!, The (2009)	Comedy|Crime|Drama|Thriller
7293	Leaves of Grass (2009)	Comedy|Crime|Drama|Thriller
19	Money Train (1995)	Action|Comedy|Crime|Drama|Thriller

```
movies[movies.title.eq('Toy Story (1995)')]
```

	movieId	title	genres
0	1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy

```
get_recommendations_based_on_genres('Toy Story (1995)')
```

	title	genres
1706	Antz (1998)	Adventure|Animation|Children|Comedy|Fantasy
2355	Toy Story 2 (1999)	Adventure|Animation|Children|Comedy|Fantasy
2809	Adventures of Rocky and Bullwinkle, The (2000)	Adventure|Animation|Children|Comedy|Fantasy
3000	Emperor's New Groove, The (2000)	Adventure|Animation|Children|Comedy|Fantasy
3568	Monsters, Inc. (2001)	Adventure|Animation|Children|Comedy|Fantasy
6194	Wild, The (2006)	Adventure|Animation|Children|Comedy|Fantasy
6486	Shrek the Third (2007)	Adventure|Animation|Children|Comedy|Fantasy
6948	Tale of Despereaux, The (2008)	Adventure|Animation|Children|Comedy|Fantasy
7760	Asterix and the Vikings (Astérix et les Viking...	Adventure|Animation|Children|Comedy|Fantasy
8219	Turbo (2013)	Adventure|Animation|Children|Comedy|Fantasy

Let's look at the pros and cons of using content-based recommendation.

Pros:

- No need for data on other users, thus no cold-start or sparsity problems.
- Can recommend to users with unique tastes.
- Can recommend new & unpopular items.
- Can provide explanations for recommended items by listing content-features that caused an item to be recommended (in this case, movie genres)

Cons:

- Finding the appropriate features is hard.
- Does not recommend items outside a user's content profile.
- Unable to exploit quality judgments of other users.

Collaborative Filtering

Types of **collaborative filtering** techniques

Memory based

- User-Item Filtering (or User-Based Filtering)
- Item-Item Filtering (or Item-Based Filtering)

Model based

- Matrix Factorization
- Clustering
- Deep Learning

The main idea behind these methods is to use other users' preferences and taste to recommend new items to a user. The usual procedure is to find similar users (or items) to recommend new items which where liked by those users, and which presumably will also be liked by the user being recommended.

In this part, I will use 2 different methods for collaborative filtering. In the first method,I will use the weighted average of the ratings for item-based filtering then I will implement the second method using model-based collaborative approaches like KNN (K nearest neighbors)and SVD (Singular Value Decomposition) for user-based filtering

Memory Based

They are called memory-based because the algorithm is not complicated, but requires a lot of memory to keep track of the results.

Item-Based Collaborative Filtering

Item-based collaborative filtering is a form of collaborative filtering for recommender systems based on the similarity between items calculated using people's ratings of those items.

It is quite similar to user-based algorithm, but instead of finding user's look-alike, we try finding movie's look-alike. Once we have movie's look-alike matrix, we can easily recommend alike movies to user who have rated any movie from the dataset. This algorithm is far less resource consuming than user-user collaborative filtering. Hence, for a new user, the algorithm takes far lesser time than user-user collaborate as we don't need all similarity scores between users. And with fixed number of movies, movie-movie look alike matrix is fixed over time.

```
df
```

	userId	movieId	rating	title	genres	rated_movie	mean_rating
0	1	1	4.0	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy	215	3.920930
1	1	3	4.0	Grumpier Old Men (1995)	Comedy|Romance	52	3.259615
2	1	6	4.0	Heat (1995)	Action|Crime|Thriller	102	3.946078
3	1	47	5.0	Seven (a.k.a. Se7en) (1995)	Mystery|Thriller	203	3.975369
4	1	50	5.0	Usual Suspects, The (1995)	Crime|Mystery|Thriller	204	4.237745
...	...	...	...	...	...	...	...
100831	610	166534	4.0	Split (2017)	Drama|Horror|Thriller	6	3.333333
100832	610	168248	5.0	John Wick: Chapter Two (2017)	Action|Crime|Thriller	7	4.142857
100833	610	168250	5.0	Get Out (2017)	Horror	15	3.633333
100834	610	168252	5.0	Logan (2017)	Action|Sci-Fi	25	4.280000
100835	610	170875	3.0	The Fate of the Furious (2017)	Action|Crime|Drama|Thriller	3	2.333333

100836 rows × 7 columns

```
# I need to create the user-item matrix. This is essentially a pivoted table from the rating data,
# where the rows will be the users, the columns will be the movies and the dataframe is filled with the rating the user has given
```

```
ratings_matrix = df.pivot_table(index=['userId'],columns=['title'],values='rating').reset_index(drop=True)

# I need to replace the NULL values by 0s since the cosine_similarity doesn’t work will NA values
ratings_matrix.fillna( 0, inplace = True )
ratings_matrix.iloc[:20,:10]
```

title	'71 (2014)	'Hellboy': The Seeds of Creation (2004)	'Round Midnight (1986)	'Salem's Lot (2004)	'Til There Was You (1997)	'Tis the Season for Love (2015)	'burbs, The (1989)	'night Mother (1986)	(500) Days of Summer (2009)	*batteries not included (1987)
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
10	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
11	0.0	0.0	0.0	0.0	0.0	0.0	5.0	0.0	0.0	0.0
12	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
13	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
14	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4.0	0.0
15	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
16	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
17	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4.0	0.0
18	0.0	0.0	0.0	0.0	0.0	0.0	2.0	0.0	0.0	0.0
19	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

- **ratings_matrix** dataframe is indexed by user_ids with movie_ids belonging to different columns and the values are the ratings with most of the values as 0 as each user watches and rates only few movies. Its a sparse dataframe.

```
ratings_matrix.shape
```

```
(610, 9719)
```

```
# I will use the weighted avg of the ratings using cosine similarity as the weights
# the item-similarity matrix will measure the similarity between any two pairs of items(movies).
movie_sim = cosine_similarity(ratings_matrix.T)
print('movie similarity shape:' ,movie_sim.shape)
```

```
movie similarity shape: (9719, 9719)
```

```
# the similarity between any two pairs of items
movie_sim_df = pd.DataFrame(movie_sim)
movie_sim_df.iloc[:10,:20].round(3)
```

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
0	1.000	0.000	0.000	0.000	0.000	0.0	0.000	0.000	0.142	0.000	0.000	0.000	0.000	0.0	0.000	0.000	0.285	0.000	0.000	0.000
1	0.000	1.000	0.707	0.000	0.000	0.0	0.000	0.000	0.000	0.000	0.000	0.716	0.000	0.0	0.000	0.000	0.000	0.000	0.000	0.000
2	0.000	0.707	1.000	0.000	0.000	0.0	0.177	0.000	0.000	0.000	0.707	0.506	0.000	0.0	0.000	0.000	0.000	0.000	0.000	0.000
3	0.000	0.000	0.000	1.000	0.857	0.0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.0	0.645	0.000	0.000	0.000	0.000	0.000

```
# Below function will take the movie name as a input and will find the movies which are similar to this movie.
# This function first find the index of movie in movies frame and then take the similarity of movie and align in movies dataframe
# so that we can get the similarity of the movie with all other movies.

def movie_similarity(movieName):


        #Enter the reference movie title based on which recommendations are to be made
        movie_name=movieName
        movie=movies[movies['title']==movie_name].index.tolist()
        movie=movie[0]

        movies2 = movies.copy()
        movies2['similarity'] = movie_sim_df.iloc[movie]
        movies2.columns = ['movieId','title', 'genre','similarity']
        similar_movies = pd.merge(movies2 ,df_[['movieId','rated_movie']].drop_duplicates(), left_index=True, right_on='movieId')
        # similar_movies.columns = ['movieId', 'title' , 'genre' , 'similarity' , 'num_rating']
        similar_movies.set_index('movieId', inplace=True)
        sim_movie = similar_movies.sort_values(by = ['similarity','rated_movie'] , ascending= [False,False])[similar_movies['ratec
        return sim_movie[['title', 'genre','similarity','rated_movie']][1:11]
```

```
movie_similarity('Edward Scissorhands (1990)')
```

movieId	title	genre	similarity	rated_movie
1086	Hamlet (1996)	Crime|Drama|Romance	0.880000	25
236	Man of the House (1995)	Comedy	0.804984	45
2959	Billy Elliot (2000)	Drama	0.800000	218
5618	Dark Portals: The Chronicles of Vidocq (Vidoc...	Action|Crime|Fantasy	0.800000	87
4262	Bend It Like Beckham (2002)	Comedy|Drama|Romance	0.800000	67
2302	Dogma (1999)	Adventure|Comedy|Fantasy	0.800000	59
1276	Amistad (1997)	Drama|Mystery	0.800000	57
2804	Butterfly (La lengua de las mariposas)	Drama	0.800000	55

```
movie_similarity('Toy Story 2 (1999)')
```

Collaborative Filtering Model Based on User Ratings

I will use the file ratings.csv first as it contains User ID, Movie IDs and Ratings. These three elements are all I need for determining the similarity of the users based on their ratings for a particular movie

Surprise Library

2355 Toy Story 2 (1999) Adventure|Animation|Children|Comedy|Fantasy 1.0 92

```
!pip install scikit-surprise
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Collecting scikit-surprise
  Downloading scikit-surprise-1.1.3.tar.gz (771 kB)
     |████████████████████████████████| 771 kB 4.0 MB/s
Requirement already satisfied: joblib>=1.0.0 in /usr/local/lib/python3.8/dist-packages (from scikit-surprise) (1.2.0)
Requirement already satisfied: numpy>=1.17.3 in /usr/local/lib/python3.8/dist-packages (from scikit-surprise) (1.21.6)
Requirement already satisfied: scipy>=1.3.2 in /usr/local/lib/python3.8/dist-packages (from scikit-surprise) (1.7.3)
Building wheels for collected packages: scikit-surprise
  Building wheel for scikit-surprise (setup.py) ... done
  Created wheel for scikit-surprise: filename=scikit_surprise-1.1.3-cp38-cp38-linux_x86_64.whl size=2626497 sha256=5c3803414
  Stored in directory: /root/.cache/pip/wheels/af/db/86/2c18183a80ba05da35bf0fb7417aac5cddbd93bcb1b92fd3ea
Successfully built scikit-surprise
Installing collected packages: scikit-surprise
Successfully installed scikit-surprise-1.1.3
```

Surprise is a Python SciKit that comes with various recommender algorithms and similarity metrics to make it easy to build and analyze recommenders.

```
from surprise import Dataset
from surprise import Reader
from surprise import SVD, SVDpp ,accuracy
from surprise.prediction_algorithms import KNNWithMeans, KNNBasic, KNNWithZScore
from surprise.model_selection import GridSearchCV
from surprise.model_selection import cross_validate
from surprise.model_selection import train_test_split
```

To load a data set from the above pandas data frame,

I will use the **load_from_df()** method,

I will also need a **Reader** object. The Reader object is used to parse a file containing ratings. The default format in which it accepts data is that each rating is stored in a separate line in the order user item rating,

and the **rating_scale** parameter must be specified to (1,5). The data frame must have three columns, corresponding to the userId, movieId, and the ratings in this order. Each row thus corresponds to a given rating.

```
reader = Reader(rating_scale=(1, 5))
data = Dataset.load_from_df(ratings[['userId', 'movieId','rating']], reader)
```

```
pd.DataFrame(data.__dict__['raw_ratings'], columns=['user_id','item_id','rating','timestamp'])
```

	user_id	item_id	rating	timestamp
0	1	1	4.0	None
1	1	3	4.0	None

With the Surprise library, I will benchmark the following algorithms:

k-NN algorithms

- **KNNBasic** (K nearest neighbors) is a basic collaborative filtering algorithm.
- **KNNWithMeans** is basic collaborative filtering algorithm, taking into account the mean ratings of each user.
- **KNNWithZScore** is a basic collaborative filtering algorithm, taking into account the z-score normalization of each user.

Matrix Factorization-based algorithms

- **SVD** (Singular Value Decomposition) algorithm is equivalent to Probabilistic Matrix Factorization
- **SVDpp** algorithm is an extension of SVD that takes into account implicit ratings.

100835	610	170875	3.0	None

KNN algorithm is simple to use but it has one drawback when size of dataset is getting increased its results gets affected because it's not able to handle data sparsity. To overcome this problem new matrix factorization based approach has been introduced.

The second category covers the Model based approaches, which involve a step to reduce or compress the large but sparse user-item matrix. For understanding this step, a basic understanding of dimensionality reduction can be very helpful.

Dimensionality Reduction In the user-item matrix, there are two dimensions:

1.The number of users

2.The number of items

If the matrix is mostly empty, reducing dimensions can improve the performance of the algorithm in terms of both space and time. You can use various methods like matrix factorization or autoencoders to do this.

Matrix factorization can be seen as breaking down a large matrix into a product of smaller ones. This is similar to the factorization of integers, where 12 can be written as 6 x 2 or 4 x 3. In the case of matrices, a matrix A with dimensions m x n can be reduced to a product of two matrices X and Y with dimensions m x p and p x n respectively.

Algorithms for Matrix Factorization One of the popular algorithms to factorize a matrix is the singular value decomposition (SVD) algorithm. SVD came into the limelight when matrix factorization was seen performing well in the Netflix prize competition. Other algorithms include PCA and its variations, NMF, and so on.

SVD performs really well with large set of data, it is not able to capture implicit data of user which can play an important role in user's selection of item. To overcome this problem new matrix factorization approach called SVD++ has been introduced.

SVD++ is an extension of SVD model which deals with both explicit feedback an implicit feedback which simply states that this model will not only take ratings given by user but also it will consider user's behavior's through implicit feedback at the time of generating result. The mathematical representation of this model is similar to SVD one, the only additional part is to consider implicit feedback.

```
# approx 10 mins execute!

benchmark = []
# Iterate over all algorithms
for algo in [SVD(), SVDpp(), KNNBasic(), KNNWithMeans(), KNNWithZScore()]:
    # Perform cross validation
    # We use RMSE and MAE as our accuracy metric for the predictions.
    result = cross_validate(algo, data, cv=5)

    # Get results & append algorithm name
    results= pd.DataFrame.from_dict(result).mean(axis=0)
    results = results.append(pd.Series([str(algo).split(' ')[0].split('.')[-1]], index=['Algorithm']))
    benchmark.append(results)
```

```
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
```

```
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
```

```
surprise_results = pd.DataFrame(benchmark).set_index('Algorithm').sort_values('test_rmse')
```

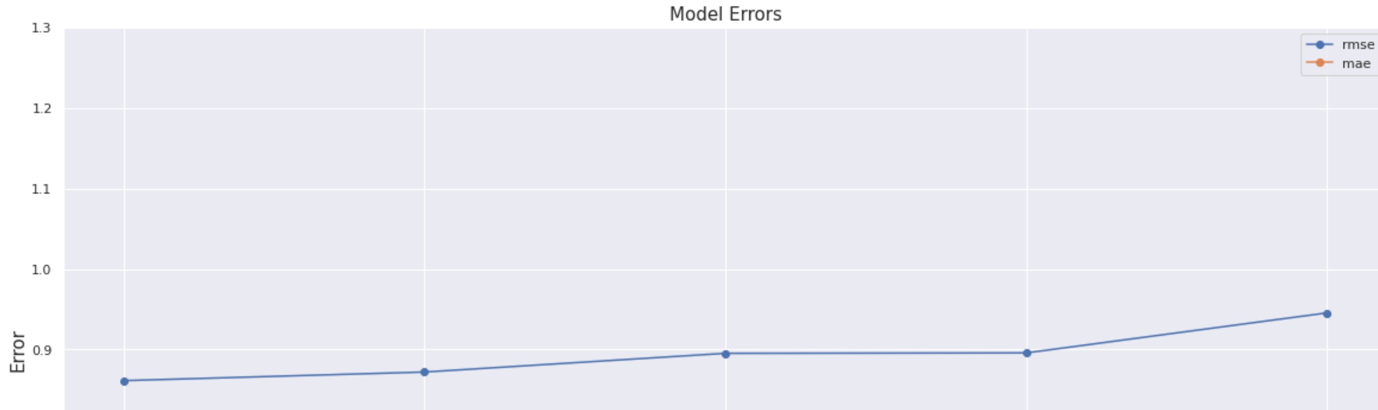
```
surprise_results
```

Algorithm	test_rmse	test_mae	fit_time	test_time
SVDpp	0.861492	0.659975	86.653256	9.610151
SVD	0.872160	0.669731	1.773452	0.253048
KNNWithMeans	0.895372	0.684281	0.176882	1.628050
KNNWithZScore	0.895900	0.679785	0.245697	1.707030
KNNBasic	0.945566	0.725200	0.139366	1.550319

```
# Get data
algo = ['SVDpp','SVD' , 'KNNWithZScore' ,'KNNWithMeans','KNNBasic' ]
rmse = surprise_results['test_rmse']
mae = surprise_results['test_mae']
x = np.arange(len(surprise_results))

# Set up the matplotlib figure
fig, ax = plt.subplots(figsize = (20, 10))
plt.xticks(np.arange(min(x), max(x) + 1, 1.0))
plt.ylim(0.5, 1.3)
ax.plot(algo, rmse, marker='o', label="rmse")
ax.plot(algo, mae, marker='o', label="mae")

# Chart setup
plt.title("Model Errors", fontsize = 15)
plt.xlabel("Algorithms", fontsize = 15)
plt.ylabel("Error", fontsize = 15)
plt.legend()
plt.show()
```



I choise two standard errors as our evaluation metrics:

Mean Absolute Error(MAE) computes the avarage of all the absolute value differences between the true and the predicted rating.

Root Mean Square Error(RMSE) computes the mean value of all the differences squared between the true and the predicted ratings and then proceeds to calculate the square root out of the result.

For both of these metrics, lower the error better the accuracy.

SVDpp algorithm gave the best RMSE, While SVDpp had the better performance, tuning SVDpp takes considerably longer time to train compared to the naive SVD.So, I chose to optimize the SVD model for number of epochs, learning rate and regularization using grid search

Tuning the Algorithm Parameters for SVD

```
# two of the most important hyperparameters when running the stochastic gradient descent (SGD) algorithm are
# learning rate and number of epochs.Thus I will tune this params
param_grid = {
    'n_epochs': [5, 10, 20, 30],            #The number of iteration of the SGD procedure. Default is 20
    'lr_all': [.0025, .005, .001, .01],     #The learning rate for all parameters. Default is 0.005
    'reg_all': [0.02, 0.04, 0.1, 0.2]       # The regularization term for all parameters. Default is 0.02

}
# algo = SVD()
gs = GridSearchCV(SVD, param_grid, measures=["rmse", "mae"], cv=5, n_jobs = -1,joblib_verbose=5) # From my experience , n_jobs = -
gs.fit(data)

print(gs.best_score['rmse'])
print(gs.best_params['rmse'])
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  10 tasks      | elapsed:    4.5s
[Parallel(n_jobs=-1)]: Done  64 tasks      | elapsed:   24.5s
[Parallel(n_jobs=-1)]: Done 154 tasks      | elapsed:   59.0s
[Parallel(n_jobs=-1)]: Done 280 tasks      | elapsed:  2.3min
0.855199034916331
{'n_epochs': 30, 'lr_all': 0.01, 'reg_all': 0.1}
[Parallel(n_jobs=-1)]: Done 320 out of 320 | elapsed:  2.8min finished
```

Based on our hyperparameter tuning, the best Matrix factorization based model that we found out was:

RMSE: 0.8548 which is better than untuned SVDpp

Best Params: number of epochs = 30 , learning rate = 0.01 , and regularization =0.1

```
param_grid2 = {
    'n_epochs': [30, 40, 50],            #The number of iteration of the SGD procedure. Default is 20
    'lr_all': [.007,.01 , .015 ],        #The learning rate for all parameters. Default is 0.005
    'reg_all': [0.07, 0.1 , 0.3]         # The regularization term for all parameters which is a penalty term added to prevent ove

}
# algo = SVD()
gs2 = GridSearchCV(SVD, param_grid2, measures=["rmse", "mae"], cv=5,n_jobs = -1,joblib_verbose=5)
gs2.fit(data)

print(gs2.best_score['rmse'])
print(gs2.best_params['rmse'])
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  10 tasks      | elapsed:    9.3s
[Parallel(n_jobs=-1)]: Done  64 tasks      | elapsed:   53.4s
0.8503715097037494
{'n_epochs': 50, 'lr_all': 0.015, 'reg_all': 0.1}
[Parallel(n_jobs=-1)]: Done 135 out of 135 | elapsed:  2.2min finished
```

RMSE: 0.8493

Best Params: number of epochs = 50 , learning rate = 0.015 , and regularization = 0.1

I got better result i will keep tuning till improvoment stop.

```
param_grid3 = {
    'n_epochs': [50,60],                      #The number of iteration of the SGD procedure. Default is 20
    'lr_all': [.015 , 0.2 , 0.5, 0,7],        #The learning rate for all parameters. Default is 0.005
    'reg_all': [0.1]                          # The regularization term for all parameters.
                                                # which is a penalty term added to prevent overfitting Default is 0.02

}
# algo = SVD()
gs3 = GridSearchCV(SVD, param_grid3, measures=["rmse", "mae"], cv=5,n_jobs = -1,joblib_verbose=5)
gs3.fit(data)

print(gs3.best_score['rmse'])
print(gs3.best_params['rmse'])
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  10 tasks      | elapsed:   14.1s
0.8491733889548673
{'n_epochs': 50, 'lr_all': 0.015, 'reg_all': 0.1}
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed:  1.1min finished
```

RMSE: 0.8495

Best Params: number of epochs = 45 , learning rate = 0.015 , and regularization = 0.1

It didnt make it better result So I will stop here and start predicting.

Predictions

I use the train_test_split() to sample a trainset and a testset with given sizes, and use the accuracy metric of rmse. I'll then use the fit() method which will train the algorithm on the trainset, and the test() method which will return the predictions made from the testset

```
# sample random trainset and testset
# test set is made of 25% of the ratings.
trainset, testset = train_test_split(data, test_size=.25)


print('Number of users: ', trainset.n_users, '\n')
print('Number of items: ', trainset.n_items, '\n')
```

```
Number of users:  610

Number of items:  8746
```

```
svd = SVD(n_epochs=30, lr_all=0.01, reg_all=0.1)
svd.fit(trainset)
predictions = svd.test(testset)
accuracy.rmse(predictions)
```

```
RMSE: 0.8569
0.856936361435199
```

```
chosen_svd = SVD(n_epochs=50, lr_all=0.015, reg_all=0.1)
chosen_svd.fit(trainset)
```

```
predictions = chosen_svd.test(testset)
print(accuracy.rmse(predictions))
```

```
RMSE: 0.8515
0.8514538960287283
```

That would mean the estimated ratings on average are about 0.8525 higher or lower than the actual ratings, on a 0 to 5 scale

```
predictions[:10]
```

```
[Prediction(uid=105, iid=7347, r_ui=4.0, est=3.720285607448477, details={'was_impossible': False}),
 Prediction(uid=335, iid=356, r_ui=4.0, est=4.189966540717784, details={'was_impossible': False}),
 Prediction(uid=393, iid=4720, r_ui=3.0, est=3.8519381658204264, details={'was_impossible': False}),
 Prediction(uid=567, iid=138036, r_ui=3.0, est=2.3219422872649798, details={'was_impossible': False}),
 Prediction(uid=274, iid=2448, r_ui=3.5, est=2.7013887255688958, details={'was_impossible': False}),
 Prediction(uid=91, iid=500, r_ui=2.5, est=3.210069566036405, details={'was_impossible': False}),
 Prediction(uid=140, iid=4921, r_ui=4.0, est=3.5586616486511833, details={'was_impossible': False}),
 Prediction(uid=96, iid=1, r_ui=5.0, est=3.8468006851521306, details={'was_impossible': False}),
 Prediction(uid=169, iid=4994, r_ui=4.5, est=4.076208977550929, details={'was_impossible': False}),
 Prediction(uid=318, iid=98809, r_ui=4.0, est=3.8755429384107627, details={'was_impossible': False})]
```

```
predictions_df = pd.DataFrame(predictions)
predictions_df
```

	uid	iid	r_ui	est	details
0	105	7347	4.0	3.720286	{'was_impossible': False}
1	335	356	4.0	4.189967	{'was_impossible': False}
2	393	4720	3.0	3.851938	{'was_impossible': False}
3	567	138036	3.0	2.321942	{'was_impossible': False}
4	274	2448	3.5	2.701389	{'was_impossible': False}
...	...	...	...	...	...
25204	140	527	5.0	3.933393	{'was_impossible': False}
25205	89	69757	2.5	3.161196	{'was_impossible': False}
25206	360	1721	4.0	3.775745	{'was_impossible': False}
25207	599	4386	1.0	2.540866	{'was_impossible': False}
25208	367	4031	2.0	3.523727	{'was_impossible': False}

25209 rows × 5 columns

Make some predictions

```
user1 = df[(df['userId'] == 1)]
user1
```

	userId	movieId	rating	title	genres	rated_movie	mean_rating
0	1	1	4.0	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy	215	3.920930
1	1	3	4.0	Grumpier Old Men (1995)	Comedy|Romance	52	3.259615
2	1	6	4.0	Heat (1995)	Action|Crime|Thriller	102	3.946078
3	1	47	5.0	Seven (a.k.a. Se7en) (1995)	Mystery|Thriller	203	3.975369
4	1	50	5.0	Usual Suspects, The (1995)	Crime|Mystery|Thriller	204	4.237745
...	...	...	...	...	...	...	...
227	1	3744	4.0	Shaft (2000)	Action|Crime|Thriller	19	2.657895
228	1	3793	5.0	X-Men (2000)	Action|Adventure|Sci-Fi	133	3.699248
229	1	3809	4.0	What About Bob? (1991)	Comedy	35	3.271429
230	1	4006	4.0	Transformers: The Movie (1986)	Adventure|Animation|Children|Sci-Fi	7	3.357143
231	1	5060	5.0	M*A*S*H (a.k.a. MASH) (1970)	Comedy|Drama|War	46	3.934783

232 rows × 7 columns

```
user1= df[(df['userId'] == 1) & (df['movieId'] == 1)][['userId', 'movieId', 'rating', 'title']]
user1
```

	userId	movieId	rating	title
0	1	1	4.0	Toy Story (1995)

```
chosen_svd.predict(1 ,1)
```

```
Prediction(uid=1, iid=1, r_ui=None, est=4.376367769767988, details={'was_impossible': False})
```

For movie with ID 1, we get an estimated prediction of 4.40 .It works purely on the basis of an assigned movie ID and tries to predict ratings based on how the other users have predicted the movie.

```
user504 = df[(df['userId'] == 504)]
user504
```

	userId	movieId	rating	title	genres	rated_movie	mean_rating
80168	504	1	4.0	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy	215	3.920930
80169	504	22	3.5	Copycat (1995)	Crime|Drama|Horror|Mystery|Thriller	36	3.222222
80170	504	186	3.0	Nine Months (1995)	Comedy|Romance	48	2.822917
80171	504	296	4.0	Pulp Fiction (1994)	Comedy|Crime|Drama|Thriller	307	4.197068
80172	504	342	3.5	Muriel's Wedding (1994)	Comedy	33	3.272727
...	...	...	...	...	...	...	...
80250	504	6953	4.0	21 Grams (2003)	Crime|Drama|Mystery|Romance|Thriller	25	3.300000
80251	504	7139	4.5	In America (2002)	Drama|Romance	7	3.857143
80252	504	7149	4.5	Something's Gotta Give (2003)	Comedy|Drama|Romance	17	3.647059
80253	504	7151	4.0	Girl with a Pearl Earring (2003)	Drama|Romance	12	3.375000
80254	504	7153	4.0	Lord of the Rings: The Return of the King, The...	Action|Adventure|Drama|Fantasy	185	4.118919

87 rows × 7 columns

```
chosen_svd.predict(504,1)
```

```
Prediction(uid=504, iid=1, r_ui=None, est=4.082764049121817, details={'was_impossible': False})
```

```
user504= df[(df['userId'] == 504) & (df['movieId'] == 1)][['userId', 'movieId', 'rating', 'title']]
user504
```

	userId	movieId	rating	title
80168	504	1	4.0	Toy Story (1995)

```
chosen_svd.predict(504,1)
```

```
Prediction(uid=504, iid=1, r_ui=None, est=4.082764049121817, details={'was_impossible': False})
```

```
user504= df[(df['userId'] == 504) & (df['movieId'] == 22)][['userId', 'movieId', 'rating', 'title']]
user504
```

	userId	movieId	rating	title
80169	504	22	3.5	Copycat (1995)

```
chosen_svd.predict(504,22)
```

```
Prediction(uid=504, iid=22, r_ui=None, est=3.4759910280345774, details={'was_impossible': False})
```

The field **est** indicates the estimated movie rating for this specific user.

```
# uid = userid
# iid = movieid
```

```
# rui = true rating
# est = estimated movie rating
# details = Stores additional details about the prediction that might be useful for later analysis.
# err = est - rui

df_pred = pd.DataFrame(predictions, columns=['uid', 'iid', 'rui', 'est', 'details'])
df_pred['err'] = abs(df_pred.est - df_pred.rui)
df_pred.sort_values(by='err')
```

	uid	iid	rui	est	details	err
5160	584	356	5.0	5.000000	{'was_impossible': False}	0.000000
23114	475	1198	5.0	5.000000	{'was_impossible': False}	0.000000
10014	53	922	5.0	5.000000	{'was_impossible': False}	0.000000
12169	30	318	5.0	5.000000	{'was_impossible': False}	0.000000
19904	12	8533	5.0	5.000000	{'was_impossible': False}	0.000000
...	...	...	...	...	...	...
6428	393	5902	0.5	4.384421	{'was_impossible': False}	3.884421
19082	393	778	0.5	4.421655	{'was_impossible': False}	3.921655
22358	594	5909	0.5	4.445121	{'was_impossible': False}	3.945121
2883	154	130634	0.5	4.546909	{'was_impossible': False}	4.046909
15353	594	7116	0.5	4.600101	{'was_impossible': False}	4.100101

25209 rows × 6 columns

Get the top-10 recommendations

```
# https://surprise.readthedocs.io/en/stable/FAQ.html

from collections import defaultdict


def get_top_n(predictions, n=10):
    """Return the top-N recommendation for each user from a set of predictions.

    Args:
        predictions(list of Prediction objects): The list of predictions, as
            returned by the test method of an algorithm.
        n(int): The number of recommendation to output for each user. Default
            is 10.

    Returns:
    A dict where keys are user (raw) ids and values are lists of tuples:
        [(raw item id, rating estimation), ...] of size n.
    """

    # First map the predictions to each user.
    top_n = defaultdict(list)
    for uid, iid, r_ui, est, _ in predictions:
        top_n[uid].append((iid, est))

    # Then sort the predictions for each user and retrieve the k highest ones.
    for uid, user_ratings in top_n.items():
        user_ratings.sort(key=lambda x: x[1], reverse=True)
        top_n[uid] = user_ratings[:n]

    return top_n


top_n = get_top_n(predictions, n=10)
```

```
# Print the recommended items for each user
for uid, user_ratings in top_n.items():
     print(uid, [iid for (iid, _) in user_ratings])
```

```
105 [2843, 170705, 55721, 48516, 83803, 3306, 4995, 6016, 858, 3147]
335 [318, 110, 593, 356, 3671, 592, 163, 2424, 2302]
```

```
393 [4993, 4011, 778, 5902, 59315, 58559, 4995, 53996, 4027, 1610]
567 [166291, 178827, 109487, 167746, 7361, 108932, 541, 260, 163645, 4144]
274 [5690, 7024, 30745, 1215, 8949, 48516, 2324, 3235, 78499, 175]
91 [1261, 541, 1249, 293, 1210, 5500, 318, 6874, 1291, 2571]
140 [3983, 356, 41863, 3741, 2889, 912, 527, 1270, 3359, 1344]
96 [1221, 1079, 110, 2028, 306, 3060, 1387, 1094, 2944, 480]
169 [2565, 6345, 6331, 1080, 4308, 1136, 2762, 2791, 7149, 5267]
318 [177593, 105197, 55721, 3038, 72226, 5379, 1222, 41863, 1273, 6440]
20 [595, 2080, 4246, 2565, 1022, 919, 364, 4027, 4865, 2085]
239 [8132, 1198, 2571, 48516, 4011, 1222, 3275, 3578, 16, 7147]
599 [8477, 6791, 3235, 1248, 83803, 2937, 4617, 898, 38095, 4103]
600 [2318, 5992, 247, 7084, 8949, 2502, 1394, 750, 26084, 1197]
477 [27156, 1283, 1222, 260, 2571, 4973, 7361, 55167, 48516, 2700]
68 [3653, 122918, 69757, 1270, 67267, 81834, 1704, 34405, 99114, 40959]
594 [8132, 1225, 7116, 919, 457, 648, 3, 2491, 3578, 5909]
18 [318, 1213, 96488, 48516, 2959, 3681, 1201, 4973, 5995, 2329]
603 [1836, 858, 1230, 923, 933, 82, 3224, 1304, 1733, 1394]
365 [159093, 6377, 4896, 104879, 159441, 69844, 4995, 106062, 92420, 2918]
216 [2239, 1244, 3996, 3435, 1273, 441, 2289, 1288, 3925, 1265]
605 [28, 8368, 5816, 40815, 76093, 5618, 54001, 1275, 2125, 51662]
608 [44191, 2959, 2571, 3275, 293, 3949, 4821, 3147, 2762, 6820]
261 [50, 2858, 318, 16, 80463, 47, 356, 69122, 5989, 4963]
177 [25771, 1223, 7121, 1104, 1945, 912, 904, 902, 953, 905]
182 [296, 4642, 50, 1267, 1104, 4226, 6874, 247, 1281, 1245]
307 [2959, 1201, 858, 1261, 296, 175, 5618, 6711, 1222, 6016]
99 [296, 266, 339, 315, 276, 380, 228, 282, 204, 344]
28 [1732, 475, 48516, 55721, 8914, 8949, 1748, 1210, 49961, 48780]
246 [28, 4144, 7153, 6016, 4881, 356, 68157, 1246, 5013, 3949]
51 [8874, 1249, 260, 1215, 482, 2951, 5377, 4865, 4437, 1845]
382 [318, 50, 58559, 63082, 1230, 7153, 2959, 356, 3703, 68954]
153 [4226, 1961, 40819, 68954, 63082, 2959, 106920, 134853, 91529, 117881]
221 [1283, 951, 8014, 5008, 905, 1136, 1219, 4973, 1208, 5225]
50 [2732, 1252, 1206, 2160, 44555, 2959, 1080, 1136, 1208, 356]
514 [115713, 58559, 1207, 1610, 69481, 1954, 6787, 1, 1641, 122926]
256 [92259, 111759, 6942, 377, 780, 134130, 7361, 68157, 3300, 5989]
527 [1387, 593, 3114, 527, 480, 2947, 1258, 1269, 1254, 595]
288 [1283, 912, 923, 1732, 1272, 2324, 32, 1234, 1282, 1262]
509 [8014, 72226, 28, 296, 71899, 58559, 5618, 2502, 93840, 1136]
159 [74946, 6942, 97304, 3114, 2671, 78499, 480, 4014, 47099, 1]
351 [85342, 8914, 7361, 2571, 6377, 81788, 57669, 296, 5608, 2762]
186 [1197, 1204, 1035, 1356, 1210, 2138, 2077, 1193, 2064, 2186]
438 [4011, 2571, 2028, 457, 4995, 3972, 6377, 1265, 6874, 1267]
520 [4993, 318, 5008, 1234, 7153, 1197, 48780, 59315, 1079, 541]
275 [3741, 1041, 3468, 1148, 2858, 1198, 4499, 3429, 1221, 2324]
404 [553, 457, 590, 480, 161, 368, 454, 357, 349, 34]
219 [741, 7361, 2959, 3671, 1213, 541, 908, 3421, 48774, 930]
448 [86142, 4226, 1208, 136562, 7706, 593, 6874, 109487, 608, 778]
135 [2959, 4226, 2858, 2502, 260, 2804, 3327, 1196, 1291, 1198]
610 [1283, 71899, 27773, 318, 58559, 1208, 296, 68157, 5952, 8949]
95 [7361, 589, 5952, 924, 1270, 608, 4954, 5618, 480, 4979]
42 [2959, 318, 2028, 2580, 2571, 1213, 1968, 1645, 2297, 457]
325 [541, 1248, 296, 1217, 1280, 924, 1197, 1234, 4117, 2912]
400 [50, 2571, 4993, 1193, 356, 1270, 6, 47, 1036, 164179]
1 [2078, 527, 1258, 2991, 1291, 1219, 1213, 296, 1224, 2542]
490 [89759, 1089, 5690, 2571, 58559, 5952, 80463, 1206, 86345, 356]
601 [50, 1221, 7361, 858, 2324, 5618, 79132, 1704, 172591, 4995]
```

```
def get_movie_recommendations(user_id, preferred_genre = 'all'):

    new_df = df.copy()

    # filtering out by genre
    if preferred_genre !='all':
        new_df = new_df[new_df[preferred_genre]==1]

    # filtering out by number of ratings
    new_df = new_df[new_df['rated_movie']>= 50]

    # filtering out all movies already rated by user
    movies_already_watched = set(new_df[new_df['userId'] == user_id].movieId.values)
    new_df= new_df[~new_df['movieId'].isin(movies_already_watched)]

    # finding expected ratings for all remaining movies in the dataset
    all_movie_ids = set(new_df['movieId'].values)
    all_movie_ratings = []

    for i in all_movie_ids:
        expected_rating = chosen_svd.predict(uid=user_id, iid=i).est
        all_movie_ratings.append((i,round(expected_rating,1)))

    # extracting top ten movies by expected rating
    expected_df = pd.DataFrame(all_movie_ratings, columns=['movieId','Expected Rating'])
```

```
    result_df = pd.merge(expected_df, df_[['movieId','title','genres','rated_movie']],on='movieId')
    # result_df = result_df[result_df['userId'] == user_id]
    result_df = result_df.sort_values(['Expected Rating','rated_movie'],ascending=[False,False])

    return result_df.head(10)
```

```
# get movie recommendation for userid = 25
get_movie_recommendations(25)
```

	movieId	Expected Rating	title	genres	rated_movie
93	318	5.0	Shawshank Redemption, The (1994)	Crime|Drama	317
87	296	4.9	Pulp Fiction (1994)	Comedy|Crime|Drama|Thriller	307
167	593	4.9	Silence of the Lambs, The (1991)	Crime|Horror|Thriller	279
279	1196	4.9	Star Wars: Episode V - The Empire Strikes Back...	Action|Adventure|Sci-Fi	211
23	50	4.9	Usual Suspects, The (1995)	Crime|Mystery|Thriller	204
39	4226	4.9	Memento (2000)	Mystery|Thriller	159
280	1197	4.9	Princess Bride, The (1987)	Action|Adventure|Comedy|Fantasy|Romance	142
278	1193	4.9	One Flew Over the Cuckoo's Nest (1975)	Drama	133
294	7361	4.9	Eternal Sunshine of the Spotless Mind (2004)	Drama|Romance|Sci-Fi	131
82	2329	4.9	American History X (1998)	Crime|Drama	129

```
# get movie recommendation for userid = 5
get_movie_recommendations(5)
```

	movieId	Expected Rating	title	genres	rated_movie
224	953	4.4	It's a Wonderful Life (1946)	Children|Drama|Fantasy|Romance	58
290	1276	4.4	Cool Hand Luke (1967)	Drama	57
214	912	4.3	Casablanca (1942)	Drama|Romance	100
73	2324	4.3	Life Is Beautiful (La Vita è bella) (1997)	Comedy|Drama|Romance|War	88
277	1225	4.3	Amadeus (1984)	Drama	76
391	6016	4.3	City of God (Cidade de Deus) (2002)	Action|Adventure|Crime|Drama|Thriller	75
254	1193	4.2	One Flew Over the Cuckoo's Nest (1975)	Drama	133
272	7361	4.2	Eternal Sunshine of the Spotless Mind (2004)	Drama|Romance|Sci-Fi	131
275	1221	4.2	Godfather: Part II, The (1974)	Crime|Drama	129
131	541	4.2	Blade Runner (1982)	Action|Sci-Fi|Thriller	124

Conclusion

In this notebook different recommendation approaches of content and collaborative filtering has been discussed.

First, I did exploratory data analysis then I started with content based filtering to recommend movie to new user based upon genre and movie popularity or the average ratings given by other users in the database.

I then progressed collaborative filtering based engines which try to find similar movies or users to make their predictions. After assessing models on **RMSE** metric, I found SVD++ to be the most accurate model but since SVD++ hyperparameters tuning time consuming I decided to go with SVD model tuned hyperparameters by using GridSearchCV

Finally, I made a recommendation engine which recommends 10 movies to specific user by using SVD model. And I added filtering options for genre and minimum number of ratings to make recommendations more accurate

Recommendations

- Most popular genres will be a relevant aspect to take into account when building the content based recommender.
- Collaborative Filtering Recommender Engine more effectively when it comes to recommend movies based on other users' preference but It doesn't solve the cold start problem. To help solve this problem we can use hybrid model of our naive recommendation engine and the model based recommendation engine.
- We optimized SVD model to prevent time consuming and cost but Optimizing SVDpp can be more efficient since SVDpp is an extension of SVD model which deals with both explicit feedback an implicit feedback

Future Work

In this notebook there is a lot of potential to do but in the future, deep learning based recommender system can be built to enhance the performance and provide better recommendations to user.

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