mm549_dukemerv_project5

August 17, 2020

0.1 Applied Deep Learning - CSE510

1 Project 5 - Recommendation Systems

1.0.1 Team :

- **Mohamed Fazil M S [ubid - mm549]**
- **Duke Mervyn Martin [ubid - dukemerv]**

[11]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from matplotlib import style
%matplotlib inline
```

1.1 Part I: ML Method for Recommendations on MovieLens 100K dataset

1.1.1 Importing Datasets and Preprocessing

[12]:
```
movies_data = pd.read_csv("ml-latest-small/movies.csv")
movies_data.info()
movies_data
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9742 entries, 0 to 9741
Data columns (total 3 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   movieId  9742 non-null   int64
 1   title    9742 non-null   object
 2   genres   9742 non-null   object
dtypes: int64(1), object(2)
memory usage: 228.5+ KB
```

[12]:
```
      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)
…        …                                        …
9737   193581  Black Butler: Book of the Atlantic (2017)
9738   193583               No Game No Life: Zero (2017)
9739   193585                               Flint (2017)
9740   193587        Bungo Stray Dogs: Dead Apple (2018)
9741   193609        Andrew Dice Clay: Dice Rules (1991)

                                           genres
0     Adventure|Animation|Children|Comedy|Fantasy
1                      Adventure|Children|Fantasy
2                                  Comedy|Romance
3                            Comedy|Drama|Romance
4                                          Comedy
…                                             …
9737              Action|Animation|Comedy|Fantasy
9738                     Animation|Comedy|Fantasy
9739                                        Drama
9740                             Action|Animation
9741                                       Comedy

[9742 rows x 3 columns]
```

The **movies_data** consist of all the movies listed in this dataset with its title, movieId, genres.

[13]:
```
ratings_data = pd.read_csv("ml-latest-small/ratings.csv")
print(ratings_data.info())
print('User Ratings Metrics')
print('--------------------')
print(ratings_data['rating'].describe())
ratings_data
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100836 entries, 0 to 100835
Data columns (total 4 columns):
 #   Column     Non-Null Count   Dtype
---  ------     --------------   -----
 0   userId     100836 non-null  int64
 1   movieId    100836 non-null  int64
 2   rating     100836 non-null  float64
 3   timestamp  100836 non-null  int64
dtypes: float64(1), int64(3)
memory usage: 3.1 MB
None
User Ratings Metrics
--------------------
count    100836.000000
mean          3.501557
```

```
std          1.042529
min          0.500000
25%          3.000000
50%          3.500000
75%          4.000000
max          5.000000
Name: rating, dtype: float64
```

[13]:

```
        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
…          …      …      …          …
100831     610   166534     4.0  1493848402
100832     610   168248     5.0  1493850091
100833     610   168250     5.0  1494273047
100834     610   168252     5.0  1493846352
100835     610   170875     3.0  1493846415

[100836 rows x 4 columns]
```

The **ratings_data** consist of all the 100k ratings given bby different users in this dataset with the attributes userid, movieid, rating and timestamp.

[6]:

```python
num_users = ratings_data['userId'].nunique()
num_movies = ratings_data['movieId'].nunique()
print(" Number of Movies =", num_movies)
print(" Number of Users =", num_users)
```

```
 Number of Movies = 9724
 Number of Users = 610
```

[7]:

```python
ratings_data['rating'].min()
```

[7]: 0.5

[8]:

```python
ratings_data['rating'].max()
```

[8]: 5.0

[9]:

```python
movies_data.isnull().any()
```

[9]:

```
movieId    False
title      False
genres     False
dtype: bool
```

[10]:
```
ratings_data.isnull().any()
```

[10]:
```
userId       False
movieId      False
rating       False
timestamp    False
dtype: bool
```

[14]:
```
# Removing Timestamps which is unecessary
ratings_data=ratings_data.drop('timestamp',axis=1)
```

[15]:
```
ratings_data.userId = ratings_data.userId.astype('category').cat.codes.values
ratings_data.movieId = ratings_data.movieId.astype('category').cat.codes.values
# Converting userId and movieId to category datatype and coding the values
ratings_data
```

[15]:
```
        userId  movieId  rating
0            0        0     4.0
1            0        2     4.0
2            0        5     4.0
3            0       43     5.0
4            0       46     5.0
…          …      …     …
100831     609     9416     4.0
100832     609     9443     5.0
100833     609     9444     5.0
100834     609     9445     5.0
100835     609     9485     3.0

[100836 rows x 3 columns]
```

1.1.2 Creating the Piviot Table of userId VS movieId which shows Ratings

[16]:
```
util_df = ratings_data.
 ↪pivot_table(index=['userId'],columns=['movieId'],values='rating')
util_df=util_df.fillna(0) # Fill N/a to 0
util_df
```

[16]:
```
movieId  0     1     2     3     4     5     6     7     8     9     …  \
userId                                                              …
0         4.0   0.0   4.0   0.0   0.0   4.0   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         4.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0  …
…        …   …   …   …   …   …   …   …   …   …   …   …
605       2.5   0.0   0.0   0.0   0.0   0.0   2.5   0.0   0.0   0.0  …
```

```
606        4.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0  …
607        2.5   2.0   2.0   0.0   0.0   0.0   0.0   0.0   0.0   4.0  …
608        3.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   4.0  …
609        5.0   0.0   0.0   0.0   0.0   5.0   0.0   0.0   0.0   0.0  …

movieId  9714  9715  9716  9717  9718  9719  9720  9721  9722  9723
userId
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
…        …    …    …    …    …    …    …    …    …    …
605        0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
606        0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
607        0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
608        0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
609        0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0

[610 rows x 9724 columns]
```

[18]:
```python
genres = [␣
↪'NA','Action','Adventure','Animation','Children','Comedy','Crime','Documentary','Drama','Fa
        ␣
↪'Horror','Musical','Mystery','Romance','Sci-Fi','Thriller','War','Western']
print('Total Number of Genres - ',len(genres))
```

```
Total Number of Genres -  19
```

Hot Encoding all Genres in Movies Dataframe

[41]:
```python
genres_cat_list = []
genres_cat_strlist = []
for i in range(movies_data.shape[0]):
    string = movies_data.iloc[i]['genres']
    str_list = string.split('|')
    genres_cat_strlist.append(str_list)
    hot = np.zeros(len(genres)).astype(int).tolist()
    string = movies_data.iloc[0]['genres']
    if(string==''):
        hot[0] = 1
        genres_cat_list.append(hot)
    else:
        for x in range(len(genres)):
            for g in str_list:
                if(genres[x]==g):
                    hot[x]=1
        genres_cat_list.append(hot)
```

```
print('Example Hot Encoding Genres')
print('==============================')
for i in range(5):
    print(movies_data.iloc[i]['title'],'-->',genres_cat_list[i])
```

```
Example Hot Encoding Genres
==============================
Toy Story (1995) --> [0, 0, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0]
Jumanji (1995) --> [0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0]
Grumpier Old Men (1995) --> [0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
0, 0]
Waiting to Exhale (1995) --> [0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0,
0, 0]
Father of the Bride Part II (1995) --> [0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0]
```

Combining Average Rating of a Movie from all the Users with the Movies Dataset

[42]:
```
movie_rating_avg_list = []
number_ratings = []
for mid in range(len(util_df.transpose().index.tolist())):
    s = 0
    n = 0
    for x in util_df.transpose().iloc[mid]:
        s = s + x
        if(x!=0):
            n=n+1
    movie_rating_avg_list.append(s/n)
    number_ratings.append(n)
movies_data_ratings = util_df.transpose()
movies_data_ratings['total_ratings'] = number_ratings
movies_data_ratings['avg_rating'] = movie_rating_avg_list

data = {'title':movies_data['title'],
        'total_ratings':movies_data_ratings['total_ratings'],
        'avg_rating':movies_data_ratings['avg_rating'],
         'genres_cat':genres_cat_strlist}

movies_data_ratings = pd.DataFrame(data)
movies_data_ratings = movies_data_ratings.dropna()
movies_data_ratings
```

[42]:

	title	total_ratings	avg_rating	\
0	Toy Story (1995)	215.0	3.920930	
1	Jumanji (1995)	110.0	3.431818	
2	Grumpier Old Men (1995)	52.0	3.259615	
3	Waiting to Exhale (1995)	7.0	2.357143	
4	Father of the Bride Part II (1995)	49.0	3.071429	

```
…                                     …             …          …
9719                      Spiral (2018)           1.0   4.000000
9720  Mission: Impossible - Fallout (2018)        1.0   3.500000
9721                    SuperFly (2018)           1.0   3.500000
9722                Iron Soldier (2010)           1.0   3.500000
9723              BlacKkKlansman (2018)           1.0   4.000000

                                       genres_cat
0     [Adventure, Animation, Children, Comedy, Fantasy]
1                    [Adventure, Children, Fantasy]
2                                 [Comedy, Romance]
3                          [Comedy, Drama, Romance]
4                                          [Comedy]
…                                               …
9719                                  [Documentary]
9720                  [Action, Adventure, Thriller]
9721                      [Action, Crime, Thriller]
9722                               [Action, Sci-Fi]
9723                         [Comedy, Crime, Drama]

[9724 rows x 4 columns]
```

1.1.3 Using Neares Neighbour Method to fit a Recomendations for a User

The K neared neighbour method is used on the Piviot Matrix to find similar users and their movie preferences and recommend those movie for them using cosine distances.

[17]:
```
from scipy.sparse import csr_matrix
from sklearn.neighbors import NearestNeighbors
# Creating a Compressed Squared Matrix of the Piviot Matrix
movie_csr = csr_matrix(util_df.values)
# Using Cosine Distance Function
knn = NearestNeighbors(metric = 'cosine', algorithm = 'brute')
knn.fit(movie_csr)
```

[17]:
```
NearestNeighbors(algorithm='brute', metric='cosine')
```

1.1.4 Recommend a List of Movies for completely new User

Methodology -

- Give the new user the **top 10 highly popular and rated movie** from all time to give the user a broad quality options to choose from.
- This will be done by calculating a **Popularity Index** which Number of Ratings to Average Rating product

[129]:
```
# create dataframe to measure Number of ratings to Average Ratings Ratio
```

```
movies_data_ratings['popularity'] =␣
 ↪movies_data_ratings['total_ratings']*movies_data_ratings['avg_rating']
movies_data_popularity = movies_data_ratings.set_index('title')
movies_data_popularity = movies_data_popularity.
 ↪sort_values(by=['popularity'],ascending=False)
print('Top 10 Recommended Movies by Popularity Index')
print('==============================================')
movies_data_popularity.head(10)
```

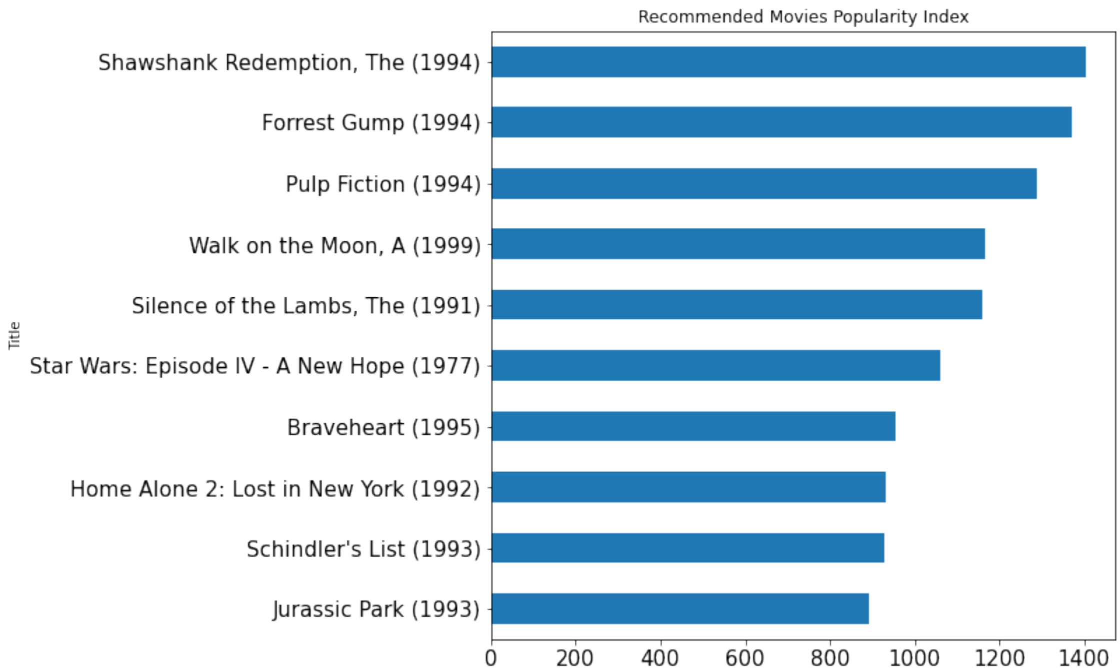
```
Top 10 Recommended Movies by Popularity Index
==============================================
```

[129]:

```
                                         total_ratings  avg_rating  \
title
Shawshank Redemption, The (1994)                 317.0    4.429022
Forrest Gump (1994)                              329.0    4.164134
Pulp Fiction (1994)                              307.0    4.197068
Walk on the Moon, A (1999)                       278.0    4.192446
Silence of the Lambs, The (1991)                 279.0    4.161290
Star Wars: Episode IV - A New Hope (1977)        251.0    4.231076
Braveheart (1995)                                237.0    4.031646
Home Alone 2: Lost in New York (1992)            218.0    4.272936
Schindler's List (1993)                          220.0    4.225000
Jurassic Park (1993)                             238.0    3.750000

                                                                   genres_cat
\
title
Shawshank Redemption, The (1994)                              [Crime, Drama]
Forrest Gump (1994)                             [Comedy, Drama, Romance, War]
Pulp Fiction (1994)                          [Comedy, Crime, Drama, Thriller]
Walk on the Moon, A (1999)                                  [Drama, Romance]
Silence of the Lambs, The (1991)                   [Crime, Horror, Thriller]
Star Wars: Episode IV - A New Hope (1977)        [Action, Adventure, Sci-Fi]
Braveheart (1995)                                     [Action, Drama, War]
Home Alone 2: Lost in New York (1992)                   [Children, Comedy]
Schindler's List (1993)                                         [Drama, War]
Jurassic Park (1993)                 [Action, Adventure, Sci-Fi, Thriller]

                                         popularity
title
Shawshank Redemption, The (1994)             1404.0
Forrest Gump (1994)                          1370.0
Pulp Fiction (1994)                          1288.5
Walk on the Moon, A (1999)                   1165.5
Silence of the Lambs, The (1991)             1161.0
Star Wars: Episode IV - A New Hope (1977)    1062.0
```

```
Braveheart (1995)                                   955.5
Home Alone 2: Lost in New York (1992)               931.5
Schindler's List (1993)                             929.5
Jurassic Park (1993)                                892.5
```

[141]:
```python
df = movies_data_popularity.head(10)
df = df.sort_values(by=['popularity'])
df = df['popularity']
ax = df.plot.barh(x='popularity',figsize =(8,8),fontsize=15, ylabel =␣
↪'Popularity Index',xlabel='Title',title = 'Recommended Movies Popularity␣
↪Index')
```



1.1.5 Recommendations for an Existing User

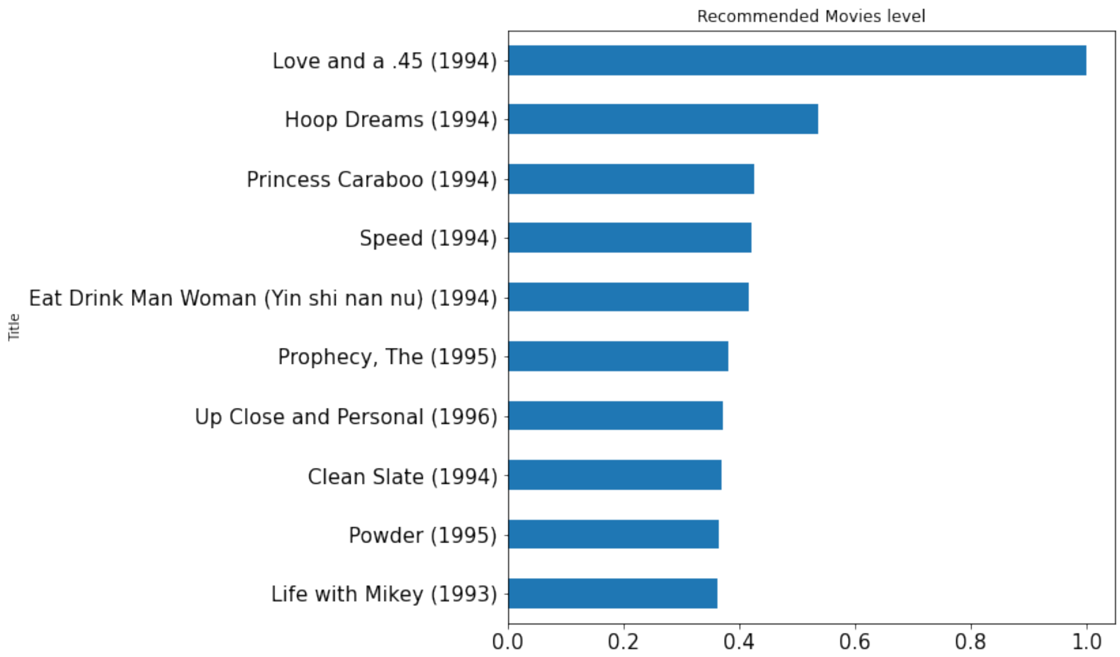
Using the K Nearest Neibhour Method similar user profiles are clustered and their prefered movies are recommended.

[142]:
```python
def get_recommendations_knn(userId):
    user_index = userId
    num_recommendations = 10
    distances, movie_indices = knn.kneighbors(util_df.iloc[user_index,:].values.
↪reshape(1, -1), n_neighbors = num_recommendations)
    movie_list_indices = movie_indices.tolist()[0]
    print('Top {} Movie Recommendation for User {}'.
↪format(num_recommendations,userId))
```

```
    print('==========================================')
    i=0
    mv_title_list = []
    for mId in list(movie_list_indices):
        i=i+1
        mv = movies_data.loc[movies_data['movieId']== mId]
        mv_title_list.append(mv['title'].values[0])
        print('Movie {} : {} from genres {}'.format(i,mv['title'].
↪values,mv['genres'].values))

    similarity_level = []
    for d in distances[0].tolist():
        similarity_level.append(1-d)
    data = {'title':mv_title_list,'recommendation':similarity_level}

    df = pd.DataFrame(data)
    df = df.set_index('title')
    df = df.sort_values(by=['recommendation'])
    df = df['recommendation']
    ax = df.plot.barh(x='recommendation',figsize =(8,8),fontsize=15, ylabel =␣
↪'Popularity Index',xlabel='Title',title = 'Recommended Movies level')
```

[143]:
```
get_recommendations_knn(600)
```

```
Top 10 Movie Recommendation for User 600
==========================================
Movie 1 : ['Love and a .45 (1994)'] from genres ['Action|Comedy|Crime']
Movie 2 : ['Hoop Dreams (1994)'] from genres ['Documentary']
Movie 3 : ['Princess Caraboo (1994)'] from genres ['Drama']
Movie 4 : ['Speed (1994)'] from genres ['Action|Romance|Thriller']
Movie 5 : ['Eat Drink Man Woman (Yin shi nan nu) (1994)'] from genres
['Comedy|Drama|Romance']
Movie 6 : ['Prophecy, The (1995)'] from genres ['Fantasy|Horror|Mystery']
Movie 7 : ['Up Close and Personal (1996)'] from genres ['Drama|Romance']
Movie 8 : ['Clean Slate (1994)'] from genres ['Comedy']
Movie 9 : ['Powder (1995)'] from genres ['Drama|Sci-Fi']
Movie 10 : ['Life with Mikey (1993)'] from genres ['Comedy']
```



1.2 # Part 2

1.3 Building a DNN model

- Sequencing the User ID's and Movie ID's

[16]:
```
users = ratings_data.userId.unique()
movies = ratings_data.movieId.unique()

userid2idx = {o:i for i,o in enumerate(users)}
movieid2idx = {o:i for i,o in enumerate(movies)}
```

[17]:
```
ratings_data['user'] = ratings_data['userId'].apply(lambda x: userid2idx[x])
ratings_data['movie'] = ratings_data['movieId'].apply(lambda x: movieid2idx[x])
```

- Adding the sequenced data to the ratings dataset

[18]:
```
ratings_data
```

[18]:

	userId	movieId	rating	user	movie
0	0	0	4.0	0	0
1	0	2	4.0	0	1
2	0	5	4.0	0	2
3	0	43	5.0	0	3
4	0	46	5.0	0	4
…	…	…	…	…	…
100831	609	9416	4.0	609	3120

```
100832     609     9443     5.0    609    2035
100833     609     9444     5.0    609    3121
100834     609     9445     5.0    609    1392
100835     609     9485     3.0    609    2873

[100836 rows x 5 columns]
```

1.4 Splitting the data for training and testing

[19]:
```python
split = np.random.rand(len(ratings_data)) < 0.9
train = ratings_data[split]
valid = ratings_data[~split]
print(train.shape , valid.shape)
```

```
(90730, 5) (10106, 5)
```

- We create the user and movie embeddings using the keras Embedding layer

[20]:
```python
embedding_factor = 64
```

- Setting the embedding size

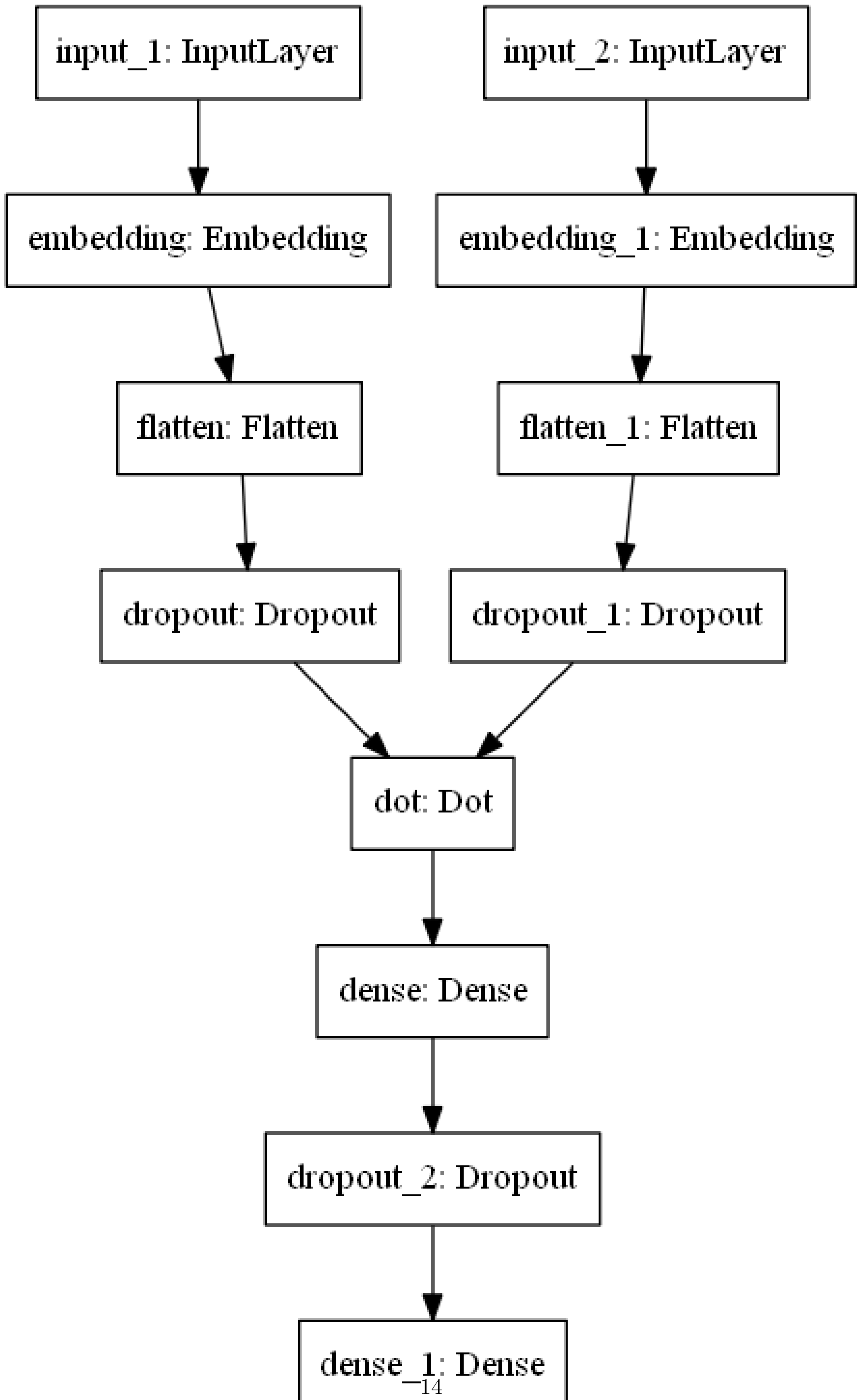
[21]:
```python
user_input = Input(shape = (1,))
user_embedding = Embedding(num_users,embedding_factor)(user_input)
user_vec = Flatten()(user_embedding)
user_vec = Dropout(0.4)(user_vec)
movie_input = Input(shape = (1,))
movie_embedding=Embedding(num_movies,embedding_factor)(movie_input)
movie_vec = Flatten()(movie_embedding)
movie_vec = Dropout(0.4)(movie_vec)
similarity=dot([user_vec,movie_vec], axes=1)
#x = BatchNormalization()(similarity)
x = Dense(96,activation='relu')(similarity)
x = Dropout(0.4)(x)
x = Dense(1,activation='relu')(x)
model = Model([user_input, movie_input], x)
```

[22]:
```python
model.summary()
plot_model(model)
```

```
Model: "functional_1"
________________________________________________________________________________
__________________
Layer (type)                    Output Shape         Param #     Connected to
================================================================================
==================
input_1 (InputLayer)            [(None, 1)]          0

________________________________________________________________________________
```

```
------------------
input_2 (InputLayer)            [(None, 1)]          0

--------------------------------------------------------------------------------
------------------
embedding (Embedding)           (None, 1, 64)        39040        input_1[0][0]

--------------------------------------------------------------------------------
------------------
embedding_1 (Embedding)         (None, 1, 64)        622336       input_2[0][0]

--------------------------------------------------------------------------------
------------------
flatten (Flatten)               (None, 64)           0            embedding[0][0]

--------------------------------------------------------------------------------
------------------
flatten_1 (Flatten)             (None, 64)           0
embedding_1[0][0]

--------------------------------------------------------------------------------
------------------
dropout (Dropout)               (None, 64)           0            flatten[0][0]

--------------------------------------------------------------------------------
------------------
dropout_1 (Dropout)             (None, 64)           0            flatten_1[0][0]

--------------------------------------------------------------------------------
------------------
dot (Dot)                       (None, 1)            0            dropout[0][0]
                                                                  dropout_1[0][0]

--------------------------------------------------------------------------------
------------------
dense (Dense)                   (None, 96)           192          dot[0][0]

--------------------------------------------------------------------------------
------------------
dropout_2 (Dropout)             (None, 96)           0            dense[0][0]

--------------------------------------------------------------------------------
------------------
dense_1 (Dense)                 (None, 1)            97           dropout_2[0][0]
================================================================================
==================
Total params: 661,665
Trainable params: 661,665
Non-trainable params: 0

--------------------------------------------------------------------------------
------------------
```

[22]:


input_1: InputLayer
input_2: InputLayer
embedding: Embedding
embedding_1: Embedding
flatten: Flatten
flatten_1: Flatten
dropout: Dropout
dropout_1: Dropout
dot: Dot
dense: Dense
dropout_2: Dropout
dense_1: Dense

[23]:
```
model.compile(optimizer=Adam(lr=1e-4),loss='mse')
```

[24]:
```
early = EarlyStopping(monitor='val_loss', min_delta=0, patience=10,verbose=0,␣
↪mode='auto')
batch_size=128
epochs=100
```

1.4.1 Training process

- Since we use the MSE as loss, we intend to reduce the loss.

[25]:
```
History = model.fit([train.userId,train.movieId],train.rating,␣
↪batch_size=batch_size,
                              epochs =epochs, validation_data = ([valid.
↪userId,valid.movieId],valid.rating),
                              verbose = 1, callbacks = [early])
```

```
Epoch 1/100
709/709 [==============================] - 6s 9ms/step - loss: 10.9792 -
val_loss: 8.1832
Epoch 2/100
709/709 [==============================] - 7s 9ms/step - loss: 5.2767 -
val_loss: 2.9571
Epoch 3/100
709/709 [==============================] - 7s 9ms/step - loss: 1.9256 -
val_loss: 1.2478
Epoch 4/100
709/709 [==============================] - 7s 9ms/step - loss: 1.2837 -
val_loss: 1.0959
Epoch 5/100
709/709 [==============================] - 7s 9ms/step - loss: 1.2562 -
val_loss: 1.0908
Epoch 6/100
709/709 [==============================] - 6s 9ms/step - loss: 1.2510 -
val_loss: 1.0871
Epoch 7/100
709/709 [==============================] - 7s 9ms/step - loss: 1.2290 -
val_loss: 1.0849
Epoch 8/100
709/709 [==============================] - 7s 10ms/step - loss: 1.1906 -
val_loss: 1.0737
Epoch 9/100
709/709 [==============================] - 7s 9ms/step - loss: 1.1433 -
val_loss: 1.0526
Epoch 10/100
```

```
709/709 [==============================] - 7s 10ms/step - loss: 1.0822 -
val_loss: 1.0259
Epoch 11/100
709/709 [==============================] - 8s 11ms/step - loss: 1.0096 -
val_loss: 0.9940
Epoch 12/100
709/709 [==============================] - 7s 10ms/step - loss: 0.9386 -
val_loss: 0.9690
Epoch 13/100
709/709 [==============================] - 7s 10ms/step - loss: 0.8973 -
val_loss: 0.9482
Epoch 14/100
709/709 [==============================] - 7s 10ms/step - loss: 0.8571 -
val_loss: 0.9326
Epoch 15/100
709/709 [==============================] - 7s 9ms/step - loss: 0.8271 -
val_loss: 0.9186
Epoch 16/100
709/709 [==============================] - 7s 9ms/step - loss: 0.7879 -
val_loss: 0.9080
Epoch 17/100
709/709 [==============================] - 7s 9ms/step - loss: 0.7665 -
val_loss: 0.8976
Epoch 18/100
709/709 [==============================] - 7s 9ms/step - loss: 0.7419 -
val_loss: 0.8899
Epoch 19/100
709/709 [==============================] - 7s 9ms/step - loss: 0.7236 -
val_loss: 0.8836
Epoch 20/100
709/709 [==============================] - 7s 10ms/step - loss: 0.7048 -
val_loss: 0.8766
Epoch 21/100
709/709 [==============================] - 7s 9ms/step - loss: 0.6892 -
val_loss: 0.8711
Epoch 22/100
709/709 [==============================] - 7s 9ms/step - loss: 0.6702 -
val_loss: 0.8658
Epoch 23/100
709/709 [==============================] - 7s 9ms/step - loss: 0.6536 -
val_loss: 0.8611
Epoch 24/100
709/709 [==============================] - 7s 9ms/step - loss: 0.6411 -
val_loss: 0.8575
Epoch 25/100
709/709 [==============================] - 7s 9ms/step - loss: 0.6276 -
val_loss: 0.8541
Epoch 26/100
```

```
709/709 [==============================] - 7s 9ms/step - loss: 0.6147 -
val_loss: 0.8512
Epoch 27/100
709/709 [==============================] - 7s 10ms/step - loss: 0.5988 -
val_loss: 0.8489
Epoch 28/100
709/709 [==============================] - 7s 9ms/step - loss: 0.5894 -
val_loss: 0.8456
Epoch 29/100
709/709 [==============================] - 7s 9ms/step - loss: 0.5803 -
val_loss: 0.8426
Epoch 30/100
709/709 [==============================] - 7s 9ms/step - loss: 0.5704 -
val_loss: 0.8392
Epoch 31/100
709/709 [==============================] - 7s 9ms/step - loss: 0.5658 -
val_loss: 0.8373
Epoch 32/100
709/709 [==============================] - 7s 9ms/step - loss: 0.5509 -
val_loss: 0.8341
Epoch 33/100
709/709 [==============================] - 7s 9ms/step - loss: 0.5443 -
val_loss: 0.8321
Epoch 34/100
709/709 [==============================] - 7s 11ms/step - loss: 0.5331 -
val_loss: 0.8304
Epoch 35/100
709/709 [==============================] - 8s 11ms/step - loss: 0.5277 -
val_loss: 0.8295
Epoch 36/100
709/709 [==============================] - 8s 11ms/step - loss: 0.5233 -
val_loss: 0.8265
Epoch 37/100
709/709 [==============================] - 8s 12ms/step - loss: 0.5166 -
val_loss: 0.8246
Epoch 38/100
709/709 [==============================] - 8s 12ms/step - loss: 0.5109 -
val_loss: 0.8229
Epoch 39/100
709/709 [==============================] - 9s 12ms/step - loss: 0.5023 -
val_loss: 0.8210
Epoch 40/100
709/709 [==============================] - 7s 10ms/step - loss: 0.4974 -
val_loss: 0.8188
Epoch 41/100
709/709 [==============================] - 7s 9ms/step - loss: 0.4896 -
val_loss: 0.8175
Epoch 42/100
```

```
709/709 [==============================] - 7s 9ms/step - loss: 0.4845 -
val_loss: 0.8163
Epoch 43/100
709/709 [==============================] - 7s 10ms/step - loss: 0.4756 -
val_loss: 0.8151
Epoch 44/100
709/709 [==============================] - 8s 11ms/step - loss: 0.4749 -
val_loss: 0.8132
Epoch 45/100
709/709 [==============================] - 7s 10ms/step - loss: 0.4722 -
val_loss: 0.8120
Epoch 46/100
709/709 [==============================] - 7s 9ms/step - loss: 0.4610 -
val_loss: 0.8105
Epoch 47/100
709/709 [==============================] - 7s 9ms/step - loss: 0.4602 -
val_loss: 0.8091
Epoch 48/100
709/709 [==============================] - 7s 9ms/step - loss: 0.4534 -
val_loss: 0.8076
Epoch 49/100
709/709 [==============================] - 7s 10ms/step - loss: 0.4505 -
val_loss: 0.8083
Epoch 50/100
709/709 [==============================] - 7s 10ms/step - loss: 0.4442 -
val_loss: 0.8075
Epoch 51/100
709/709 [==============================] - 7s 9ms/step - loss: 0.4405 -
val_loss: 0.8052
Epoch 52/100
709/709 [==============================] - 7s 9ms/step - loss: 0.4376 -
val_loss: 0.8044
Epoch 53/100
709/709 [==============================] - 7s 10ms/step - loss: 0.4331 -
val_loss: 0.8035
Epoch 54/100
709/709 [==============================] - 7s 10ms/step - loss: 0.4289 -
val_loss: 0.8028
Epoch 55/100
709/709 [==============================] - 7s 10ms/step - loss: 0.4264 -
val_loss: 0.8017
Epoch 56/100
709/709 [==============================] - 7s 10ms/step - loss: 0.4219 -
val_loss: 0.8014
Epoch 57/100
709/709 [==============================] - 7s 10ms/step - loss: 0.4158 -
val_loss: 0.8010
Epoch 58/100
```

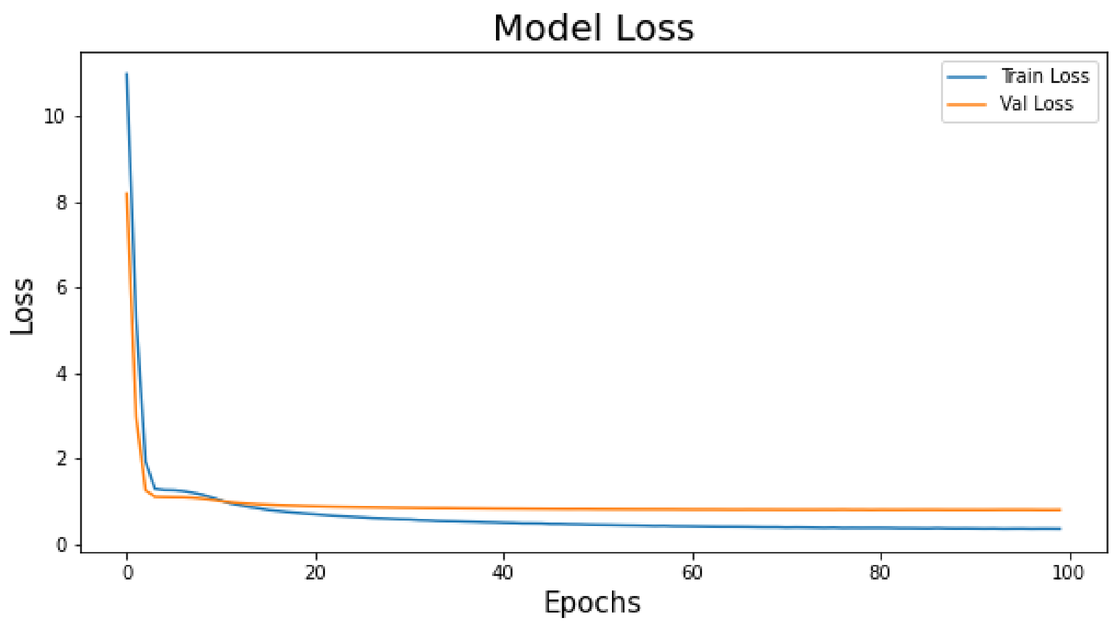
```
709/709 [==============================] - 7s 10ms/step - loss: 0.4182 -
val_loss: 0.8004
Epoch 59/100
709/709 [==============================] - 7s 10ms/step - loss: 0.4103 -
val_loss: 0.7999
Epoch 60/100
709/709 [==============================] - 7s 10ms/step - loss: 0.4088 -
val_loss: 0.7982
Epoch 61/100
709/709 [==============================] - 7s 11ms/step - loss: 0.4065 -
val_loss: 0.7973
Epoch 62/100
709/709 [==============================] - 7s 10ms/step - loss: 0.4029 -
val_loss: 0.7968
Epoch 63/100
709/709 [==============================] - 7s 10ms/step - loss: 0.3995 -
val_loss: 0.7964
Epoch 64/100
709/709 [==============================] - 7s 10ms/step - loss: 0.3971 -
val_loss: 0.7956
Epoch 65/100
709/709 [==============================] - 7s 10ms/step - loss: 0.3968 -
val_loss: 0.7944
Epoch 66/100
709/709 [==============================] - 7s 10ms/step - loss: 0.3957 -
val_loss: 0.7939
Epoch 67/100
709/709 [==============================] - 7s 9ms/step - loss: 0.3934 -
val_loss: 0.7949
Epoch 68/100
709/709 [==============================] - 7s 10ms/step - loss: 0.3890 -
val_loss: 0.7939
Epoch 69/100
709/709 [==============================] - 7s 10ms/step - loss: 0.3868 -
val_loss: 0.7938
Epoch 70/100
709/709 [==============================] - 8s 11ms/step - loss: 0.3866 -
val_loss: 0.7931
Epoch 71/100
709/709 [==============================] - 8s 11ms/step - loss: 0.3800 -
val_loss: 0.7926
Epoch 72/100
709/709 [==============================] - 7s 9ms/step - loss: 0.3830 -
val_loss: 0.7919
Epoch 73/100
709/709 [==============================] - 7s 10ms/step - loss: 0.3801 -
val_loss: 0.7925
Epoch 74/100
```

```
709/709 [==============================] - 7s 10ms/step - loss: 0.3762 -
val_loss: 0.7919
Epoch 75/100
709/709 [==============================] - 7s 9ms/step - loss: 0.3719 -
val_loss: 0.7929
Epoch 76/100
709/709 [==============================] - 8s 12ms/step - loss: 0.3758 -
val_loss: 0.7920
Epoch 77/100
709/709 [==============================] - 9s 12ms/step - loss: 0.3682 -
val_loss: 0.7941
Epoch 78/100
709/709 [==============================] - 9s 13ms/step - loss: 0.3700 -
val_loss: 0.7910
Epoch 79/100
709/709 [==============================] - 8s 11ms/step - loss: 0.3684 -
val_loss: 0.7915
Epoch 80/100
709/709 [==============================] - 7s 10ms/step - loss: 0.3690 -
val_loss: 0.7887
Epoch 81/100
709/709 [==============================] - 8s 11ms/step - loss: 0.3688 -
val_loss: 0.7909
Epoch 82/100
709/709 [==============================] - 7s 10ms/step - loss: 0.3672 -
val_loss: 0.7900
Epoch 83/100
709/709 [==============================] - 7s 10ms/step - loss: 0.3625 -
val_loss: 0.7897
Epoch 84/100
709/709 [==============================] - 7s 10ms/step - loss: 0.3622 -
val_loss: 0.7905
Epoch 85/100
709/709 [==============================] - 8s 11ms/step - loss: 0.3597 -
val_loss: 0.7903
Epoch 86/100
709/709 [==============================] - 7s 10ms/step - loss: 0.3574 -
val_loss: 0.7907
Epoch 87/100
709/709 [==============================] - 7s 10ms/step - loss: 0.3633 -
val_loss: 0.7903
Epoch 88/100
709/709 [==============================] - 7s 10ms/step - loss: 0.3574 -
val_loss: 0.7888
Epoch 89/100
709/709 [==============================] - 7s 10ms/step - loss: 0.3555 -
val_loss: 0.7888
Epoch 90/100
```

```
709/709 [==============================] - 7s 10ms/step - loss: 0.3565 -
val_loss: 0.7883
Epoch 91/100
709/709 [==============================] - 7s 10ms/step - loss: 0.3542 -
val_loss: 0.7882
Epoch 92/100
709/709 [==============================] - 7s 10ms/step - loss: 0.3516 -
val_loss: 0.7878
Epoch 93/100
709/709 [==============================] - 7s 10ms/step - loss: 0.3535 -
val_loss: 0.7886
Epoch 94/100
709/709 [==============================] - 7s 11ms/step - loss: 0.3480 -
val_loss: 0.7902
Epoch 95/100
709/709 [==============================] - 7s 10ms/step - loss: 0.3502 -
val_loss: 0.7898
Epoch 96/100
709/709 [==============================] - 7s 10ms/step - loss: 0.3514 -
val_loss: 0.7900
Epoch 97/100
709/709 [==============================] - 7s 10ms/step - loss: 0.3473 -
val_loss: 0.7894
Epoch 98/100
709/709 [==============================] - 8s 11ms/step - loss: 0.3493 -
val_loss: 0.7869
Epoch 99/100
709/709 [==============================] - 7s 10ms/step - loss: 0.3489 -
val_loss: 0.7863
Epoch 100/100
709/709 [==============================] - 7s 10ms/step - loss: 0.3474 -
val_loss: 0.7873
```

[33]:

```
plt.figure(figsize=(10,5))
plt.plot(History.history['loss'],  label='Train Loss')
plt.plot(History.history['val_loss'], label='Val Loss')
plt.title('Model Loss', size = 20)
plt.ylabel('Loss', size = 15)
plt.xlabel('Epochs', size = 15)
plt.legend()
plt.show()
```



[27]:
```
#test_user = ratings_data.userId.sample(1).iloc[0]
test_user = 600
watched = ratings_data[ratings_data.userId == test_user]
val = movies_data['movieId'].isin(watched.movieId.values)
not_watched = movies_data[~val]['movieId']
util_val =  set(not_watched).intersection(set(movieid2idx.keys()))
not_watched = list(util_val)
not_watched = [[movieid2idx.get(x)] for x in not_watched]
test_user = userid2idx.get(test_user)
test_user = np.asarray(test_user).astype(np.float32)
not_watched = np.asarray(not_watched).astype(np.float32)
test_user_arr = np.array([test_user for i in range(not_watched.shape[0])])
not_watched = not_watched.reshape(-1)
```

[28]:
```
rat = model.predict([test_user_arr,not_watched])
```

[29]:
```
top_rat = rat.argsort(axis=0)[-10:][::-1]
```

[30]:
```
recommended_movie_ids = [movieid2idx.get(not_watched[x][0]) for x in top_rat]
```

[31]:
```
print("Showing recommendations for user: {}".format(test_user))
print("====================================================")
print("Movies with high ratings from user")
print("====================================================")
top_movies_user = (watched.sort_values(by="rating", ascending=False).head(5).
 ↪movieId.values)
```

```
movie_df_rows = movies_data[movies_data["movieId"].isin(top_movies_user)]
for row in movie_df_rows.itertuples():
    print(row.title, ":\t", row.genres)

print("====================================================")
print("Top 10 movie recommendations")
print("====================================================")
recommended_movies = movies_data[movies_data["movieId"].
 ↪isin(recommended_movie_ids)]
for row in recommended_movies.itertuples():
    print(row.title, ":\t", row.genres)
```

```
Showing recommendations for user: 600.0
====================================================
Movies with high ratings from user
====================================================
Kissed (1996) :  Drama|Romance
Jackie Brown (1997) :    Crime|Drama|Thriller
Lost Weekend, The (1945) :       Drama
Thirteen (2003) :        Drama
====================================================
Top 10 movie recommendations
====================================================
Eat Drink Man Woman (Yin shi nan nu) (1994) :    Comedy|Drama|Romance
Jason's Lyric (1994) :   Crime|Drama
Angels in the Outfield (1994) :  Children|Comedy
Robin Hood: Prince of Thieves (1991) :   Adventure|Drama
Citizen Ruth (1996) :    Comedy|Drama
Blame It on Rio (1984) :         Comedy|Romance
```

[32]:
```
recommended_movies
```

[32]:
```
      movieId                                        title  \
198       232  Eat Drink Man Woman (Yin shi nan nu) (1994)
348       391                         Jason's Lyric (1994)
779      1021                Angels in the Outfield (1994)
784      1027         Robin Hood: Prince of Thieves (1991)
1072     1392                          Citizen Ruth (1996)
1678     2259                       Blame It on Rio (1984)

                    genres
198   Comedy|Drama|Romance
348            Crime|Drama
779        Children|Comedy
784        Adventure|Drama
1072          Comedy|Drama
1678        Comedy|Romance
```

1.5 Result discussion

- From the tasks we can see a list of recomendations for the user 600
- Both the models recommended movies that belonged to a variety of genres from the users wated pattern. * The surprising thing is that only one recommendation of Nearest Neighbour based approach and deep learning based approach matched.
- This can be attributed to the stochasticity of the model.