Music Recommender Project

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1 Music Recommender System

1.1 ISI Delhi (Remote) Summer Internship Project

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2 Introduction

In this Project, I have used (a Subset) of *Million Song Dataset (MSD)*, Provided by turi.com which is taken from a subset of *The Echo Nest Taste Profile Subset* from here. It contains triplets of **(user_id, song_id, listen_count)** and has been provided in a text file with triplets being seperated by *'/t' (tab)*. Song metadata consisting of features related to song wasn't available anywhere except the official site of *MSD*. I have downloaded the summary file of the whole 280GB Dataset. It was in .h5 format and I used utility (edited it alot for my own specific requirements) from GitHub to convert that md5 file into .csv file. It contains metadata for **Unique 10k Songs** contained in triplets file of MSD.

I have used this dataset to train and evaluate the Recommender System using four Algorithms: 1. **Popularity Model:** Sort the Songs according to their Popularity Score. 2. **KNN Model:** Aggregate Similar Songs according to their features or Metadata. 3. **Collaborative Filtering (Memory Based) Model:** 1. **Item-Item CF Model:** Find Similar Songs according to the No. of Users who have rated/ listened them 1. **Jaccard Based Score:** Sorted Songs according to the Jaccard Index/ Score (More Info here or given in the report of this project) 2. **Conditional Probability Score:** Sorted according to the Score obtained using Conditional Probability (More Info here or given in the report of this project) 2. **User-User CF Model:** Find Similar Songs according to the No. of Songs listened by Similar Users 1. **Jaccard Based Score:** Sorted Songs according to the Jaccard Index/ Score (More Info here or given in the report of this project) 2. **Conditional Probability Score:** Sorted according to the Score obtained using Conditional Probability (More Info here or given in the report of this project) 4. **Latent Factors (SVD) Model:** Find the latent factors of User and Songs by using SVD on User_Song Rating (Implicit Rating) Matrix.

So, **Our Objective using above Models / Algorithms is to return an *Ordered (Ranked) List of Songs* that we call Recommendation List using the Listening History of the**

User and Obviously, we must not recommend a user, the songs which he/she has already listened to and hence, our Recommendation List contains only Recommendations for our User with no Songs already listened by them.

2.1 Let's Begin

First take a Glance on the Data that we have for our Music Recommender System.

[1]:
```python
#Importing Required Packages
import pandas as pd
import numpy as np
# import joblib
from sklearn.model_selection import train_test_split
import Rec as Recommenders
import importlib
importlib.reload(Recommenders)
import utility_script as utility
import importlib
importlib.reload(Recommenders)
from scipy.sparse import csc_matrix
import pickle
import Evaluation as Evaluation
# import Evaluation as Evaluation
```

[2]:
```python
# Read songs metadata
songs_metadata = pd.read_csv(r'./data/original/songs_metadata.csv')
```

[3]:
```python
# Read (user_id, song_id, listen_count) triplets data
# File has been downloaded from https://static.turi.com/datasets/millionsong/
↪10000.txt
# Which is a subset of The Echo Nest Taste Profile Subset from http://
↪millionsongdataset.com/tasteprofile
users_data = pd.read_fwf(r'./data/original/users_data.txt')
```

[4]:
```python
# Create Pandas DataFrame from songs metadata
songs_metadata = pd.DataFrame(songs_metadata)
songs_metadata
```

[4]:
```
                 song_id                              release  \
0     SOSZNRJ12A8AE46E38  Juno - Music From The Motion Picture
1     SOGKGLB12A81C22AFA                            Graduation
2     SOWZDNH12A6D4F7237                           Page Avenue
3     SOQBGZD12AB0184341                                 Riot!
4     SOTPWHK12A8AE46DC8                            Love Songs
…                    …                                    …
9995  SOKGVJH12A58A77920                        Rubber Factory
9996  SOINBEP12AB017FEE1                                 Rules
9997  SOETNKM12A8AE47EEA                   The Shepherd's Dog""
```

```
9998  SOKATLY12A8C132FE2                             The Score
9999  SOBPQCK12AF72A2FD5                       In A Safe Place

      release_7digitalid           artist_id             artist_name  \
0                 186998  AR62GN71187B9AAD0C  Michael Cera & Ellen Page
1                 131059  ARRH63Y1187FB47783       Kanye West / Mos Def
2                  44099  ARF6ZTO1187FB3684F         Story Of The Year
3                 512467  AR4OU721187FB4549D                  Paramore
4                 299449  ARWPYQI1187FB4D55A               Rick Astley
…                      …                   …                         …
9995              556606  ARS8GNX1187B9B5141            The Black Keys
9996              411787  AR5NQPT1187FB45A43      The Whitest Boy Alive
9997              135301  AR4XX0N1187FB45C21             Iron And Wine
9998              284274  ARGYWM01187B98DB75                    Fugees
9999              507084  ARVIZ6L1187FB509A5            The Album Leaf

      artist_hotttnesss   duration  key_confidence  loudness  mode_confidence  \
0              0.464981  116.71465           0.819   -12.947            0.629
1              1.082503  313.28608           0.812    -7.750            0.768
2              0.580095  235.78077           0.245    -4.103            0.380
3              0.658925  226.95138           0.420    -5.120            0.543
4              0.507464  185.67791           0.615    -5.471            0.513
…                     …          …               …         …                …
9995           0.741724  147.93098           0.089    -5.114            0.577
9996           0.502305  423.49669           0.450    -9.291            0.639
9997           0.535342  261.82485           0.180    -8.754            0.314
9998           0.514986  260.12689           0.570   -10.944            0.469
9999           0.507750  262.29506           0.599    -9.205            0.687

      song_hotttnesss    tempo  time_signature_confidence  \
0                 NaN  145.921                      0.401
1                 NaN  165.589                      1.000
2            0.470560  183.976                      0.535
3            0.726918   96.135                      0.301
4            0.480611  120.074                      0.540
…                   …        …                          …
9995         0.809308   86.709                      0.661
9996         0.837390   83.041                      1.000
9997         0.820511  117.137                      0.530
9998              NaN   89.962                      1.000
9999         0.727529   83.446                      0.430

                                  title           track_id  year
0                  Anyone Else But You  TRMMCDR128F423AB03  2007
1                  Drunk and Hot Girls  TRMMFSL128F4234583  2007
2     Until The Day I Die (Album Version)  TRMMQSP128F1486267  2003
3                        Rewind (Demo)  TRMMQOL128F9340687     0
```

```
4                          Never Knew Love  TRMMZKU128F4296801  1991
…                                        …                   …    …
9995                        Grown So Ugly  TRYYJHJ128F9340B19  2004
9996                               Island  TRYYJQY128F9320622  2009
9997              House By the Sea (Album)  TRYYDLF128F423BB17  2007
9998                            FU-GEE-LA  TRYYONN128F426A856  1996
9999                      The Outer Banks  TRYYXRZ128F9331D61  2004

[10000 rows x 16 columns]
```

[5]:

```python
# Fill NaN or missing values by Mean Value of the Column of songs metadata
songs_metadata.fillna(songs_metadata.mean(), inplace=True)

# Columnwise Statistical Analysis of songs_metadata
songs_metadata.describe()
```

[5]:

```
       release_7digitalid  artist_hotttnesss      duration  key_confidence  \
count        10000.000000       10000.000000  10000.000000     10000.00000
mean        292757.994300           0.562495    248.918150         0.45785
std         235662.258444           0.131789     98.301002         0.27146
min             20.000000           0.000000     11.989750         0.00000
25%          62241.000000           0.488339    200.646080         0.24600
50%         274648.000000           0.549302    235.519550         0.47800
75%         476071.000000           0.607257    277.975060         0.65800
max         823416.000000           1.082503   3024.665670         1.00000

           loudness  mode_confidence  song_hotttnesss         tempo  \
count  10000.000000     10000.000000     10000.000000  10000.000000
mean      -8.034781         0.492390         0.715694    125.165801
std        3.900603         0.189487         0.156077     32.700260
min      -39.217000         0.000000         0.000000      0.000000
25%       -9.823500         0.378000         0.669003    100.027000
50%       -7.153000         0.503000         0.716719    122.816000
75%       -5.316000         0.621000         0.810360    145.917250
max        1.421000         1.000000         1.000000    260.231000

       time_signature_confidence          year
count               10000.000000  10000.000000
mean                    0.559688   1645.790700
std                     0.362232    764.117466
min                     0.000000      0.000000
25%                     0.234000   1984.000000
50%                     0.620000   2002.000000
75%                     0.902250   2007.000000
max                     1.000000   2010.000000
```

[6]:
```
# Add Columns to the user triplets data
users_data.columns = ['user_id', 'song_id', 'listen_count']

# Create Pandas DataFrame from user triplets data
users_data = pd.DataFrame(users_data)
users_data
```

[6]:
```
                                          user_id             song_id  \
0        b80344d063b5ccb3212f76538f3d9e43d87dca9e  SOBBMDR12A8C13253B
1        b80344d063b5ccb3212f76538f3d9e43d87dca9e  SOBXHDL12A81C204C0
2        b80344d063b5ccb3212f76538f3d9e43d87dca9e  SOBYHAJ12A6701BF1D
3        b80344d063b5ccb3212f76538f3d9e43d87dca9e  SODACBL12A8C13C273
4        b80344d063b5ccb3212f76538f3d9e43d87dca9e  SODDNQT12A6D4F5F7E
…                                             …                   …
1999994  d8bfd4ec88f0f3773a9e022e3c1a0f1d3b7b6a92  SOJEYPO12AAA8C6B0E
1999995  d8bfd4ec88f0f3773a9e022e3c1a0f1d3b7b6a92  SOJJYDE12AF729FC16
1999996  d8bfd4ec88f0f3773a9e022e3c1a0f1d3b7b6a92  SOJKQSF12A6D4F5EE9
1999997  d8bfd4ec88f0f3773a9e022e3c1a0f1d3b7b6a92  SOJUXGA12AC961885C
1999998  d8bfd4ec88f0f3773a9e022e3c1a0f1d3b7b6a92  SOJYOLS12A8C13C06F

         listen_count
0                   2
1                   1
2                   1
3                   1
4                   5
…                 …
1999994             2
1999995             4
1999996             3
1999997             1
1999998             1

[1999999 rows x 3 columns]
```

[7]:
```
# No. of Unique Users in the users triplets Dataset
users = list(users_data["user_id"].unique())
print("Unique Users in the users triplets Dataset:",␣
 ↪len(set(users_data["user_id"])))

# No. of Unique Songs in the users triplets Dataset
songs = list(users_data["user_id"].unique())
print("Unique Songs in the users triplets Dataset:",␣
 ↪len(set(users_data["song_id"])))

# No. of Unique Songs in the songs metadata Dataset
```

```
print("Unique Songs in the songs metadata Dataset:",␣
↪len(set(songs_metadata["song_id"])))
```

```
Unique Users in the users triplets Dataset: 76353
Unique Songs in the users triplets Dataset: 10000
Unique Songs in the songs metadata Dataset: 10000
```

[8]:
```
# Merge user_data and song_data to visulaize the DataFrame
data = pd.merge(users_data, songs_metadata.drop_duplicates(["song_id"]),␣
↪how="left", on="song_id")
# data = data.head(100000)
data
```

[8]:
```
                                         user_id             song_id  \
0        b80344d063b5ccb3212f76538f3d9e43d87dca9e  SOBBMDR12A8C13253B
1        b80344d063b5ccb3212f76538f3d9e43d87dca9e  SOBXHDL12A81C204C0
2        b80344d063b5ccb3212f76538f3d9e43d87dca9e  SOBYHAJ12A6701BF1D
3        b80344d063b5ccb3212f76538f3d9e43d87dca9e  SODACBL12A8C13C273
4        b80344d063b5ccb3212f76538f3d9e43d87dca9e  SODDNQT12A6D4F5F7E
…                                            …                   …
1999994  d8bfd4ec88f0f3773a9e022e3c1a0f1d3b7b6a92  SOJEYPO12AAA8C6B0E
1999995  d8bfd4ec88f0f3773a9e022e3c1a0f1d3b7b6a92  SOJJYDE12AF729FC16
1999996  d8bfd4ec88f0f3773a9e022e3c1a0f1d3b7b6a92  SOJKQSF12A6D4F5EE9
1999997  d8bfd4ec88f0f3773a9e022e3c1a0f1d3b7b6a92  SOJUXGA12AC961885C
1999998  d8bfd4ec88f0f3773a9e022e3c1a0f1d3b7b6a92  SOJYOLS12A8C13C06F

         listen_count                        release  release_7digitalid  \
0                   2     Flamenco Para Ni\xc3\xb1os              241239
1                   1                     Graduation              130573
2                   1              In Between Dreams              221729
3                   1  There Is Nothing Left To Lose              298758
4                   5   Antolog\xc3\xada Audiovisual               19998
…                 …                              …                   …
1999994             2                      Ignorance              528820
1999995             4                      Love Drunk              565820
1999996             3                 What I've Done""              81728
1999997             1                       My Worlds              767482
1999998             1                         The Con              113817

                  artist_id                  artist_name  \
0        ARC1SF21187FB51D0F               Paco De Lucia
1        ARRH63Y1187FB47783                  Kanye West
2        ARC8CQZ1187B98DECA                Jack Johnson
3        AR6XPWV1187B9ADAEB                Foo Fighters
4        AR3SPD91187B9B63E3   H\xc3\xa9roes del Silencio
…                       …                          …
1999994  AR4OU721187FB4549D                    Paramore
```

```
1999995  ARG72Q21187FB36243  Boys Like Girls featuring Taylor Swift
1999996  ARQUMH41187B9AF699                             Linkin Park
1999997  ARFCWSZ123526A0AFD                           Justin Bieber
1999998  ARAI3JW1187FB52DE1                          Tegan And Sara

         artist_hotttnesss   duration  key_confidence  loudness  \
0                 0.417718  358.24281           0.745    -7.164
1                 1.082503  311.84934           0.183    -8.394
2                 0.694129  201.63873           0.051   -12.595
3                 0.550762  235.28444           0.699    -4.128
4                 0.524063  231.36608           0.376    -4.555
…                        …          …             …         …
1999994           0.658925  218.09587           0.619    -2.829
1999995           0.587033  242.83383           0.599    -5.468
1999996           0.791143  208.92689           0.752    -5.109
1999997           0.691249  234.91873           0.557    -4.560
1999998           0.632884   82.96444           0.514   -10.958

         mode_confidence  song_hotttnesss    tempo  time_signature_confidence  \
0                  0.724         0.735295  192.975                      0.392
1                  0.180         0.715694  138.570                      1.000
2                  0.453         0.785447  121.868                      0.277
3                  0.855         0.986142  136.099                      0.764
4                  0.536         0.715694  169.836                      0.377
…                    …              …        …                       …
1999994            0.523         1.000000  170.970                      0.921
1999995            0.628         0.853353  127.987                      0.553
1999996            0.488         1.000000  120.065                      0.792
1999997            0.545         0.809942  125.944                      0.886
1999998            0.680         0.910720  131.166                      0.698

                             title            track_id  year
0                  Entre Dos Aguas  TRMHBXZ128F4238406  1976
1                         Stronger  TRHNCIR128F42334A5  2007
2                   Constellations  TRYBNIB128F428E704  2005
3                     Learn To Fly  TRKRHYM128F42934A9  1999
4       Apuesta Por El Rock 'N' Roll""  TRPTWGR128F1452734  2007
…                                …                 …    …
1999994       Ignorance (Album Version)  TRGQGIM128F92F438F     0
1999995          Two Is Better Than One  TRAWVYP128F9305DF2  2009
1999996  What I've Done (Album Version)""  TRTWFKE128EF35F93B  2007
1999997                               Up  TRZAVEC12903CD2DD2  2010
1999998        Soil_ Soil (Album Version)  TRZWHPU128F429B80F  2007

[1999999 rows x 18 columns]
```

```
[9]: # Print the Length of the merged Dataset
print(len(data))
```

```
1999999
```

2.2 Randomly Split Dataset into Train and Test Data

Our Data Contains about **76k Unique Users and 10k Unique Songs and their Listen Count alongwith Song Metadata**. Each User in the Dataset has listened to a Song in the Past i.e every User has Listen Count >0 and thus, each Song has been listened atleast once.

Let us split the Data into Train Data (80%) and Test Data (20%). So that we can Train, Evaluate and Compare our various Models.

```
[10]: # Randomly split data into train (80%) and test (20%) data with seed = 0
train_data, test_data = train_test_split(data, test_size = 0.20, random_state=0)
```

```
[11]: # Unique Users in train_data Dataset
train_users = list(train_data["user_id"].unique())
print("No. of Unique Users in train_data Dataset:", len(train_users))

# Unique Songs in the train_data Dataset
train_songs = list(train_data["song_id"].unique())
print("No. of Unique Songs in train_data Dataset:", len(train_songs))

# Unique Users in the test_data Dataset
test_users = list(test_data["user_id"].unique())
print("No. of Unique Users in test_data Dataset:", len(test_users))

# Unique Songs in the test_data Dataset
test_songs = list(test_data["song_id"].unique())
print("No. of Unique Songs in test_data Dataset:", len(test_songs))

# Unique Common Users in train_data and test_data Dataset
common_users = list(set(test_users).intersection(set(train_users)))
print("No. of Unique Common Users in train_data and test_data Dataset:",␣
 ↪len(common_users))

# Unique Common Songs in train_data and test_data Dataset
common_songs = list(set(test_songs).intersection(set(train_songs)))
print("No. of Unique Common Songs in train_data and test_data Dataset:",␣
 ↪len(common_songs))
```

```
No. of Unique Users in train_data Dataset: 76104
No. of Unique Songs in train_data Dataset: 10000
No. of Unique Users in test_data Dataset: 68637
No. of Unique Songs in test_data Dataset: 10000
No. of Unique Common Users in train_data and test_data Dataset: 68388
```

```
No. of Unique Common Songs in train_data and test_data Dataset: 10000
```

2.3 Normalising Songs Metadata

Features or Metadata of Songs in our Dataset contain varying values with different scales or ranges. Some of the Features are string and thus needed to be dropped for the Normalisation so that we can fit our KNN Model on the Train Set. Also, Songs Metadata is not much useful for other Techniques/ Models discussed below and hence we should irrelevant features from our Dataset.

[12]:
```python
# Extracting Unique Songs Metadata from train_data Dataset
train_songs_df = train_data.drop_duplicates(['song_id'])

# Extracting Unique Songs Metadata from test_data Dataset
test_songs_df = test_data.drop_duplicates(['song_id'])

# Dropping not needed features from train and test Songs Metadata
drop_features_songs =␣
 ↪["user_id","song_id","release","release_7digitalid","artist_id","artist_name","title","trac
train_songs_metadata = train_songs_df.drop(drop_features_songs, axis=1)
test_songs_metadata = test_songs_df.drop(drop_features_songs, axis=1)
```

[13]:
```python
# Dropping not needed features from train_data and test_data Datasets
data = data[['user_id','song_id','title','listen_count']]
train_data = train_data[['user_id','song_id','title','listen_count']]
test_data = test_data[['user_id','song_id','title','listen_count']]

# Saving the cleaned dataset (in pickle i.e .pkl file format) for future␣
 ↪computations
data.to_pickle("./data/data.pkl")
train_data.to_pickle("./data/train_data.pkl")
test_data.to_pickle("./data/test_data.pkl")
```

[14]:
```python
# data normalization with sklearn
from sklearn.preprocessing import MinMaxScaler

# fit scaler on training data
norm = MinMaxScaler().fit(train_songs_metadata)

# transform training data
train_songs_metadata_norm = norm.transform(train_songs_metadata)

# transform testing data
test_songs_metadata_norm = norm.transform(test_songs_metadata)
```

[15]:
```python
# Loading the Cleaned Dataset for Training and Testing Our Models.
data = pd.read_pickle("./data/data.pkl")
train_data = pd.read_pickle("./data/train_data.pkl")
test_data = pd.read_pickle("./data/test_data.pkl")
```

2.4 Import Utilities

While doing the code, I realised that there are few things about our Dataset which is required in Training and Testing of the Models that we are going to implement. So, I prepared a Script (which can be found in the root folder of this Project) to generate:

1. **Utility Dictionary**: Python Dictionary (Hash Table) containing Dictionaries of:
    1. **Songs_to_Users (s2u) Mapping**: Key as Song and Value as List of Listeneres of that Song
    2. **Users_to_Songs (u2s) Mapping**: Key as User and Value as List of Songs User has listened
    3. **Songs_to_Titles (s2t) Mapping**: Key as Song and Value as Title of that Song
    4. **Songs_to_Index (s2i) Mapping**: Key as Song and Value as Index of that Song
    5. **Users_to_Index (u2i) Mapping**: Key as Song and Value as Index of that Song
    6. **Songs (songs) Mapping**: List of all Unique Songs
    7. **Users (users) Mapping**: List of all Unique Users
2. **Rating Matrix(M)**: *Sparse Matrix* of order **(no. of users x no. of songs)** with $M_{ij} = 1$ **if User i has listened to Song j otherwise 0**. This is what we call **Implicit Feedback or Implicit Rating**. It is this Spase Nature of this Matrix (Implicit Feedback i.e No Rating Given by User) which makes this problem really Challenging.

[16]:
```python
# Import Utility Functions/ Mappings from utility_script
import utility_script as utility

util_dict = utility.gen_util_dict()
data_util_dict = util_dict["data"]
train_util_dict = util_dict["train_data"]
test_util_dict = util_dict["test_data"]
```

2.5 Popularity Model

As the Name Suggests, this Model is a naive approach for recommending the Most Popular Songs (sorted by their percentage of listen count indicating their popularity) to the User. After sorting them by their popularity, we remove songs already listened by the User from Recommendation List. There is no personalisation involved in this Model which can be confirmed below as our Model will recommend same popular songs to all the users. However, It is very helpful in the case when our Users are Guest Users, those who don't share any Preferences or Information about themselves about which song they like or not and hence, these models can help make our Recommender Systems Smart by even recommending something *Trending* to the Users to listen to (better than recommending nothing :))

[17]:
```python
# Create Popularity Model Instance
popularity_model = Recommenders.popularity_recommender()
popularity_model.create(train_util_dict)
```

[18]:
```python
# Get Recommendations for a User
popularity_model.recommend(test_users[50])
```

[18]:
```
                 song_id                            title  listen_count  \
2220  SOFRQTD12A81C233C0                   Sehr kosmisch          6612
317   SOAUWYT12A81C206F1                            Undo          5647
352   SOAXGDH12A8C13F8A1  Dog Days Are Over (Radio Edit)          5485
614   SOBONKR12A58A7A7E0                You're The One""          5085
7416  SOSXLTC12AF72A7F54                          Revelry          4952
…                    …                               …          …
7289  SOSNOSA12A67ADA05B                            Woman           390
7754  SOTUARP12A8C13CB54                              Rio           390
4596  SOLOZRE12A8C133256                      M79 (Album)           389
6636  SOQTPLM12B0B809575                    Strange Times           389
7584  SOTHQRU12A58A78698              I Put A Spell On You          389

         score
2220  0.413250
317   0.352938
352   0.342813
614   0.317813
7416  0.309500
…          …
7289  0.024375
7754  0.024375
4596  0.024313
6636  0.024313
7584  0.024313

[500 rows x 4 columns]
```

2.5.1 Calculation of mAP@500 score for Popularity Model

Using mAP (Mean Average Precision) to evaluate a recommender algorithm implies that we are treating the recommendation like a ranking task. This often makes perfect sense because a user has a finite amount of time and attention and we want to show the top recommendations first and maybe market them more aggressively. We have used it as percentage i.e in %. A recommender system typically produces an ordered list of recommendations for each user in the test set. mAP gives insight into how relevant the list of recommended items are. The Higher the mAP score, the Better is our Recommender System.

[19]:
```
%%time
# Calcuate mAP@500 for test Sample
mAP_at_tau = Evaluation.maptau(popularity_model, common_users, test_util_dict,␣
 ↪sampling_rate=0.3, tau=500)
print("----------------------------------")
print("mAPat500 for test sample is:", mAP_at_tau, "%")
print("----------------------------------")
```

```
Length of user_test_and_training:68388
Length of user sample:20516
```

```
1 0.3153779897965944 %
10001 2.7252125005106373 %
20001 2.624632763284519 %
20516 2.6147447408969695 %
---------------------------------
mAPat500 for test sample is: 2.6147447408969695 %
---------------------------------
CPU times: user 1min 5s, sys: 1.04 s, total: 1min 6s
Wall time: 1min 11s
```

2.6 K Nearest Neighbors (KNN) Model

Songs in our Dataset have a limited (or rather very few) amount of Metadata associated with each song and this make it a tough job for KNN to figure the most similar Songs among the available Dataset. This Algorithm returns two ordered Lists namely Indices and Distances after single pass through our songs metadata (training data) (after Normalisation) which contains the indices of Songs which are most similar to the given songs, sorted in order w.r.t the distances between them calculated using Ball Tree Algorithm in which *The number of candidate points for a neighbor search is reduced through use of the triangle inequality.* From these Indices and Distances, I have assigned a *Score (equal to -ve of the distance value)* to each Recommended Song and then after removing the songs already listened by the user, Sorted the Final Recommended Songs as per their Scores (in reverse Order) for the final Recommendations. More Detail about the implementation can be understood using/ through the Code provided in root folder of this Project.

[20]:
```
# Create KNN Model Instance
knn_model = Recommenders.knn_recommender()
knn_model.create(train_songs_metadata_norm,train_util_dict,n_neighbors=10)
```

[21]:
```
# Get Recommendations for a User
knn_model.recommend(test_users[10])
```

[21]:
```
               song_id                                  title     score
0   SOPRFNT12AB017F8E9                      Genie In A Bottle -0.092336
1   SOFKYDZ12AB017F425                           Stadium Love -0.094529
2   SOFHEAN12AB018A760                                  Drugs -0.108188
3   SORRBVQ12A58A7AA33                                 Change -0.113325
4   SOVMSAW12A6D4F95A4            Mount Wroclai (Idle Days) -0.116675
..                 …                                      …         …
67  SOODRHW12A6310D8FF                                   Rent -0.334263
68  SOODWNJ12AC4688DA4                               Evidence -0.336109
69  SOGOZLT12A6D4FB302            Teenagers (Album Version) -0.346826
70  SOUXTDJ12A6D4F95B7  A Boy Brushed Red Living In Black And White -0.351125
71  SOTUARP12A8C13CB54                                    Rio -0.361572

[72 rows x 3 columns]
```

[22]:
```
# Get Similar Songs for a Song
knn_model.get_similar_items(test_songs[180])
```

[22]:

```
                song_id                              title     score
0  SOOVJIX12A6D4F8B6B  You Are the Moon (Album Version)  0.197179
1  SODWXJW12AAA8C5C29              Hochmah (Interlude)  0.198826
2  SOMUWFQ12AB0184608         Lookin' Out My Back Door""  0.214250
3  SODCOKD12A8C138E59                       TULENLIEKKI  0.215058
4  SOBGQHH12A8151CAC5        M\xc3\xbasica Para Una Boda  0.226117
5  SOSTPEJ12AB017F9A5                    Fiddlin' Bill""  0.228197
6  SOIZFTE12AB0186842                        Fuck Kitty  0.240095
7  SOTJXIH12A6D228208                        The Vision  0.241915
8  SOGTWVV12AB0180C03                   Where I Come From  0.249239
```

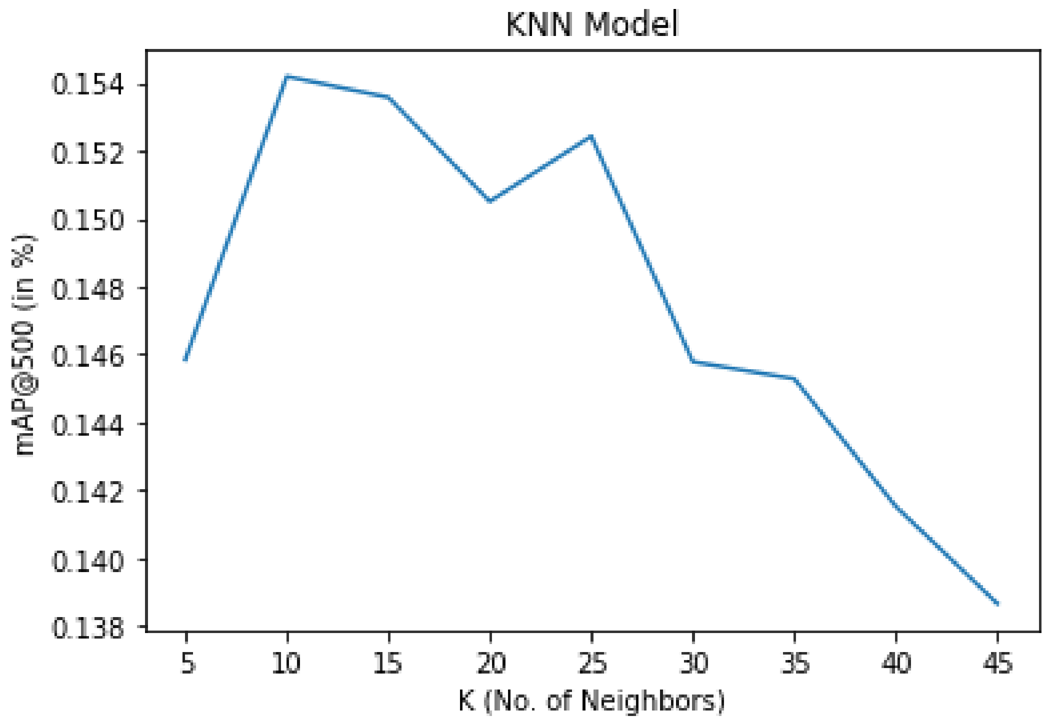
2.6.1 Tuning the Hyperparameter k i.e No. of Nearest Neighbors for kNN Model

A hyperparameter, k (no. of nearest neighbors) is involved with KNN Model. Now our Goal is to find the value of k for which maP@500 score for KNN Model comes out to be maximum. For this, I calculated mAP@500 score at different values of k and noted the value of k at which mAP@500 is max. The Max. Value of mAP@500 is acheived at $k = 10$ with $mAP@500 = 0.154$ (in %).

[23]:

```
from matplotlib import pyplot as plt

# Load the Values of mAP@500 precomputed by me on Kaggle Kernel for KNN Model
k_values, map_values = pickle.load(open("./list/knn/k_map_list_knn.pkl","rb"))

map_max = max(map_values)
k_map_max = k_values[map_values.index(map_max)]

# Print Max value of mAP@500 (in %)
print("Max Value of mAP@500 (in %) is:", map_max, "for k:", k_map_max)

# Plot the Graph
plt.plot(k_values,map_values)
plt.title("KNN Model")
plt.xlabel("K (No. of Neighbors)")
plt.ylabel("mAP@500 (in %)")
plt.show()
```

```
Max Value of mAP@500 (in %) is: 0.15418329988580978 for k: 10
```



2.6.2 Calculation of mAP@500 score for kNN Model

[24]:
```
%%time
# Calcuate mAP@500 for test Sample
mAP_at_tau = Evaluation.maptau(knn_model, common_users, test_util_dict,␣
 ↪sampling_rate=0.3, tau=500)
print("----------------------------------")
print("mAPat500 for test sample is:", mAP_at_tau, "%")
print("----------------------------------")
```

```
Length of user_test_and_training:68388
Length of user sample:20516
1 0.0 %
10001 0.14833763166523334 %
20001 0.15692185261736744 %
20516 0.16250122951196716 %
---------------------------------
mAPat500 for test sample is: 0.16250122951196716 %
---------------------------------
CPU times: user 9.28 s, sys: 98.6 ms, total: 9.38 s
Wall time: 9.59 s
```

2.7 SVD - Latent Factors Based Model

In its simplest form, a latent factor model decomposes the Rating/ Feedback matrix M into a latent feature space which relates users to items (and vice versa). This is usually achieved by factoring the matrix M as $M = U.S.Vt$ where **Matrix U is of shape(m,k), S is of shape(k,k) and Vt of shape(k,n) (by shape, i mean Order) where m = No. of users, n = No. of Songs and k = No. of latent factors associated with Users and Songs**. Here, Matrix U contains Latent Factors for the users (row wise) and Matrix Vt contains Latent Factors of the Songs (column wise) and then the Recommendation Matrix R is calculated as Product of Matrices U and Vt i.e $R = U.Vt$ such that **R is of shape(m,n)** and we call this Matrix, the Recommendation Matrix. Now, Given a User u, We find the List (or Row) of Songs R_u and Sort the Values of it in Decreasing Order and then we call it the Recommendation List containg Recommended Songs in Sorted Order of their Score calculated via SVD. Finally, We Remove the Songs Already listened by User from our Recommendation List.

[25]:
```
# Generate Feedback / Rating Matrix M for SVD
M = utility.gen_M()
```

[26]:
```
%%time
# Create SVD Model Instance
svd_model = Recommenders.svd_recommender()
svd_model.create(M, train_util_dict , k=1300)
```

```
CPU times: user 5min 22s, sys: 13 s, total: 5min 35s
Wall time: 3min 43s
```

[27]:
```
# Get Recommendations for a User
svd_model.recommend(test_users[4000])
```

[27]:
```
                song_id                                       title  \
0    SOFOSTI12A6701D7BE                               The Last Song
1    SOYPRBR12A8C14396C         Mona Lisa (When The World Comes Down)
2    SOKOTYF12A8C13F2E7                                 Too Far Gone
3    SOIPFGR12B0B8063CB                                   Drive Away
4    SONXHLT12A8AE48546                                 October Song
..                  …                                           …
495  SOLMDRD12A8C132D16                             Ciega_ Sordomuda
496  SOHWNCK12A67020845                             Used To Love Her
497  SOOSVUB12A8C13B13F  Aber Dich Gibt's Nur Einmal F\xc3\xbcr Mich""
498  SOPLVFB12A8C141022                                     Undantag
499  SOWCUCK12AB0182AD1                                  End Credits

        score
0    0.007911
1    0.007695
2    0.007560
3    0.006776
4    0.005017
```

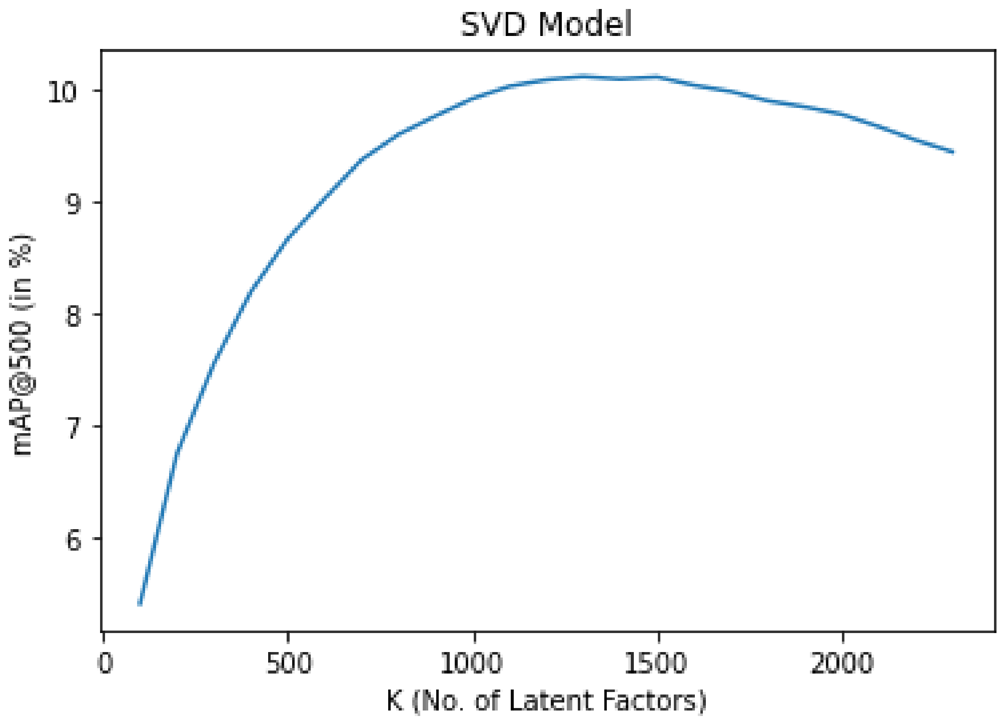
```
..        …
495   0.000937
496   0.000937
497   0.000937
498   0.000936
499   0.000936

[500 rows x 3 columns]
```

2.7.1 Tuning the Hyperparameter k i.e No. of Latent Factors for SVD Model

A hyperparameter, k (no. of latent factors) is involved with SVD Model. Now our Goal is to find the value of k for which maP@500 score for SVD Model comes out to be maximum. For this, I calculated mAP@500 score at different values of k and noted the value of k at which mAP@500 is max. The Max. Value of mAP@500 is acheived at $k = 1300$ with $mAP@500 = 10.124$ (in %).

[28]:
```python
from matplotlib import pyplot as plt

# Load the Values of mAP@500 precomputed by me on Kaggle Kernel for SVD Model
k_values, map_values = pickle.load(open("./list/svd/k_map_list_svd.pkl","rb"))

map_max = max(map_values)
k_map_max = k_values[map_values.index(map_max)]

# Print Max value of mAP@500 (in %)
print("Max Value of mAP@500 (in %) is:", map_max, "for k:", k_map_max)

#Plot the Graph
plt.plot(k_values,map_values)
plt.title("SVD Model")
plt.xlabel("K (No. of Latent Factors)")
plt.ylabel("mAP@500 (in %)")
plt.show()
```

```
Max Value of mAP@500 (in %) is: 10.12416129008201 for k: 1300
```



2.7.2 Calculation of mAP@500 score for SVD Model

[29]:
```
%%time
# Calcuate mAP@500 for test Sample
mAP_at_tau = Evaluation.maptau(svd_model, common_users, test_util_dict,␣
 ↪sampling_rate=0.3, tau=500)
print("----------------------------------")
print("mAPat500 for test sample is:", mAP_at_tau, "%")
print("----------------------------------")
```

```
Length of user_test_and_training:68388
Length of user sample:20516
1 11.953183874204882 %
10001 9.923972849060076 %
20001 9.990921248911903 %
20516 9.988868009326358 %
---------------------------------
mAPat500 for test sample is: 9.988868009326358 %
---------------------------------
CPU times: user 53.4 s, sys: 1.83 s, total: 55.2 s
Wall time: 1min 7s
```

2.8 Collaborative Filtering (Memory CF)

Collaborative filtering involves collecting information from many users and then making predictions based on some similarity measures between users and between items. This can be classified into user_user and item_item based models. In **item_item based model**, it is assumed that songs that are often listened together by some users tend to be similar and are more likely to be listened together in future also by some other user i.e If Songs S_i and S_j are listened together by the users U_1, U_2 , ... U_{n-1} and now a new user Un listens to a song S_i , then there is very high probability that user Un will also listen to song S_j as Both S_i and S_j have similar listening histories. Similarly, **User_User based model**, it is assumed that users who have similar listening histories, i.e., have listened to the same songs in the past tend to have similar interests and will probably listen to the same songs i.e If users U_u and U_v listened together the songs S_1, S_2 , ... S_{n-1} and now user Uu listens to a new song S_n , then there is very high probability that user Uv will also listen to song Sn as Both U_u and U_v have similar listening histories. Now, for both the Models, We need some similarity measure $w_{i,j}$ (for item item) and $w_{u,v}$ (for user user) to compare between two songs or between two users. One of the Similarity scores, can be Cosine similarity, but it weighs each of the users equally which is usually not the case. A user should be weighted less if he has shown interest in many varieties of items (it shows that either he/she does not discern between songs based on their quality, or just likes to explore). So, I have used two Similarity Measures namely: 1. **Jaccard Based Score:** Sorted Songs according to the Jaccard Index/ Score (More Info here or given in the report of this project) 2. **Conditional Probability Score:** Sorted according to the Score obtained using Conditional Probability (More Info here or given in the report of this project) One by One Implementation of the above measures into item_item CF and user_user CF Models have been given below:

2.8.1 Item_Item_Jaccard_CF Model

[30]:
```
import Rec as Recommenders
import importlib
importlib.reload(Recommenders)
# Create Item_Item_Jaccard_Prob Model Instance
song_sim_jaccard_model = Recommenders.cf_sim_recommender(type="item_item",␣
↪method="jaccard")
song_sim_jaccard_model.create(train_util_dict)
```

[31]:
```
%%time
# Get Recommendations for a User
song_sim_jaccard_model.recommend(test_users[40])
```

```
CPU times: user 1min 21s, sys: 1.34 s, total: 1min 22s
Wall time: 1min 28s
```

[31]:

	song_id	title	score
0	SOKLRPJ12A8C13C3FE	The Scientist	1.202910
1	SOWEJXA12A6701C574	Fix You	1.109421
2	SONYKOW12AB01849C9	Secrets	0.999492
3	SOCVTLJ12A6310F0FD	Clocks	0.984298
4	SOPXKYD12A6D4FA876	Yellow	0.934155

```
..                   …                              …         …
495  SOAVWHY12AB017C6C0                   Losing Touch  0.195036
496  SOEMUXL12A58A7B848                           Reha  0.194938
497  SOODHLO12AF72A1980                      The Joker  0.194718
498  SOQUJLT12A8C141F8A  My Life Would Suck Without You  0.194511
499  SOLWEKA12A8C145D56             Not Every Man Lives  0.194358

[500 rows x 3 columns]
```

[32]:
```
%%time
# Get Similar Songs for a Song
song_sim_jaccard_model.get_similar_items(test_songs[1080])
```

```
CPU times: user 834 ms, sys: 14.7 ms, total: 849 ms
Wall time: 887 ms
```

[32]:
```
                song_id                     title     score
0     SOHGFMT12A6D4FA66F    Red Rabbits (Album)  0.185874
1     SOTCPQN12A6D4FA673    Girl Sailor (Album)  0.180451
2     SOKZKDF12A6D4FA670     Turn On Me (Album)  0.172185
3     SOVFFSK12A6BD55C96      Australia (Album)  0.162371
4     SOSVTWI12A6D4FA672  Spilt Needles (Album)  0.159696
…                    …                      …        …
9995  SOIWAFI12A6D4F722E           A Good Heart  0.000000
9996  SORPBJG12AB017EA14          Aero Zeppelin  0.000000
9997  SOEBPPM12AB0187E1C  Sunshine Of Your Love  0.000000
9998  SOKBSZY12AB017BD8B           When In Rome  0.000000
9999  SOSHVVD12AF72A3EB9    A Cloak Of Elvenkind  0.000000

[10000 rows x 3 columns]
```

2.8.2 Calculation of mAP@500 score for Item_Item_Jaccard_CF Model

[33]:
```
# Importing Pre Computed R Matrix for evaluation of Item_Item_Jaccard_Eval_CF␣
↪Model
R_item_jaccard = pickle.load(open("./data/item_item/R_item_jaccard.pkl","rb"))
```

[34]:
```
%%time
# Create the Item_Item_Jaccard_Eval_CF Model for Evaluation
song_sim_jaccard_eval_model = Recommenders.cf_recommender(type="item_item",␣
↪method="jaccard")
song_sim_jaccard_eval_model.create(M, train_util_dict, R=R_item_jaccard)

# Calcuate mAP@500 for test Sample
mAP_at_tau = Evaluation.maptau(song_sim_jaccard_eval_model, common_users,␣
↪test_util_dict, sampling_rate=0.3, tau=500)
print("----------------------------------")
```

```
print("mAPat500 for test sample is:", mAP_at_tau, "%")
print("---------------------------------")
```

```
Length of user_test_and_training:68388
Length of user sample:20516
1 2.247618120731598 %
10001 14.442092575568658 %
20001 14.46629331958562 %
20516 14.48872617213902 %
---------------------------------
mAPat500 for test sample is: 14.48872617213902 %
---------------------------------
CPU times: user 24.7 s, sys: 3.64 s, total: 28.4 s
Wall time: 36 s
```

2.8.3 Item_Item_Prob_CF Model

[35]:
```
import Rec as Recommenders
import importlib
importlib.reload(Recommenders)
# Create Item_Item_Prob_CF Similarity Model Instance
song_sim_prob_model = Recommenders.cf_sim_recommender(type="item_item",␣
↪method="prob")
song_sim_prob_model.create(train_util_dict, A=0.85, Q=1)
```

[36]:
```
%%time
#Get Recommendations for a user
song_sim_prob_model.recommend(test_users[87])
```

```
CPU times: user 51.8 s, sys: 863 ms, total: 52.7 s
Wall time: 1min 2s
```

[36]:

	song_id	title	score
0	SOYHKYO12AB018224C	My Maudlin Career	3.252165
1	SOFUYTQ12AC90719F0	Happy New Year	3.188823
2	SOCFPBP12AB0182D2B	Swans	3.154597
3	SOGXWGC12AF72A8F9A	Leave The Bourbon On The Shelf	3.147676
4	SOZFHVL12AB0182D22	You Told A Lie	3.147258
..	…	…	…
495	SODHJHX12A58A7D24C	Cold Desert	1.497701
496	SOQXTDZ12AF729F8B4	The List	1.496984
497	SOYMQKD12A6310D7EB	Take The Box	1.495764
498	SORXTFK12AB018A177	Blake\x19s View	1.494797
499	SOXMARU12AB017CDF7	Hello	1.492035

[500 rows x 3 columns]

[37]:
```
%%time
# Get Similar Songs for a Song
song_sim_prob_model.get_similar_items(test_songs[440])
```

```
CPU times: user 626 ms, sys: 11.3 ms, total: 638 ms
Wall time: 668 ms
```

[37]:
```
                song_id                                    title  \
0     SOPJLOZ12A8C132642                          Lafayette Blues
1     SOOYIHH12AB018C2C7       Let's Build A Home (Album Version)""
2     SOCVHMA12AB0185829         We Are Going To Be Friends (Live)
3     SODTTCN12A81C21907                               Good To Me
4     SOLCTNA12AB0185F52                           Nobody But You
…                    …                                         …
9995  SOEBPPM12AB0187E1C                     Sunshine Of Your Love
9996  SOYJUXS12AC95F02EF  I Swear This Time I Mean It (Album Version)
9997  SOKBSZY12AB017BD8B                              When In Rome
9998  SOWUVOQ12A58A80BD7                         Magic (LP Version)
9999  SOSHVVD12AF72A3EB9                       A Cloak Of Elvenkind

         score
0     0.267410
1     0.180568
2     0.140585
3     0.112257
4     0.106177
…          …
9995  0.000000
9996  0.000000
9997  0.000000
9998  0.000000
9999  0.000000

[10000 rows x 3 columns]
```

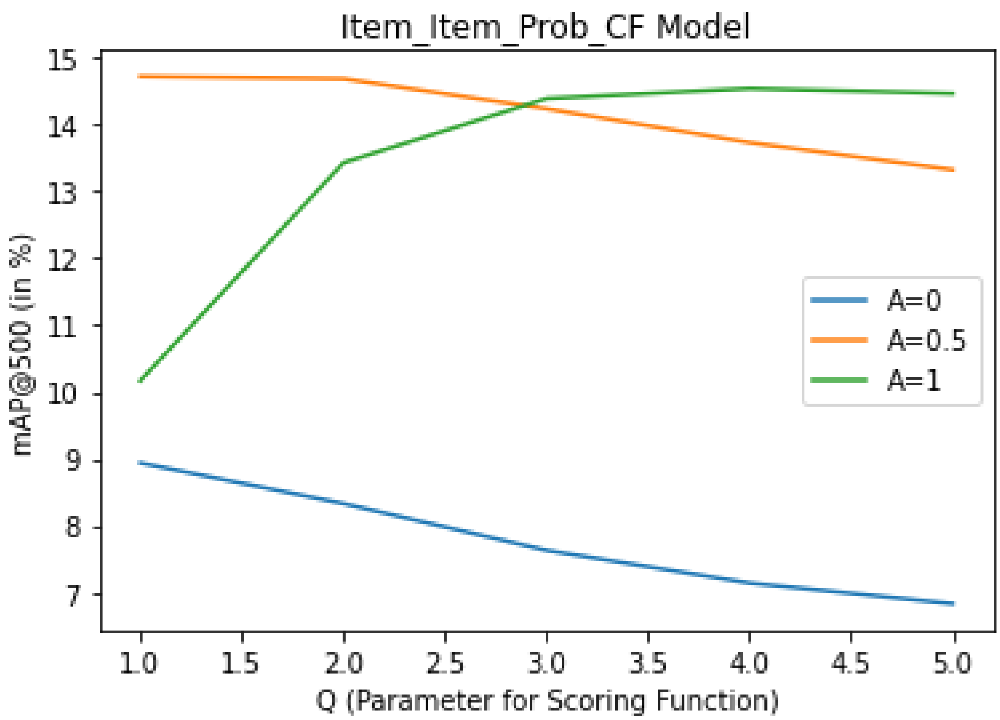
2.8.4 Tuning the Hyperparameters A (Similarity Function Parameter) and Q (Scoring Function Parameter) i.e for Item_Item_Prob Model

Hyperparameter, A and Q are involved with Item_Item_Prob Model. Now our Goal is to find the value of A and Q for which maP@500 score for Item_Item_Prob Model comes out to be maximum.

Tuning Hyperparameter Q For this, I calculated mAP@500 score for Item_Item_Prob Model at different values of Q keeping A as constant being equal to 0, 0.5 and 1 (corner values for A as $ 0<=A<=1 $) and noted the value of Q (keeping A constant) at which mAP@500 is max. The Max. Value of mAP@500 is acheived at $Q = 1$ for $A = 0.5$ with $mAP@500 = 14.723$ (in %).

[38]:
```
from matplotlib import pyplot as plt

# Load the Values of mAP@500 precomputed by me on Kaggle Kernel for␣
↪Item_Item_Prob_CF Model Model
Q_values_A0, map_values_A0 = pickle.load(open("./list/item_item_prob/
↪AQ_map_list_item_prob_A0.pkl","rb"))
Q_values_A05, map_values_A05 = pickle.load(open("./list/item_item_prob/
↪AQ_map_list_item_prob_A0.5.pkl","rb"))
Q_values_A1, map_values_A1 = pickle.load(open("./list/item_item_prob/
↪AQ_map_list_item_prob_A1.pkl","rb"))

map_max_A0 = max(map_values_A0)
Q_map_max_A0 = Q_values_A0[map_values_A0.index(map_max_A0)]

# Print Max value of mAP@500 (in %) at A=0
print("Max Value of mAP@500 (in %) at A=0 is:", map_max_A0, "for Q:",␣
↪Q_map_max_A0)

map_max_A05 = max(map_values_A05)
Q_map_max_A05 = Q_values_A05[map_values_A05.index(map_max_A05)]

# Print Max value of mAP@500 (in %)at A=0.5
print("Max Value of mAP@500 (in %) at A=0.5 is:", map_max_A05, "for Q:",␣
↪Q_map_max_A05)

map_max_A1 = max(map_values_A1)
Q_map_max_A1 = Q_values_A1[map_values_A1.index(map_max_A1)]

# Print Max value of mAP@500 (in %) at A=1
print("Max Value of mAP@500 (in %) at A=1 is:", map_max_A1, "for Q:",␣
↪Q_map_max_A1)

# Plot the Graph
plt.plot(Q_values_A0, map_values_A0, label='A=0')
plt.plot(Q_values_A05, map_values_A05, label='A=0.5')
plt.plot(Q_values_A1, map_values_A1, label='A=1')
plt.title("Item_Item_Prob_CF Model")
plt.xlabel("Q (Parameter for Scoring Function)")
plt.ylabel("mAP@500 (in %)")
plt.legend()
plt.show()
```

```
Max Value of mAP@500 (in %) at A=0 is: 8.938716173257392 for Q: 1
Max Value of mAP@500 (in %) at A=0.5 is: 14.723728738262002 for Q: 1
Max Value of mAP@500 (in %) at A=1 is: 14.544515334276923 for Q: 4
```

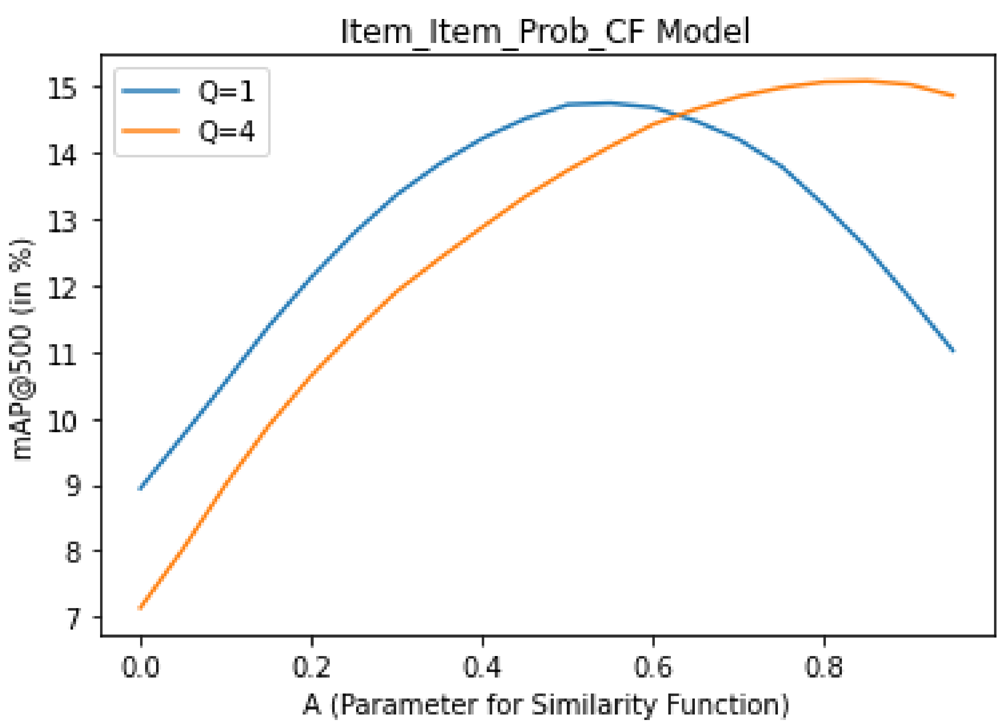


Tuning Hyperparameter A For this, I calculated mAP@500 score for Item_Item_Prob at different values of A keeping Q as constant being equal to 1 and 4 (corner values for Q for which mAP@500 was maximum for constant A) and noted the value of A (keeping Q constant) at which mAP@500 is max. The Max. Value of mAP@500 is acheived at $A = 0.85$ for $Q = 4$ with $mAP@500 = 15.080$ (in %).

[39]:
```
from matplotlib import pyplot as plt

# Load the Values of mAP@500 precomputed by me on Kaggle Kernel for␣
↪Item_Item_Prob_CF Model Model
A_values_Q1, map_values_Q1 = pickle.load(open("./list/item_item_prob/
↪AQ_map_list_item_prob_Q1.pkl","rb"))
A_values_Q4, map_values_Q4 = pickle.load(open("./list/item_item_prob/
↪AQ_map_list_item_prob_Q4.pkl","rb"))

map_max_Q1 = max(map_values_Q1)
A_map_max_Q1 = A_values_Q1[map_values_Q1.index(map_max_Q1)]

# Print Max value of mAP@500 (in %) at Q=1
print("Max Value of mAP@500 (in %) at Q=1 is:", map_max_Q1, "for A:",␣
↪A_map_max_Q1)

map_max_Q4 = max(map_values_Q4)
```

```
A_map_max_Q4 = A_values_Q4[map_values_Q4.index(map_max_Q4)]

# Print Max value of mAP@500 (in %) at Q=4
print("Max Value of mAP@500 (in %) at Q=4 is:", map_max_Q4, "for A:",␣
↪A_map_max_Q4)

# Plot the Graph
plt.plot(A_values_Q1, map_values_Q1, label='Q=1')
plt.plot(A_values_Q4, map_values_Q4, label='Q=4')
plt.title("Item_Item_Prob_CF Model")
plt.xlabel("A (Parameter for Similarity Function)")
plt.ylabel("mAP@500 (in %)")
plt.legend()
plt.show()
```

```
Max Value of mAP@500 (in %) at Q=1 is: 14.74604423601075 for A: 0.55
Max Value of mAP@500 (in %) at Q=4 is: 15.080580555134441 for A:
0.8500000000000001
```



2.8.5 Calculation of mAP@500 score for Item__Item__Prob__CF Model

[40]:
```
# Importing Pre Computed R Matrix for evaluation of Item_Item_Prob_Eval_CF Model
R_item_prob_A085Q4 = pickle.load(open("./data/item_item/R_item_prob_A0.85Q4.
↪pkl","rb"))
```

[41]:
```
%%time
# Create Item_Item_Prob_Eval_CF Similarity Model Instance
song_sim_prob_eval_model = Recommenders.cf_recommender(type="item_item",␣
↪method="prob")
song_sim_prob_eval_model.create(M, train_util_dict, R=R_item_prob_A085Q4, A=0.
↪85, Q=1)

# Calcuate mAP@500 for test Sample
mAP_at_tau = Evaluation.maptau(song_sim_prob_eval_model, common_users,␣
↪test_util_dict, sampling_rate=0.3, tau=500)
print("----------------------------------")
print("mAPat500 for test sample is:", mAP_at_tau, "%")
print("----------------------------------")
```

```
Length of user_test_and_training:68388
Length of user sample:20516
1 2.2811295725401832 %
10001 14.813566961485181 %
20001 14.887188978398763 %
20516 14.909024207833758 %
---------------------------------
mAPat500 for test sample is: 14.909024207833758 %
---------------------------------
CPU times: user 25.4 s, sys: 2.77 s, total: 28.2 s
Wall time: 32.6 s
```

2.8.6 User__User__Jaccard__CF Model

[42]:
```
# Creating a Random Subset (2%) of Dataset for Training & Testing User_User CF␣
↪Models
newtrain_data = data.sample(frac=0.02, random_state=0)
newtrain_data
```

[42]:
```
                                         user_id             song_id  \
1181498  4b96ba3b9768637a915b9cc5c26f7bf4cb29ba70  SOHLLRP12A6701F2F4
113995   67f01613b368c58c44949ace64dc17eb7b5a407e  SODPPBT12A8C141D90
1071914  4b1ca9ef64bd1e61e79fde143c3aa84fcb468a14  SOCUQMK12A8C135B78
1871428  a84df449cbbd943b246030425a146f91222d8968  SOOOICO12A8C139457
941931   0a6c1c6c88bbd53d04806d022cf45e5e45cd0c24  SODCNJX12A6D4F93CB
…                                              …                   …
812648   940ed4a83f5a3f9ac29d55a7d5b2e3b9cc55c3c5  SOCYOTN12A8C13A4B1
```

```
951118   3ad8bbb05e77171ab8aa13f520cb3d9a2f71d891  SOFGJCW12AF72A812D
980151   30d9cf518bce7019bc7dd6908c444c3f6fbdb3db  SOOWXAQ12AB0188996
1707429  6b13b3cb83f88bbe978bf8dc3679f0736343c2b0  SOLRGVL12A8C143BC3
596648   a985cdd36e762528ae686ef132e941b5f9e57316  SOYIBGP12AF729A397

                                   title  listen_count
1181498  Under The Bridge (Album Version)             9
113995                             Closer             1
1071914                        Cannonball             4
1871428                          Old Song             1
941931   Jamaica Roots II(Agora E Sempre)             1
…                                    …           …
812648                    My Happy Ending             1
951118                       Already Gone             1
980151                     Docking Bay 94             1
1707429                       Bulletproof             9
596648                Elevator Love Letter            1

[40000 rows x 4 columns]
```

[43]:
```
# Create util_dict for newtrain_data for User_User_CF Models
newtrain_util_dict = utility.gen_util_dict(dataset_list=[newtrain_data],␣
↪dataset_names_list=["newtrain_data"])
newtrain_util_dict = newtrain_util_dict["newtrain_data"]

# Create Ranking Matrix new_M for newtrain_data for User_User_CF Models
new_M = utility.gen_M(newtrain_data, dataset_name="newtrain_data")

# Get pre computed test sample (common with other models) for User_User_CF␣
↪Models
newtest_sample = pickle.load(open("./data/newtest_sample.pkl","rb"))
print("Length of Test Sample for User_User_CF Models:",len(newtest_sample))

# Get pre computed test_u2s mapping for newtest_sample for User_User_CF Models
newtest_u2s = pickle.load(open("./data/newtest_u2s.pkl","rb"))
```

```
Length of Test Sample for User_User_CF Models: 7761
```

[44]:
```
import Rec as Recommenders
import importlib
importlib.reload(Recommenders)

# Create User_User_Jaccard_CF Similarity Model Instance
user_sim_jaccard_model = Recommenders.cf_sim_recommender(type="user_user",␣
↪method="jaccard")
user_sim_jaccard_model.create(train_util_dict)
```

[45]:
```
%%time
#Get Recommendations for a user
user_sim_jaccard_model.recommend(test_users[190])
```

```
CPU times: user 2.39 s, sys: 54.3 ms, total: 2.44 s
Wall time: 2.76 s
```

[45]:
```
                song_id                                              title  \
0    SOAUWYT12A81C206F1                                               Undo
1    SOBONKR12A58A7A7E0                                     You're The One""
2    SOFRQTD12A81C233C0                                       Sehr kosmisch
3    SOEGIYH12A6D4FC0E3  Horn Concerto No. 4 in E flat K495: II. Romanc…
4    SOSXLTC12AF72A7F54                                             Revelry
..                  …                                                  …
495  SOXHPVI12A6D4F903A                                      It Wasn't Me""
496  SOYPWKK12A8C136494                     Ready_ Steady_ Go (Album Version)
497  SOTJDDY12AB017DC5B                                 I'm In Miami Bitch""
498  SOMMMFT12A67ADC119                        Temperature (Album Version)
499  SOZQLLE12A6D4F7170                                      Intermission 1

         score
0    22.277953
1    19.038643
2    18.777527
3    17.813121
4    17.806683
..         …
495   1.025084
496   1.024302
497   1.024272
498   1.022082
499   1.020366

[500 rows x 3 columns]
```

[46]:
```
%%time
# Get Similar Users for a User
user_sim_jaccard_model.get_similar_items(test_users[56])
```

```
CPU times: user 3.14 s, sys: 53.2 ms, total: 3.19 s
Wall time: 3.5 s
```

[46]:
```
                                    user_id     score
0    ba84933e06baa936ed69b4240deb9bbbc8c26d63  0.195652
1    d408a12db28ca42c2fbe288d6d50ce71a4f457ed  0.166667
2    06529e2d4c86b50d4425d844220541ec99aa562e  0.155556
3    150ed31f94be90359dc5f59b6de72f54ad9e38f8  0.142857
```

```
4      9f5991bb8cf794d90dd88a21da70febabdf91c8a  0.133333
…                                          …        …
12339  4fa22edbfd4fcebb74956c8701e20b15fa1fc3e8  0.002439
12340  1aa4fd215aadb160965110ed8a829745cde319eb  0.002268
12341  a15075a926c1998d91940f118342ba8356efc7d4  0.002257
12342  b04e41133dd3d30a5631cc8589a1eadd48a8bd53  0.002222
12343  4e11f45d732f4861772b2906f81a7d384552ad12  0.002058

[12344 rows x 2 columns]
```

2.8.7 Calculation of mAP@500 score for User_User_Jaccard_CF Model

[47]:
```
# Importing Pre Computed R Matrix for evaluation of User_User_Jaccard_Eval_CF␣
↪Model
newR_user_jaccard = pickle.load(open("./data/new_user_user/newR_user_jaccard.
↪pkl","rb"))
```

[48]:
```
%%time
# Create User_User_Jaccard_Eval_CF Similarity Model Instance
user_sim_jaccard_eval_model = Recommenders.cf_recommender(type="user_user",␣
↪method="jaccard")
user_sim_jaccard_eval_model.create(new_M, newtrain_util_dict,␣
↪R=newR_user_jaccard)

# Calcuate mAP@500 for test Sample
mAP_at_tau = Evaluation.maptau(user_sim_jaccard_eval_model, newtest_sample,␣
↪{'u2s': newtest_u2s}, sampling_rate=1, tau=500)
print("---------------------------------")
print("mAPat500 for test sample is:", mAP_at_tau, "%")
print("---------------------------------")
```

```
Length of user_test_and_training:7761
Length of user sample:7761
1 0.04995004995004995 %
7761 0.3853756924059717 %
---------------------------------
mAPat500 for test sample is: 0.3853756924059717 %
---------------------------------
CPU times: user 4.18 s, sys: 157 ms, total: 4.33 s
Wall time: 4.65 s
```

2.8.8 User_User_Prob_CF Model

[49]:
```
# Create User_User_Prob_CF Similarity Model Instance
user_sim_prob_model = Recommenders.cf_sim_recommender(type="user_user",␣
↪method="prob")
user_sim_prob_model.create(train_util_dict, A=0.5, Q=1)
```

[50]:
```
%%time
#Get Recommendations for a user
user_sim_prob_model.recommend(test_users[89])
```

```
CPU times: user 2.3 s, sys: 43.8 ms, total: 2.35 s
Wall time: 3.18 s
```

[50]:
```
                song_id                                              title  \
0    SOBONKR12A58A7A7E0                                     You're The One""
1    SOAUWYT12A81C206F1                                               Undo
2    SOSXLTC12AF72A7F54                                            Revelry
3    SOEGIYH12A6D4FC0E3  Horn Concerto No. 4 in E flat K495: II. Romanc…
4    SOHTKMO12AB01843B0  Catch You Baby (Steve Pitron & Max Sanna Radio…
..                  …                                                  …
495  SOMCWAZ12A67ADBCE3                                In The Waiting Line
496  SOLQXDJ12AB0182E47                                                Yes
497  SOHMJJQ12AF72AD2A2                          Slow Dancing In A Burning Room
498  SOYRJTL12A67AD9551                                            My List
499  SOCHPTV12A6BD53113  Die Kunst der Fuge_ BWV 1080 (2007 Digital Rem…

         score
0    43.887066
1    41.703039
2    35.397879
3    33.971951
4    32.415250
..         …
495   1.899017
496   1.893435
497   1.889924
498   1.887002
499   1.884664

[500 rows x 3 columns]
```

[51]:
```
%%time
# Get Similar User for a User
user_sim_prob_model.get_similar_items(test_users[45])
```

```
CPU times: user 1.45 s, sys: 17 ms, total: 1.47 s
Wall time: 1.59 s
```

[51]:
```
                                      user_id     score
0    ca30555363881683c41b24389b8f1e468c01c6b4  0.500000
1    6f1ce98898ebb8fb94223a96a4bd1fcd137108c8  0.500000
2    3d0182d96be2ba26aa3d419583824a81254eb69f  0.408248
3    17017c985eb7467bf763306de691fb67ecb01f9b  0.408248
4    1865e60449c4edbc0b9551777b95ea08e1373651  0.408248
..                                        …         …
699  212092cf656fb03828351a6e6fda32a73ebb7ad3  0.051164
700  0abc7b26e61609909c5cd8dec4668b9c9cdfdd3b  0.048224
701  656684e0c8cd25284cbc29715b3669fd33018d1d  0.046324
702  0720ca8f3cc2d0c0c126e784b846785536ddefbc  0.046029
703  f89e6c35a468ba075b07e687b1f4a1ca6c9b4f74  0.042718

[704 rows x 2 columns]
```

2.8.9 Tuning the Hyperparameters A (Similarity Function Parameter) and Q (Scoring Function Parameter) i.e for User_User_Prob Model

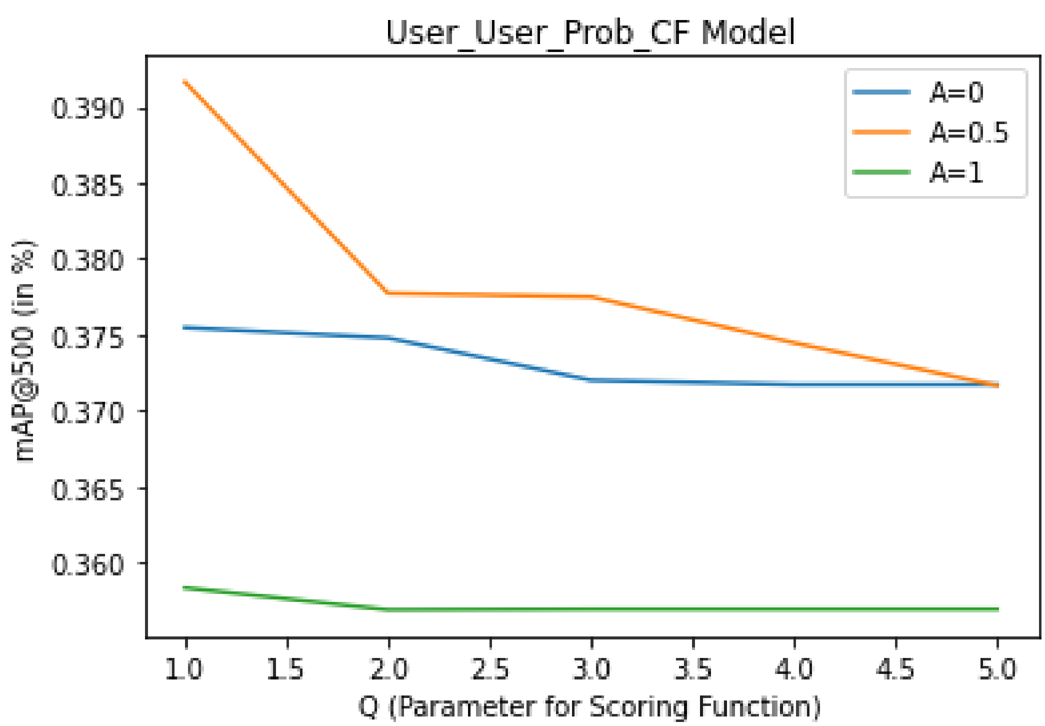
Hyperparameter, A and Q are involved with User_User_Prob Model. Now our Goal is to find the value of A and Q for which maP@500 score for User_User_Prob Model comes out to be maximum.

Tuning Hyperparameter Q For this, I calculated mAP@500 score for User_User_Prob Model at different values of Q keeping A as constant being equal to 0, 0.5 and 1 (corner values for A as $ 0<=A<=1 $) and noted the value of Q (keeping A constant) at which mAP@500 is max. The Max. Value of mAP@500 is acheived at $Q = 1$ for $A = 0.5$ with $mAP@500 = 0.3916$ (in %).

[52]:
```
from matplotlib import pyplot as plt

# Load the Values of mAP@500 precomputed by me on Kaggle Kernel for KNN Model
Q_values_A0, map_values_A0 = pickle.load(open("./list/new_user_user_prob/
 ↪new_AQ_map_list_user_prob_A0.pkl","rb"))
Q_values_A05, map_values_A05 = pickle.load(open("./list/new_user_user_prob/
 ↪new_AQ_map_list_user_prob_A0.5.pkl","rb"))
Q_values_A1, map_values_A1 = pickle.load(open("./list/new_user_user_prob/
 ↪new_AQ_map_list_user_prob_A1.pkl","rb"))

map_max_A0 = max(map_values_A0)
Q_map_max_A0 = Q_values_A0[map_values_A0.index(map_max_A0)]

# Print Max value of mAP@500 (in %) at A=0
print("Max Value of mAP@500 (in %) at A=0 is:", map_max_A0, "for Q:",␣
 ↪Q_map_max_A0)

map_max_A05 = max(map_values_A05)
Q_map_max_A05 = Q_values_A05[map_values_A05.index(map_max_A05)]

# Print Max value of mAP@500 (in %) at A=0.5
```

```
print("Max Value of mAP@500 (in %) at A=0.5 is:", map_max_A05, "for Q:",␣
 ↪Q_map_max_A05)

map_max_A1 = max(map_values_A1)
Q_map_max_A1 = Q_values_A1[map_values_A1.index(map_max_A1)]

# Print Max value of mAP@500 (in %) at A=1
print("Max Value of mAP@500 (in %) at A=1 is:", map_max_A1, "for Q:",␣
 ↪Q_map_max_A1)

# Plot the Graph
plt.plot(Q_values_A0, map_values_A0, label='A=0')
plt.plot(Q_values_A05, map_values_A05, label='A=0.5')
plt.plot(Q_values_A1, map_values_A1, label='A=1')
plt.title("User_User_Prob_CF Model")
plt.xlabel("Q (Parameter for Scoring Function)")
plt.ylabel("mAP@500 (in %)")
plt.legend()
plt.show()
```

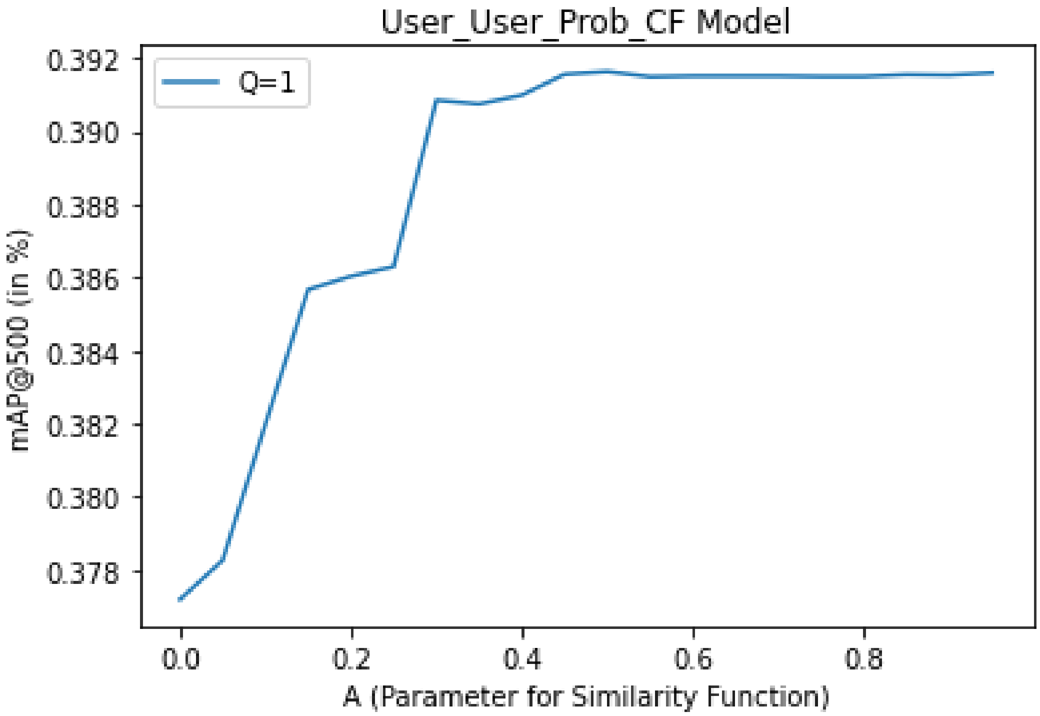
```
Max Value of mAP@500 (in %) at A=0 is: 0.37544780466619465 for Q: 1
Max Value of mAP@500 (in %) at A=0.5 is: 0.3916379794288577 for Q: 1
Max Value of mAP@500 (in %) at A=1 is: 0.3583087411879638 for Q: 1
```



Tuning Hyperparameter A For this, I calculated mAP@500 score for User__User__Prob Model at different values of A keeping Q as constant being equal to 1 (corner values for Q for which mAP@500 was maximum for constant A) and noted the value of A (keeping Q constant) at which mAP@500 is max. The Max. Value of mAP@500 is acheived at $A = 0.5$ for $Q = 1$ with $mAP@500 = 0.3916$ (in %).

[53]:
```python
from matplotlib import pyplot as plt

# Load the Values of mAP@500 precomputed by me on Kaggle Kernel for␣
↪Similarity_Item_Item Model
A_values_Q1, map_values_Q1 = pickle.load(open("./list/new_user_user_prob/
↪new_AQ_map_list_user_prob_Q1.pkl","rb"))

map_max_Q1 = max(map_values_Q1)
A_map_max_Q1 = A_values_Q1[map_values_Q1.index(map_max_Q1)]

# Print Max value of mAP@500 (in %) at Q=1
print("Max Value of mAP@500 (in %) at Q=1 is:", map_max_Q1, "for A:",␣
↪A_map_max_Q1)

# Plot the Graph
plt.plot(A_values_Q1, map_values_Q1, label='Q=1')
plt.title("User_User_Prob_CF Model")
plt.xlabel("A (Parameter for Similarity Function)")
plt.ylabel("mAP@500 (in %)")
plt.legend()
plt.show()
```

```
Max Value of mAP@500 (in %) at Q=1 is: 0.3916379794288577 for A: 0.5
```



2.8.10 Calculation of mAP@500 score for User__User__Prob__CF Model

[55]:
```
# Importing Pre Computed R Matrix for evaluation of User_User_Prob_Eval_CF Model
newR_user_prob_A05Q1 = pickle.load(open("./data/new_user_user/newR_user_prob_A0.
↪5Q1.pkl","rb"))
```

[57]:
```
%%time
# Create User_User_Prob_Eval_CF Similarity Model Instance
user_sim_prob_eval_model = Recommenders.cf_recommender(type="user_user",␣
↪method="prob")
user_sim_prob_eval_model.create(new_M, newtrain_util_dict,␣
↪R=newR_user_prob_A05Q1, A=0.5, Q=1)

# Calcuate mAP@500 for test Sample
mAP_at_tau = Evaluation.maptau(user_sim_prob_eval_model, newtest_sample, {'u2s':
↪ newtest_u2s}, sampling_rate=1, tau=500)
print("----------------------------------")
print("mAPat500 for test sample is:", mAP_at_tau, "%")
print("----------------------------------")
```

```
Length of user_test_and_training:7761
Length of user sample:7761
1 0.04995004995004995 %
```

```
7761 0.3916379794288571 %
---------------------------------
mAPat500 for test sample is: 0.3916379794288571 %
---------------------------------
CPU times: user 3.75 s, sys: 133 ms, total: 3.89 s
Wall time: 4.02 s
```

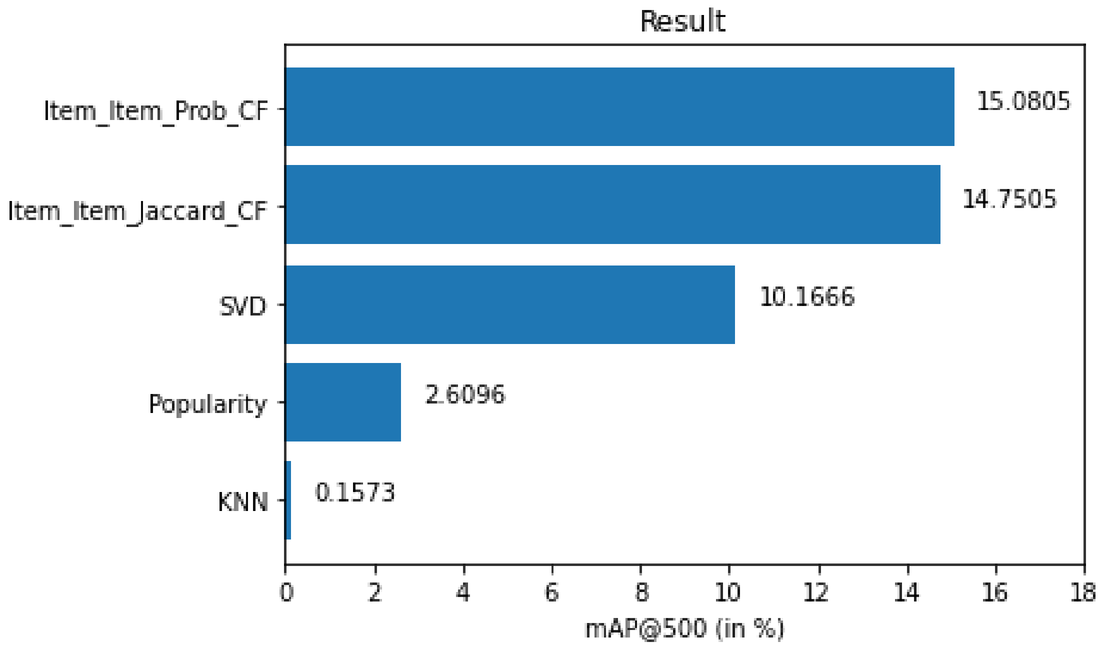
2.9 Results

To Compare the Different Models Discussed Above, I have used a common test sample (generated randomly with sample rate = 0.3 (i.e 30%) from the set containing users and songs common between train and test set). It contains about **21k unique users and 10k unique songs common among train and test test.** Note that the test sample must contain users common between test and train set All of the Models are tested on Kaggle Kernel Online due to limited processing power and RAM in our local system.

Out of the Different Models Discussed Above, Item_Item_CF_Prob Model has performed best with $mAP@500 = 15.08$(in %).

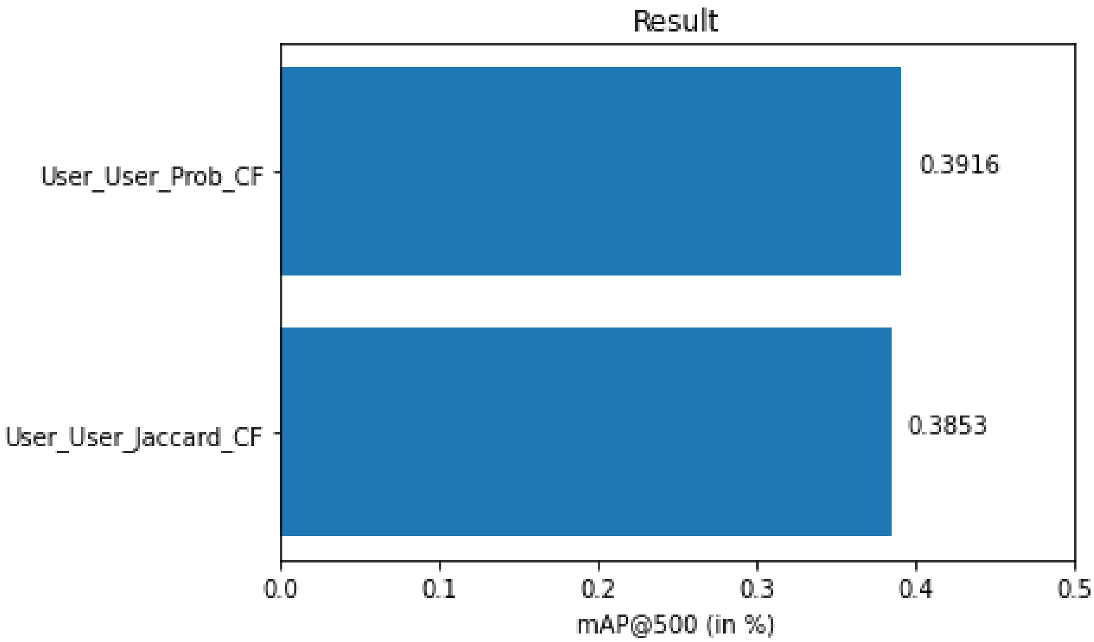
A Graphical Comparison between Different Models is is Given Below (*Note that I haven't included User_User_CF Models in this comparison because they both were tested on a different (very smaller) test sample due to availability of limited processing power and RAM in our local system and even in Kaggle Kernel Online*).

[58]:
```python
from matplotlib import pyplot as plt

# Load the Values of mAP@500 precomputed by me on Kaggle Kernel for Different␣
 ↪Models
models, map_values = pickle.load(open("./list/result/models_map_list.pkl","rb"))

# Don't Compare User_User_CF Models with Rest of the Models
models = models[:len(models)-2]
map_values = map_values[:len(map_values)-2]

# Plot the Bar Graph
plt.barh(models, map_values)
for index, value in enumerate(map_values):
    plt.text(value+0.5, index, str(value))

# Set xlimit and Title for the Graph
plt.xlim(0,18)
plt.xlabel("mAP@500 (in %)")
plt.title("Result")
plt.show()
```



Since User__User__CF Models were trained and tested on a different (a very smaller) dataset/ test sample because of the limited computational power available on our local system and on Kaggle Kernel Online. So, I have compared them seperately below with each other. It is due to the smaller training dataset, User__User__CF Models are having such a low mAP@500 (in %) scores.

[59]:
```python
from matplotlib import pyplot as plt

# Load the Values of mAP@500 precomputed by me on Kaggle Kernel for Different␣
↪Models
models, map_values = pickle.load(open("./list/result/models_map_list.pkl","rb"))

# Compare Only User_User_CF Models with themselves
models = models[len(models)-2:]
map_values = map_values[len(map_values)-2:]

# Plot the Bar Graph
plt.barh(models, map_values)
for index, value in enumerate(map_values):
    plt.text(value+0.01, index, str(value))

# Set xlimit and Title for the Graph
plt.xlim(0,0.5)
plt.xlabel("mAP@500 (in %)")
plt.title("Result")
plt.show()
```



2.9.1 Results from the Data Contained in Rating Matrix M

Min, Max, Mean and Median for users per song and songs per user has been given below. All of it, is derived from Rating Matrix M. We can see that the **Matrix M is highly sparse (contains about 0.2% non-zeros Entries)** this makes the computation and prediction a very difficult task. Also, the results suggests that **Each Song in dataset has atleast 33 listeners and almost half of the songs have about 100 listeners. While, Each User in dataset have listened to atleast 1 song and almost half of the users have listened to about 13 songs.** These statistics helped our Collaborative Filtering Model fit well with the Train Data and for it's maximum mAP@500 Score.

[60]:
```
# Generate Rating Matrix M using utility function
M = utility.gen_M()
M = M.toarray()
```

[61]:
```
# Density of Matrix M
print("Density of Matrix M:", np.mean(M)*100,"%")

# Songs per User Column Matrix
s = np.sum(M,axis=1)

# Users per Song Row Matrix
r = np.sum(M,axis=0)

# Creating DataFrame for Results of Rating Matrix M
```

```
row = [[min(s),max(s),np.mean(s),np.median(s)],[min(r),max(r),np.mean(r),np.
 ↪median(r)]]
column = ['Min','Max','Mean','Median']
index = ['songs per user','users per song']
result_M = pd.DataFrame(row, columns=column, index=index)
result_M
```

```
Density of Matrix M: 0.21023848094046116 %
```

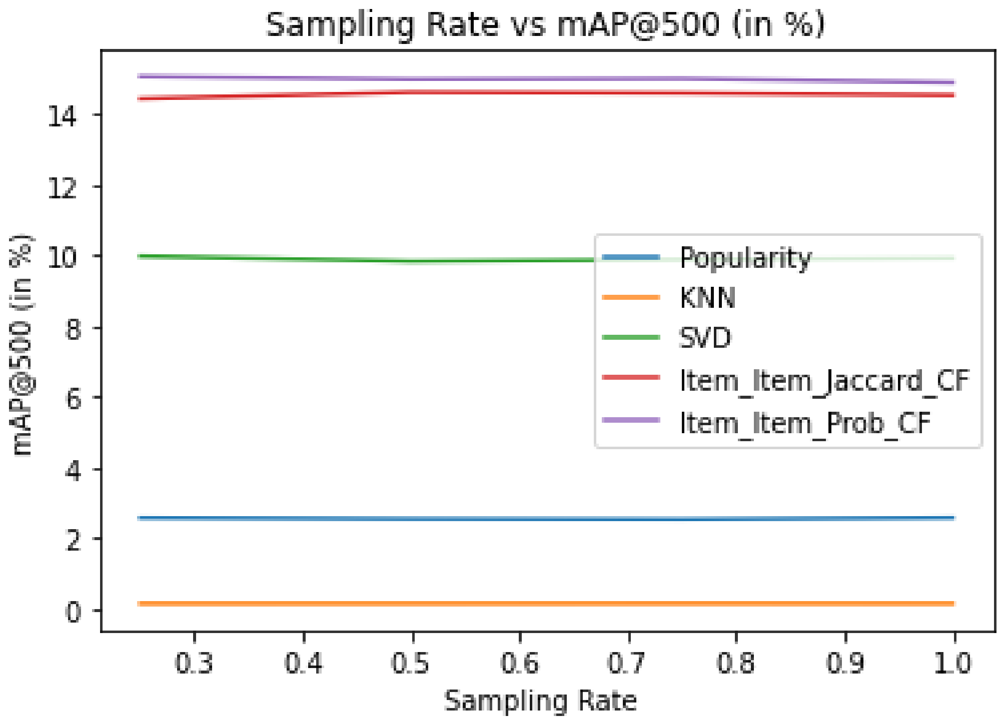
[61]:

	Min	Max	Mean	Median
songs per user	1.0	570.0	21.023849	13.0
users per song	33.0	6612.0	159.999893	99.0

2.9.2 Results from Sampling Rate vs mAP@500 Score

This Visulisation helps in analyzing our Models for new users which it hasn't seen before. Clearly, mAP@500 score almost remains consistent with each of the models and varies very slightly in magnitude. Item_Item_CF models still results in max mAP@500 score even with different and increasing sample rate, followed by SVD and Popularity Model.

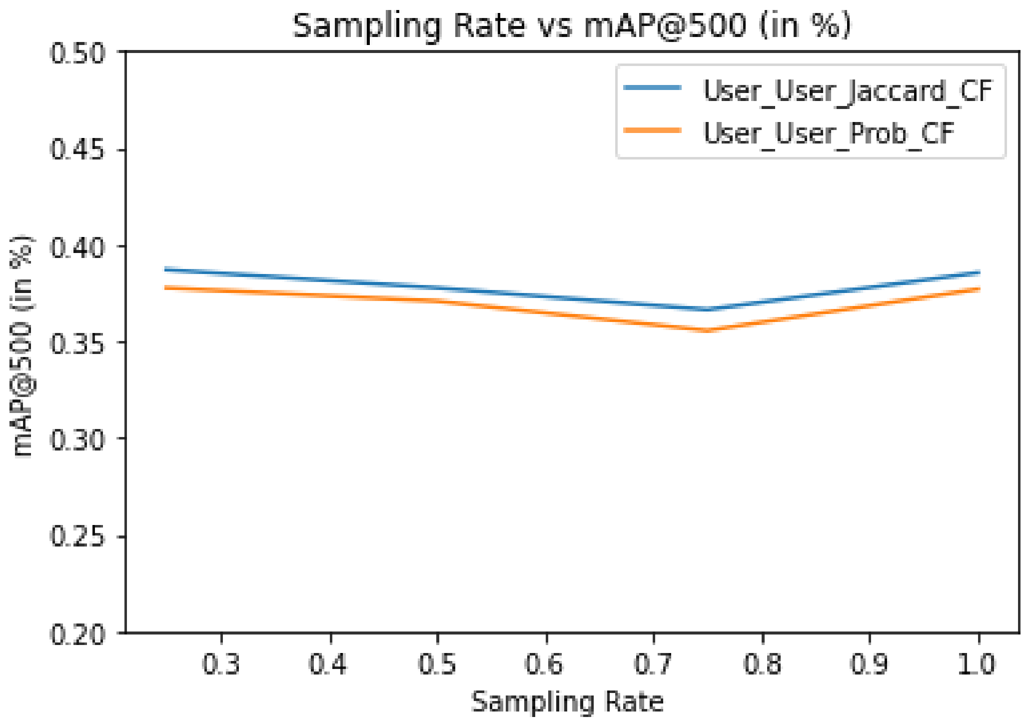
[62]:
```
from matplotlib import pyplot as plt

# Load the Values of mAP@500 precomputed by me on Kaggle Kernel for Different␣
 ↪Models
prec_values, map_values_popularity = pickle.load(open("./list/popularity/
 ↪perc_map_list_popularity.pkl","rb"))
_, map_values_knn = pickle.load(open("./list/knn/perc_map_list_knn.pkl","rb"))
_, map_values_svd = pickle.load(open("./list/svd/perc_map_list_svd.pkl","rb"))
_, map_values_item_jaccard = pickle.load(open("./list/item_item_jaccard/
 ↪perc_map_list_item_jaccard.pkl","rb"))
_, map_values_item_prob = pickle.load(open("./list/item_item_prob/
 ↪perc_map_list_item_prob.pkl","rb"))

# Plot the Graph
plt.plot(prec_values, map_values_popularity, label='Popularity')
plt.plot(prec_values, map_values_knn, label='KNN')
plt.plot(prec_values, map_values_svd, label='SVD')
plt.plot(prec_values, map_values_item_jaccard, label='Item_Item_Jaccard_CF')
plt.plot(prec_values, map_values_item_prob, label='Item_Item_Prob_CF')
plt.title("Sampling Rate vs mAP@500 (in %)")
plt.xlabel("Sampling Rate ")
plt.ylabel("mAP@500 (in %)")
plt.legend()
plt.show()
```



Since User_User_CF Models were trained and tested on a different (a very smaller) dataset/ test sample because of the limited computational power available on our local system and on Kaggle Kernel Online. So, We are comparing them below with each other. It is due to the smaller training dataset, User_User_CF Models are having such a low mAP@500 (in %) scores. User_User_CF also performed consistent with the sampling rate and generalised well with the unseen examples but we can see a slight dip in both the Models near sample rate = 0.75.

[63]:
```
from matplotlib import pyplot as plt

# Load the Values of mAP@500 precomputed by me on Kaggle Kernel for Different␣
↪Models
prec_values, map_values_user_prob = pickle.load(open("./list/new_user_user_prob/
↪new_perc_map_list_user_prob.pkl","rb"))
_, map_values_user_jaccard = pickle.load(open("./list/new_user_user_jaccard/
↪new_perc_map_list_user_jaccard.pkl","rb"))

# Plot the Graph
plt.plot(prec_values, map_values_user_jaccard, label='User_User_Jaccard_CF')
plt.plot(prec_values, map_values_user_prob, label='User_User_Prob_CF')
plt.title("Sampling Rate vs mAP@500 (in %)")
plt.xlabel("Sampling Rate ")
plt.ylabel("mAP@500 (in %)")
plt.ylim(0.2, 0.5)
```

```
plt.legend()
plt.show()
```



2.10 Conclusion

I find this project as an opportunity to practice theory that I have learnt in various online courses related to ML and AI, to do some implementation and to try to get a better understanding of a real world problem: Music Recommendation. The MSD is a huge Dataset and handling it is a difficult problem, so, By manipulating the dataset, changing the learning set and testing set, changing some parameters of the problem and analyzing the result, I learnt a lot of practicing skills. The Music Recommender System is itself a Research Oriented, Wide, Open and Complicated Domain. I also got to realize that building it is not a trivial task. Its large scale dataset makes it difficult in many aspects. Firstly, recommending Hundreds of correct songs out of Hundreds of millions Songs for different users is not an easy task to get a high precision which is evident by the above result not being better than 15 % (which is relatively good but can be better). Secondly, the metadata includes huge information and when exploring it, it is difficult to extract relevant features for a song and its memory and CPU intensive. All these difficulties due to the data and to the system itself make it more challenging and also more attractive Domain for Researchers. But anyways, I learnt a lot from this project and it was a great experience in learning and working for this problem.

Thank You Umesh Yadav 2018UCS0078 IIT JMU