ACKNOWLEDGEMENT

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ABSTRACT

Streaming music have become one of the top sources of entertainment for millennials. Because of globalization people all around the world are now able to access different kinds of music. The global recorded music industry is worth $15.7 billion and is growing at 6% as per 2016. Digital music is responsible for driving 50% of those sales. There are 112 million paid subscribers for the streaming business and roughly a total of 250 million users, if we include those who don't pay. Thus, it becomes very important for streaming service providers like Youtube, Spotify and Pandora to continuously improve their service to the users.

Recommendation Systems are one such information retrieval technique to predict the ratings or popularity a user would give/have for an item. In this project I would be exploring bunch of methods to predict ratings of users for different artists using GroupLen's Last.FM dataset.

CONTENT

ABOUT DATA

The data for this project uses records of play counts of an artist by various users from the Last.Fm website. Figure 1 shows the the present screenshot of the website.

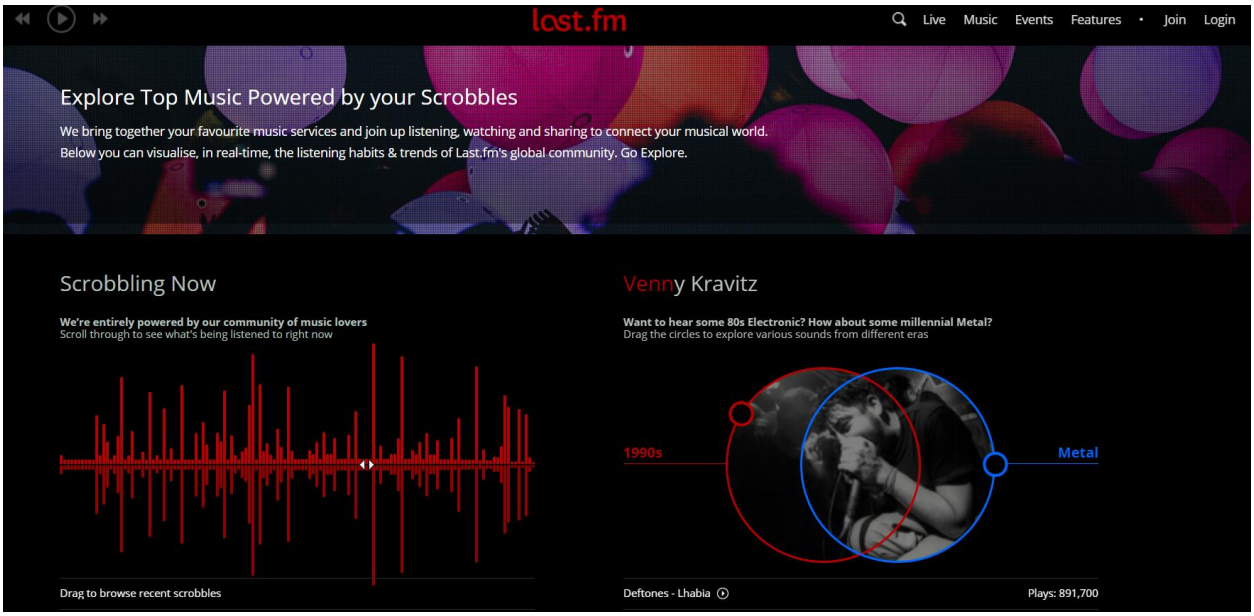

Figure 1: The present screenshot of the home page of Last.fm website

The data for the project is available free to use for non-commercial purposes here by GroupLens. GroupLens is a research lab at the University of Minnesota which publish research articles in conferences and journals primarily in the field of computer science, but also in other fields including psychology, sociology, and medicine. The owners constantly update the dataset in the page. At the time of writing this report this dataset contained social networking, tagging, and music artist listening information from a set of 2K users from Last.FM online music streaming site. The zip file contains namely the files shown in the table 1 below:

File Name	Information
artists.dat	Contains information about music artists listened and tagged by the users
tags.dat	Contains the set of tags available in the dataset
users_artists.dat	Contains information on listening counts of an artist by a user
user_friends.dat	Contains information on bi-directional user-friend relation
user_taggedartists.dat	Contains information on tag assignments of an artists provided by each particular user
user_taggedartists-timestamp.dat	Contains above information which the timestamp

Table 1: Data files details

Some detailed information about the data:

1. Information about 17632 artists tagged by 1892 users
2. An artist can be tagged differently by a different user
3. Weights in user_artists dataset is the listening count of an artist by a user

All the datasets would be used for making a recommendation system except user_taggedartists-timestamp.dat because it doesn't provide any new useful information. The number of time a user listened an artist will be used as a rating (or proxy for rating). Below is a screenshot of the Last.FM website.

LITERATURE SURVEY

According to various blogs read, it is found that we can implement recommendation system in many ways: each with a different algorithm running them. One of the most popular technique is Collaborative Filtering. It can be done performed in two ways:

a. ***User Based Filtering***: Where similar users are first found using their similar decisions in the past and then their items are recommended to each other. The rating prediction is done based on calculating the weighted average of user ratings and their similarity to the user in question. For calculating the similarity, the most popular choice is: centered-cosine-distance which easily differentiates a tough and an easy user.

b. ***Content Based Filtering****:* Where if a user decides on an item, he/she is recommended the next item based on the item which is like the item he just decided upon. Here the predicted rating is calculated in a similar fashion as in user-based filtering.

Other important and popular technique is a model-based algorithm called Matrix Factorization. There are several variants of it. Singular Value Decomposition or SVD is one of them.

In general, it has been reported that for many cases Content Based Filtering (also known as item-item) outperforms User Based Filtering (or user-user). And the reason is very interesting. Items are "simpler" than users in the sense that items can have only certain genres, but a user's taste can vary largely. For example, an artist can belong to metal rock but very unlikely that he/she would also belong to classical opera music. Whereas users can like metal rock and can listen to classical opera music occasionally. But this again highly depends on the data, and for the Last.FM data, it was found that the User-Based Collaborative Filtering outperformed all other methods.

Other possible methods were also explored like Popularity-Based Collaborative Filtering but were found to be not very useful in this case along with SVD in this case.

DATA CLEANING

Out of 6 datasets, the dataset with information on artists was found to be a little messy. There were bunch of 636 artist names which were not in plain English. Also, most of their play counts were less. Few names used foreign language characters and hence were obscure. So, to keep the future results understandable those artist names were removed from further analysis.

DATA EXPLORATION

Next, the data was explored to identify most played artists and artists who were played by most number of unique users in the last.fm. Following were observations:

1. Britney Spears, Depeche Mode and Lady Gaga were the most played artists by all users

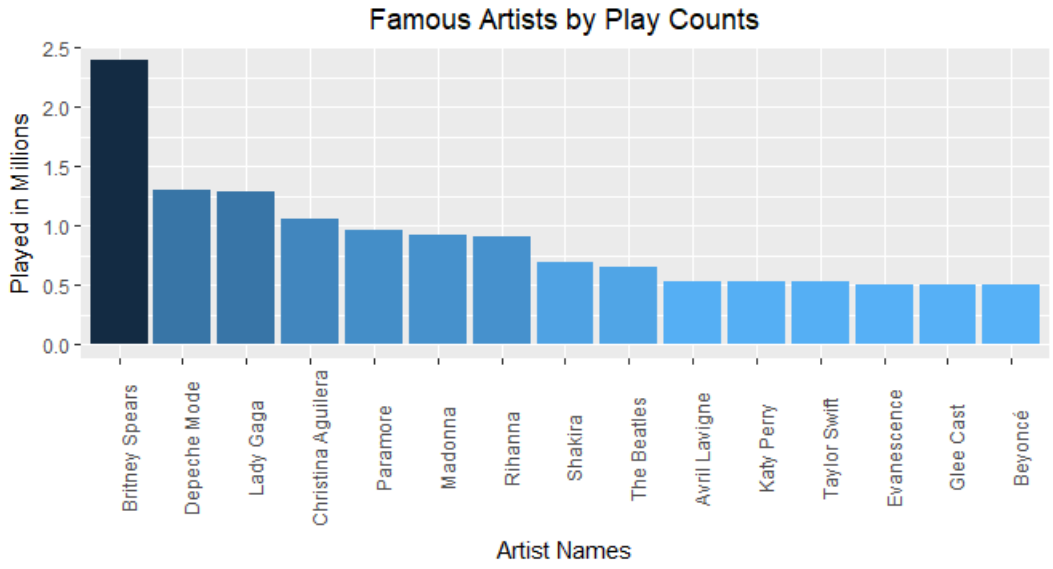

Figure 2: Top artists and their play counts in the dataset

2. While most of the artists who were played the most, were also played by the most number of users/ But surprisingly Depeche Mode even after being listened to more than a million times, they were not played by many users. This indicates that: *Some users tend to play a lot of certain artists which others might not be playing. Hence, this can be a room to recommend artists in the future.*

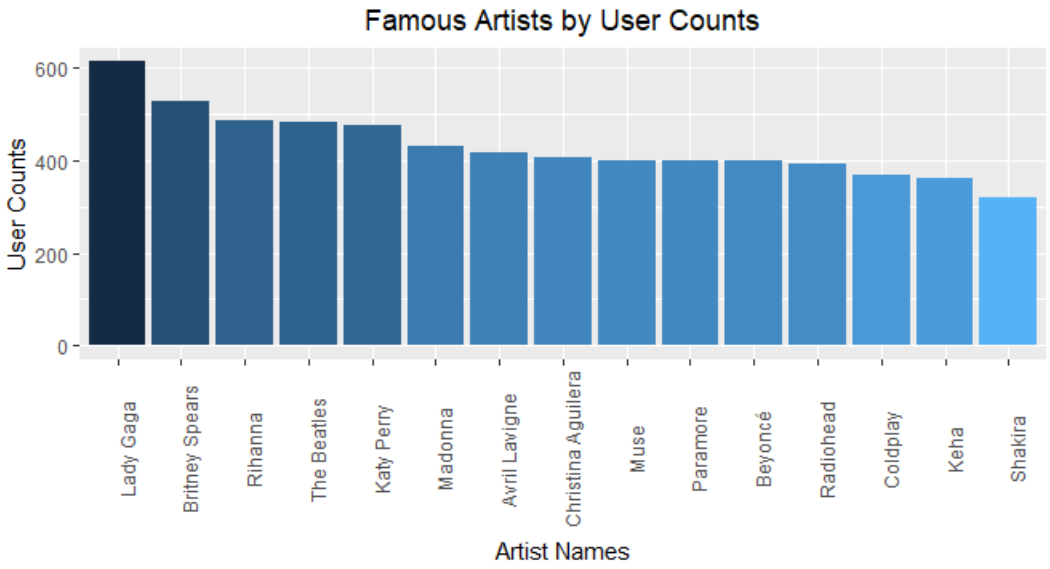

Figure 3: Top artists and count of unique users who played them

3. Out of 16996 available artists, a whopping 15605 (=91.8%) artists were listened only by 10 or even less users. Hence in the dataset the users were mostly listening to very selected artists.

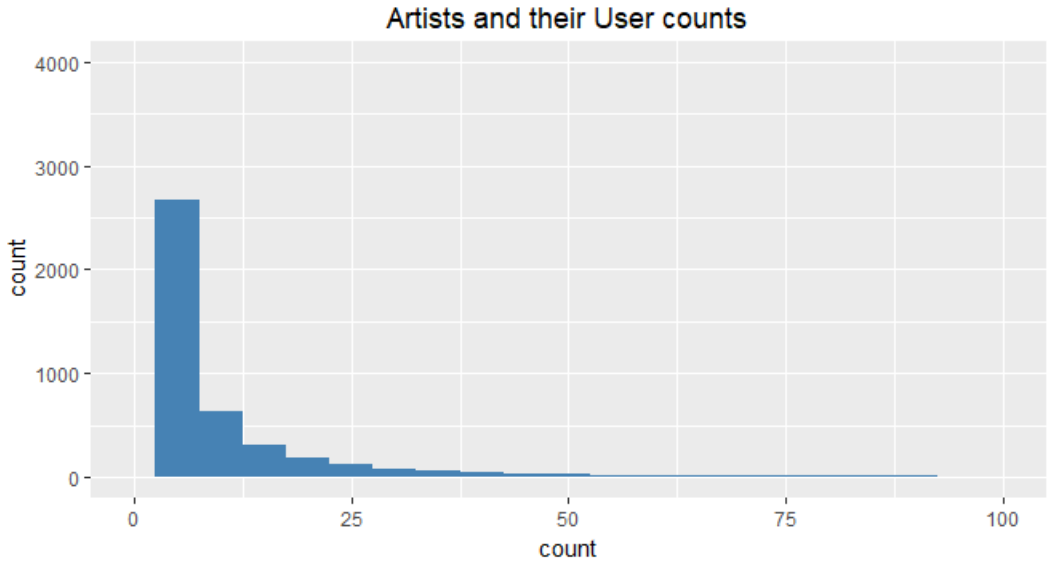

Figure 4: Distribution of unique user counts. This plot reveals that most of the artists are listened by 5 or less users.

4. Out of 1891 users, 1506 (=79.6%) users have listened to 50 artists. But these set of 50 artists for one user can be entirely different from a set of 50 artists of another user, since the total available artists are 16996.

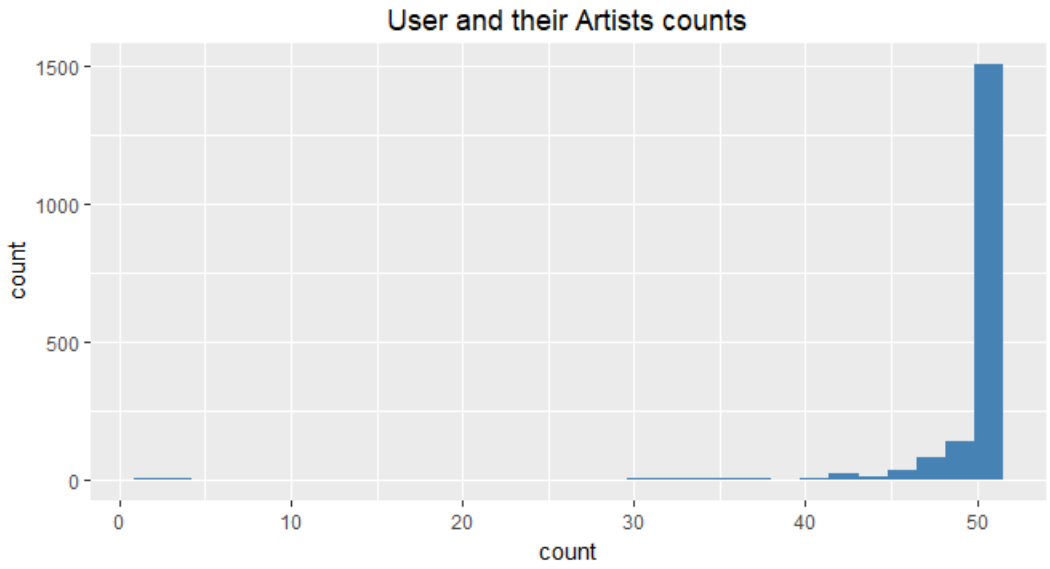

Figure 5: Distribution of artist counts. This plot reveals that most of the users are listening to 50 artists.

5. Below histograms show that out of 16996 artists, 16201 (= 9827 + 6374) artists were played less than 2500 times (very small compared to some artists like Britney Spear who was played 2.5 million times). Thus, it clearly shows that only a handful of artists are popular and dominating in the dataset.

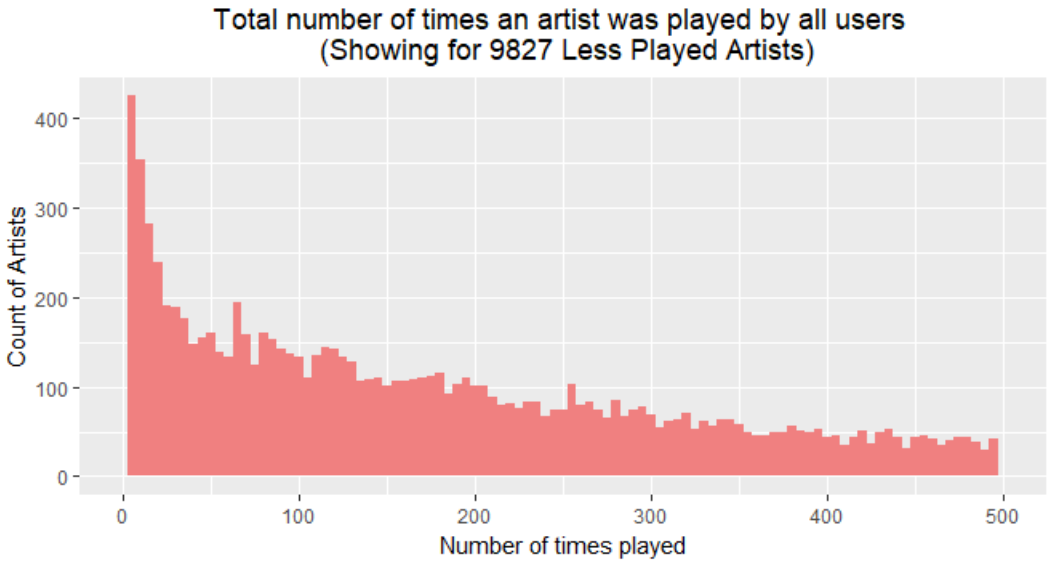

Figure 6: Distribution of play counts. This plot reveals that most of the artists are listened less than 50 times and not many artists are listened high number of times like Britney spears who was listened 2.5 million times. Artist counts decreases sharply with increasing play counts.

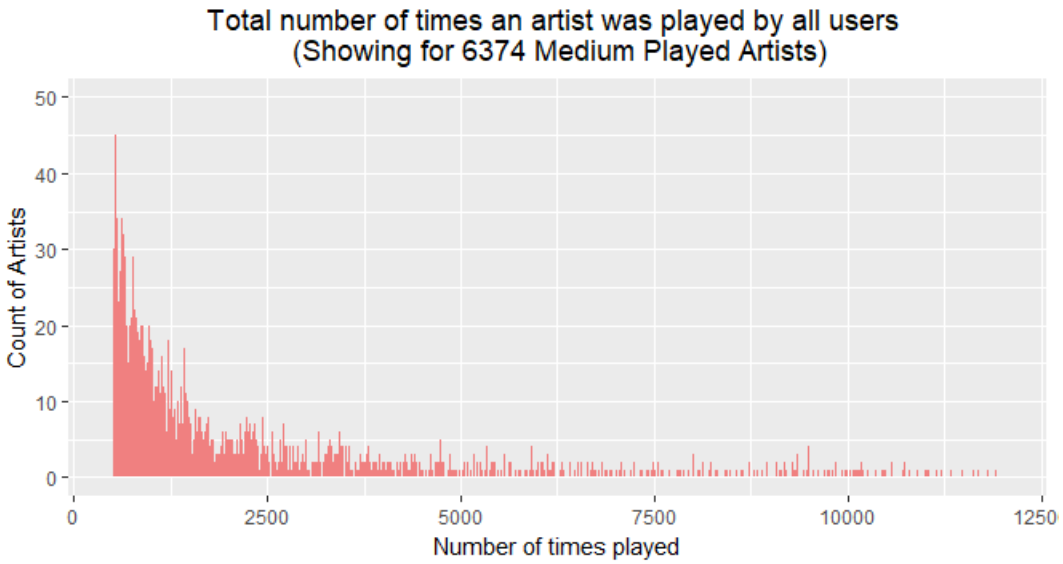

Figure 7: Zoom in view of the distribution at higher play counts. This plot reveals that only very few artists have high play counts. These are all popular artists.

DATA PROCESSING

It was found that some artists which were present in artists table were not present in the user – artist data. Same case was with few tags. Hence, a master dataset was prepared using only the userID, artistsID, and tagID which were common across all the tables.

It reduced the data size from that of 1891 users and 16996 artists to 1870 users and 6640 artists. Now again, in this reduced dataset there were some users who had listened only to one, two or basically a very handful of artists. For collaborative filtering, the recommendations are made based on similarity between users or items. Similarity can be measure in different ways: Euclidean, Cosine, Pearson, Jaccard etc. In all these measures, the similarity between two users or two items is calculated using vector of ratings. If the vector size is not big enough, then the recommendations will not be accurate. Hence, we needed to make sure that the rating vector for each user should be sufficiently larger. So, in the next step, those users were excluded who had not played enough artists.

Now if 1 single artist is listened million times but only by 1 single user, it doesn't give enough information that this artist would be liked by other users as well and thus this artist can't be recommended to any new user. So, it was assumed that any listening count which was below 30%ile of all the counts was not helpful. *Hence, some more artists were excluded to retain only those artists who were played by at least 6 unique users and with more than 211 times (40 %lie).* This further reduced the final data to 446 users and 262 artists. The sparse density at this stage was 4.5%

FITTING RECOMMENDERS

Next step was to fit recommenders to the above dataset. This step requires the data to be in the matrix form. Hence, the above user – artist data was transformed into a larger and sparse user – artist matrix. This is how the user-artists matrix looked like. Every row represents each user and every column represents each artist. The numbers in the cell are the number of times that artist was played by that user.

ArtistID / userID	A1001	A1013	A1044	A1045	A1047	A1048
U1003	261					
U1007						
U1009						84
U101					4218	
U1010		3				
U102						
U1020			530			

Table 2: User-Artist Matrix where each cell represents play counts of an artist by that user.

Next, we considered making two recommender systems because in some cases the absolute ratings produce weaker ratings while converting them to binary produce much better recommendations. For each of these systems, a different data matrix was needed.

Non-Binary version: The existing range of listening counts was very huge (as seen in exploratory data analysis) and the recommenderlab package in R (which was used to fit the recommenders) works best with a rating scale of 1-5. Hence, the absolute listening counts were converted to a scale of 1-5 based on the quantile the listening count belonged to. Table 3 below were the new ratings:

Quantile of Listening Count	New Rating (1-5 Scale)
0-20	1
20-40	2
40-60	3
60-80	4
80-100	5

Table 3: Conversion of absolute raw listening counts into a scale of 1-5 as recommenderlab package in R works bets with a scale of 1-5

Binary Version: One based on whether a user has listened to an artist. For this we coded 1 for any play count or user-artists interaction which was greater than the 30% ile of all the counts. (1 = Yes and 0 = No). Table 4 below shows the quantile of the counts.

0%	10%	20%	30%	40%	50%	60%	70%	80%	90%
1	73.6	139	211	297	411	570	821	1238.8	2361

Table 4: Quantiles of the listening counts

Table 5 below is the final table with binary coding which uses above Table 4 quantiles.

ArtistID / userID	A1001	A1013	A1044	A1045	A1047	A1048
U1003	1	0	0	0	0	0
U1007	0	0	0	0	0	0
U1009	0	0	0	0	0	1
U101	0	0	0	0	1	0
U1010	0	1	0	0	0	0
U102	0	0	0	0	0	0
U1020	0	0	1	0	0	0

Table 5: Quantiles of the listening counts

Next in both the versions following recommenders were fit and evaluated.

Non-Binary	Binary
User-Based	User-Based
Item-Based	Item-Based
Popularity-based	Popularity-based
Random	Random
Single Value Decomposition	*SVD can't be applied in case of Binary

Table 6: Applied recommenders in different data matrix: Binary and Non-binary

RECOMMENDER EVALUATION

After preparing the data matrix as "**realRatingMatrix**" object, we started search for the best recommender in each version. It was found that the User-Based recommender was consistent and outperformed other algorithms in both the versions. This is shown in Figure 8 below:

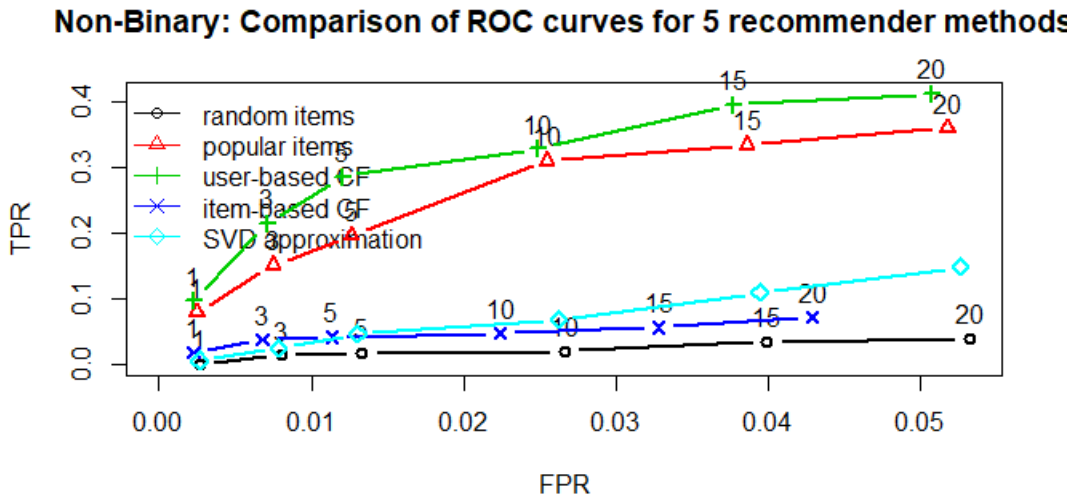

Figure 8: ROC based performance comparison of different recommenders in non-binary matrix. User-based CF outperformed other algorithms.

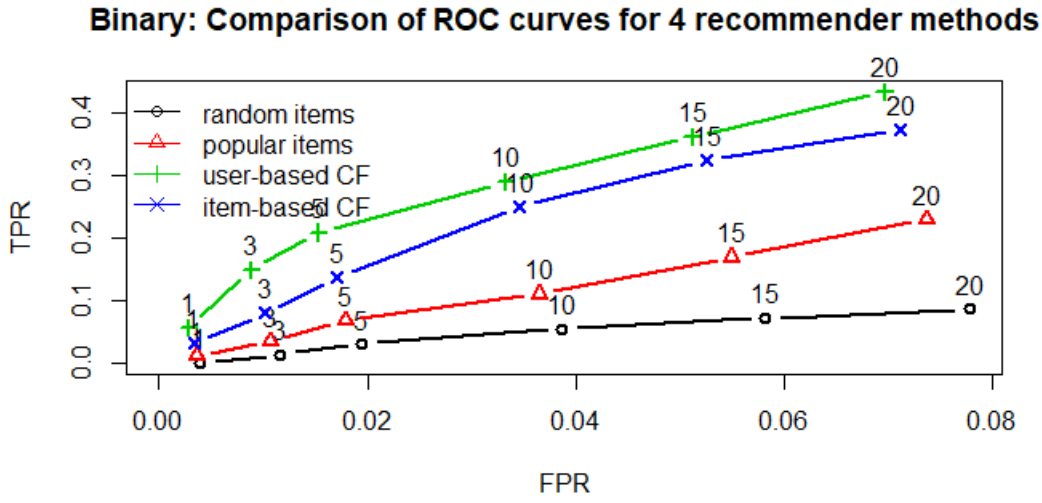

Figure 9: ROC based performance comparison of different recommenders in binary matrix. Again, user-based CF outperformed other algorithms.

After that a comparison was made between the Binary and the Non-Binary version of the same user-Based algorithm. It was found that the Non-Binary version had a higher performance than a binary version. Below is the ROC comparison:

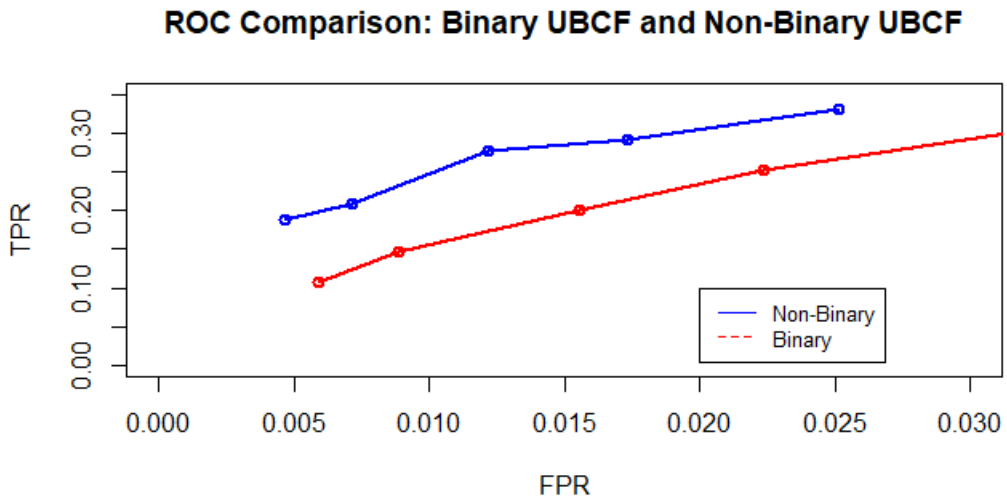

Figure 10: ROC based performance comparison of user-based CF in binary and non-binary setting. It was observed that for Top 2,3,5,7 and 10 recommendations, non-binary setting performs well.

Next, we dig deeper in user-based CF for Non-binary version. Table 7 and Figure 11 below shows that the RMSE and other errors were lowest for the user-based recommender. Next plots are of ROC curves showing that user-based CF performs better than others. It should be noted here the ROC plots were done for top – 2,3,5,7 and 10 recommendations.

Method / Error	RMSE	MSE	MAE
UBCF	1.02595	1.05258	0.78212
POPULAR	1.02601	1.05269	0.79576
SVD	1.03972	1.08101	0.79256
IBCF	1.42426	2.02851	1.03236
RANDOM	1.28214	1.64389	0.95135

Table 7: Errors from different recommender fit for non-binary data matrix

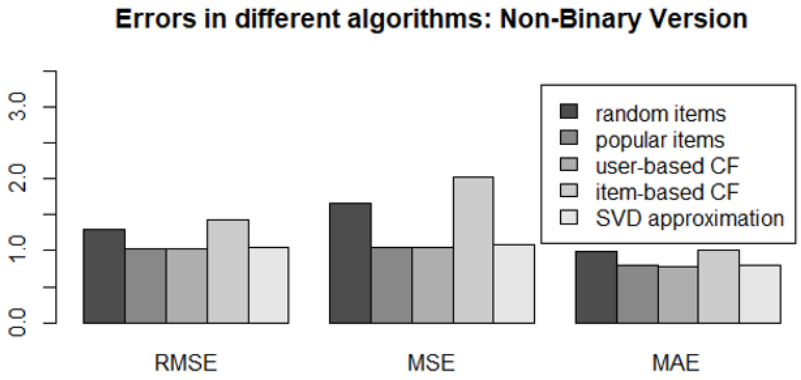

Figure 11: Errors from different recommender fit for non-binary data matrix

Hence, it can be concluded that for this dataset, user-based collaborative filtering with Non-Binary setting can be used to recommend new artists to users.

SVD performance: The reason why the SVD didn't work as per our expectation is because the way data gets collected in Last.fm. The website stores the click counts on an artist by a user but there is no option to give that artist an explicit rating by the user. SVD performs well when datasets have a rating scale. This dataset lacks that rating scale which could have been a true reflection of a user's preference and thus constraints us to use listening counts to provide recommendations which may not be able to fully utilize SVD's potential to unearth factors.

SAMPLE RECOMMENDATIONS

Next, we made recommendations for unseen new users (Table 8 below) who were not used to train the final recommender. From the recommendations we can see that artists with similar genres and who were more popular were recommended and thus in line with the expectations.

UserID	Type of Artist	Artists Names	Genres
u10	Previous	Arcade Fire, The National, Beirut	Indie, Alternative Rock
	Recommended	MGMT	Indie Pop, Psychedelic, Alterative
u1003	Previous	Duran, Madonna, Queen	80s, 1992, Pop
	Recommended	Lady Gaga, Depeche Mode	Techno, Synthpop, Female Vocalist, Electronic

Table 8: Recommendations for unseen users

Conclusion from the recommendations:

U10: First user was more into indie, alternative rock music and other popular indie and alternative artists were recommended.

U1003: Second user was more into pop and electronic music and artists like Lady Gaga and Depeche Mode were recommended.

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- Data Source: Grouplens.org http://files.grouplens.org/datasets/hetrec2011/hetrec2011-lastfm-2k.zip
- Role of Matrix Factorization Model in Collaborative Filtering Algorithm: A Survey https://arxiv.org/ftp/arxiv/papers/1503/1503.07475.pdf
- Matrix Factorization: http://www.quuxlabs.com/blog/2010/09/matrix-factorization-a-simple-tutorial-and-implementation-in-python/

APPENDIX

The statistical software and the version used was: **R version 3.5.0 (2018-04-23)**

Below is the code used to generate above report.

```
###### Music Recommendation Code ######################################

setwd('C:/0000/Cincinnati Projects/Recommender System/')

library("dplyr")

library("tidyr")

library("ggplot2")

library("recommenderlab")

library("readr")

artists <- suppressMessages(read_delim("artists.dat", "\t", escape_double =
FALSE, trim_ws = TRUE))

artists<-artists %>%

  mutate(name = gsub("[^[:alnum:][:space:]]","",name)) %>%

  arrange(desc(name)) %>%

  filter(row_number(name)>=637)

valid_artist<-artists$id
```

```
tags <- suppressMessages(read_delim("tags.dat", "\t", escape_double = FALSE,trim_ws = TRUE))


user_artists <- suppressMessages(read_delim("user_artists.dat","\t", escape_double = FALSE, trim_ws = TRUE))

user_artists<-user_artists[user_artists$artistID %in% valid_artist,]


user_friends <- suppressMessages(read_delim("user_friends.dat","\t", escape_double = FALSE, trim_ws = TRUE))

user_taggedartists <- suppressMessages(read_delim("user_taggedartists.dat","\t", escape_double = FALSE, trim_ws = TRUE))

user_taggedartists<-user_taggedartists[user_taggedartists$artistID %in% valid_artist,]


user_taggedartists_timestamps <- suppressMessages(read_delim("user_taggedartists-timestamps.dat","\t", escape_double = FALSE, trim_ws = TRUE))

user_taggedartists_timestamps<- user_taggedartists_timestamps[user_taggedartists_timestamps$artistID %in% valid_artist,]


###### EDA ################################################################

# Famous Artists By Play Counts

user_artists %>%

  inner_join(artists, by = c("artistID" = "id")) %>%

  select(userID,name,weight) %>%

  group_by(name) %>%

  summarise(play_counts = round((sum(weight)/1000000),2)) %>%

  arrange(desc(play_counts)) %>%

  top_n(15) %>%

  ggplot(aes(x = reorder(factor(name),-play_counts), y = play_counts, fill = -play_counts)) + geom_bar(stat = "identity") +
```

```
  theme(plot.title    =    element_text(hjust    =    0.5),axis.text.x    =
element_text(angle  =  90,  hjust  =  0.5))  +  ggtitle("Famous  Artists  by  Play
Counts") +
  xlab("Artist Names") + ylab("Played in Millions") + guides(fill=FALSE)


# Famous Artists By User Counts
user_artists %>%
  inner_join(artists, by = c("artistID" = "id")) %>%
  select(userID,name) %>%
  group_by(name) %>%
  summarise(user_counts = n()) %>%
  arrange(desc(user_counts)) %>%
  top_n(15) %>%
  ggplot(aes(x = reorder(factor(name),-user_counts), y = user_counts, fill = -
user_counts)) + geom_bar(stat = "identity") +
  theme(plot.title    =    element_text(hjust    =    0.5),axis.text.x    =
element_text(angle  =  90,  hjust  =  0.5))  +  ggtitle("Famous  Artists  by  User
Counts") +
  xlab("Artist Names") + ylab("User Counts") + guides(fill=FALSE)


# most artists are listened less than 10 times
user_artists %>%
  select(userID,artistID) %>%
  group_by(artistID) %>%
  summarise(count = n()) %>%
  ggplot(aes(x=count)) +
  geom_histogram(binwidth = 5, fill = "steelblue") +
  scale_x_continuous(limits = c(0,100)) +
  scale_y_continuous(limits  =  c(0,4000))  +  ggtitle("Artists  and  their  User
counts") + theme(plot.title = element_text(hjust=0.5))


# most users listen 50 artists
```

```
user_artists %>%
  select(userID,artistID) %>%
  group_by(userID) %>%
  summarise(count = n()) %>%
  ggplot(aes(x=count)) +
  geom_histogram(fill = "steelblue") +
  ggtitle("User and their Artists counts") +
  theme(plot.title = element_text(hjust=0.5))


# Very few artists who were played more than 5000 times
user_artists %>%
  select(artistID,weight) %>%
  group_by(artistID) %>%
  summarize(play_counts = sum(weight)) %>%
  ggplot(aes(x=play_counts)) +
  geom_histogram(binwidth = 5, fill = "LightCoral") +
  scale_x_continuous(limits = c(0,500)) +
  xlab("Number of times played") + ylab("Count of Artists") +
  ggtitle("Total number of times an artist was played by all users \n (Showing
for 9827 Less Played Artists)") + theme(plot.title = element_text(hjust=0.5))


user_artists %>%
  select(artistID,weight) %>%
  group_by(artistID) %>%
  summarize(play_counts = sum(weight)) %>%
  ggplot(aes(x=play_counts)) +
  geom_histogram(binwidth = 5, fill = "LightCoral") +
  scale_x_continuous(limits = c(500,12000)) +
  scale_y_continuous(limits = c(0,50)) +
  xlab("Number of times played") + ylab("Count of Artists") +
```

```
  ggtitle("Total number of times an artist was played by all users \n (Showing for 6374 Medium Played Artists)") + theme(plot.title = element_text(hjust=0.5))



artists$id<-paste0("A",artists$id)

tags$tagID<-paste0("T",tags$tagID)

user_artists$userID<-paste0("U",user_artists$userID)

user_artists$artistID<-paste0("A",user_artists$artistID)

user_taggedartists$userID<-paste0("U",user_taggedartists$userID)

user_taggedartists$artistID<-paste0("A",user_taggedartists$artistID)

user_taggedartists$tagID<-paste0("T",user_taggedartists$tagID)


master<-user_artists %>%

  select(userID,artistID,weight) %>%

  inner_join(user_taggedartists,by=c("userID"    =    "userID","artistID"    = "artistID")) %>%

  inner_join(artists,by = c("artistID"="id")) %>%

  inner_join(tags,by = c("tagID" = "tagID")) %>%

  select(userID,artistID,name,tagID,tagValue,weight)

sub_master<-master[,c(1:2,6)] %>% distinct(userID,artistID,weight)



# Non Binary Version: How many times an user would listen to an artist (on scale of 1-5; 5 being the most and 1 least)

# Creating new rating

quantile(as.vector(sub_master$weight),na.rm = TRUE, probs = seq(0,1,0.2))

sub_master$new_rating<-ifelse(sub_master$weight<139.0,1,     #  This  equally distributes the 1-5 rating scale across final matrix

                              ifelse(sub_master$weight<=297.0,2,

                                     ifelse(sub_master$weight<=570.0,3,
```

```
ifelse(sub_master$weight<=1238.8,4,5))))

# Creating sparse matrix

sub_master_wide_NR<-sub_master %>% # very sparse matrix

  select(userID,artistID,new_rating) %>%

  spread(artistID,new_rating)

sub_master_wide_NR<-
sub_master_wide_NR[,colSums(!is.na(sub_master_wide_NR),na.rm  =  TRUE)>=10]  #
Artists who were played atleast 10 times by all users

sub_master_wide_NR<-
sub_master_wide_NR[rowSums(!is.na(sub_master_wide_NR),na.rm  =  TRUE)>=6,]  #
Users who played atleast 6 overall artists

# By doing these, some users who played some 50 artists, some of those artists
were played only by them and hence are removed

1-(sum(!is.na(sub_master_wide_NR))/sum(is.na(sub_master_wide_NR)))

# Matrix Sparsity = 0.9644405

# Matrix Density = 0.03555949

sub_master_mat_NR<-as.matrix(sub_master_wide_NR[,-1])

sub_rRM<-as(sub_master_mat_NR,"realRatingMatrix")

set.seed(12396911)

eval_non_bin<-evaluationScheme(sub_rRM, method ="split", train=0.8, given = 4,
goodRating = 5)

algorithms <- list("random items" = list(name="RANDOM", param=NULL),

                   "popular items" = list(name="POPULAR", param=NULL),

                   "user-based CF" = list(name="UBCF", param=list(nn=32)),   #
Calculate within 32 similar users (5% of all users in final matrix)

                   "item-based CF" = list(name="IBCF", param=list(k=20)),    #
Calculate within 20 similar items (5% of all artists in final matrix)

                   "SVD approximation" = list(name="SVD", param=list(k = 50))

)

results_non_bin <- evaluate(eval_non_bin, algorithms, type = "topNList", n=c(1,
3, 5, 10, 15, 20))
```

```
# ROC Curves

plot(results_non_bin, annotate=c(1:4), lwd = 2, legend = "topleft")

title(main = "Non-Binary: Comparison of ROC curves for 5 recommender methods")

results<-evaluate(eval_non_bin, algorithms, type = "ratings")

plot(results, ylim = c(0,3.5))

title(main = "Errors in different algorithms: Non-Binary Version")

r1 <- Recommender(getData(eval_non_bin, "train"), "UBCF")    # learned using
511 users

r2 <- Recommender(getData(eval_non_bin, "train"), "POPULAR") # learned using
511 users

r3 <- Recommender(getData(eval_non_bin, "train"), "SVD")     # learned using
511 users

r4 <- Recommender(getData(eval_non_bin, "train"), "IBCF")    # learned using
511 users

r5 <- Recommender(getData(eval_non_bin, "train"), "RANDOM")  # learned using
511 users


p1 <- predict(r1, getData(eval_non_bin, "known"), type="ratings")

p2 <- predict(r2, getData(eval_non_bin, "known"), type="ratings")

p3 <- predict(r3, getData(eval_non_bin, "known"), type="ratings")

p4 <- predict(r4, getData(eval_non_bin, "known"), type="ratings")

p5 <- predict(r5, getData(eval_non_bin, "known"), type="ratings")


# Error between the prediction and the unknown part of the test data

error <- rbind(UBCF = calcPredictionAccuracy(p1, getData(eval_non_bin,
"unknown")),

               POPULAR = calcPredictionAccuracy(p2, getData(eval_non_bin,
"unknown")),

               SVD = calcPredictionAccuracy(p3, getData(eval_non_bin,
"unknown")),

               IBCF = calcPredictionAccuracy(p4, getData(eval_non_bin,
"unknown")),
```

```
               RANDOM   =   calcPredictionAccuracy(p5,   getData(eval_non_bin,
"unknown"))

)

error

# Conclusion: User-Based performs better than popularity-based CF and
outperforms rest of all other algorithms




# Binary Version: Whether an user would listen an artist or not

# Creating sparse matrix

sub_master_wide<-sub_master %>% # sub_master_wide: 1st column is userID,  #
very sparse matrix

  spread(artistID,weight)

quantile(sub_master$weight, probs = seq(0,1,0.1))

# 0%      10%      20%      30%      40%      50%      60%      70%      80%
90%     100%

# 1.0     73.6    139.0    211.0    297.0    411.0    570.0    821.0   1238.8
2361.0 352698.0

nrow(sub_master_wide) # 1820

sum(!is.na(sub_master_wide)) # 12,064,443

sum(is.na(sub_master_wide))

sub_master_wide[,][sub_master_wide[,]<211]<-NA


sub_master_wide<-sub_master_wide[,colSums(!is.na(sub_master_wide),na.rm     =
TRUE)>=10] # Artists who were played atleast 10 times by all users

sub_master_wide<-sub_master_wide[rowSums(!is.na(sub_master_wide),na.rm      =
TRUE)>=6,] # Users who played atleast 6 overall artists

# By doing these, some users who played some 50 artists, some of those artists
were played only by them and hence are removed

1-(sum(!is.na(sub_master_wide))/sum(is.na(sub_master_wide)))
```

```
# Matrix Sparsity = 0.9547748

# Matrix Density = 0.04522523


sub_bin<-sub_master_wide

sub_bin<-as.matrix(sub_bin[,-1])

sub_bin[,][is.na(sub_bin[,])]<-0

sub_bin[,][sub_bin[,]>0]<-1

sub_bRM<-as(sub_bin,"binaryRatingMatrix")

set.seed(12396911)

eval_bin<-evaluationScheme(sub_bRM, method ="split", train=0.8, given = 4,
goodRating = 1) # Give 4 rating to recommender and test 2 for error evaluation

algorithms <- list("random items" = list(name="RANDOM", param=NULL),

                   "popular items" = list(name="POPULAR", param=NULL),

                   "user-based CF" = list(name="UBCF", param=list(nn=32)),   #
Calculate within 32 similar users (5 % of all users in final matrix)

                   "item-based CF" = list(name="IBCF", param=list(k=20))     #
Calculate within 20 similar items (5% of all artists in final matrix)

                   #,"SVD  approximation"  =  list(name="SVD",  param=list(k  =
50))

                   # SVD does not implement a method for binary data

                   )

results_bin <- evaluate(eval_bin, algorithms, type = "topNList", n=c(1, 3, 5,
10, 15, 20))



# ROC Curves

plot(results_bin, annotate=c(1:4), lwd = 2, legend = "topleft")

title(main = "Binary: Comparison of ROC curves for 4 recommender methods")

# Precision Recall Curves

plot(results_bin, "prec/rec", annotate=c(1:4), legend="topleft", lwd = 2)

title(main = "Binary: Comparison of Precision Recall curves for 4 recommender
methods")
```

```
# Conclusion: User-Based CF outperforms all other algorithms



# Between Binary and Non-Binary

bin_results <- evaluate(eval_bin, method = "UBCF",n = c(2, 3, 5, 7, 10)) # Top 10 recommendations in Binary UBCF

non_bin_results <- evaluate(eval_non_bin, method = "UBCF",n = c(2, 3, 5, 7, 10)) # Top 10 recommendations  in Non-Binary UBCF

# Extract binary confusion matrix metrics

b_conf <- getConfusionMatrix(bin_results)[[1]]

b_conf <- as.data.frame(b_conf)

# Extract listen count confusion matrix metrics

c_conf <- getConfusionMatrix(non_bin_results)[[1]]

c_conf <- as.data.frame(c_conf)



# ROC Comparison: Binary and Non-Binary

# ROC

plot(y = c_conf$TPR, x = c_conf$FPR, type = "o", col = "blue", xlab = "FPR", ylab = "TPR", xlim=c(0,0.03), ylim=c(0,0.35), lwd = 2)

lines(y = b_conf$TPR, x = b_conf$FPR, col = "red", type = "o", lwd = 2)

# Add a legend

legend(0.020,  0.1,  legend=c("Non-Binary",  "Binary"),col=c("blue",  "red"), lty=1:2, cex=0.8)

title("ROC Comparison: Binary UBCF and Non-Binary UBCF")



############## PREDICTIONS ########################################

#####################################################################

#####################################################################
```

```
# Predictions: Binary and Non-Binary

# Learning Matrix

learningM<-as(as.matrix(sub_master_wide_NR[3:nrow(sub_master_wide_NR),-
1]),"realRatingMatrix")

testingM<-as(as.matrix(sub_master_wide_NR[1:2,-1]),"realRatingMatrix")

rec_sys<-Recommender(learningM, method = "UBCF")

pre <- predict(rec_sys, testingM, n=3)

non_bin_list<-as(pre,"list")

# "U10" "U1003"

# [[1]]

# [1] "A1400" "A227"  "A230"

#

# [[2]]

# [1] "A89" "A72"



non_bin_list<-non_bin_list[[1]]

new_user<-sub_master_wide_NR[1:2,] %>%

  gather(artistID,new_rating,names(sub_master_wide_NR)[2:381]) %>%

  filter(!is.na(new_rating)) %>%

  inner_join(artists, by = c("artistID" = "id")) %>%

  inner_join(user_taggedartists, by = c("userID" = "userID", "artistID" =
"artistID")) %>%

  inner_join(tags, by = c("tagID" = "tagID")) %>%

  select(userID,artistID,name,tagID,tagValue,new_rating) %>%

  arrange(userID,name,tagValue)


new_user_data<-new_user %>%

  distinct(userID,name,tagValue) %>%

  group_by(userID,tagValue) %>%
```

```
  summarize(tag_count = n()) %>%
  arrange(userID,desc(tag_count))
```

U10: First user was more into indie, alternative rock music and other indie and alternative artists were recommended

U1003: Second user was more into Synthpop and electronic and artists like Lady Gaga and Depeche Mode were recommended