Machine Learning Music Recommendation System from Social and Content based Algorithms

Group - 8

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Introduction

The project involves a Music mining and recommendation system. A centralized database of all music associated with each user's taste is the data sink for the project. Each user is obligated to label each song they upload with four features- Genre, Culture, Mood and Rating(on a scale of 1-5, 5 being the highest and 1 being lowest).Users upload 10 songs and rate them accordingly. We as a group will have to mine the songs of all users, use a machine learning technique to extract structure in the data and apply learning algorithms on it. As an output we should recommend another song which is already existent in the database, hoping that it's similar to the user's liking.

Problem Overview

There are several challenges starting with on this system. The foremost thing to do is come up with a proper feature vector which depicts the true scenario or at-least the near-to-real scenario. This involves lot of information into each user's behavior to get a neat measure of his/her liking. Since we are presented only with a song and few tags on it, we need to come up with a combinational feature vector with whatever information we have in the 'interact'.

Addressing the problem

We started iteratively by addressing each step at once and trying different methods at each level. We first brainstormed on constructing the feature vector and used it in the first Phase. The details are in the subsequent sections. We made some assumptions that the songs available from each user are representative samples of their likings. However, in the real-world it may not be the case. So keeping this idea in mind, we proceeded forward through the phases. We implemented the algorithm and came up with song recommendations for the third round as well, but couldn't recommended as it wasn't formally put in place.

Phase- I

For the 1st phase our objective was to find the user who is most similar to a particular user. Then we recommended a song from that "closest" user's list that seemed most relevant to the original user. For this we decided to represent every user as a feature vector and then run the nearest neighbor search on them to find which user is closest to whom. However, before running the algorithm we did some preprocessing that we thought was needed. When we had a look at the song_list.csv file we realized that there were a lot of redundant information in it. There were as many as 116 genres and over 40 types of cultures and moods, and many of these were much similar to each other. Hence we decided to merge some these categories that we felt were not much different from each other. For this, we did some manual check of the “Genre: Other” and defined in our own file whether it can be safely assumed to a well-known Genre.

Methodology

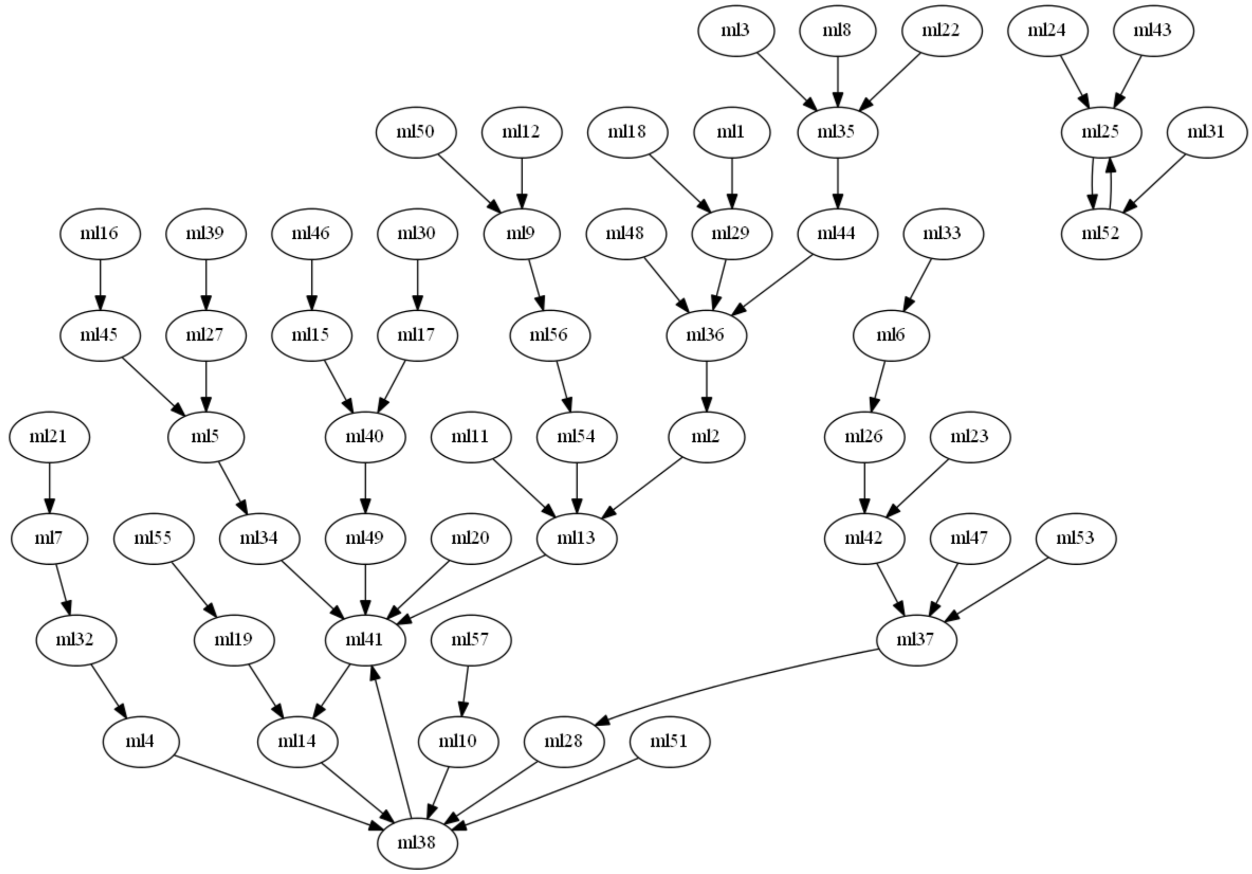
Once the preprocessing was done we generated the feature vectors for each user. The user’s vector was constructed in such a way that for each value of the Mood, Culture, Genre we had a separate placeholder in the vector. The reason for doing this was to avoid misinterpretations of the vector when different user have the same rating on a song but belonged to a different category of Genre/Mood/Culture. Hence each type inside this feature got a placeholder in the vector. The value would be populated with the rating given to that particular song. Finally a user vector is constructed by summing this up over all songs the user uploaded.

The span for each feature is as follows - Mood: 1-14 Culture: 15-33 Genre: 34-117. So a 117 size vector was formed

For e.g. Given a song categorized as Rock, Indian, Danceable, 5 means that the song array will have value of 5 in the corresponding Rock, Indian and Danceable placeholders of the array.

Now, that we have a vector for every song we take the sum of all the 10 songs uploaded by the user and form a final vector that represents that user. For users who have uploaded more than 10 songs, we have randomly selected the 10 that we felt were most similar to each other and generated that user’s vector from these 10 songs. This we decided to do instead of scaling the values down by the number of songs uploaded by the user to make sure that we are working with integers.

We later used K-Nearest Neighbor algorithm to find the most nearest person to him. In this first phase, we manually chose among the 10 songs of that nearest user to recommend to the user under consideration. The below social graph gives a picture of users nearby each other.



Nearest Neighbor for each user based on Euclidean metric

Observing the graph above, we can see there were some users like ml38, ml41 were most similar to majority of users. So we can say these users carried the taste of many users in our class.

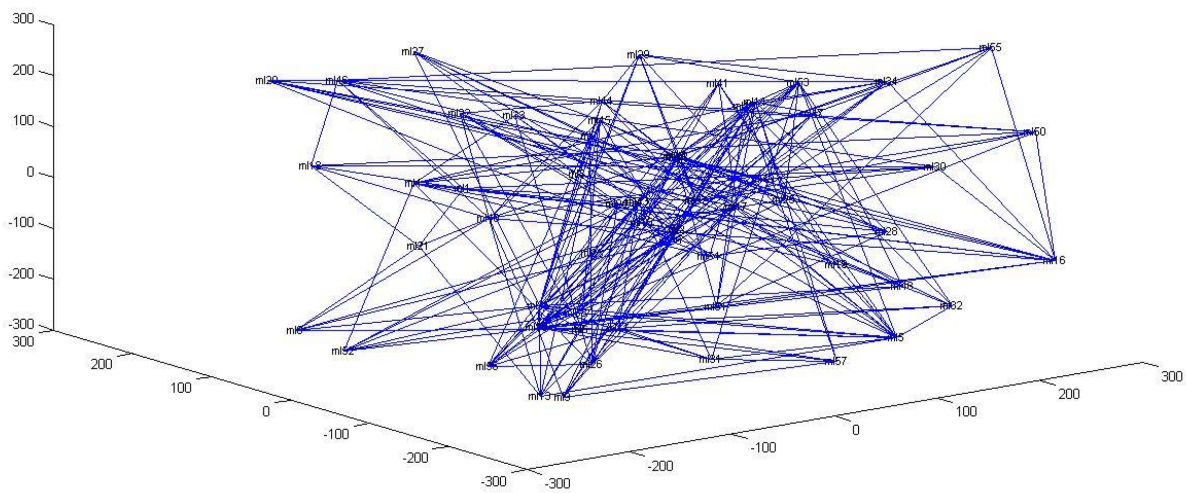
Phase-II

For the 2nd round we implemented divisive(top-down) Hierarchical Clustering i.e. started with all the users in one cluster and then recursively performed the splits depending on the Genre, Culture, Mood and Rating of the songs as uploaded by the users. At first level we cluster the users based on the Mood similarity, and in the second level based on the Culture for each clusters at the first level, at last in the third level on Genre. We chose Hierarchical Clustering over k-means or EM algorithm because

i) It does not require us to pre-specify the number of clusters and is deterministic.

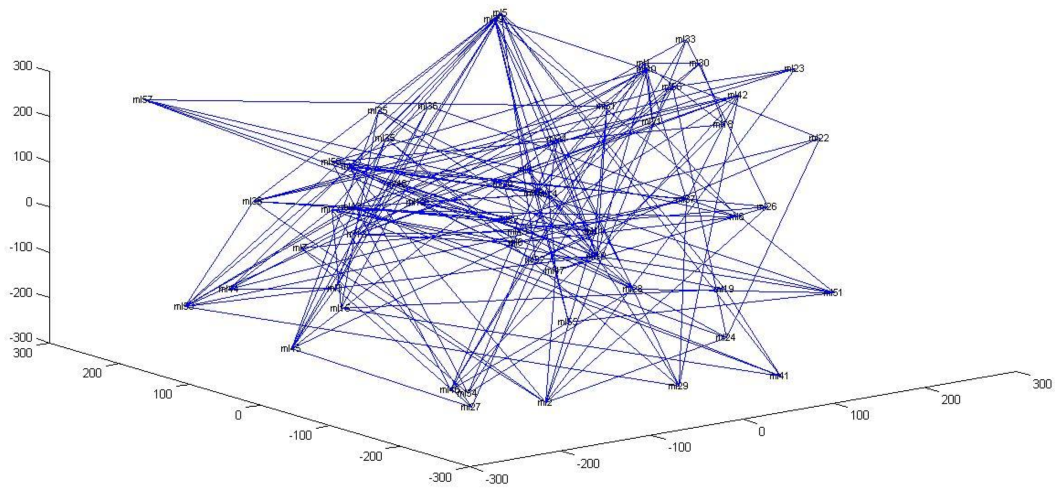
ii) It outputs a hierarchy, a structure that is more informative than the unstructured set of clusters returned by flat clustering.

We changed the metric from a simple Euclidean to Chebychev's distance to compute the proximity between the user vectors. Since the Chebychev's distance finds the largest possible co-ordinate difference, we get to know how two users can the farther apart in the worst case. Hence taking the minimum on such distances will give us a definitely nearest one to look upon. Such distances were used finally and done hierarchical clustering on to get the best song for each user. The best song was selected from the algorithm based on the cluster having the largest size in the algorithm. Hence we improvised on the algorithm level.



Nearest neighbor using Euclidean after Heirarchical Clustering

We can see lot of users in some cluster in the center while the others are sparser. So we can infer that it's better if we can recommend users with the songs of users in the largest clusters in its own hierarchy.



Nearest neighbor using Chebychev after Heirarchical Clustering

Phase-III

In this phase, we wanted to change our secret sauce to use a different set of feature vectors other than using the user labeled meta-tags on the songs. We decided on using the audio and wave features of the songs which can give a more generalized similarity metric. The reason this can be a good metric is, the audio wave beats the crests and troughs of the wave will give a good idea of what kinds of beats and bass will a user like the most. So finding a similar or a near beat pattern will essentially make the user like it irrespective of the culture tag or others. This is a more interesting feature metric since the user himself may have not known some songs which he may like after we recommend.

For this purpose we investigated many audio feature extraction applications and finally boiled down to jAudio which gives us lots of different features on the audio level. We selected the features which is recommended as “music recommendation features” in audio signal from a technical paper and used them. The overview of jAudio application and what it presents to us is given below.

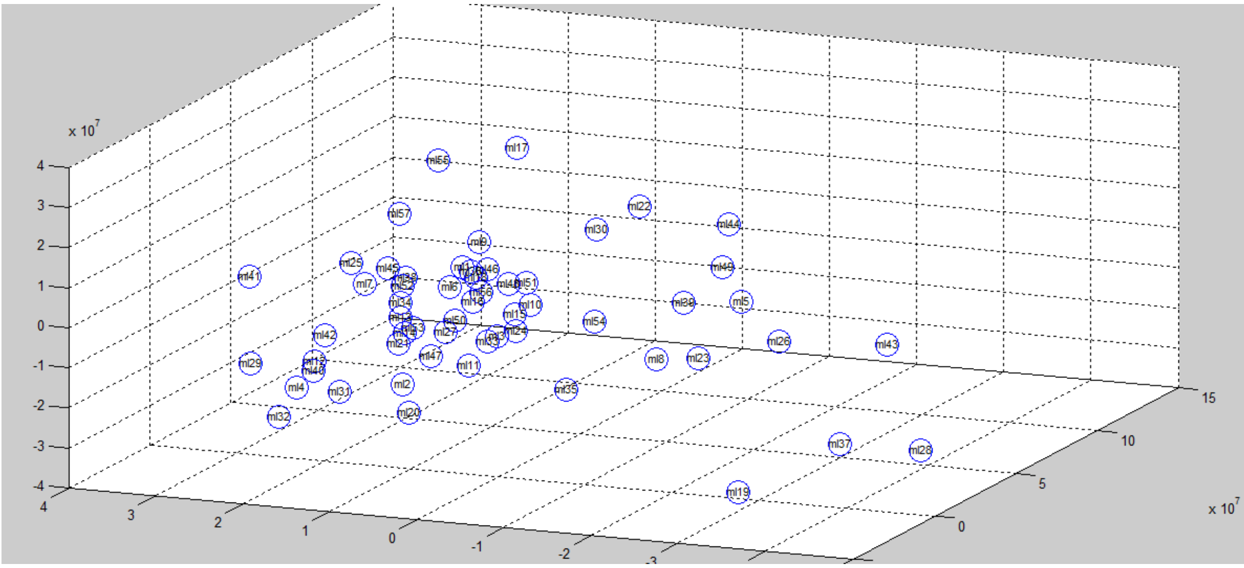
jAudio

Audio feature extraction plays an essential role in automatic music classification. Features, or characteristic pieces of information that can be used to describe objects or abstractions, play an essential role in any classification task. Features are the percepts to classification system, and even a perfect classifier will not be able to make correct classifications if it does not have access to features that properly segment the objects to be classified. Features can be particularly problematic with respect to audio signals. When asked how to distinguish between two different types of sound, a typical person might have a difficulty expressing a precise list of features, even if he or she can easily make the classification. Even in cases where one is able to vocalize audio features, the features are likely to be abstractions that are difficult to quantify and extract digitally from an audio signal. Determining which features are best-suited for a particular task can be difficult, as humans do not tend to perceive or think about sound in terms that are meaningful in a low-level signal processing sense. Although low level features are not usually intuitive to humans in a perceptual sense, an individual well-trained in signal processing and in auditory perception can use his or her expertise to gain insights into how certain low-level features can be useful. Furthermore, one can take an iterative approach to feature extraction, where low-level features derived directly from audio signals are used to derive mid-level representations, which can in turn be used to derive high-level features that are perceptually meaningful to humans. For example, basic spectral features can currently be used to track note onsets and pitch in the special case of monophonic music, which can in turn be used to generate MIDI transcriptions, which can then be used to generate high-level features related to rhythmic patterns and melodies. An additional important point is that, even though it may be the case that a particular low level feature is not used by humans to perform a certain classification, this does not necessarily means that this feature cannot effectively be used by a computer to perform the same classification. Feature selection techniques can be used to experimentally and statistically determine which features are useful and which are not in a given context.

The jAudio system currently has a total of 26 features implemented. These 26 features may be extracted for individual windows, and the averages and standard deviations of each of these features may be calculated for each recording as a whole. These features are well documented in the general literature, and precise and well-documented implementation details are available online.

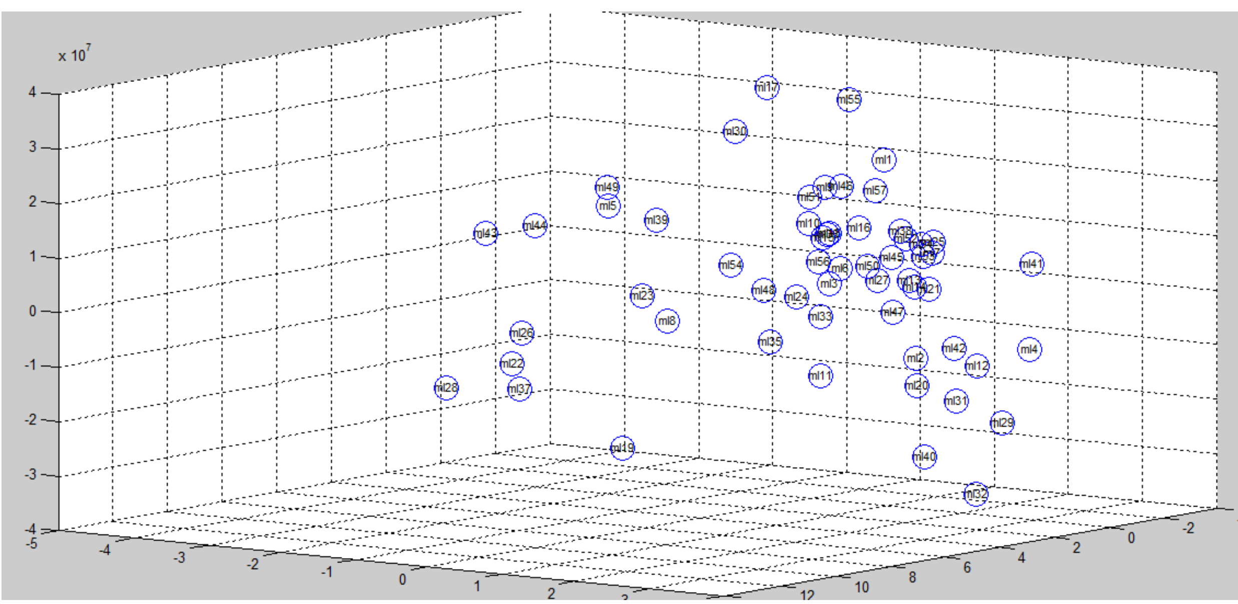
Several of the features described above extract standard deviations and averages over a short number of preceding windows. Although these features are redundant with respect to features calculated for recordings as a whole, they are useful for window-based classification, as they provide data on local history to classifiers classifying individual windows.

Now we considered different unsupervised algorithms on this feature vector space to find the similar song for each user. Principal Component Analysis was targeted to use at first. We wanted to reduce the dimensionality of the feature vectors to a lower dimension and then find the similar user using a k-NN search. The motivation for this is to get a more visual picture of the users in the space and also get similarity at that dimension hoping PCA would have preserved the dominant components via the highest Eigen vectors.



PCA using Euclidean Distance

As we can see majority of users clustered near to each other and some lie very different all. That signifies that many users taste in our class are comparatively near and only few cases where people are completely different in their music taste.



PCA using Chebychev's Distance

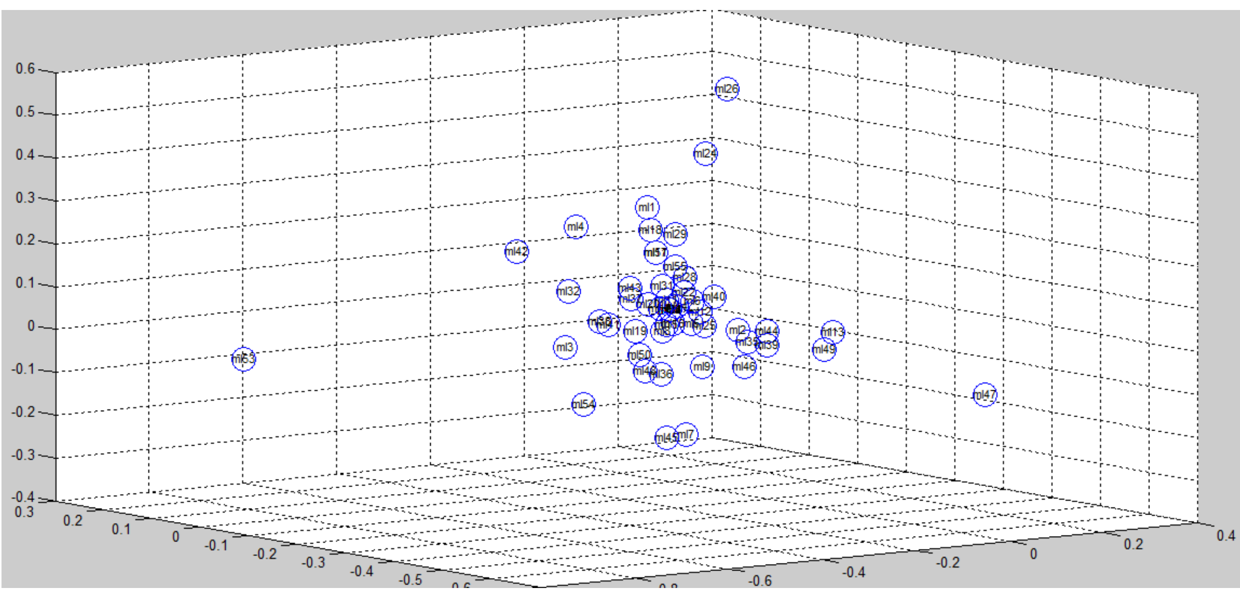
Again here too we got a new separation where we got lots of users separated far from each other unlike in a Euclidean metric.

Finally we argued that the Chebychev metric maybe more suitable for recommending and see the feedback.

Kernel-PCA

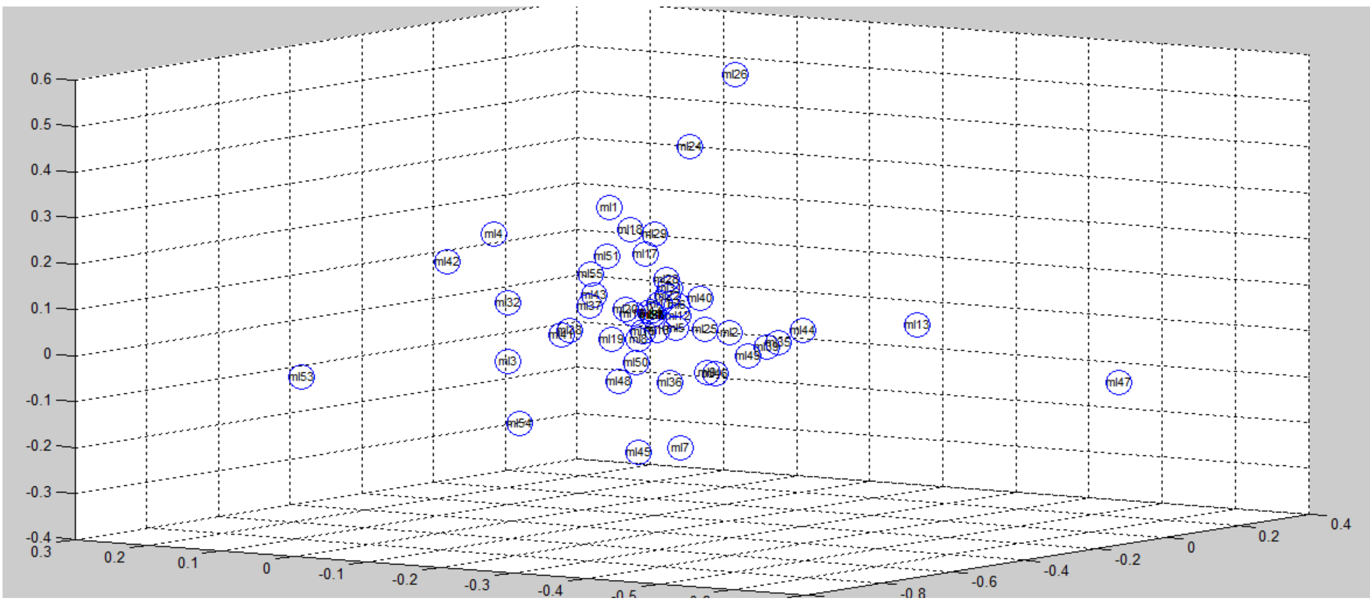
We changed over to Kernel-PCA so that we can get a higher dimensional classifier and found 4 nearest neighbor using the toolbox functionality in matlab. The Kernel-PCA was motivated by the fact that higher dimensional Hilbert space may give a good separation of data points (users in our case) to find the nearest persons in the lower dimensions. Kernel PCA is a non-linear form of Principal Component Analysis. By the use of integral operator on kernel functions one can efficiently compute principal components in high dimensional (possibly infinite) feature space, related to the input by some non-linear function.

The distance was also defined differently to see which one suited better to our real need. So we used Euclidean-metric and the Chebychev metric to get the plots of data points as shown in the next pages.



KPCA using Euclidean Distance

The KPCA representation gave us a good clustering of the data points and since this was a kernelized version of PCA, the separation would be better in higher dimensions. However, since we bring it down to lower dimension, it may lose some components, but still the representation of the data points based on Euclidean distances above, tells us that only few users are very different from the rest and the others are somewhat similar in their music taste.



KPCA using Chebychev's Distance

This is a different version of the KPCA using Chebychev's metric for the k-NN search. This too looks pretty similar to the Euclidean metric graph, but the clustering is slightly loosely packed. However, after careful verification for some users, we found that Chebychev's distance metric will give a better recommendation for the user from our view point.

All the above graphs and figures are packed as .fig file and delivered to the professor.

Conclusion

The KPCA learning algorithm on the jAudio feature vectors gave us better recommendations for each user. We progressed incrementally from using a feature vector formulated from the meta-tags of the users' songs to a more scientific measurement of the songs. Hence we can safely conclude at this level that the algorithm KPCA with chebychev distance with our feature vector will give a good approximation of each user liking. However, the likeness of a person's taste in real world depends on various natural and environmental metrics and it's a hard problem. Our problem solution gives a close approximation to the problem of music recommendation and by the feedback's received; we can safely assume that our solution fared decently well.

The project exposed us to the real-world data-mining and the learning problems. Most of the difficulties we encountered were on the different definitions of people for the features available in interact. That's the reason in Phase-I, we tried manually checking the nearest user's 10 songs to check if the two users definition of 'Rock', 'Pop' etc. meant the same and then recommended. Also due to lot of dynamic nature of the system, theer were times when we had to keep changing our output or rather re-test our algorithm due to changes in the likings of the user after a period of time. Overall, it was good learning experience of the current problems faced in computer science in the field of Machine Learning and its practical toughness.

Individual Reports

sandeep.nl: Sandeep N L: ml19

Uploaded: 14 songs uploaded within the time frame.

Recommended songs: The group worked together in generating the recommendations mappings for each user. The recommendation process was divided among us as 20 users per person and it was recommended within the stipulated time.

Ratings: Overall we received a feedback on our recommendation and it seemed decent by the ratings and the feedback text from the users. The average rating we received was 3.21 which seemed positive. I rated all songs recommended to me within the time

Observations on recommendation received:

There was confined spread in the kind of songs I received. I got some songs repeatedly from different users which was not very near to my liking. Also I observe most of recommendations were using one feature available in interact "Culture" to recommend songs for me. Even though the most prominent feature in my uploads were culture, there could have been other metrics and features which may have interested me. In our third phase, we have used the audio metrics to classify the songs which could have given a different kind of culture song to me but with the same wave characteristics.

List of Recommendations received:

Recommended Songs :

Song ID	Title	Artist	Album	Link
209	Roobaroo	A.R.Rahman	Rang De Basanti OST	Play
Feedback				
1404	Dream on	Aerosmith	Aerosmith	Play
Feedback				
484	Shivoham	Bhanumati Narsimhan	Sacred Chants of Shiva	
Feedback				
971	Lehrein	Nikhil D'Souza, Anusha Mani and Neuman Pinto	Aisha	
Feedback				
535	Pal Bhar ke liye koi hame	Kishore Kumar	Johny Mera Naam	Play
Feedback				
535	Pal Bhar ke liye koi hame	Kishore Kumar	Johny Mera Naam	Play
Feedback				
1087	Baatein Kuch Ankahee Si	Adnan Sami	Life in a Metro	
Feedback				
1391	Crying In The Rain	a-ha	East of the Sun, West of the Moon	Play
Feedback				
1400	May it be	Enya	Felloship of the Ring	Play
Feedback				
924	Dalgalandim da Duruldum	Gripin	Gripin	
Feedback				
1407	So gaye hain	Lata Mangeshkar	Zubaida	
Feedback				
1350	10 years (十年)	Eason Chan	Black, White and Grey	
Feedback				
770	Remember the name	Fort Minor	The Rising Tied	

Feedback				
1234	Lough Erin Shore	The Corrs	Unplugged	Play
Feedback				
1421	Because of You	Kelly Clarkson	Breakaway	
Feedback				
1437	White & Nerdy	"Weird Al" Yankovic	Straight Outta Lynwood	Play
Feedback				
1130	not going anywhere	Karen Ann	not going anywhere	
Feedback				
1059	Let me be Myself (Amake Amar Moto Thakte Dao)	Anupam Roy	Autograph	
Feedback				
1398	Scary Monsters And Nice Sprites	Skrillex	Scary Monsters And Nice Sprites	Play
Feedback				
1122	I don't want you to be alone(我不願讓你一個人)	MAYDAY	Second life	Play
Feedback				
1343	Hotel California	The eagles	Hotel California	
Feedback				
1409	Nashik Dhol	Open Source	Nashik dhol	
Feedback				
1354	Alaipayuthey	A. R. Rahman	Alaipayuthey	
Feedback				
662	Shake it up (Sekerim)	Kenan Dogulu		Play
Feedback				
1040	Touching my heart(Chhukar mere mann ko)	Kishore Kumar	Yarana	
Feedback				
550	Everyway That I Can	Sertab Erener	Everyway That I Can	Play

Feedback				
505	Bolo Ta Ra Ra	Daler Mehndi	Bolo Ta Ra Ra	Play
Feedback				
1057	Your Gesture Touched my Heart (Chukar Mere Mann Ko)	Kishore Kumar	Yaarana	——
Feedback				
808	Madhuban Mein Radhika	Mohammed Rafi	Kohinoor	——
Feedback				
914	Gurus of peace	nusrat fateh ali khan and AR rahman	the best of AR Rahman	——
Feedback				
1042	With the colors of flowers(Phoolon ke rang se)	Kishore Kumar	Prem Pujari	——
Feedback				
1040	Touching my heart(Chhukar mere mann ko)	Kishore Kumar	Yarana	——
Feedback				
629	Danza Kuduro	Don Omar		Play
Feedback				
51	Koi Kahe Kehta Rahe	Shaan, Shankar Mahadevan, Kay Kay	Dil Chahta Hai	Play
Feedback				
270	Tunak Tunak Tun	Daler Mehndi	Tunak Tunak Tun	Play
Feedback				
512	Geet	Amit Trivedi	Udaan	Play
Feedback				
1099	I Need A Doctor	Eminem & Dr. Dre & Skylar Grey	I Need A Doctor	——
Feedback				
1091	Breathless	Shankar Mahadevan	Breathless	Play
Feedback				
1049	Know the Mysteries of Love (Dil Ka Bhawar Kare Pukar)	Mohd. Rafi	Tere Ghar Ke Samne	——

Feedback				
56	Maa Tujhe Salam	A R Rehman	Vande Mataram	Play
Feedback				
1195	Kab Tak Ginney	Shankar Mahadevan	Zindagi Na Milegi Dobara	
Feedback				
51	Koi Kahe Kehta Rahe	Shaan, Shankar Mahadevan, Kay Kay	Dil Chahta Hai	Play
Feedback				
287	Aadu Pambe	Avial	Avial	
Feedback				
478	Kasto Mazza He Relaima	Sonu Nigam, Shreya Goshal	Parineeta	Play
Feedback				
924	Dalgalandim da Duruldum	Gripin	Gripin	
Feedback				
957	Senorita (Miss)	Shankar Ehsaan Loy	Zindagi Na Milegi Dobara (You don't get life a second time)	
Feedback				
1195	Kab Tak Ginney	Shankar Mahadevan	Zindagi Na Milegi Dobara	
Feedback				
1195	Kab Tak Ginney	Shankar Mahadevan	Zindagi Na Milegi Dobara	
Feedback				

ML52: Dhruv Gakkhar

Uploaded Songs: I uploaded 15 songs in the initial upload period. I provided their metadata to the best of my knowledge.

Song ID	Song	Artist	Album	Culture	Genre	Mood	Rating
1226	Fear of the dark	Iron Maiden	Fear of the dark	Western	Metal	Aggressive	3
122	Rockstar	Nickelback	All the right	Internatio	Rock	Fun	4

7			reasons	nal			
1228	Shine on	James Blunt	All the lost souls	International	Rock	Melancholic	4
1229	Phir Dekhiye	Caralisa Monteiro	Rock On	Eastern	Other:	Calm	4
1230	Lambi Judai	Komal Rizvi	Coke Studios Season 4	Indian	Other:	Melancholic	5
1231	Jugni	Alif Allah, Jugni, Arif Lohar & Meesha	Coke Studio, Season 3	Indian	Other:	Happy	5
1232	Stairway to Heaven	Led Zeppelin	Led Zeppelin IV	Western	Rock	Fun	5
1233	Cats in the Cradle	Harry Chaplin	Verities & Balderdash	Western	Other: Folk Rock	Relaxing	4
1234	Lough Erin Shore	The Corrs	Unplugged	Western	Instrumental	Relaxing	4
1235	Zombie	The Cranberries	No Need to Argue	Western	Rock	Melancholic	4
1383	Kuch is Tarah	Aatif Aslam	Jal Pari	International	Rock	Melancholic	4
1384	Doorie	Aatif Aslam	Doorie	International	Rock	Happy	4
1385	Sweet Child O mine	Guns 'n' Roses	Appetite for Destruction.	Western	Rock	Happy	4
1386	November Rain	Guns 'n' Roses	Use Your Illusion I	International	Rock	Melancholic	4
1387	Hero of the day	Metallica	Load	Western	Metal	Aggressive	4

Recommendations: The project was coded together. Once, the code for each phase was finished. Each of us made recommendations for around 20 users. I was generally responsible for making recommendations for user ml20-ml40. The average rating that I got for the songs for the first round was around 3.3.

Observations:

I learnt a lot from this project. I got a chance to work on KPCA and PCA in matlab and also enjoyed listening to songs recommended by others. I had heard many songs recommended to me before but some were new to me. I felt that the songs recommended by other people to me were way better than songs recommended in the first round of recommendations.

Round 1

Song ID	To User	Song	Artist	Album
1301	ml20	Turn around	Bruno Mars	Earth To Mars
Feedback	2			
1279	ml40	You belong with me	Taylor swift	
Feedback	5	great song!		
1422	ml39	If Tomorrow Never Comes	Ronan Keating	Destination
Feedback	4			
1301	ml38	Turn around	Bruno Mars	Earth To Mars
Feedback	5			
1381	ml36	Hide And Seek	Imogen Heap	Speak For Yourself
Feedback	2			
1301	ml34	Turn around	Bruno Mars	Earth To Mars
Feedback	2			
1073	ml33	The Logical Song	Supertramp	Breakfast in America
Feedback	2			
887	ml31	Pinch Me	Barenaked Ladies	Maroon
Feedback	2	lyrics don't really impress me, and the vocals getting faster isn't pleasant		
771	ml30	Consecrate to love(爱的供养)	Yang Mi(杨幂)	Lock your heart(宫锁心玉)
Feedback	5			
996	ml29	Lucky	Jason Mraz	We Sing. We Dance. We Steal Things.
Feedback	2	Sorry but I don't like it.		
950	ml28	Let it be	Beatles	The beatles
Feedback	4			
906	anand	High Hopes	Pink Floyd	The Division Bell
Feedback	3	Not bad.		
1384	ml25	Doorie	Aatif Aslam	Doorie
Feedback	2			
806	ml24	Mission	Rush	Hold Your Fire
Feedback	3	just as I was saying not bad, I reach 3:20, do not like the interlude		

910	ml23	Nothing else Matters	Metallica	Metallica
Feedback	5	Very nice! I know this song and like it very much :)		
1194	ml22	Chopin Nocturne For Piano In F Minor, Op. 551, CT 122	Vladimir Horowitz	Vladimir Horowitz
Feedback	3	It's tricky to recommend to me Chopin played by Horowitz. Some pieces are good, but in my opinion, a su		
1117	ml21	1874	Eason Chen	
Feedback	5			

Round 2

Song ID	**To USER**	**Song**	**Artist**	**Album**
1391	ml45	Crying In The Rain	a-ha	East of the Sun, West of the Moon
889	ml44	Moonlight sonata movement 3	Wilhelm Kempff	Beethoven
794	ml43	Morning Bell	Radiohead	Kid A
1000	ml42	Falling in Love at a Coffee Shop	Landon Pigg	Falling in Love at a Coffee Shop
1054	ml41	From the Heart (Dil Se Re)	A.R. Rahman	Dil Se
1032	ml40	be be your love	rachael yamagata	happenstance
948	ml40	If	Bread	Menna
1015	ml39	If I were a boy	Beyonce	I Am Sasha Fierce
1032	ml39	be be your love	rachael yamagata	happenstance
888	ml38	Iris	Goo Goo Dolls	City Of Angels Soundtrack
834	ml37	Us Against the World	Westlife	Back Home
843	ml37	Rolling in the Deep	Adele	
1385	ml36	Sweet Child O mine	Guns 'n' Roses	Appetite for Destruction.
1404	ml35	Dream on	Aerosmith	Aerosmith
1029	ml34	all you need is love	lynden david hall	love actually ost
1027	ml34	Christmas is all around	billy mack	love actually ost
806	ml33	Mission	Rush	Hold Your Fire
1404	ml32	Dream on	Aerosmith	Aerosmith
1026	ml31	I forgive you	kelly clarkson	stronger
1161	ml30	Silent love(一直很安静)	Judy	Melody of being lonely
766	ml8	Masterpiece	Madonna	W.E.
1000	ml29	Falling in Love at a Coffee Shop	Landon Pigg	Falling in Love

				at a Coffee Shop
1024	ml28	Apologize	One republic	Dream out loud
1379	ml27	Young Blood	The Naked And Famous	Passive Me, Aggressive You
1106	anand	Supermassive Black Hole	Muse	Black Holes and Revelations
982	anand	Goodbye	My Darkest Days	My Darkest Days
981	anand	Diamond Eyes (Boom-Lay Boom-Lay Boom)	Shinedown	Diamond Eyes (Boom-Lay Boom-Lay Boom)
1408	ml25	O Humdum	A R Rahman	Sathiya
912	ml24	Let it be	Beatles	Let it Be
908	ml23	Putting out the fire	David Bowie and Giorgio Moroder	Cat People
889	ml22	Moonlight sonata movement 3	Wilhelm Kempff	Beethoven
1122	ml21	I don't want you to be alone(我不願讓你一個人)	MAYDAY	Second life

Rating Incoming Recommendations: I rated recommendation at par with the songs that I uploaded. I was recommended many songs that I had listened before. I rated the recommendations for the second round as well.

Round 1 Ratings

Song ID	Song	Artist	Album	Ratings
952	Never say never	Justin Bieber	Never say never	2
946	Lemon Tree	Fool's Garden	Dish of the Day	3
1073	The Logical Song	Supertramp	Breakfast in America	4
1004	You're beautiful	James Blunt	Back to Bedlam	4
905	people like me	Knaan	Troubadoor	4
1240	Going to California	Led Zeppelin	Led Zeppelin IV	3
625	Garaj baras	Ali azmat	Paap	4
16	Orion	Metallica	Master of Puppets	4
797	Visitors From Dreams	Dma-Sc (Mathieu Stempell)	Darwinia	2
1043	Somewhere only we know	Keane	Hopes and Fears	4
968	Drops Of Jupiter	Train	Drops of Jupiter	4
1240	Going to California	Led Zeppelin	Led Zeppelin IV	3

19	Supermans Dead	Our Lady Peace	Clumsy	3
672	Everything	Michael Buble		3
1043	Somewhere only we know	Keane	Hopes and Fears	3
1044	Fix you	cold play	X & Y	4
1069	Therapy	All time low	Nothing personal	4
64	My Body Is A Cage	Peter Gabriel	Scratch My Back	2
422	Streamline	Newton		2
914	Gurus of peace	nusrat fateh ali khan and AR rahman	the best of AR Rahman	3
806	Mission	Rush	Hold Your Fire	3
1103	Only One	Alex Band	Alex Band EP	3

Round 2 Ratings

Song ID	Song	Artist	Album	Ratings
910	Nothing else Matters	Metallica	Metallica	4
1203	Chinese democracy	Guns N' Roses	Chinese democracy	3
1201	Civil war	Guns N' Roses	Use Your Illusion II	4
1446	The World Is New	Save Ferris	Save Ferris	3
983	Slide	Goo Goo Dolls	Dizzy Up the Girl	4
15	Someday	The Strokes	Is This It	3
1179	Yahoo..	Mohammad Rafi	Shammi Kapoor	3
1302	Beat it	MJ	Thriller	4
299	That's the way	Led Zeppelin	Led Zeppelin III	3
1184	Darkness and Starlight	The Black Mages	The Black Mages III: Darkness and Starlight	4
795	Comfortably Numb	Pink Floyd	The Wall	3
56	Maa Tujhe Salam	A R Rehman	Vande Mataram	4
148	But it rained	Parikrama	N/A	4
1130	not going anywhere	Karen Ann	not going anywhere	3
1437	White & Nerdy	"Weird Al" Yankovic	Straight Outta Lynwood	3
1171	Rasputin	BoneyM	BoneyM	2
1421	Because of You	Kelly Clarkson	Breakaway	4
770	Remember the name	Fort Minor	The Rising Tied	4
1210	Jinke Marina	Emil	Kannada	3
1350	10 years (十年)	Eason Chan	Black, White and Grey	3
988	Surrender	Digital Daggers	Surrender	4

924	Dalgalandim da Duruldum	Gripin	Gripin	3
1391	Crying In The Rain	a-ha	East of the Sun, West of the Moon	3
926	Beni Benimle Birak	Manga	Sehr-i Huzun	3
498	Blood Brothers	Iron Maiden	Brave New World	3
364	Piyu Bole			3
968	Drops Of Jupiter	Train	Drops of Jupiter	4
849	Buddy Holly	Weezer	Weezer	3
1151	Inridescent	Linkin Park	Transfromer 3	4

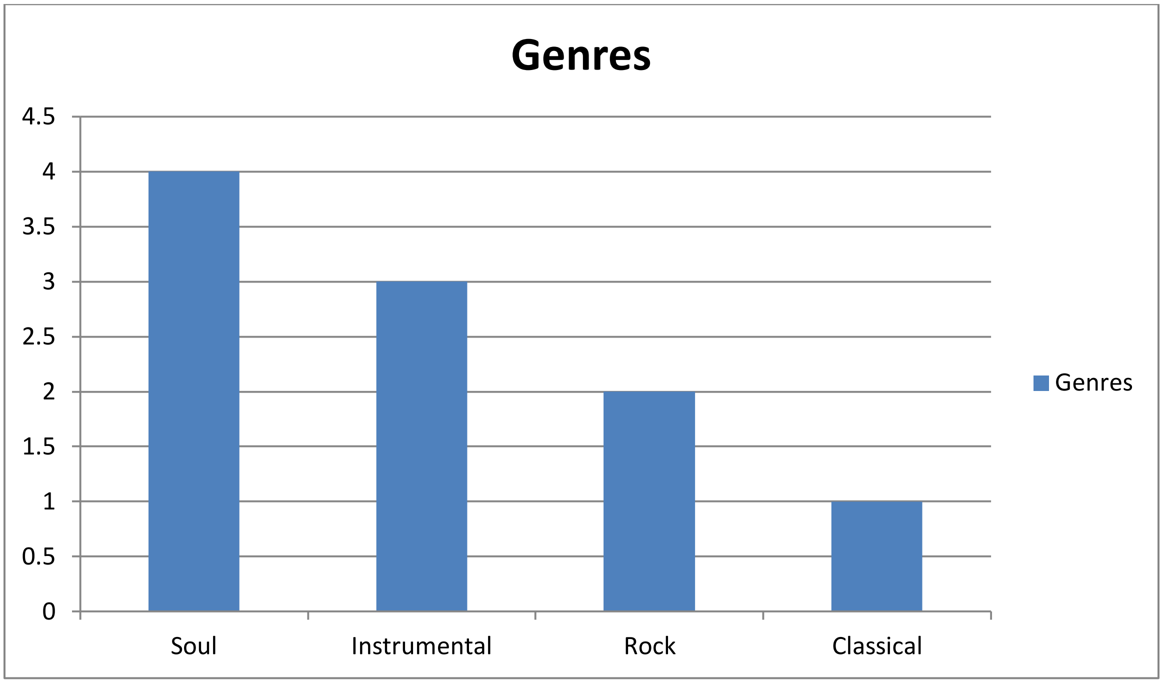
Individual Report – ml17- Abhishek Banerjee

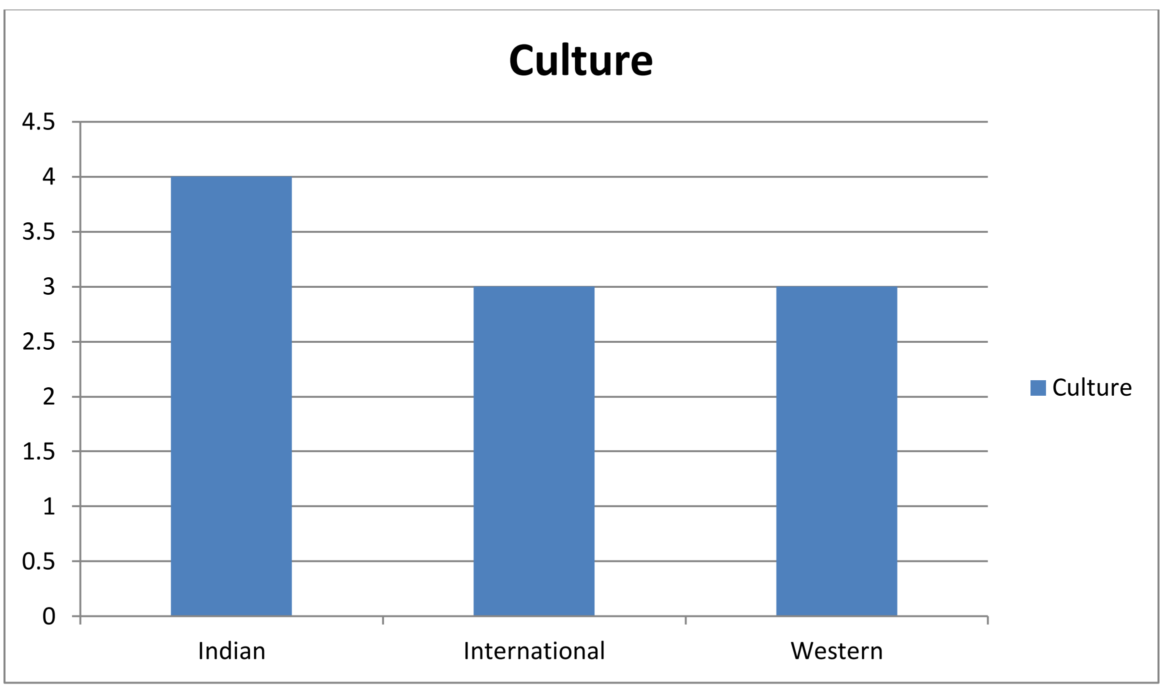
I had uploaded 10 songs with metadata as close to the original as possible, all with ratings of 5.

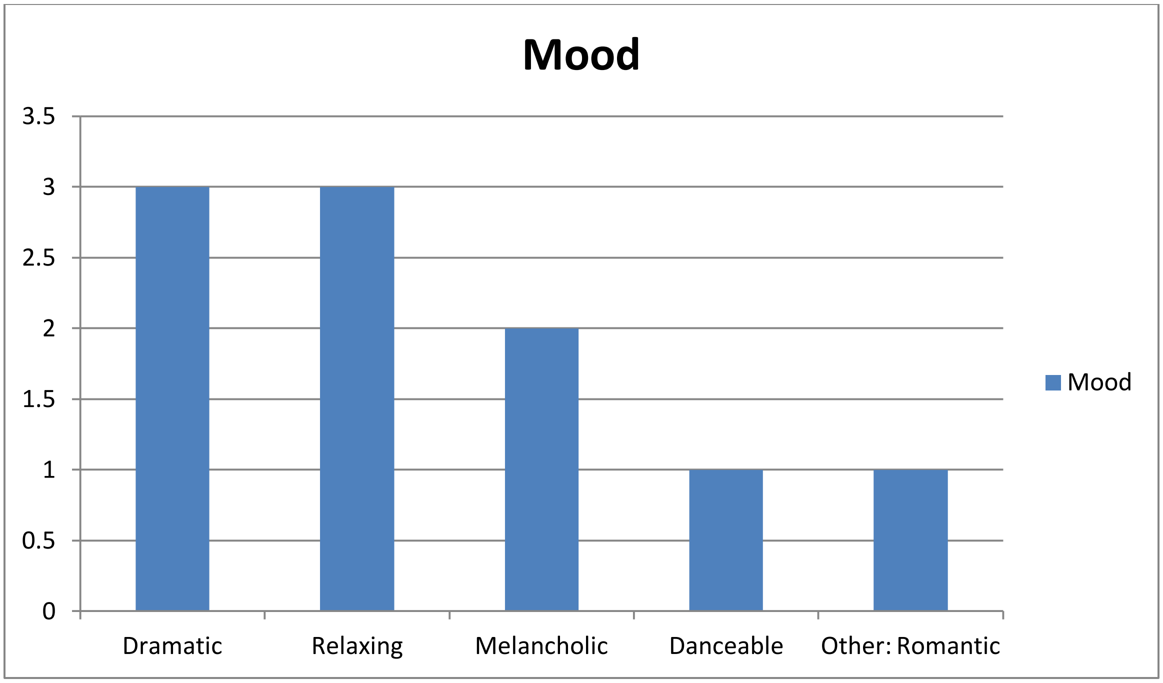
My uploads were:-

Song ID	Title	Link	Artist	Album	Uploaded By	Genre	Culture	Mood	Rating
1062	Jurassic Park Theme Song	Play	John William	Jurassic Park	ml17	Instrumental	International	Dramatic	5
1061	Raindrops (Chanchan)	Play	Sukhwinder Singh	Water	ml17	Classical	Western	Relaxing	5
1059	Let me be Myself (Amake Amar Moto Thakte Dao)	Play	Anupam Roy	Autograph	ml17	Soul	Indian	Melancholic	5
1057	Your Gesture Touched my Heart (Chukar Mere Mann Ko)	Play	Kishore Kumar	Yaarana	ml17	Soul	Indian	Other: Romantic	5
1056	Nuvone Bianche	Play	Ludovico Einaudu	Una Mattina	ml17	Instrumental	International	Relaxing	5
1054	From the Heart (Dil Se Re)	Play	A.R. Rahman	Dil Se	ml17	Rock	Western	Dramatic	5
1052	Enough of Hide & Seek (Luka Chhupi)	Play	Lata Mangeskar	Rang De Basanti	ml17	Soul	Indian	Melancholic	5
1050	528491	Play	Hans Zimmer	Inception	ml17	Instrumental	International	Dramatic	5
1049	Know the Mysteries of Love (Dil Ka Bhawar Kare Pukar)	Play	Mohd. Rafi	Tere Ghar Ke Samne	ml17	Soul	Indian	Relaxing	5
1048	Run D.K.Bose	Play	Ram Sampath	Delhi Belly	ml17	Rock	Western	Danceable	5

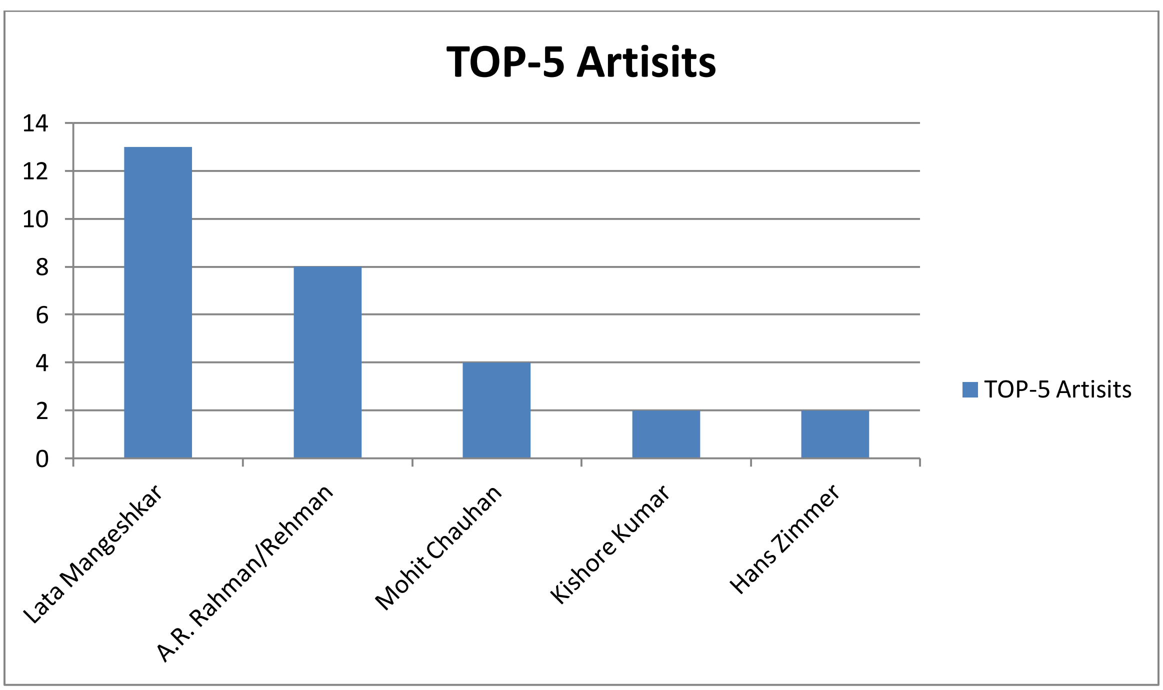
My Upload Statistics



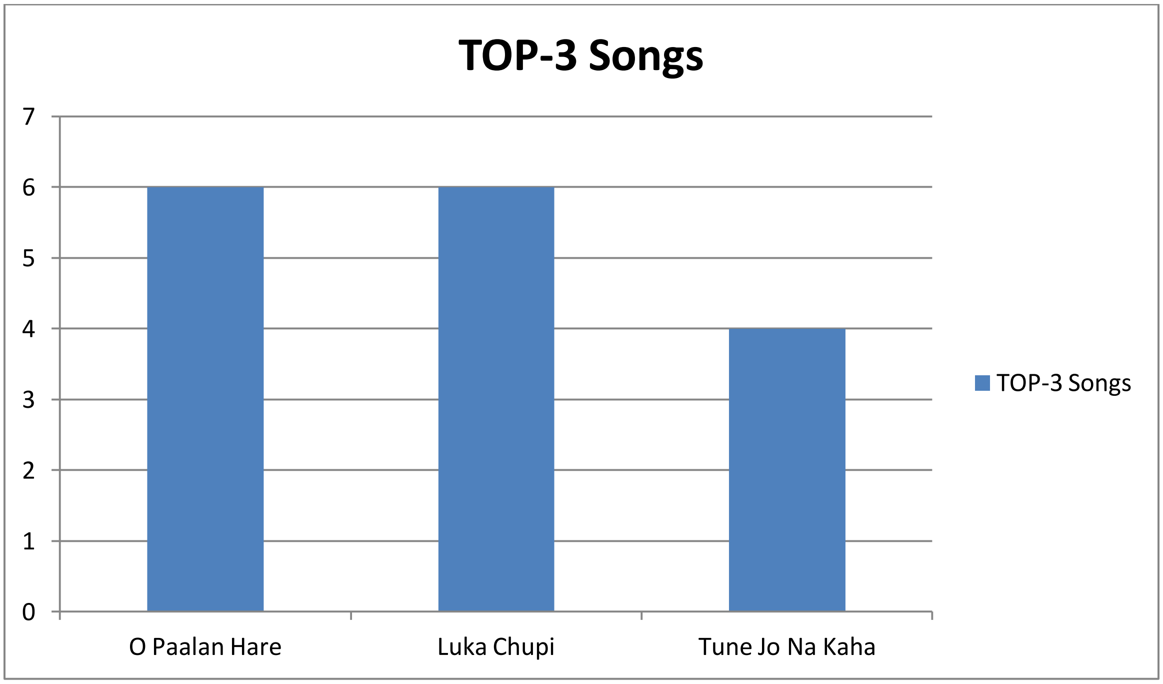




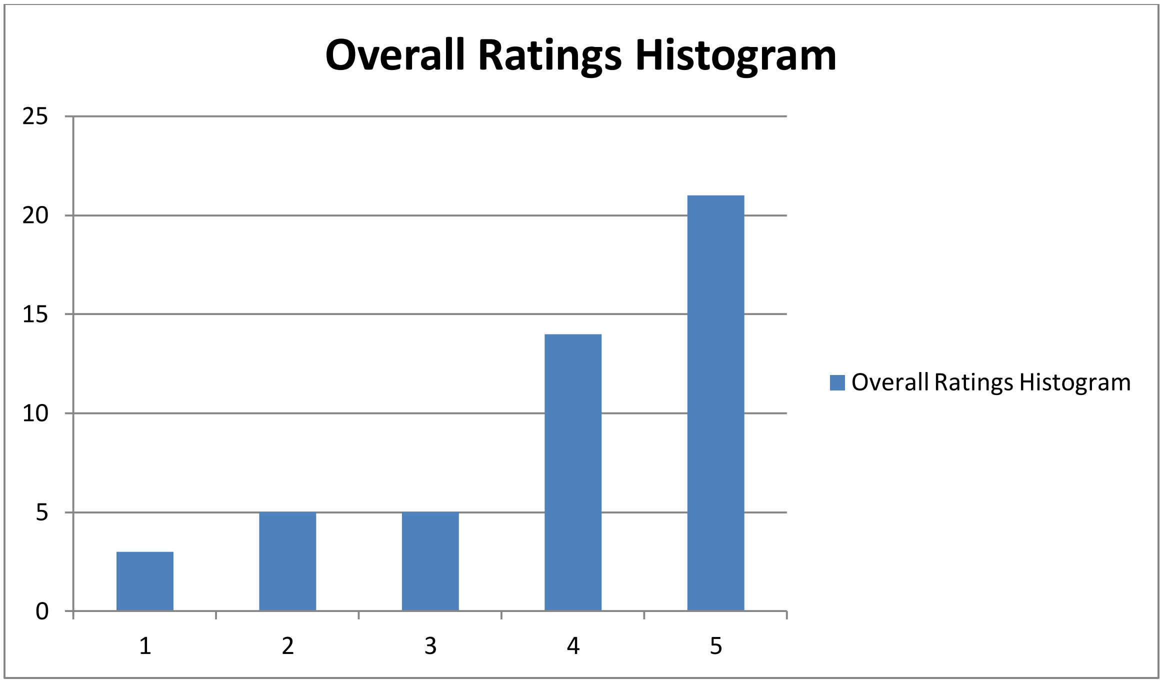
Statistics of Incoming Recommendations



1. 4 out of the Top-5 artists were Indian, although I had uploaded only 4 Indian songs out of 10.
2. Although I had uploaded only 1 Lata Mangeshkar's song, she came out as the most recommended artist for me.
3. Would have been happier to have received more from Hans Zimmer.



1. All my top-3 songs were Indian.
2. The top 2 songs are sung by the same artist.
3. Luka Chupi, is song that I had uploaded myself and also received it as recommendations (same song having different SongIDs)
4. There are other artists like Kim Dong Ryul, Japan Comic, Clint Mansel and Eason Chan among many that I was not aware of earlier and would definitely like to check them out.



Average Outgoing Rating: 3.91*

*this does not include the ones I rated 0. 0 ratings were given to the songs whose links to YouTube did not exist anymore.

Recommended Songs :

Song ID	**Title**	**Artist**	**Album**	**Link**
725	BYOB	System of a Down	Mezmerize	Play
Feedback				
935	sorry seems to be the hardest word	Elton John	Blue moves	______
Feedback				
998	The Truth in Wine (취중진담)	Kim Dong Ryul (김동률)	Second Concert	______
Feedback				
1291	To the end of world	japan comic	slum dunk	______
Feedback				
167	That's the way it is	Celine Dion		Play
Feedback				
1000	Falling in Love at a Coffee Shop	Landon Pigg	Falling in Love at a Coffee Shop	______
Feedback				

958	Luka Chupi	Lata Mangeshkar , AR Rehman	Rang De Basanti	
Feedback				
959	Requiem for a Dream	Clint Mansel	Lord Of The Rings - The TwoTowers	
Feedback				
840	Ma Sandhai	Axata		
Feedback				
203	Rainman Main Theme	Hans Zimmer	Rainman OST	Play
Feedback				
958	Luka Chupi	Lata Mangeshkar , AR Rehman	Rang De Basanti	
Feedback				
1391	Crying In The Rain	a-ha	East of the Sun, West of the Moon	Play
Feedback				
1400	May it be	Enya	Felloship of the Ring	Play
Feedback				
924	Dalgalandim da Duruldum	Gripin	Gripin	
Feedback				
56	Maa Tujhe Salam	A R Rehman	Vande Mataram	Play
Feedback				
1350	10 years (十年)	Eason Chan	Black, White and Grey	
Feedback				
1210	Jinke Marina	Emil	Kannada	
Feedback				
770	Remember the name	Fort Minor	The Rising Tied	
Feedback				
1234	Lough Erin Shore	The Corrs	Unplugged	Play
Feedback				
1421	Because of You	Kelly Clarkson	Breakaway	
Feedback				

1171	Rasputin	BoneyM	BoneyM	Play
Feedback				
1437	White & Nerdy	"Weird Al" Yankovic	Straight Outta Lynwood	Play
Feedback				
1130	not going anywhere	Karen Ann	not going anywhere	
Feedback				
827	Salted Fish (咸鱼)	Mayday(五月天)	just my pride best of album(知足最真杰作选)	
Feedback				
958	Luka Chupi	Lata Mangeshkar , AR Rehman	Rang De Basanti	
Feedback				
1239	Defying Gravity	Kristin Chenoweth	The Wicked	
Feedback				
1218	ONE	Yeasayer	Odd Blood	
Feedback				
1302	Beat it	MJ	Thriller	
Feedback				
271	Tune Jo Na Kaha	Mohit Chuahan	New York	Play
Feedback				
1354	Alaipayuthey	A. R. Rahman	Alaipayuthey	
Feedback				
158	Akele hum nadiya kinare	Shubha Mudgal	Raincoat	
Feedback				
271	Tune Jo Na Kaha	Mohit Chuahan	New York	Play
Feedback				
1225	Now We Are Free	Hans Zimmer	Gladiator	
Feedback				
958	Luka Chupi	Lata Mangeshkar , AR Rehman	Rang De Basanti	

Feedback				
958	Luka Chupi	Lata Mangeshkar , AR Rehman	Rang De Basanti	____
Feedback				
1042	With the colors of flowers(Phoolon ke rang se)	Kishore Kumar	Prem Pujari	____
Feedback				
271	Tune Jo Na Kaha	Mohit Chuahan	New York	Play
Feedback				
57	O Paalan Hare	Lata Mangeshkar	Lagaan	Play
Feedback				
57	O Paalan Hare	Lata Mangeshkar	Lagaan	Play
Feedback				
736	comptine d'un autre	yann tiersen		Play
Feedback				
271	Tune Jo Na Kaha	Mohit Chuahan	New York	Play
Feedback				
57	O Paalan Hare	Lata Mangeshkar	Lagaan	Play
Feedback				
57	O Paalan Hare	Lata Mangeshkar	Lagaan	Play
Feedback				
57	O Paalan Hare	Lata Mangeshkar	Lagaan	Play
Feedback				
119	Jagadananda Karaka	U Srinivas	Millenium - Vol7	____
Feedback				
1409	Nashik Dhol	Open Source	Nashik dhol	____
Feedback				
443	Iktara	Kavita Seth	Wake up sid	Play
Feedback				
958	Luka Chupi	Lata Mangeshkar , AR Rehman	Rang De Basanti	____
Feedback				
1040	Touching my heart(Chhukar mere mann ko)	Kishore Kumar	Yarana	____
Feedback				

826	Stubborn(倔强)	Mayday(五月天)	God's Children Are All Dancing(神的孩子都在跳舞)	——
Feedback				
1407	So gaye hain	Lata Mangeshkar	Zubaida	——
Feedback				
57	O Paalan Hare	Lata Mangeshkar	Lagaan	Play
Feedback				
1167	Ellello Oduva	Avinash chebbi	Sidlingu	——
Feedback				

Appendix

· **Average Spectral Flux:** The mean spectral flux over the last 100 windows.

· **Beat Sum:** The sum of all bins in the beat histogram. This is a good measure of the importance of regular beats in a signal.

· **Compactness**: A measure of the noisiness of a recording. Found by comparing the components of a window's magnitude spectrum with the magnitude spectrum of its neighboring windows.

· **FFT Bin Frequency Labels:** The bin label, in Hz, of each power spectrum or magnitude spectrum bin. Not useful as a feature in itself, but useful for calculating other features from the magnitude spectrum and power spectrum.

· **Fraction Of Low Energy Frames**: The fraction of the last 100 windows that has an RMS less than the mean RMS of the last 100 windows. This can indicate how much of a signal section quiet relative to the rest of the signal section is.

· **Magnitude Spectrum:** A measure of the strength of different frequency components. Derived directly from the FFT.

· **Power Spectrum**: A measure of the power of different frequency components. Derived directly from the FFT.

· **Root Mean Square (RMS)**: A measure of the power of a signal over a window.

· **Root Mean Square Derivative:** The window to window change in RMS. An indication of change in signal power.

· **Root Mean Square Variability:** The standard deviation of the RMS of the last 100windows.

· **Spectral Centroid:** The centre of mass of the power spectrum.

· **Spectral Centroid Variability:** The standard deviation of the spectral centroid over the last 100 windows.

· **Spectral Flux:** A measure of the amount of spectral change in a signal. Found by calculating the change in the magnitude spectrum from frame to frame.

· **Spectral Roll off Point:** The fraction of bins in the power spectrum at which 85% of the power is at lower frequencies. This is a measure the right-skewedness of the power spectrum.

· **Spectral Variability:** The standard deviation of the magnitude spectrum. A measure of how varied the magnitude spectrum of a signal is.

· **Strength Of Strongest Beat:** How strong the strongest beat in the beat histogram is compared to other potential beats.

· **Strongest Beat:** The strongest beat in a signal, in beats per minute, found by finding the highest bin in the beat histogram.

· **Strongest Frequency Variability:** The standard deviation of the frequency of the power spectrum bin with the highest power over the last 100 windows.

· **Strongest Frequency via FFT Maximum:** An estimate of the strongest frequency component of a signal, in Hz, found via finding the FFT bin with the highest power.

· **Strongest Frequency via Spectral Centroid:** An estimate of the strongest frequency component of a signal, in Hz, found via the spectral centroid.

· **Strongest Frequency via Zero Crossings:** An estimate of the strongest frequency component of a signal, in Hz, found via the number of zero-crossings.

· **Zero Crossings:** The number of times the waveform changed sign in a window. An indication of frequency as well as noisiness.

· **Zero Crossings Derivative:** The absolute value of the window to window change in zero crossings. An indication of change of frequency as well as noisiness.

· **Zero Crossing Variability:** The standard deviation of the zero-crossings of the last 100 windows.