

HumoRadio

A music Recommender system based on user's mood

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RoadMap Overview

- 1. Idea
- 2. Technologies Used
- 3. Dataset Collection
- 4. How the Application works
- 5. Running Demonstration
- 6. Clustering Issues
- 7. Conclusions

Idea

Our idea is to create a recommender system based on user's mood, with 2 fields: Happy/Sad and Relaxing/Exciting Levels.

Step 1

The user selects the music genre and provides his mood status.

Step 2

The application selects a collection of songs to be listened based on an apriori made survey.

Step 3

The user implicitly rates this songs for further selections.

Technologies Used

We developed a Java web based application using JEE. The application consists of an HTML page in which the user specifies a genre, if he wants, and a specific mood or he leaves it indifferent. In another HTML5 page a servlet will manage requests coming from the first page and will provide user the playlist to listen or will let the user come back to change his mood.

The application will play songs through Youtube, displaying also the video related in order to have a better entertainment. We worked with the Youtube Api to interact with player parameters.

We exploited Java to manage all the logic behind the service, Javascript to handle Youtube player aspects and user interaction.

NetBeans IDE with Glassfish server were used as environment of the project.

Technologies Used

















Overview



Dataset Collection

Cold start problem:

• online survey on Google form to

Dataset structure:

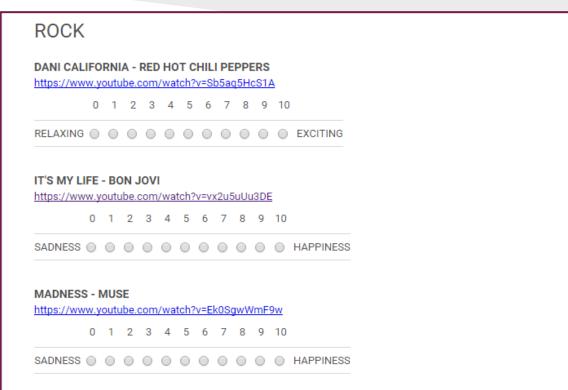
- 5 genres (Rock, Pop, Blues)
- **30** songs per genre

Rating values:

- 2 mutual exclusive bar of mo
- *10* degrees of freedom within

Tables created:

- 1. **SONG_DATA**(TITLE, TIME
- 2. **SONG_RATING**(ID, TITLE



Dataset Collection

#	TITLE	TIME	LINK
1	Pretty Fly – Offspring		192 nzY2Qcu5i2A
2	Basket case – Green Day		192 NUTGr5t3MoY
3	Knocking on Heaven's door – Guns n' Roses		341 2tmc8rJgxUI
4	Sweet Home Alabama - Lynyrd Skynyrd		300 ye5BuYf8q4o
5	Roxanne – The Police		314 3T1c7GkzRQQ
6	Dani California – Red Hot Chili Peppers		328 Sb5aq5HcS1A
7	Wonderwall – Oasis		318 bx1Bh8ZvH84
8	Do I wanna know – Artic Monkeys		305 bpOSxM0rNPM
9	Seven nation army – The White Stripes		240 0J2QdDbelmY
10	Zombie – Cranberries		316 6Ejga4kJUts
11	21 guns – Green Day		327 r00ikilDxW4
12	Can't stop – Red Hot Chili Peppers		278 BfOdWSiyWoc



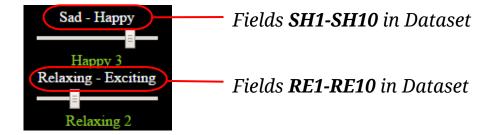
SONG_DATA

SONG_RATING



#	ID	TITLE	RE1	RE2	RE3	RE4	RE5	RE6	RE7	RE8	RE9	RE10	SH1	SH2	SH3	SH4	SH5	SH6	SH7	SH8	SH9	SH10	GENRE
1	nzY2Qcu5i2A	Pretty fly – Offspring	1	. 1	. 0) 1	1 :	1 1	1 1	. 8	3 2	6	j 1	1 0	2	4	0	0	3	5	4	3	1
2	NUTGr5t3MoY	Basket case – Green Day	1	. 0	0) 1	1 7	2 3	3 4	1 3	3 5	3	3	1 0	1	. 1	1	. 4	4	4	4	2	. 1
3	2tmc8rJgxUI	Knocking on Heaven's door – Guns	4	2	2 2	2 5	5 3	3	1 0	3	3 0	4	2	2 0	3	0	2	3	5	2	2	2 3	1
4	ye5BuYf8q4o	Sweet home Alabama - Lynyrd Sky	2	3	3 1	1 2	2 () 2	2 3	3	2 5	2	2 () 1	. 0	0	1	. 1	. 4	6	5	3	1
5	3T1c7GkzRQQ	Roxanne – The Police	2	. 1	1 3	3 5	5 :	1 3	3 1	1 2	2 1	. 0) :	1 2	2 1	. 2	2	. 2	4	0	1	. 0	1
6	Sb5aq5HcS1A	Dani California – Red Hot Chili Pepp	2	. 0	0) 3	3 () 4	1 5	5 3	3	2	2 :	1 0	0	3	2	. 2	4	5	2	2 2	. 1
7	bx1Bh8ZvH84	Wonderwall – Oasis	6	2	2 3	3 6	5 2	2 :	1 2	2 2	2 0	1	. 3	3 2	2 1	. 2	3	1	. 1	. 3	3	3 1	. 1
8	bpOSxM0rNPM	Do I wanna know – Artic Monkeys	3	0) 3	3	3 () 3	3 4	1	١ 0	0	2	2 3	1	. 3	4	2	0	1		0	1
9	0J2QdDbelmY	Seven nation army – The White Str	1	. 0	1	L 1	1 () () 3	3	1	. 8	1	1 0	0	2	1	. 1	. 3	5	1	4	1

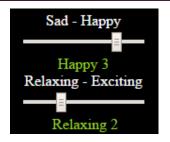
Creates a decreasing rank based on the sum of the support each song has in the fields selected.



<u>Possible combinations of selections:</u>

- 1. 2 values not "Indifferent"
- 2. 1 value "Indifferent" and the other not
- 3. Both "Indifferent"

When an "Indifferent" value is selected we perform the sum on the fields right above and below the middle one (which are SH5, SH6 and RE5, RE6).



In this case the application sums the related 2 values in order to get the rank

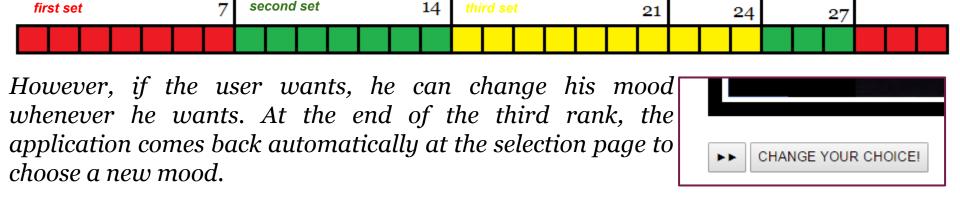
In this case one values has been left "Indifferent" and, for this reason, the application sums the specific value for the selected aspect of mood and 2 values that are the 2 boundary values for the other aspect. In this example we take for the Sad-Happy field the values Sad = 5 and Happy = 1 which are the next boundaries of the middle "Indifferent" value.





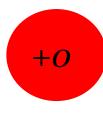
In this last case both are left "Indifferent" and so the procedure here is repeated for both aspects, considering 4 values for the final sum.

The application creates 3 ranks of 10 songs divided as shown in the picture below. After a complete rank has been listened, the application asks the user if he wants to change his mood or continue listening songs maintaining the previous mood.



The user is not able to change the current execution time of a song in order not to alter statistics in the dataset. **How is the dataset updated?**

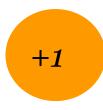
The updating task is performed implicitly taking into consideration the percentage of listened time (t) w.r.t. the total song time. When a song is proposed to the user, the application considers significant the moment at which he skips the song and it adds a value to the current rate present in the dataset. If a song is listened entirely, the last case will be triggered.



Percentage: t <= 25%

The user consider this song not appropriate for this mood.

No points is added to the dataset rate



Percentage: 25% < t <= 50%

The user consider this song not so appropriate for this mood.

One point is added to the dataset rate



Percentage: 50% < t <= 75%

The user consider this song

appropriate for this mood.

Two points are added to the dataset rate

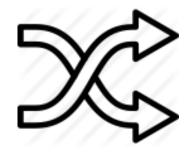


Percentage: t > 75%

The user consider this song very appropriate for this mood.

Three points are added to the dataset rate

How to avoid the situation in which the user, selecting twice the same mood, has to play the same selection of songs?

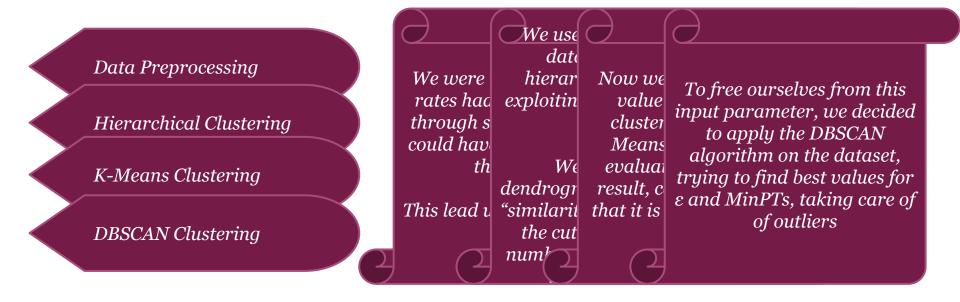


After songs have been selected and all three ranks have been set up, on these three selections a **shuffle function** is applied to mix the songs disposal.

Random Selection

Clustering Issues

A-posteriori Clustering to visualize similar songs that represent a specific mood.



Data Preprocessing

Our database values can be considered as counters which could be increased at each selection.

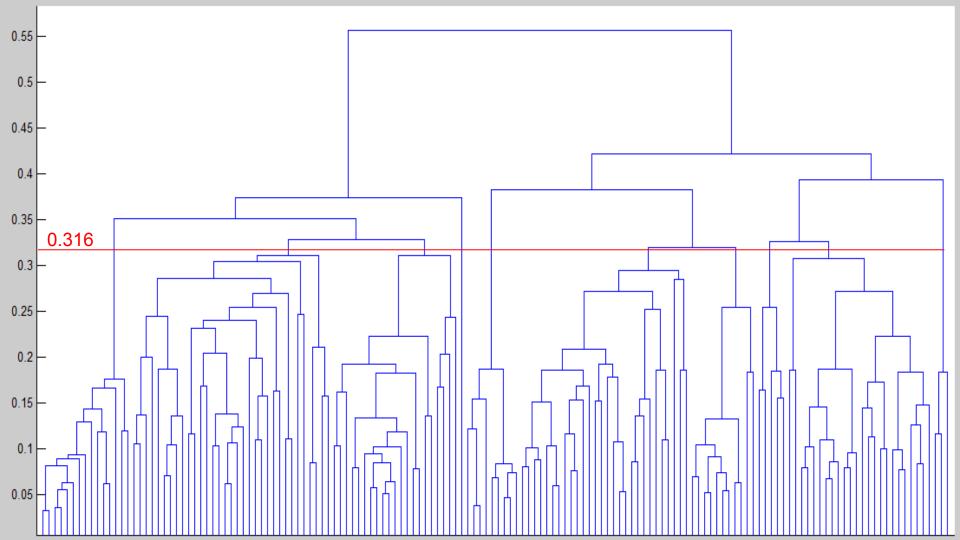
We could have songs more listened than others.

In order to have comparable weights on every song we decided to **Normalize** the entire dataset.

We used the Unsupervised filter Normalize provided by Weka Api.

14	vx2u5uUu3DE	It's my life – Bon Jovi	0	1	0	0	2	3	0	3	4	13	1	0	1	1	0	4	2	6	2	(10)	1
																						\cup	
20	L_jWHffIx5E	All star – Smash Mouth	0	2	0	2	0	1	4	2	3	3	1	0	1	0	1	4	3	2	4	3	1

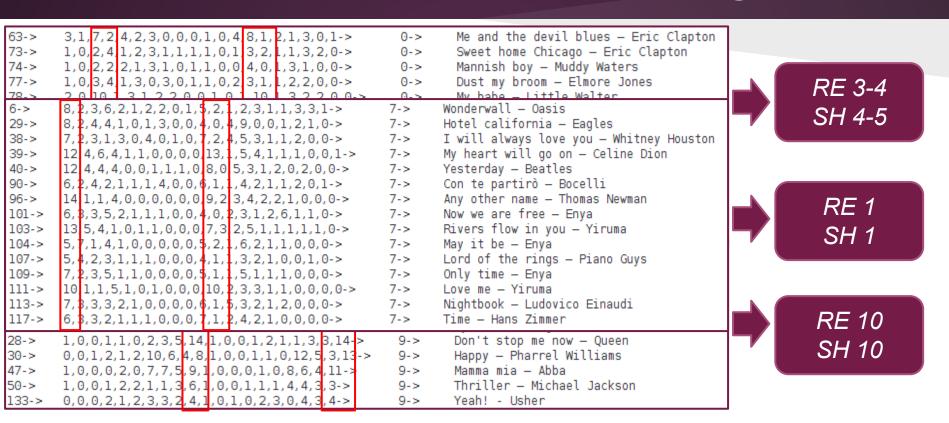
Once the dataset is normalized, we are allowed to use the Euclidean Distance to compute the similarities between objects.



K-Means Clustering

kMeans =====										Clustered In	stances
Within clus Missing val Cluster cen	terations: 6 ter sum of sq ues globally troids: Full Data			e	3	4	5	6	-	0 14 1 12 2 30 3 24 4 10 5 13	(9%) (8%) (20%) (16%) (7%) (9%)
Attribute	(150)	(14)	(12)	(30)	(24)	(10)	(13)	(5)	(15)	6 5	(3%)
RE1 RE2 RE3 RE4	0.1798 0.1103 0.1999 0.1978	0.1664 0.0453 0.3689 0.2368	0.1768 0.1438 0.1483 0.2017	0.0438 0.0315 0.1238 0.1508	0.0627 0.0362 0.0782 0.1093	0.2501 0.262 0.5136 0.1438	0.2093 0.1897 0.3374 0.3623	0.3696 0.2791 0.39 0.175	0.5706 0.2187 0.211 0.2534	7 15 8 16 9 11	(10%) (11%) (7%)
RE5	0.1593	0.2427	0.1819	0.1759	0.089	0.1795	0.1699	0.0969	0.0858	0.2621	0.0852
RE6	0.1788	0.1521	0.1593	0.3291	0.1622	0.0682	0.131	0.1547	0.0463	0.25	0.1051
RE7	0.2186	0.1906	0.3418	0.3711	0.2925	0.0881	0.099	0.0229	0.0684	0.1445	0.204
RE8	0.1676	0.1205	0.186	0.2437	0.3257	0.0497	0.0638	0.0775	0.0542	0.0754	
RE9	0.0887	0.0251	0.047	0.0531	0.303	0	0.0217	0.0229	0.0086	0.0761	0.1618
RE10	0.1208	0.0706	0.1476	0.0842	0.2057		0.0122	0.1255	0.0048	0.0619	0.5505
SH1	0.1541	0.137	0.1756	0.0686	0.0726	0.2106	0.1953	0.2084	0.4569	0.1252	0.0684
SH2	0.0848	0.0178	0.2385	0.034	0.0233	0.1154	0.1728	0.3758	0.089	0.0881	0
SH3	0.152	0.1356	0.3084	0.0813	0.0532	0.1769	0.4107	0.1976	0.1795	0.1416	0.0387
SH4	0.2313	0.5298	0.3265	0.0971	0.0781	0.4748	0.3447	0.2184	0.3004	0.197	0.0545
SH5	0.184	0.1468	0.2381	0.2836	0.0893	0.1492	0.1795	0.1397	0.1194	0.2885	
SH6	0.1954	0.1285	0.176	0.3053	0.2091	0.1165	0.1679	0.0636	0.0807	0.33	0.0976
SH7	0.2274	0.1472	0.1541	0.3236	0.3841	0.0929	0.1515	0.1441	0.0833	0.26	0.2045
SH8	0.1668	0.1331	0.0693	0.2137	0.347	0.0758	0.0347	0.2346	0.0606	0.0933	0.2544
SH9 SH10	0.0919 0.1007	0.0825 0.0052	0.068 0.046	0.1113 0.0772	0.1966 0.1783	0.0332	0.0347	0.0763 0.053	0.035 0.0136	0.0417 0.081	0.1678 0.5057

K-Means Clustering



DBSCAN Clustering

--> NOTSE

--> NOTSE

--> NOTSE

--> NOTSE

--> NOTSE

--> NOTSE

```
DBSCAN clustering results
Clustered DataObjects: 150
Number of attributes: 20
Epsilon: 0.7: minPoints: 2
Index: weka.clusterers.forOPTICSAndDBScan.Databases.SequentialDatabase
Distance-type: weka.clusterers.forOPTICSAndDBScan.DataObjects.EuclideanDataObject
Number of generated clusters: 11
Elapsed time: ,06
   0.) 0.065653.0.065653.0.0.065653.0.131306.0.065653.0.131306.0.459573.0.13
   1.) 0.082761,0,0,0.082761,0.165521,0.248282,0.331042,0.248282,0.413803,0.
   2.) 0.257248.0.171499.0.171499.0.428746.0.257248.0.085749.0.0.257248.0.0.
                                                                               --> NOTSE
   3.) 0.16169, 0.242536, 0.080845, 0.16169, 0.0.16169, 0.242536, 0.16169, 0.404226
                                                                              --> NOTSE
   4.) 0.210819.0.105409.0.316228.0.527046.0.105409.0.316228.0.105409.0.2108
                                                                               --> NOTSE
```

5.) 0.167248,0,0,0.250873,0,0.334497,0.418121,0.250873,0.250873,0.167248,

6.) 0.57886.0.144715.0.217072.0.434145.0.144715.0.072357.0.144715.0.14471

7.) 0.304604.0.0.304604,0.304604,0.304604,0.406138,0.101535,0.0.20306

8.) 0.050965,0,0.050965,0.050965,0.152894,0.152894,0.152894,0.203859,0.05 9.) 0.228748,0.304997,0,0.228748,0.152499,0.076249,0.381246,0.228748,0.07

(11.) 0.074125,0,0.074125,0.074125,0.074125,0.074125,0.44475,0.074125,0.444 (12.) 0.0.0.178885,0.178885,0.0.268328.0.447214.0.178885,0.089443,0.447214.

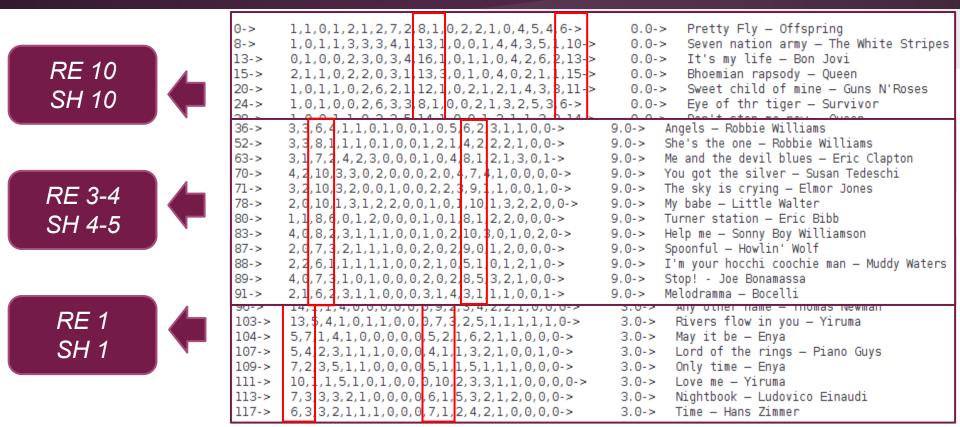
10.) 0.16221.0.0.324443.0.081111.0.243332.0.243332.0.243332.0.324443.0.0.

(13.) 0,0.043561,0,0,0.087121,0.130682,0,0.130682,0.174243,0.696971,0.04356
(14.) 0.076923,0,0.0.153846,0,0.230769,0.153846,0.461538,0.384615,0.230769.

(15.) 0.094281,0.04714,0.04714,0.0.094281,0.094281,0.0.141421,0.04714,0.612
(16.) 0.079556,0,0.079556,0,0.079556,0.079556,0.397779,0.318223,0.318223,0.
(17.) 0.0,0.128831,0.128831,0.322078,0.386494,0.386494,0.193247,0,0.064416,

The value of ε and MinPts were chosen based on different trials

DBSCAN Clustering



Thanks

"The validation of clustering structures is the most difficult and frustrating part of cluster analysis.

Without a strong effort in this direction, cluster analysis will remain a black art accessible only to those true believers who have experience and great courage."

Algorithms for Clustering Data, Jain and Dubes