Exploring Large Scale 20th Century Music Features Historical Patterns and Discoveries

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I. INTRODUCTION

We analyse various music features and scores and correlate their temporal variations with historical events or trends. This project thus provides a new approach to history for the sake of curiosity. It could also be used for educational purposes.

II. PROBLEM DEFINITION

The idea is to detect variations of music features and correlate them with historical events or trends. Step one is to define meaningful scores using machine learning tools and to visualize their evolution with time. Then, signal processing techniques should help us detect mathematically significant variations of these scores.

III. RELATED WORKS

A. MUSIC INFORMATION RETRIEVAL

Retrieving and processing music information from large datasets are essential for our project [13]. With the growing number of music datasets, research has been done to extract features from a song, identify patterns and infer metrics to characterize songs [14]. Many of these studies focused on music classification by genre [15], exploiting the loudness, the timbre [16], the pitch or even lower-level features obtained by signal processing techniques such as Fourier transform. Researchers suffered from the lack of publicly available benchmark data sets [17]. The Million Songs dataset, which we will use, aims at addressing this issue [18]. To detect continuous or discontinuous changes in popular music, some have exploited musical characteristics while others have inferred semantically meaningful features [20], as described by Weihs *et al.* [21], which provide insight on how humans understand and interpret music.

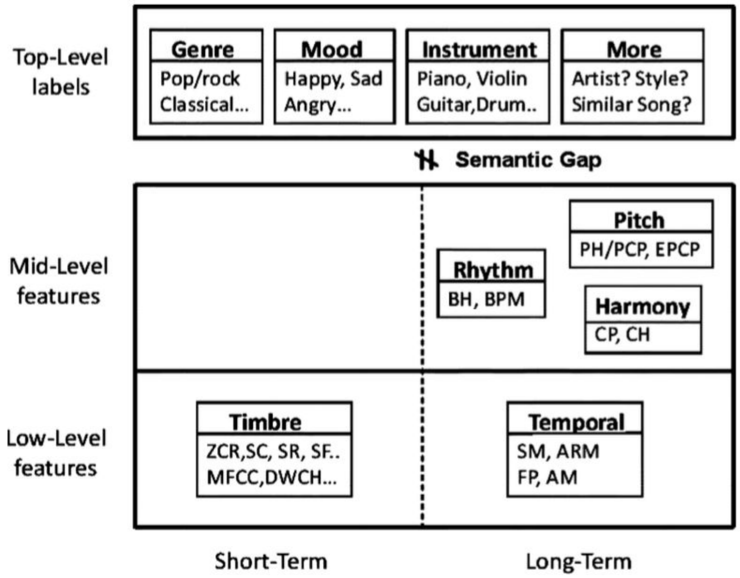

Figure 1: Characterization of audio features

B. MUSIC MOOD CLASSIFICATION IN WESTERN MUSIC

Classification of music by mood clusters has been done by analysing text information, acoustic features or combination of both. The main issue is emotion subjectivity[3]. Thus the accuracy of these classifications is limited. Merging synonyms into clusters instead of focusing on only one emotion per cluster can improve it[4]. We should implement this kind of categorization of moods. Moreover, the evolution of the language should be considered as some words are less and less used and vice-versa[5].

Besides lyrics and audio features, [10] also considers genre to better classify music by mood. We expect that a combination of the three approaches will give us significant results.

Cluster 1	passionate, rousing, confident, boisterous, rowdy
Cluster 2	rollicking, cheerful, fun, sweet, amiable/good natured
Cluster 3	literate, poignant, wistful, bittersweet, autumnal, brooding
Cluster 4	humorous, silly, campy, quirky, whimsical, witty, wry
Cluster 5	aggressive, fiery, tense/anxious, intense, volatile, visceral

Figure 2: Clusters of mood adjectives used in the MIREX Audio Mood Classification task [5]

	Audio	Lyrics	Mixed	Voting
Angry	98.2%(3.8)	77.9%(10.3)	**98.3%(3.7)**	95.0% (4.3)
Happy	84.6%(11.5)	80.8%(11.2)	**86.8%(10.6)***	86.5% (10.8)
Sad	87.7%(11.0)	84.4%(11.2)	92.8%(8.7)*	**95.6% (8.2)***
Relaxed	91.4%(7.3)	79.7%(9.5)	91.7%(7.1)	**93.4% (6.7)***

Figure 3: Classification scores in [10] with SVM and language model differences using audio features and lyrics

In [11], audio features are studied to show that American music has become sadder-sounding and more emotionally ambiguous since the 60s because listeners appreciate it. So we have to keep in mind that artists might just want to fulfill the emotional needs of purchasers which are not necessarily correlated to ongoing major events.

Supervised learning will be used in our approach. One possible algorithm is pairwise SVM which classifies musics by mood using audio features in [19].

These works will allow us to assess the evolution of emotions in music across time in order to, hopefully, deduce historical events. For instance, we expect to see happiness dropping in wartime.

C. LINKING MUSIC TO HISTORICAL EVENTS

Authors have studied how public mood evolved over time. [2] did it using frequencies of mood words in books. [2] provides us with a referential for mood evolution, independent from music, that we can use to detect if music trends differ from literature. Finally, [2] discusses normalization methods for features based on word counts which may also be relevant to lyrics studies.

An important aspect of music is the role it may play for movements [2]. This offers another perspective to our study which is how music may even be shaped by some historical events. Besides, it is interesting to realize that the political meanings of a music is often conveyed by its form more than by its contents. It is also controversial whether or not people really agree with or are influenced by the lyrics.

We will need to use [1] to provide us with a timeline of events in the USA for interpreting and validating our results.

D. A GOOD VISUALIZATION

While designing our system, we need to keep in mind the goal of the project, as well as the keys to create an appealing visualization, according to Figure 4.

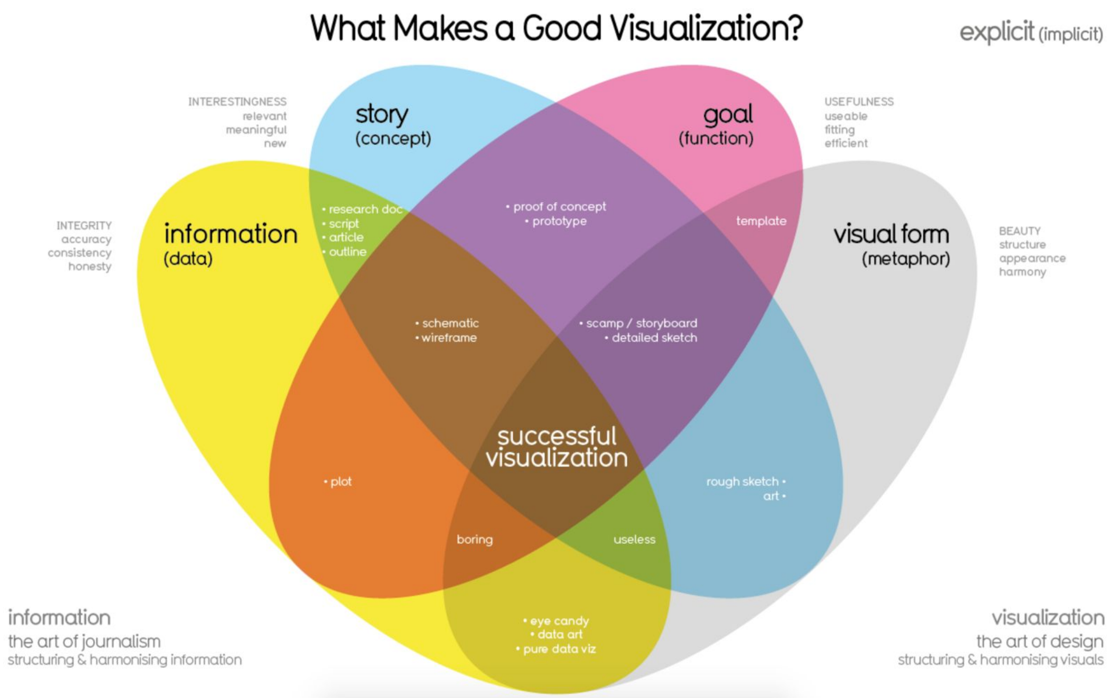

Figure 4 : A successful visualization [9]

IV. PROPOSED METHOD

A. INTUITION (Why should it be better than the state of the art?)

With the growing number of music datasets, research has been done to extract features from a song, identify patterns and infer metrics to characterize songs [14]. Many of these studies focused on music classification by genre [15], exploiting different features.

Both historical [6] and musical [7] timeline visualizations exist but they are not merged yet. Some papers do present the correlation between music and history [8] but they are difficult to read and only analyse the evolution of music due to a specific historical event. Conversely, we analyse music features (lyrics, mood, etc.) across years to detect major historical events. History events will be used as ground-truths to check our results.

Innovations:

- Deduce History from music and lyrics evolution
- Focus on intuitive visualization

B. STATISTICS OF THE DATASET

The Million Song Dataset was created from several other datasets (mainly Echo Nest and Musicbrainz).

- 1,000,000 songs
- 54 characteristics per song (appendix 2)

- 273 GB of data
- 44,745 unique artists
- 7,643 unique terms (lyrics) from The Echo Nest tags
- 2,321 unique musicbrainz tags (genre)
- 515,576 dated tracks starting from 1922

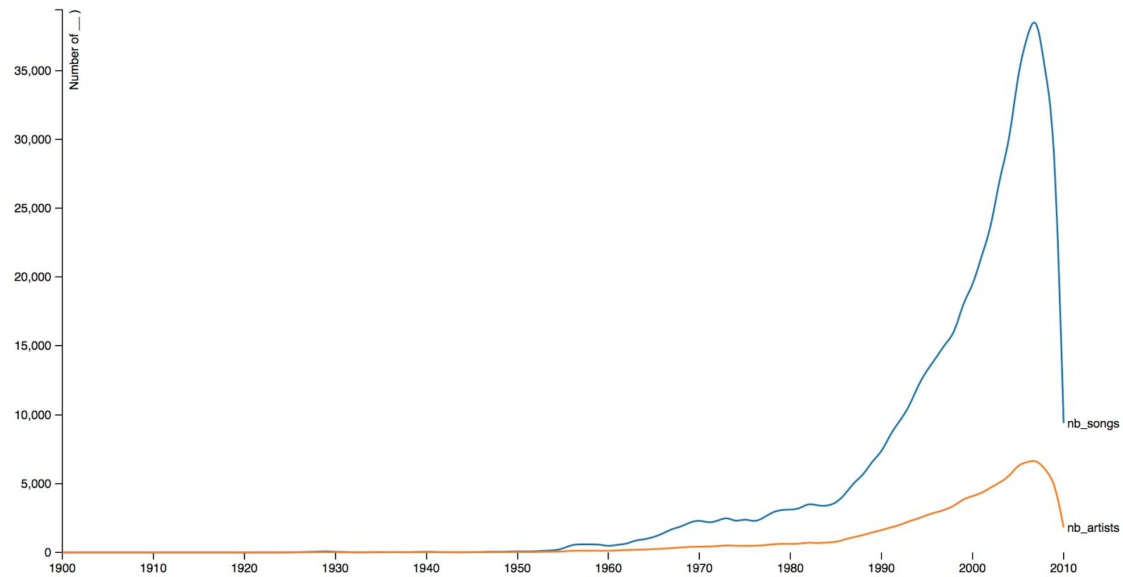

Figure 5: Counts of songs and artists per year in the Million Song Dataset. Our analysis will be relevant only from 1960 to 2010. Please notice that nearly 500 000 songs do not have "year" information.

C. DESCRIPTION OF OUR APPROACH

a. RAW DATA EXTRACTION

The million song dataset is accessible as a snapshot on Amazon Web Services. We also downloaded the dataset to perform some computation on our machines. Each song is stored in a hdf5 file. To improve the speed of access to these files, the database is organized as a hierarchy of folders. The problem with this organization is that opening and closing a file is very long, especially if you have to do it one million times. So in order to improve the efficiency of our algorithms, we created a csv file containing, for each song, the values of all its numerical and string features.

However, doing the same maneuver for arrays would result in files of several gigabytes, after days of computation. Besides, retrieving an array from a file requires some parsing anyway. It was thus decided to retrieve the array features from the hdf5 files directly.

In order to perform lyrics analysis, we joined to our dataset the musiXmatch dataset which provides lyrics for 237,662 tracks and the Last.fm dataset which contains tags that are useful for classification tasks. 505,216 tracks have at least one tag.

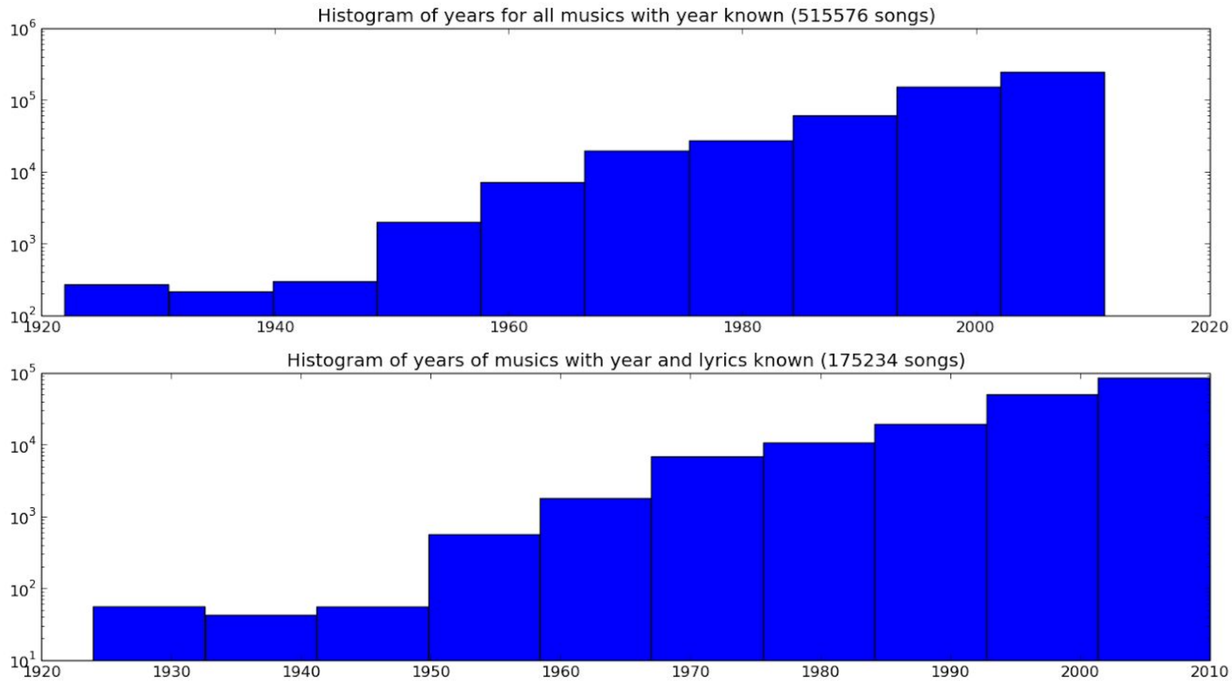

Figure 6: Lyrics availability per decade

Finally, as our primary goal is to detect history trend, dates are paramount. In order to get more accurate results (additional or more precise date) we decided to extract the release date of each track from the Spotify API and combine this data to our original dataset.

As we combined different data sources. We had to clean and consolidate the resulting raw data. We used OpenRefine to merge the year information provided by the dataset and the year information from Spotify.

b. FEATURE EXTRACTION FROM LYRICS AND MACHINE LEARNING

Artists get their inspiration from the context in which they live in and they aim at expressing emotions through music and lyrics. That is why we use some audio features of the Million Song Dataset and the related lyrics from the musiXmatch dataset in order to associate each music of the dataset with an emotion.

[27] maps many of the songs with a genre by using the Last.fm dataset, the Top-MAGD dataset and the beaTunes Genre Dataset. In [10], a genre is linked to one or more emotions among relaxed, sad, happy and angry. We use this to label the subset of songs for which we have the lyrics, the year and an assigned genre. When the genre of a track is related to more than one emotion, we create a copy of this track in the dataset for each emotion. We have 175,234 songs with year and lyrics available and only 72,004 of them have a reported genre (they give us 130,147 non-unique labeled songs with an emotion). So we cannot map them to emotions. That is why we use Machine Learning to deduce the main emotion associated to the 103,230 other tracks.

Genre	Angry	Sad	Relaxed	Happy
Rock	+	-	-	+
Alternative	+	-	-	+
Rap	+	-	-	-
Electronic	+	-	-	-
Blues	-	+	+	-
Folk	-	+	+	-
Jazz	-	+	+	-
Classical	-	+	+	-
Soundtrack	-	+	+	-
Vocal	-	+	+	-
Country	-	+	+	+
Reggae	-	-	-	+
Pop	-	-	-	+
RBSoul	-	-	-	+
Latin	-	0	-	+

Figure 7: Significant mood for each genre

We only consider the following audio features to describe each track: duration, key, loudness, mode and tempo. We do not use pitch and timbre.

Then, we use Natural Language Processing to extract new features from the lyrics.

The first set of features expresses the amount of 6 emotional states (anger, sadness, swear, anxiety, positive affect and negative affect) in the lyrics. We use a lexicon for each of them made with LIWC (Linguistic Inquiry and Word Count [22]). Thus, each lyric is mapped to 6 LIWC scores, one for each emotional state.

$$LIWC\ score = \frac{number\ of\ matching\ words\ in\ the\ lyrics}{total\ number\ of\ whitespace\ tokens\ in\ the\ lyrics}$$

The second set of features is supposed to measure the importance of relevant lexical fields in the lyrics. We arbitrarily select the following topics: happiness (53 words), love (12 words), peace (63 words), sadness (96 words) and war (76 words).

The importance score of a thematic in a text is computed as follows. N(m) is the number of words corresponding to the topic in the lyrics of music m, D is the number of all lyrics and $E_{thematic}$ is the number of other lyrics containing at least 1 word of the topic.

$$Importance(m)_{thematic} = N(m)_{thematic} log(\frac{D}{E_{thematic}})$$

Therefore we get 5 more features from the lyrics. Note that this score is inspired by the TF-IDF score.

So the dataset used for this machine learning task has 130,147 tracks described by 16 features and labeled with 4 emotions. After standardizing the features, we compare the performance of three classifiers with several metrics: accuracy, precision ($precision = \frac{TP}{TP+FP}$), recall($recall = \frac{TP}{TP+FN}$) and F1 score ($F_1 = 2\frac{precision*recall}{precision+recall}$). The classifiers are Random Forest (100 trees), Naive Bayes and SVM (RBF kernel). We will also try a One versus Rest strategy with Random Forest. Meaning that we will train 4 Random Forest classifiers, each one classifying one class versus the others.

We split the dataset into a training (29,784 entries) and a testing (100,363) dataset so that the training dataset is balanced ($\frac{1}{4}$ of elements of each class). For the testing dataset the proportions of 'happy', 'angry', 'sad' and 'relax' labels are respectively 0.48, 0.50, 0.01 and 0.01.

As far as the Machine Learning is concerned, we also designed a Python script to infer the year of tracks for which the information is unavailable. It does classification of the decade. It uses Random Forest with tempo, duration and loudness as features. But eventually we did not use this code since we found a way to get missing years with the Spotify API.

Random Forest

Accuracy: 0.366

	precision	recall	f1-score	support
Angry	0.50	0.45	0.48	50,168
Happy	0.42	0.29	0.34	48,406
Relax	0.00	0.04	0.01	961
Sad	0.00	0.04	0.01	828
Avg/Total	0.45	0.37	0.40	100,363

Confusion matrix

	Angry	Happy	Relax	Sad
Angry	22,725	19,560	4,004	3,879
Happy	22,678	13,979	5,945	5,804
Relax	21	59	34	847
Sad	17	54	728	29

SVM

Accuracy: 0.306

	precision	recall	f1-score	support
Angry	0.48	0.34	0.4	50,168
Happy	0.41	0.28	0.33	48,406
Relax	0.00	0.04	0.00	961
Sad	0.00	0.03	0.00	828
Avg/Total	0.44	0.31	0.36	100,363

Confusion matrix

	Angry	Happy	Relax	Sad
Angry	17,017	19,034	8,683	5,434
Happy	18,583	13,603	9,536	6,684
Relax	84	101	41	725
Sad	75	91	637	25

Gaussian Naive Bayes

Accuracy: 0.364

	precision	recall	f1-score	support
Angry	0.57	0.34	0.43	50,168
Happy	0.50	0.39	0.44	48,406
Relax	0.02	0.19	0.04	961
Sad	0.02	0.50	0.03	828
Avg/Total	0.53	0.36	0.42	100,363

Confusion matrix

	Angry	Happy	Relax	Sad
Angry	17,055	18,690	3,403	11,020
Happy	12,558	18,840	4,001	13,007
Relax	107	197	181	476
Sad	87	164	160	417

OvR Random Forest

Accuracy: 0.367

	precision	recall	f1-score	support
Angry	0.50	0.45	0.48	50,168
Happy	0.42	0.29	0.34	48,406
Relax	0.00	0.03	0.00	961
Sad	0.00	0.05	0.01	828
Avg/Total	0.45	0.37	0.40	100,363

Confusion matrix

	Angry	Happy	Relax	Sad
Angry	22,805	19,357	4,039	3,967
Happy	22,539	13,997	5,946	5,924
Relax	18	60	25	858
Sad	16	49	723	40

Figure 8: Machine Learning algorithms results for Emotion classification

	1920	1930	1940	1950	1960	1970	1980	1990	2000	2010
A	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
B	4.48e-05	9.74e-05	3.00e-04	0.00565	0.0225	0.0478	0.0811	0.243	0.583	0.0179
C					0.17	0.17	0.17	0.17	0.17	0.17
D					0.0226	0.0489	0.00155	0.244	0.586	0.0188

Figure 9: Proportion of labels for all decades in (A): train dataset; (B): test dataset; for decades from 1960 in (C): train dataset; (D): test dataset.

Random Forest for all decades

Accuracy: 0.229

	precision	recall	f1-score	support
1920	0.00	0.35	0.00	23
1930	0.00	0.38	0.00	50
1940	0.00	0.34	0.01	154
1950	0.02	0.25	0.04	2,902
1960	0.06	0.19	0.09	11,539
1970	0.06	0.17	0.09	24,546
1980	0.11	0.15	0.13	41,625
1990	0.27	0.15	0.19	124,606
2000	0.72	0.23	0.35	298,915
2010	0.02	0.29	0.05	9,196
Avg/Total	0.5	0.20	0.27	513,556

Confusion matrix

	1920	1930	1940	1950	1960	1970	1980	1990	2000	2010
1920	8	6	5	1	1	1	0	1	0	0
1930	12	19	8	3	1	2	1	1	1	2
1940	26	28	52	15	12	8	4	6	2	1
1950	238	258	460	719	506	204	154	184	100	79
1960	625	743	1,286	2,334	2,245	1,177	1,035	927	623	544
1970	1,026	1,035	1,397	2,586	2,672	4,159	3,440	3,445	2,172	2,614
1980	1,673	1,501	1,952	3,960	3,745	6.574	6,276	5,912	4,688	5,164
1990	4,049	3,926	5,276	10,775	10,622	18,234	15,558	18,104	18,122	19,940
2000	5,016	4,691	7,084	16,101	19,112	33,059	28,504	37,623	69,934	77,791
2010	112	121	214	409	568	1,013	814	1,131	2,122	2,692

Random Forest for decades from 1960

Accuracy: 0.306

	precision	recall	f1-score	support
1960	0.13	0.85	0.23	11,539
1970	0.17	0.49	0.25	24,546
1980	0.22	0.37	0.27	41,625
1990	0.37	0.22	0.28	124,606
2000	0.77	0.28	0.41	298,915
2010	0.08	0.93	0.14	9,196
Avg/Total	0.57	0.31	0.35	510,427

Confusion matrix

	1960	1970	1980	1990	2000	2010
1960	9,858	543	394	334	213	197
1970	3,810	12,033	3,154	2,365	1,534	1,650
1980	6,666	6,792	15,313	4,946	3,957	3,951
1990	21,176	19,586	19,000	28,000	18,556	18,288
2000	32,402	31,916	33,190	40,850	82,626	77,931
2010	98	96	100	108	243	8,551

Figure 10: Machine Learning algorithms results for year prediction

c. VISUALIZATION

We believed that a storytelling design, such as an infinite-scroll page, was a perfect way to share our results [28]. We invite the user to follow the guidelines and explore the different graphs we provided. All the interactive graphs are generated thanks to d3 to give the user a comprehensive and immediate insight into the data.

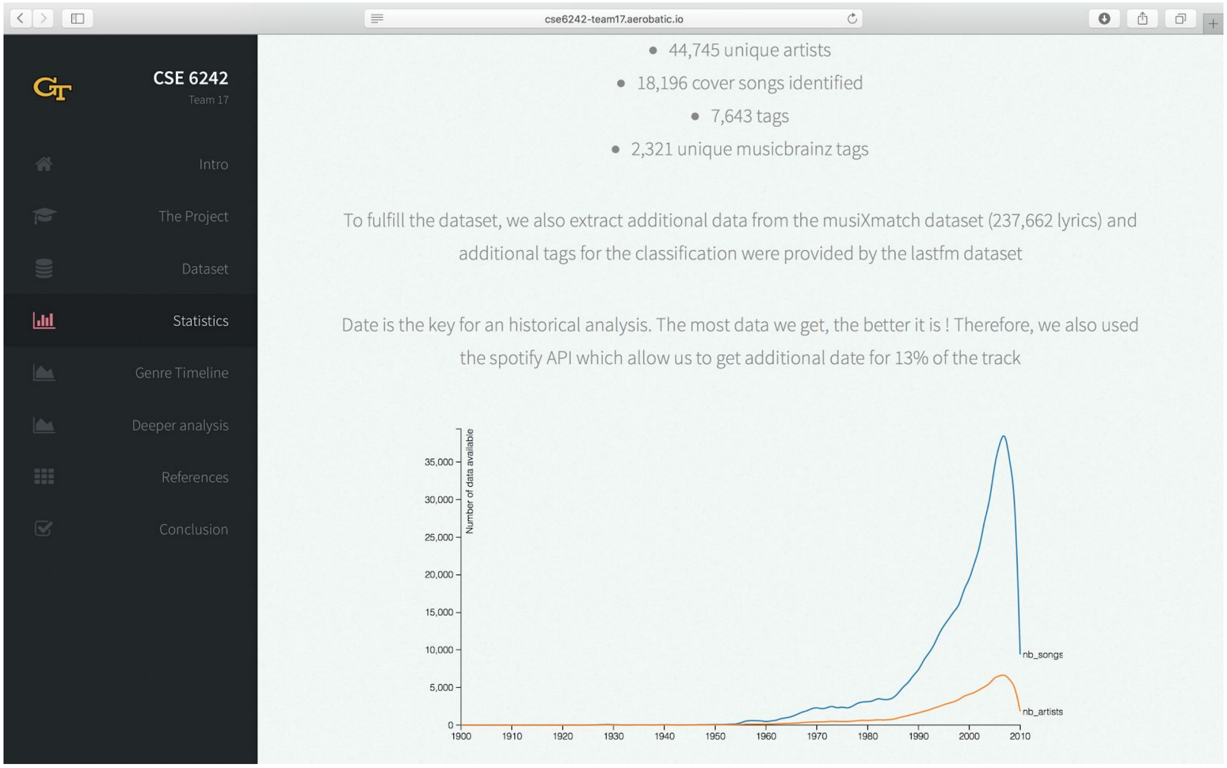

Figure 11: The user interface. A web-site is used to display our results and let the user interact with the data.

The information in the dataset is too big to be processed and rendered in real-time on an interactive web-page. Moreover, it is not relevant to display all the raw data we have directly into the visualization framework. We thus used preprocessed data (see Feature Extraction) to accelerate the calculations in the web browser. For a few cases we then applied k-means clusterization to reduce the number of points, without affecting the intrinsic meaning of the data.

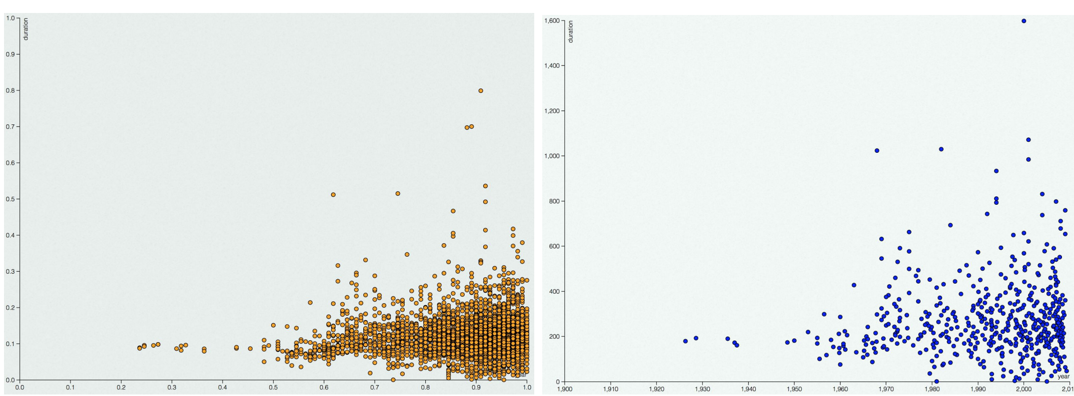

Figure 12: The main concern is about the display performance. Using k-means to reduce the size of the data can tackle this issue. The same dataset before and after k-means. The meaning of the dataset is preserved.

V. EXPERIMENTS AND OBSERVATIONS

A. TESTBED

Two key components need to be evaluated:

- The correctness of our results
- The suitability of our web design

We use the “top 25 events that changed America”[31] according to Time Magazine as our historical ground truth to which we added the top 5 wars involving american casualties.

We also did a 20-peer survey to compare our project with a similar one available on Tiki-Toki website[26].

B. HISTORICAL ANALYSIS

We need to define the different categories of historical events we want to detect and for each of them, choose the proper methodology to detect them (e.g. which emotion to monitor). Because of the lack of data before 1950, we weighted the information per year according to the number of songs available at a given year.

1. Global analysis

While processing data with respect to the machine learning algorithms, we obtained interesting insight into the overall evolution of music throughout the years.

On average, a song lasts for approximately 4 minutes, while the loudness is getting louder and louder.

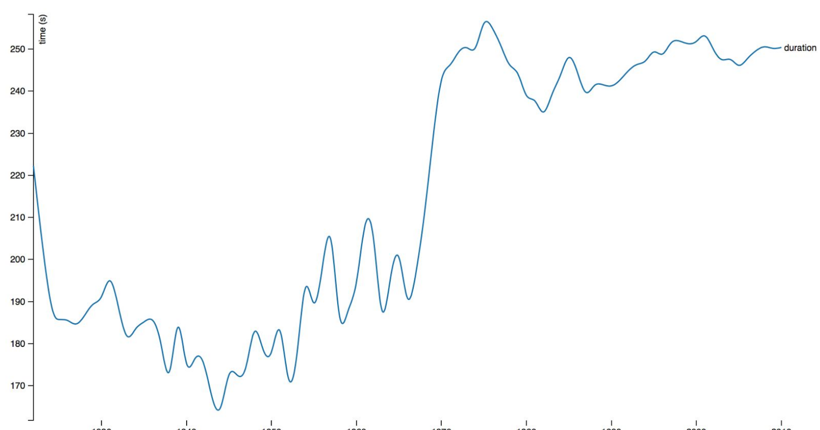

Figure 13: Average duration of a song per year [25]

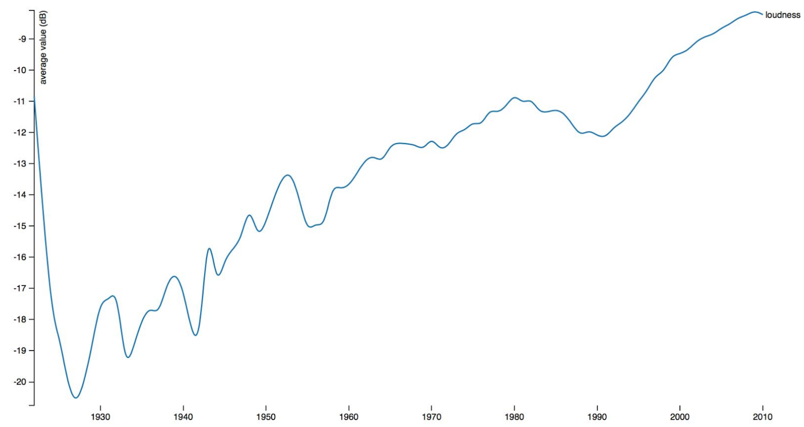

Figure 14: Average loudness for a song per year [25]

The tempo of a song stabilizes to the well-known 128 bpm. This is maybe why we think that all songs look the same.

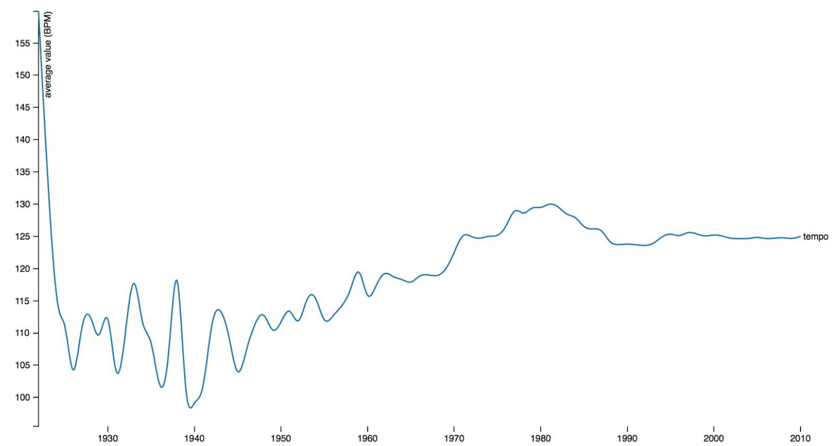

Figure 15: Average tempo value of a song per year [25]

Those features were plotted across time, one can go to http://cse6242-team17.aerobatic.io [28] to explore data in a interactive 2-axis graph.

2. Lyrics

We study the evolution of lyrics across 6 different scores. Positive and negative scores follow the same trend and reflect a manichean language. Swear and anger scores rise together, whereas the others dwindle from the mid-sixties. An evolution of our results is visible across time.

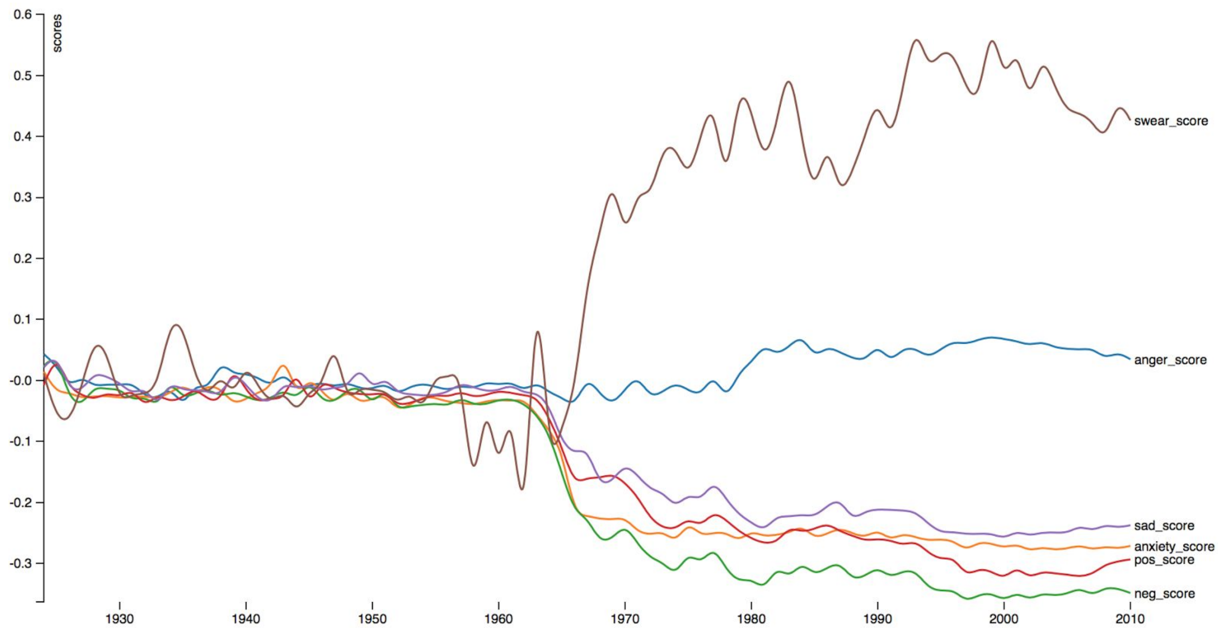

Figure 16: Scores computed from LIWC lexicon. Noise can be seen in earlier years, and recent years show too smoothed results. We plan to weight the values.

3. Emotions

Angry (dark blue) and happy (light blue) appear together in the mid-forties. From 1950 to 1953, which corresponds to the Korean war, we can see a peak of anger. Relax (light orange) and sadness (dark orange) have been less present since 1980.

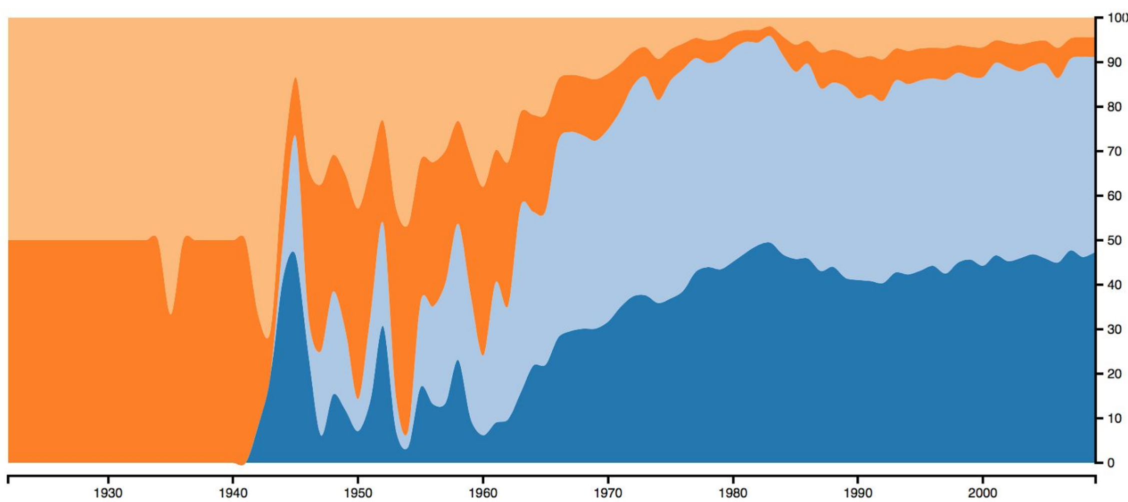

Figure 17: Emotions across time. From top to bottom there are relax, sadness, happy, angry

4. Lexical fields

We also study the evolution of 5 lexical fields in lyrics across time. The peace and love period, specific of the sixties, is well represented on this graph. We can observe a peak of love. Moreover, sad and love thematics importance grows during the Vietnam war.

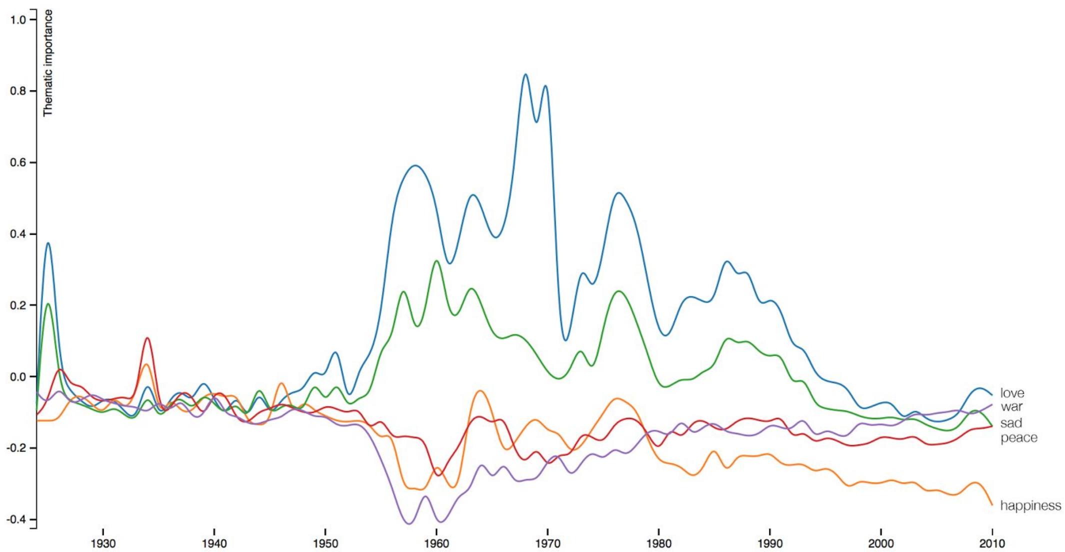

Figure 18: Lexical fields across time

5. Genre

Along with the study of lyrics and emotions, we obtained an interesting evolution of music styles since 1960. Rock music is taking a major part of the music market while some styles like Punk or Blues are slowly disappearing.

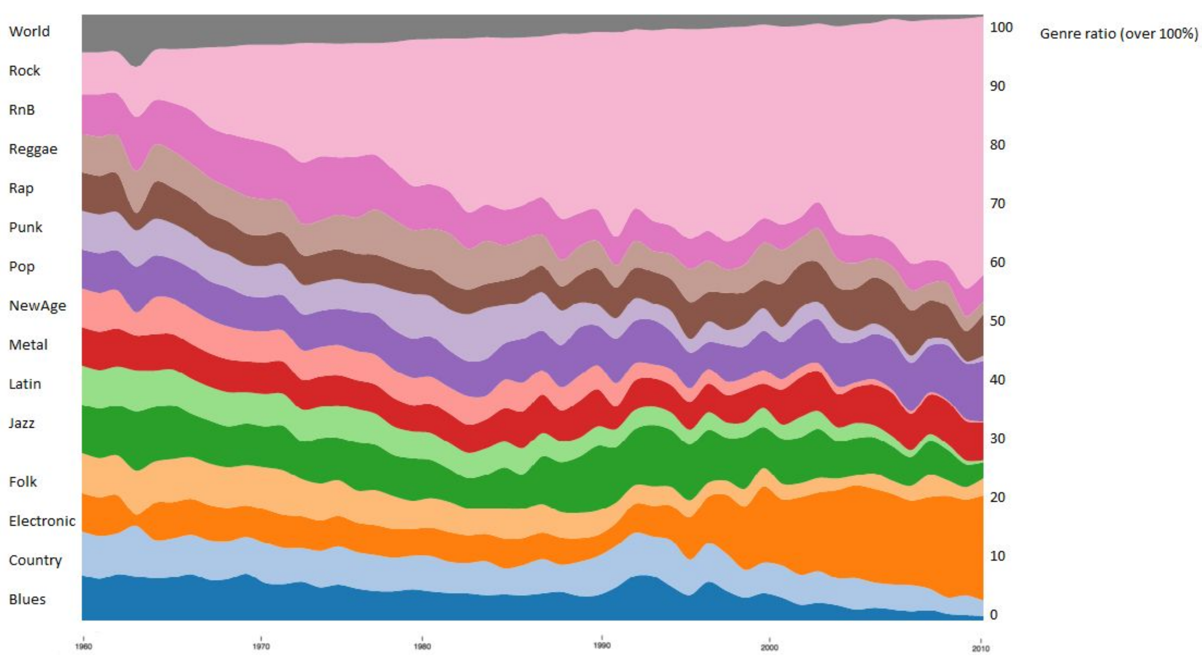

Figure 19: Evolution of music genres since 1960

This result has been obtained thanks to the work of H. Schreiber [30]. We weighted the genre data according to the number of music available per year.

C. USER SURVEY

We successfully managed to draw the user's attention to our strategy in providing useful knowledge without sacrificing the understandability of the subject. Users agree that the way we deliver the information is appealing and easy to use.

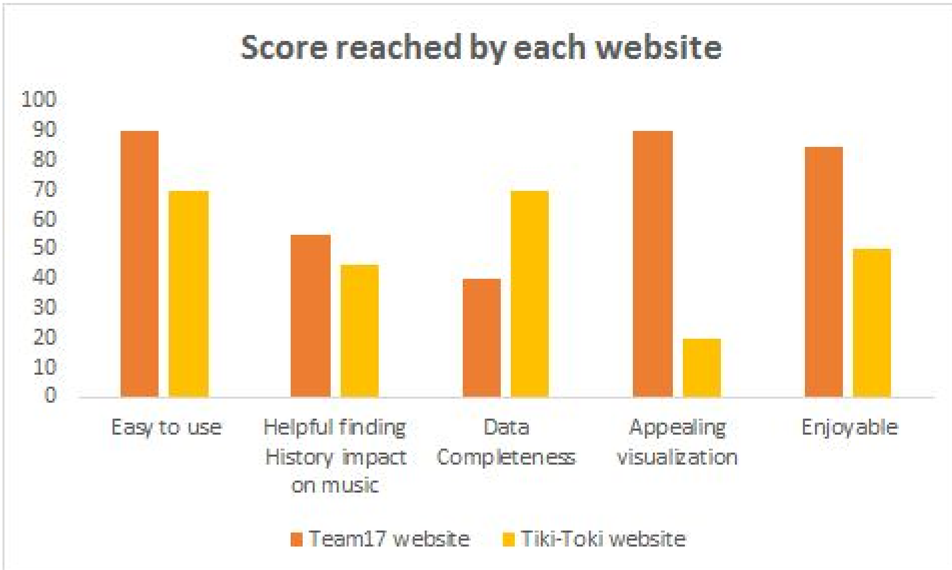

Figure 20: Result of the survey

Thanks to the interpolation capability of D3, we delivered nice and clean graphs that help the user focus on what is important, the meaning behind the data.

VI. CONCLUSION

We successfully managed to visualize the evolution of various features and music scores across time. Our graphs show some clear tendencies in the long term. However, the Million Song Dataset proved to be misadjusted to our study. Indeed, most of the dated song it provides were released after 1960. Besides, the dates for these songs are no more precise than a year. This had two impacts on our study: first the period of time is short, second, we cannot see short-term evolutions. We can only detect historical or social events that lasted several years. However, we believe this kick-off project has proven the capacity of explaining historical facts in another manner.

VII. FUTURE WORKS

Improvements can be made for both the visualization and the backend of the project. We can enhance the user experience by adding a trendy parallax effect [29].

To be really scientific, our event detection should be based on signal processing techniques. This was left to future works.

Our results could benefit also from using other features, especially the array ones which have not all been used.

Refining the date precision to month or day could also provide a better detection of historical events, especially of one-day events.

For the Natural Language Processing part enhancing our lexicons with more words should give more accurate LIWC and thematic importance scores. And getting more data for the period from 1920 to 1960 is very likely to improve the results of the Machine Learning tasks.

APPENDIX

APPENDIX 1:

	Tasks	Data Mining					Machine Learning				Visualization			
	Paper Review	Complete the Dataset	Spotify API	Pre-work on Subset	Work on Dataset	Design	Lyrics	Audio Features	Emotions	Score Estimation	Website Design	Data Storage on AWS S3	Historical Event Overlay	Integration
Team member														
Auguste BYIRINGIRO	x	x				x	x	x	x	x				x
Gireg DE KERDANET	x			x	x	x		x	x	x				x
Mathieu LAPEYRE	x			x	x	x					x	x	x	x
Flore MAGNARD	x		x		x	x					x		x	x
Workload	1 week	1 week	1 week	2 weeks	4 weeks	1 week	2 weeks	1 week	1 week	1 week	3 week	1 week	1 week	1 week

Appendix 1 : Team workload and overall time spent on each task

APPENDIX 2:

Field name	Type	Description	Link
analysis sample rate	float	sample rate of the audio used	url
artist 7digitalid	int	ID from 7digital.com or -1	url
artist familiarity	float	algorithmic estimation	url
artist hotttnesss	float	algorithmic estimation	url
artist id	string	Echo Nest ID	url
artist latitude	float	latitude	
artist location	string	location name	
artist longitude	float	longitude	
artist mbid	string	ID from musicbrainz.org	url
artist mbtags	array string	tags from musicbrainz.org	url
artist mbtags count	array int	tag counts for musicbrainz tags	url
artist name	string	artist name	url
artist playmeid	int	ID from playme.com, or -1	url
artist terms	array string	Echo Nest tags	url
artist terms freq	array float	Echo Nest tags freqs	url
artist terms weight	array float	Echo Nest tags weight	url
audio md5	string	audio hash code	
bars confidence	array float	confidence measure	url
bars start	array float	beginning of bars, usually on a beat	url
beats confidence	array float	confidence measure	url
beats start	array float	result of beat tracking	url
danceability	float	algorithmic estimation	
duration	float	in seconds	
end of fade in	float	seconds at the beginning of the song	url
energy	float	energy from listener point of view	
key	int	key the song is in	url

key confidence	float	confidence measure	url
loudness	float	overall loudness in dB	url
mode	int	major or minor	url
mode confidence	float	confidence measure	url
release	string	album name	
release 7digitalid	int	ID from 7digital.com or -1	url
sections confidence	array float	confidence measure	url
sections start	array float	largest grouping in a song, e.g. verse	url
segments confidence	array float	confidence measure	url
segments loudness max	array float	max dB value	url
segments loudness max time	array float	time of max dB value, i.e. end of attack	url
segments loudness max start	array float	dB value at onset	url
segments pitches	2D array float	chroma feature, one value per note	url
segments start	array float	musical events, ~ note onsets	url
segments timbre	2D array float	texture features (MFCC+PCA-like)	url
similar artists	array string	Echo Nest artist IDs (sim. algo. unpublished)	url
song hotttnesss	float	algorithmic estimation	
song id	string	Echo Nest song ID	
start of fade out	float	time in sec	url
tatums confidence	array float	confidence measure	url
tatums start	array float	smallest rythmic element	url
tempo	float	estimated tempo in BPM	url
time signature	int	estimate of number of beats per bar, e.g. 4	url
time signature confidence	float	confidence measure	url
title	string	song title	
track id	string	Echo Nest track ID	
track 7digitalid	int	ID from 7digital.com or -1	url
year	int	song release year from MusicBrainz or 0	url

Table: Fields available for each file of the dataset

Here is an example of all the features given for one song:

```
analysis_sample_rate: 22050
artist_7digitalid: 165270
artist_familiarity: 0.581793765845
artist_hotttnesss: 0.401997543364
artist_id: b'ARD7TVE1187B99BFB1'
artist_latitude: nan
artist_location: b'California - LA'
artist_longitude: nan
artist_mbid: b'e77e51a5-4761-45b3-9847-2051f811e366'
artist_mbtags: shape = (0,)
artist_mbtags_count: shape = (0,)
artist_name: b'Casual'
artist_playmeid: 4479
artist_terms: shape = (37,)
artist_terms_freq: shape = (37,)
artist_terms_weight: shape = (37,)
audio_md5: b'a222795e07cd65b7a530f1346f520649'
bars_confidence: shape = (83,)
bars_start: shape = (83,)
beats_confidence: shape = (344,)
beats_start: shape = (344,)
danceability: 0.0
duration: 218.93179
end_of_fade_in: 0.247
energy: 0.0
```

```
key: 1
key_confidence: 0.736
loudness: -11.197
mode: 0
mode_confidence: 0.636
release: b'Fear Itself'
release_7digitalid: 300848
sections_confidence: shape = (10,)
sections_start: shape = (10,)
segments_confidence: shape = (971,)
segments_loudness_max: shape = (971,)
segments_loudness_max_time: shape = (971,)
segments_loudness_start: shape = (971,)
segments_pitches: shape = (971, 12)
segments_start: shape = (971,)
segments_timbre: shape = (971, 12)
similar_artists: shape = (100,)
song_hotttnesss: 0.602119989906
song_id: b'SOMZWCG12A8C13C480'
start_of_fade_out: 218.932
tatums_confidence: shape = (688,)
tatums_start: shape = (688,)
tempo: 92.198
time_signature: 4
time_signature_confidence: 0.778
title: b"I Didn't Mean To"
track_7digitalid: 3401791
track_id: b'TRAAAAW128F429D538'
year: 1994
```

APPENDIX 3:

No match at all	1
Missing data over a too long period	1
Not enough relevant music features	1
Data too complex to be correctly processed	2
Overlapping information	2
Missing music features fot too many data	2
Historically biased	3
Music features misunderstanding (sarcasm, irony, poetry, …)	3
Not enough relevant music features	3

1	High risk
2	
3	Low risk

Appendix 3 : Estimated risks

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