The Million Song Dataset

AUDIO FEATURES

Features for Audio Indexing and Classification

General Audio Class	Classical Music	Popular Music	Speech	Noise	Crowd Noise
Number of Files	35	188	31	25	31

Popular Music Class	Jazz	Folk	Electronica	R&B	Rock	Reggae	Vocal
Number of Files	38	23	27	43	37	11	9

Table 1: Audio database by class: number of audio files in each class.

Low Level Features (Li et al. 2001)

- root-mean-square (RMS) level
- Spectral centroid
- Bandwidth
- zero-crossing rate
- Spectral roll-off frequency
- band energy ratio
- delta spectrum magnitude,
- Pitch
- pitch strength

Mel-frequency cepstral coefficients (MFCC) derived Features (Slaney et al. 1998)

- MFCC
- Modulation Energy of MFFC
- Note in Speech Recognition MFFC, delta MFCC, delta^2 MFCC are used

Psycho Acoustic Features

- Roughness, sdev roughness, loudness, sharpness, modulations of them

Filterbank temporal envelopes

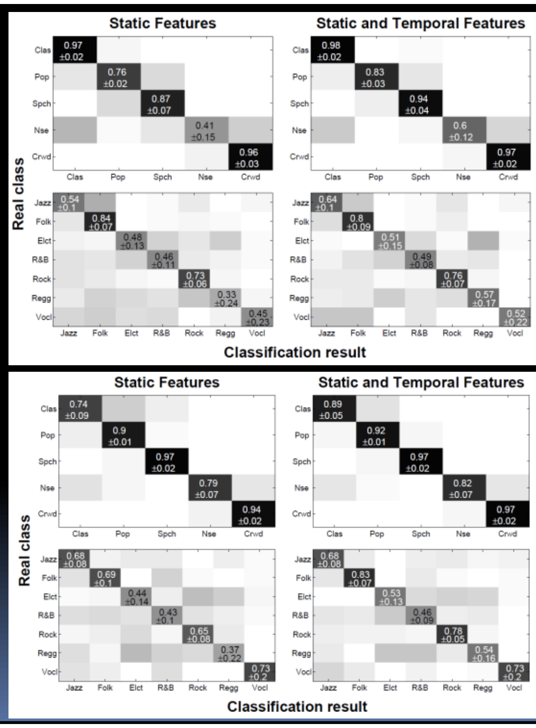
M.F. McKinney, J. Breebaart, Features for Audio and Music Classification, ISMIR 2003

Confusion Matrices

Best 9 static

Low Level

MFCC



Best 9 overall
Static + temporal

The Million Song Dataset

"There is no data like more data" Bob Mercer of IBM (1985).

T. Bertin-Mahieux, D.P.W. Ellis, B. Whitman, P. Lamere, **The Million Song Dataset**, In Proceedings of the 12th International Society for Music Information Retrieval Conference (ISMIR 2011), 2011.

Introduction

- The Million Song Dataset (MSD)
  - metadata and extracted audio features for a million songs from The Echo Nest.
- Licensing
  - GZTAN a smaller dataset
  - Magnatagatune
  - MSD Legally available

Other audio data sets:

- http://www.audiocontentanalysis.org/data-sets/
- http://www.ismir.net/resources/datasets/

MIREX 2021 **http://www.music-ir.org/mirex/wiki/MIREX_HOME**

- **Chord Estimation, Cover Song Detection, Melody Extraction,**
- **Lyrics Transcription, Drum Transcription, Music Detection**
- **Query by Singing, Humming**
- **Set List Identification: determine the song sequence in a live concert**

Previously:

- **Multiple Fundamental Frequency Estimation and Tracking**
- **K-POP Mood and Genre Classification**
- **Singing Transcription, Lyrics Transcription**
- Audio Key detection, Audio Fingerprinting, and Mood-, Genre-, Tag-Classification, etc,

MSD Goals: Reference Benchmark Dataset

- Scale MIR related research to commercial sizes
- Provide reference dataset for research evaluation
- Alternative shortcut for The Echo Nest's API
  - >=2016 only Spotify https://en.wikipedia.org/wiki/The_Echo_Nest
  - https://acousticbrainz.org/ (shut down 2022-02-16)
- API of the 7digital service, 30-s audio previews
- Kick start new MIR researchers

MIR Datasets Critical Requirements

- Algorithms should be scalable
- Realistically sized datasets are necessary

dataset	# songs / samples	audio
RWC	465	Yes
CAL500	502	No
GZTAN genre	1,000	Yes
USPOP	8,752	No
Swat10K	10,870	No
Magnatagatune	25,863	Yes
OMRAS2	50,000?	No
MusiCLEF	200,000	Yes
MSD	1,000,000	No

MusiCLEF 2012: http://www.cp.jku.at/datasets/musiclef/index.html

MSD Creation

- The Echo Nest API with Python wrapper pyechonest. (*)
- Echo Nest provided:
  - Metadata: artist, title, etc.
  - Audio Features: short time scale – global scale
  - Defined by Echo Nest Analyze API (per segment)
- Additional info from musicbrainz server
- 5 Threads during 10 days
- Code available (not relevant anymore)

*) 'Retired' since 2016
Alternative: http://acousticbrainz.org/ (shut down 2022-02-16)

MSD Content

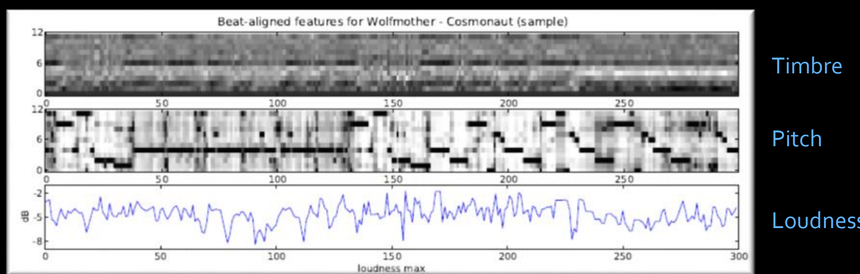
- 280 GB of data
- 1, 000, 000 songs/files
- 44, 745 unique artists
- 7, 643 unique terms (Echo Nest tags)
- 2, 321 unique musicbrainz tags
- 43, 943 artists with at least one term
- 2, 201, 916 asymmetric similarity relationships
- 515, 576 dated tracks starting from 1922

MSD Content

- HDF5 format
- 55 fields per song
- Audio Features
  - Timbre
  - Pitches
  - Loudness max
  - Beats
  - Bars (~3 – 4 beats)
  - Note onsets/tatum

analysis_sample_rate	artist_7digitalid
artist_familiarity	artist_hotttnesss
artist_id	artist_latitude
artist_location	artist_longitude
artist_mbid	artist_mbtags
artist_mbtags_count	artist_name
artist_playmeid	artist_terms
artist_terms_freq	artist_terms_weight
audio_md5	bars_confidence
bars_start	beats_confidence
beats_start	danceability
duration	end_of_fade_in
energy	key
key_confidence	loudness
mode	mode_confidence
num_songs	release
release_7digitalid	sections_confidence
sections_start	segments_confidence
segments_loudness_max	segments_loudness_max_time
segments_loudness_start	segments_pitches
segments_start	segments_timbre
similar_artists	song_hotttnesss
song_id	start_of_fade_out
tatums_confidence	tatums_start
tempo	time_signature
time_signature_confidence	title
track_7digitalid	track_id
year	

MSD Audio Features



- Timbre, Pitches (both 12 elements per segment) and Loudness max for one song.

MSD Integration

- Echo Nest identifiers
  - (track, song, album, artist) => updates on dynamic values: popularity, familiarity, etc.
- Yahoo Music Ratings Datasets provides user ratings for 97 954 artists
  - 15 780 artists in MSD (91% overlap with the more popular artists in MSD)
  - At the time one of the largest benchmarks for evaluating content-based music recommendation
- Identifiers
  - Artist, album, song names
  - Echo Nest id
  - Musicbrainz id
  - MusiXmatch id => lyrics
  - 7digital identifiers > 30sec samples

MSD Usage

- Metadata Analysis
- Artist Recognition
- Automatic Music Tagging
- Recommendation
- Cover Song Recognition
  - SecondHandSong Dataset 18 196 covers of 5 854 songs
  - Most methods based on chroma features
- Lyrics
  - Mood prediction
- Year Prediction

Metadata Analysis

- Are all good artist names already taken?

"Tim and Sam's Tim and the Sam Band with Tim and Sam"

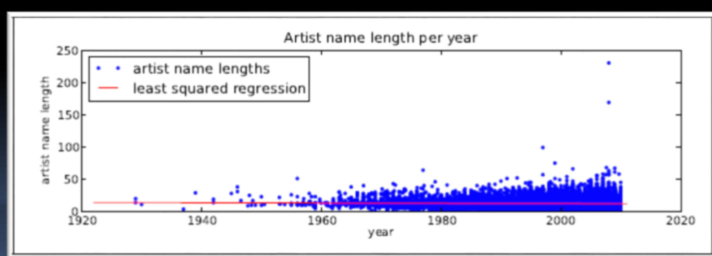
- Do newer bands have to use longer names?
  - …
- Etc.

Metadata Analysis

- Are all good artist names already taken?

"Tim and Sam's Tim and the Sam Band with Tim and Sam"

- Do newer bands have to use longer names?
  - Seems false, apart from outliers. See graph.
- Etc.



Artist Recognition

- 18 073 artists with at least 20 songs in MSD
- 2 standard training/test datasets
  - 20 songs/artist
  - 15 songs/artist
- Benchmark k-NN algorithm with accuracy of 4% provided => much room for improvement?

Automatic Music Tagging

- Core of MIR research for many years
- 300 most popular terms in The Echo Nest
- Split all artists in training/test sets according to terms
- Correlations between artist names and genre, or year and genre etc.

artist	EN terms	musicbrainz tags
Bon Jovi	adult contemporary arena rock 80s	hard rock glam metal american
Britney Spears	teen pop soft rock female	pop american dance

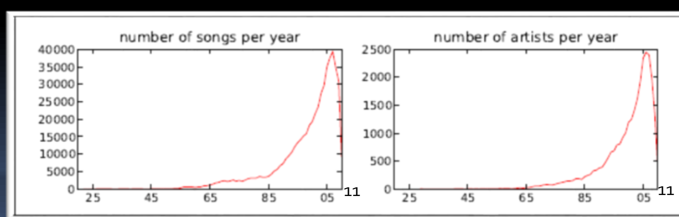
Music Recommendation

- Music recommendation and music similarity have high commercial value.
- Content based systems underperform when compared to collaborative filtering methods (2011)
  - Also novelty and suprise are important.
- Integration with Yahoo Music Ratings
  - Enables large scale experiments
  - Clean ground truth
- Similar Artists according to Echo Nest:

Ricky Martin	Weezer
Enrique Iglesias Christina Aguilera Shakira Jennifer Lopez	Death Cab for Cutie The Smashing Pumpkins Foo Fighters Green Day

Year Prediction

- Little studied
- Practical applications in music recommendation
- Years-of-release field (1922 – 2011)
  - 515 576 tracks of 28 223 artists
  - Errors
  - Non-uniformity over the years



Year Prediction

- K-NN: the predicted year is the average of the k nearest training songs
- Vowpal & Wabbit (**VW**): regression by learning a linear transformation **T** of the features using gradient descent => predicted year is equal to the application of **T** on the features of the song
- Table shows
  - average absolute difference between predicted and actual year
  - the square root of the average squared difference between predicted and actual year.
- Benchmark average release year predicted from the training set. VW improves this baseline.

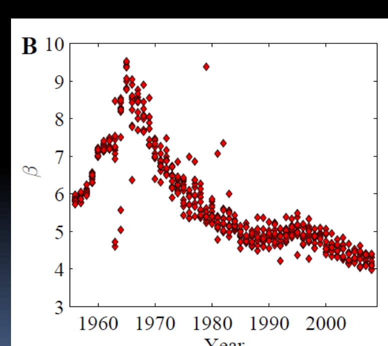
method	diff	sq. diff
constant pred.	8.13	10.80
1-NN	9.81	13.99
50-NN	7.58	10.20
vw	**6.14**	**8.76**

Evolution of Pop Music

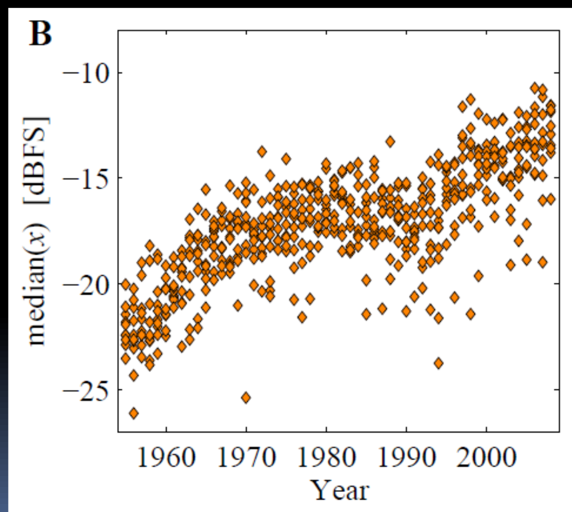
Measuring the evolution of contemporary western popular music, J. Serra, A. Corral, M. Boguna, M. Haro and J.L. Arcos, *2012*

Timbre of Pop Music

- The distributions of timbre codewords are fitted to a power-law distribution with parameter β.
- Lower β indicates less timbre variety, i.e., frequent code words become more frequent and infrequent ones less frequent.
- More homogeneity in timbre



Loudness of Pop Music



MSD Limitations

- No or limited access to original audio
  - Novel audio feature analysis and acoustic features
- Lack of album and song level meta data and tags
- Limited Diversity
  - World, ethnic, and classic music almost not represented
- Accurate time stamps problematic
  - No guarantee that audio features have been computed using the same audio track
  - As a result from many official releases, different ripping and encoding schemes, etc

the Million Song Dataset Challenge

B. McFee, et al., WWW 2012 Companion, April 16-20 2012, Lyon, France.

Personalized music recommendation challenge.

Goal:

- predict the songs that a user will listen to, given the user's listening history and full information (including meta-data and content analysis) for all songs.

the Million Song Dataset Challenge

http://www.kaggle.com/c/msdchallenge

"What is the task in a few words? You have:

1) the full listening history for 1M users,
2) half of the listening history for 110K users (10K validation set, 100K test set), and
3) you must predict the missing half. .."

Winner: *aio* with a MAP@k score of 0.17910

(MAP@k = Mean average precision over k queries)

Future (of 2012)

- Success? Time will tell.
- Hopefully used as one of the default benchmarks
- Depends on efforts of research community
- Preserving commonality and comparability
- Important for visibility of MIR research
- Subsets on UCI Machine Learning Repository

2021: Number of citations 1211.
2022: Number of citations 1378
Recent citations in work on recommender systems, etc.
Example: https://zenodo.org/record/1240485#.W78ZtPloSUk
MSD-I: Million Song Dataset with Images for Multimodal Genre Classification

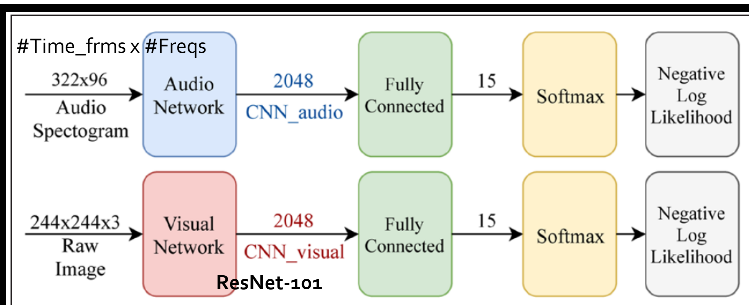
Multimodal Deep Learning for Music Genre Classification. Transactions of the International Society for Music Information Retrieval
Oramas, S., et al. (2018)

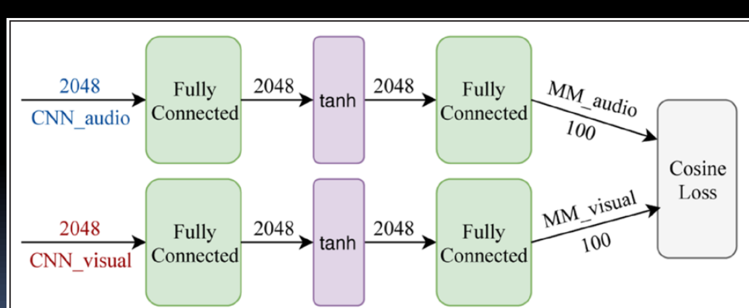
- learn and combine multimodal data representations for music genre classification
- deep neural networks are trained with:
  - audio tracks
  - text reviews
  - cover art images
- single label genre classification (only A + V)
  - using Million Songs Data set (MSD-I)
- multi label genre classification (A + V + T)
  - using their MuMu (combines Amazon Review dataset)

Cover Art

New Aged misclassified as Heavy Metal

Genre Heat-Maps





CNN’s and Feature Space Network

Genre Classification

$$\text{precision} = \frac{|\{\text{relevant documents}\} \cap \{\text{retrieved documents}\}|}{|\{\text{retrieved documents}\}|}$$

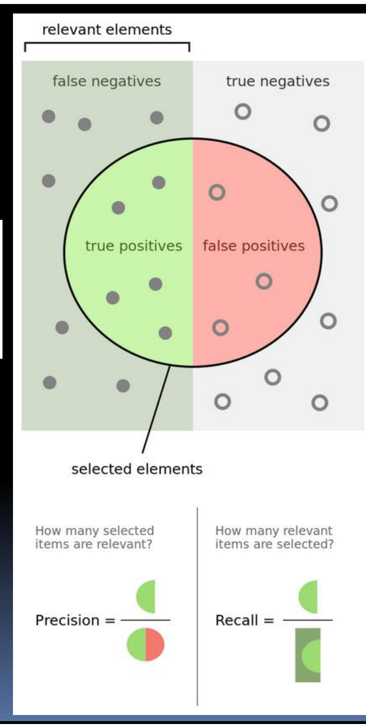
$$\text{recall} = \frac{|\{\text{relevant documents}\} \cap \{\text{retrieved documents}\}|}{|\{\text{relevant documents}\}|}$$

$$\text{Precision} = \frac{tp}{tp + fp}$$

$$\text{Recall} = \frac{tp}{tp + fn}$$

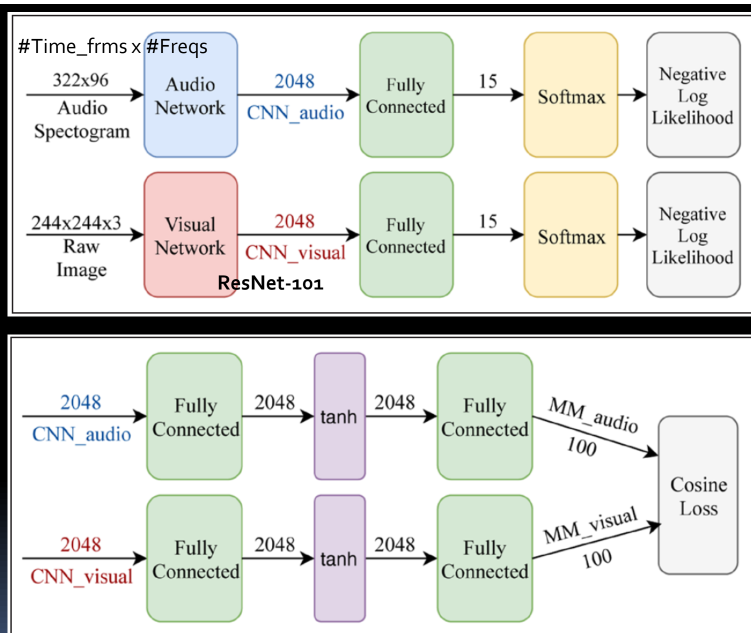
$$F = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

https://en.wikipedia.org/wiki/Precision_and_recall



Genre Classification

Input	Model	Precision	Recall	F1
Audio	CNN_Audio	0.385 ± 0.006	0.341 ± 0.001	0.336 ± 0.002
	MM_Audio	0.406 ± 0.001	0.342 ± 0.003	0.334 ± 0.003
	CNN_Audio + MM_Audio	0.389 ± 0.005	0.350 ± 0.002	**0.346 ± 0.002**
Video	**CNN_Visual**	0.291 ± 0.016	0.260 ± 0.006	**0.255 ± 0.003**
	MM_Visual	0.264 ± 0.005	0.241 ± 0.002	0.239 ± 0.002
	CNN_Visual + MM_Visual	0.271 ± 0.001	0.248 ± 0.003	0.245 ± 0.003
A + V	CNN_Audio + CNN_Visual	0.485 ± 0.005	0.413 ± 0.005	0.425 ± 0.005
	MM_Audio + MM_Visual	0.467 ± 0.007	0.393 ± 0.003	0.400 ± 0.004
	ALL	0.477 ± 0.010	0.413 ± 0.002	**0.427 ± 0.000**



CNN's and Feature Space Network

Genre	Human Annotator			Neural Model		
	Audio	Visual	A + V	Audio	Visual	A + V
Blues	0	0.50	0.67	0.05	0.36	0.42
Country	0.40	0.60	0.31	0.37	0.21	0.40
Electronic	0.62	0.44	0.67	0.64	0.44	0.68
Folk	0	0.33	0	0.13	0.23	0.28
Jazz	0.62	0.38	0.67	0.47	0.27	0.49
Latin	0.33	0.33	0.40	0.17	0.08	0.13
Metal	0.80	0.43	0.71	0.69	0.49	0.73
New Age	0	0	0	0	0.12	0.10
Pop	0.43	0.46	0.42	0.39	0.43	0.49
Punk	0.44	0.29	0.46	0.04	0	0.30
Rap	0.74	0.29	0.88	0.73	0.39	0.73
Reggae	0.67	0	0.80	0.51	0.34	0.55
RnB	0.55	0	0.46	0.45	0.31	0.51
Rock	0.58	0.40	0.40	0.54	0.20	0.58
World	0	0.33	0	0	0	0.03
Average	**0.41**	**0.32**	**0.46**	**0.35**	**0.25**	**0.43**

MSD-I: Million Song Dataset with Images for Multimodal Genre Classification

For data see:

https://zenodo.org/record/1240485#.XamLyn9S-Uk

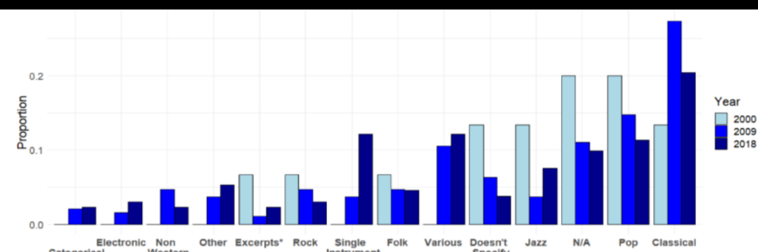
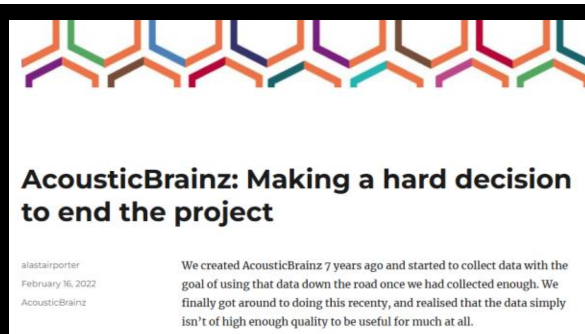


Figure 1: Proportion [3] of the number of papers that use different genres of data from first ISMIR conference in 2000 [1] to the 10th ISMIR in 2009 [2], to the 19th ISMIR in 2018 [3]. "Excerpts*" refers to music excerpts under 3 seconds, and "categorical" refers to music selected for a non-genre category such as mood. The "non-Western" category does not include genres such as J-pop and K-pop, which were classified as solely "pop".

W. Chen et al., DATA USAGE IN MIR: HISTORY & FUTURE RECOMMENDATIONS. ISMIR 2019.



Goals

- Musical characteristics of audio recordings: musical key, bpm
- Use extracted data to predict: instrumentation, genre, mood, etc.
- Source of features to build and train models for prediction

Problems

- Musical key accurate on some styles but not on the full range
- BPM worked well but on many recordings incorrect, also no confidence levels available
- Existing models for genre not working very well and not covering the full range
- AcousticBrainz data extractor has not high enough resolution for Deep Learning
- Conten-based similarity methods by AcousticBrainz did not work well

https://mtg.github.io/acousticbrainz-genre-dataset/

MSD Related publications

https://www.researchgate.net/publication/220723656_The_Million_Song_Dataset

Some examples:

H. Eghbal-Zadeh, M. Dorfer, G. Widmer, A Cosine-Distance based Neural Network for Music Artist Recognition using Raw I-vector Features, Proceedings of the 19th International Conference on Digital Audio Effects (DAFx-16), Brno, Czech Republic, September 5–9, 2016

K. Choi, G. Fazekas, M. Sandler, K. Cho, Convolutional Recurrent Neural Networks for Music Classification, arXiv:1609.04243v1 [cs.NE] 14 Sep 2016

Oramas S., Nieto O., Sordo M., & Serra X. (2017) A Deep Multimodal Approach for Cold-start Music Recommendation. https://arxiv.org/abs/1706.09739

J. Kim, J. Urbano, C.C.S. Liem, A. Hanjalic, One deep music representation to rule them all? A comparative analysis of different representation learning strategies, Neural Computing and Applications, Vol. 32, pp 1067 - 1093, 2020 https://link.springer.com/article/10.1007/s00521-019-04076-1

- Uses MSD
- how effective are various deep representation learning strategies for multitask learning
- desired properties of a deep representation learning
- pre-trained music representation networks for multiple semantic learning sources.

Contrastive learning of musical representations
J Spijkervet, JA Burgoyne - arXiv preprint arXiv:2103.09410, 2021 - arxiv.org
… We evaluate CLMR in the downstream task of music classification on the MagnaTagATune and **Million Song datasets**. A linear classifier fine-tuned on representations from a pretrained …
☆ Opslaan 99 Citeren Geciteerd door 14 Verwante artikelen Alle 6 versies

Multimodal metric learning for tag-based music retrieval
M Won, S Oramas, O Nieto, F Gouyon… - ICASSP 2021-2021 …, 2021 - ieeexplore.ieee.org
… Furthermore, we release the MSD500: a subset of the **Million Song Dataset** (MSD) containing 500 cleaned tags, 7 manually annotated tag categories, and user taste profiles. …
☆ Opslaan 99 Citeren Geciteerd door 13 Verwante artikelen Alle 4 versies

Semi-Supervised Music Tagging Transformer
M Won, K Choi, X Serra - arXiv preprint arXiv:2111.13457, 2021 - arxiv.org
… **DATASET** We use the **million song dataset** (MSD) [8] which consists of one **million** songs with audio features and metadata. Most of the previous works [2–6] relied on the Last.fm tags, a …
☆ Opslaan 99 Citeren Geciteerd door 3 Verwante artikelen Alle 3 versies

High-dimensional sparse embeddings for collaborative filtering
J Van Balen, B Goethals - Proceedings of the Web Conference 2021, 2021 - dl.acm.org
… R and CHOL models on the **Million Song Dataset** as a function of … **datasets**, weighted matrix factorization and several non-linear auto-encoders. On the challenging **Million Song Dataset**, …
☆ Opslaan 99 Citeren Geciteerd door 2 Verwante artikelen Alle 4 versies

Melon Playlist **Dataset**: a public **dataset** for audio-based playlist generation and music tagging
A Ferraro, Y Kim, S Lee, B Kim, N Jo… - ICASSP 2021-2021 …, 2021 - ieeexplore.ieee.org
… The **Million Song Dataset** [2] (MSD) contains audio features extracted for one **million** songs, it was expanded by the MIR community with additional metadata, including collaborative …
☆ Opslaan 99 Citeren Geciteerd door 4 Verwante artikelen Alle 7 versies

Next Week's ToDo's

API Paper Selection

- For next time select a research paper on some audio related subject, that you would like to present and send the complete reference by email to erwin@liacs.nl

Audio Features Workshop

ISMIR 2021

https://www.ismir.net/conferences/ismir2021.html

- S. Showdhury, G. Widmer, ON PERCEIVED EMOTION IN EXPRESSIVE PIANO PERFORMANCE: FURTHER EXPERIMENTAL EVIDENCE FOR THE RELEVANCE OF MID-LEVEL PERCEPTUAL FEATURES, ISMIR 2021, pp128 – pp134
- B. Cornelissen, W. Zuidema, J.A. Burgoyne, COSINE CONTOURS: A MULTI PURPOSE REPRESENTATION FOR MELODIES, ISMIR 2021, pp135 – pp142.

Data Sets

- D. Foster, S. Dixon, FILOSAX: A DATASET OF ANNOTATED JAZZ SAXOPHONE RECORDINGS, ISMIR 2021, pp205 – pp212.
- M. Zehren, M. Alunno, P. Bientinesi, ADTOF: A Large Dataset of Non-synthetic Music for Automatic Drum Transcription, ISMIR2021, pp818 – pp824.

Some Links for Finding Research Papers

- https://www.isca-speech.org/iscaweb/index.php/online-archive
- https://dblp.org/search?q=interspeech
- https://dblp.org/db/conf/ismir/index.html

See also:

- https://liacs.leidenuniv.nl/~bakkerem2/api/

MIREX 2020 Challenges
http://www.music-ir.org/mirex/wiki/MIREX_HOME

- **August 30th 2020**
  - 2020:Audio Fingerprinting <TC: Chung-Che Wang>
  - 2020:Audio Classification (Train/Test) Tasks <TC: Yun Hao (IMIRSEL)>, including
    - Audio US Pop Genre Classification
    - Audio Latin Genre Classification
    - Audio Music Mood Classification
    - Audio Classical Composer Identification
  - 2020:Audio K-POP Mood Classification <TC: Yun Hao (IMIRSEL)>
  - 2020:Audio K-POP Genre Classification <TC: Yun Hao (IMIRSEL)>
  - 2020:Audio Tag Classification <TC: Emre Demir>
- **September 6th 2020**
  - 2020:Audio Chord Estimation <TC: Johan Pauwels>
  - 2020:Audio Cover Song Identification <TC: Yun Hao (IMIRSEL)>
  - 2020:Audio Downbeat Estimation <TC: Mickaël Zehren>
  - 2020:Audio Key Detection <TC: Johan Pauwels>
  - 2020:Audio Melody Extraction <TC: An-Qi Huang>
  - 2020:Patterns for Prediction (offshoot of 2017:Discovery of Repeated Themes & Sections) <TC: Berit Janssen, Iris Ren, and Tom Collins>
  - 2020:Query by Singing/Humming <TC: Makarand Velankar>
  - 2020:Multiple Fundamental Frequency Estimation & Tracking <TC: Yun Hao (IMIRSEL)>
- **September 13th 2020**
  - *NEW!* 2020:Singing_Transcription_from_Polyphonic_Music <TC: Jun-You Wang>
  - 2020:Lyrics Transcription (former: Automatic Lyrics-to-Audio Alignment) <TC: Georgi Dzhambazov, Daniel Stoller, Chitralekha Gupta>

MIREX 2021 Challenges

https://www.music-ir.org/mirex/wiki/2021:Main_Page

MIREX 2021 Possible Evaluation Tasks

- 2021:Audio Beat Tracking
- 2021:Audio Chord Estimation
- 2021:Audio Cover Song Identification
- 2021:Audio Downbeat Estimation
- 2021:Audio Fingerprinting
- 2021:Audio Key Detection
- 2021:Audio Melody Extraction
- 2021:Audio Onset Detection
- 2021:Audio Tag Classification
- 2021:Audio Tempo Estimation
- 2021:Automatic Lyrics Transcription
- 2021:Drum Transcription
- 2021:Multiple Fundamental Frequency Estimation & Tracking
- 2021:Music Detection
- 2021:Patterns for Prediction (offshoot of 2017:Discovery of Repeated Themes & Sections)
- 2021:Query by Singing/Humming
- 2021:Query by Tapping
- 2021:Real-time Audio to Score Alignment (a.k.a Score Following)
- 2021:Set List Identification
- 2021:Structural Segmentation

ISMIR 2016

https://wp.nyu.edu/ismir2016/event/proceedings/

MIREX 2016 Possible Evaluation Tasks

- Grand Challenge on User Experience (J-DISC)
- Grand Challenge on User Experience
- **Audio Classification:**
  - Audio US Pop Genre Classification
  - Audio Latin Genre Classification
  - Audio Music Mood Classification
  - Audio Classical Composer Identification
  - 2016:Audio K-POP Mood Classification
  - 2016:Audio K-POP Genre Classification
- **Audio Cover Song Identification**
- Audio Tag Classification
- **Audio Music Similarity and Retrieval**
- Symbolic Melodic Similarity
- Audio Onset Detection
- Audio Key Detection
- Real-time Audio to Score Alignment (a.k.a Score Following)
- **Query by Singing/Humming**
- Audio Melody Extraction
- Multiple Fundamental Frequency Estimation & Tracking
- Audio Chord Estimation
- **Query by Tapping**
- Audio Beat Tracking
- Structural Segmentation
- **Audio Tempo Estimation**
- Discovery of Repeated Themes & Sections
- Audio Downbeat Estimation
- Audio Fingerprinting
- **Singing Voice Separation**
- Set List Identification
- Audio Offset Detection

ISMIR 2016
https://wp.nyu.edu/ismir2016/event/proceedings/

Some Examples (random, many more):

- Music Recommendation
- Composer Recognition
- Cover Song Identification
- Deep Learning: Chord Estimation, Medoly Extraction, Automatic Tagging
- Symbolic: Extraction ground-truth from MIDI-files, etc.
- Rhythm: beat tracking with Recurrent Neural Networks
- Brain Beats: Tempo Extraction from EEG Data

ISMIR 2018 Proceedings
https://dblp.org/db/conf/ismir/ismir2018

- Deep Learning !
- Music Transcription
- Chord Recognition
- Music Generation
- Playlist generation
- Singing Voice detection
- Etc. etc.

https://ismir2021.ismir.net/

Proceedings: https://www.ismir.net/conferences/ismir2021.html

Previous Conferences
https://dblp.uni-trier.de/db/conf/ismir/index.html