

THE WEB CONFERENCE

Lyon

April 27, 2018

CHALLENGE OVERVIEW:
LEARNING TO RECOGNIZE
MUSICAL GENRE FROM AUDIO

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Sean F. CARROLL (EPFL)
Marcel SALATHÉ (EPFL)

Outline

FMA: a dataset for music analysis

Challenge design

Results



Fei-Fei Li

@drfeifei

Following



Datasets play crucial roles in advancing AI. **#ImageNet** helped to enable the latest deep learning advances.

	Datasets (first Available)
sch	Spoken Wall Street Journal articles and other texts (1993)
Keapane	700,000 Grandmaster chess games, aka "The Extended Book" (1991)
n-English	1.0 trillion tokens from Google Web and News pages (collected in 2001)
2 Inexpensib	8.6 million documents from Wikipedia, Wiktionary, Wikisource, and Project Gutenberg (distributed in 2010)
ification	ImageNet corpus of 1.5 million labeled images and 1,000 object categories (2010)
ntain	Atari Learning Environment dataset of over 50 Atari games (2013)
s by	
atio	
ough:	3 years

Datasets Over Algorithms

Content without method leads to fantasy; method without content to empty sophistry. — Johann Wolfgang von Goethe ("Maxims and Reflections", 1892) "Perhaps the most important news of ...

spacemachine.net

5:12 AM - 22 Apr 2016

103 Retweets 174 Likes



2



103



174



Motivations

Goal: open dataset for Music Information Retrieval (MIR)
and Machine Learning (ML)

- ▶ Accelerate machine learning research on audio.
- ▶ Promote open data and open evaluation.
- ▶ Need both open benchmarking and standardized challenges.

There is a lot to learn from so much data!

The Free Music Archive

<https://freemusicarchive.org>



Free Music Archive



[Curators](#)

[Genres](#)

[Charts](#)

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Rock

Genres > Rock



	Artist	Track	Album	Genre	Date Added
	half cocked	Magazines	Refractory	Rock, Punk, Lo-Fi	+ ↓
	Small Tall Order	Cameo Appearance	Perfect Situation	Pop, Folk, Indie-Rock	+ ↓
	Small Tall Order	Always Been Gone	Perfect Situation	Pop, Folk, Indie-Rock	+ ↓

Data: key numbers & subsets

- ▶ 106,574 tracks from 16,341 artists and 14,854 albums.
- ▶ 917 GiB and 343 days of Creative Commons-licensed audio.
- ▶ Arranged in a hierarchical taxonomy of 161 genres.
- ▶ 518 pre-computed features per track.

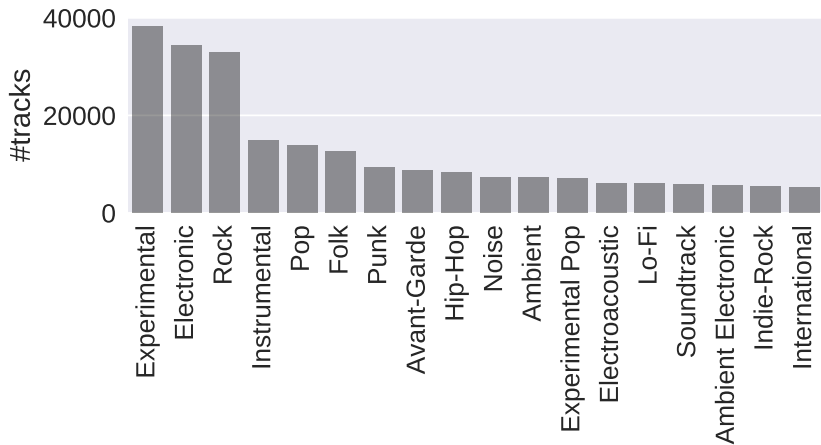
dataset	clips	genres	length [s]	size	
				[GiB]	#days
small	8,000	8	30	7.4	2.8
medium	25,000	16	30	23	8.7
large	106,574	161	30	98	37
full	106,574	161	278	917	343

Data: metadata

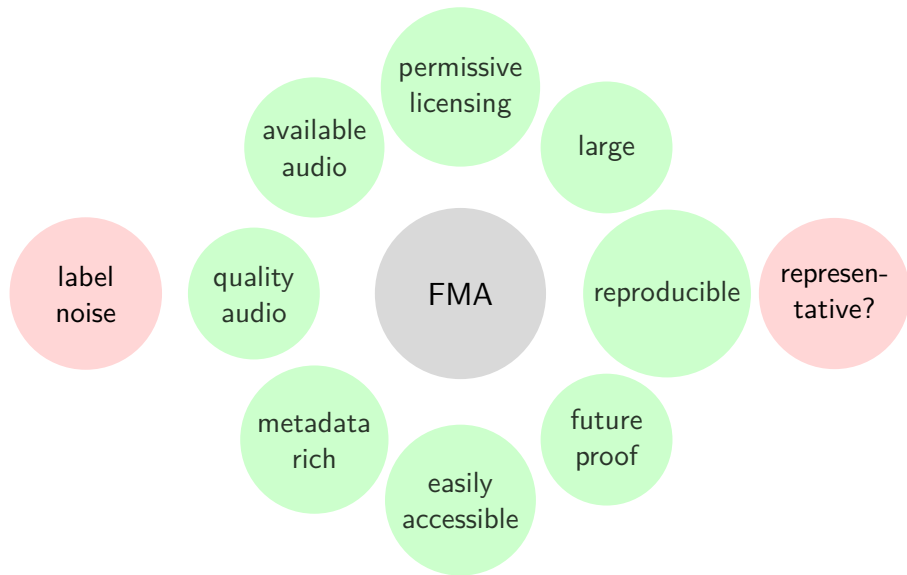
100% track_id	100% title	93% number
2% information	14% language_code	100% license
4% composer	1% publisher	1% lyricist
98% genres	98% genres_all	98% genres_top
100% duration	100% bit_rate	100% interest
100% #listens	2% #comments	61% #favorites
100% date_created	6% date_recorded	22% tags
100% album_id	100% title	
94% type	96% #tracks	
76% information	16% engineer	18% producer
97% #listens	12% #comments	38% #favorites
97% date_created	64% date_released	18% tags
100% artist_id	100% name	25% members
38% bio	5% associated_labels	
43% website	2% wikipedia_page	
	5% related_projects	
37% location	23% longitude	23% latitude
11% #comments	48% #favorites	10% tags
99% date_created	8% active_year_begin	
	2% active_year_end	

Data: genre distribution

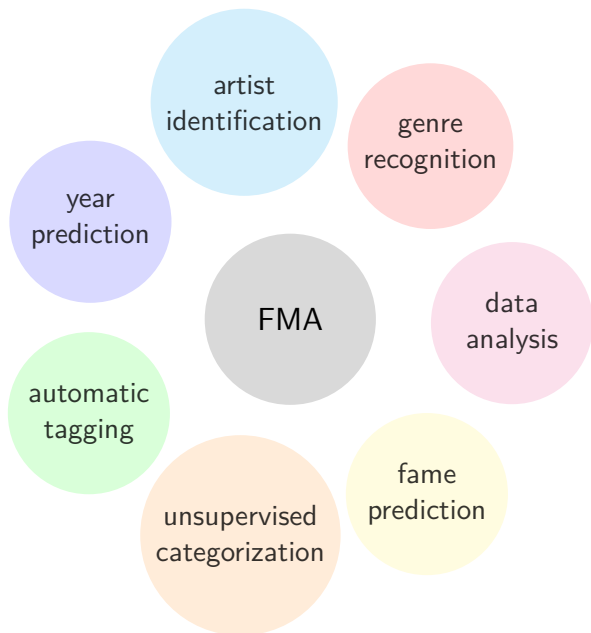
Large class imbalance!



Qualities & Limitations



Usage



People like it!

mdeff / fma

<> Code 1 Issues 9 Pull requests 0 Insights Settings

FMA: A Dataset For Music Analysis <https://arxiv.org/abs/1612.01840>

Edit

dataset music-analysis music-information-retrieval deep-learning open-data open-science reproducible-research Manage topics

181 commits

2 branches

2 releases

1 contributor

MIT



Michaël Defferrard

@m_deff

Our FMA dataset is online! 106,574 songs, 161 hierarchical genres, 917 GiB, 343 days of audio under [#creativecommons](#)
github.com/mdeff/fma

track_id	title	number
information	language_code	license
composer	publisher	lyricist
genres	genres_all	genre_top
duration	bit_rate	interest
#lists	#comments	#Favorites
date_created	date_recorded	tags
album_id	title	type
information	engineer	producer
#lists	#comments	#Favorites
date_created	date_released	tags
artist_id	name	associated_labels
bio	members	related_projects
website	wikipedia_page	longitude
location	#comments	latitude
date_created	active_year_end	#Favorites
		tags

Table 4. List of available per-track, per-album and per-artist metadata, i.e. the columns of tracks.csv.

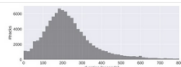


Figure 2. Track duration, from 0 to 3 hours.

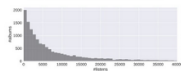


Figure 3. Album listens, from 0 to 3.6 millions.

RETWEETS

102

LIKES

178



6:45 PM - 9 May 2017

4 102 178



Sander Dieleman

@sedielem

Following

Replying to @Kikohs @m_deff @AtulAcharya

I wish this had existed when I was doing my PhD! Data drives research, so I think the impact of this on MIR could be massive. Amazing work!

RETWEET

1

LIKES

8



9:46 PM - 9 May 2017



1



8

cheyenne_h on 05/22/2017 at 06:15AM

A Music Information Retrieval Dataset, Made With FMA

You may recall some news we shared last summer about a [music dataset](#) that was in progress - now it's complete!

Michaël Defferrard, Kirell Benzi, Pierre Vanderghyest & Xavier Bresson, a team of researchers interested in MIR (music information retrieval), have put together

Outline

FMA: a dataset for music analysis

Challenge design

Results

Challenge design

Main issue: all the data is public

Solution: **two rounds**

- ▶ Round 1: public leaderboard, participants submit predictions
- ▶ Round 2: private test set, participants submit self-contained prediction systems

Challenge design: round 1

- ▶ Good to get continuous feedback.
- ▶ Used as a validation set to tweak the models.
- ▶ Cheating is possible by fingerprinting.
Mitigated by providing many clips.

Challenge design: round 2

Real unseen test set → used to rank participants

- ▶ Detect overfitting (or cheating) on validation set.
- ▶ Round2 test is significantly harder than round1.
- ▶ No cheating as systems are run by ourselves.
- ▶ Remaining issue: participants might have trained on a larger dataset than provided.

Emphasis on openness and reproducibility

- ▶ Open data.
- ▶ Open evaluation.
- ▶ All systems are open source and fully reusable.
- ▶ The challenge is completely reproducible.

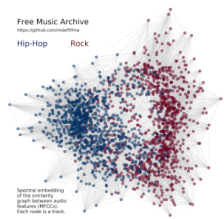
Outline

FMA: a dataset for music analysis

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WWW 2018 Challenge: Learning to Recognize Musical Genre



Learning to Recognize Musical Genre from Audio on the Web



By EPFL

Completed





























11931	271	716
Views	Participants	Submissions



UNFOLLOW

- ▶ First round: 716 submissions from 38 participants
- ▶ Second round: 6 submitted systems

First round: leaderboard

 #	Participant	Log Loss	F1 Score	Entries	Last Submission (UTC)	
01.	 lyjeong	0.33	0.909	54	Thu, 1 Mar 2018 08:36	
02.	 hglim	0.333	0.923	110	Thu, 1 Mar 2018 12:45	
03.	 mimbres	0.41	0.899	22	Thu, 1 Mar 2018 05:14	
04.	 minzwon	0.55	0.851	47	Sat, 10 Feb 2018 22:43	
05.	 ryanti	0.629	0.814	26	Wed, 24 Jan 2018 04:19	
06.	 PKU_DL	0.639	0.817	12	Wed, 27 Dec 2017 12:45	
07.	 AlgoHunt	0.659	0.8	34	Tue, 20 Feb 2018 07:25	
08.	 Leukas	0.66	0.805	16	Fri, 9 Feb 2018 15:23	
09.	 check	0.662	0.801	18	Thu, 1 Mar 2018 11:26	
10.	 Jaehun	0.664	0.807	69	Mon, 25 Dec 2017 17:44	
11.	 gg12	0.68	0.81	33	Sun, 18 Feb 2018 21:34	
12.	 Philipp	0.82	0.751	17	Wed, 7 Feb 2018 16:29	
13.	 Benjami...	0.824	0.742	30	Tue, 19 Dec 2017 07:55	

First round: confusion matrix

True label \ Predicted label	Blues	Classical	Country	Easy Listening	Electronic	Experimental	Folk	Hip-Hop	Instrumental	International	Jazz	Old-Time / Historic	Pop	Rock	Soul-RnB	Spoken
Blues	4	0	0	0	0	1	0	0	0	0	0	0	0	2	0	0
Classical	0	66	0	0	1	3	2	0	1	1	0	0	0	1	0	0
Country	0	0	12	0	0	0	1	0	0	0	0	0	0	4	0	0
Easy Listening	0	0	0	2	2	1	0	0	0	1	0	0	0	0	0	0
Electronic	0	2	0	0	724	26	3	8	11	1	0	0	3	15	0	0
Experimental	0	2	0	0	26	211	7	2	4	1	0	0	1	15	0	0
Folk	0	1	0	0	3	9	142	0	2	1	0	1	2	17	0	0
Hip-Hop	0	0	0	0	26	5	1	232	0	0	0	0	0	4	0	2
Instrumental	0	2	0	0	18	11	4	0	116	0	0	0	1	14	0	0
International	0	1	0	0	8	4	3	2	1	94	0	0	0	6	0	1
Jazz	0	3	0	0	7	5	2	0	3	1	26	0	0	5	0	0
Old-Time / Historic	0	0	0	0	0	1	0	0	0	0	0	53	0	0	0	0
Pop	0	0	0	0	20	5	5	4	2	2	0	0	69	35	0	0
Rock	0	1	0	0	28	16	8	1	4	2	0	0	2	693	0	2
Soul-RnB	0	0	0	0	2	1	0	1	0	0	0	0	0	4	11	0
Spoken	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	14

Second round: submitted systems

1. Transfer Learning of Artist Group Factors to Musical Genre Classification by Jaehun Kim (@jaehun), TU Delft and Minz Won (@minzwon), Universitat Pompeu Fabra.
2. Ensemble of CNN-based Models using various Short-Term Input by Hyungui Lim (@hglim), <http://cochlear.ai>.
3. Detecting Music Genre Using Extreme Gradient Boosting by Benjamin Murauer, Universität Innsbruck.
4. ConvNet on STFT spectrograms by Daniyar Chumbalov (@check), EPFL and Philipp Pushnyakov (@gg12), Moscow Institute of Physics and Technologies (MIPT).
5. Xception¹ on mel-scaled spectrograms by @viper and @algho hunt.
6. Audio Dual Path Networks² on mel-scaled spectrograms by Sungkyun Chang (@mimbres), Seoul National University.

¹Xception: Deep Learning with Depthwise Separable Convolutions, <https://arxiv.org/pdf/1610.02357>

²Dual Path Networks, <https://arxiv.org/abs/1707.01629>

Second round: systems' performance

Team	Log loss			Rank	F1 score		
	R1a	R1b	R2		R1a	R1b	R2
minzwon & jaehun	0.55	0.67	1.31	1	85%	80%	63%
hglim	0.33	0.34	1.34	2	92%	92%	64%
benjamin_murauer	0.82	0.86	1.44	3	74%	74%	60%
gg12 & check	0.66	0.49	1.50	4	80%	86%	61%
viper & algohunt	0.66	0.65	1.52	5	80%	81%	60%
mimbres	0.41	0.43	2.08	6	90%	90%	60%

- ▶ *R1a* references the best scores obtained on the public leaderboard during the first round. The test data consisted of 35000 clips.
- ▶ *R1b* references the scores obtained by the submitted systems on a 3000 clips subset of the public test set used in the first round.
- ▶ *R2* references the scores obtained by the submitted systems on a 3000 clips private test set collected for the second round.

Second round: confusion matrix

True label \ Predicted label	Blues	Classical	Country	Easy Listening	Electronic	Experimental	Folk	Hip-Hop	Instrumental	International	Jazz	Old-Time / Historic	Pop	Rock	Soul-RnB	Spoken
Blues	0	0	0	0	1	0	3	0	0	0	0	0	0	0	0	0
Classical	0	49	0	0	8	3	2	0	24	1	0	0	1	8	0	0
Country	0	0	0	0	1	6	11	0	0	1	0	0	0	8	0	0
Easy Listening	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Electronic	0	1	0	0	380	24	2	12	9	2	0	0	6	18	0	0
Experimental	0	4	0	0	90	165	16	3	13	3	1	0	4	36	0	1
Folk	0	1	0	0	8	10	138	0	6	14	1	1	7	44	0	0
Hip-Hop	0	0	0	0	41	0	0	103	0	0	0	0	1	3	0	0
Instrumental	0	10	0	0	82	52	18	6	101	0	0	0	2	22	0	0
International	0	0	0	0	18	9	18	2	3	79	1	0	2	16	0	0
Jazz	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0
Old-Time / Historic	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Pop	0	0	0	0	38	5	38	10	5	2	0	0	8	97	0	0
Rock	0	1	1	0	73	48	37	4	21	7	1	0	12	774	0	0
Soul-RnB	0	0	0	0	0	1	0	0	0	1	0	0	0	3	0	0
Spoken	0	0	0	0	0	2	0	2	0	0	0	0	0	1	0	2

Conclusion

- ▶ Most participants did not alter their system for the second round.
- ▶ Systems are often trained to overfit on validation data.
- ▶ Most systems used Deep Learning.
- ▶ Deep Learning on audio is hard: much larger samples³, not a lot of battle tested architectures.
- ▶ All participants used DL architectures on spectrograms, which are images.

³At a sampling rate of 22050 Hz, a 3 minutes song is ≈ 4 million floating point numbers. To be compared with $256 \times 256 \approx 65000$ pixels on ImageNet.

Lessons learned

- ▶ Challenge design is hard.
- ▶ There is a real interest in the ML community and it's fun.
- ▶ Organizing a challenge will take more time than you think.
- ▶ Challenges inspire young people and encourage them to learn.

Special thanks to all the participants!

Slides <https://doi.org/10.5281/zenodo.1243501>

Paper Defferrard, Benzi, Vandergheynst, Bresson,
FMA: A Dataset For Music Analysis, ISMIR, 2017
<https://arxiv.org/abs/1612.01840>

Paper Defferrard, Mohanty, Carroll, Salathé,
Learning to Recognize Musical Genre from Audio, WWW, 2018
<https://arxiv.org/abs/1803.05337>

Code & Data <https://github.com/mdeff/fma>

Challenge [https://www.crowdai.org/challenges/
www-2018-challenge-learning-to-recognize-musical-genre](https://www.crowdai.org/challenges/www-2018-challenge-learning-to-recognize-musical-genre)
[https://github.com/crowdAI/
crowdai-musical-genre-recognition-starter-kit](https://github.com/crowdAI/crowdai-musical-genre-recognition-starter-kit)

Thanks Questions?