the data challenge in music information retrieval

FRSM 2023

alexander lerch

github.com/alexanderlerch/2023-FRSM

Georgia Tech Center for Music Technology
College of Design

about
about me

Georgia Tech | Center for Music Technology
College of Design

education
- Electrical Engineering (Technical University Berlin)
- Tonmeister (music production, University of Arts Berlin)

professional
- Associate Professor at the School of Music, Georgia Institute of Technology
- 2000-2013: CEO at zplane.development

background
- audio algorithm design (20+ years)
- commercial music software development (10+ years)
- entrepreneurship (10+ years)

www.linkedin.com/in/lerch

about
research directions

- field: music information retrieval, audio content analysis
  - audio classification
    - genre, instrument, auto-tagging, ...
  - music transcription
    - pitch, chord, performance data, ...
  - music processing
    - separation, ...
  - sound and music generation
    - controllability

- technical areas of interest
  - representation learning
  - machine learning with insufficient data
  - evaluation of generative systems

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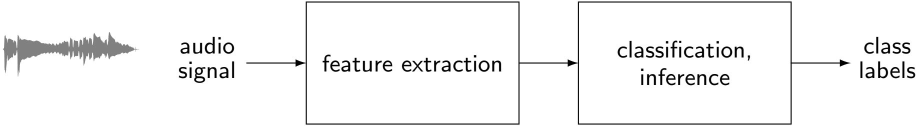
introduction

audio classification — traditional



feature representation

- compact and non-redundant
- task-relevant
- easy to analyze
- e.g., MFCCs etc.

classification

- map or convert feature to comprehensible domain
- e.g., Support Vector Machines etc.

[1] J. J. Burred and A. Lerch, "Hierarchical Automatic Audio Signal Classification," *Journal of the Audio Engineering Society (JAES)*, vol. 52, no. 7/8, pp. 724–739, 2004. [Online]. Available: http://www.musicinformatics.gatech.edu/wp-content_nondefault/uploads/2016/10/Burred-and-Lerch-2004-Hierarchical-Automatic-Audio-Signal-Classification.pdf.

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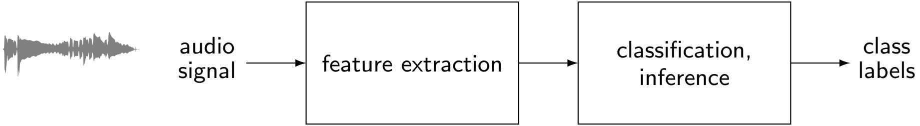

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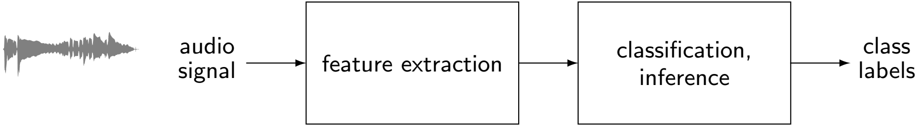

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neural network based approaches

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- no custom-designed features anymore
- learn features from basic inputs (like spectrograms)

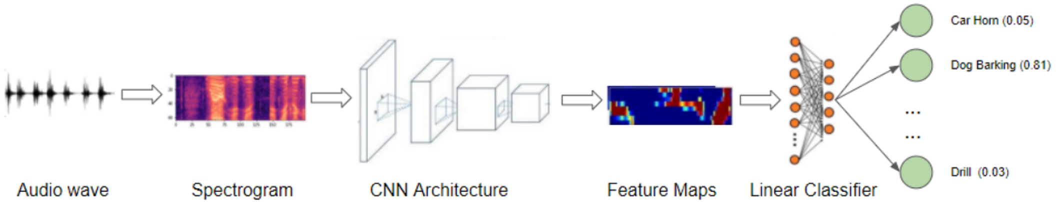

Fig.: towardsdatascience.com

- less required expert-knowledge, more complex systems
- less expert-tweaking, more rigorous experimental requirement
- much **higher data requirements**

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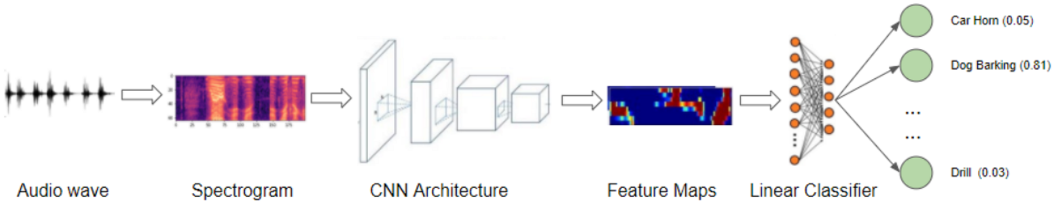

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Fig.: towardsdatascience.com

data
importance of data

machine learning: generic algorithm mapping an input to an output

- mapping function is learned from patterns and characteristics **from data**

⇒ model **success largely depends on training data**

- **general challenges** concerning data
  - subjectivity
  - noisiness
  - imbalance & bias
  - diversity & representativeness
  - amount

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insufficient data in music

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- **consumer annotations** are more difficult to collect, but there are some large collections

insufficient data in music

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- **consumer annotations** are more difficult to collect, but there are some large collections
- **detailed musical annotations** are hard to come by, because
  - time consuming & tedious annotation process
  - experts needed for annotations

data

previous work on insufficient data

- literature proposes many ways of **dealing with insufficient data**
  - data synthesis
  - data augmentation[2]
  - transfer learning
  - semi- and self-supervised approaches
  - ...

[2] Y. Qin and A. Lerch, "Tuning Frequency Dependency in Music Classification," en, in *Proceedings of the International Conference on Acoustics Speech and Signal Processing (ICASSP)*, Brighton, UK: Institute of Electrical and Electronics Engineers (IEEE), 2019, pp. 401–405. DOI: 10.1109/ICASSP.2019.8683340. [Online]. Available: http://www.musicinformatics.gatech.edu/wp-content_nondefault/uploads/2019/04/Qin-and-Lerch-2019-Tuning-Frequency-Dependency-in-Music-Classificatio.pdf.

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[2] S. Gururani, M. Sharma, and A. Lerch, "An Attention Mechanism for Music Instrument Recognition," in *ISMIR*, Delft, 2019.

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[2] C.-W. Wu and A. Lerch, "Automatic drum transcription using the student-teacher learning paradigm with unlabeled music data," in *ISMIR*, Suzhou, 2017.

[3] S. Gururani and A. Lerch, "Semi-Supervised Audio Classification with Partially Labeled Data," in *Proceedings of the IEEE International Symposium on Multimedia (ISM)*, online: Institute of Electrical and Electronics Engineers (IEEE), 2021. [Online]. Available: https://arxiv.org/abs/2111.12761.

overview

overview

1. **self-supervised representation learning**
   - utilize pre-trained features to improve classification
2. **reprogramming**
   - utilize pre-trained model to improve classification
3. **data challenge revisited**

reprogramming
introduction

- **observation**
  - pre-trained deep models can be very powerful if trained with sufficient data, even for different tasks
- **idea**
  - re-using pre-trained models for a new task **without** re-training
- **goals**
  - keep number of training parameters minimal
  - utilize unmodified network trained on different task

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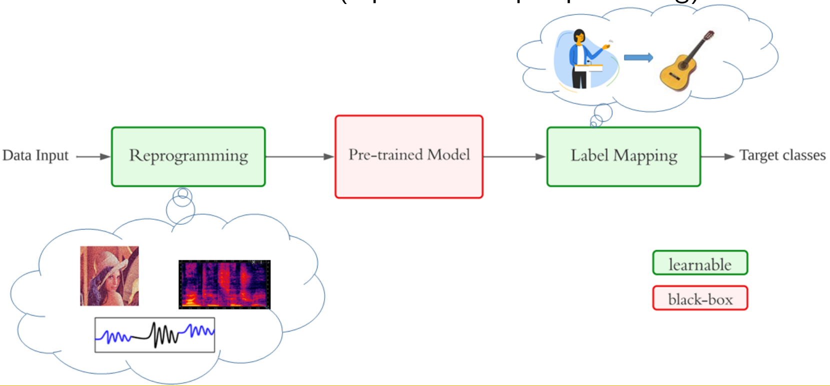
reprogramming

overview

- inspired by
  - transfer learning
  - adversarial learning
- allows for small trainable model (input and output processing)



reprogramming
experimental setup: data

- OpenMic:
  - 20 classes of musical instruments
  - 10 s audio snippets (20000)

reprogramming

experimental setup: baselines

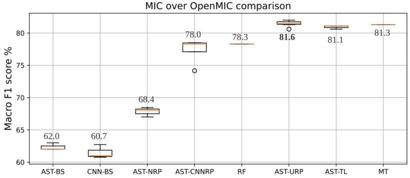
- Baseline AST:
  - good performance on audio event classification[4]
- ablation study:
  - CNN only
  - U-Net only
  - CNN + AST + FC
  - U-Net + AST + FC

[4] Y. Gong, Y.-A. Chung, and J. Glass, "AST: Audio Spectrogram Transformer," in *Proceedings of Interspeech*, arXiv: 2104.01778, Brno, Czechia, Jul. 2021. [Online]. Available: http://arxiv.org/abs/2104.01778 (visited on 04/17/2022).

reprogramming

results: classification metrics

method	F1 (macro)	train. param. (M)
AST + simple output mapping	62.03	0.001
CNN	60.77	0.017
U-Net	62.73	0.017
CNN + AST + FC	78.08	0.017
U-Net + AST + FC	**81.60**	0.018



- a powerful model trained on a different task cannot easily be used directly
- proper input and output processing can significantly improve performance
- *re-programming can beat the state-of-the-art* with a fraction of trainable parameters (at least factor 10)

[5] H.-H. Chen and A. Lerch, "Music Instrument Classification Reprogrammed," in *Proceedings of the International Conference on Multimedia Modeling (MMM)*, Bergen, Norway, 2023. [Online]. Available: https://arxiv.org/abs/2211.08379.

embeddings as teachers

introduction

- **question**:
  - how can we provide extra training information without additional data labels
- **idea**:
  - use proven pre-trained embeddings (e.g., VGGish, OpenL3, . . .)
- **goals**:
  - *impart knowledge* of pre-trained deep models
  - *improve model generalization* by utilizing pre-trained embeddings
  - *reduce model complexity*
- **general approach**:
  - combine transfer learning and knowledge distillation ideas

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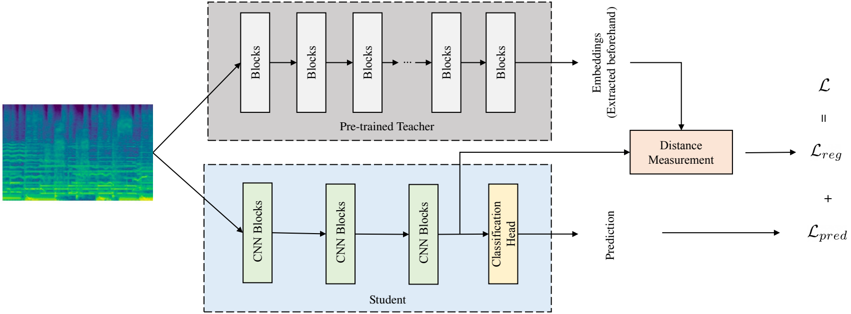
method overview



- **transfer learning**
  - use embeddings from a different task for the target task
- **knowledge distillation**
  - use a teacher to train a less complex student on the same task

embeddings as teachers

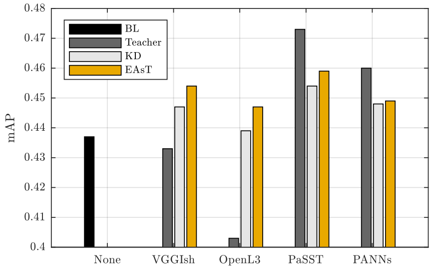
experimental setup

- task: auto-tagging
  - MagnaTagATune (MTAT) dataset:
    - 50 music tags
    - 30 s audio snippets ($\approx$ 21000)
- systems:
  - baseline: student without teacher
  - teacher: embedding plus logistic regression
    - VGGish
    - OpenL3
    - PaSST
    - PANNs
  - KD: student trained with soft targets from teacher
  - EAsT: student regularized with teacher embeddings

embeddings as teachers

results

- student model consistently outperforms baseline
- student model consistently outperforms knowledge distillation
- student model outperforms teacher for "old" embeddings
- modern embeddings are powerful but complex



[6] Y. Ding and A. Lerch, "Audio Embeddings as Teachers for Music Classification," in *Proceedings of the International Society for Music Information Retrieval Conference (ISMIR)*, Milan, Italy, 2023. DOI: 10.48550/arXiv.2306.17424. [Online]. Available: http://arxiv.org/abs/2306.17424 (visited on 07/03/2023).

data challenge revisited

insufficiency vs. representativeness

moderate improvements can be made to deal with insufficient data, but

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is the amount of data really the main issue

data challenge revisited

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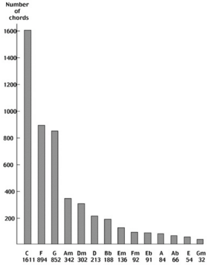
moderate improvements can be made to deal with insufficient data, but

is the amount of data really the main issue

- maybe not...
  - a closer look at example music datasets for popular tasks

data challenge revisited
dataset example 1: chord detection

- Beatles dataset for chord detection
  - chord progressions from Beatles albums (181 songs)
  - chord vocabulary



- potential problems
  - stylistic homogeneity
    - timbre and instrumentation, style, release dates, audio quality...
  - chord imbalance
    - very skewed distribution, key dependence

⇒ **may not generalize**

⇒ **may only recognize most common chords**

data challenge revisited

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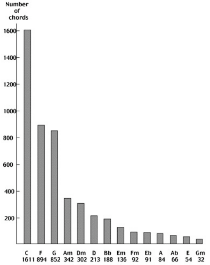

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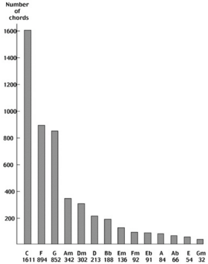

data challenge revisited

dataset example 2: music genre classification

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- GTZAN dataset for genre classification
  - 10 classes
  - 1000 30 s snippets
- problems with labeling
  - what are the 10 most relevant music genres, why 10?
  - how are genres categorized? examples:
    - baroque, christmas songs, fugue, indian art music, symphony, fusion
  - single-label vs. multi-label

⇒ **mismatch between dataset labels and 'real' task**

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Hip Hop
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data challenge revisited

dataset example 3: source separation

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    - 150 songs
    - 4 stems: vocals, drums, bass, other

- problems
    - stem selection does not reflect many real world scenarios
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data challenge revisited

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data challenge revisited

dataset examples: summary

- false homogeneity/**non-representativeness impacts generalization**
  - system cannot learn what is hasn't seen or what seems irrelevant
- imbalance can lead to **unwanted bias**
  - *training*: system wrongly favors certain categories
  - *testing*: results may imply good performance yet cannot be generalized
- mismatch between dataset labels and real task may **feign good performance**
  - misleading results
  - architectural bias

conclusion
data challenge

- we presented **2 recent approaches**
  - a novel *self-supervised regularization loss*
  - *reprogramming* for audio classification
- all approaches perform **at or above the state-of-the-art** with different trade-offs between
  - *training complexity*
  - *inference complexity*
  - *classification accuracy*
- **but:** maybe we tried to solve the wrong challenges

thank you!

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links

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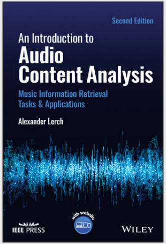
mail: alexander.lerch@gatech.edu

book: www.AudioContentAnalysis.org

zplane.development: www.zplane.de

music informatics group: musicinformatics.gatech.edu



github.com/alexanderlerch