music information retrieval

Santa Cruz Artificial Intelligence

github.com/alexanderlerch/2023-SantaCruz-AI

alexander lerch

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College of Design

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- **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

introduction
chain of musical communication

composition → performance → production → distribution → consumption

- **creation of musical ideas** ("score")
  - defines style and idea
- **realization of musical ideas** into acoustical rendition
  - interpretation, modification, addition, and dismissal of score information
  - unique acoustic representation of score
- **recording, mixing, and editing** (in case of record media)
  - editing and splicing of recorded data; timbre, equalization choices
  - not separable from performance in a recording
- **distribution & listening**
  - music recommendation and discovery

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musical communication and AI

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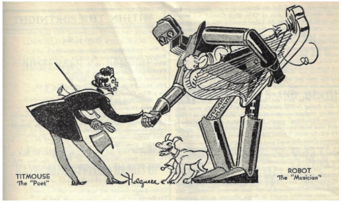
  - intelligent assistance, e.g., ideas, auto-arrangements
  - automatic composition
- **performance**
  - interactive music education systems
  - generation of 'human' performance
- **production**
  - auto-edit and auto-mix
- **distribution**
  - match music style and consumer
- **consumption**
  - intelligent music discovery & adaptable music

- example:
  DeepBach



longstreet.typepad.com/thesciencebookstore/2017/06/the-invasion-of-musical-robots-1929

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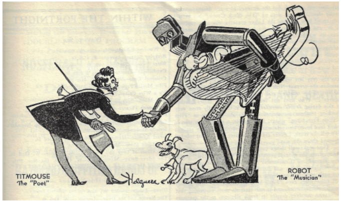
- example:

  Hatsune Miku



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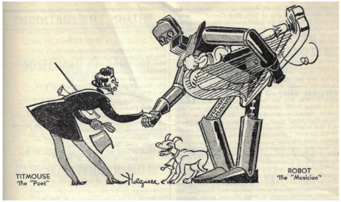

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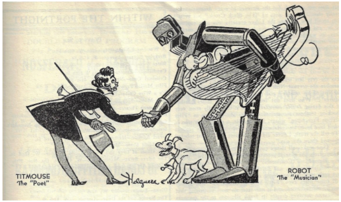

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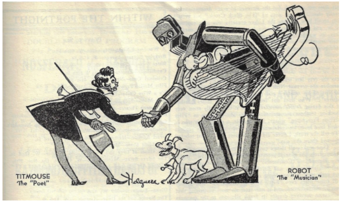

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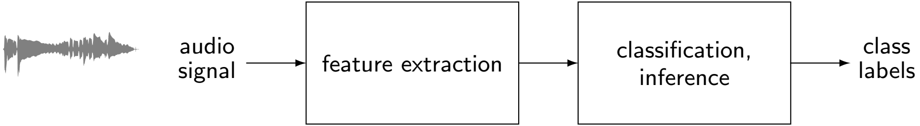
How can we teach a computer to listen to and understand music?

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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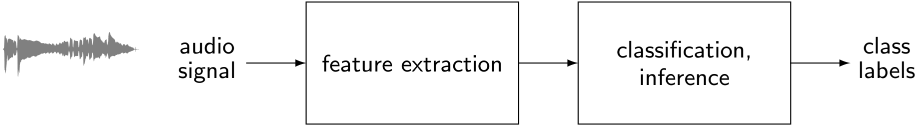

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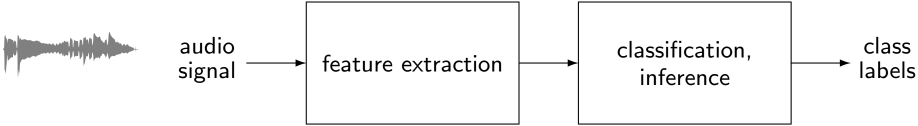

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neural network based approaches

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

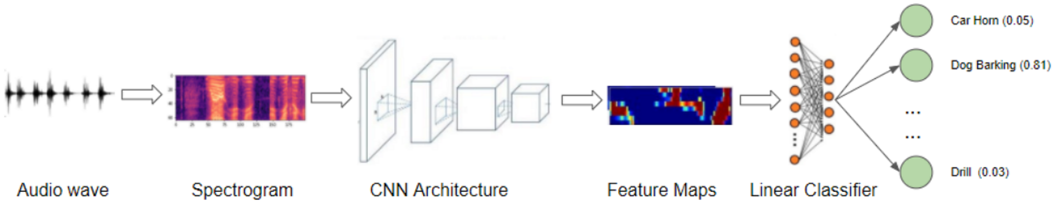

Fig.: towardsdatascience.com

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

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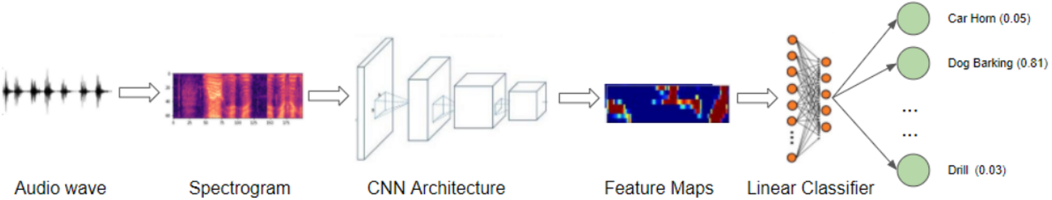

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Fig.: towardsdatascience.com

overview
research interests

- tasks of interest
  - 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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overview

structure

1. **data**
   - introducing the data challenge in music
2. **reprogramming**
   - utilize pre-trained model to improve classification
3. **embeddings as teachers**
   - utilize pre-trained features to improve classification

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

https://imgs.xkcd.com/comics/machine_learning.png

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data

insufficient data

- **music data** itself is not scarce (although there might be copyright issues...)
- **consumer annotations** are more difficult to collect, but there are some large collections
- **detailed musical annotations** are hard to come by, because
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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.

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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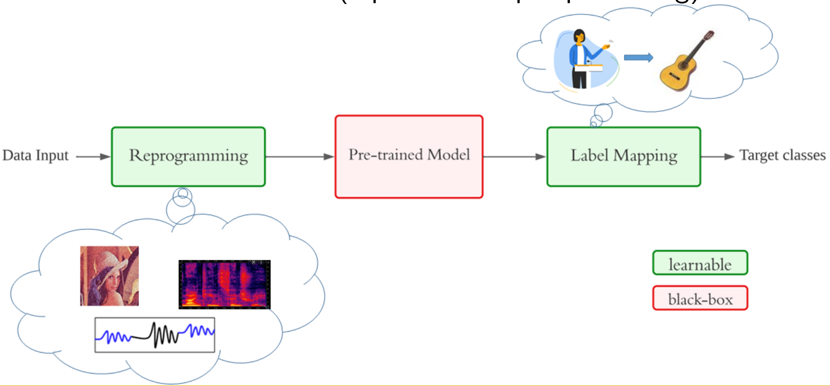
reprogramming
overview

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



reprogramming

experimental setup: baselines

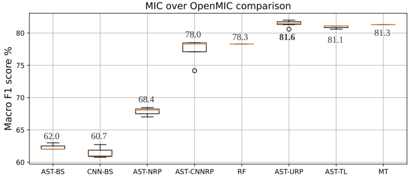
- Baseline AST:
  - good performance on audio event classification[4]
- data
  - OpenMic:
    - 20 classes of musical instruments
    - 10 s audio snippets (20000)
- ablation study:
  - CNN only
  - U-Net only
  - CNN + AST + FC
  - U-Net + AST + FC

[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* at 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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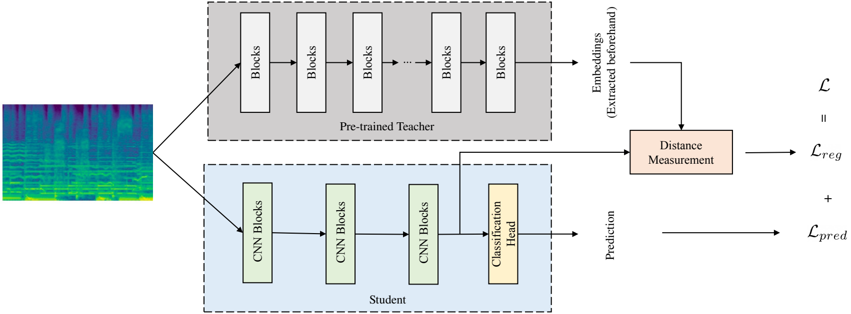
method overview



- **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

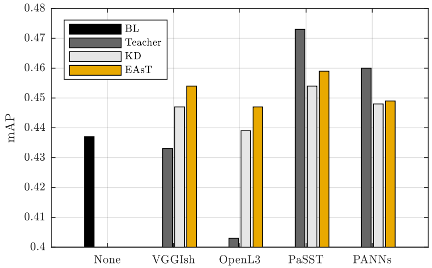
- task: auto-tagging
  - MagnaTagATune (MTAT) dataset:
    - 50 music tags
    - 30 s audio snippets ($\approx$ 21000)

- 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).

conclusion
data challenge

- we presented **2 recent approaches** to address the challenge of insufficient training data
  - 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 should address the data problems directly

thank you!

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links

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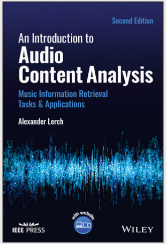

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