Machine Listening for Music and Sound Analysis

Lecture 3 – Music Information Retrieval I

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https://machinelistening.github.io

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Overview

- Music Information Retrieval
- Music Tagging
- Music Similarity
- Tempo Estimation

Music Information Retrieval
Examples

- Examples:
  - Musical Instrument
    AUD-1 AUD-2
  - Musical Genre / Tempo
    AUD-3 AUD-4

Music Information Retrieval
Motivation

- Large music collections
- Mobile device apps / instruments
- Music industry shifts almost completely to online products & services
- Growing market of music streaming services

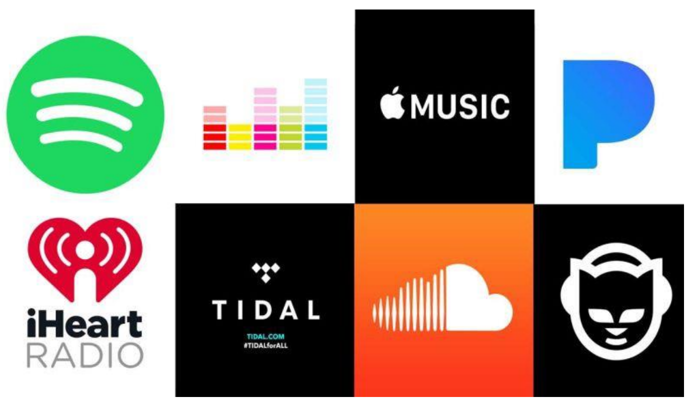


Fig. 1

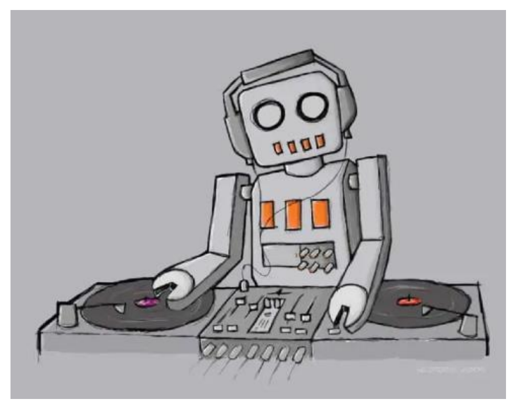


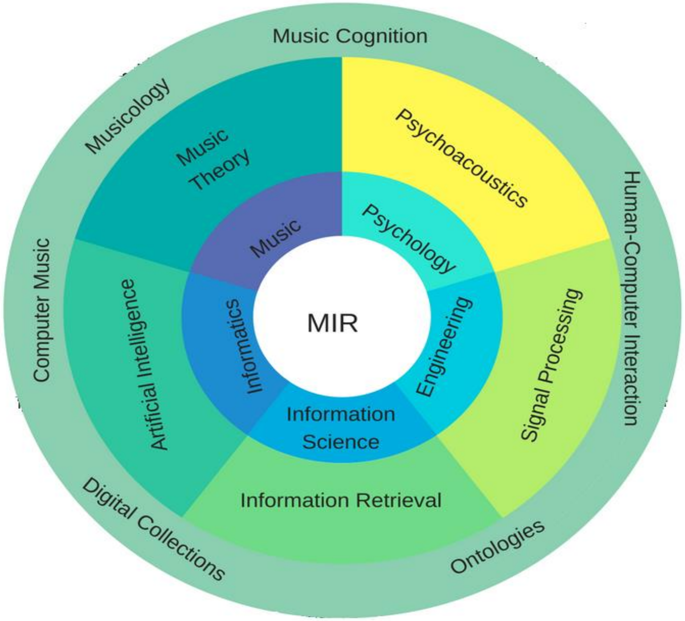
Fig. 2

Music Information Retrieval
Typical Research Tasks

- What’s that song again? Who’s singing that?
  - Audio identification
- I want to learn that song on my instrument!
  - Automatic music transcription
- What songs are similar? How to generate a playlist?
  - Audio similarity search
- How to organize my music? Which genre / style?
  - Audio classification

Music Information Retrieval
Research Landscape

- Interdisciplinary research community since 2000
- Conferences
  - ISMIR (International Society for Music Information Retrieval)
  - IEEE ICASSP, DAFx, AES, ICMC, SMC
- MIREX competition (Music Information Retrieval Evaluation eXchange)



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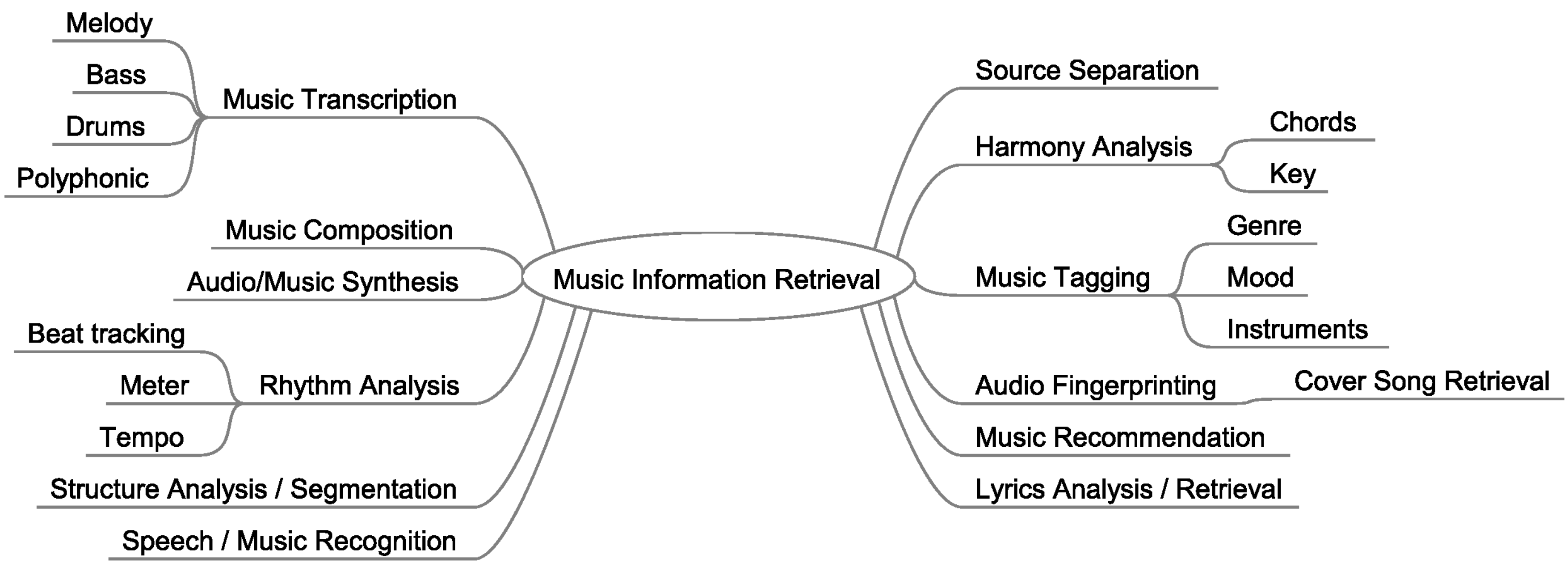
Music Information Retrieval
Research Landscape

- MIR @ Fraunhofer IDMT
    - Semantic music technologies (SMT) group
        - Staff + PhD / master / bachelor students + interns
- National / international research groups
    - International Audio Laboratories Erlangen, Germany
    - Centre for Digital Music, Queen Mary University, London, UK
    - Universitat Pompeu Fabra, Barcelona, Spain
    - Institute for music/acoustic research and coordination (IRCAM), Paris, France
    - USA, China, Taiwan, Japan, Korea, etc.

Music Information Retrieval
Research Task Taxonomy



Music Information Retrieval
Case Studies

- MIR 1 lecture
  - Music tagging / music similarity → general tasks
  - Tempo estimation → rhythm
- MIR 2 lecture
  - Pitch detection → pitch / tonality
  - Source separation & instrument recognition → timbre

- Teaching Concept

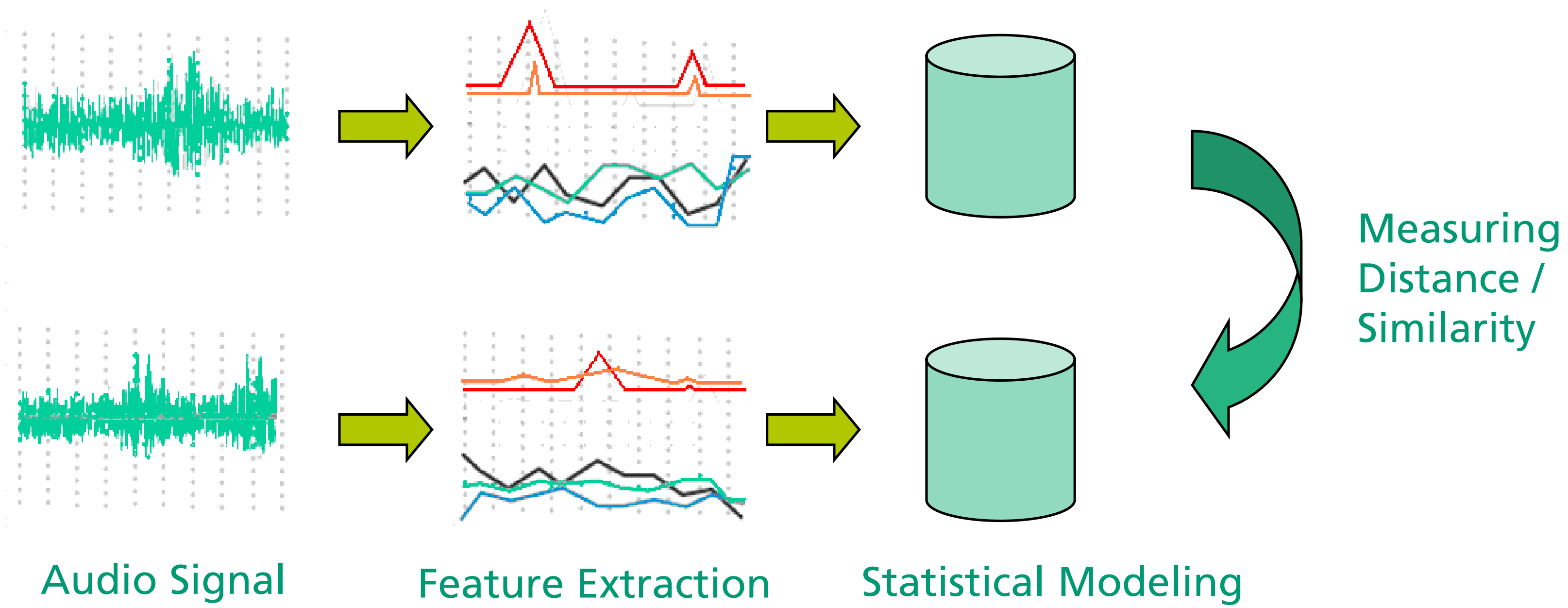
Task Introduction → Traditional Approach → Novel Approaches

Music Tagging
Introduction

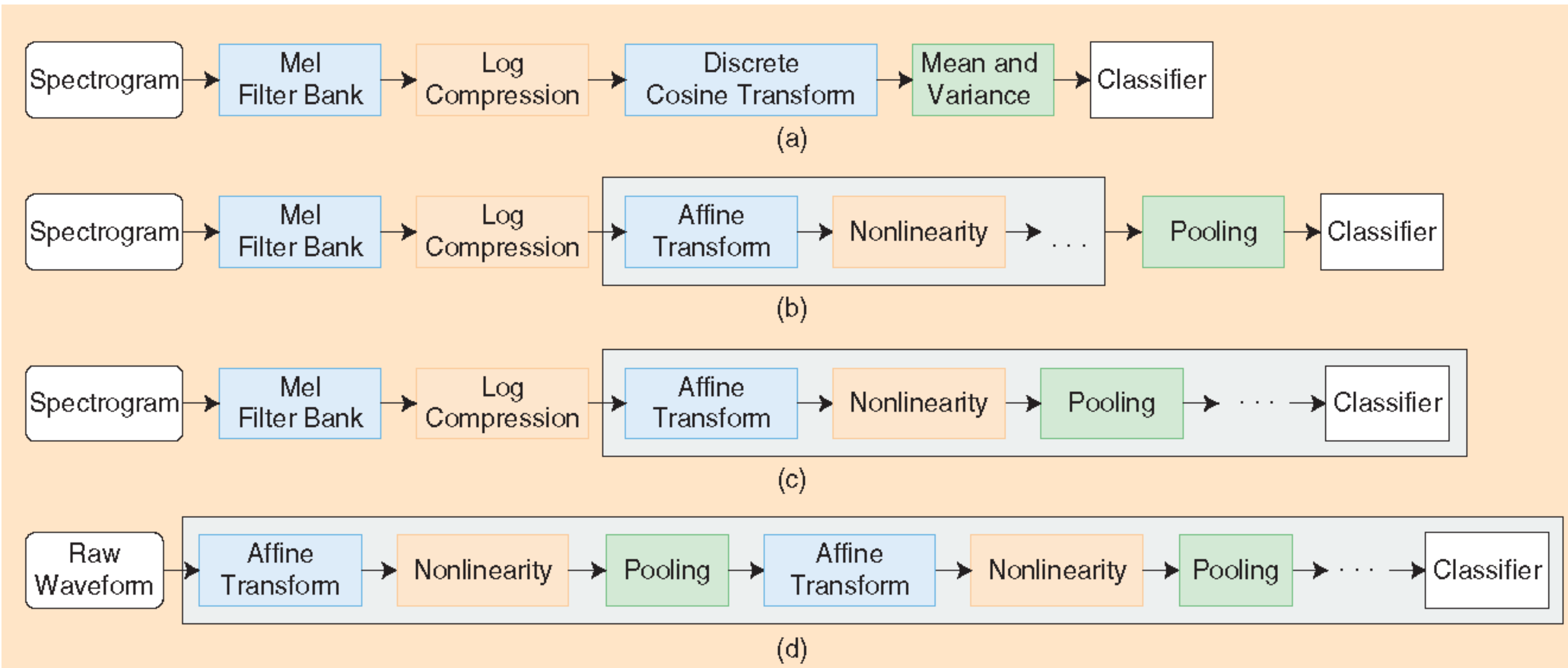
- Tags
  - Textual (objective / subjective) annotations of songs
  - Examples
    - Instruments (drums, bass, guitar, vocals …)
    - Genre (classical, electro, hip hop)
    - Mood (mellow, romantic, angry, happy)
    - Miscellaneous (noise, loud, ambient)
- Challenge
  - Music pieces change their characteristics over time
    - E.g.: trumpet plays only in the chorus (jazz)

Music Tagging
Traditional Approach

- Audio feature engineering & music domain knowledge
- Standard classification methods (GMM, SVM, kNN)



Music Tagging
Novel Approaches



Trend

Fig. 3

(a) Feature engineering (MFCC)

(b) Low-level feature

(c) Joint feature learning & classification (CNN)

(d) End-to-end learning

Music Tagging
Novel Approaches

- Joint representation learning & classification using CNNs
    - Input: spectrograms (2D) or audio samples (1D end-to-end)

- Integrate musical knowledge in network design (e.g., filter shapes)

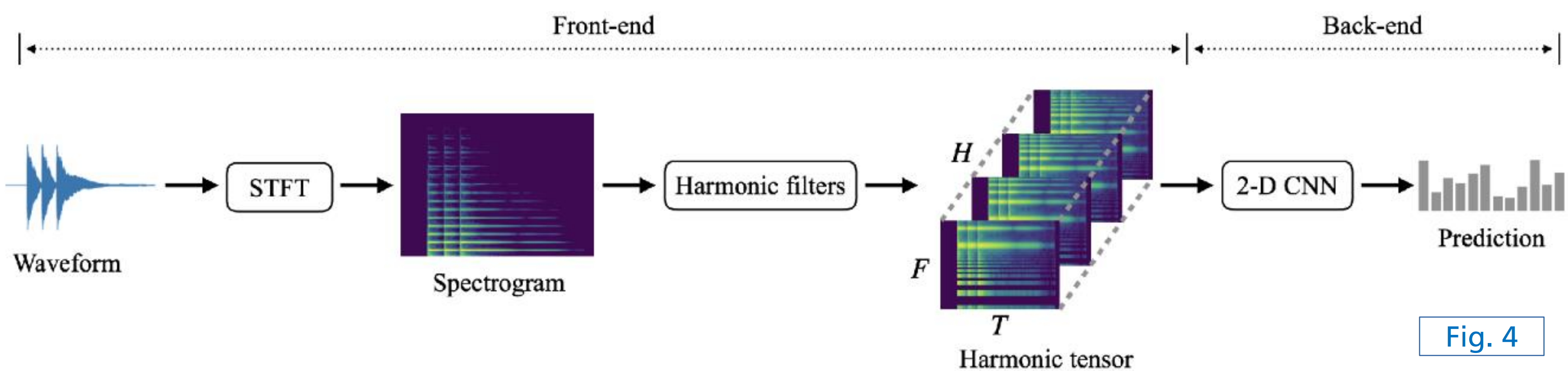


Fig. 4

Music Tagging
Novel Approaches

- End-to-end Learning
  - Model input is low-level representation (audio waveform)
  - No pre-processing / assumptions required
  - Not restricted to spectral magnitudes → can model phase!
  - Requires large amounts of training data

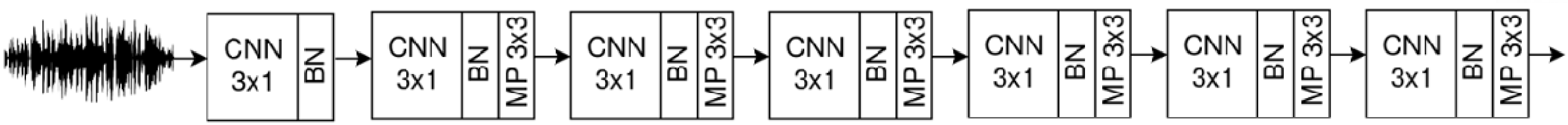


Fig. 6

Music Tagging
Novel Approaches

- Transfer Learning
  - Pre-train model on source task (lot of data available)
  - Fine-tune model on target task (only little data available)

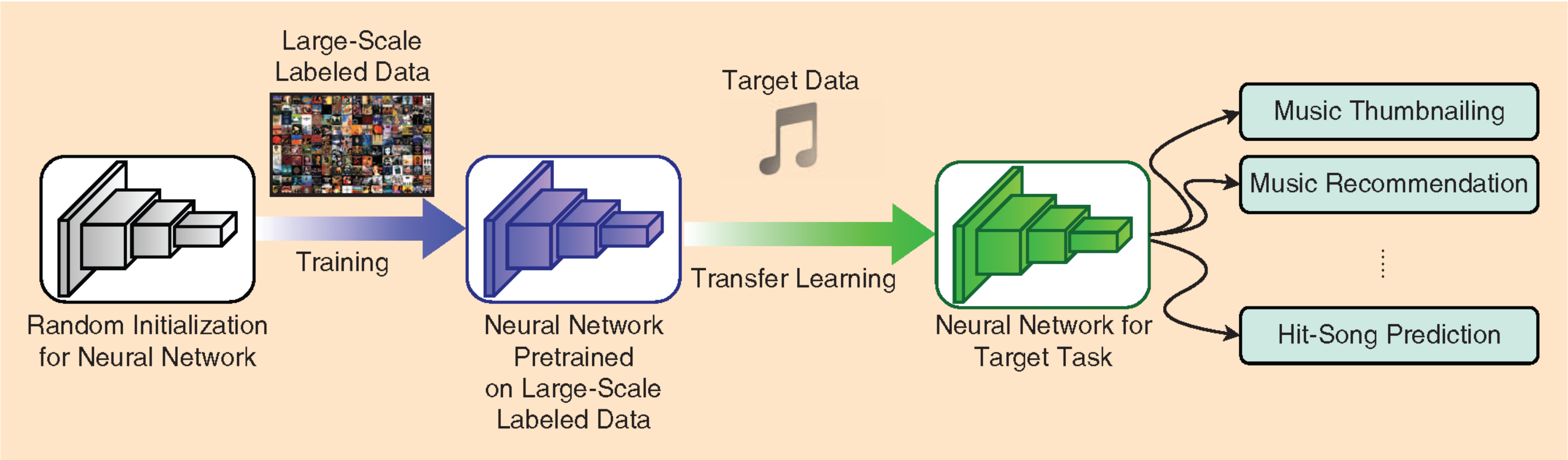


Fig. 5

- Source model (CNN) → Target model (embeddings + shallow classifier)

Music Similarity
Introduction

- Music → inherently multi-dimensional
- Challenge
  - Large music databases
  - Incomplete / missing metadata
- Query by example → general retrieval approach
  - Retrieval most similar song *S* given a query song *Q*

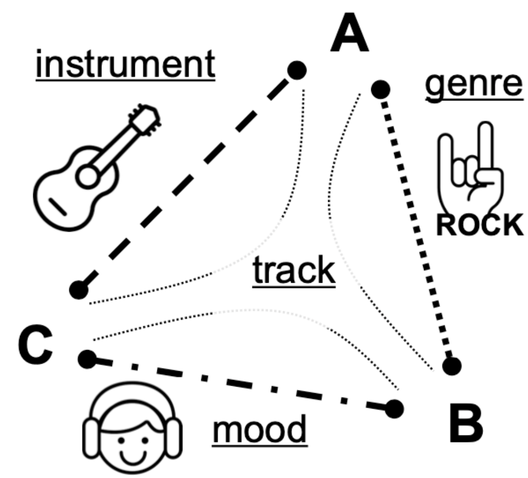


Fig. 7

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Music Similarity
Introduction

- Retrieval tasks
  - Music fingerprinting (retrieve title, artist, e.g., Shazam app)
  - Cover song identification (similar text, chord progressions …)
  - Music replacement (similar style, instrumentation)

- Specificity of different tasks

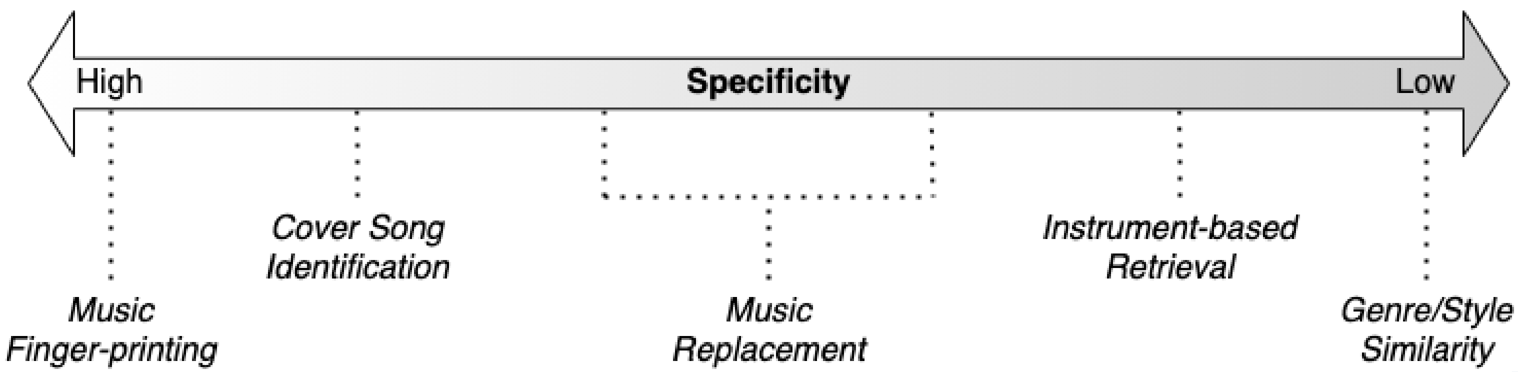
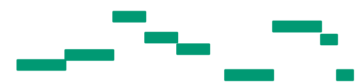


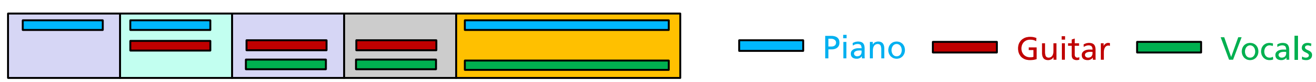
Fig. 8

Music Similarity
Traditional Approaches

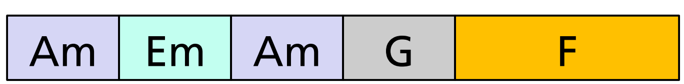
- Different dimensions of music similarity
  - Melodic similarity (pitch contours)



  - Timbral similarity (instrumentation)



  - Structural / harmonic similarity (segments, chords)



  - Rhythmic similarity (patterns)

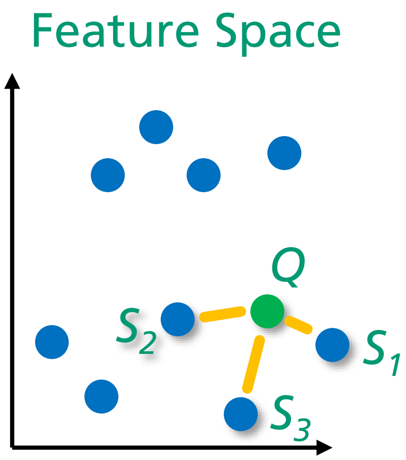
Music Similarity
Novel Approaches

- Metric learning
  - Model (abstract) notion of similarity between data instances
    - Pair-wise distance between feature representations

- Training → Preserve similarity in the feature space
  - Proximity between similar instances
  - Distance between dissimilar instances

- Distance measures (Euclidean, cosine)

- Query Q → Ranked list of most similar items (S_i)



Music Similarity
Novel Approaches

- Disentanglement learning
  - Similarity → multiple semantic concepts (e.g., genre, instrument, mood)
    - learnt jointly
    - remain separable in the embedding space
- Improves tagging (classification) and recommendation (similarity)

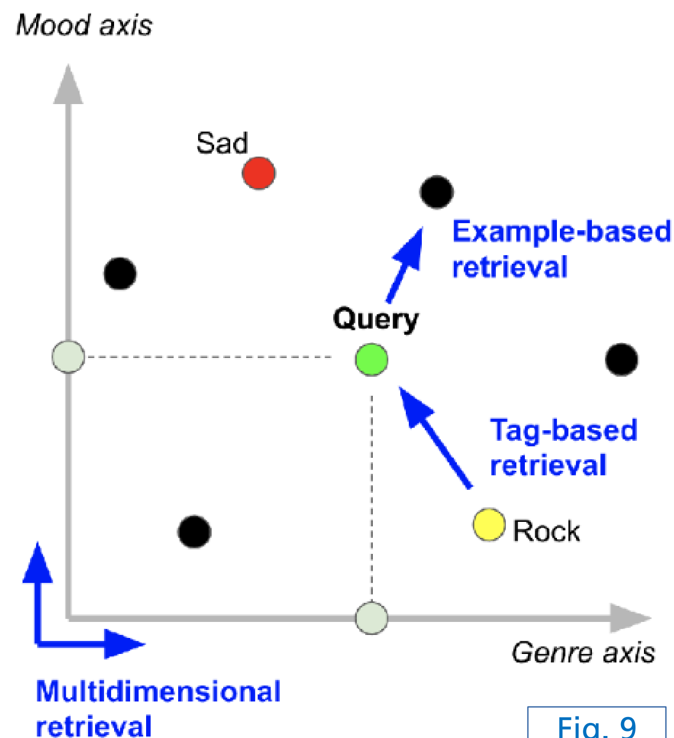


Fig. 9

Music Similarity
Novel Approaches

- Triplet-based Training
  - Conditional Similarity Networks (CSN) [Lee, 2020]

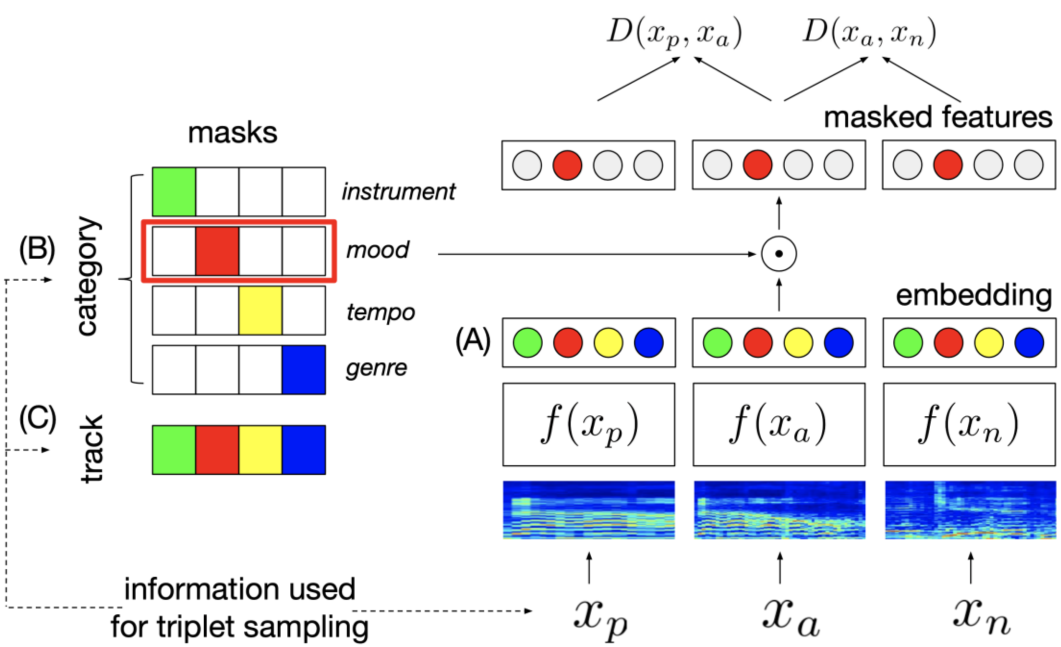


Fig. 10

Pair-wise distances

Embedding

Deep Neural Network

Spectrogram

Tempo Detection
Introduction

- Tempo [beats / minute]
  - Frequency with which humans tap along the beat

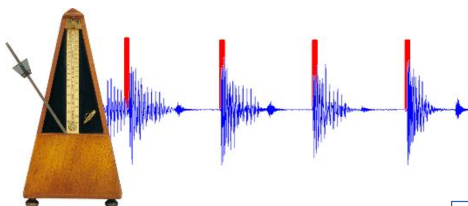


Fig. 11

- Beat tracking
  - Estimating precise beat positions

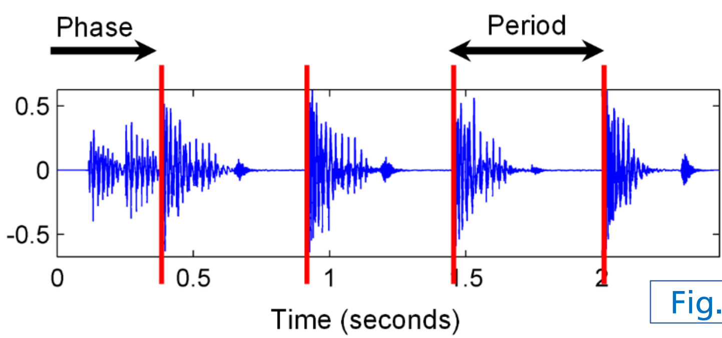
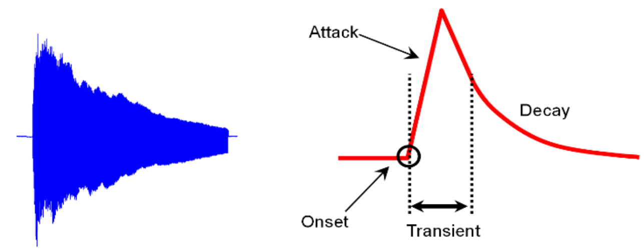


Fig. 12

FMP Notebooks

Tempo Detection
Introduction

- Note onsets → note beginning times
    - Clearly defined for plucked string and percussion instruments
    - Ambiguous for wind & brass instruments
- Onset detection
    - Onset detection function
    - Peak picking



Audio samples → Note envelope

Fig. 13

Audio samples ↓ Onset detection function & peaks

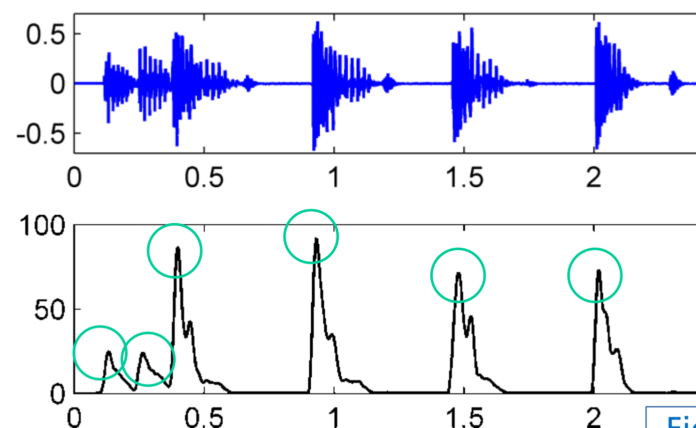


Fig. 14

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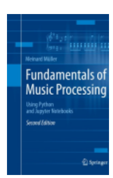
Tempo Detection
Traditional Methods

- Predominant local pulse (PLP)
  - Correlation with local (windowed) periodic patterns
- Tempogram [Grosche & Müller, 2009]
  - Local likelihood of different tempo candidates
  - Allows to follow tempo changes (classical music)



FMP Notebooks

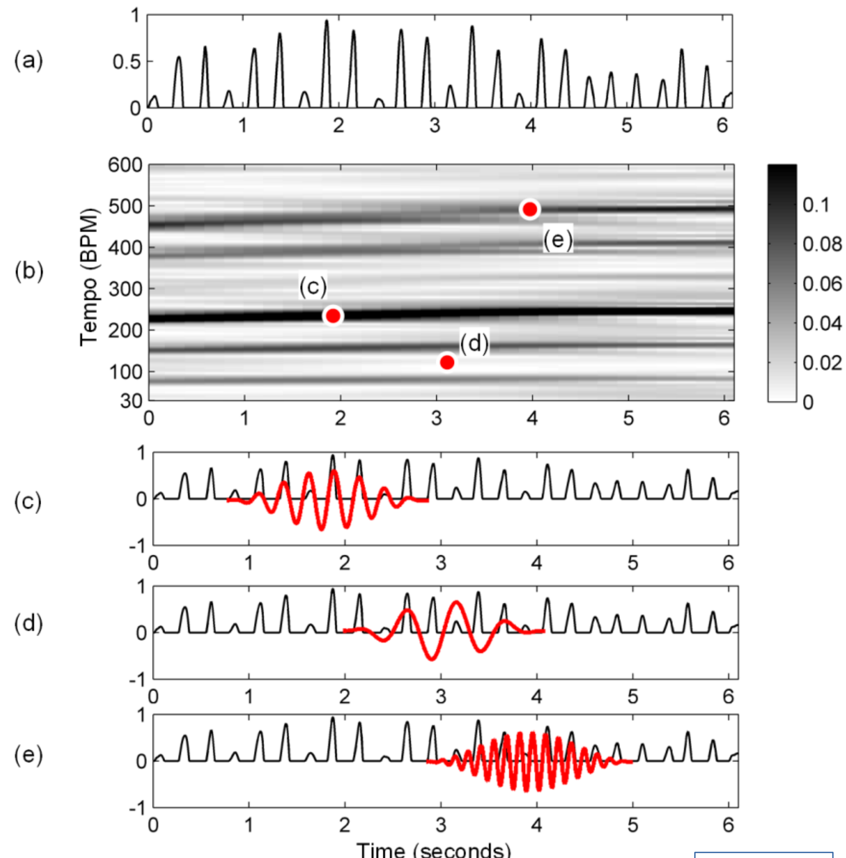


Fig. 15

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Tempo Detection
Novel Methods

- Approach [Böck et al., 2015]

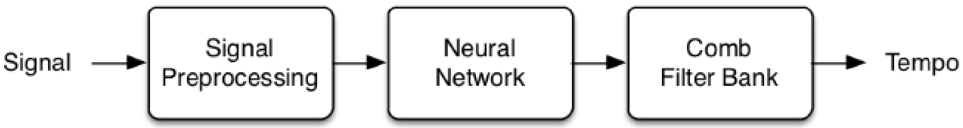
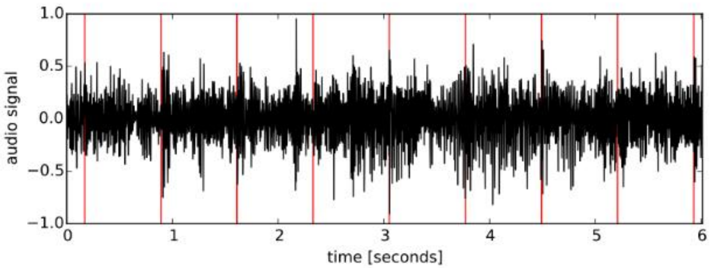
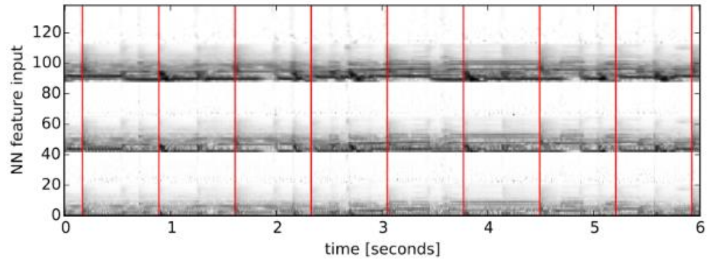


Fig. 16



(a) Input audio signal



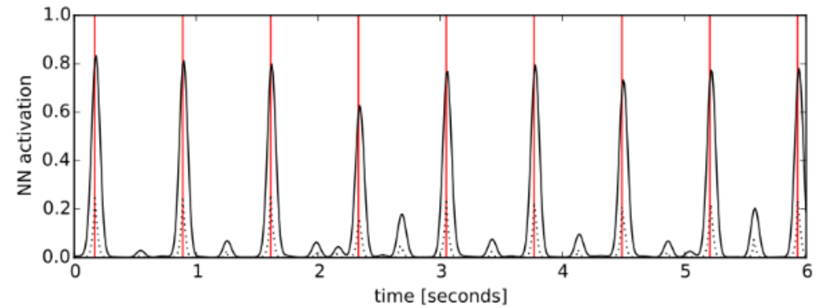
(b) Input to the neural network

Fig. 17

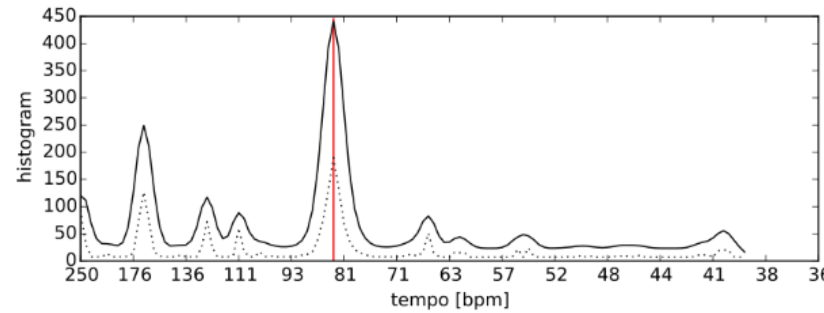
- Signal representation
  - Stacking of 3 STFT magnitude spectrograms (N=1024, 2048, 4096)
  - Log-amplitude & log-frequency

Tempo Detection
Novel Methods

- Neural Network
    - Recurrent (bi-directional LSTM) layer
    - Outputs beat activation function
- Comb filter bank
    - Multiple comb filters → detect periodicities
- Estimate tempo from histogram maximum



(c) Neural network output (beat activation function)



(f) Weighted histogram with summed maxima

Fig. 18

Tempo Detection
Novel Methods

- Approach [Schreiber & Müller, 2018]
  - Sample rate ~ 11 kHz, 40-band mel spectrogram
- Tempo estimation → classification (256 classes: 30 – 285 bpm)
- Neural Network
  - 3 layers (short filters) → onsets
  - 4 multi-filter modules (parallel conv layers) → compress along frequency & find periodicities
  - Dense layers → tempo classification

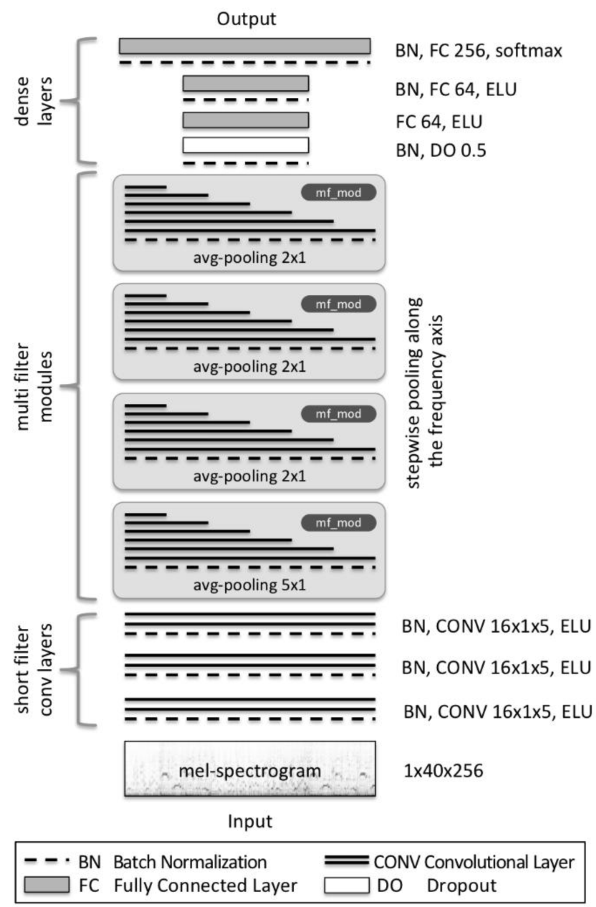


Fig. 19

Summary

- Music Information Retrieval
- Music Tagging
- Music Similarity
- Tempo Estimation

- Main trends
    - Adapt (data-driven) deep learning methods to music domain
    - Incorporate music domain knowledge

References

Böck, S., Krebs, F., & Widmer, G. (2015). Accurate tempo estimation based on recurrent neural networks and resonating comb filters. *Proceedings of the International Society for Music Information Retrieval Conference (ISMIR)*, 625–631.

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Pons, J., Nieto, O., Prockup, M., Schmidt, E., Ehrmann, A., & Serra, X. (2018). End-to-End Learning for Music Audio Tagging at Scale. *Proceedings of the International Society for Music Information Retrieval (ISMIR)2*, 637–644. Paris, France.

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Schreiber, H., & Müller, M. (2018). A Single-Step Approach to Musical Tempo Estimation using a Convolutional Neural Network. *Proceedings of the International Society for Music Information Retrieval Conference (ISMIR)*, 98–105. Paris, France.

Won, M., Chun, S., Nieto, O., & Serra, X. (2020). Data-Driven Harmonic Filters for Audio Representation Learning. *Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP)*, 536–540. Barcelona, Spain.

Images

Fig. 1: https://www.synchtank.com/wp-content/uploads/2018/06/1476277072027.jpg

Fig. 2: https://miro.medium.com/max/800/1*cC1KOdyzzt1nazak42cBdg.jpeg

Fig. 3: [Nam, 2019], p. 42, Fig. 1

Fig. 4: [Won, 2020], p. 537, Fig. 1a

Fig. 5: [Nam, 2019], p. 48, Fig. 4

Fig. 6: [Pons, 2018], p. 639, Fig. 2 (top left)

Fig. 7: [Lee, 2020, ICASSP], p. 1, Fig. 1

Fig. 8: [Ribecky, 2021], p. 26, Fig. 2.11

Fig. 9: [Lee, 2020, ISMIR], p. 1, Fig. 1

Fig. 10: [Lee, 2020, ICASSP], p. 2, Fig. 2

Fig. 11: [Müller, 2021], p. 309, chapter 6 (cover image)

Fig. 12: [Müller, 2021], p, 310, Fig. 6.1(b)

Fig. 13: [Müller, 2021], p. 311, Fig. 6.2

Fig. 14: [Müller, 2021], p. 313, Fig. 6.3(a)&(b)

Images

Fig. 15: [Grosche & Müller, 2009], p. 2, Fig. 1(e-g) & p. 3, Fig. 2 (a)

Fig. 16: [Böck et al., 2015], p. 2, Fig. 1

Fig. 17: [Böck et al., 2015], p. 3, Fig. 2 (a) & (b)

Fig. 18: [Böck et al., 2015], p. 3, Fig. 2 (c) & (f)

Fig. 19: [Schreiber & Müller, 2018], p. 3, Fig. 2

Sounds

AUD-1: Mr Smith – Black Top (2021), https://freemusicarchive.org/music/mr-smith/studio-city/black-top

AUD-2: Crowander – Humbug (2021), https://freemusicarchive.org/music/crowander/from-the-piano-solo-piano/humbug

AUD-3: Bumy Goldson: Keep Walking (2021), https://freemusicarchive.org/music/bumy-goldson/parlor/keep-walking

AUD-4: Cloudjumper: Mocking the god (2016), https://freemusicarchive.org/music/Cloudjumper/Memories_of_Snow/05_Cloudjumper_-_Mocking_the_gods

Thank you!

- Any questions?

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