2016 Intelligent Sensing Summer School Matrix Decomposition Methods for Audio Analysis

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centre for digital music

Matrix Decomposition Methods for Audio Analysis

Outline





3 Application: Music Signal Analysis

4 Application: Sound Scene Analysis



Outline



- 2) Matrix/Spectrogram Factorization
- 3 Application: Music Signal Analysis
- 4 Application: Sound Scene Analysis
- 5 Discussion

Machine listening: extracting meaningful information from audio signals.

- Sounds: speech, music, environmental/everyday sounds
- Disciplines: signal processing, machine learning, acoustics, perception



Machine Listening for Music Signals

Core problems:

- Tonality: multi-pitch detection, chord/key estimation
- Rhythm: onset detection, beat tracking, meter induction
- Source (instrument) separation/identification

Applications:

- Music information retrieval
- Interactive music systems
- Computer music
- Musicology



Machine Listening for Everyday Sounds

Core problems:

- Sound event detection
- Sound scene recognition
- Source separation

Applications:

- Audio archiving
- Security/surveillance
- Smart homes/cities
- Acoustic ecology



Outline



2 Matrix/Spectrogram Factorization

- 3 Application: Music Signal Analysis
- 4 Application: Sound Scene Analysis

5 Discussion

Matrix/spectrogram factorization (1)

- Non-negative Matrix Factorization (NMF) (Lee and Seung, 1999)
- Unsupervised algorithm for factorizing a matrix into a low rank decomposition
- Constraint: non-negative data
- This allows a parts-based representation
- Applications: detection, dimensionality reduction, clustering, classification, denoising, prediction...



Matrix/spectrogram factorization (2)

NMF Model:

• Given a non-negative matrix V find non-negative matrix factors W and H such that:

$V \approx WH$

where:

- $V \in \mathbb{R}^{n \times m}$
- $W \in \mathbb{R}^{n \times r}$
- $H \in \mathbb{R}^{r \times m}$
- The rank *r* of the factorization is chosen as (n + m)r < nm, so that data is compressed
- Various algorithms (e.g. EM, ALS) and cost functions (e.g. KL, IS) have been proposed in the literature

Matrix/spectrogram factorization (3)

NMF can be applied to audio (magnitude) spectrograms:



Probabilistic Latent Semantic Analysis (PLSA)

- In 1999, Thomas Hofmann proposed a technique for text processing and retrieval, called Probabilistic Latent Semantic Indexing (PLSI)
- ...which is also called structure Probabilistic Latent Semantic Analysis (PLSA)
- ...and also Probabilistic Latent Component Analysis (PLCA)!
- In fact, PLSA/PLSI/PLCA are the probabilistic counterparts of NMF using a specific cost function (KL divergence)
- This interpretation offers a framework that is easy to generalise and extend

Matrix/spectrogram factorization (5)

PLCA model

$$V_{\omega,t} \approx P(\omega,t) = P(t) \sum_{z} P(\omega|z)P(z|t)$$

 $V_{\omega,t}$: input spectrogram, P(t) frame energy, $P(\omega|z)$: basis spectra, P(z|t): component activations.

- PLCA can decompose a spectrogram into a series of spectral bases that correspond to `sound events' and a series of event activations
- Applications in machine listening: sound event detection, multi-pitch detection, source separation/identification

Matrix/spectrogram factorization (6)

- Convolutive models: extracting shifted structures from non-negative data
- Shift-invariant PLCA (across 1 dimension):

$$V_{\omega,t} \approx P(\omega,t) = \sum_{z} P(z) \sum_{f} P(\omega-f|z) P(f,t|z)$$

 $V_{\omega,t}$: log-frequency spectrogram, P(z): component prior, $P(\omega|z)$: basis spectra, P(f,z|t): pitch impulse distribution.



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Matrix/spectrogram factorization (7)

SIPLCA example (across 2 dimensions): detecting footstep sounds



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Application: Music Signal Analysis (1)

Goal:

- Create a multiple-instrument music transcription system
- Express frequency modulations & tuning changes through shift-invariance
- Express each note as a temporal succession of sound state spectral templates



Application: Music Signal Analysis (2)

- Proposed model: Hidden Markov Model-constrained Shift-Invariant PLCA
- Fixed (pre-extracted) dictionary of spectral templates per instrument, pitch, sound state



E. Benetos and S. Dixon, "Multiple-instrument polyphonic music transcription using a temporally constrained shift-invariant model", *Journal of the Acoustical Society of America*, 133(3):1727-1741, 2013

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Application: Music Signal Analysis (3)



Figure : (a) The ground-truth piano-roll of Mozart's Piano Sonata K.333, 3rd mvt. (b) The transcription output piano-roll. Original recording:
Synthesized transcription:

Application: Music Signal Analysis (4)



Figure : A time-pitch representation in 20 cent resolution for a recording of J.S. Bach's Musical Offering, BWV 1079.

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Application: Music Signal Analysis (5)

NMF convergence (video)



Speed:

- Convergence is observed with 10-15 iterations
- Runtime: $1-2.5 \times \text{real-time}$ (CPU)
- $\bullet\,$ Faster matrix multiplications with GPU processing (0.3 $\times\,$ real-time)

Evaluation:

 Proposed method ranked first in public evaluations for multiple-F0 estimation and note tracking (MIREX 2013, 2015)

Code:

• http://www.eecs.qmul.ac.uk/~emmanouilb/code.html

Application: Music Signal Analysis (7)

Priors in PLCA / Music Language Models

- Combine PLCA acoustic model with Recurrent Neural Network music language model (MLM) for prediction
- MLM is incorporated into PLCA using Dirichlet priors



S. Sigtia, E. Benetos, S. Cherla, T. Weyde, A. d'Avila Garcez, and S. Dixon, "An RNN-based music language model for improving automatic music transcription", in Proc. ISMIR, 2014.

Application: Music Signal Analysis (8)

 Silvet note transcription plugin: https://code.soundsoftware.ac.uk/projects/silvet/



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Application: Sound Scene Analysis (1)

Motivation

- Adapt PLCA model for detecting overlapping sound events
- Each event class contains several exemplars; each exemplar consists of a sequence of sound states
- Appearance of sound states controlled by event-wise HMMs
- Input representation: (auditory-motivated) Equivalent Rectangular Bandwidth filterbank



Application: Sound Scene Analysis (2)

Proposed Model

$$V_{\omega,t} \approx P(\omega,t) = P(t) \sum_{q,c,s} P(\omega|q,c,s) P(s|t) P(c|s,t) P(q|s,t)$$

- $V_{\omega,t}$: ERB spectrogram
- P(t): spectrogram energy (known quantity)
- P(ω|q, c, s): spectral template for event class s, exemplar c, and sound state q (pre-extracted, fixed)
- P(s|t): event activation over time
- P(c|s, t): exemplar contribution for each event class, over time
- P(q|s, t): sound state contribution for each event class, over time
- P(q|s,t) controlled by an event-wise HMM

Application: Sound Scene Analysis (3)



Top: P(s|t). Bottom: post-processed binary event-roll.

Application: Sound Scene Analysis (4)

 Dataset: DCASE 2013 OS (office sounds in different density/noise conditions) ●



E. Benetos, G. Lafay, M. Lagrange, and M. D. Plumbley, "Detection of overlapping acoustic events using a temporally-constrained probabilistic model", ICASSP, 2016. https://code.soundsoftware.ac.uk/projects/sound-event-detection-plca

Application: Sound Scene Analysis (5)

 Goal: identifying multiple bird species from continuous recordings



- Approach: PLCA with pre-extracted templates per species
- Participated in ICML 2013 Bird Challenge on identifying 35 bird species; system in the top 25% of submissions

E. Benetos, "Acoustic identification of bird species using probabilistic latent component analysis", in ICML Workshop on Machine Learning for Bioacoustics, pp. 77-78, 2013.

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Discussion (1)

Conclusions

- Matrix factorization: powerful tool for audio analysis
- Interpretable, extensible, computationally efficient
- Additional uses: sound scene recognition, drum transcription, instrument recognition...
- Used in several commercial & public tools



Discussion (2)

Future Directions

- Input time-frequency representations
- Beyond the Short-time Fourier Transform: CQT, VQT, auditory spectra...



Future Directions (cont'd)

Acoustic language models



- Sound event taxonomy
- Source/acoustic environment adaptation

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