Identifying Repeated Patterns in Music Using Sparse Convolutive Non-Negative Matrix Factorization

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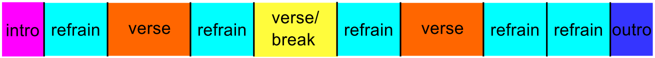
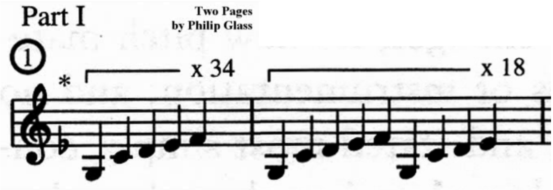
Repetitive patterns in music

- Repetition is ubiquitous is music
  - long-term verse-chorus structure

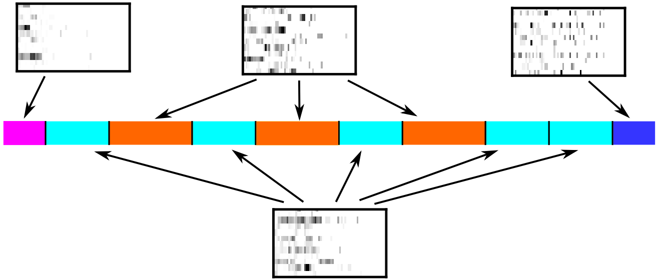


  - repeated motifs



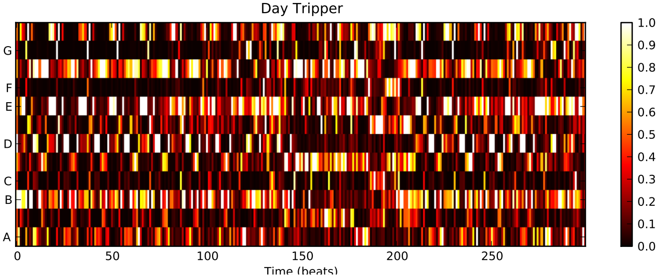
- Can we identify this structure directly from audio?
  - What about the repeated units?

Proposed approach



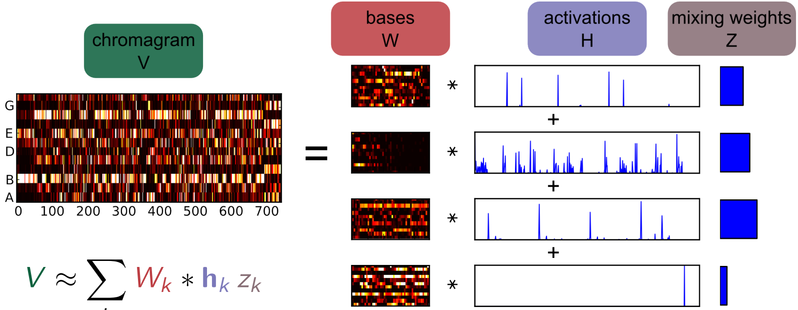
- Treat song as concatenation of short, repeated template patterns
- Inspired by source separation / text topic modeling
  - Convolutive Non-negative Matrix Factorization (NMF)

Beat-synchronous chroma features [Ellis and Poliner, 2007]



- Summarize energy at each pitch class during each beat
- Normalize frame energy to ignore dynamics

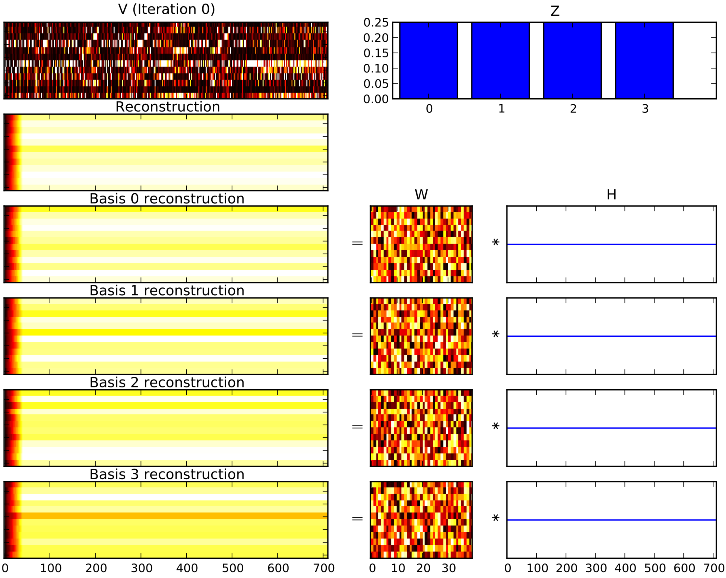
- Shift-invariant Probabilistic Latent Component Analysis
  i.e. probabilistic convolutive NMF



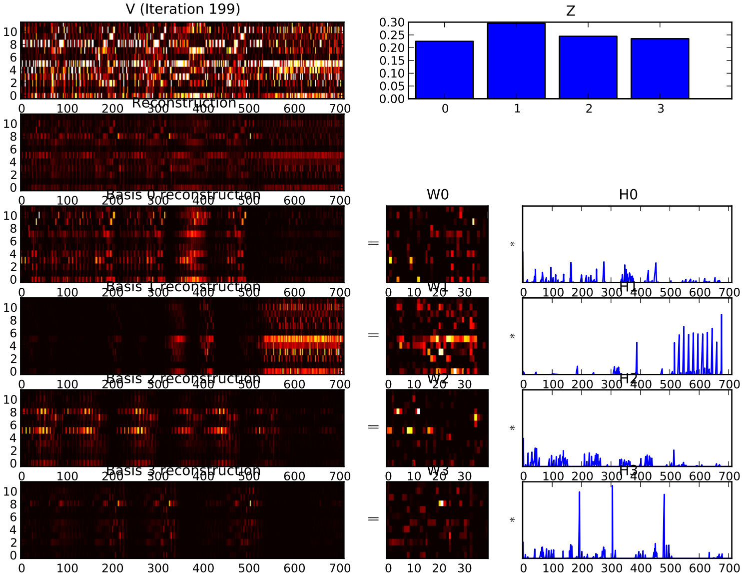
$$V \approx \sum_k W_k * \mathbf{h}_k \, z_k$$

- Decompose matrix V into weighted (by Z) sum of latent components
  - each component is convolution of basis W with activations H
- Short-term structure in W, long-term structure in H
- Must specify number, length of patterns
- Iterative EM learning algorithm

Learning algorithm example – Initialization

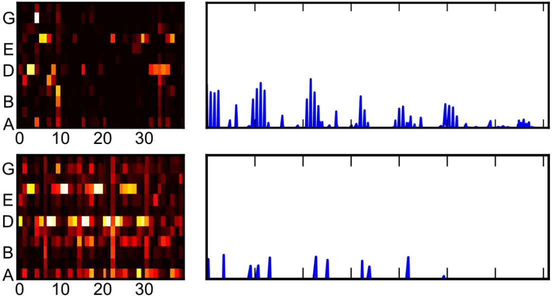


Learning algorithm example – Converged



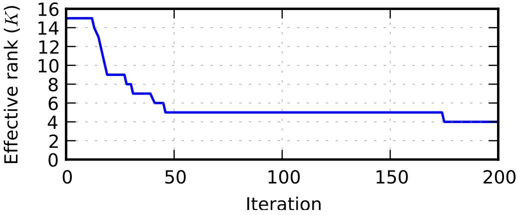
Sparsity

- Encourage sparse (mostly zero) parameters using prior distributions
- Use entropic prior over activations H [Smaragdis et al., 2008]
    - low entropy $\implies$ less uniform
- Leads to more meaningful patterns
    - but reduces temporal information in activations
    - sparse H $\implies$ dense W

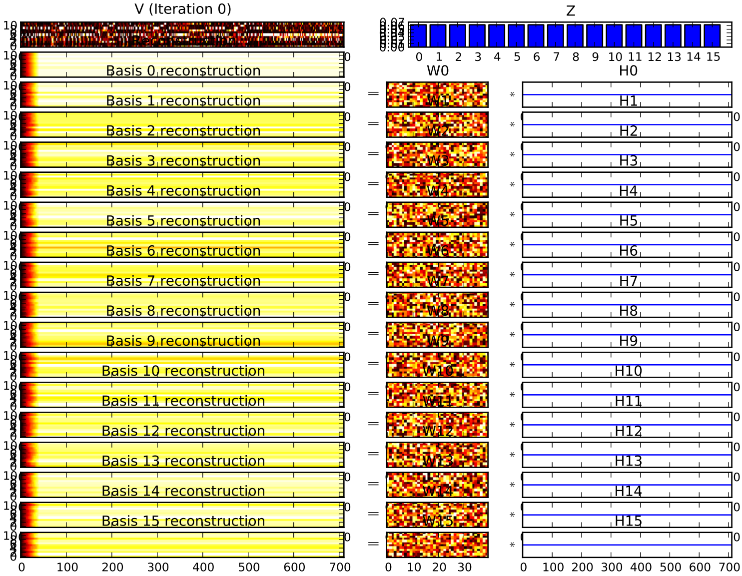


Automatic relevance determination [Tan and Févotte, 2009]

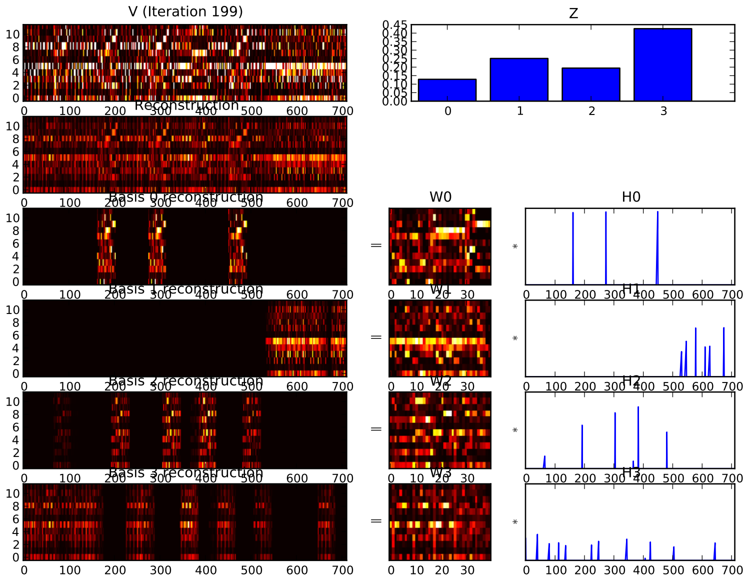
- Avoid having to specify number of patterns in advance
  - Initialize decomposition with large number of patterns
  - Sparse Dirichlet distribution over mixing weights Z
  - Discard unused patterns



Sparse learning example – Initialization

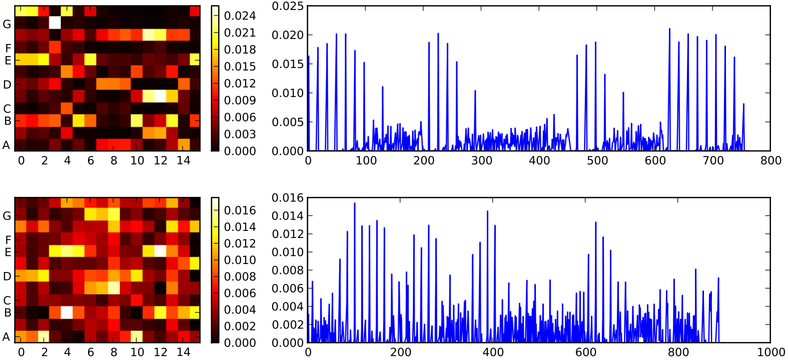


Sparse learning example – Converged

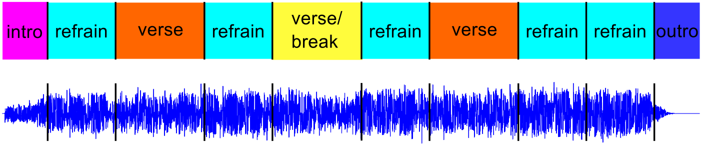


Applications: Riff identification / Thumbnailing

- Reconstruct song using a single pattern
  - Sparse activations
  - Riff length known in advance (for now)
  - Thumbnail corresponds to largest activation in H

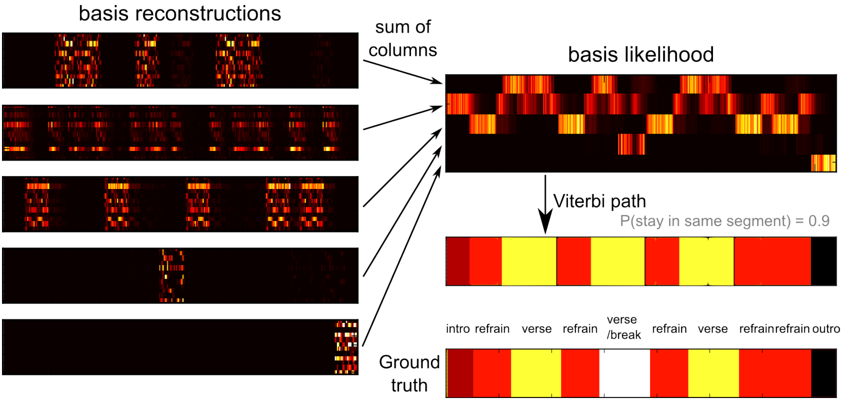


Applications: Structure segmentation



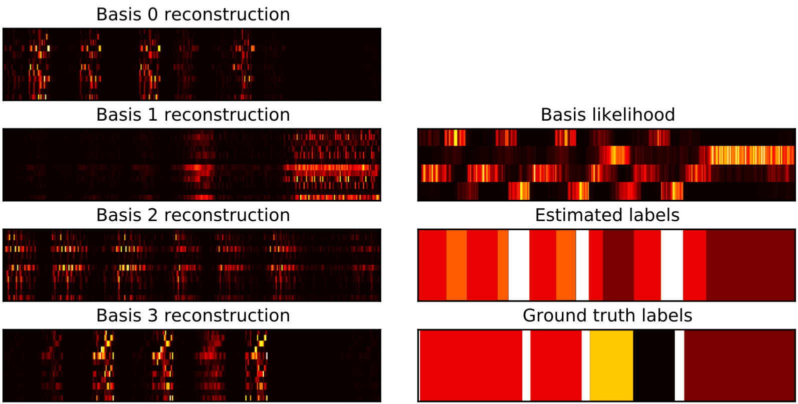
- Identify long-term song structure (verse, chorus, bridge, etc.)
- Assume one-to-one mapping between chroma patterns and segments
- Use SI-PLCA decomposition with longer patterns
  - no prior on activations

Structure segmentation example



Estimated	intro	refrain	verse	refrain	verse	refrain	verse	refrain	refrain	outro
Ground truth	intro	refrain	verse	refrain	vs/break	refrain	verse	refrain	refrain	outro

Structure segmentation example 2



segments tend to be broken into multiple motifs

Est verse1 verse2 verse1 verse2 refrain. verse1 verse2 refrain. verse1 outro. verse1 refrain. verse1 out

GT verse verse refrain. verse refrain. $\frac{1}{2}$ verse inst. $\frac{1}{2}$ verse refrain. outro

Experiments

- Evaluate on 180 songs from *The Beatles* catalog

System	f-meas	prec	recall	over-seg	under-seg
[Mauch et al., 2009]	0.66	0.61	0.77	0.76	0.64
SI-PLCA (sparse Z)	0.60	0.58	0.68	0.61	0.56
SI-PLCA (rank=4)	0.58	0.60	0.59	0.56	0.59
[Levy and Sandler, 2008]	0.54	0.58	0.53	0.50	0.57
Random	0.30	0.36	0.26	0.07	0.24

- Compare to systems based on self-similarity and HMM clustering
  - middle of the pack performance
  - sparse Z gives $\sim 10\%$ improvement in recall over fixed rank
- Needs better post-processing?

Summary

- Novel algorithm for identifying repeated harmonic patterns in music
- Use sparsity to minimize number of fixed parameters, control structure
- Applications to thumbnailing and structure segmentation
- Future work
  - Adaptive model of pattern length, better downbeat alignment
  - 2D convolution to compensate for key changes
  - Time-warp invariance (beat-tracking errors, fixed hop size)

Open source Python/Matlab implementation available:
http://ronw.github.com/siplca-segmentation

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