

# CLUSTERING BEAT-CHROMA PATTERNS IN A LARGE MUSIC DATABASE

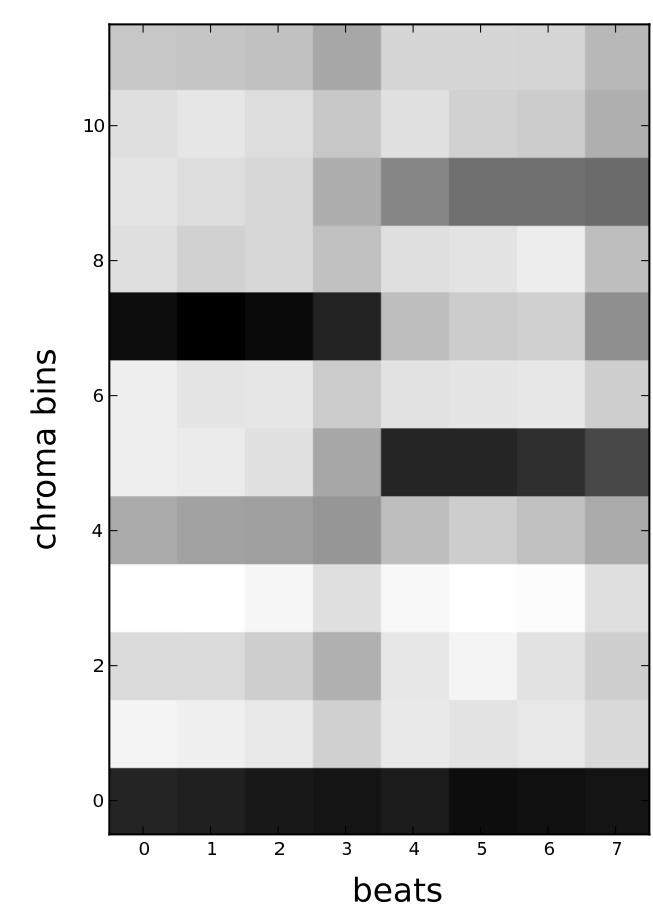
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## Introduction

- Can we infer anything about the underlying structure and common features of commercial pop music by analyzing very large collections of music audio?
- Our interest: tonal content of the music – i.e. the harmony and melody.
- Beat-synchronous chromagrams: rich enough to generate musically-relevant results, simplified enough to abstract away instrumentation and other stylistic details.



Typical codeword spanning 2 bars, each bar considered to be 4 beats. Codebook size was 200.

A codeword can also be seen as the centroid of a cluster.

- Goal:** identify meaningful information about the musical structure represented in the entire database by examining individual entries in this codebook.
- Method:** identify common patterns in beat-synchronous chromagrams by learning codebooks from a large set of examples. Individual codewords consist of short beat-chroma patches of between 1 and 8 beats, optionally aligned to bar boundaries.
- Prior work: “shingles” of [1], beat-synchronous analysis to identify the chorus by [2], and cover recognition by [3].

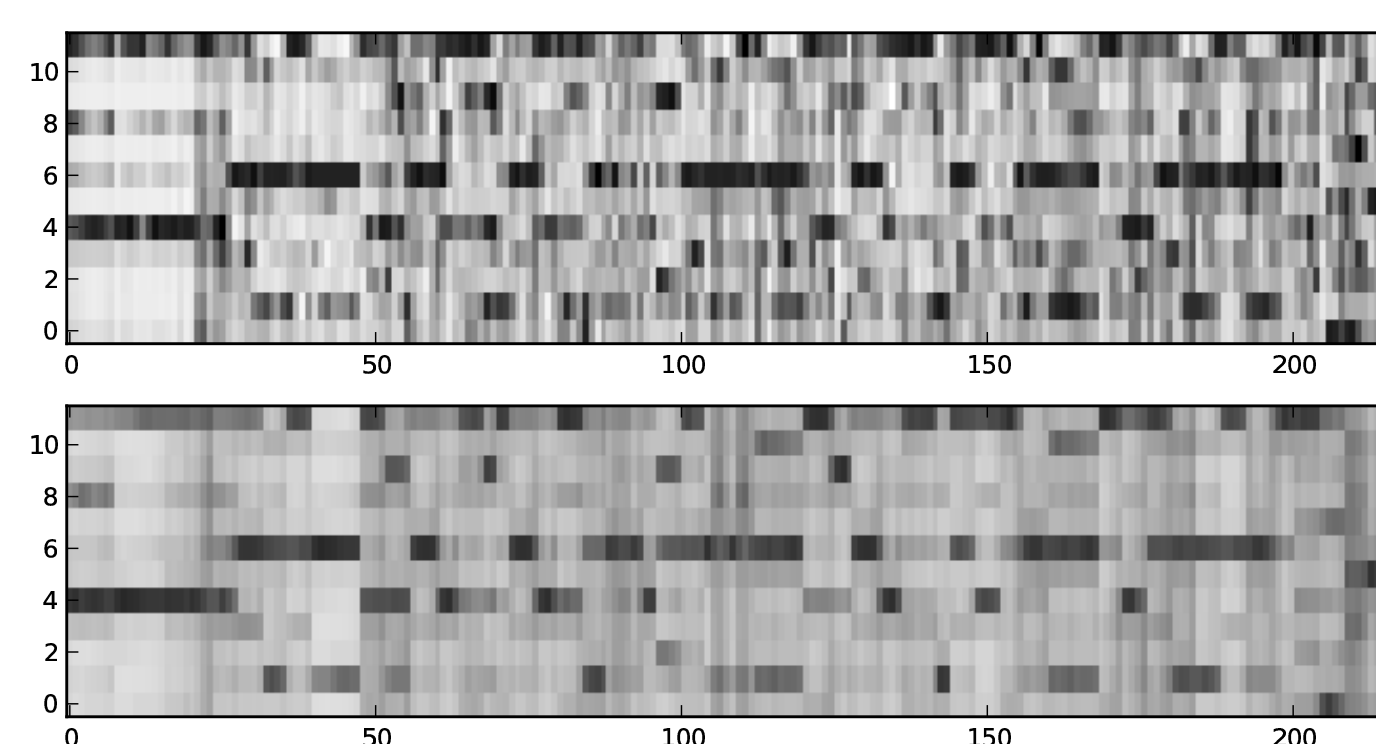
## Audio Features - Echo Nest

### Chromagrams from the Echo Nest online API.

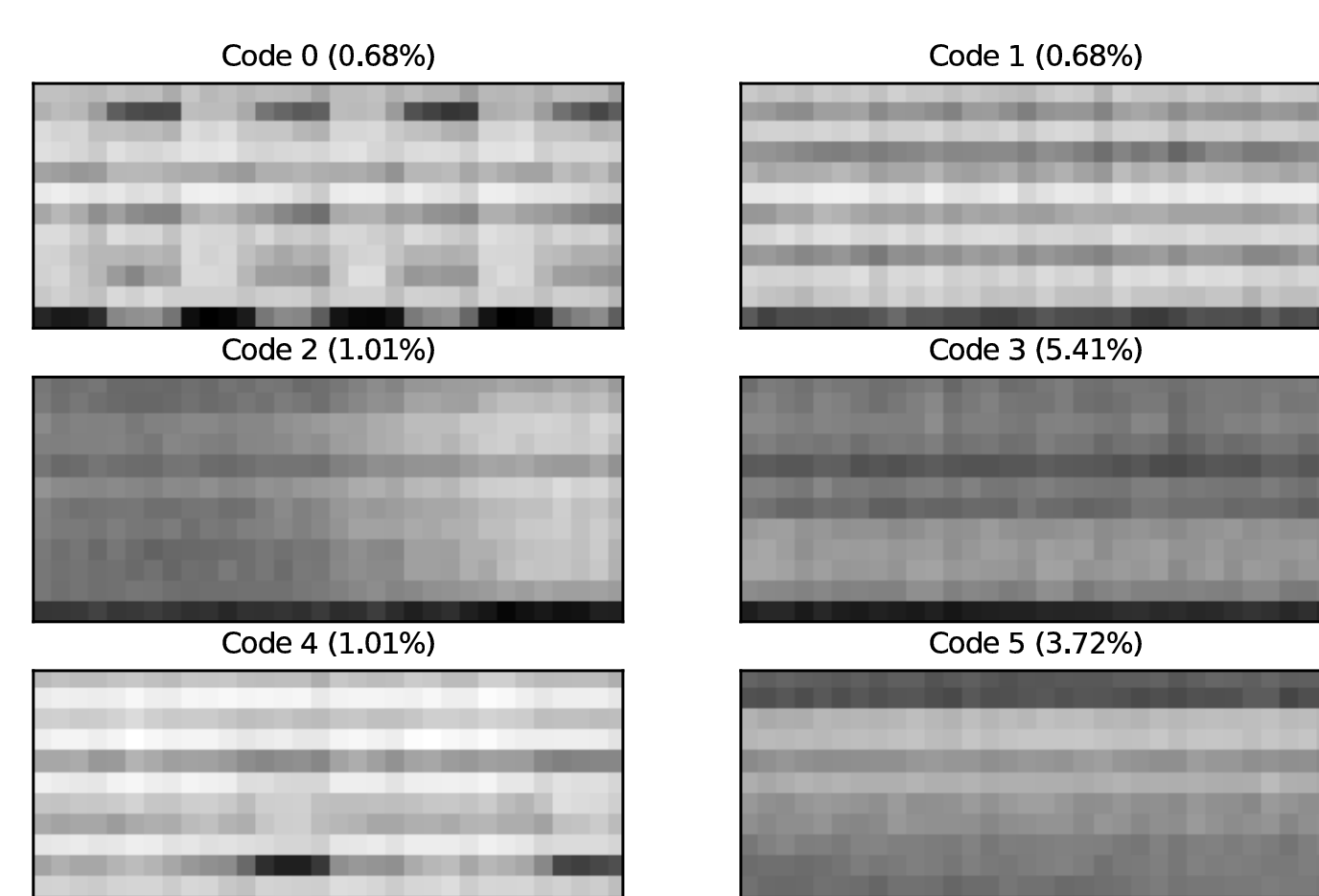
- Feature analysis based on Echo Nest analyze API [4].
- For any song, EchoNest provides a chroma vector (length 12) for every music event (called “segment”), and a segmentation of the song into beats and bars.
- Averaging per-segment chroma over beat times results in a beat-synchronous chroma feature representation.
- Dataset size: 43,000 songs.

### Beat-Chroma Patches.

- We use Echo Nest analysis to break a song into a collection of beat-chroma “patches”, typically one or two bars in length.
- 82% of the bars in our data were 4 beats long.
- Other cases: we resample patches to a fixed length of 4 beats.
- We rotate patches so that the first row contains the most energy. This is analogous to key normalization, but each patch is normalized independently.



Example of an encoded song (Good Day Sunshine by *The Beatles*) using a codebook. Codebook size: 200, codewords: 2 bars.



Longer codewords spanning 8 bars, randomly selected from a 100-entry codebook. Most patterns consist of sustained notes or chords, but code 0 shows one-bar alternations between two chords, and code 4 contains two cycles of a 1 → 1 → 1 → 2 progression.

## Vector Quantization

- Vector Quantization algorithm [5] to cluster beat-chroma patches
- Can be seen as online  $k$ -means
- Initialized with  $k$  random patches from the data
- Although not optimal, scales linearly with the number of patches seen

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ℓ learning rate
{Pn} set of patches
{Ck} codebook of K codes
for nIter do
  for p ∈ {Pn} do
    c ← minc ∈ Ck dist(p, c)
    c ← c + (p - c) * ℓ
  end for
end for
return {Ck}

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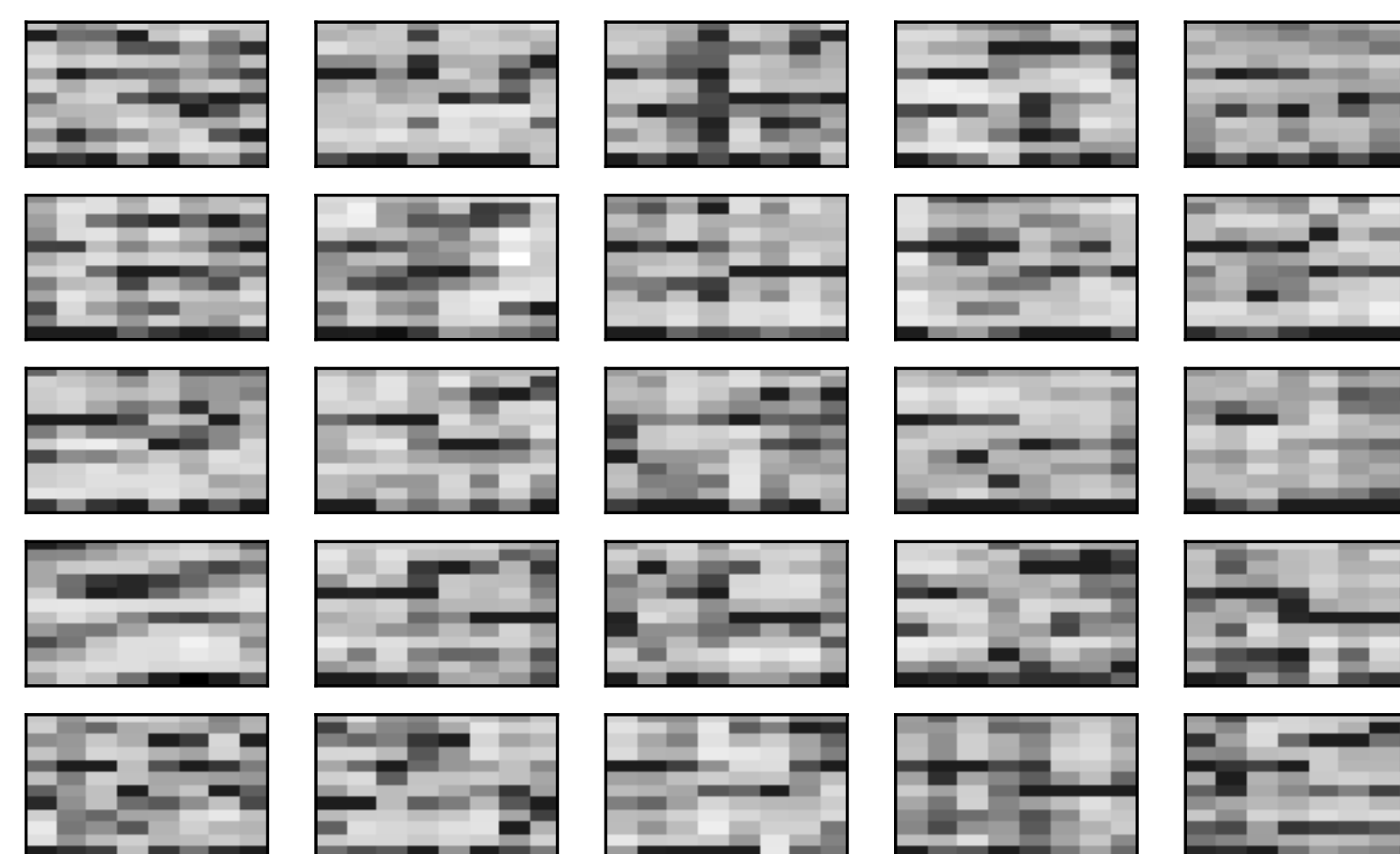
Intuitively:

- For each new patch, find the closest codeword.
- Bring that codeword closer to the patch by some learning rate.
- Iterate.

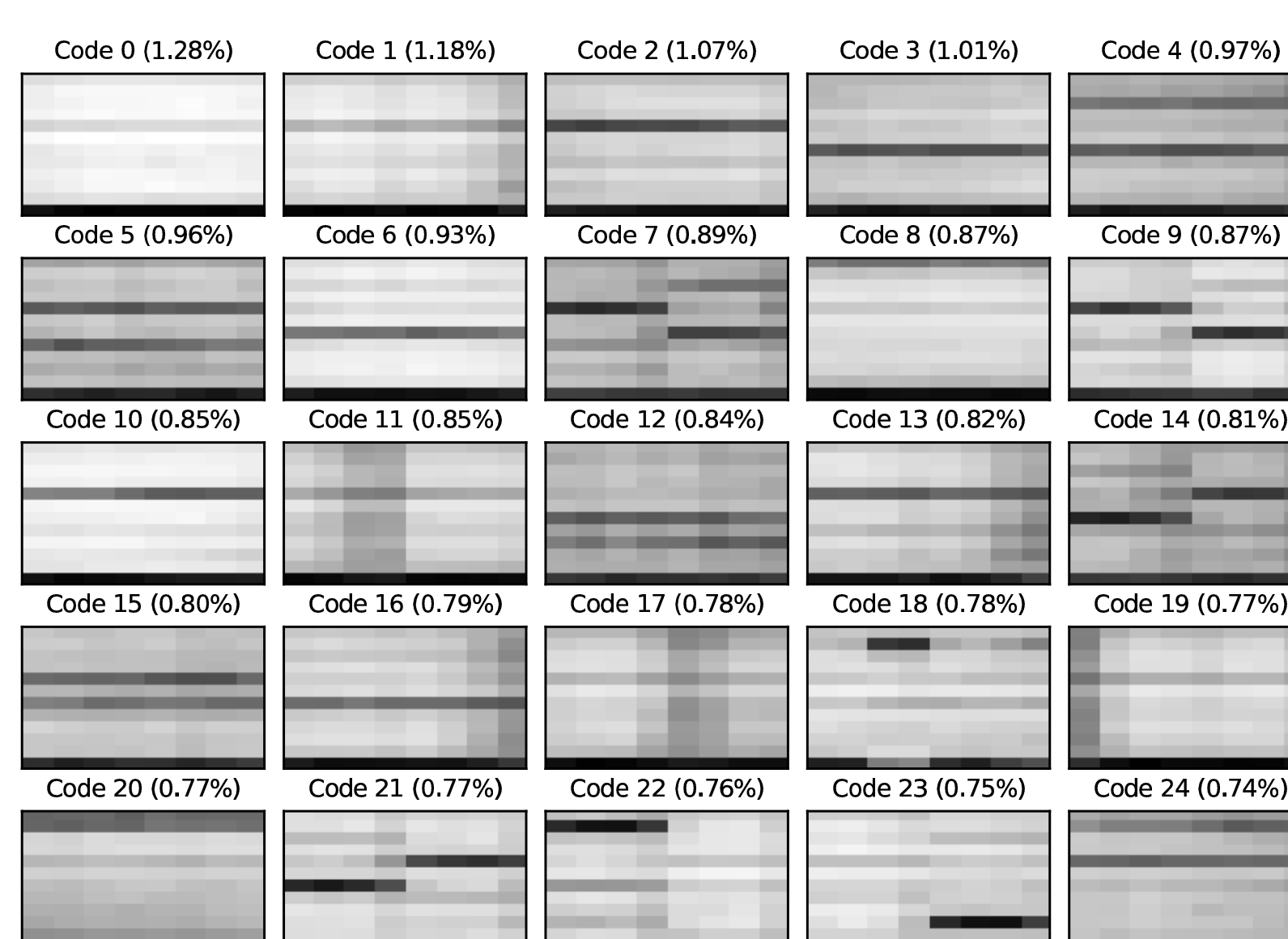
## Pattern Analysis

Additional graphs on distortion, codeword size, etc. can be seen in the paper. As expected, a larger codebook improves distortion, longer codewords are more difficult to learn, and a larger training set improves the results.

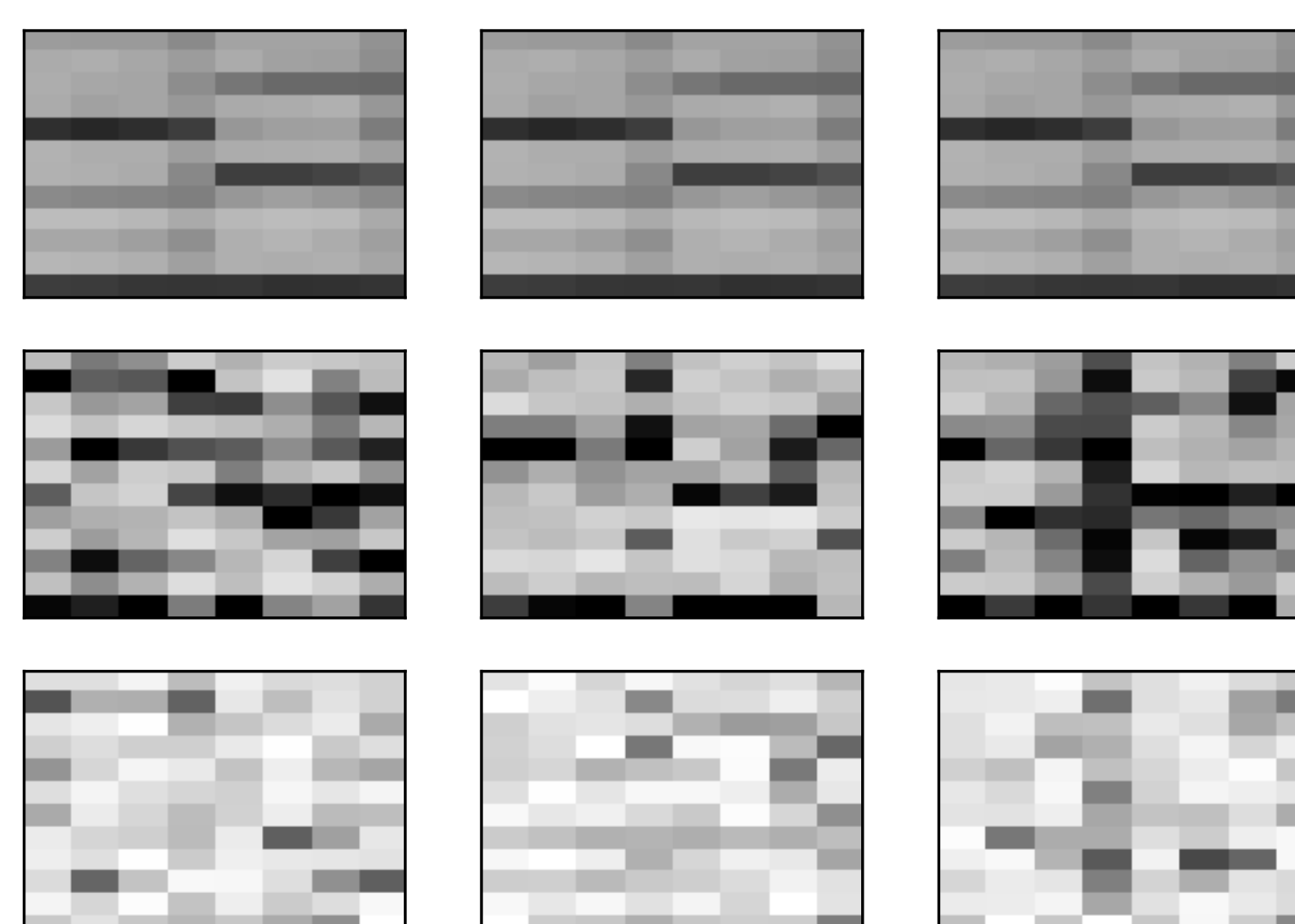
Below are samples from actual codebooks and centroids.



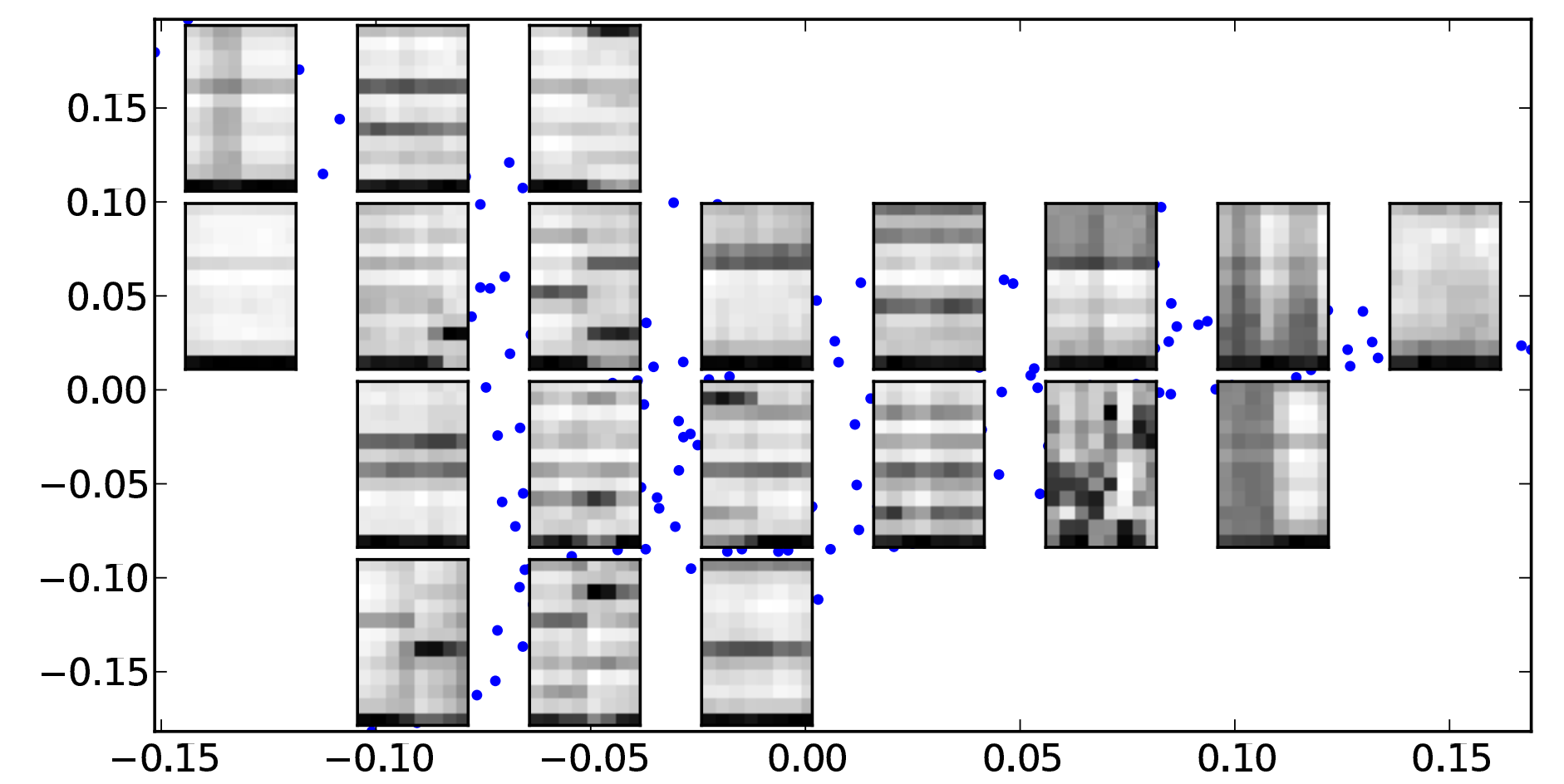
Cluster around first centroid (in *introduction* section). Random selection from a cluster of size 639. This gives an intuition of the variance in one cluster.



The 25 codes most commonly used. Codes are from a 200-entry codebook trained on 2 bars, 128 patches. The proportion of patches accounted for by each pattern is shown in parentheses.



First three patterns from figure above (2nd row) presented with the centroid (1st row) and the absolute difference between both (3rd row).



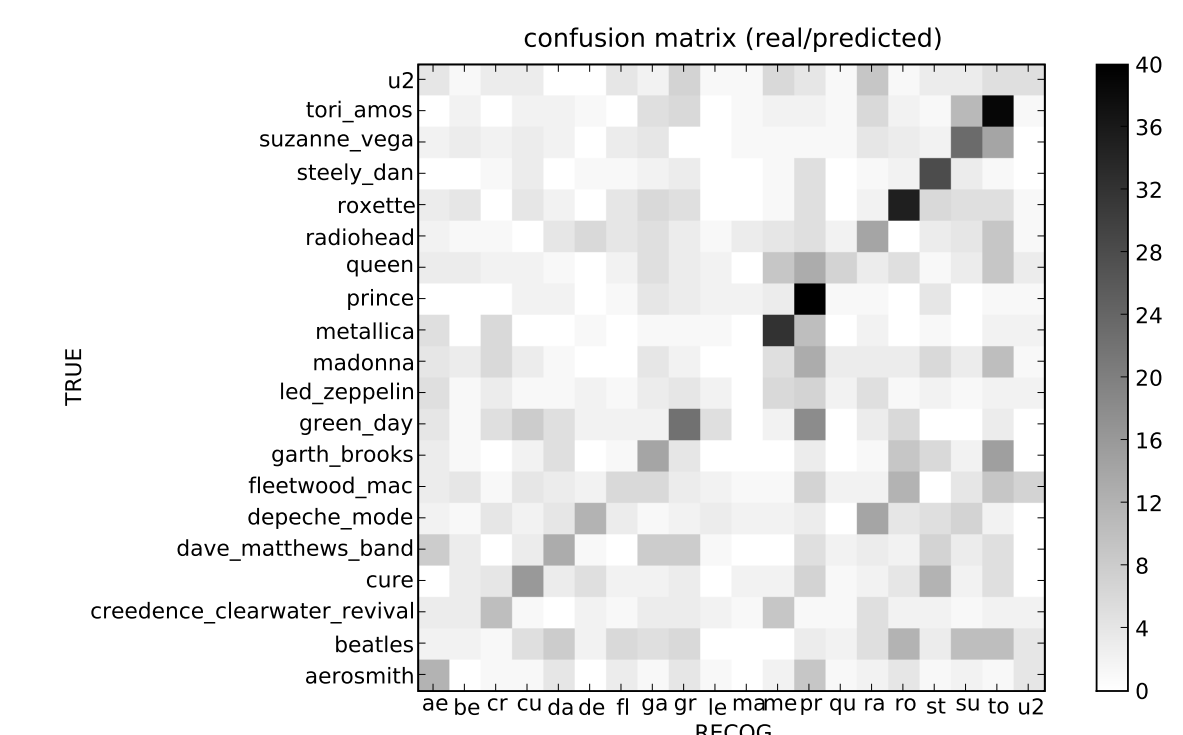
Possible visualization of the codebook using locally linear embedding (LLE).

## Experiments

We present two applications of the beat-chroma codebooks to illustrate how the “natural” structure identified via unsupervised clustering can provide useful features for subsequent supervised tasks.

### Artist recognition task.

- artist20* data set: 1402 songs from 20 artists.
- Baseline: GMM - MFCC 59%, GMM - chromas 33%, random 5%.
- We get an accuracy of **23.4%**.



### Bar alignment task.

- Clustering based on the signal segmented in bars.
- Codewords should contain bar information (e.g. a strong first beat).
- Our encoding finds the right alignment 62% of the time.

Offset	% of times chosen
0	<b>62.6</b>
1	16.5
2	9.4
3	11.5

## Conclusion

- Practical method for large-scale clustering of tonal patterns.
- Ways to inspect the resulting codebook.
- Links to existing MIR tasks.
- Python code available.

## References

- [1] M. Casey and M. Slaney, “Fast recognition of remixed music audio,” in *Proceedings of the International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2007.
- [2] M. A. Bartsch and G. H. Wakefield, “To catch a chorus: using chroma-based representations for audio thumbnailing,” in *Proc. IEEE Workshop on Applications of Signal Processing to Audio and Acoustics*, Mohonk, New York, October 2001.
- [3] D. Ellis and G. Poliner, “Identifying cover songs with chroma features and dynamic programming beat tracking,” in *Proceedings of the International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2007.
- [4] The Echo Nest Analyze, API, <http://developer.echonest.com>.
- [5] A. Gersho and R. Gray, *Vector quantization and signal compression*. Kluwer Academic Publishers, 1991.
- [6] D. Ellis, “Classifying music audio with timbral and chroma features,” in *Proceedings of the 8th International Conference on Music Information Retrieval (ISMIR)*, 2007.