



# CLUSTERING BEAT-CHROMA PATTERNS IN A LARGE MUSIC DATABASE

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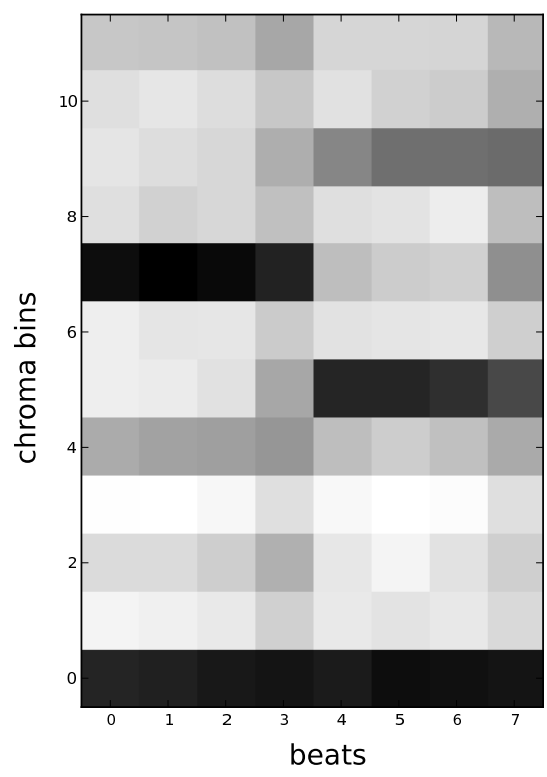
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## Introduction

- Availability of very large collections of music audio: can we infer anything about the underlying structure and common features of e.g. commercial pop music?
- 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.
- This paper identifies common patterns in beat-synchronous chromagrams by learning codebooks from a large set of examples. The individual codewords consist of short beat-chroma patches of between 1 and 8 beats, optionally aligned to bar boundaries.



- Goal: identify meaningful information about the musical structure represented in the entire database by examining individual entries in this codebook.
- Prior work: “shingles” of [1], beat-synchronous analysis to indeitfy the chorus by [2], and cover recognition by [3].
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## Audio Features - Echo Nest

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## Vector Quantization

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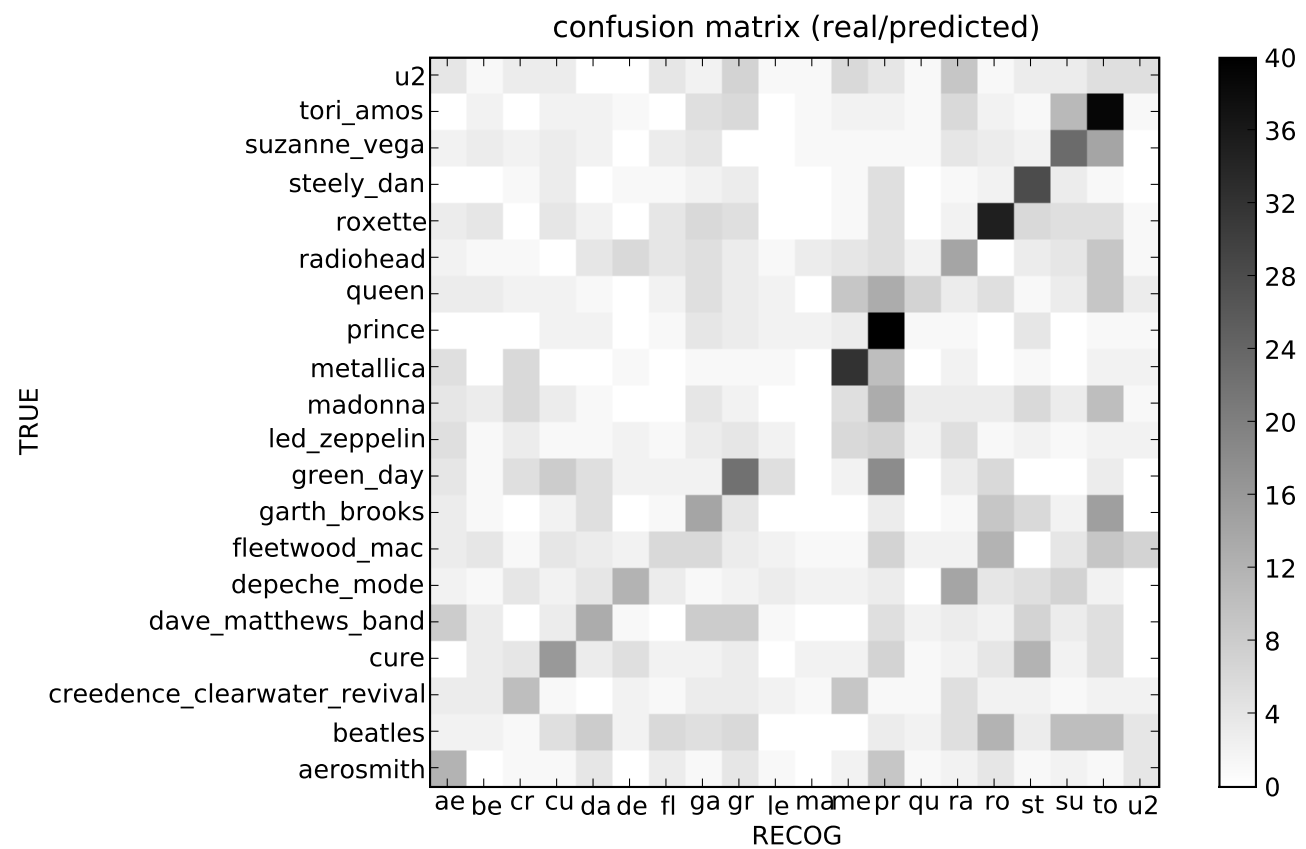
## Pattern Analysis

## 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.** We use the *artist20* data set: 1402 songs from 20 artists, mostly rock and pop of different subgenres. Previously published results using GMMs on MFCC features achieve an accuracy of 59%, whereas using only chroma as a representation yields an accuracy of 33% [4].

We get an accuracy of **23.4%**, random baseline is around 5%. The confusion matrix is shown here, note that certain artists are recognized at an accuracy far above the average.



**Bar alignment task.** Since the clustering described is based on the segmentation of the signal in to bars, the codewords should contain information related to bar alignment, such as the presence of a strong beat on the first beat.

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

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## Conclusion

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## 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] D. Ellis, “Classifying music audio with timbral and chroma features,” in *Proceedings of the 8th International Conference on Music Information Retrieval (ISMIR)*, 2007.