A Classification Approach to Melody Transcription

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OUTLINE

1. Motivation and task definition
2. Classification approach
3. Experimental results

MOTIVATION

Content-based retrieval:

- Query by humming, etc
- Recurring melodic themes

Music Analysis:

- Transcription
- Reduction

TASK DEFINITION

f_0 transcription of predominant melody

(10 ms grid)

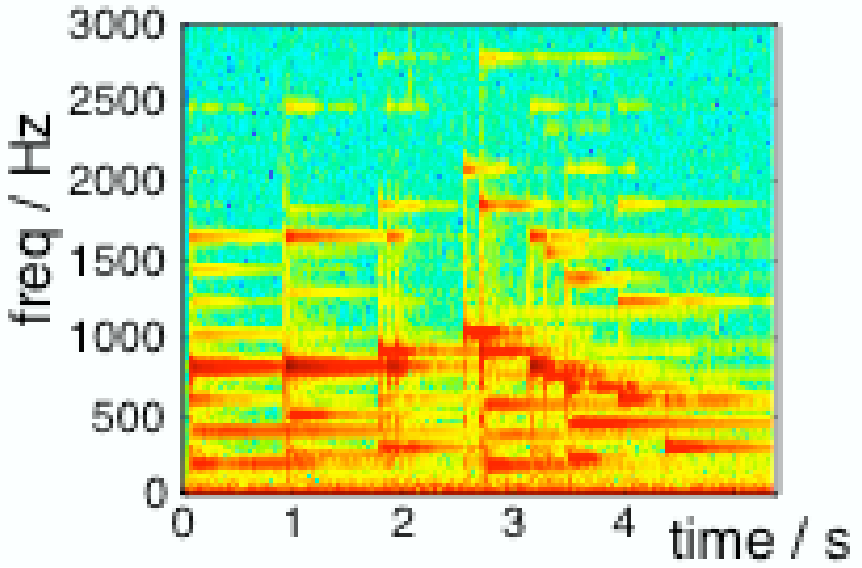
Evaluation metrics:

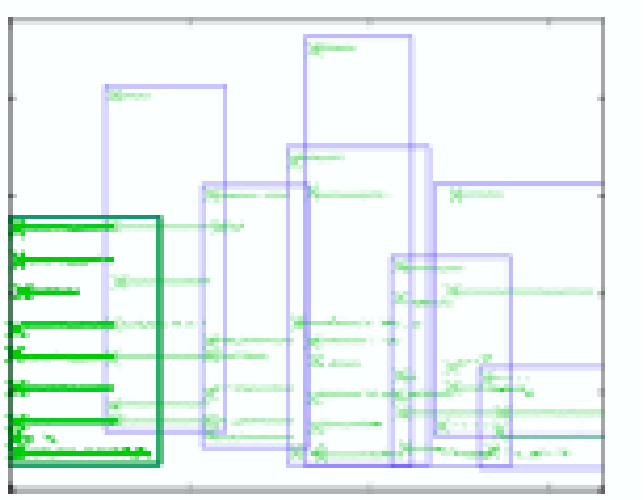
- Success = f_0 prediction within ±1/4 tone
- Chroma = integer (sub)multiple of f_0 (octave errors)

At this time, consider only voiced segments

Model-Based Approach

- Previous systems use e.g. sine models:

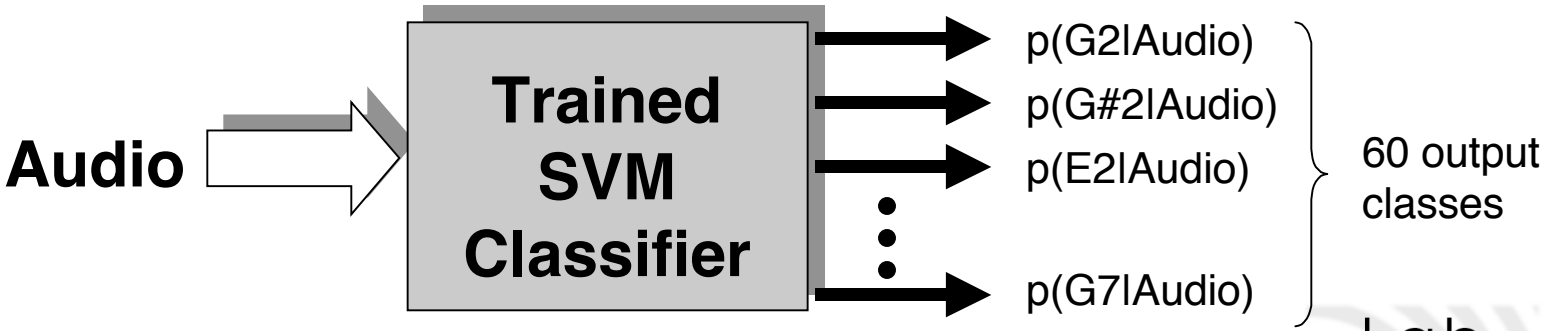




Our Approach: Classification

- Signal models may not capture everything
- Instead, trade domain knowledge for data

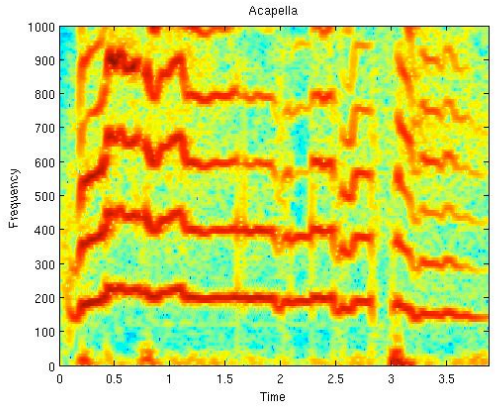
N-Way discrimination for melody



TRAINING DATA

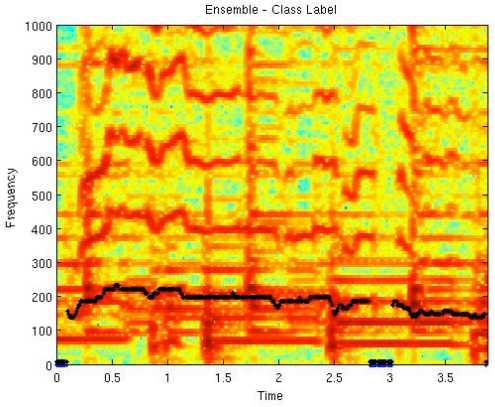
Audio ⇨ Labeled Data

- Multi-track Recordings
- MIDI Audio



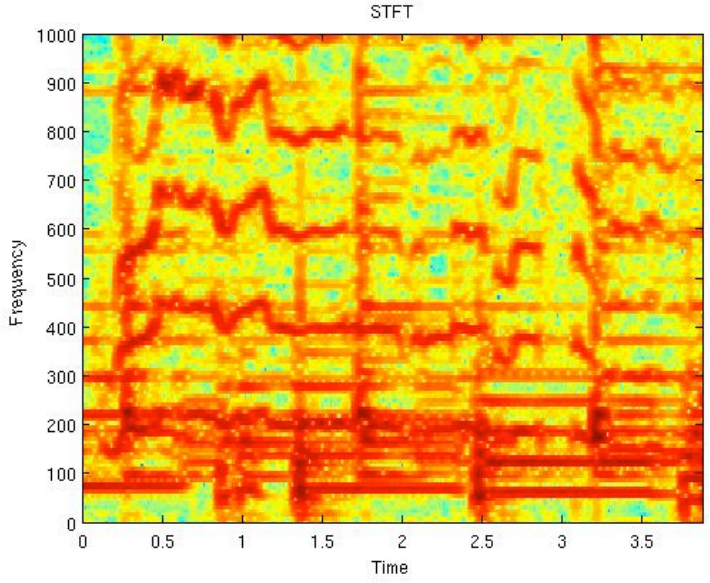
Features: column of STFT

Labels: MIDI Note Number



Feature Normalization

Normalization	Rate
STFT	59.0
51-pt Norm	**62.7**
Cube root	62.4
Autocorr	59.0
Cepstrum	52.1
Liftering Ceps	60.3



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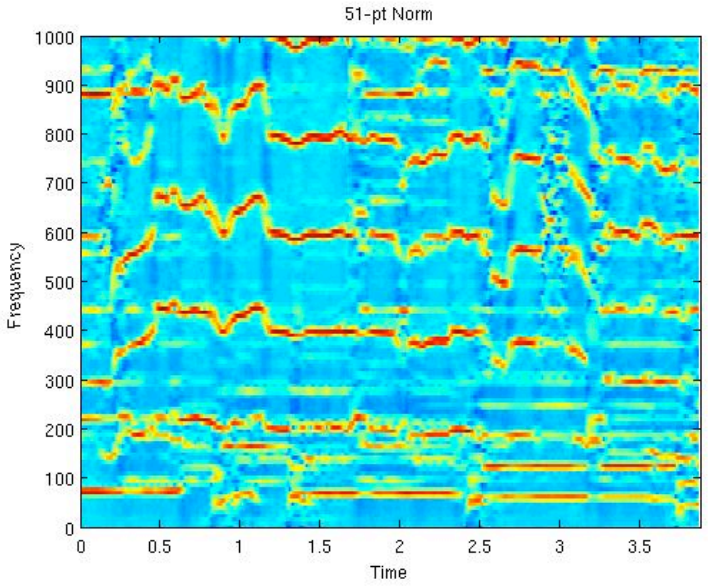

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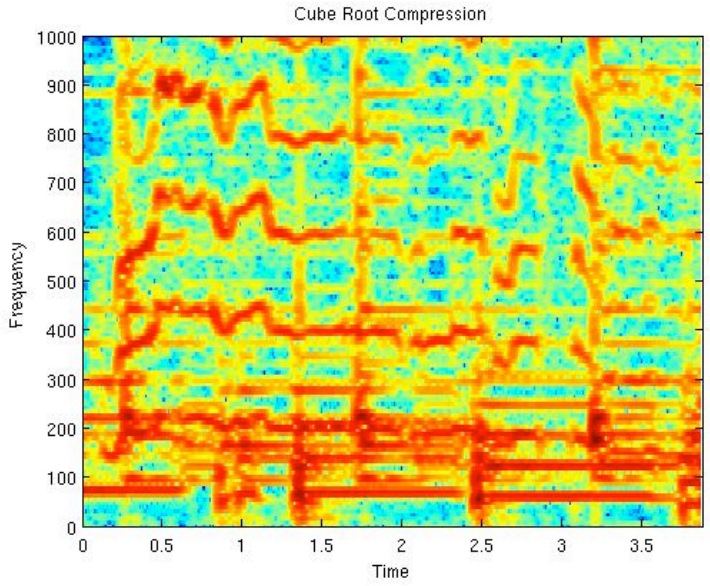

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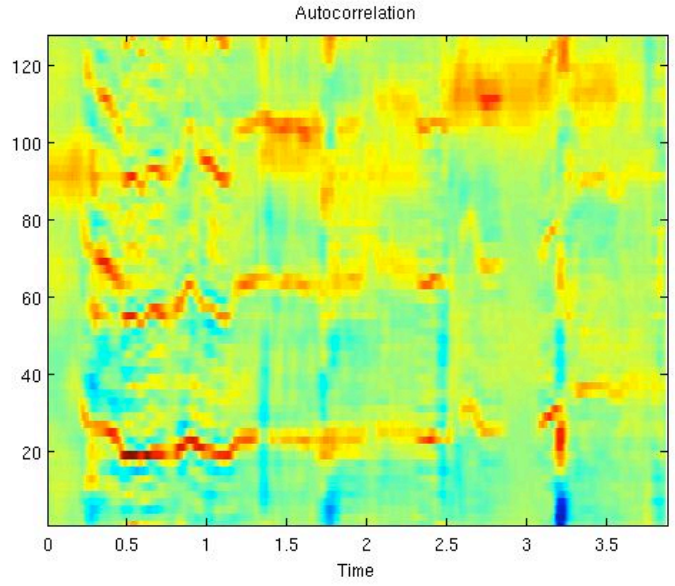

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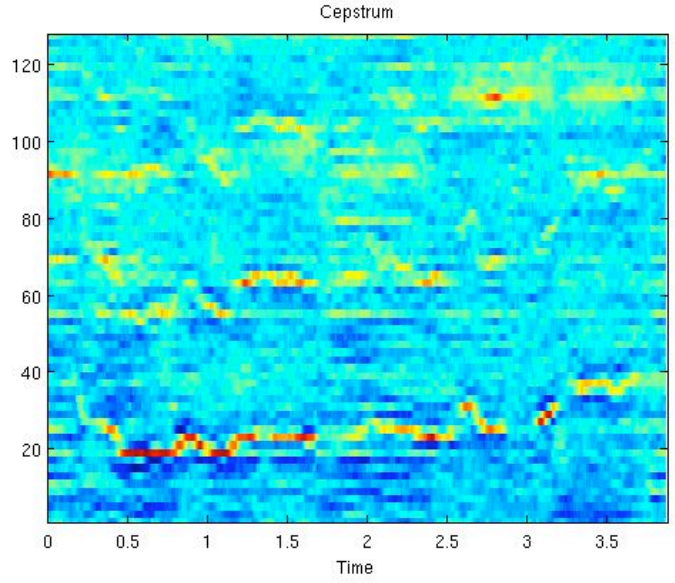

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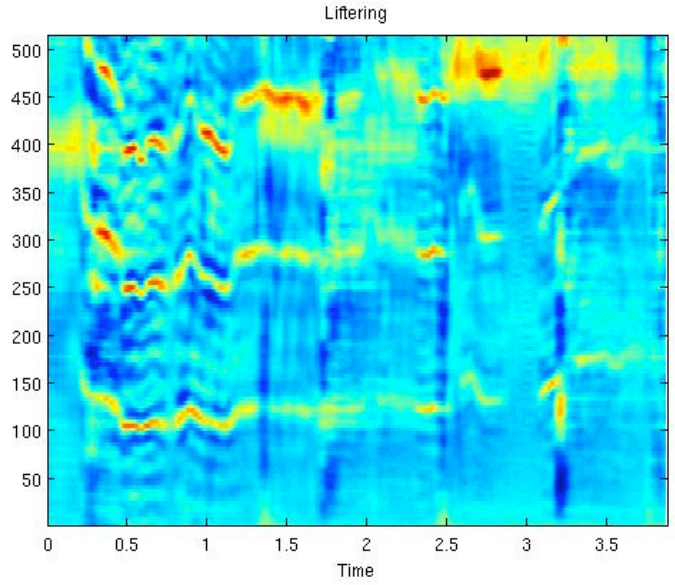
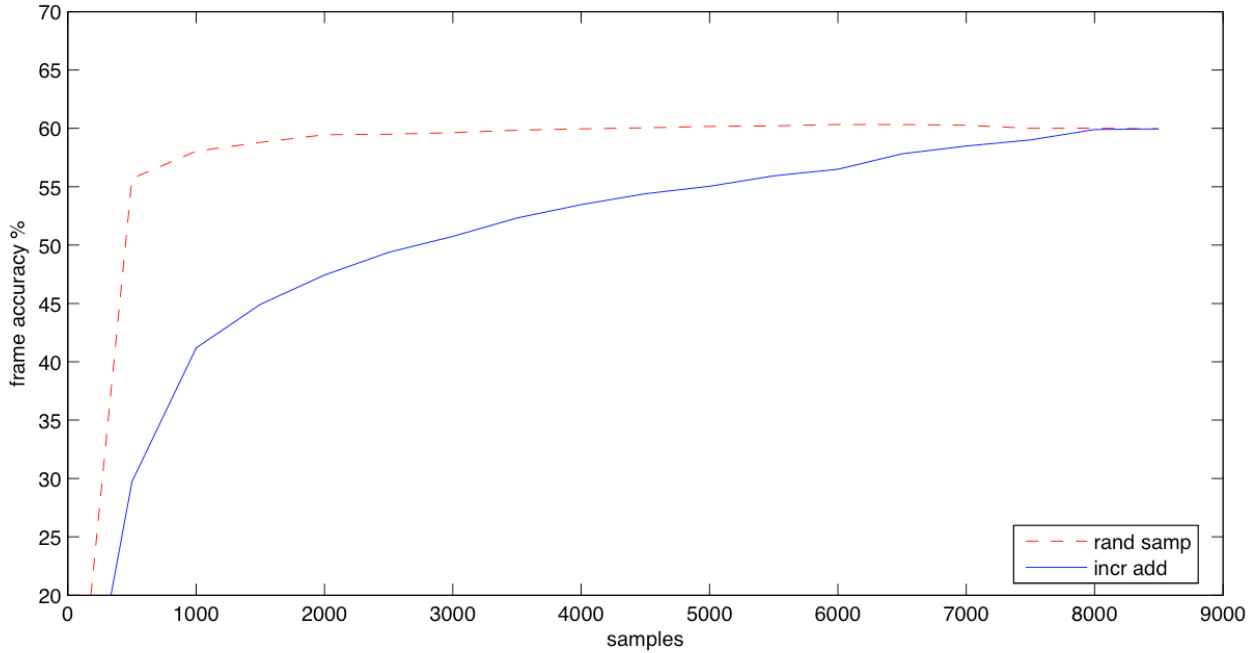


CLASSIFICATION EXPERIMENTS

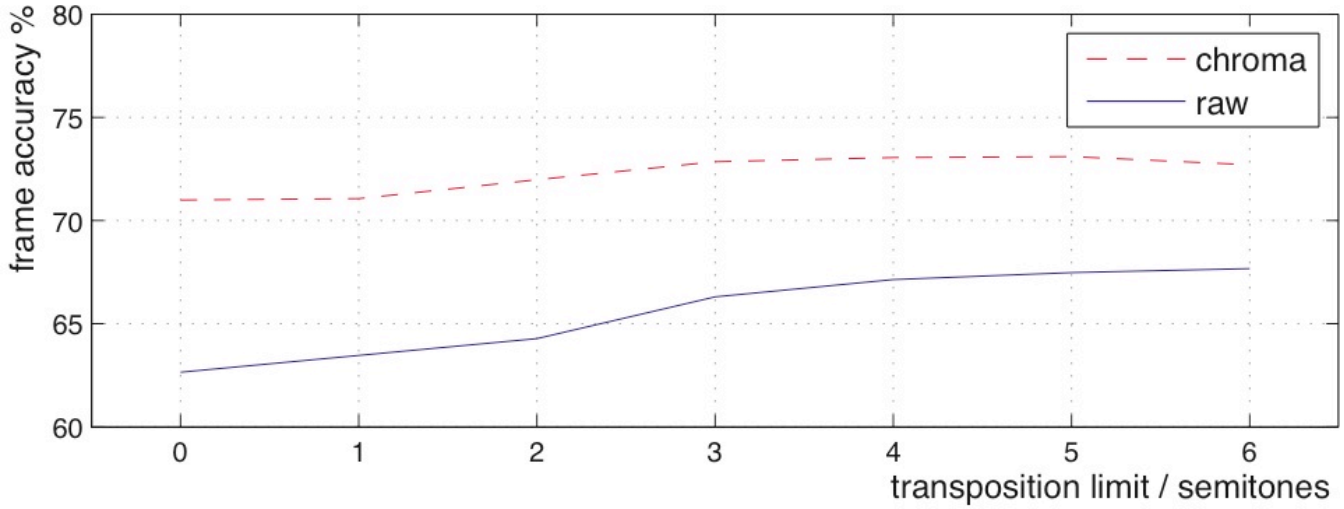
- Greatest influence - **more data**



Resampled Audio

Reduce cost of data

- Resample labeled audio ±1…6 semitones
- Classification accuracy increases over 5 %



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MIREX RESULTS

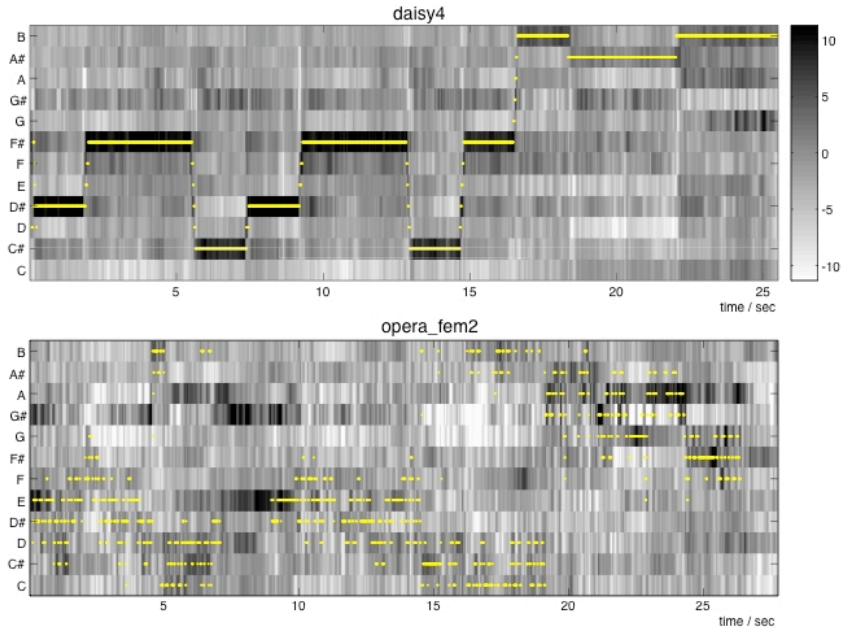
Excellent candidate identification

Rank	Participant	Overall Accuracy	Voicing d'	Raw Pitch	Raw Chroma	Runtime / s
1	Dressler	**71.4%**	**1.85**	68.1%	71.4%	32
2	Ryynänen	64.3%	1.56	**68.6%**	**74.1%**	10970
3	Paiva 2	61.1%	1.22	58.5%	62.0%	45618
3	Poliner	61.1%	1.56	67.3%	73.4%	5471
5	Marolt	59.5%	1.06	60.1%	67.1%	12461
6	Paiva 1	57.8%	0.83	62.7%	66.7%	44312
7	Goto	49.9%*	0.59*	65.8%	71.8%	211
8	Vincent 1	47.9%*	0.23*	59.8%	67.6%	?
9	Vincent 2	46.4%*	0.86*	59.6%	71.1%	251
10	Brossier	3.2%* †	0.14 * †	3.9% †	8.1% †	41

Classification Posteriors

Exploit temporal structure of music

- N Binary classifiers
  - (one vs. all classification)
- Fit logistic models to distance from class boundary
- Pseudo-posteriors



Conclusion

- Simple implementation
- Low training data requirements
- Competitive transcription method
- Excellent potential for future work

http://labrosa.ee.columbia.edu/projects/melody/