

Phrase-based Rāga Recognition using Vector Space Modeling

Sankalp Gulati*, Joan Serrà^, Vignesh Ishwar*, Sertan Şentürk* and Xavier Serra*

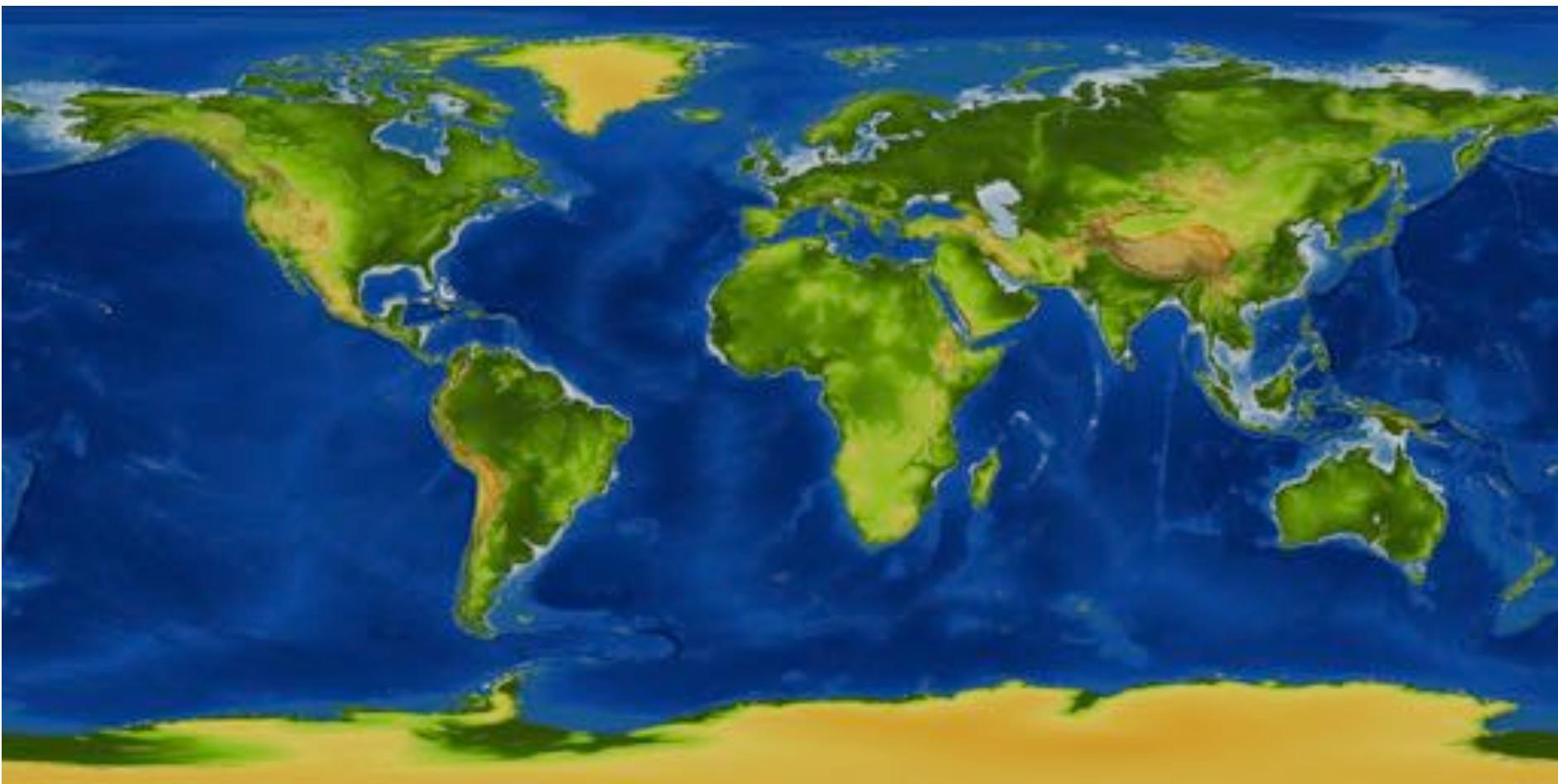
*Music Technology Group, Universitat Pompeu Fabra, Barcelona, Spain

^Telefonica Research, Barcelona, Spain

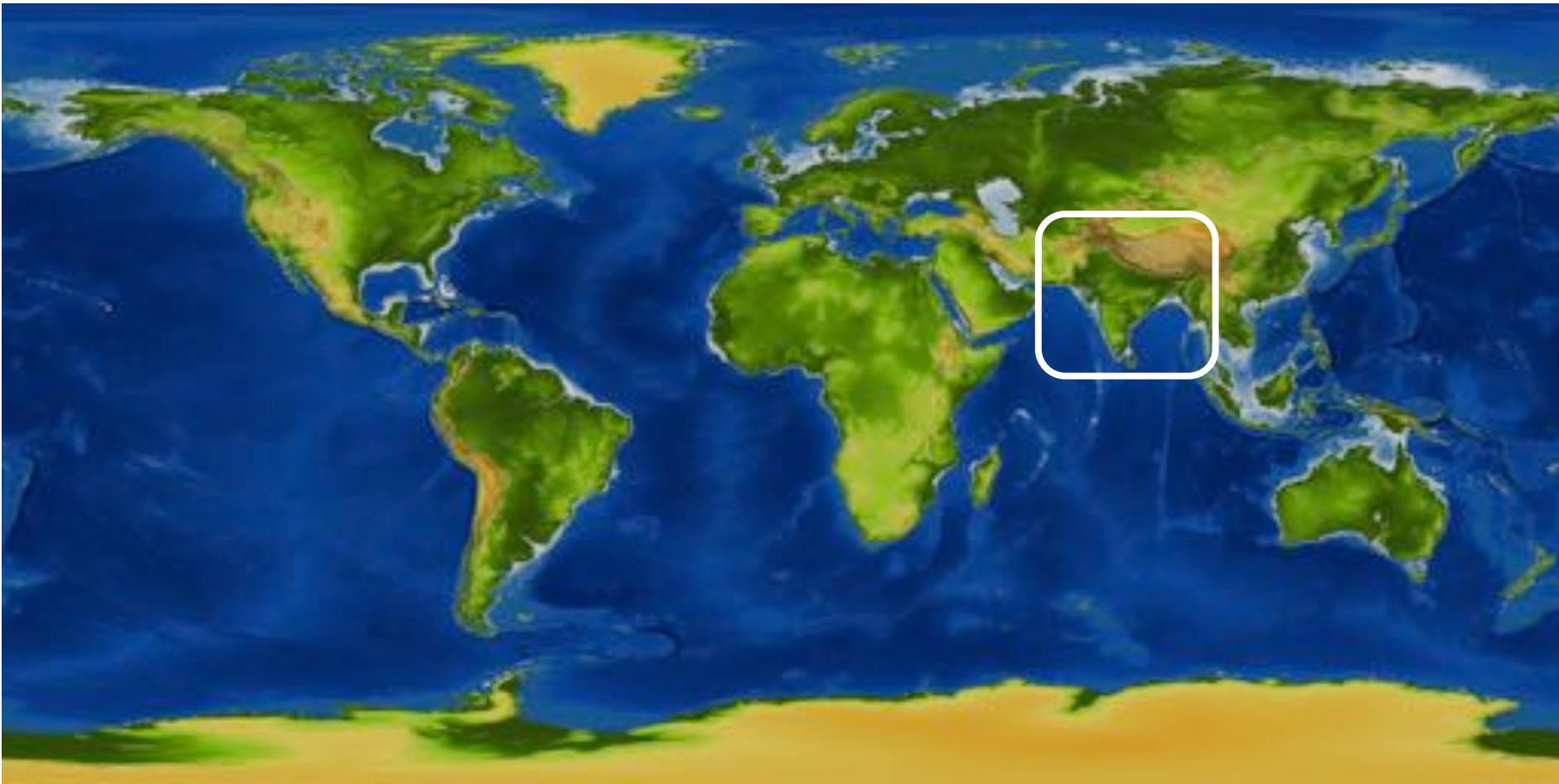
The 41st IEEE International Conference on Acoustics, Speech and Signal Processing
Shanghai, China, 2016



Indian Art Music



Indian Art Music

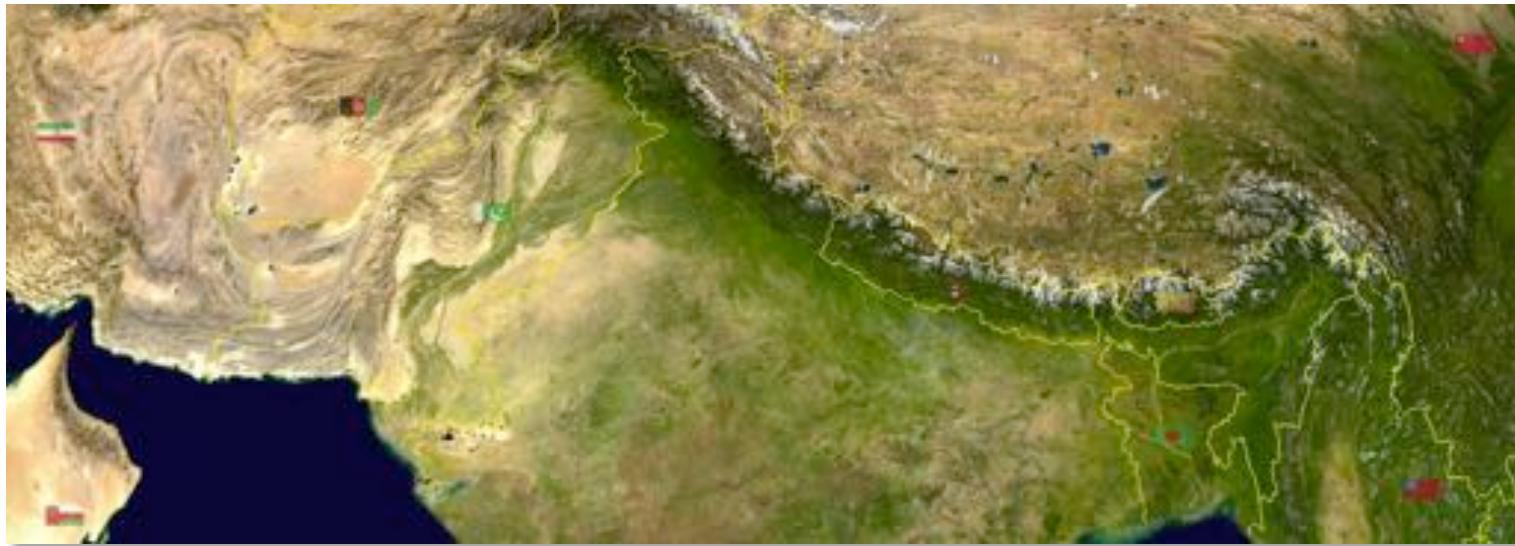


Indian subcontinent: India, Pakistan, Bangladesh, Srilanka, Nepal and Bhutan

Indian Art Music



Indian Art Music: Hindustani music



Indian Art Music: Carnatic music

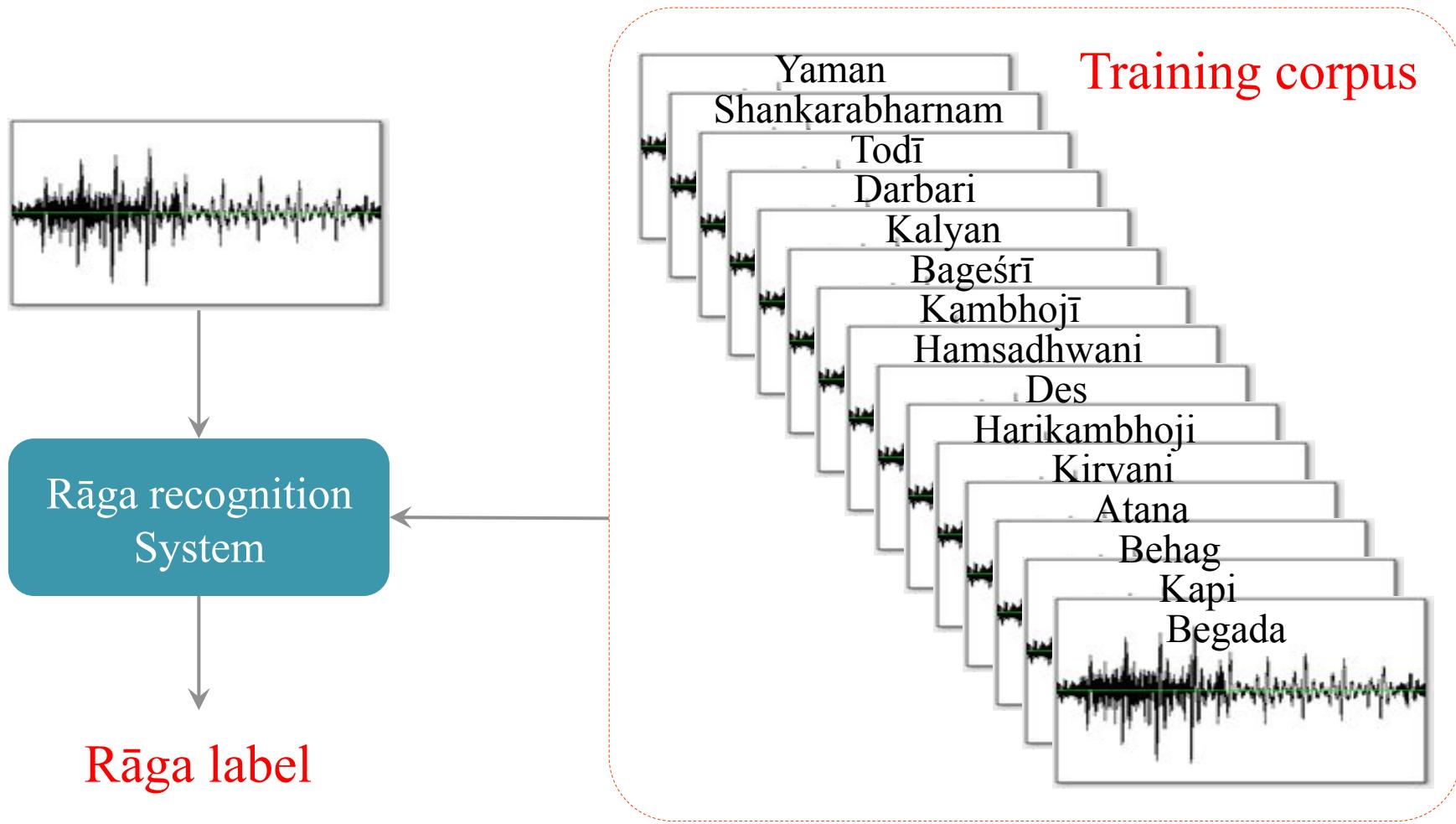


Rāga: melodic framework

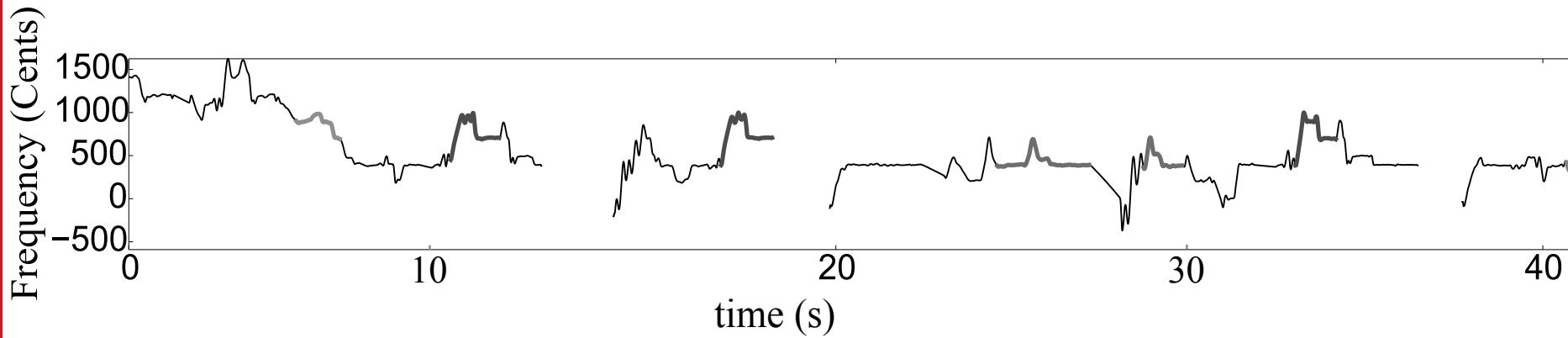
- Grammar for improvisation and composition



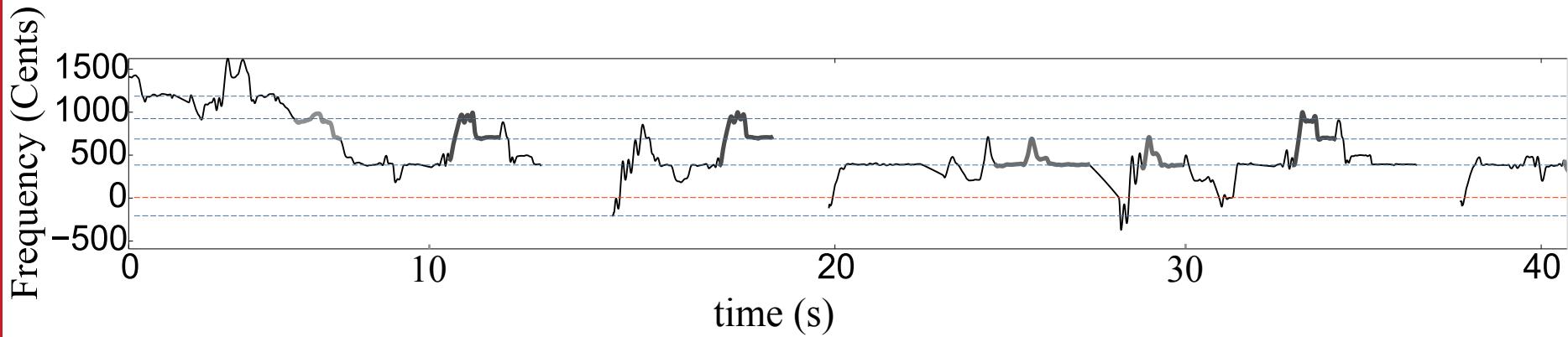
Automatic Rāga Recognition



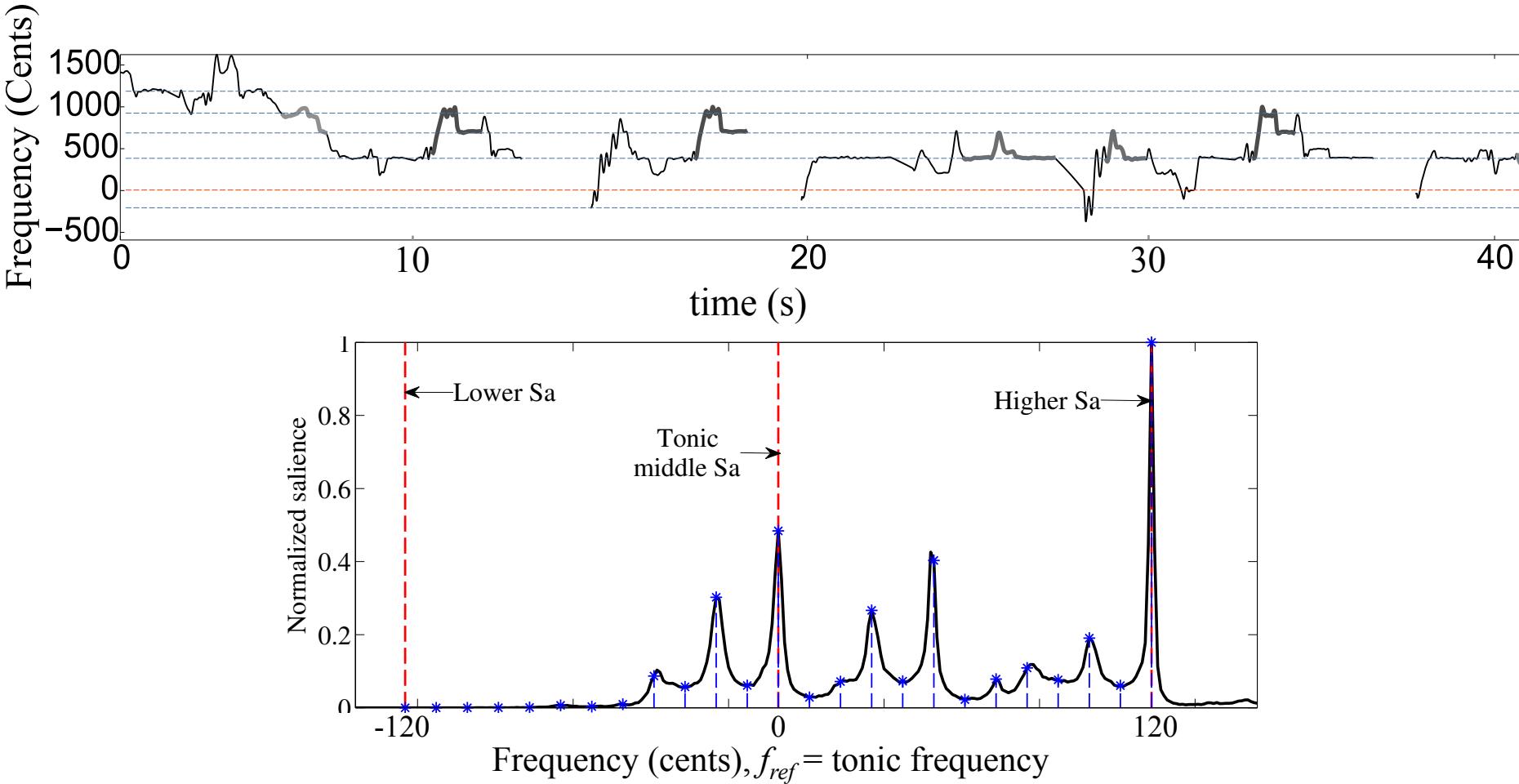
Rāga Characterization: Svaras



Rāga Characterization: Svaras

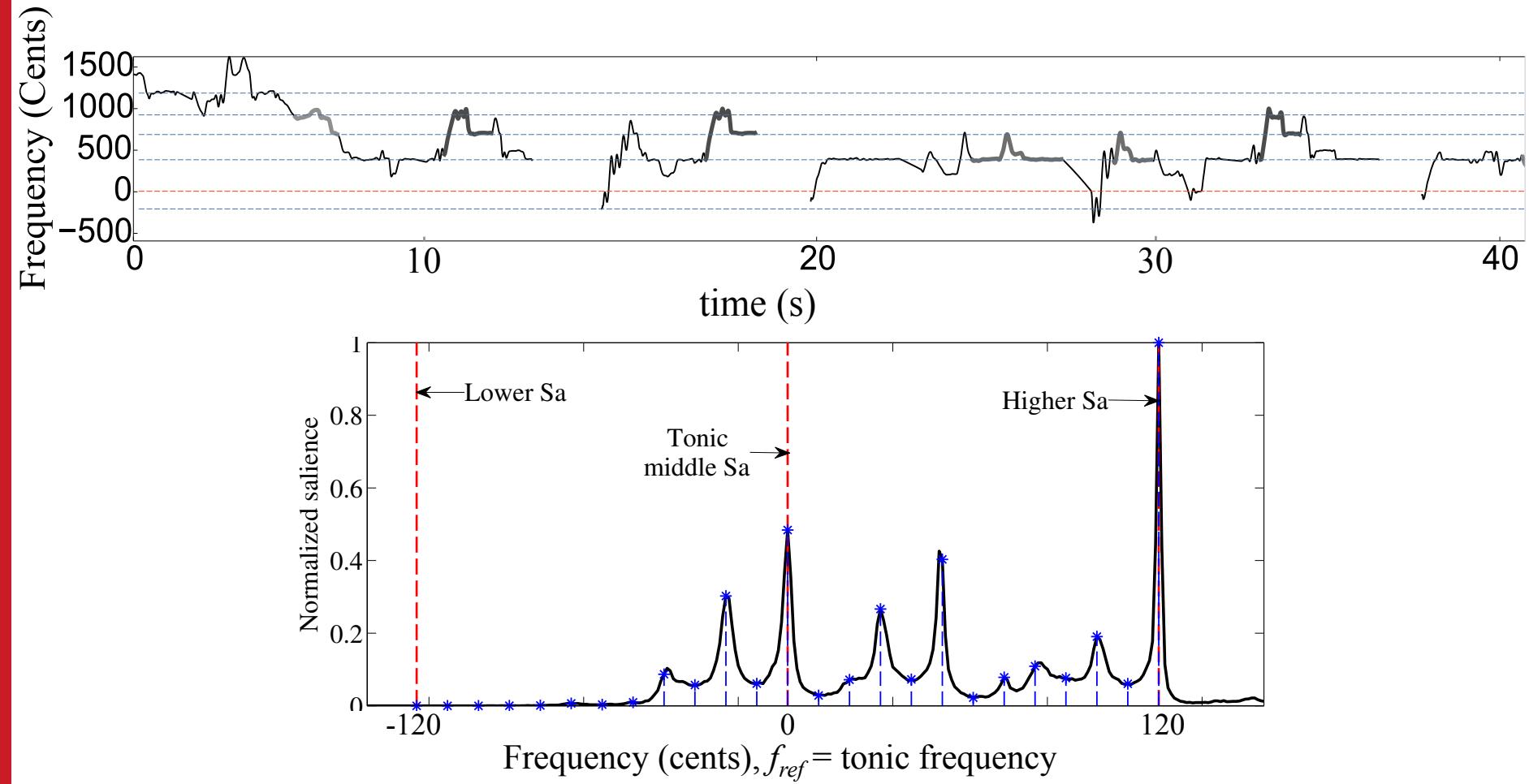


Rāga Characterization: Svaras

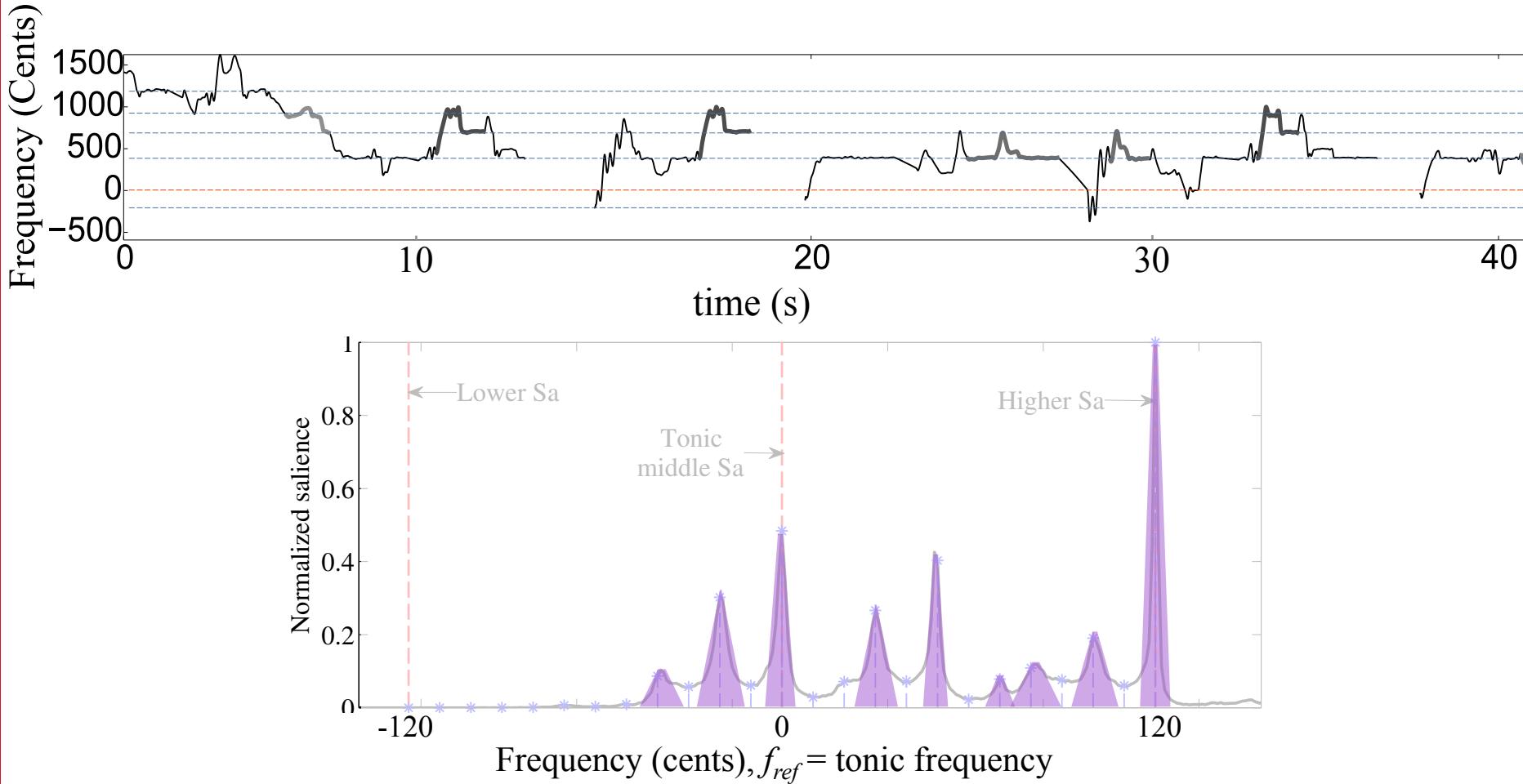


- ❑ P. Chordia and S. Şentürk, “Joint recognition of raag and tonic in North Indian music,” Computer Music Journal, vol. 37, no. 3, pp. 82–98, 2013.
- ❑ G. K. Koduri, S. Gulati, P. Rao, and X. Serra, “Rāga recognition based on pitch distribution methods,” Journal of New Music Research, vol. 41, no. 4, pp. 337–350, 2012.

Rāga Characterization: Intonation

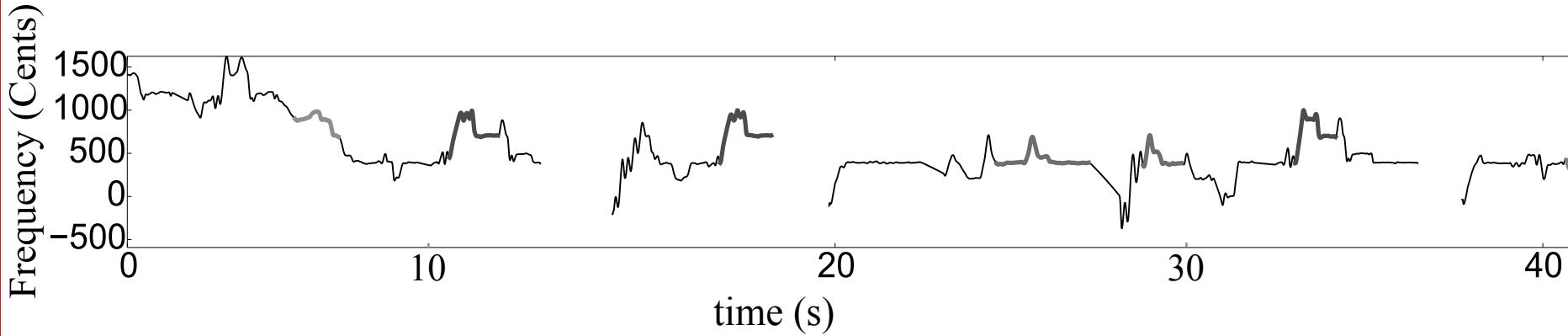


Rāga Characterization: Intonation



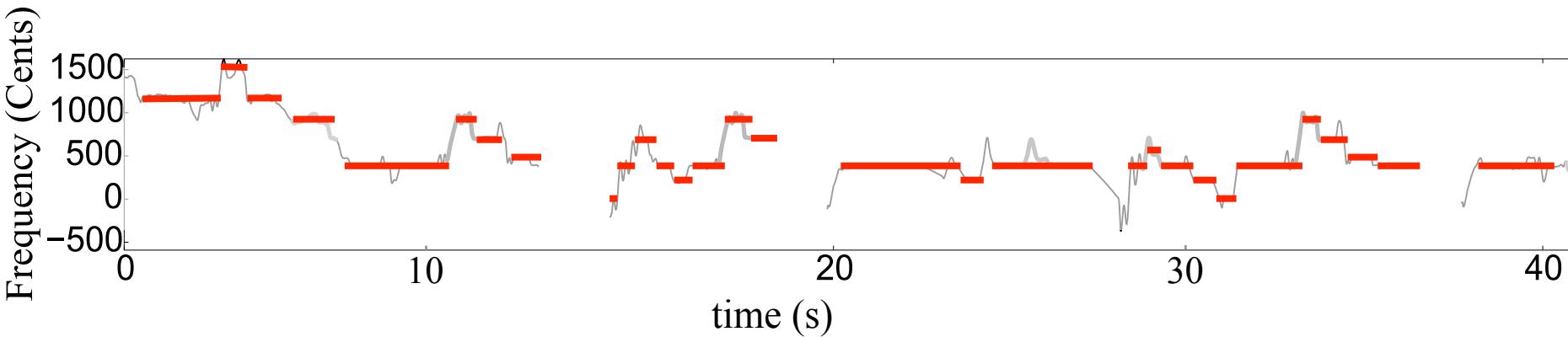
- ❑ G.K.Koduri,V.Ishwar,J.Serrà, and X.Serra, “Intonation analysis of rāgas in Carnatic music,” Journal of New Music Research, vol. 43, no. 1, pp. 72–93, 2014.
- ❑ H. G. Ranjani, S. Arthi, and T. V. Sreenivas, “Carnatic music analysis: Shadja, swara identification and raga verification in alapana using stochastic models,” in IEEE WASPAA, 2011, pp. 29–32.

Rāga Characterization: Ārōh-Avrōh



- Ascending-descending svara pattern; melodic progression

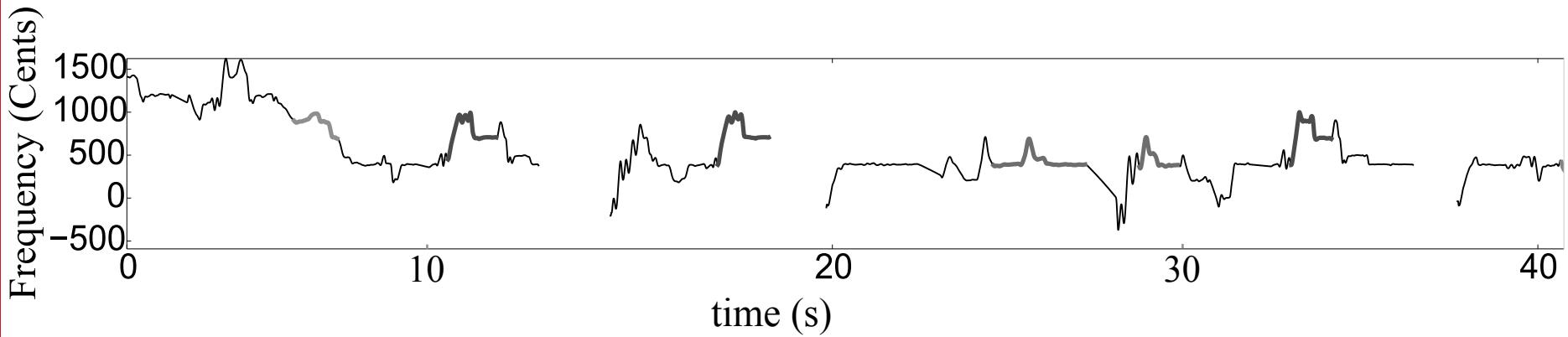
Rāga Characterization: Ārōh-Avrōh



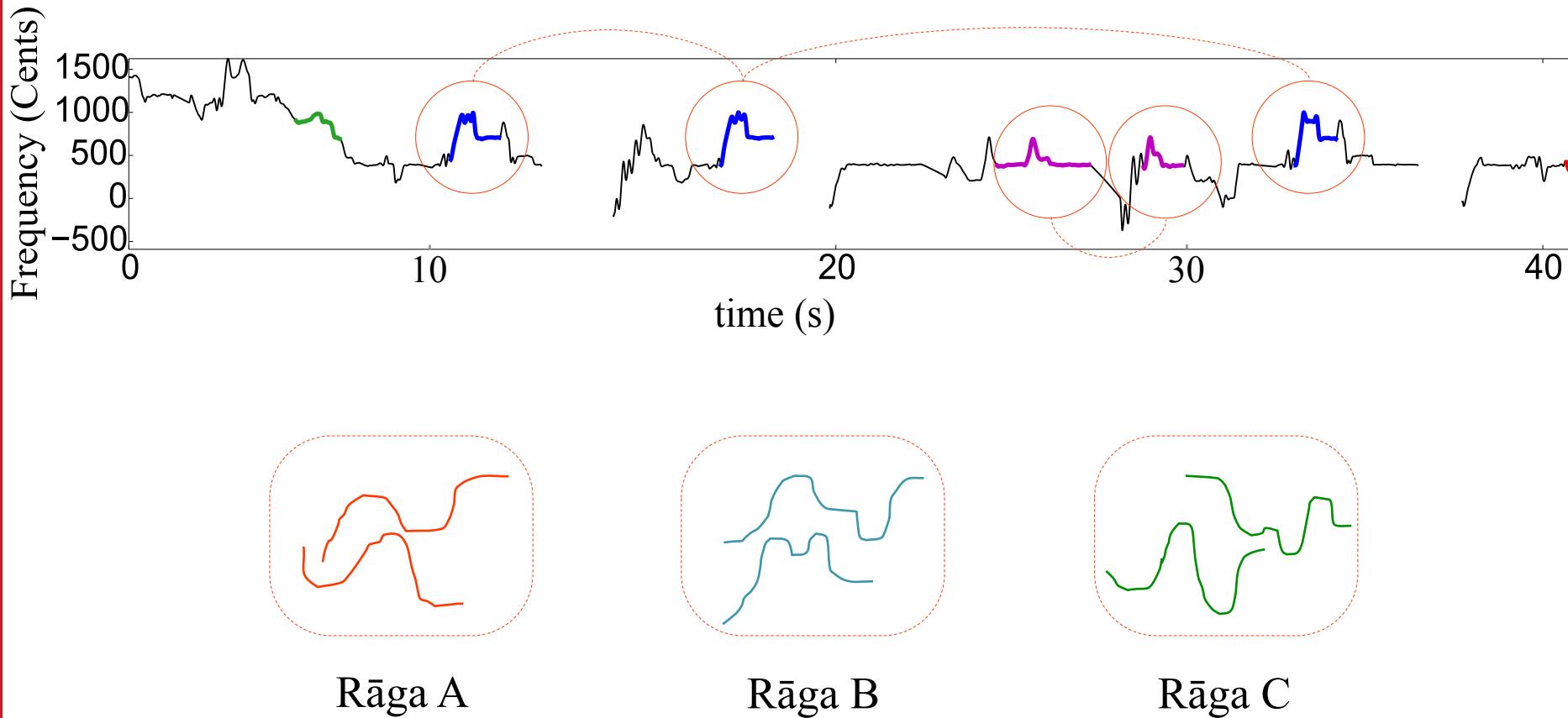
Melodic Progression Templates
N-gram Distribution
Hidden Markov Model

- ❑ S. Shetty and K. K. Achary, “Raga mining of indian music by extracting arohana-avarohana pattern,” Int. Journal of Recent Trends in Engineering, vol. 1, no. 1, pp. 362–366, 2009.
- ❑ V. Kumar, H Pandya, and C. V. Jawahar, “Identifying ragas in indian music,” in 22nd Int. Conf. on Pattern Recognition (ICPR), 2014, pp. 767–772.
- ❑ P. V. Rajkumar, K. P. Saishankar, and M. John, “Identification of Carnatic raagas using hidden markov models,” in IEEE 9th Int. Symposium on Applied Machine Intelligence and Informatics (SAMI), 2011, pp. 107–110.

Rāga Characterization: Melodic motifs



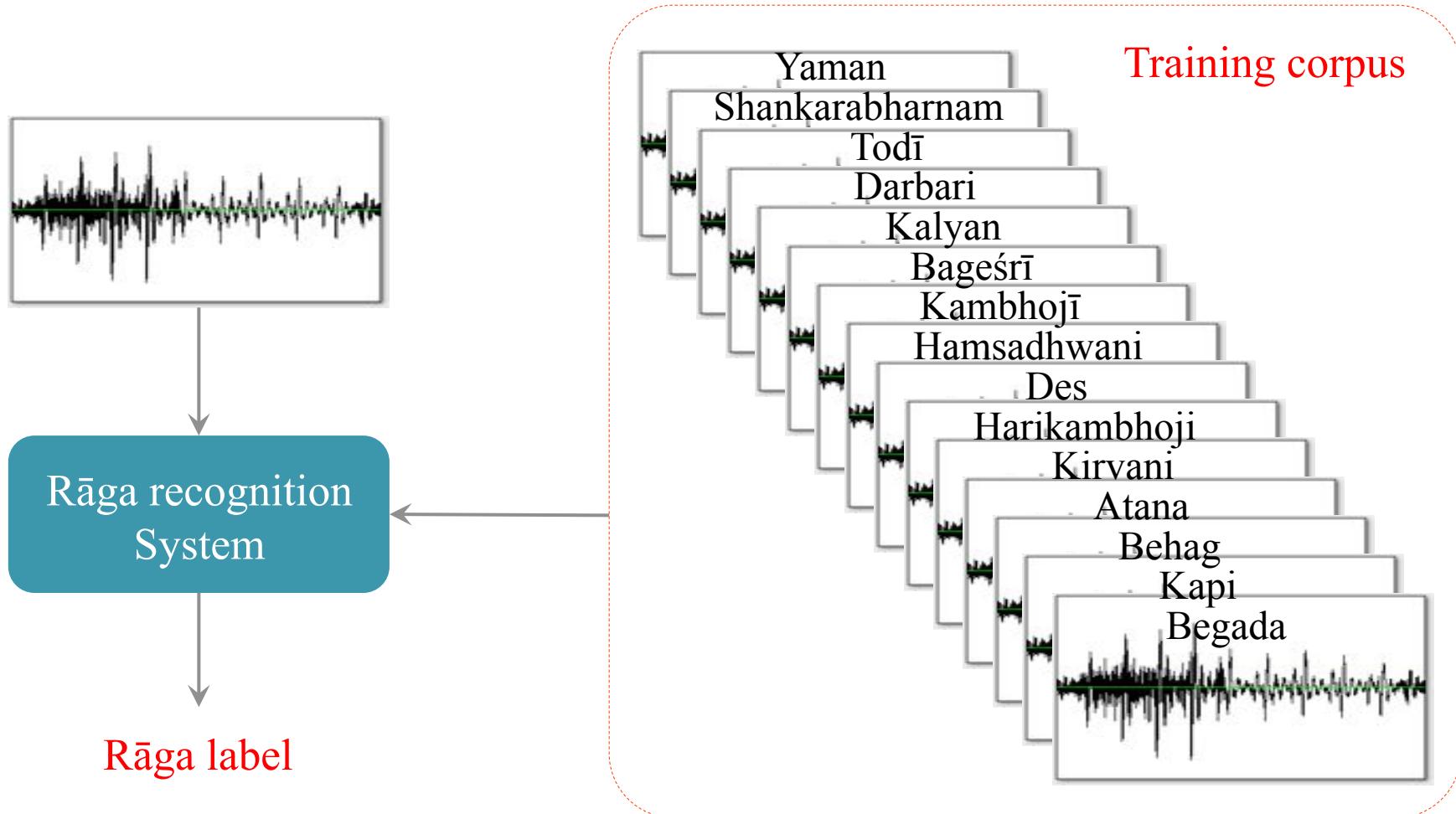
Rāga Characterization: Melodic motifs



- ❑ R. Sridhar and T. V. Geetha, “Raga identification of carnatic music for music information retrieval,” International Journal of Recent Trends in Engineering, vol. 1, no. 1, pp. 571–574, 2009.
- ❑ S. Dutta, S. PV Krishnaraj, and H. A. Murthy, “Raga verification in carnatic music using longest common segment set,” in Int. Soc. for Music Information Retrieval Conf. (ISMIR), pp. 605-611, 2015

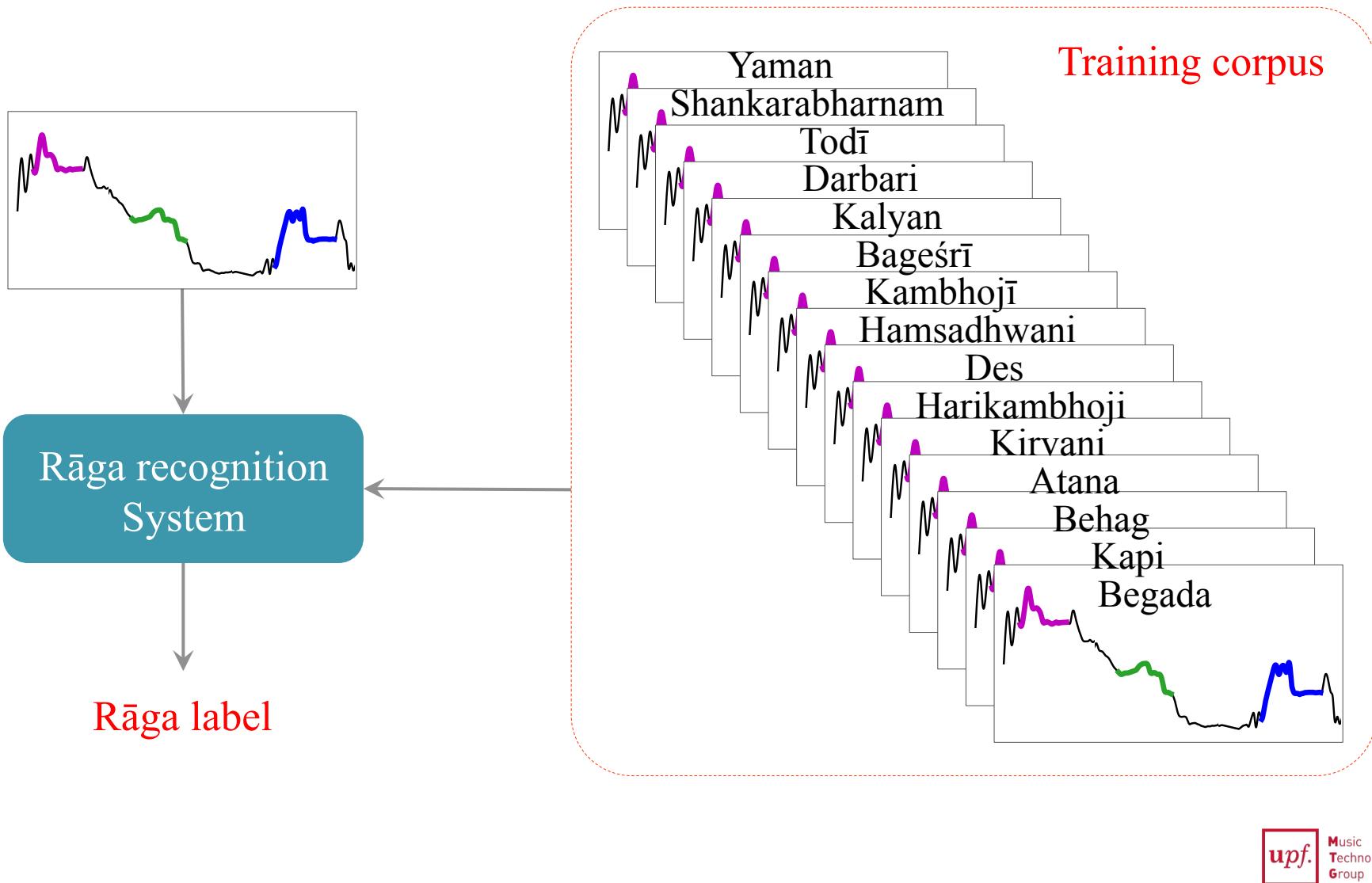
Goal

- Automatic rāga recognition

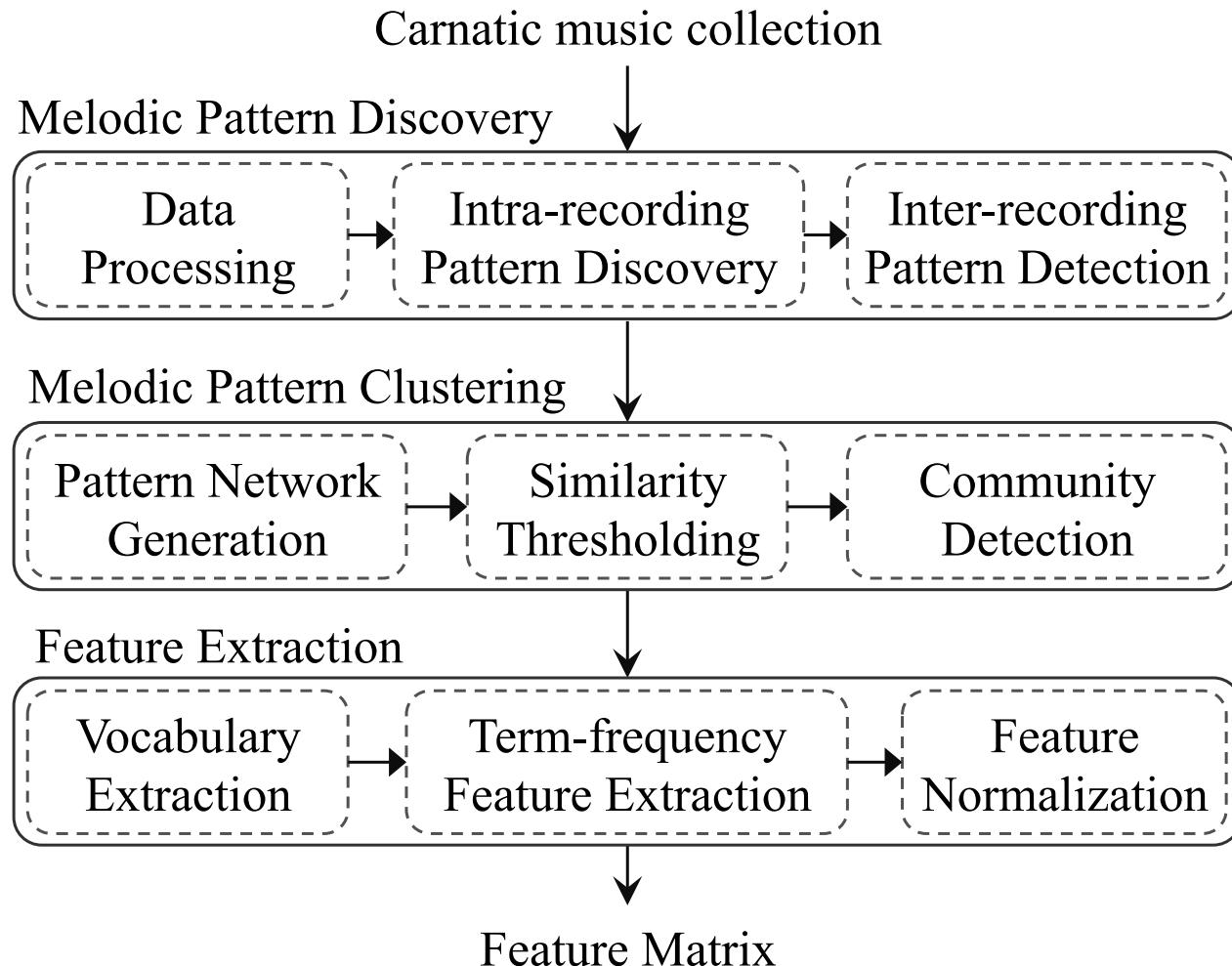


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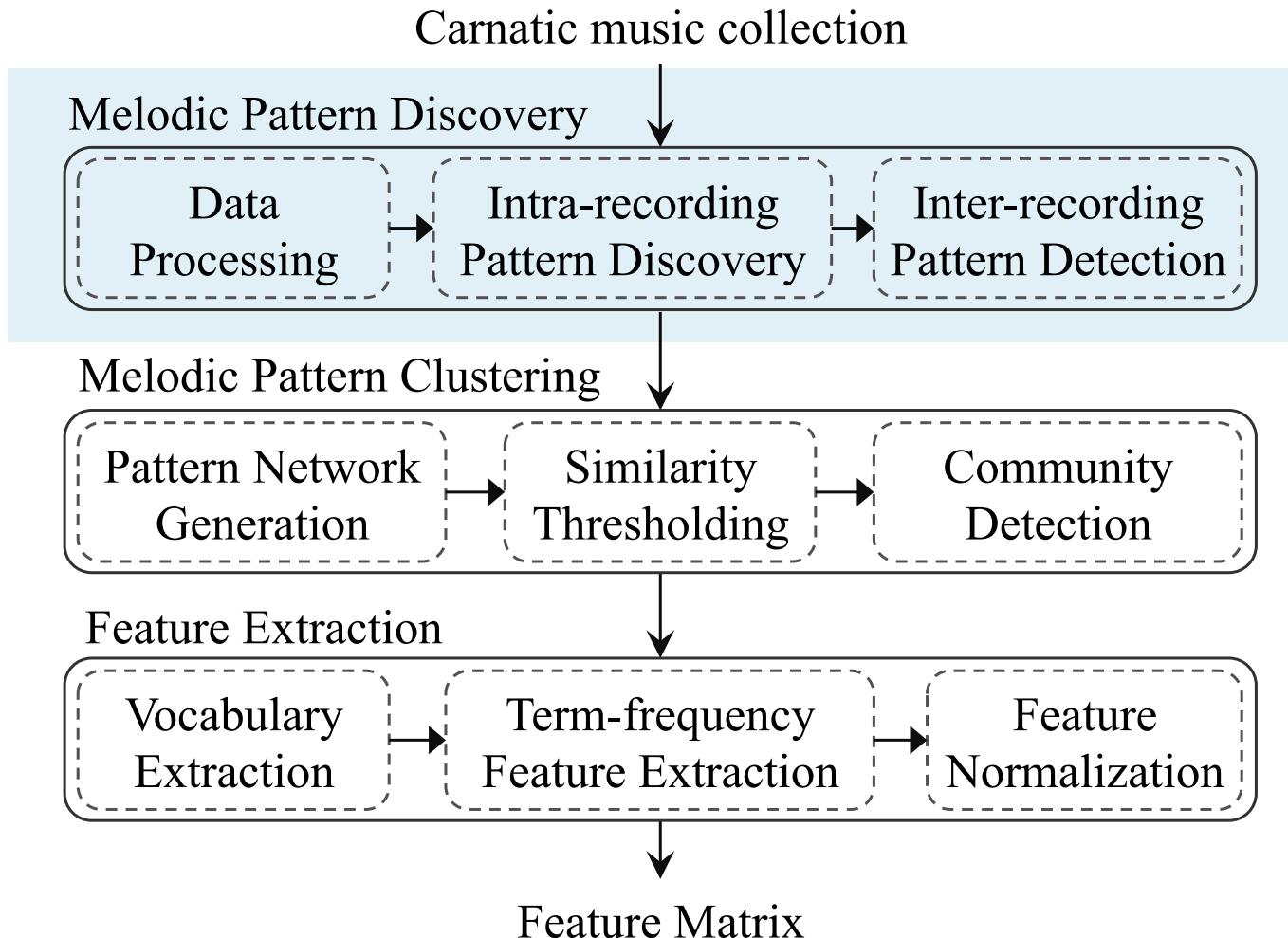
□ Automatic rāga recognition



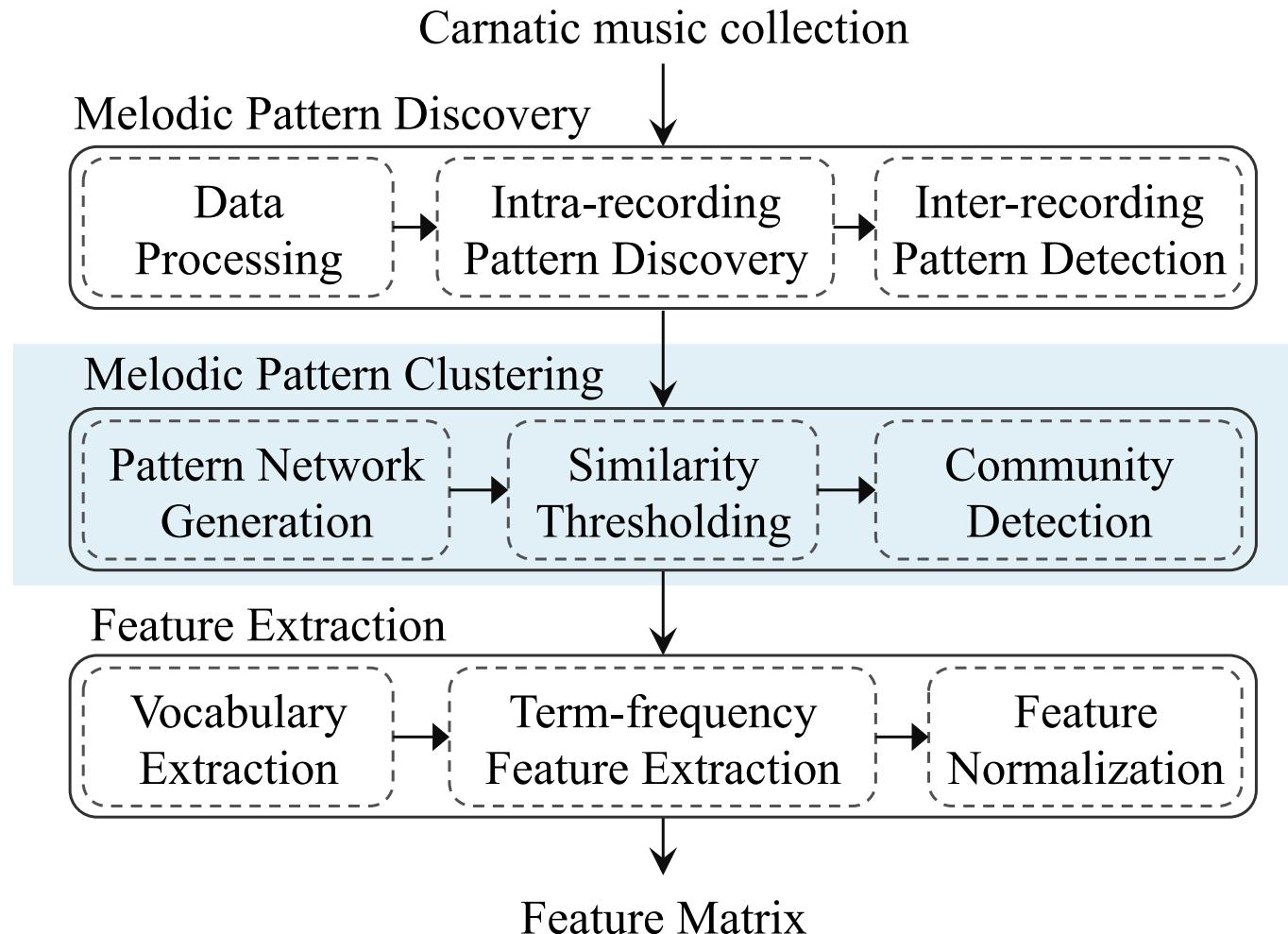
Block Diagram: Proposed Approach



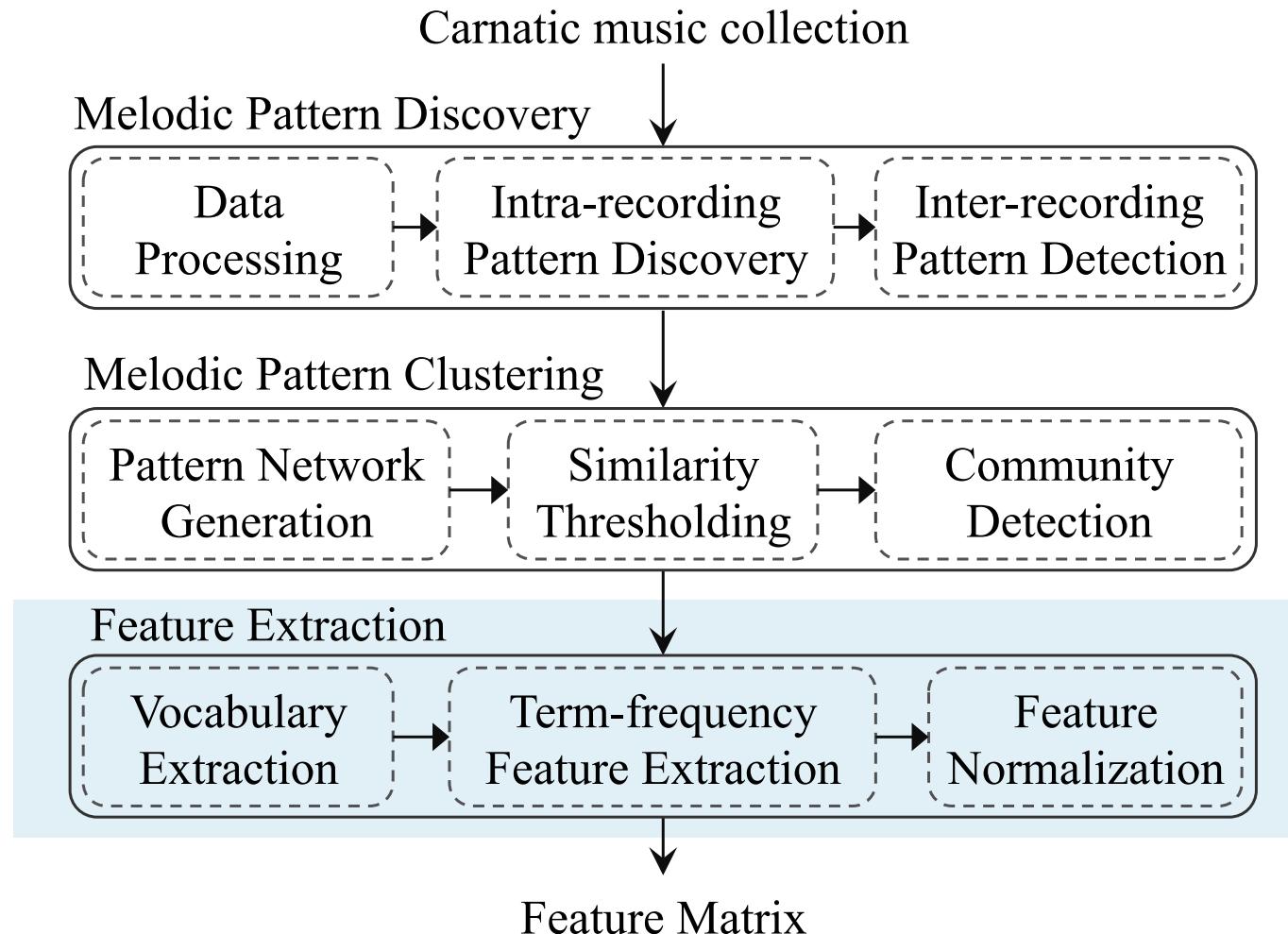
Block Diagram: Pattern Discovery



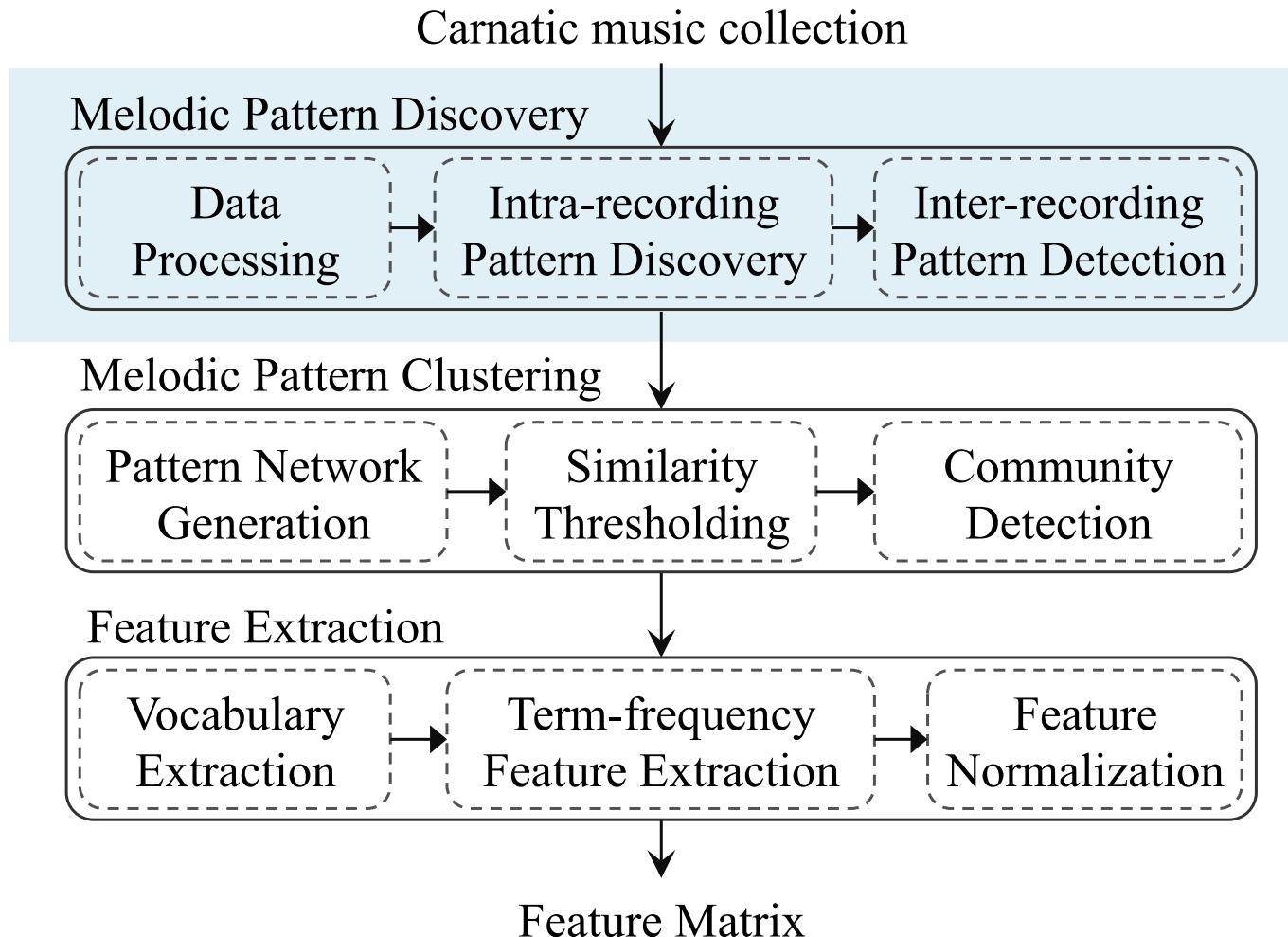
Block Diagram: Pattern Clustering



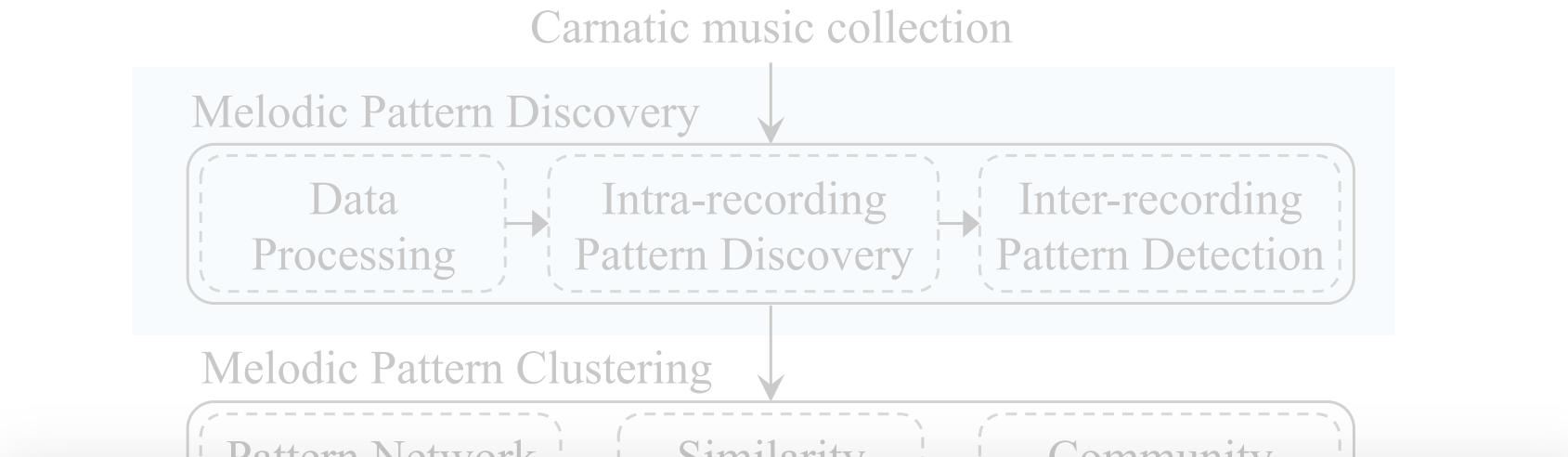
Block Diagram: Feature Extraction



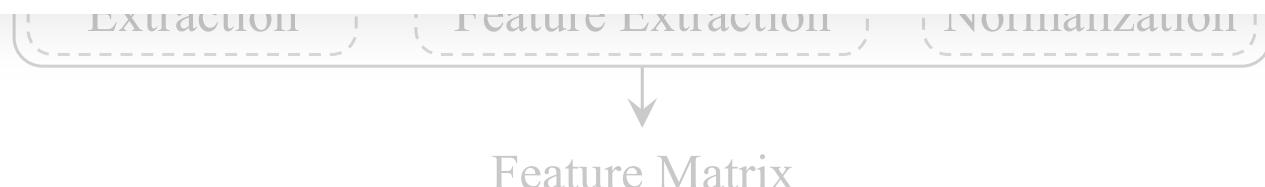
Block Diagram: Pattern Discovery



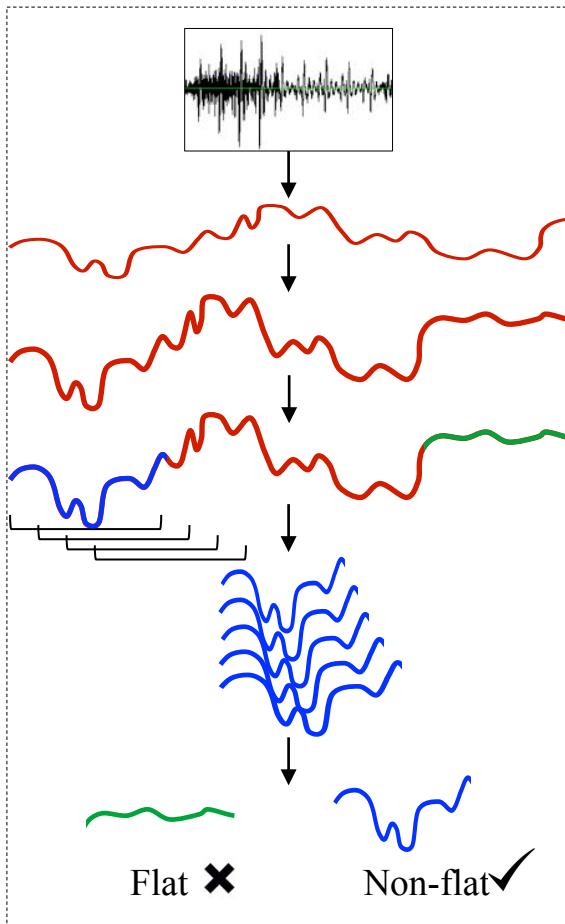
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S. Gulati, J. Serrà, V. Ishwar, and X. Serra, “Mining melodic patterns in large audio collections of Indian art music,” in Int. Conf. on Signal Image Technology & Internet Based Systems - MIRA, Marrakesh, Morocco, 2014, pp. 264–271.

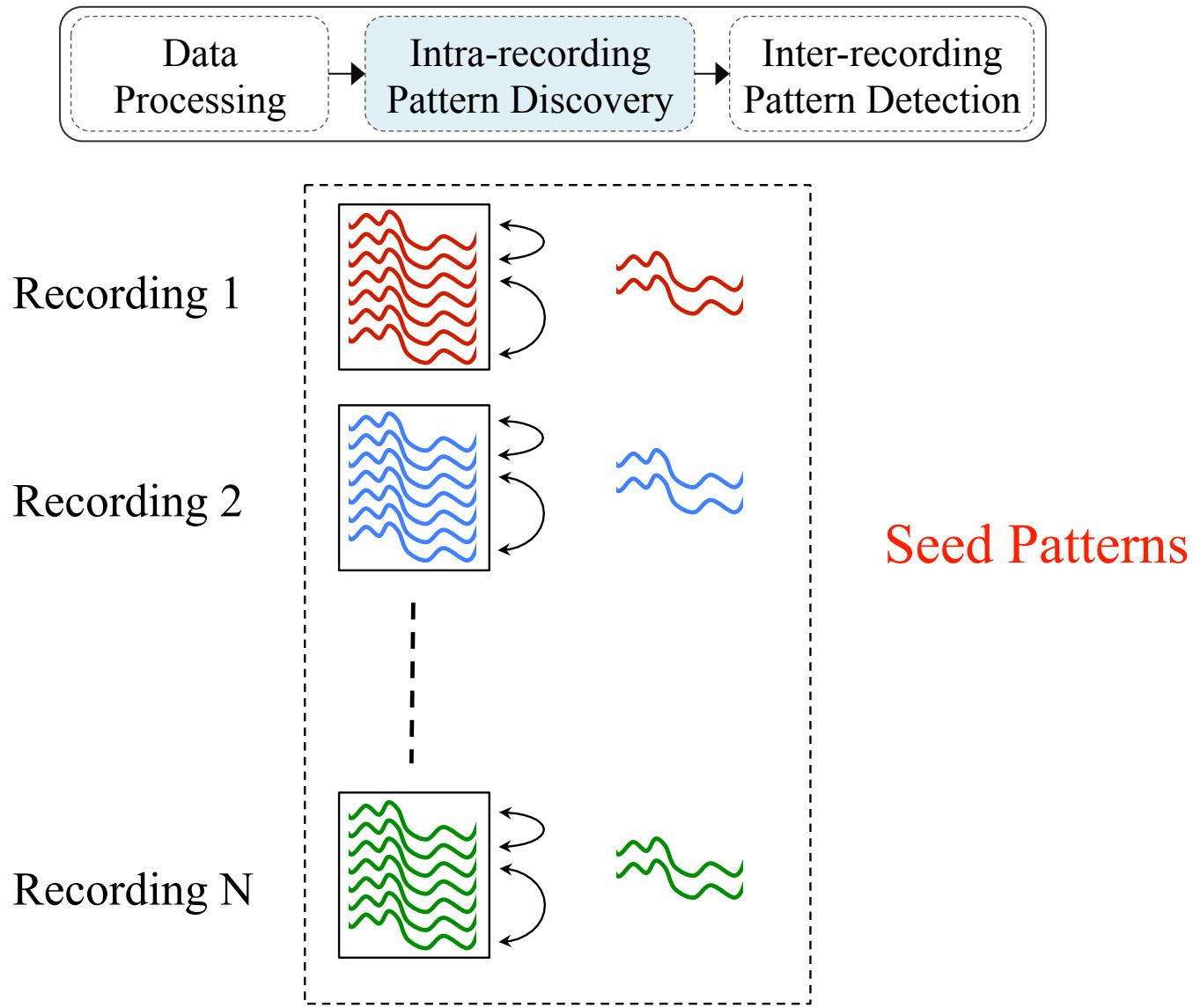


Proposed Approach: Pattern Discovery

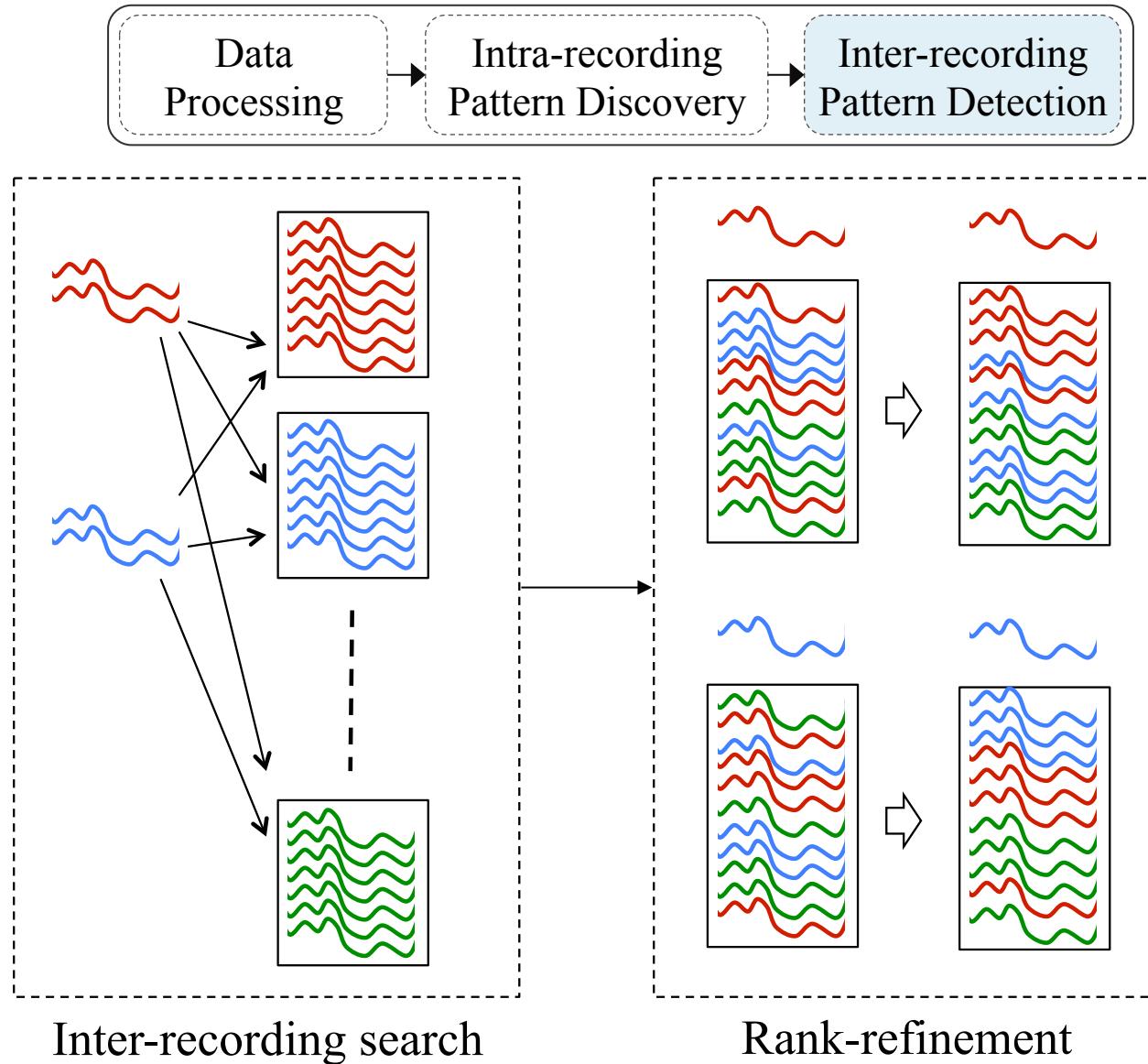


- Predominant pitch estimation
- Downsampling
- Hz to Cents
- Tonic normalization
- Brute-force segmentation
- Uniform Time-scaling
- Segment filtering

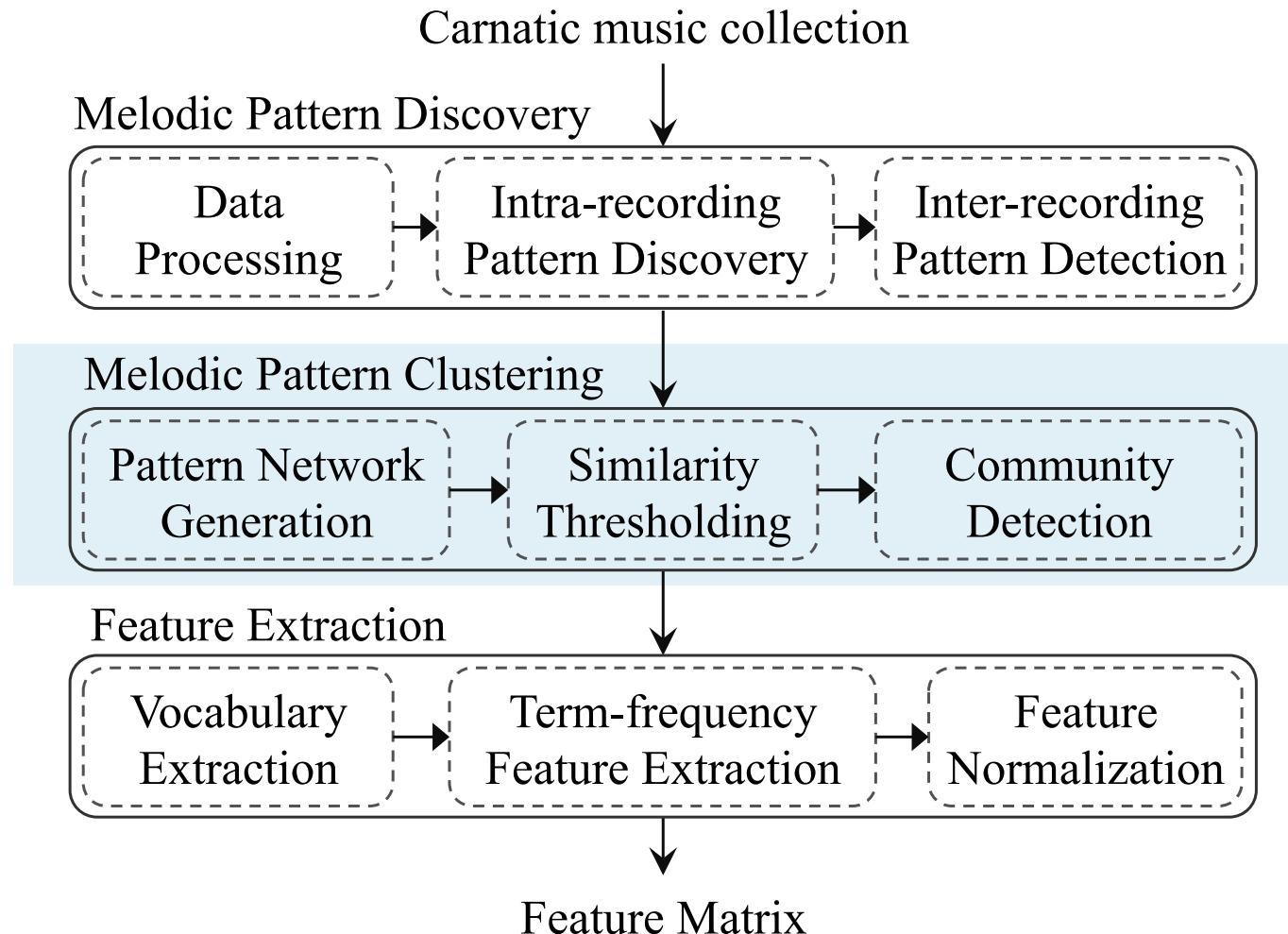
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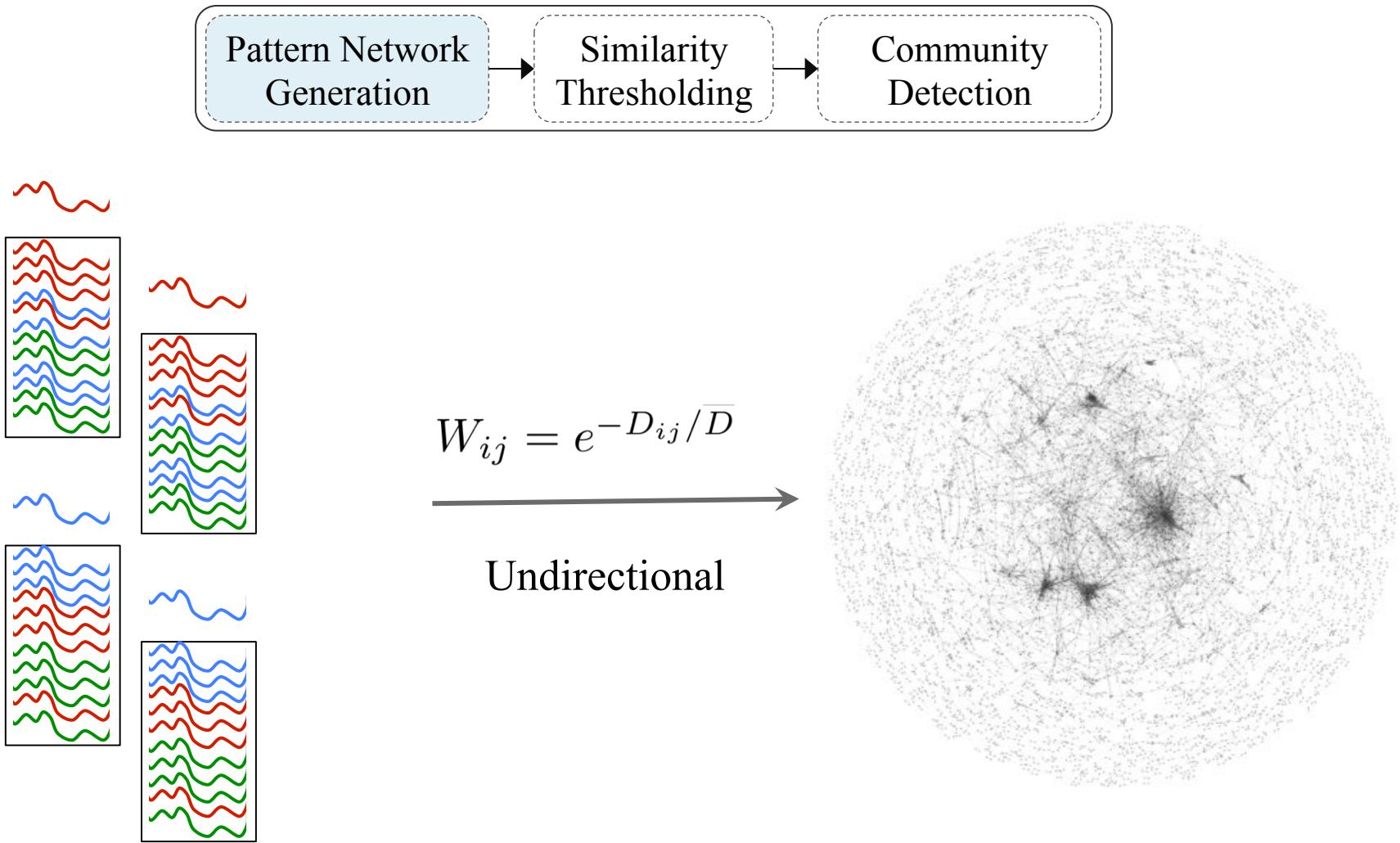
Proposed Approach: Pattern Discovery



Block Diagram: Pattern Clustering

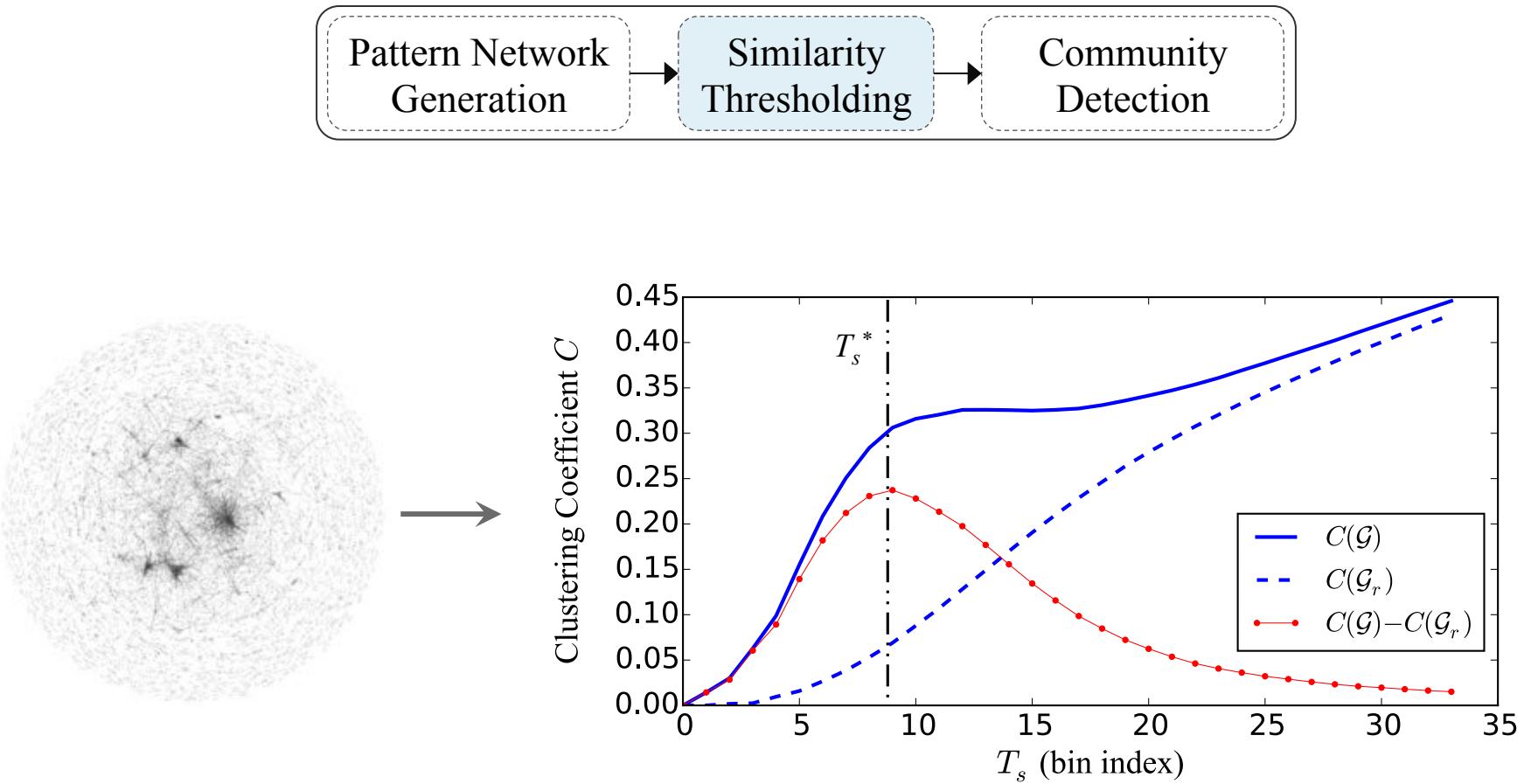


Proposed Approach: Pattern Clustering



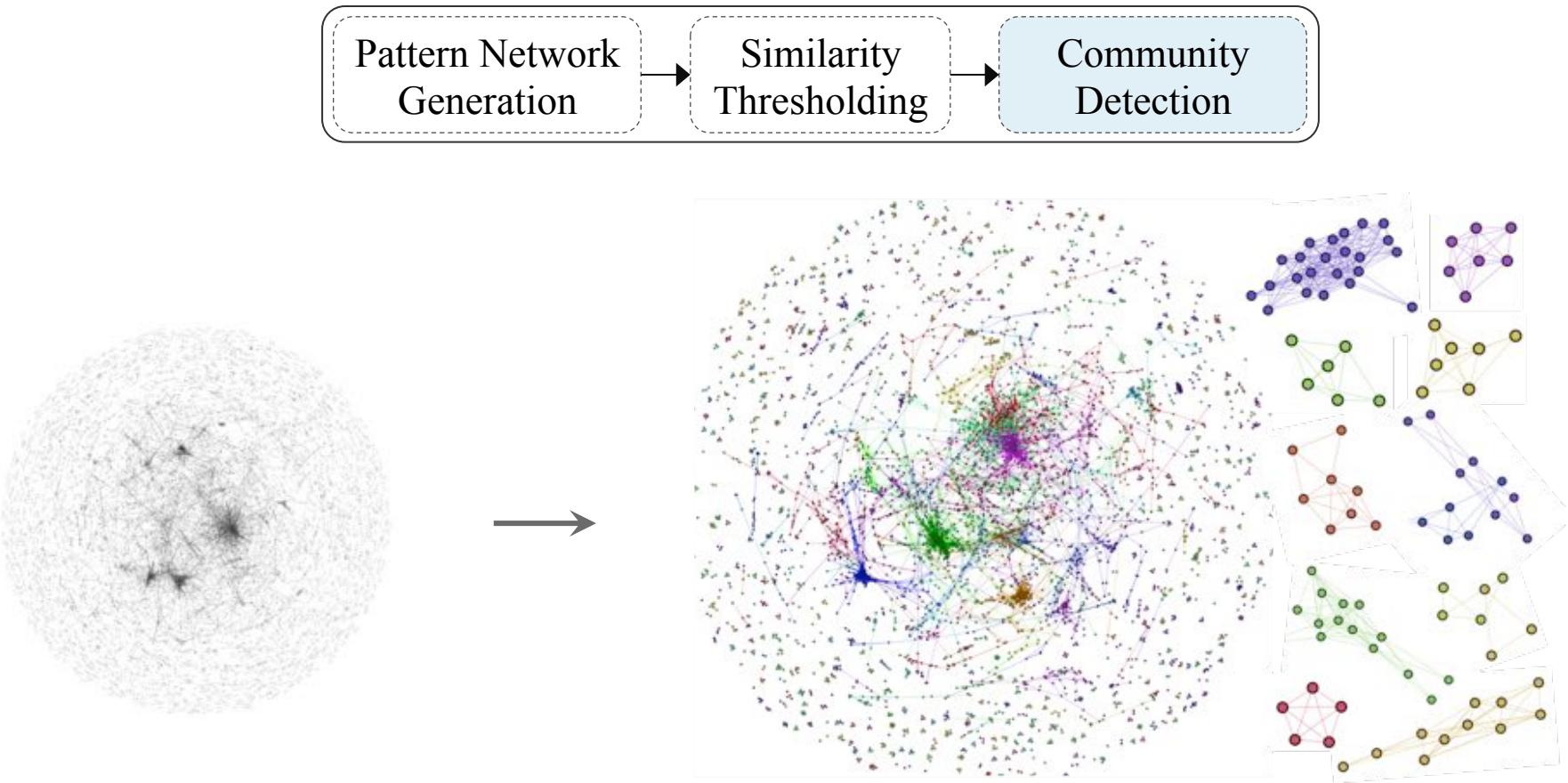
- M. EJ Newman, “The structure and function of complex networks,” Society for Industrial and Applied Mathematics (SIAM) review, vol. 45, no. 2, pp. 167–256, 2003.

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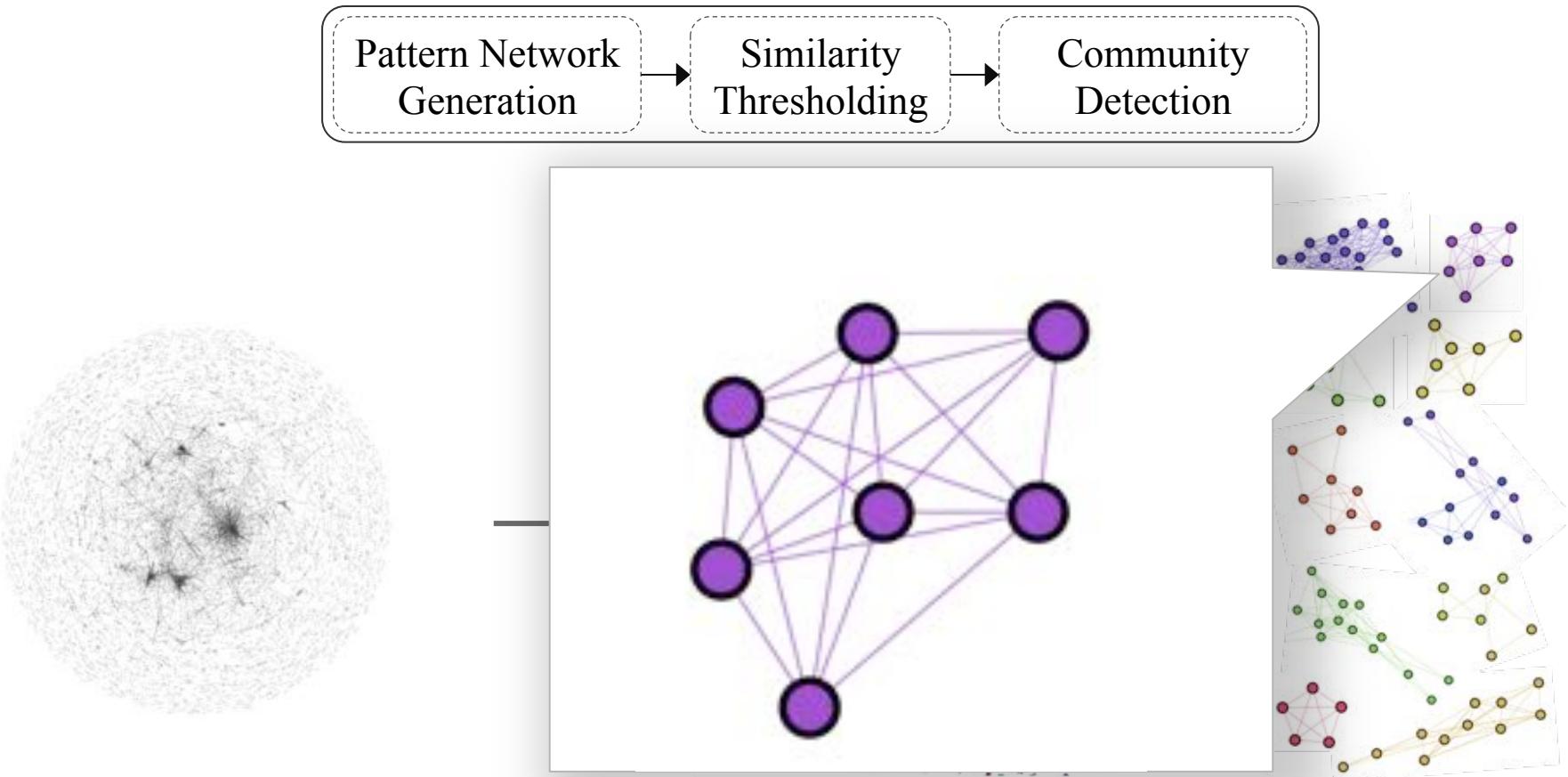
- ❑ M. EJ Newman, “The structure and function of complex networks,” Society for Industrial and Applied Mathematics (SIAM) review, vol. 45, no. 2, pp. 167–256, 2003.
- ❑ S. Maslov and K. Sneppen, “Specificity and stability in topology of protein networks,” Science, vol. 296, no. 5569, pp. 910– 913, 2002.

Proposed Approach: Pattern Clustering



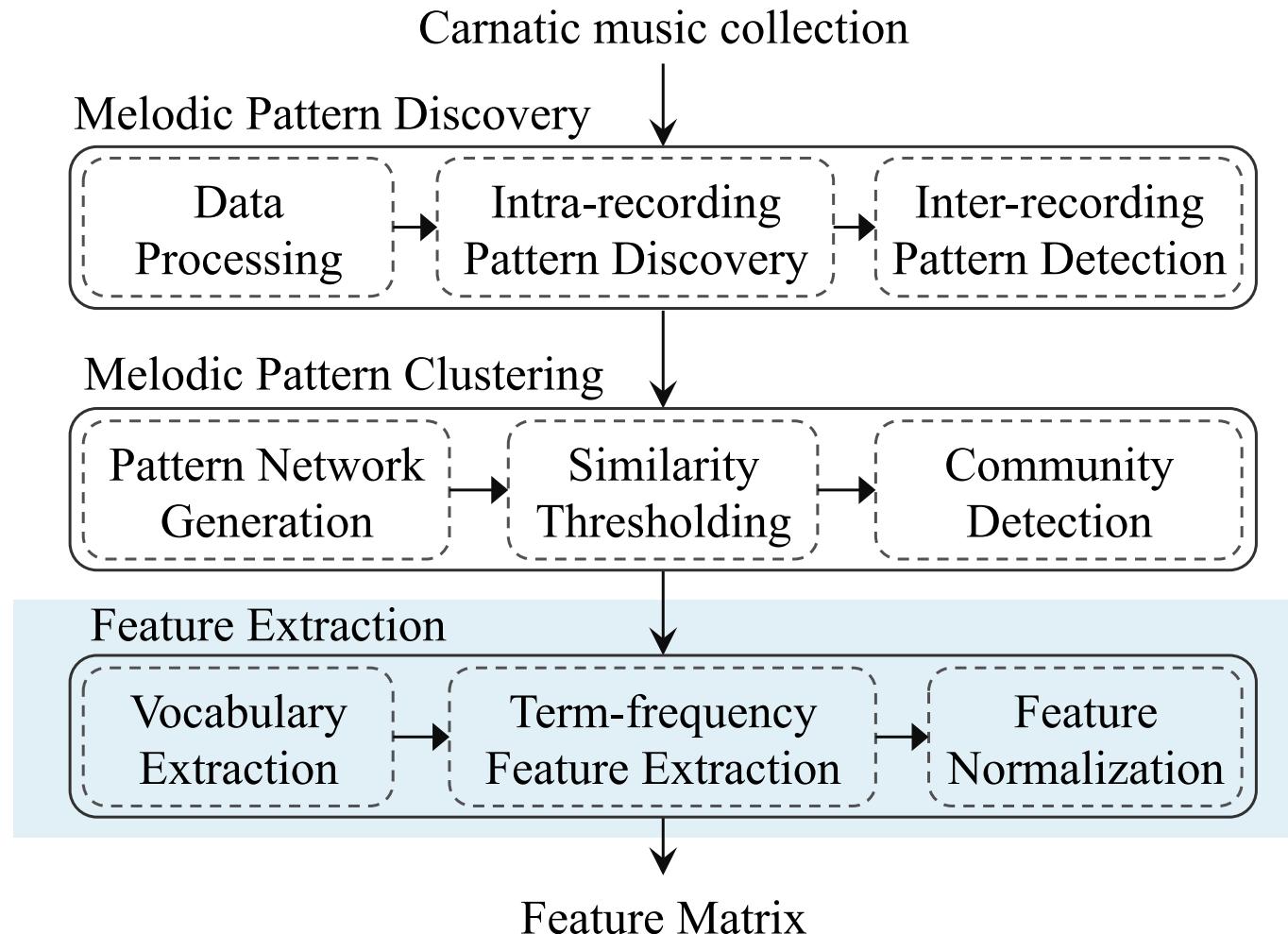
- ❑ V. D. Blondel, J. L. Guillaume, R. Lambiotte, and E. Lefebvre, “Fast unfolding of communities in large networks,” *Journal of Statistical Mechanics: Theory and Experiment*, vol. 2008, no. 10, pp. P10008, 2008.
- ❑ S Fortunato, “Community detection in graphs,” *Physics Reports*, vol. 486, no. 3, pp. 75–174, 2010.

Proposed Approach: Pattern Clustering

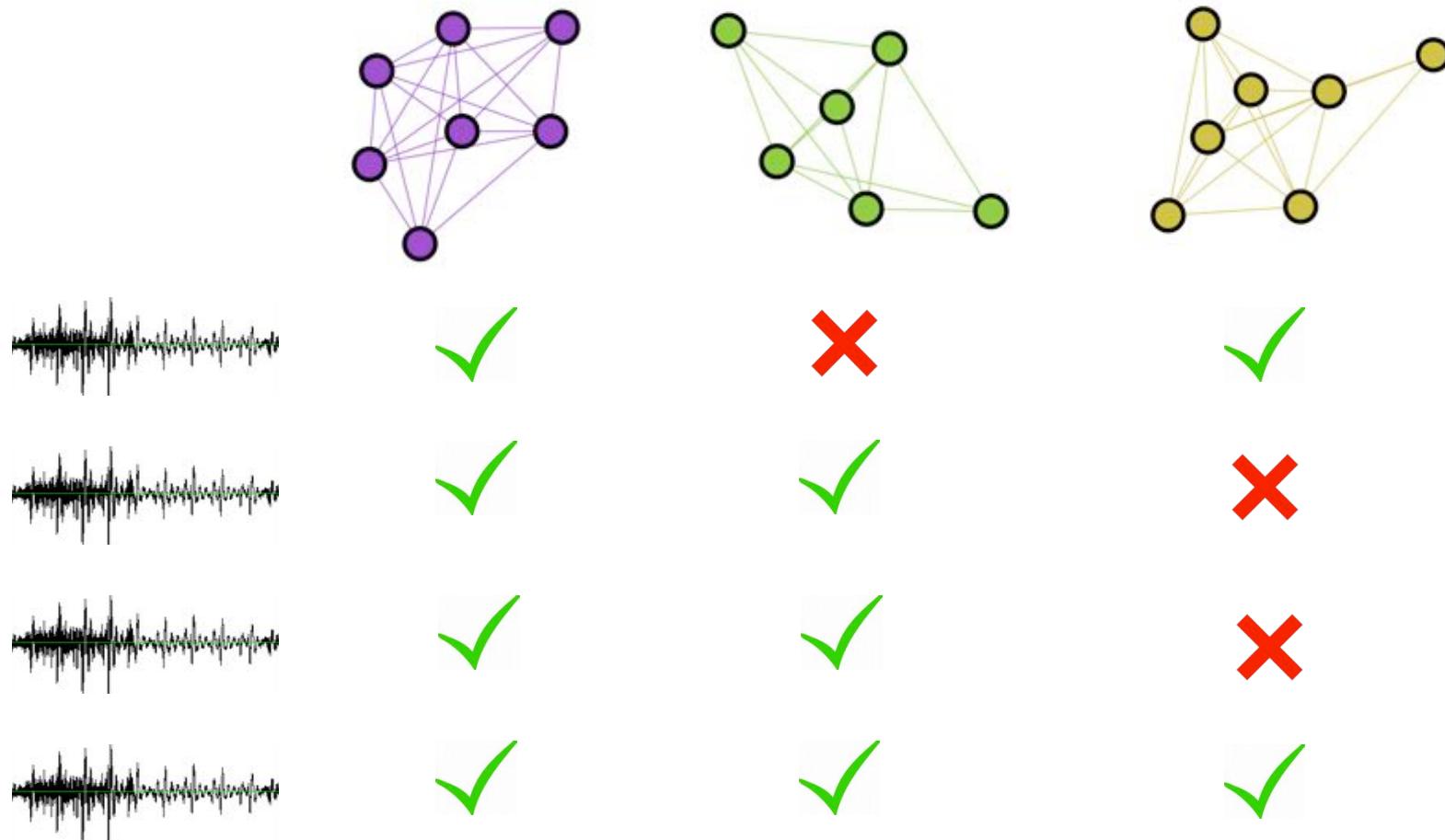


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Block Diagram: Feature Extraction



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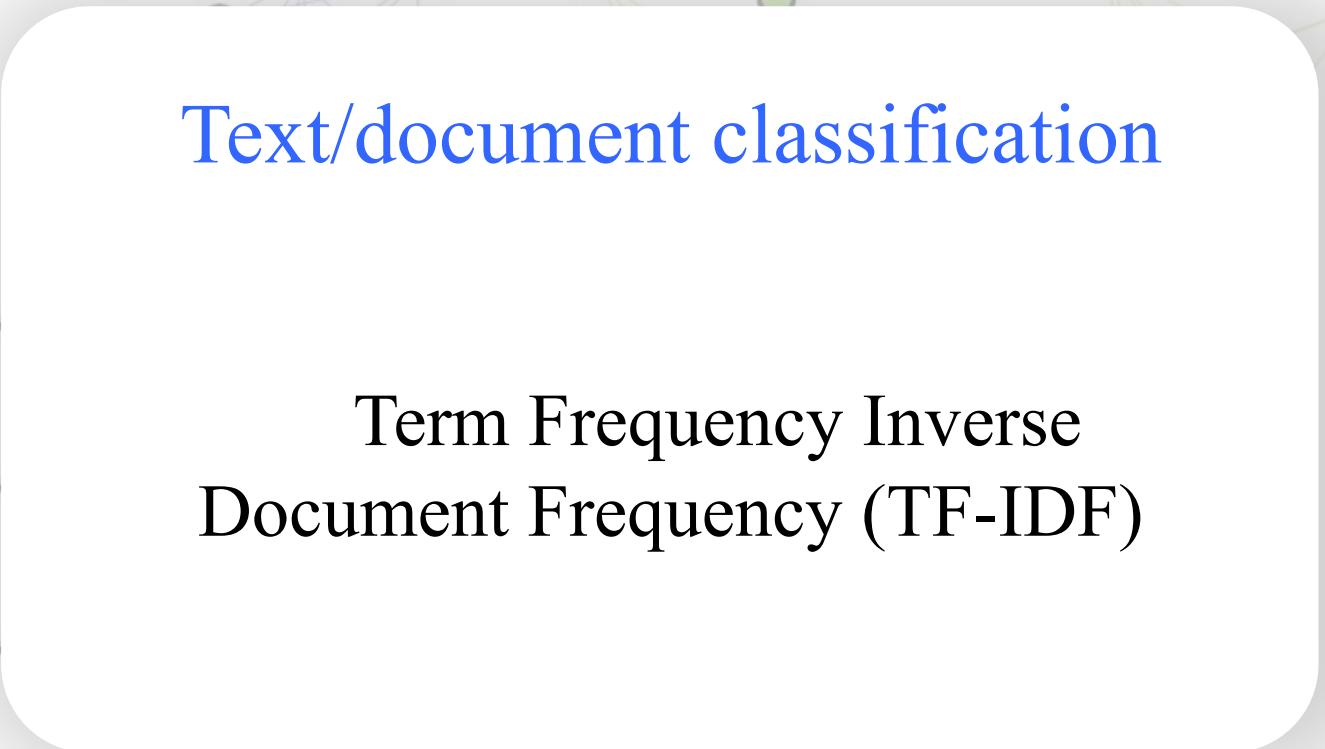
Text/document classification

Phrases \leftrightarrow Words

Rāga \leftrightarrow Topic

Recordings \leftrightarrow Documents

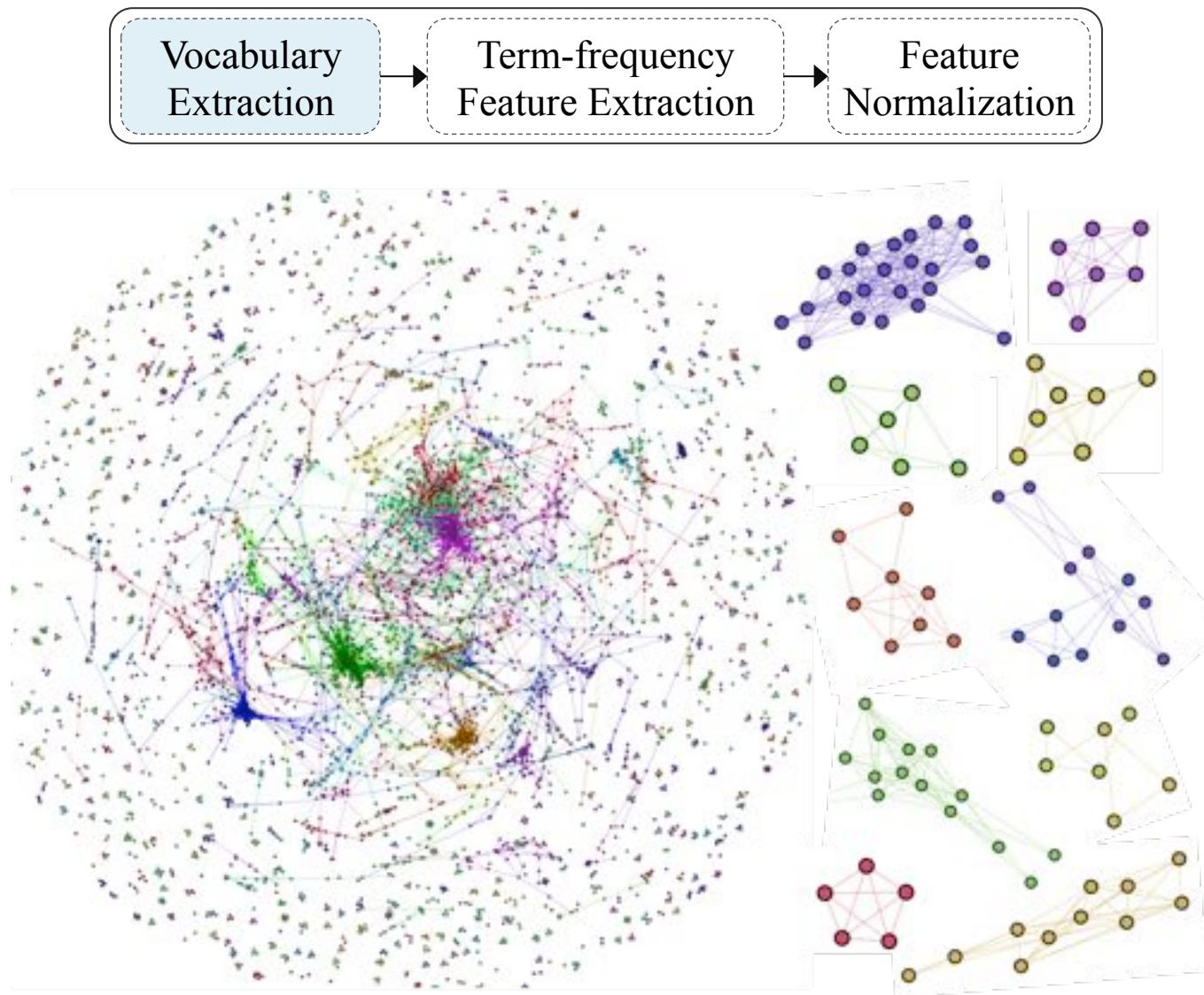
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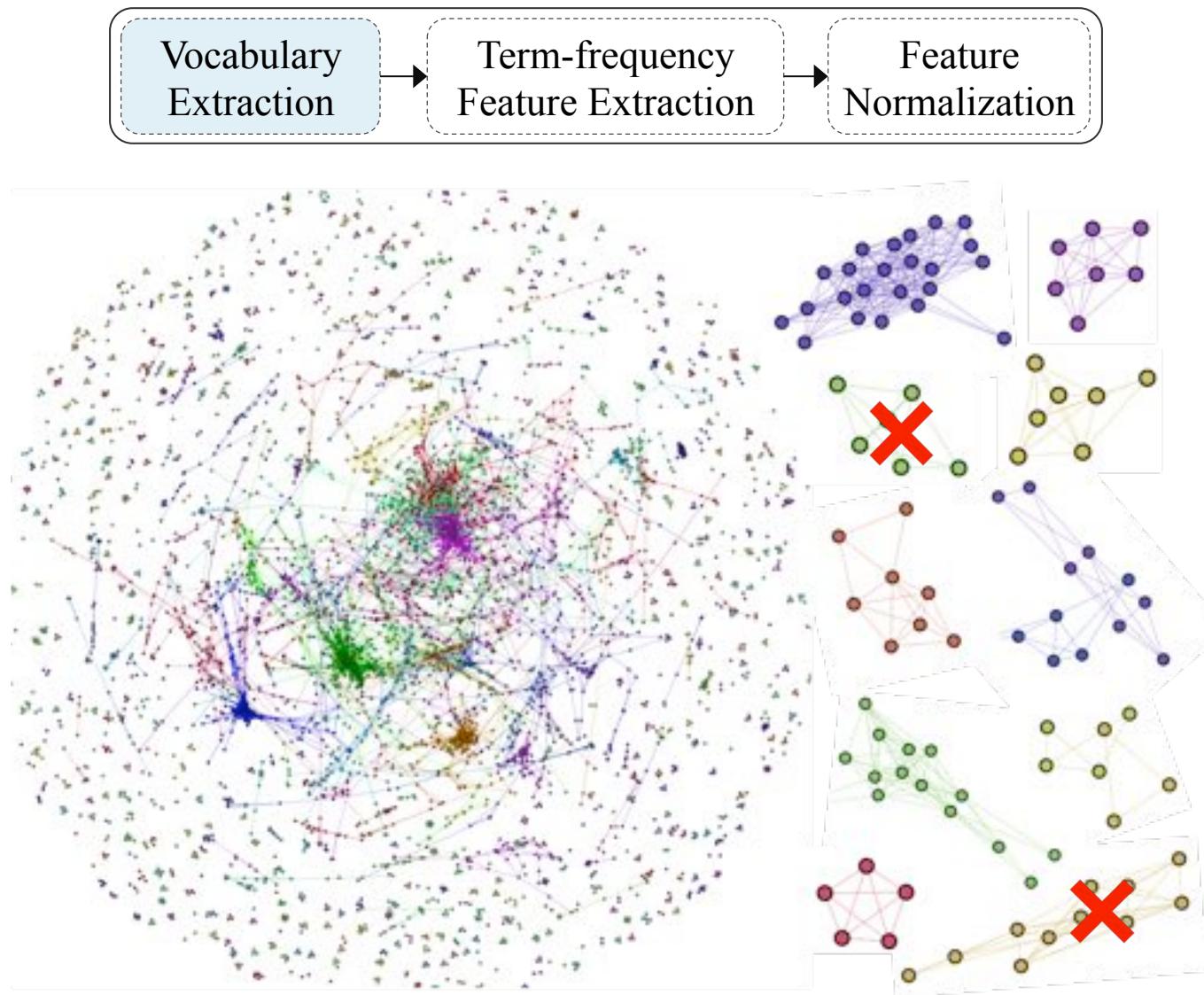
Text/document classification

Term Frequency Inverse
Document Frequency (TF-IDF)

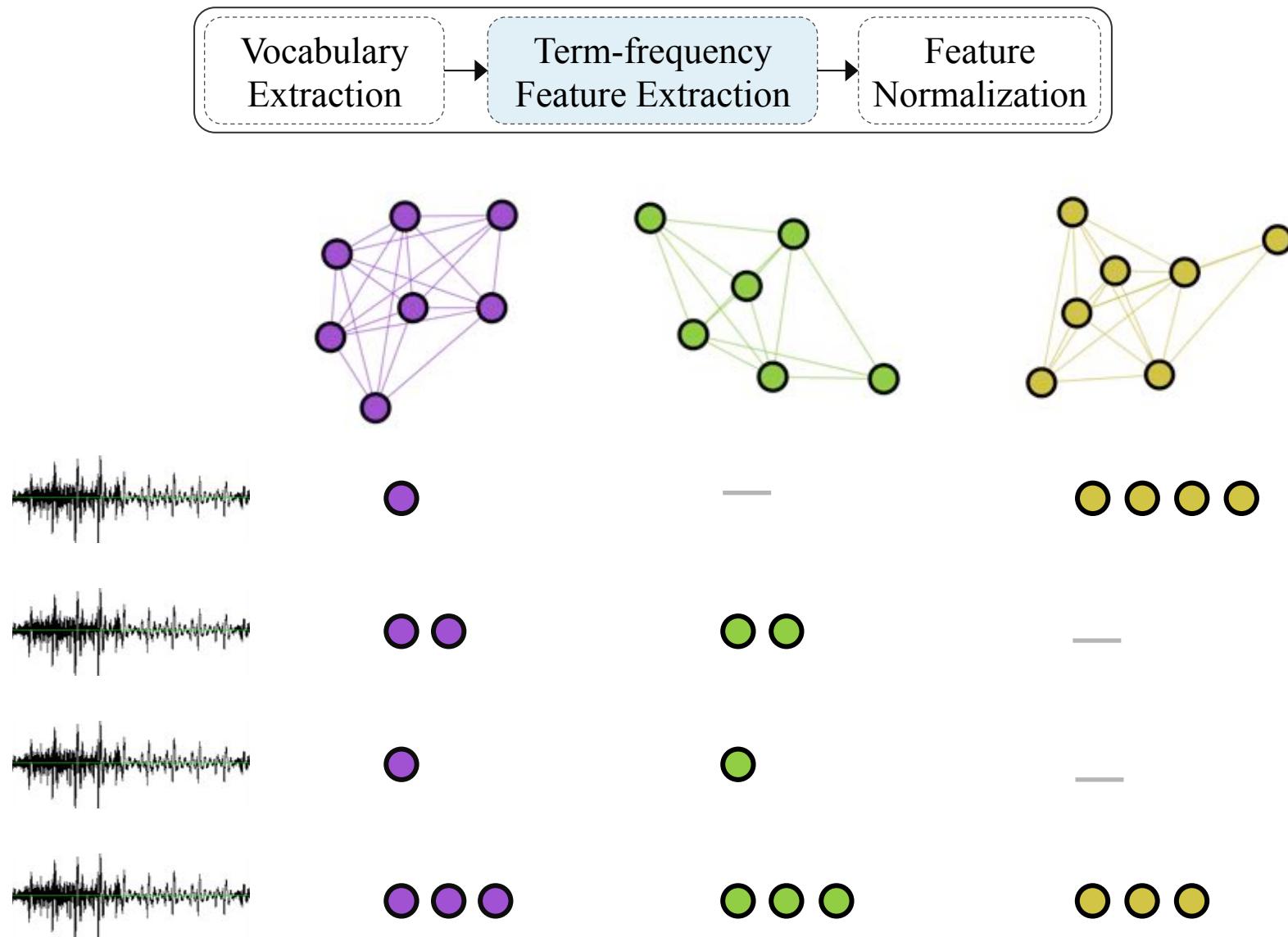
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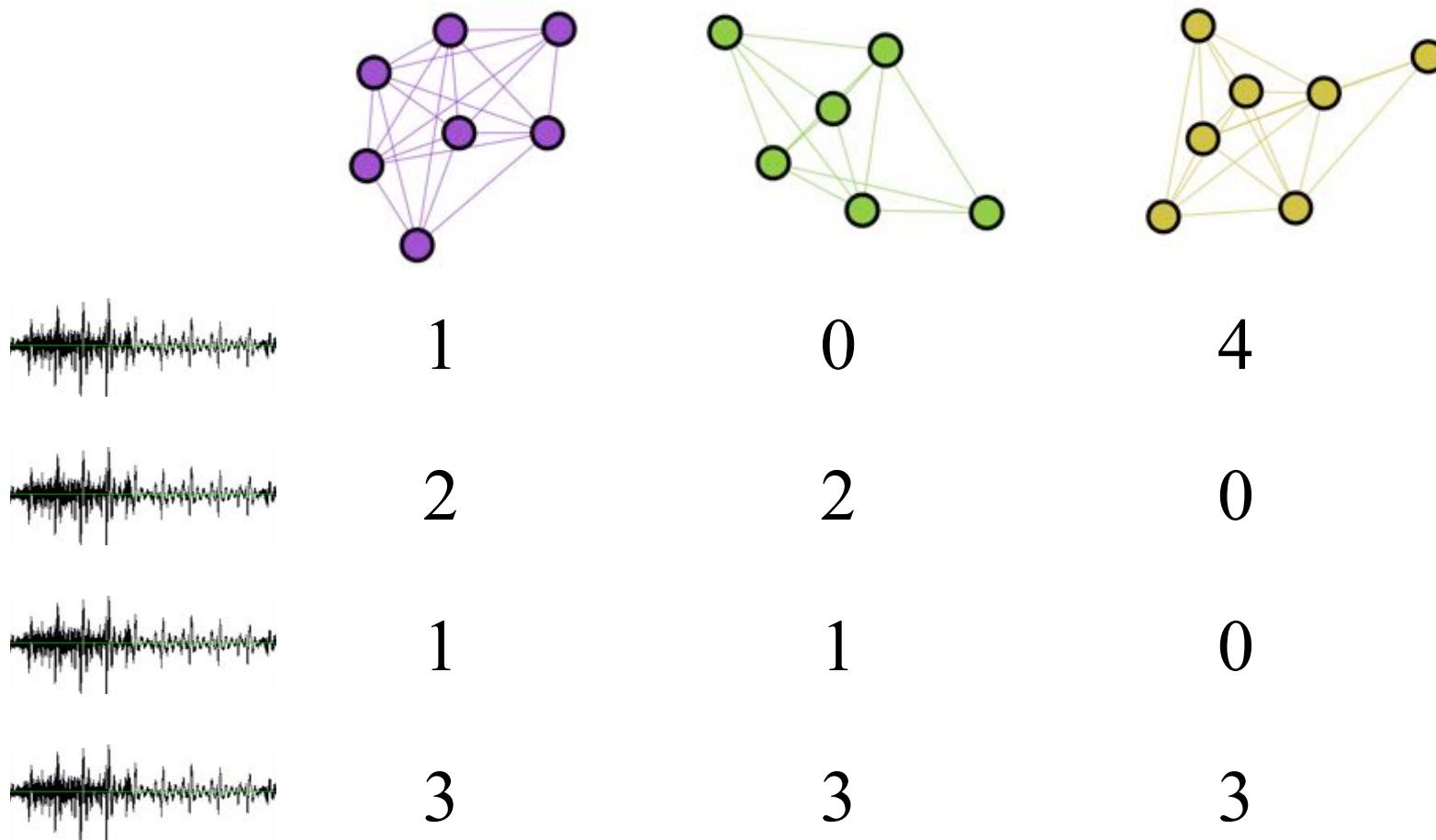
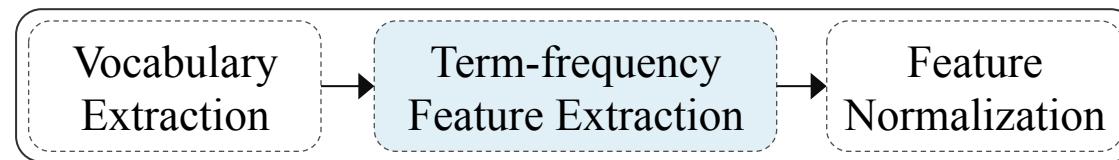
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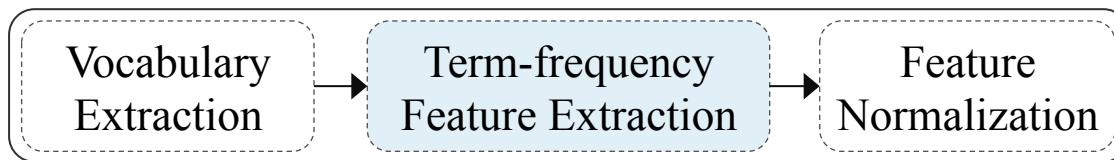
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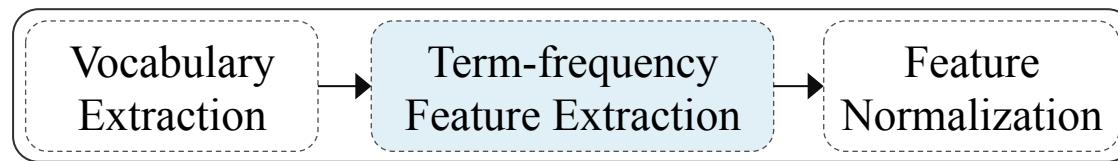
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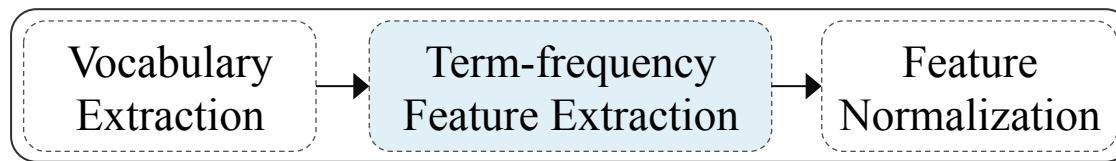


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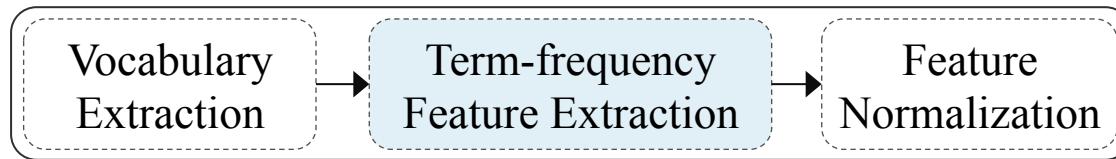
$$\rightarrow F_1(p, r) = \begin{cases} 1, & \text{if } f(p, r) > 0 \\ 0, & \text{otherwise} \end{cases}$$

Proposed Approach: Feature Extraction



- $F_1(p, r) = \begin{cases} 1, & \text{if } f(p, r) > 0 \\ 0, & \text{otherwise} \end{cases}$
- $F_2(p, r) = f(p, r)$

Proposed Approach: Feature Extraction



$$\Rightarrow F_1(p, r) = \begin{cases} 1, & \text{if } f(p, r) > 0 \\ 0, & \text{otherwise} \end{cases}$$

$$\Rightarrow F_2(p, r) = f(p, r)$$

$$\Rightarrow F_3(p, r) = f(p, r) \times \text{irf}(p, R)$$

$$\text{irf}(p, R) = \log \left(\frac{N}{|\{r \in R : p \in r\}|} \right)$$

Evaluation: Music Collection



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- Corpus: CompMusic Carnatic music
 - Commercial released music (~325) CDs
 - Metadata available in Musicbrainz



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- Datasets: subsets of corpus
 - DB40rāga
 - 480 audio recordings, 124 hours of music
 - 40 diverse set of rāgas
 - 310 compositions, 62 unique artists
 - DB10rāga
 - 10 rāga subset of DB40rāga



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<http://compmusic.upf.edu/node/278>

Evaluation: Classification methodology

□ Experimental setup

- Stratified 12-fold cross validation (balanced)
- Repeat experiment 20 times
- Evaluation measure: mean classification accuracy

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- Repeat experiment 20 times
- Evaluation measure: mean classification accuracy

□ Classifiers

- Multinomial, Gaussian and Bernoulli naive Bayes (NBM, NBG and NBB)
- SVM with a linear and RBF-kernel, and with a SGD learning (SVML, SVMR and SGD)
- logistic regression (LR) and random forest (RF)

Evaluation: Classification methodology

□ Statistical significance

- Mann-Whitney U test ($p < 0.01$)
- Multiple comparisons: Holm Bonferroni method

- H. B. Mann and D. R. Whitney, “On a test of whether one of two random variables is stochastically larger than the other,” *The annals of mathematical statistics*, vol. 18, no. 1, pp. 50–60, 1947.
- S. Holm, “A simple sequentially rejective multiple test procedure,” *Scandinavian journal of statistics*, vol. 6, no. 2, pp. 65–70, 1979.

Evaluation: Classification methodology

□ Statistical significance

- Mann-Whitney U test ($p < 0.01$)
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□ Comparison with the state-of-the-art

- S_1 : Pitch-class-distribution (PCD)-based method (PCD₁₂₀, PCD_{full})
- S_2 : Parameterized (PCD)-based method (PCD_{param})

- H. B. Mann and D. R. Whitney, “On a test of whether one of two random variables is stochastically larger than the other,” *The annals of mathematical statistics*, vol. 18, no. 1, pp. 50–60, 1947.
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Results

db	Mtd	Ftr	NBM	NBB	LR	SVML	1NN
DB10rāga	M	F_1	90.6	74	84.1	81.2	-
		F_2	91.7	73.8	84.8	81.2	-
		F_3	90.5	74.5	84.3	80.7	-
	S_1	PCD_{120}	-	-	-	-	82.2
		PCD_{full}	-	-	-	-	89.5
	S_2	PD_{param}	37.9	11.2	70.1	65.7	-
DB40rāga	M	F_1	69.6	61.3	55.9	54.6	-
		F_2	69.6	61.7	55.7	54.3	-
		F_3	69.5	61.5	55.9	54.5	-
	S_1	PCD_{120}	-	-	-	-	66.4
		PCD_{full}	-	-	-	-	74.1
	S_2	PD_{param}	20.8	2.6	51.4	44.2	-

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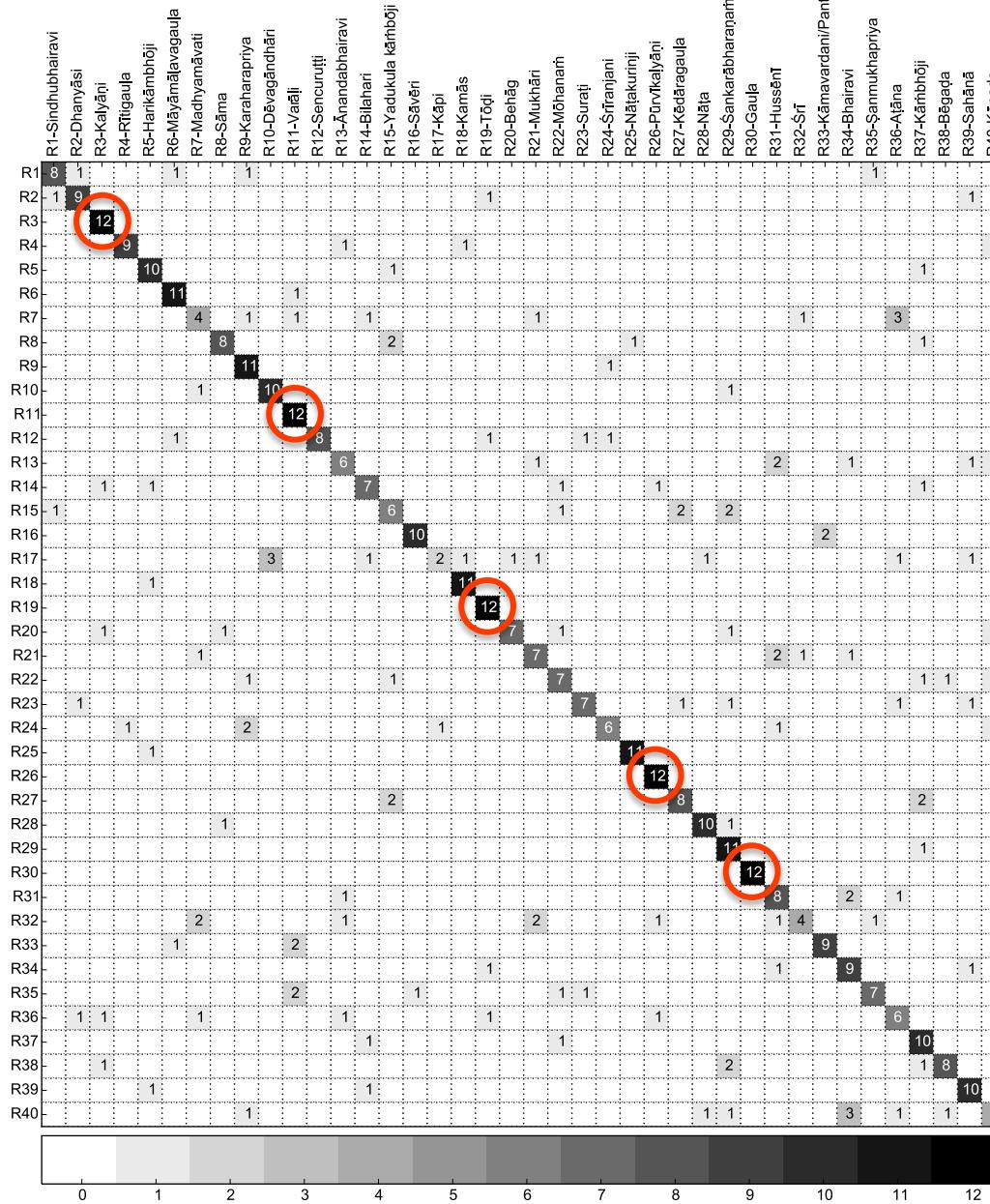
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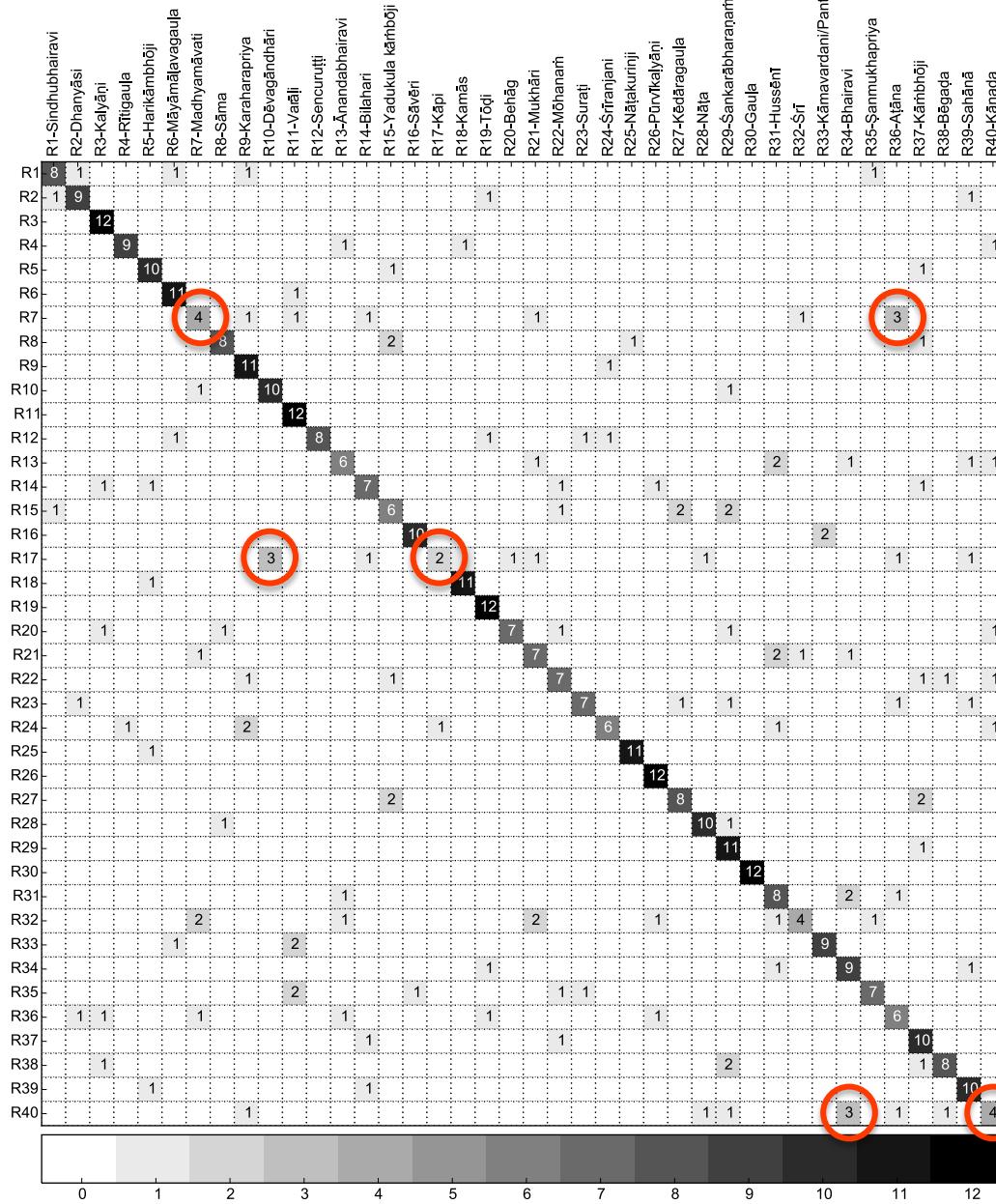
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	S_1	PCD_{120}	-	-	-	-	66.4
		PCD_{full}	-	-	-	-	74.1
	S_2	PD_{param}	20.8	2.6	51.4	44.2	-

Error Analysis



Kalyāṇi
Varāli
Tōdi
Pūrvikalyāṇi

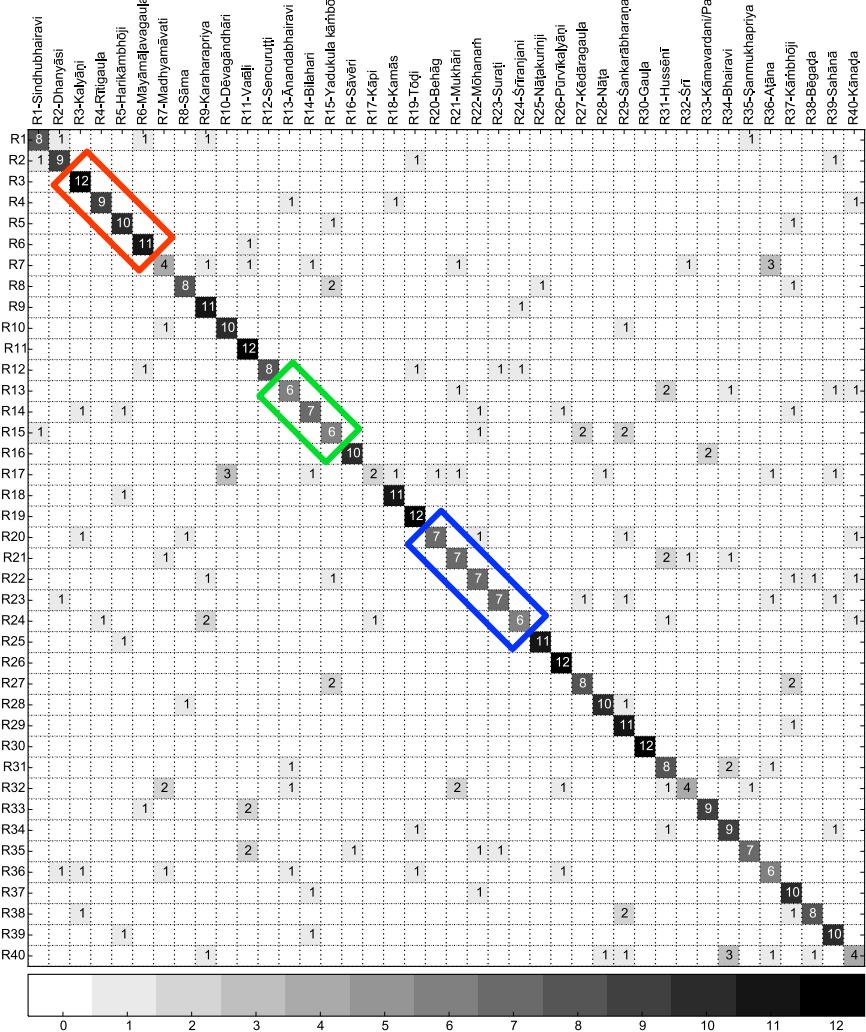
Error Analysis



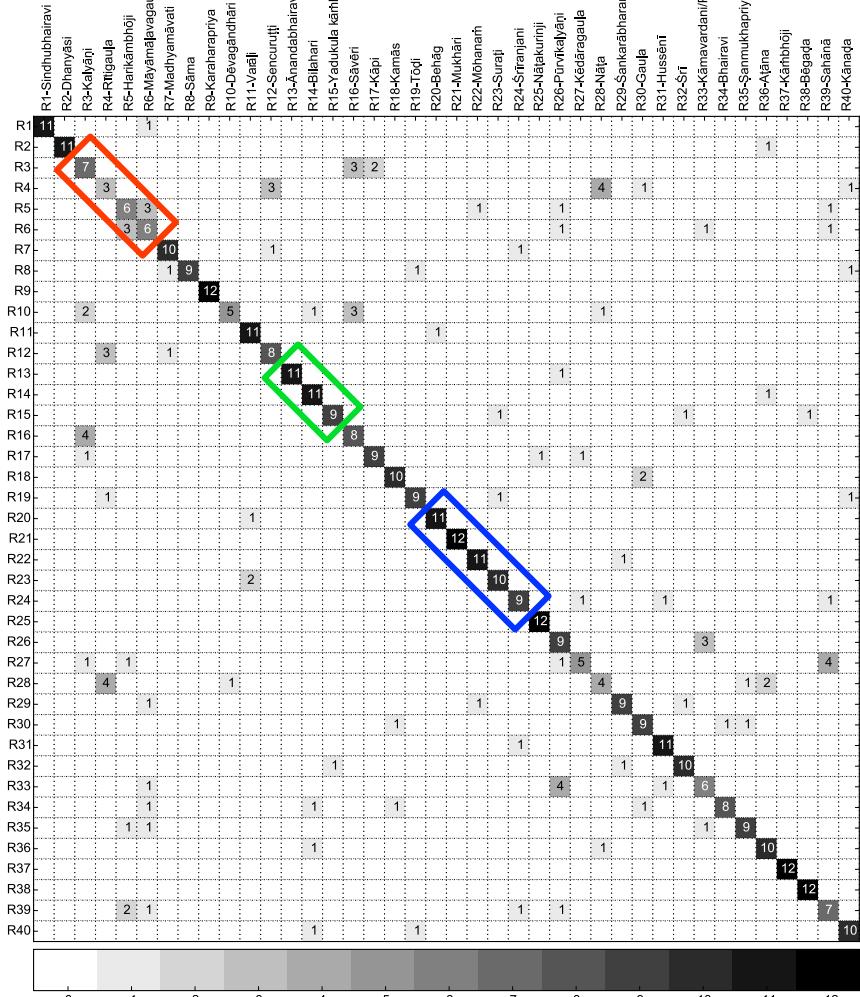
Allied rāgas

Error Analysis: complementary with S_1

$M(F_1)$



$S_1 (PCD_{full})$



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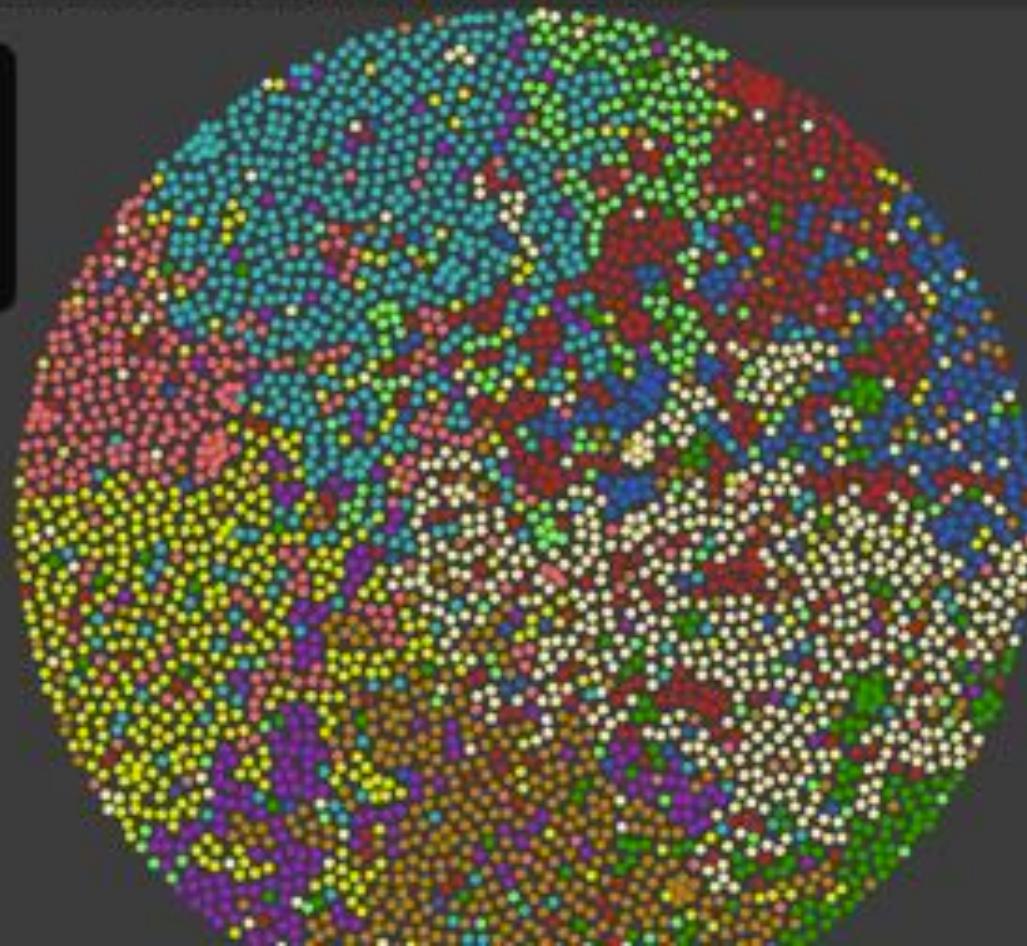
Resources

- Rāga dataset:
 - <http://compmusic.upf.edu/node/278>
- Demo:
 - http://dunya.compmusic.upf.edu/pattern_network/
- CompMusic:
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- Related datasets:
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Resources

■ Rāga dataset:

Nodes: 40747
Title: Yehudi Naggar
Converted: December, 2009
Artist: Ananda Murali
Raga: Mard
Tuning: 100 Hz ►
Start-time: 17 s
End-time: 21 s



- <http://compmusic.upf.edu/datasets>

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Phrase-based Rāga Recognition using Vector Space Modeling

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