# CompMusic Workshop II: Motivic Analysis and its Relevance to Raga Identity in Carnatic Music

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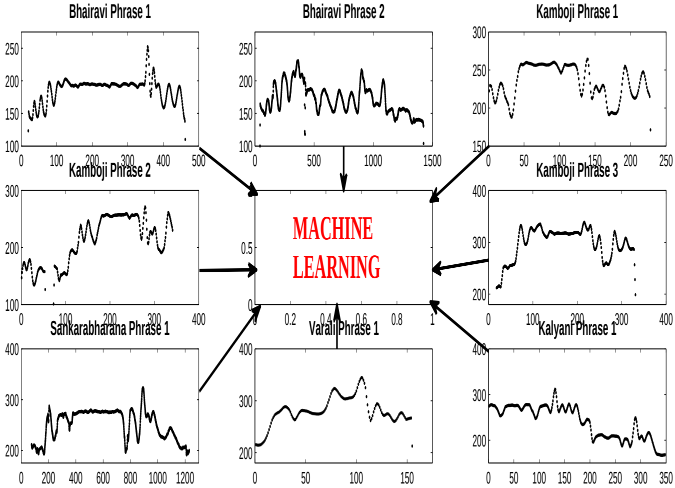
# Outline

# Introduction

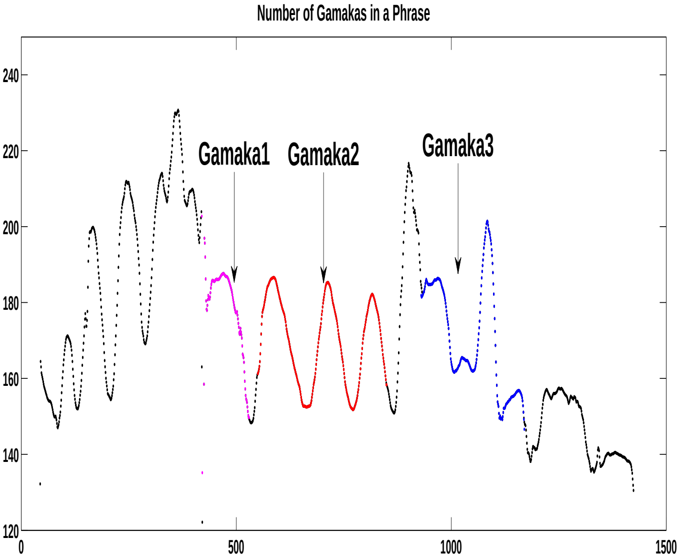
- Necessity of Motivic Analysis



# Database

- A Database of 1 TeraByte of Carnatic Music Concerts was mined.
- Occurrences of 35 rAgas in the database were monitored.
- The rAgas chosen for analysis being:
  - tOdi - 1797 occurrences.
  - kalyAni - 1712 occurrences.
  - kAmbOji - 1622 occurrences.
  - bhairavI - 1384 occurrences.
  - sankarAbharanA - 1206 occurrences.
  - varALi - 483 occurrences.
- rAgas across various artists, male and female, and instrumental were chosen for analysis.
- tOdi being a complex rAga, has scope for analysis of its own, and hence, has been excluded from this set.
- Tha AlApanA section of the piece in that rAga was used for labelling of phrases.

# Attempt to quantize phrases into gamakAs



# The Next Step : Labelling Motifs

- rAgas and characteristic motifs.
- These characteristic phrases were identified by a professional musician.
- Table below shows the number of phrases labelled for each rAga with the number of instances of each phrase across the phrases.

| rAga Name | Phrases labelled | Instances | Artists |
|---|---|---|---|
| bhairavI | 10 | 205 | 20 |
| kalyAni | 9 | 138 | 12 |
| kAmbOji | 30 | 343 | 20 |
| sankarAbharanA | 10 | 366 | 20 |
| varALi | 5 | 144 | 5 |

Table : Total number of phrases

- Number of phrases, as seen above, are more. However, number of occurrences are meagre.
- Machine learning algorithms require a substantial number of occurrences for training and testing of a single phrase.
- Based on number of occurrences, the following phrases were chosen for building models.

| rAga | Phrases | Instances |
|---|---|---|
| bhairavI | Phrase 1 | 52 |
| | Phrase 2 | 70 |
| kalyAni | Phrase 1 | 52 |
| kAmbOji | Phrase 1 | 104 |
| | Phrase 2 | 49 |
| | Phrase 3 | 45 |
| sankarAbharanA | Phrase 1 | 81 |
| | Phrase 2 | 51 |
| | Phrase 3 | 101 |
| varALi | Phrase 1 | 52 |

Table : Phrases for Modelling

## Motif from Signal Procesing Perspective

- Motifs can be thought of as signature prosodic phrases.
- Different rAgas may be composed of the same set of notes, or even phrases, but the prosody may be completely different.
- Prosodic modifications include :
  - Increasing/decreasing the duration of notes.
  - Using an appropriate intonation pattern by employing gamakas.
  - Modulating the energy.
- Thus a Motif is a ”Prosodic Phrasing of a Sequence of Notes”.

# Pitch Contours of Motifs Labelled in bhairavI and sankarAbharanA

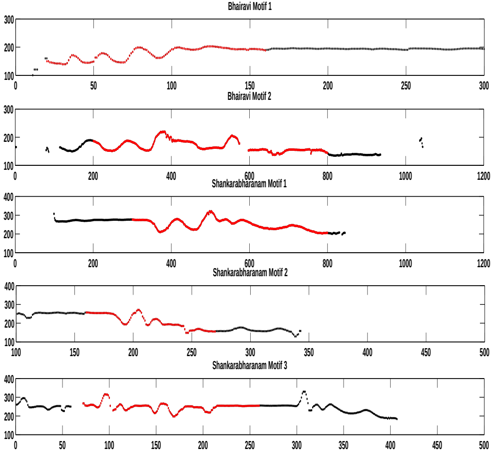



Figure : Motifs of bhairavI, sankarAbharanA

# Pitch Contours of Motifs Labelled in kAmbOji, kalyAni and varALi

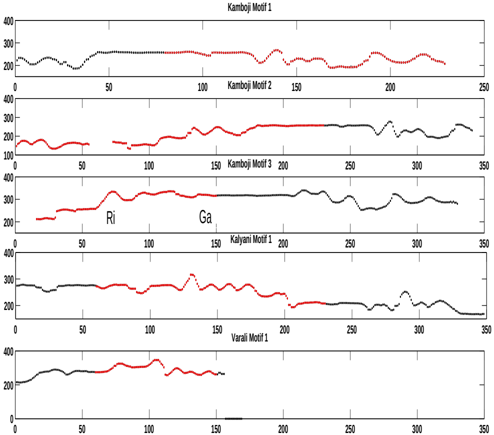



Figure : Motifs of kAmbOji, kalyAni and varALi

# DYNAMIC TIME WARPING

- DTW gives almost accurate for continuous feature vectors.
- DTW also gives good distance measures if the query and reference are similar looking.

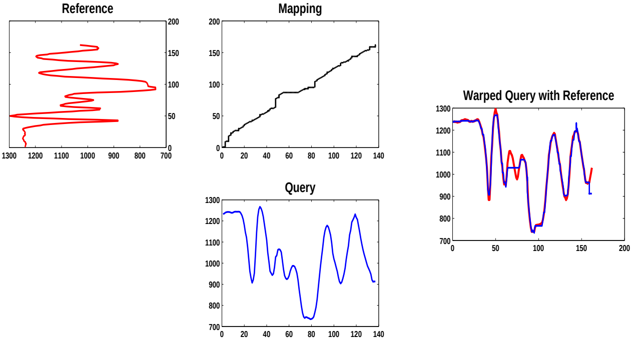



Figure : DTW

# DTW ON PITCH CONTOUR

- Various musicians sing the same phrases with substantial variations.
- This results in dissimilarities in reference and query vectors.
- Feature Vectors for the phrases are discontinuous in many cases.
- Hence DTW gives distorted distance measures for such cases.

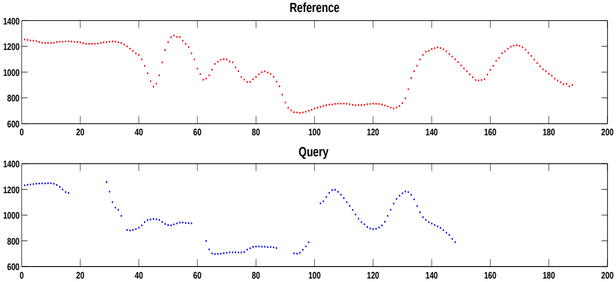



Figure : Dissimilar Contours

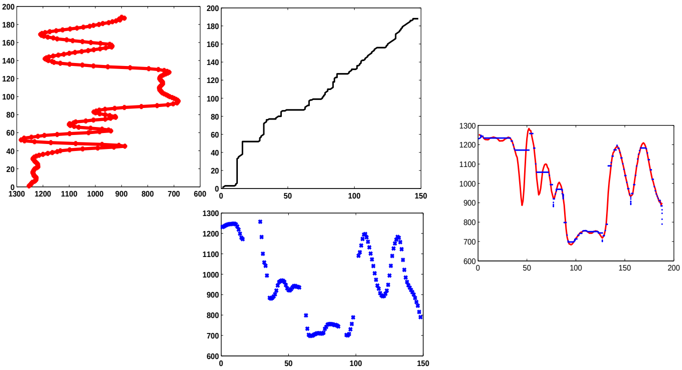
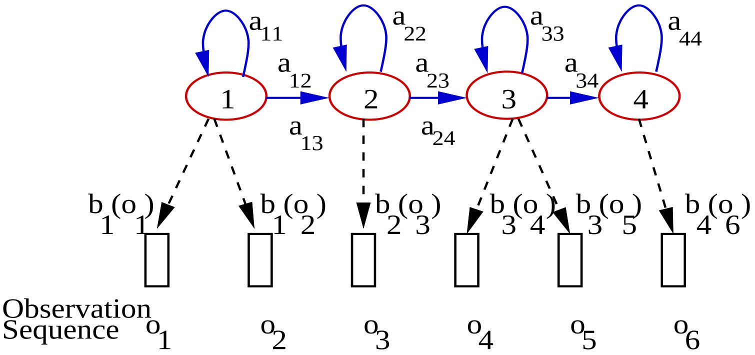


Figure : Distorted DTW measure

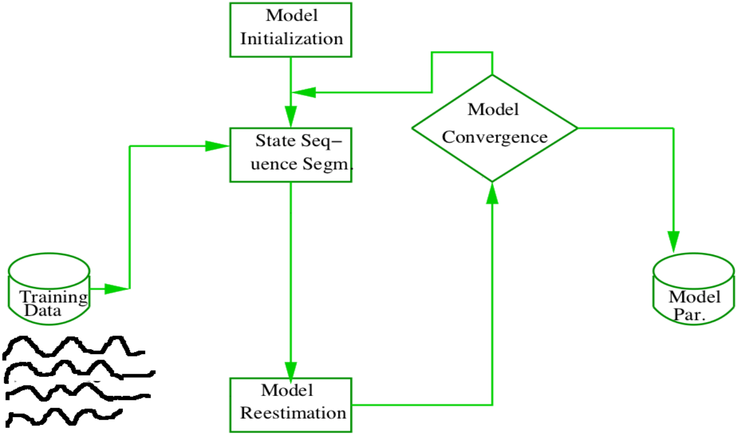
# Markov Model for Music



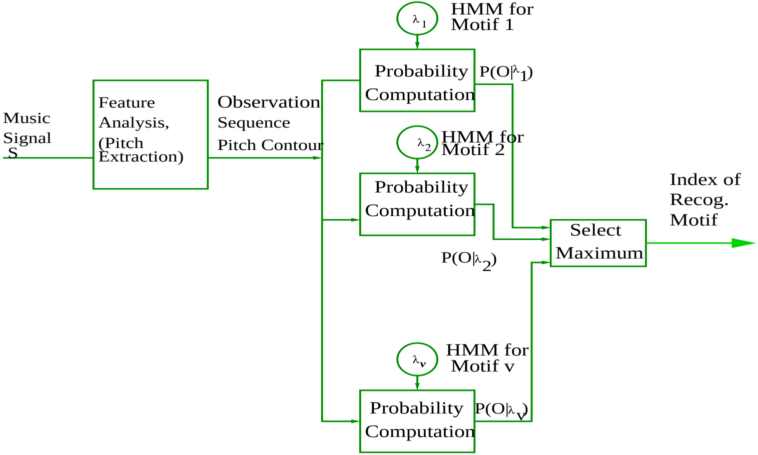

$a_{ij} = 0, \quad j < i$

$\pi_\iota = 0, \ \iota \neq 1$
$\pi_\iota = 1, \ \iota = 1$

# Building of Models - Training

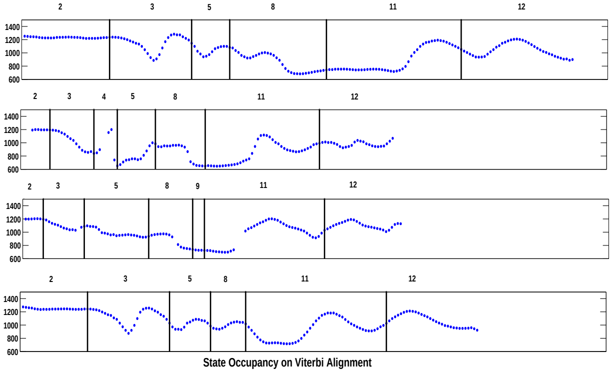


# Testing


HMM for Motif 1
HMM for Motif 2
HMM for Motif v
Music Signal S
Feature Analysis, (Pitch Extraction)
Observation Sequence
Pitch Contour
Probability Computation
P(O|λ1)
Probability Computation
P(O|λ2)
Probability Computation
P(O|λv)
Select Maximum
Index of Recog. Motif

# CONTINUOUS DENSITY HMM'S FOR MODELING MOTIFS

- HMM's were chosen for Modenling Motifs to accommodate Prosody of the Motif.
- Number of notes in the Motif determined the HMM Structure.
- The Number of States determined based on the changes obsereved in the pitch contour.
- Two Mixtures used for each State.



# MOTIF RECOGNITION RESULTS

- A total of 10 motifs were experimented with.
  - 2 Motifs for Bhairavi
  - 3 Motifs for Shankarabharanam
  - 3 Motifs for Kamboji
  - 1 Motif for Kalyani
  - 1 Motif for Varali
- The table below gives the confusion matrix for Motif Recognition

| rAga | bh1 | bh2 | ky1 | kb1 | kb2 | kb3 | sk1 | sk2 | sk3 | va1 |
|---|---|---|---|---|---|---|---|---|---|---|
| bh1 | **40** | 2 | 1 | 0 | 0 | 6 | 0 | 0 | 0 | 3 |
| bh2 | 0 | **61** | 4 | 1 | 4 | 1 | 1 | 0 | 0 | 0 |
| ky1 | 0 | 1 | **23** | 10 | 0 | 0 | 11 | 2 | 5 | 0 |
| kb1 | 0 | 0 | 3 | **91** | 0 | 0 | 6 | 3 | 1 | 0 |
| kb2 | 0 | 0 | 1 | 2 | **44** | 0 | 0 | 0 | 1 | 0 |
| kb3 | 0 | 0 | 2 | 1 | 0 | **41** | 0 | 0 | 0 | 0 |
| sk1 | 0 | 2 | 18 | 13 | 3 | 0 | **28** | 7 | 9 | 0 |
| sk2 | 0 | 0 | 7 | 0 | 1 | 0 | 4 | **34** | 2 | 4 |
| sk3 | 0 | 1 | 23 | 25 | 1 | 0 | 29 | 5 | **10** | 2 |
| va1 | 3 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | **48** |

Table : Confusion matrix for motif recognition using HMMs(bh – bhairavi, ky – Kalyani, kb – Kamboji, sk – Sankarabharana, va – Varali)

# PHRASE SPOTTING

- J.Rose et al. illustrate a method to spot motifs in a Bandish using percussive cues from the Tabla. [1]
- The phrase most probably lies in one intonation unit or breath group.
- AlApanAs have to be split into these intonation units or breath groups.

[1] J.Rose and P. Rao, Detecting melodic motifs from audio for hindustani classic music, in International Society for Music Information Retrieval Conference, Portugal, October 2012.

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