Knowledge-based Probabilistic Modeling for Tracking Lyrics in Music Audio Signals

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Acknowledgements

Knowledge-based **Probabilistic Modeling** for Tracking Lyrics in Music Audio Signals

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- Modeling - different computational models
- Probabilistic - can handle the temporal variability of music

Knowledge-based Probabilistic Modeling for **Tracking Lyrics** in Music Audio Signals

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- Tracking the progression of sung lyrics in time
- For automatic alignment between written lyrics and audio

Knowledge-based Probabilistic Modeling for Tracking Lyrics in Music Audio Signals

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- Take advantage of knowledge of simultaneous music events

Knowledge-based Probabilistic Modeling for Tracking Lyrics in **Music Audio Signals**

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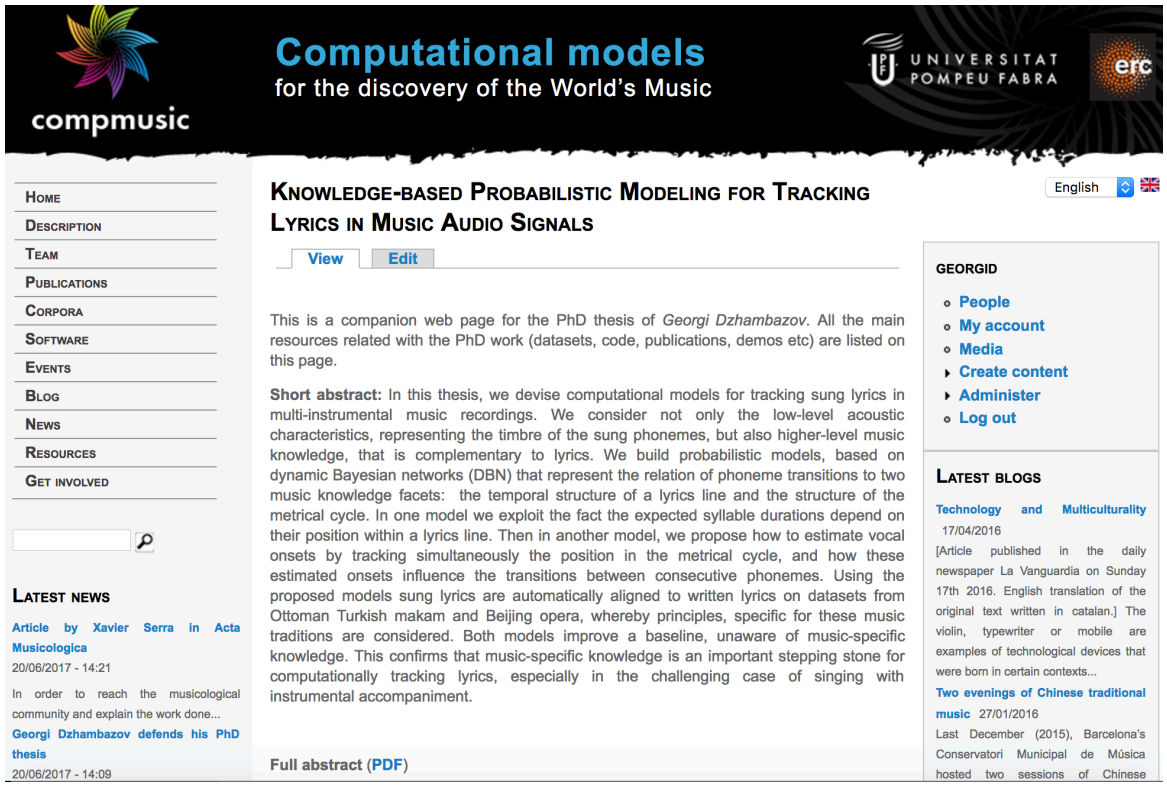
- Recordings of music

Additionally…

- Emphasis on reproducible and open research
- Code – Open source, Data: publicly available



http://compmusic.upf.edu/phd-thesis-georgi

Outline

compmusic

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- Setting the stage
  - Introduction (Chapter 1)
  - Background (Chapter 2)
  - Baseline lyrics-to-audio alignment (Chapter 3)

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- Conclusion (Chapter 6) and Applications (Appendix)

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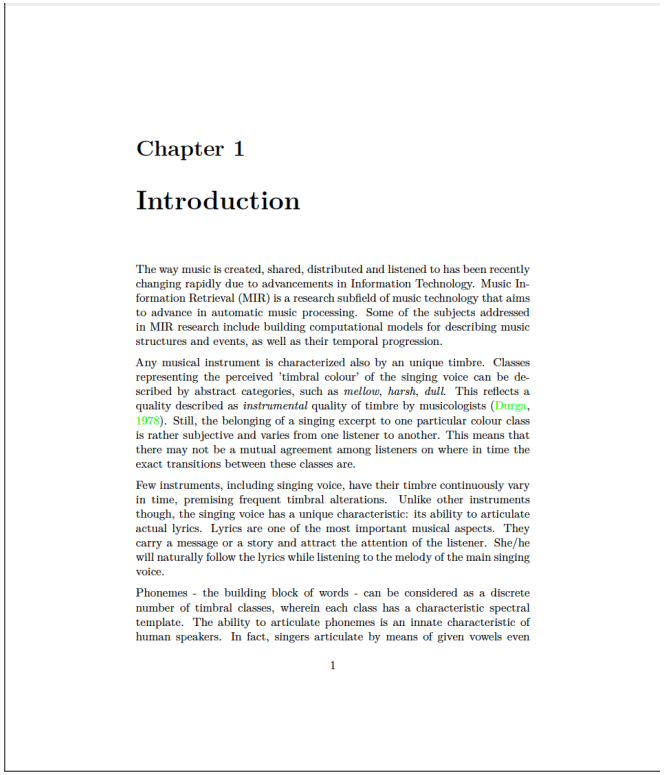
Chapter 1
Introduction



Chapter 1

Introduction

The way music is created, shared, distributed and listened to has been recently changing rapidly due to advancements in Information Technology. Music Information Retrieval (MIR) is a research subfield of music technology that aims to advance in automatic music processing. Some of the subjects addressed in MIR research include building computational models for describing music structures and events, as well as their temporal progression.

Any musical instrument is characterized also by an unique timbre. Classes representing the perceived 'timbral colour' of the singing voice can be described by abstract categories, such as *mellow*, *harsh*, *dull*. This reflects a quality described as *instrumental* quality of timbre by musicologists (Durga, 1978). Still, the belonging of a singing excerpt to one particular colour class is rather subjective and varies from one listener to another. This means that there may not be a mutual agreement among listeners on where in time the exact transitions between these classes are.

Few instruments, including singing voice, have their timbre continuously vary in time, premising frequent timbral alterations. Unlike other instruments though, the singing voice has a unique characteristic: its ability to articulate actual lyrics. Lyrics are one of the most important musical aspects. They carry a message or a story and attract the attention of the listener. She/he will naturally follow the lyrics while listening to the melody of the main singing voice.

Phonemes - the building block of words - can be considered as a discrete number of timbral classes, wherein each class has a characteristic spectral template. The ability to articulate phonemes is an innate characteristic of human speakers. In fact, singers articulate by means of given vowels even

1

Research objectives

- Creation of computational models for tracking lyrics
- Considering music-specific knowledge
  - for a specific music tradition with its music principles
- Application to music with predominant singing voice
- Evaluation of the models on an end task - lyrics-to-audio alignment
  - contribution of music knowledge compared to baseline
  - perfect alignment not an end goal

Scientific context

- Singing voice has unique ability - to articulate actual words

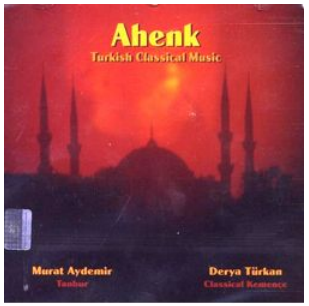
- Various works on singing voice (Goto, 2014)
  - little work on sung lyrics
  - almost no work on sung lyrics with music-specific knowledge

Project context – CompMusic

- Music-tradition aware Music Information Retrieval (MIR)

Hindustani

Carnatic



Ottoman Turkish makam

Arab-Andalusian

Beijing Opera

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Project context – CompMusic

- Music-tradition aware Music Information Retrieval (MIR)
- Vocal-centered traditions

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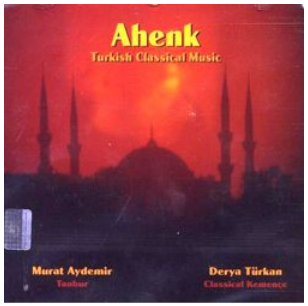

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Project context – CompMusic

- Music-tradition aware Music Information Retrieval (MIR)
- Vocal-centered traditions
- Well-grounded music principles

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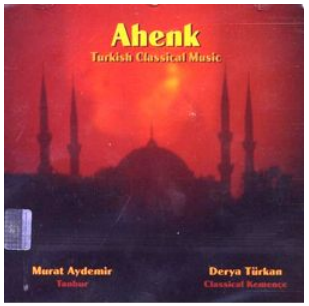

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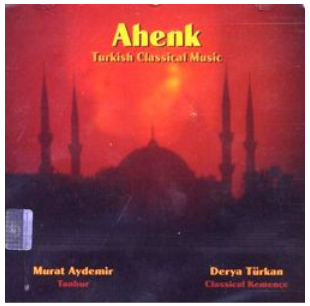

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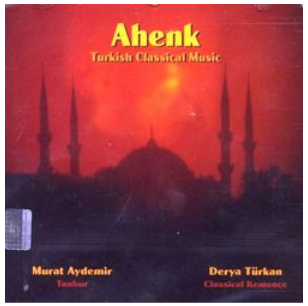
Project context – CompMusic

Ottoman Turkish Makam Music (OTMM)

- has machine-readable music scores
- with significant musicological literature
- OTMM seemed fairly familiar to me



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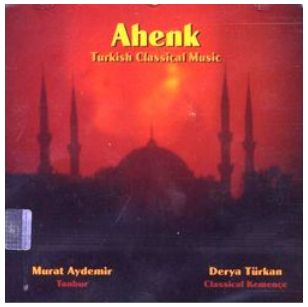
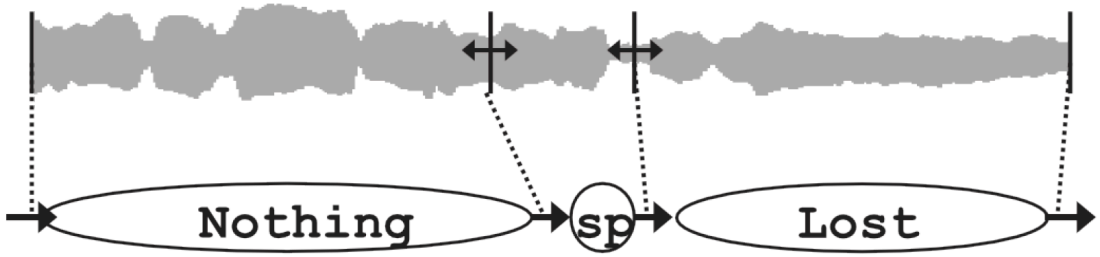


Beijing opera (jingju)

- challenging language
- difference between interpretations and music score

Lyrics-to-audio alignment

- Goal: Automatic synchronisation between an audio recording and its written lyrics: phrases/words/ syllables



- State of the art approach: phonetic recognizer adopted from automatic speech recognition

- Applications
  - automatic highlighting of lyrics
  - automatic thumbnail generation
  - lyrics-based navigation

Lyrics-based navigation

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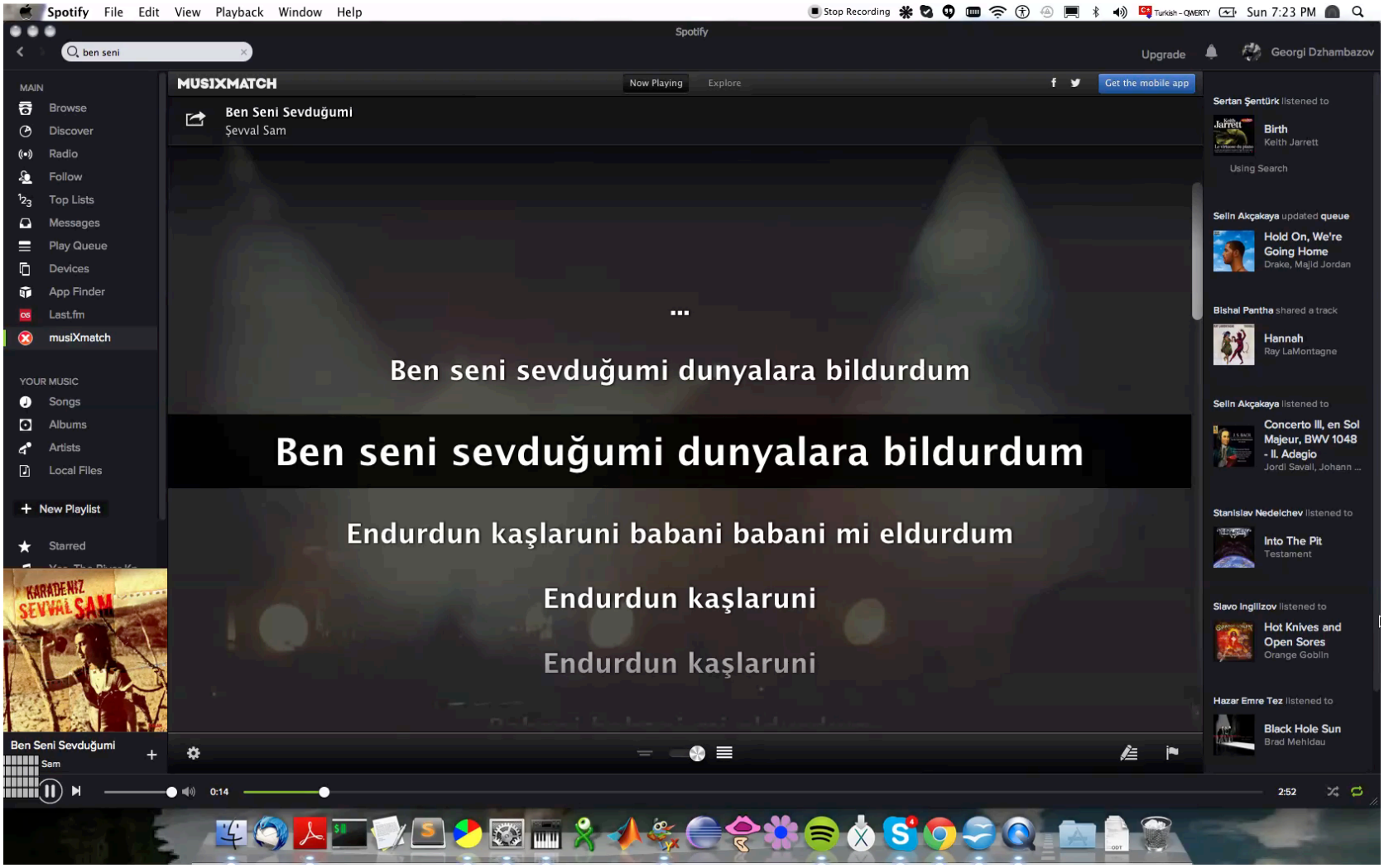

Lyrics-based navigation

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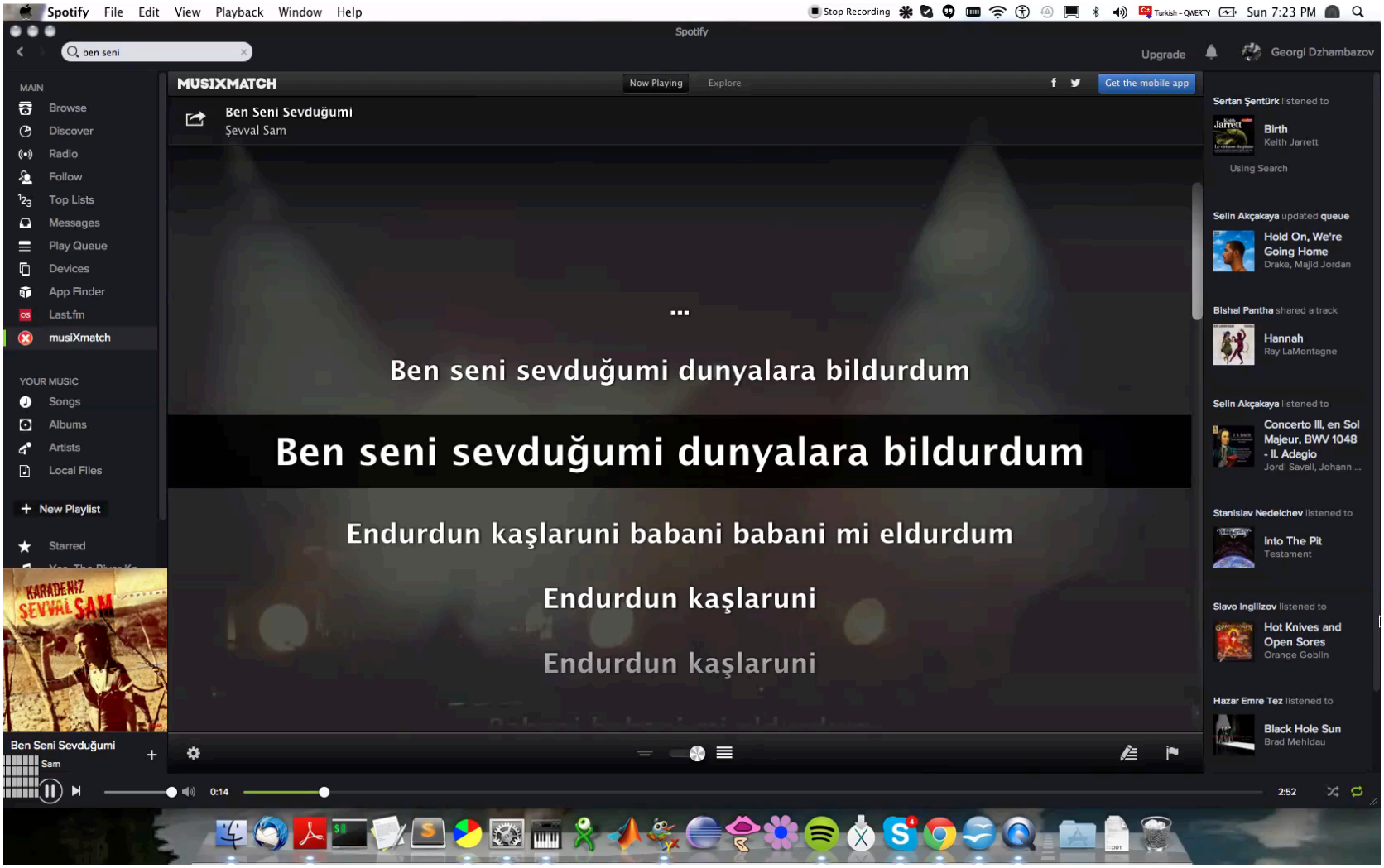

Why consider music knowledge?

- Lyrics structure has granularity
  - verse-chorus-like structure
  - lyrics lines structure
  - metrical structure

```
[Verse 2]

Am              G
Black bandana, sweet Louisiana,
Dm                              Am
Robbin' all the banks in the state of Indiana,
Am                G
 She's a runner, rebel and a stunner,
Dm                              Am
Condemned everywhere sayin, 'baby whatcha gonna'
Am                  G            Dm          Am
  Lookin down the barrel of a hot metal .45,
Am                G         | Dm
  Just another way to survive


[Chorus]

      F         C         Dm
California, Rest In Peace,
 G     F         C   Dm
Simultaneous release,
   G F         C           Dm
California, show your teeth,
       G   F           C          | Dm
She's my priestess, I'm your priest, yeah, yeah
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compmusic

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- Lyrics units are related to music facets
  - chords
  - accents in the melody (Nichols, 2009)
  - musical rhythm and meter

Complementary context

- What is complementary temporal music context?
  - any music facet, occurring simultaneously to sung lyrics
- Different granularity levels

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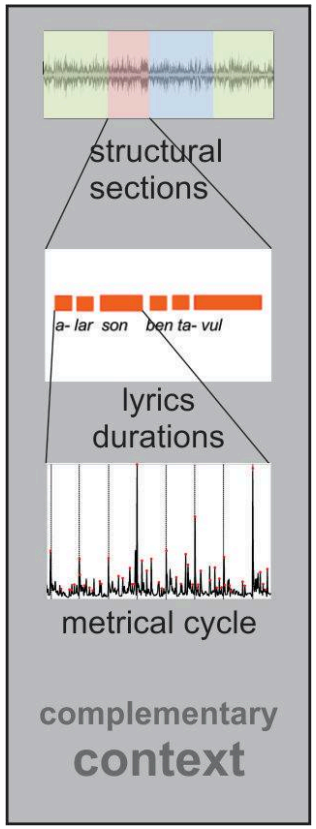

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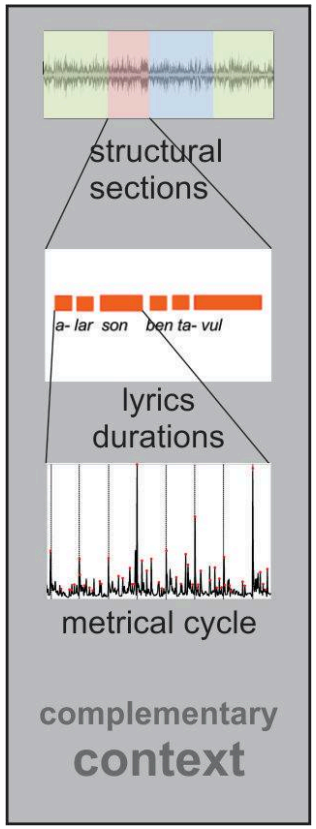
  - any music facet, occurring simultaneously to sung lyrics
- Different granularity levels
  - Coarse level: structure of composition



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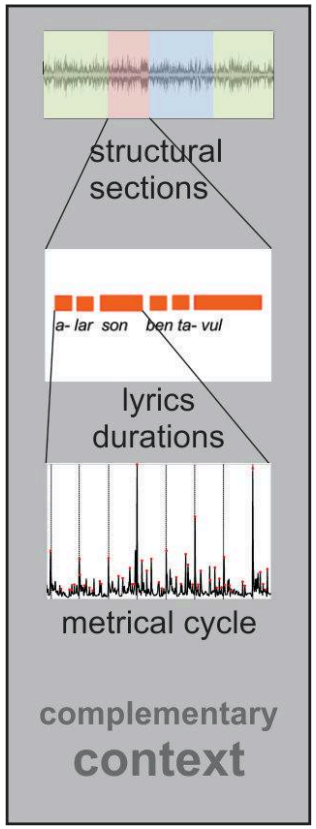
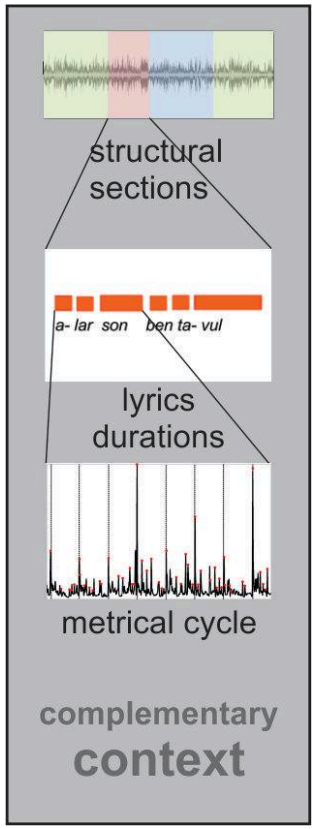


Complementary context

- What is complementary temporal music context?
  - any music facet, occurring simultaneously to sung lyrics
- Different granularity levels
  - Coarse level: structure of composition
  - Middle level: temporal structure of lyrics lines



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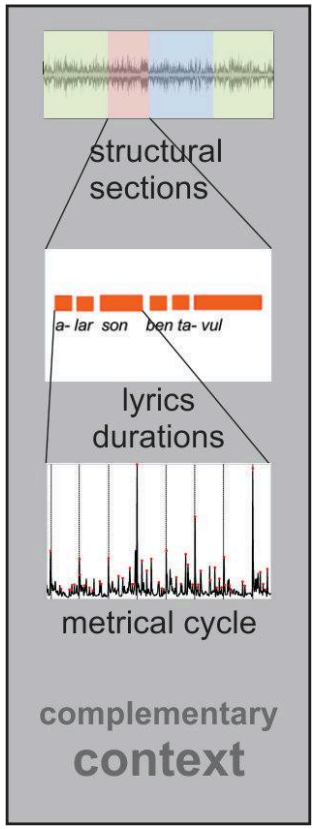
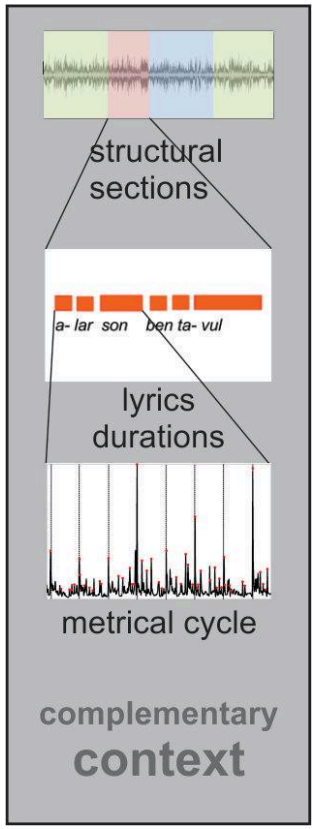


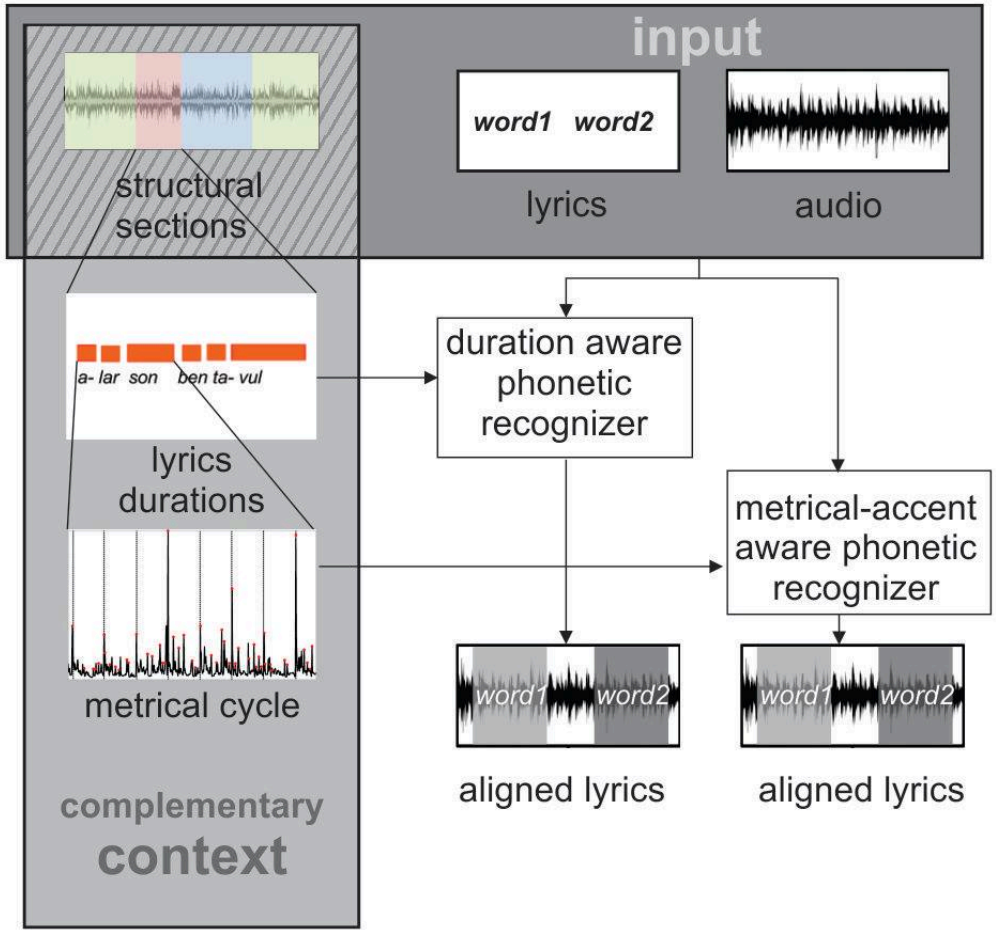
Complementary context

- What is complementary temporal music context?
  - any music facet, occurring simultaneously to sung lyrics
- Different granularity levels
  - Coarse level: structure of composition
  - Middle level: temporal structure of lyrics lines
  - Fine level: structure of metrical cycle



Models overview

- Integrate knowledge from complementary music context into the phonetic recognizer



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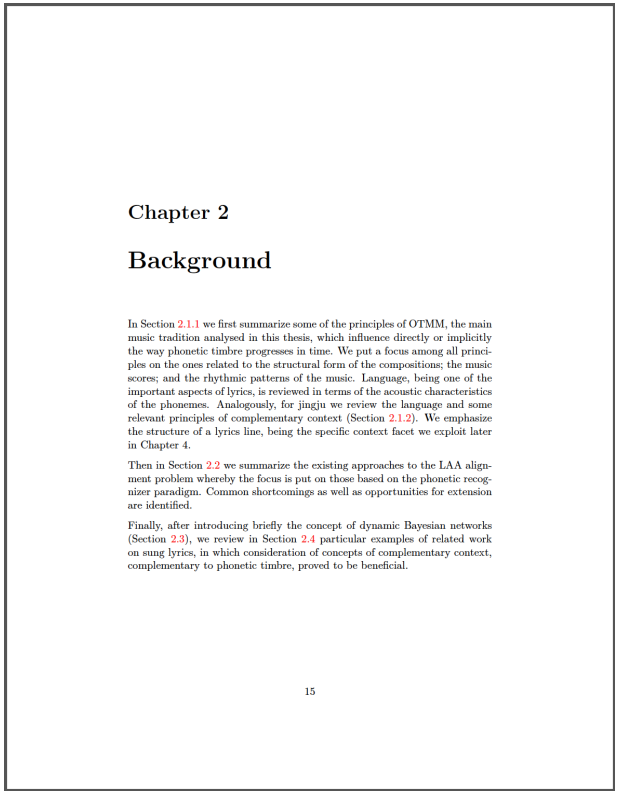
Chapter 2
Background

Review of state of the art phonetic recognizer alignment approaches



Chapter 2

Background

In Section 2.1.1 we first summarize some of the principles of OTMM, the main music tradition analysed in this thesis, which influence directly or implicitly the way phonetic timbre progresses in time. We put a focus among all principles on the ones related to the structural form of the compositions; the music scores; and the rhythmic patterns of the music. Language, being one of the important aspects of lyrics, is reviewed in terms of the acoustic characteristics of the phonemes. Analogously, for jingju we review the language and some relevant principles of complementary context (Section 2.1.2). We emphasize the structure of a lyrics line, being the specific context facet we exploit later in Chapter 4.

Then in Section 2.2 we summarize the existing approaches to the LAA alignment problem whereby the focus is put on those based on the phonetic recognizer paradigm. Common shortcomings as well as opportunities for extension are identified.

Finally, after introducing briefly the concept of dynamic Bayesian networks (Section 2.3), we review in Section 2.4 particular examples of related work on sung lyrics, in which consideration of concepts of complementary context, complementary to phonetic timbre, proved to be beneficial.

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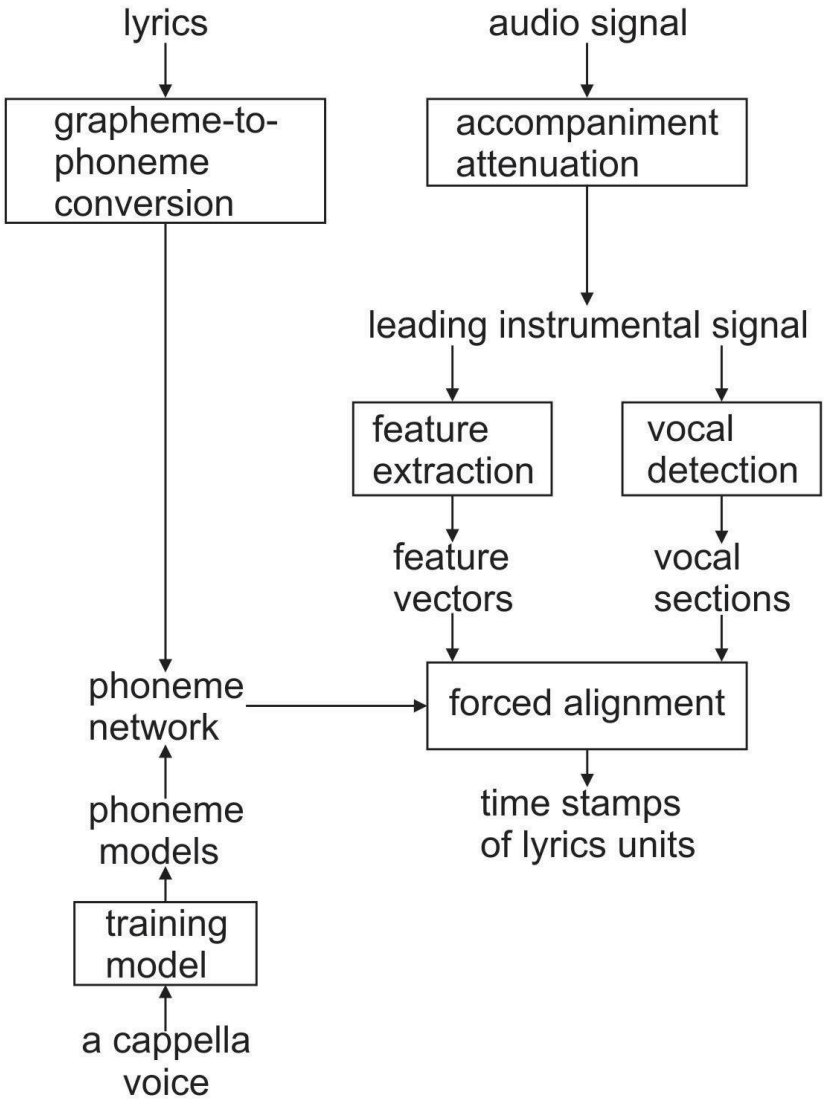
Modules of existing approaches



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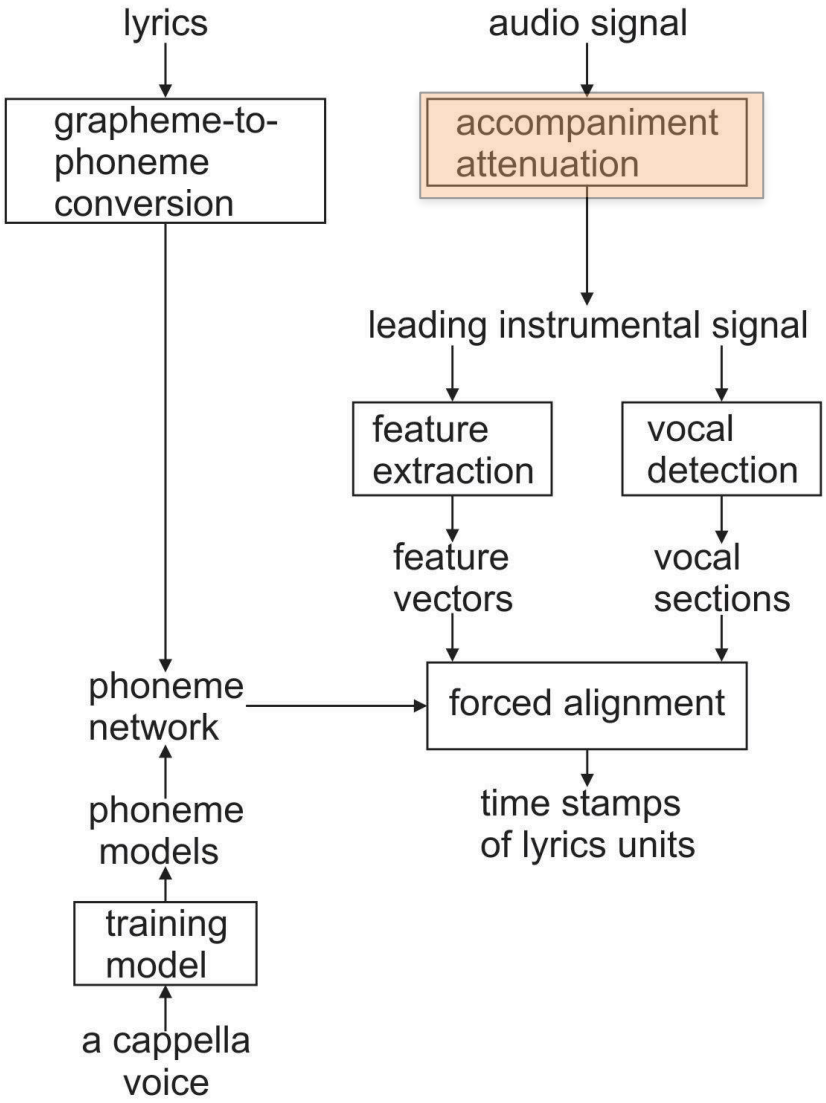

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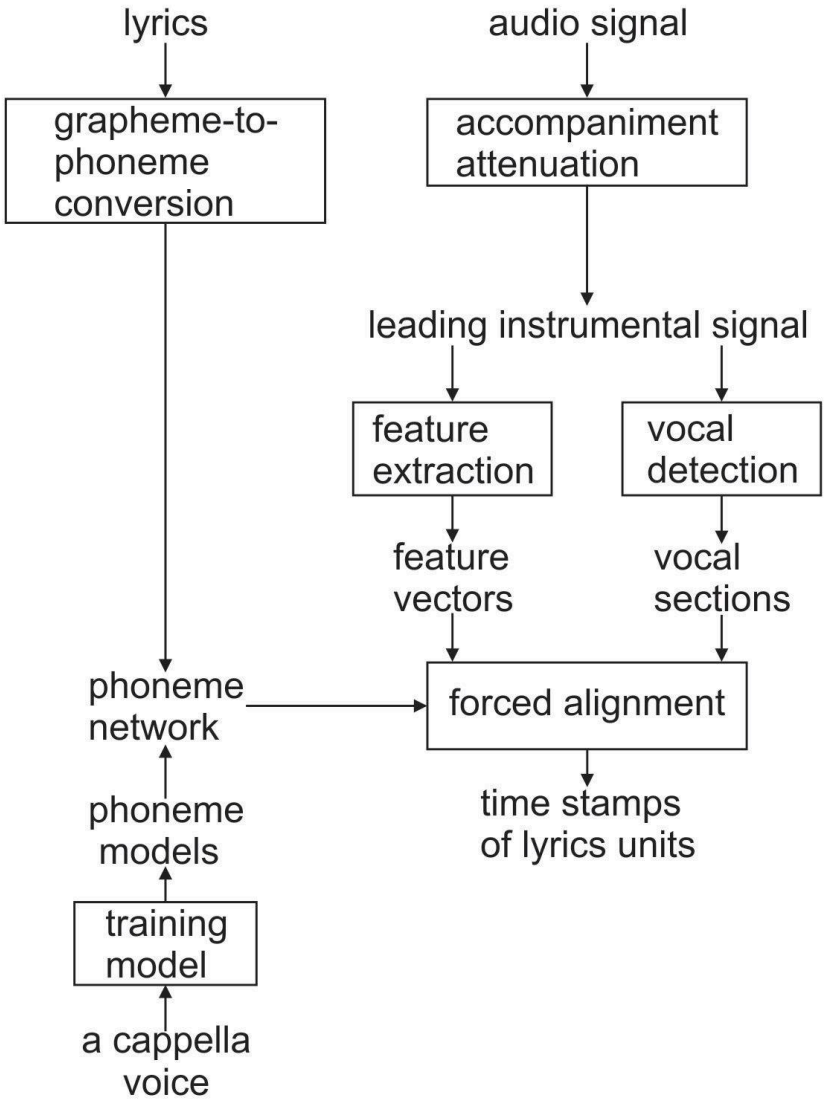

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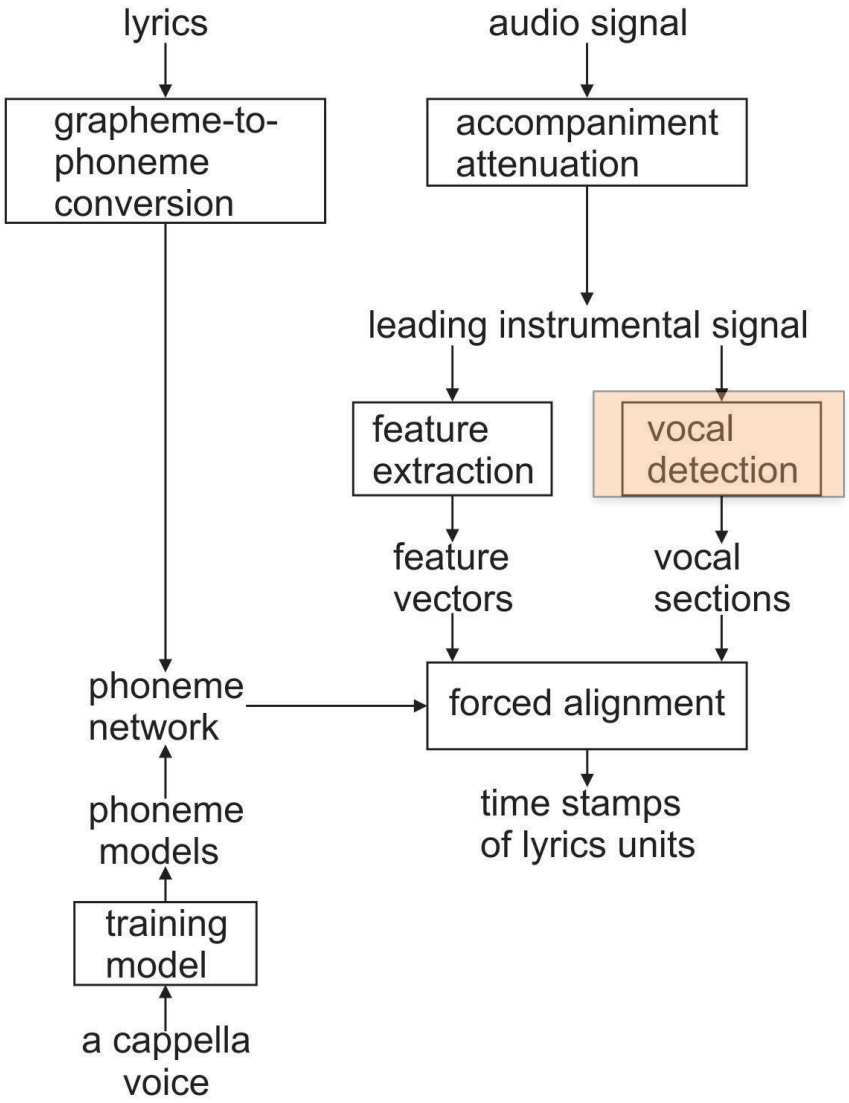

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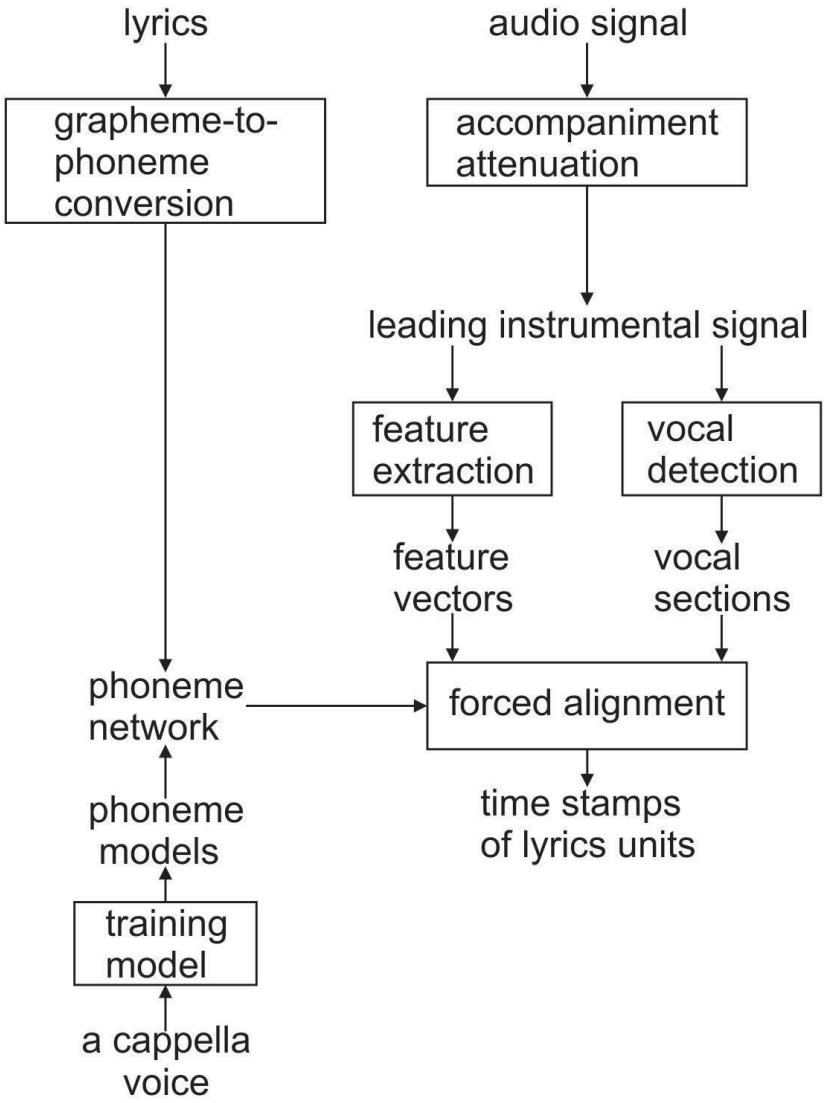

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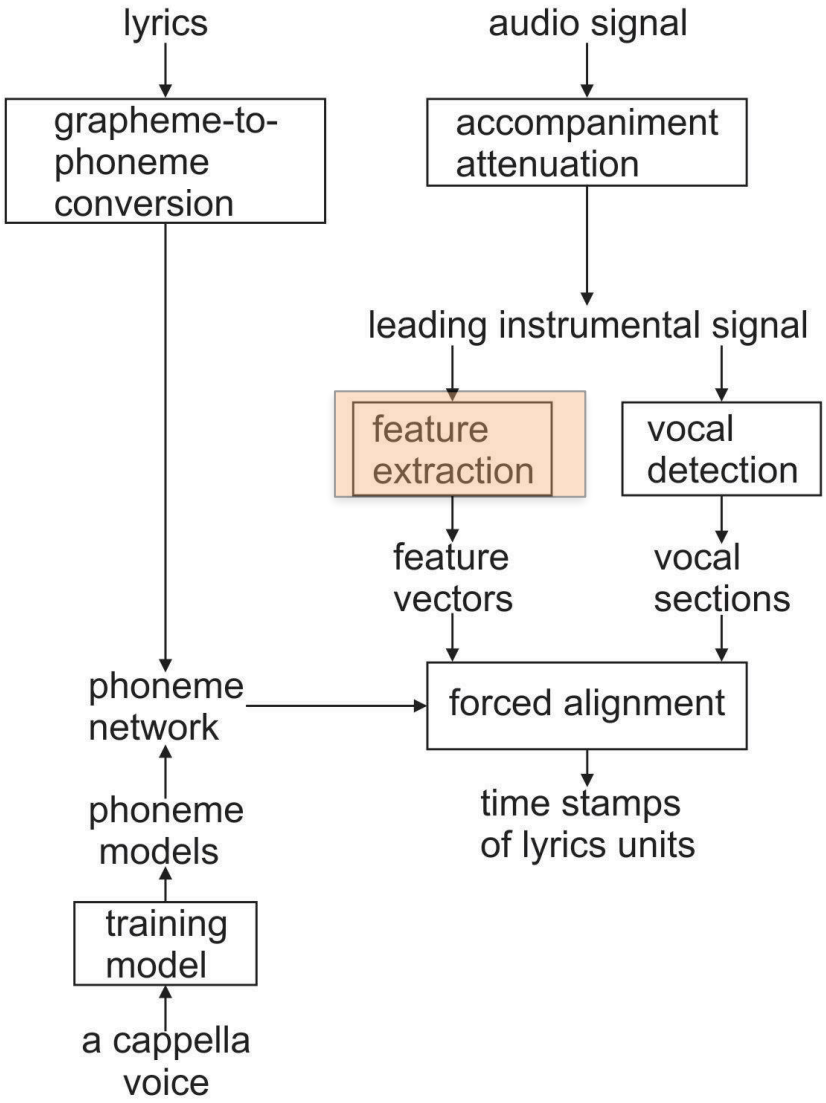

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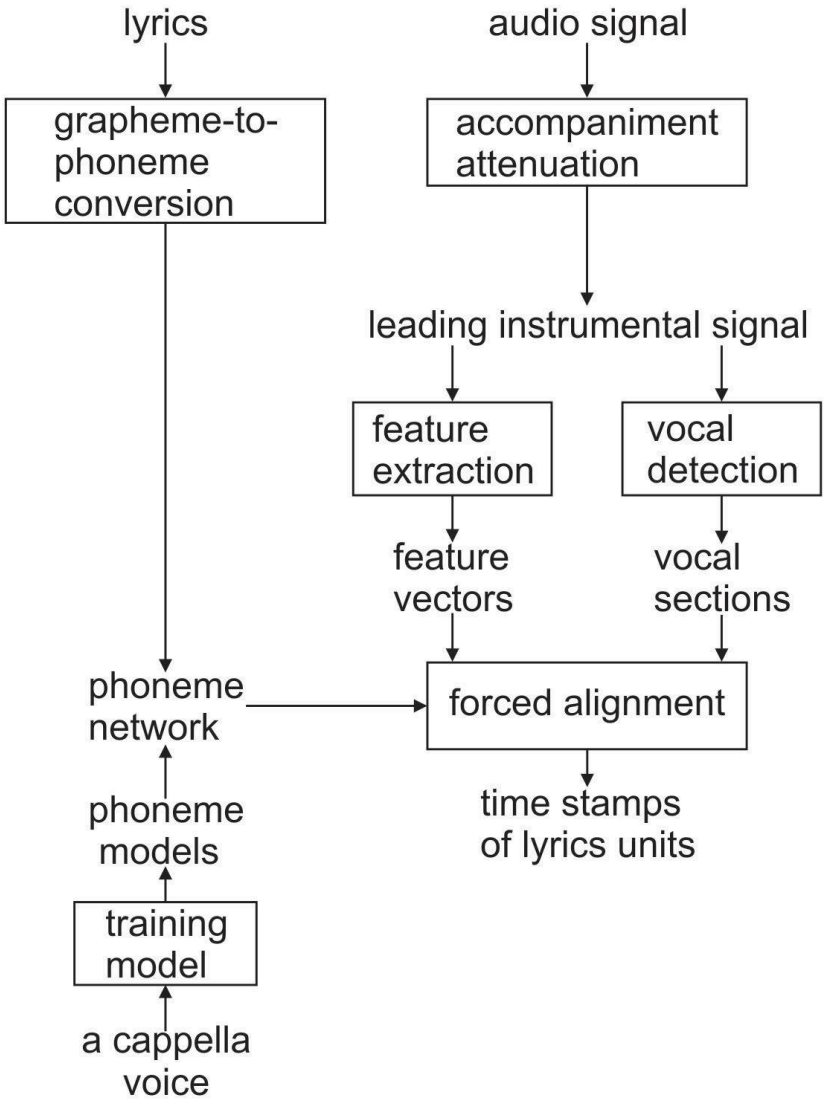

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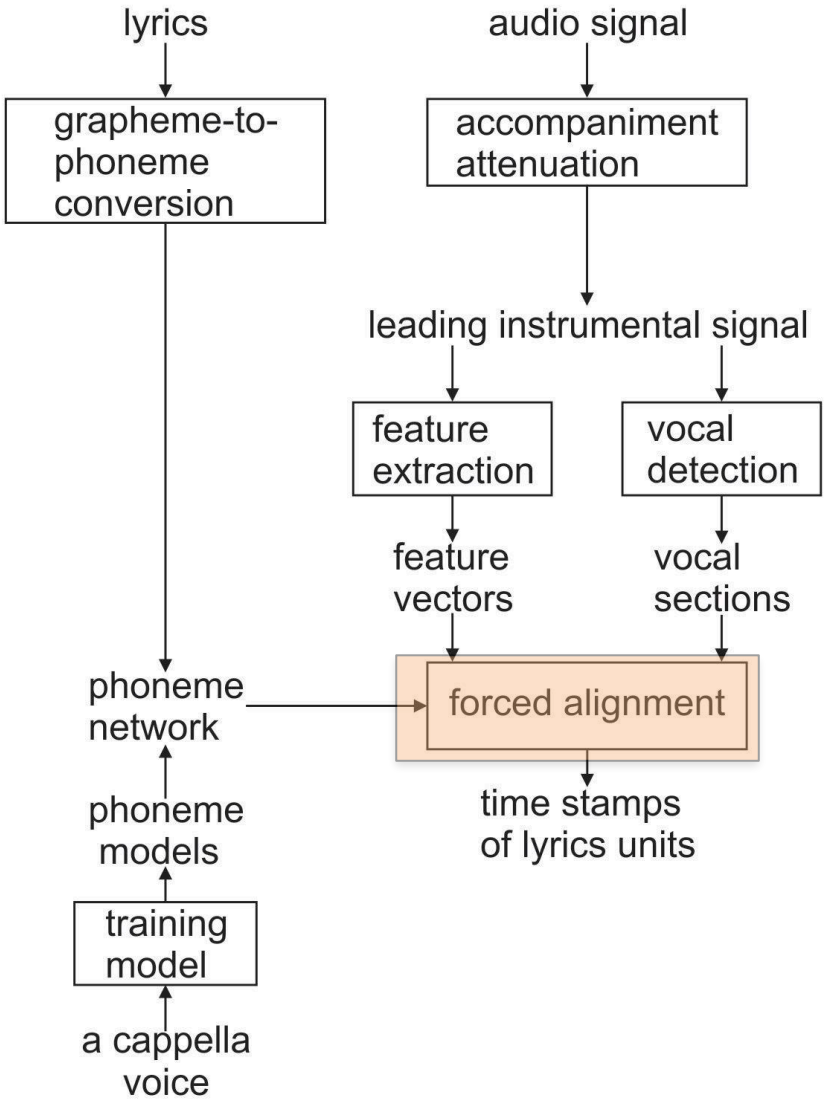

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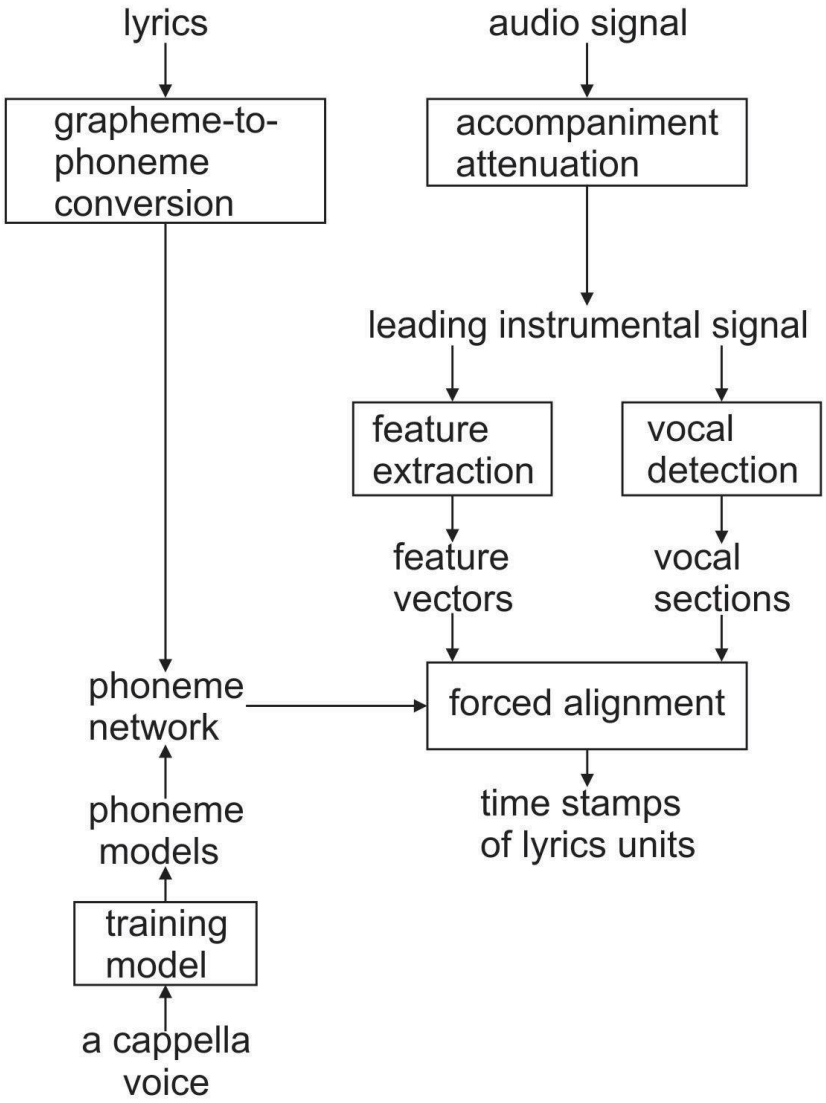

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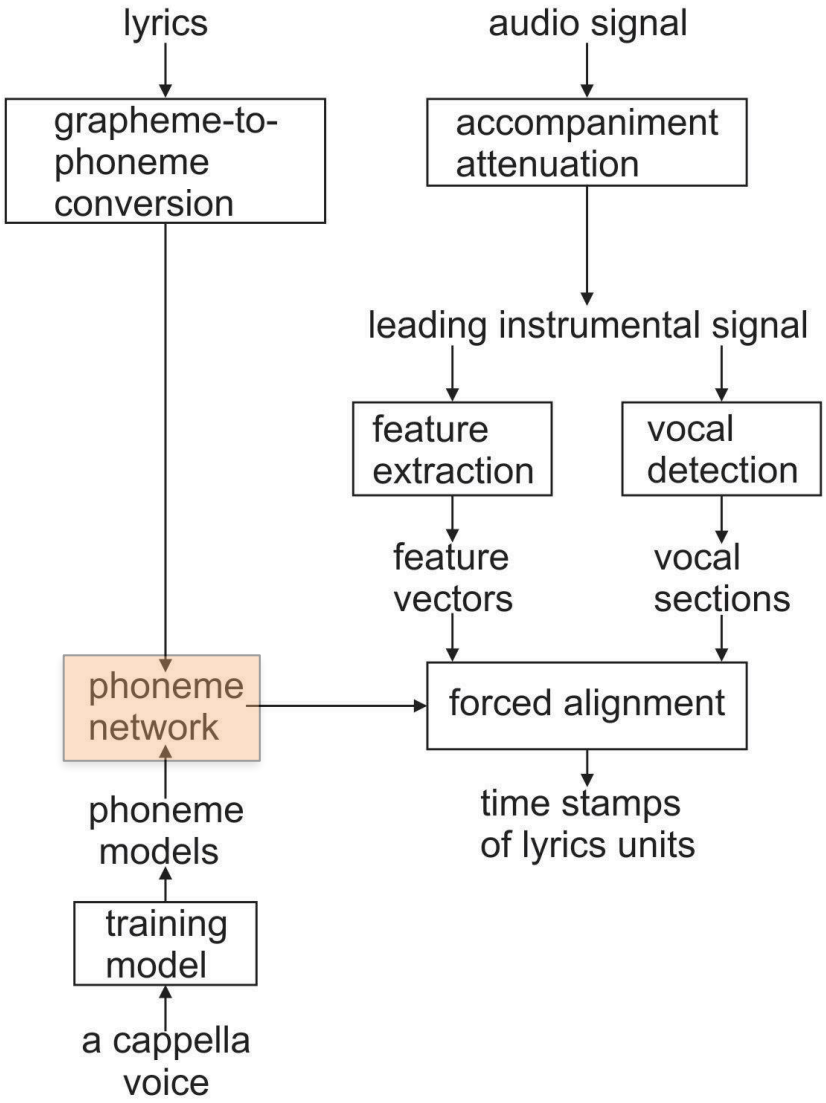

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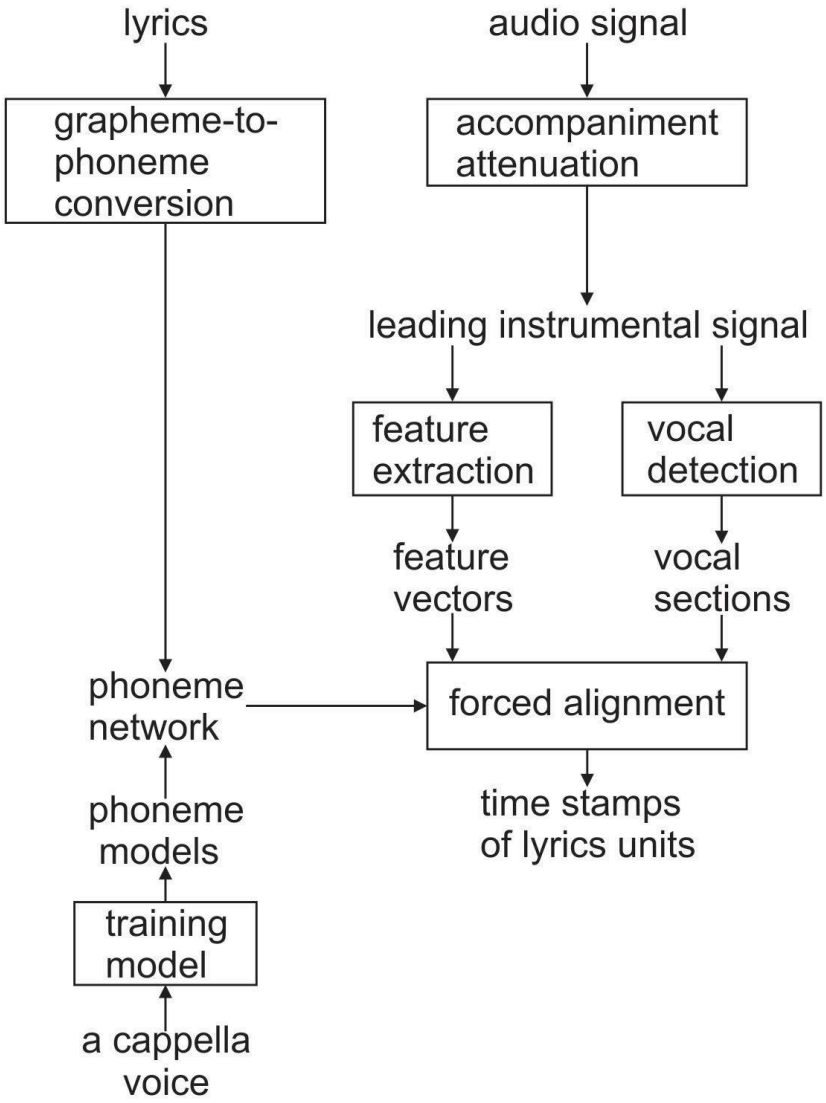

Comparison of existing approaches

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Author	Features	Training approach
(Mesaros, 2008)	MFCC	Speech + adaptation
(Fujihara, 2011)	MFCC	Speech + singer adaptation
(Kruspe, 2016)	MFCC+PLP	Singing

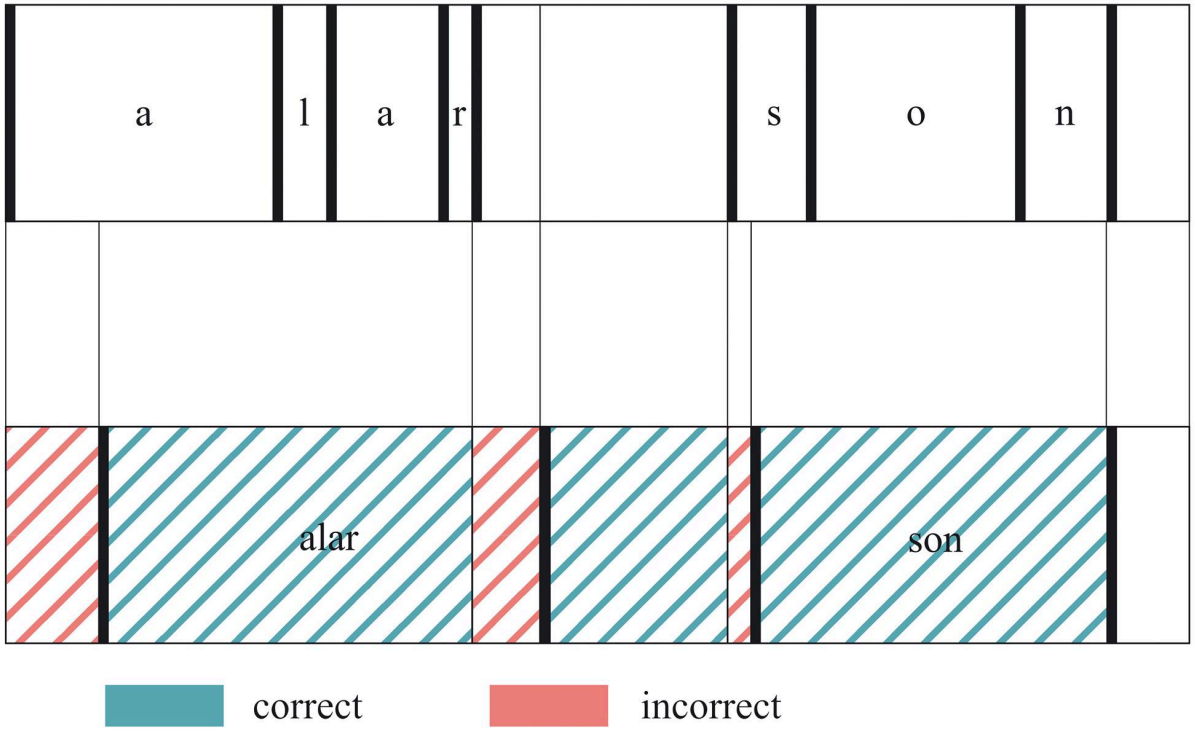
Comparison of existing approaches

compmusic

Author	Features	Training approach	>1 language	reproducible
(Mesaros, 2008)	MFCC	Speech + adaptation	✗	✗
(Fujihara, 2011)	MFCC	Speech + singer adaptation	✓	✗
(Kruspe, 2016)	MFCC+PLP	Singing	✗	✓

- Almost all are trained and tested on one language (English)
- None is fully reproducible
- None considers knowledge of simultaneously occurring musical events

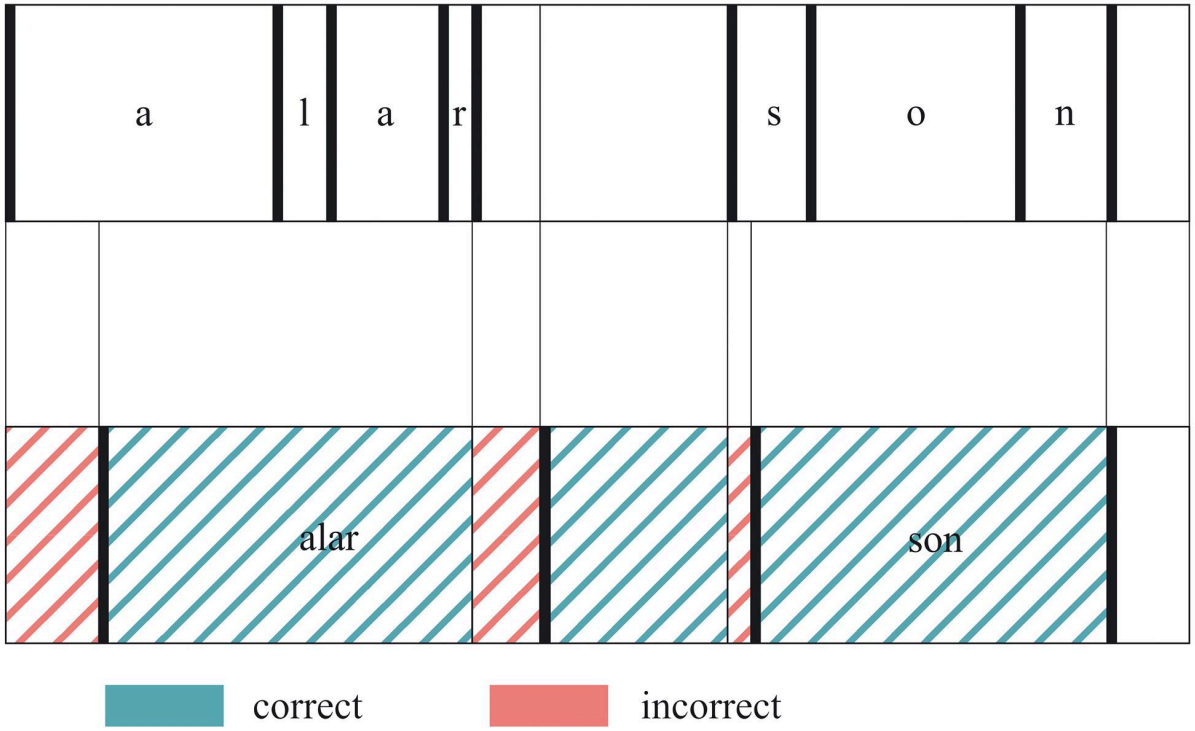
Evaluation metrics



ground truth

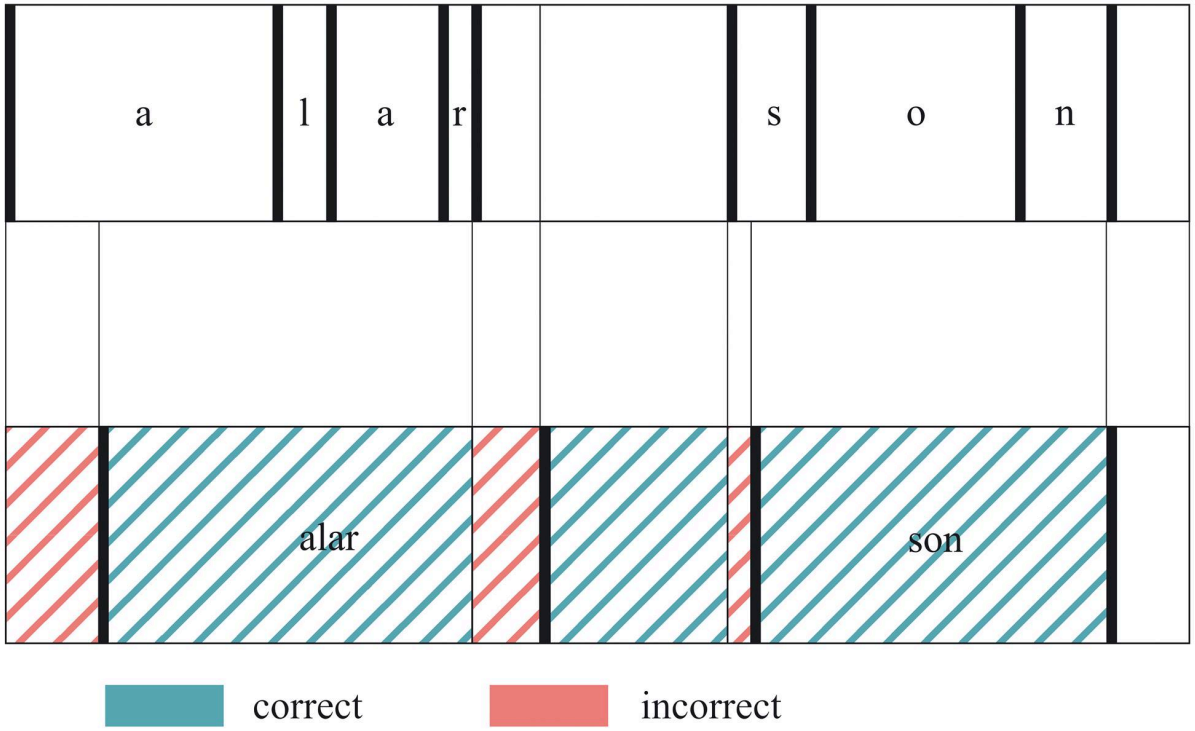
detection

Evaluation metrics



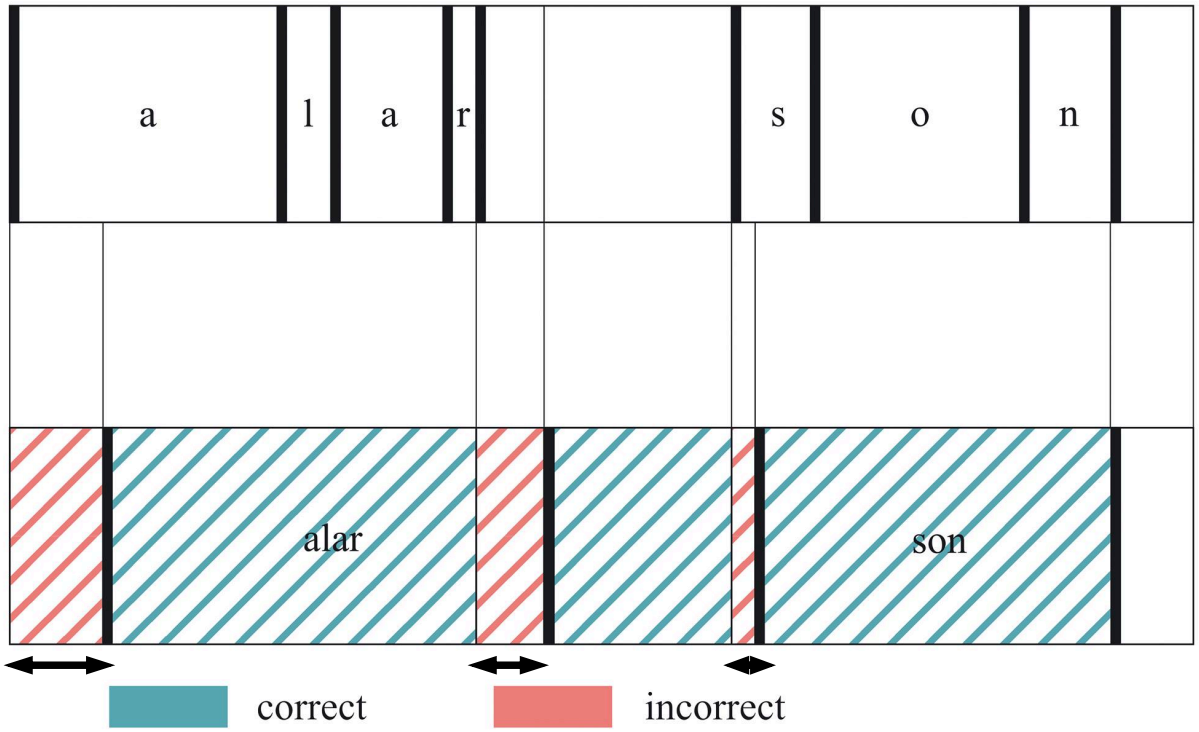
- Alignment accuracy (in %)

Evaluation metrics



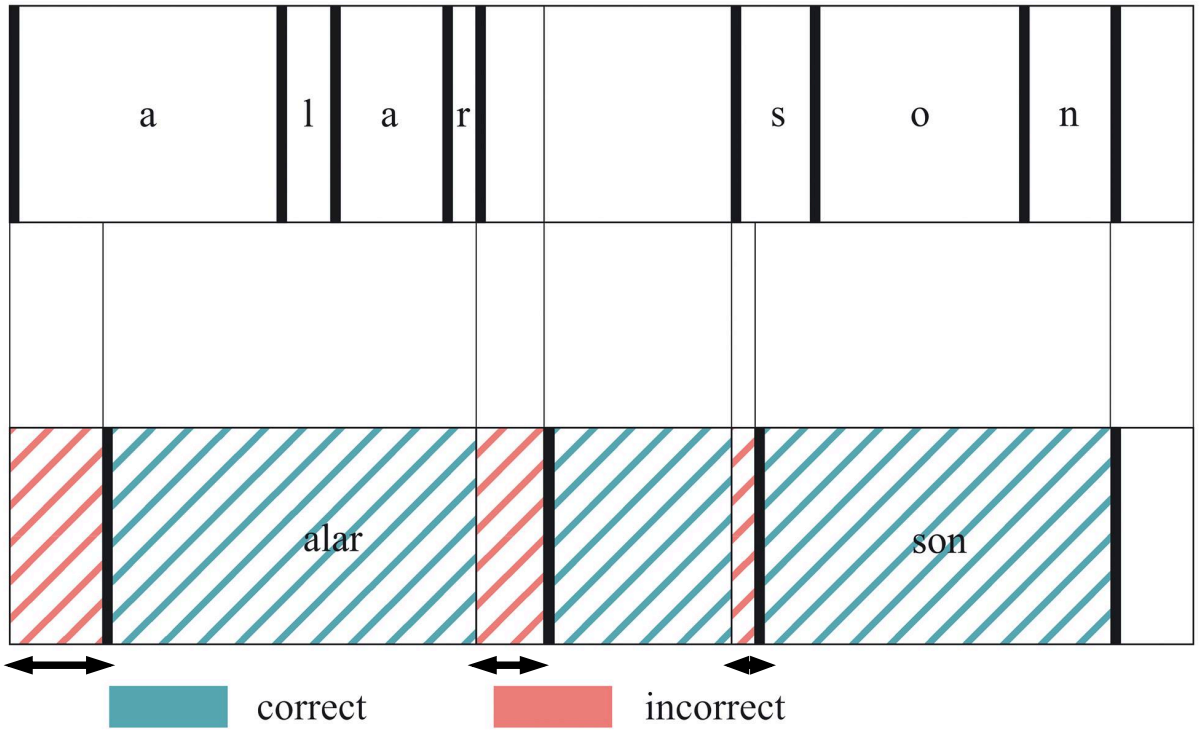
- Alignment accuracy (in %) $= \frac{\text{correct}}{\text{correct} + \text{incorrect}}$

Evaluation metrics



- Alignment accuracy (in %) $= \frac{\text{correct}}{\text{correct} + \text{incorrect}}$
- Average absolute error (in seconds)

Evaluation metrics



- Alignment accuracy (in %) $= \frac{\text{correct}}{\text{correct} + \text{incorrect}}$ (Fujihara, 2011)
- Average absolute error (in seconds)

Sec 2.2.1

Outline

- Setting the stage
  - Introduction (Chapter 1)
  - Background (Chapter 2)
  - Baseline lyrics-to-audio alignment (Chapter 3)
- Main
  - Lyrics-duration aware lyrics-to-audio alignment (Chapter 4)
  - Metrical-accent aware lyrics-to-audio alignment (Chapter 5)
- Conclusion (Chapter 6) and Applications (Appendix)

Outline

- Setting the stage
  - Introduction (Chapter 1)
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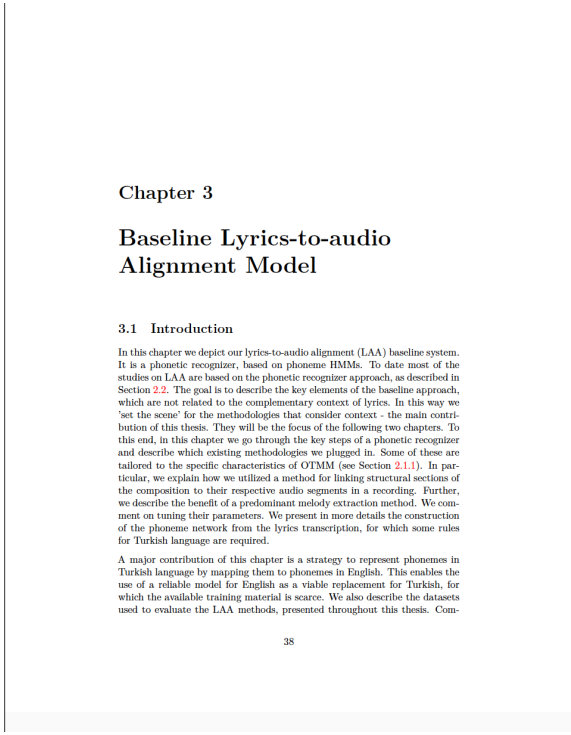
Chapter 3
Baseline Lyrics-to-audio Alignment



Chapter 3

Baseline Lyrics-to-audio Alignment Model

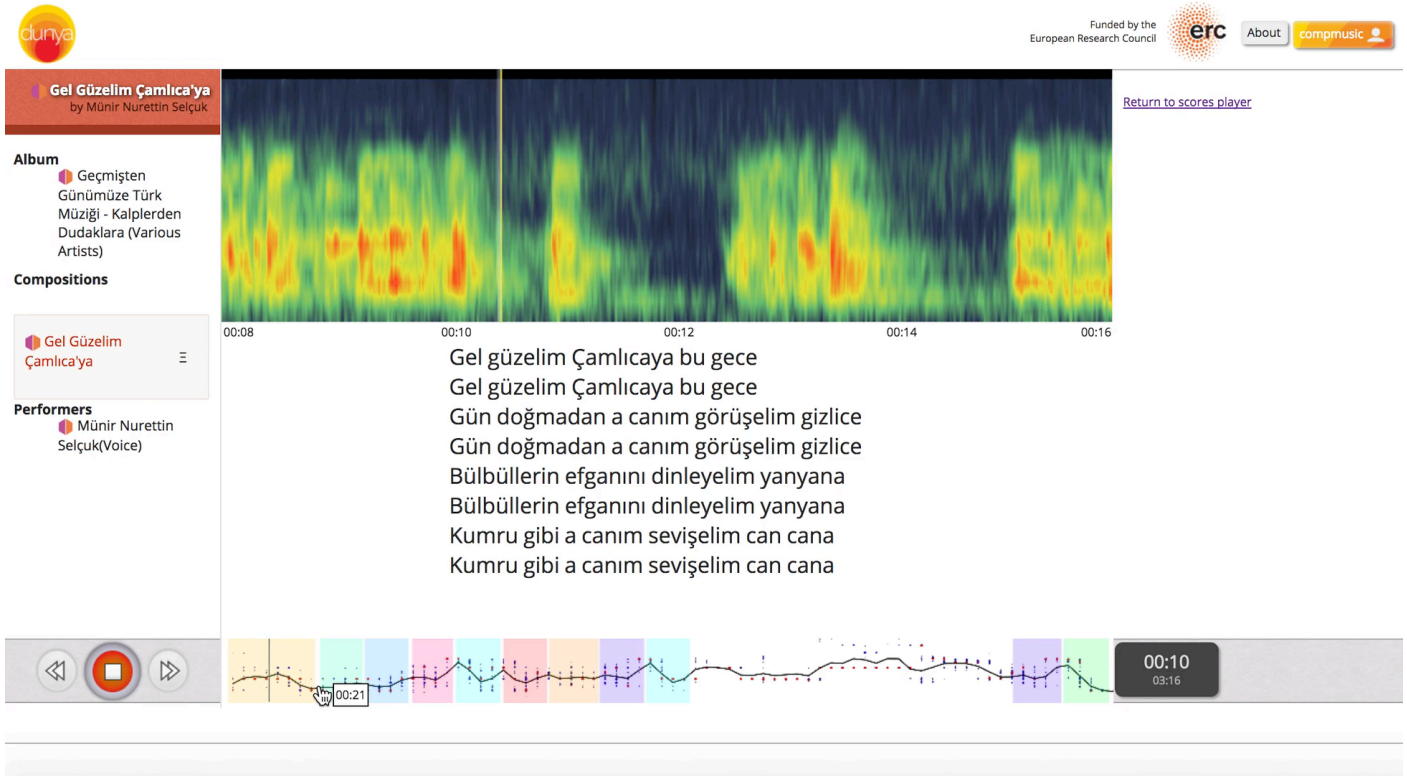
3.1 Introduction

In this chapter we depict our lyrics-to-audio alignment (LAA) baseline system. It is a phonetic recognizer, based on phoneme HMMs. To date most of the studies on LAA are based on the phonetic recognizer approach, as described in Section 2.2. The goal is to describe the key elements of the baseline approach, which are not related to the complementary context of lyrics. In this way we 'set the scene' for the methodologies that consider context - the main contribution of this thesis. They will be the focus of the following two chapters. To this end, in this chapter we go through the key steps of a phonetic recognizer and describe which existing methodologies we plugged in. Some of these are tailored to the specific characteristics of OTMM (see Section 2.1.1). In particular, we explain how we utilized a method for linking structural sections of the composition to their respective audio segments in a recording. Further, we describe the benefit of a predominant melody extraction method. We comment on tuning their parameters. We present in more details the construction of the phoneme network from the lyrics transcription, for which some rules for Turkish language are required.

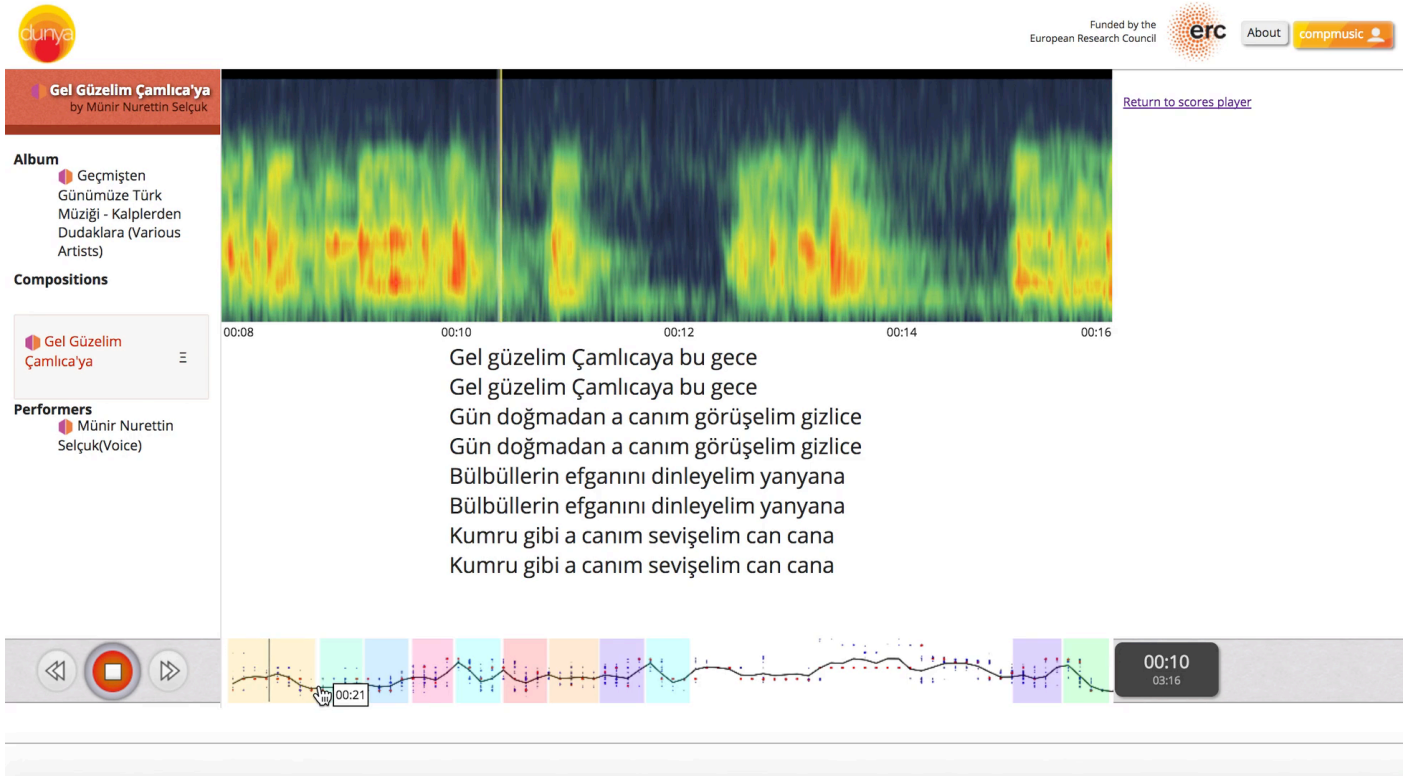
A major contribution of this chapter is a strategy to represent phonemes in Turkish language by mapping them to phonemes in English. This enables the use of a reliable model for English as a viable replacement for Turkish, for which the available training material is scarce. We also describe the datasets used to evaluate the LAA methods, presented throughout this thesis. Com-

38

Demo


Funded by the European Research Council
erc
About
compmusic
Gel Güzelim Çamlıca'ya
by Münir Nurettin Selçuk
Return to scores player
Album
Geçmişten Günümüze Türk Müziği - Kalplerden Dudaklara (Various Artists)
Compositions
Gel Güzelim Çamlıca'ya
Performers
Münir Nurettin Selçuk(Voice)
00:08
00:10
00:12
00:14
00:16
Gel güzelim Çamlıcaya bu gece
Gel güzelim Çamlıcaya bu gece
Gün doğmadan a canım görüşelim gizlice
Gün doğmadan a canım görüşelim gizlice
Bülbüllerin efganını dinleyelim yanyana
Bülbüllerin efganını dinleyelim yanyana
Kumru gibi a canım sevişelim can cana
Kumru gibi a canım sevişelim can cana
00:21
00:10
03:16

Demo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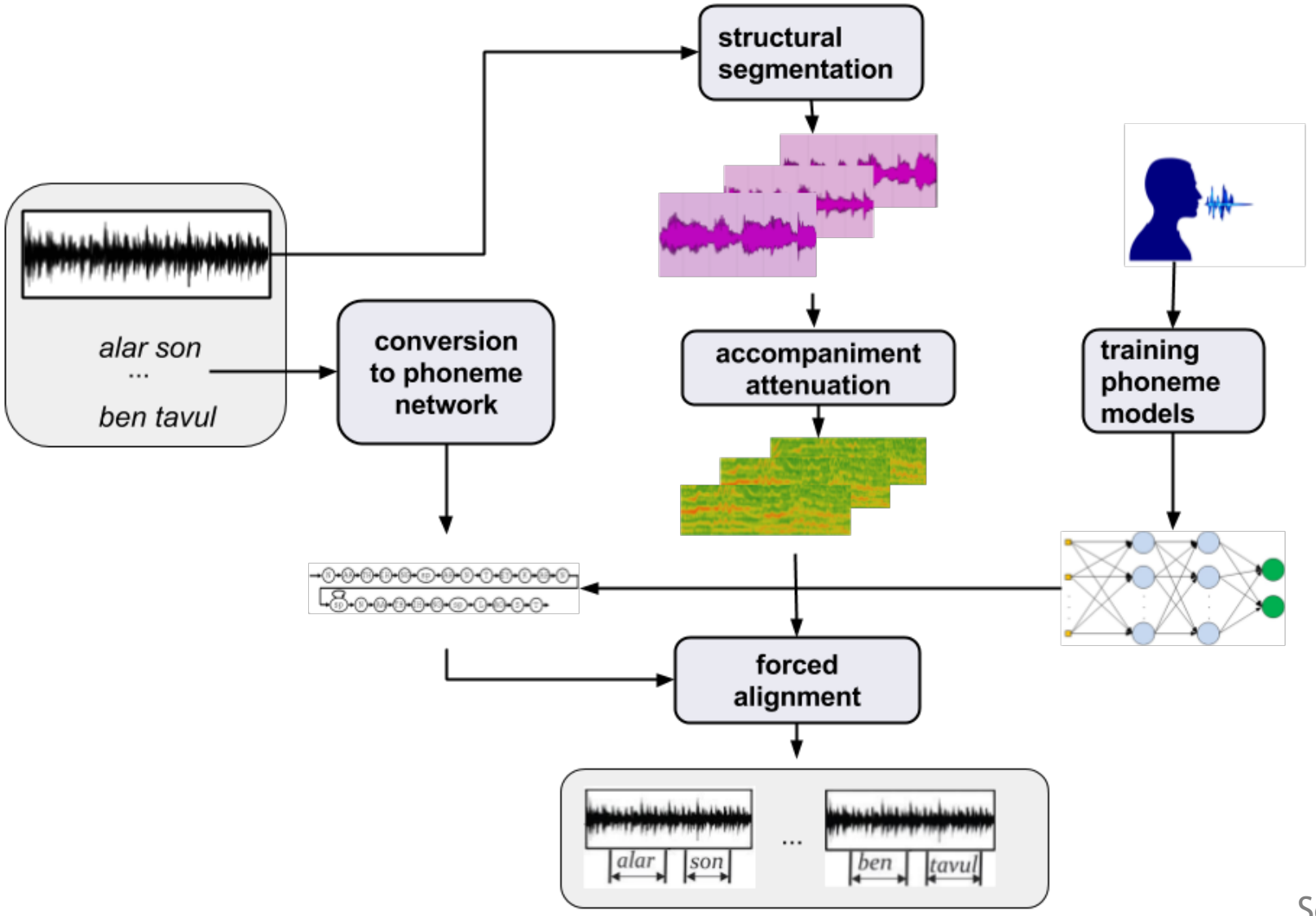
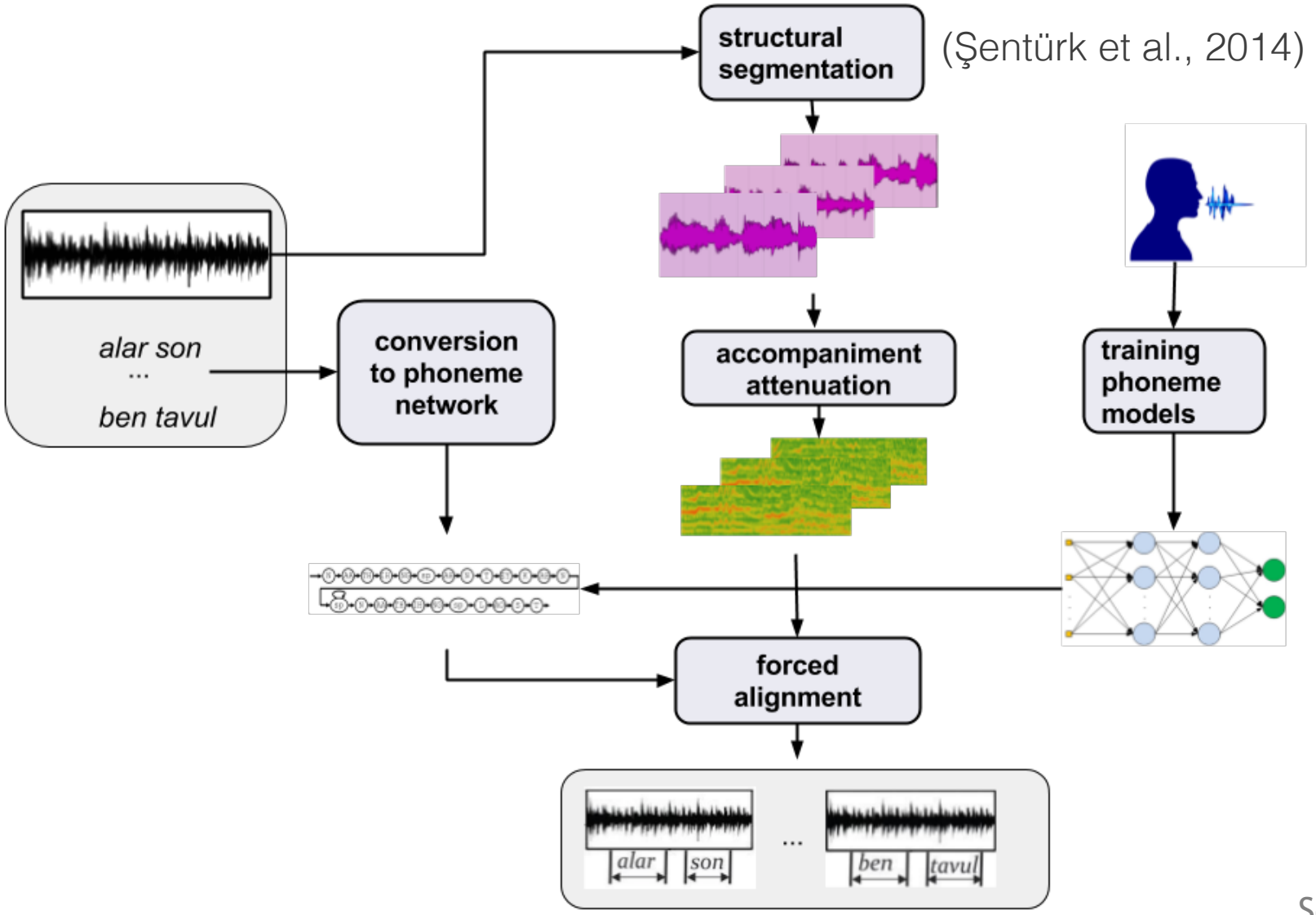
00:21
00:10
03:16

Steps of baseline alignment



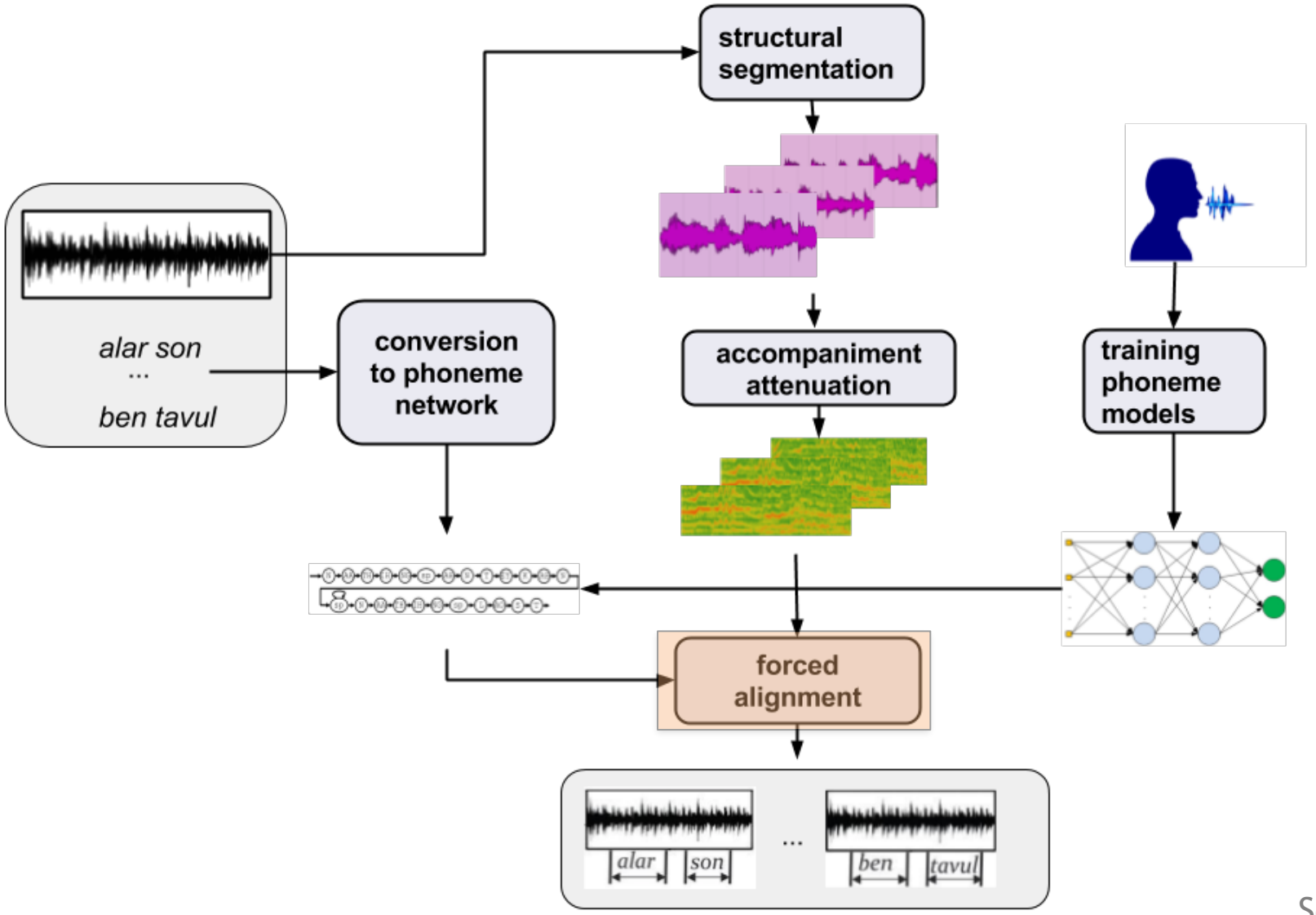
Sec 3.3

Steps of baseline alignment



Sec 3.3

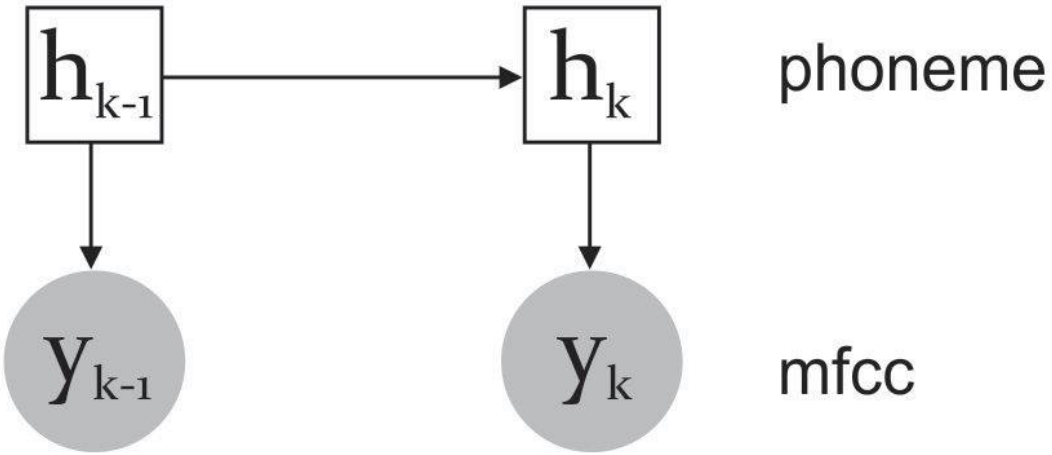
Forced alignment



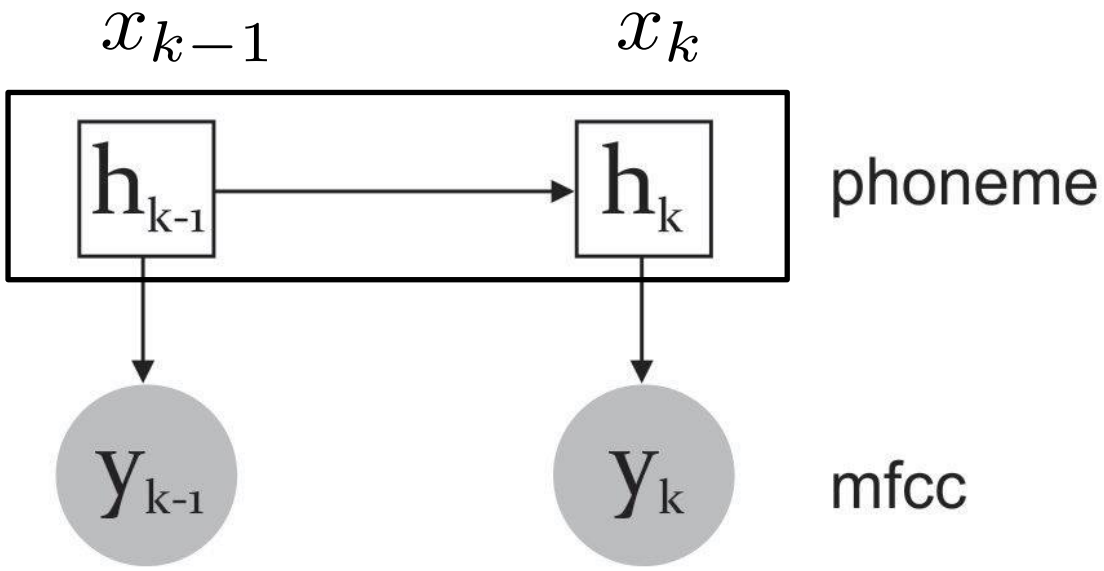
Sec 3.3.4

Model components

- based on Hidden Markov models

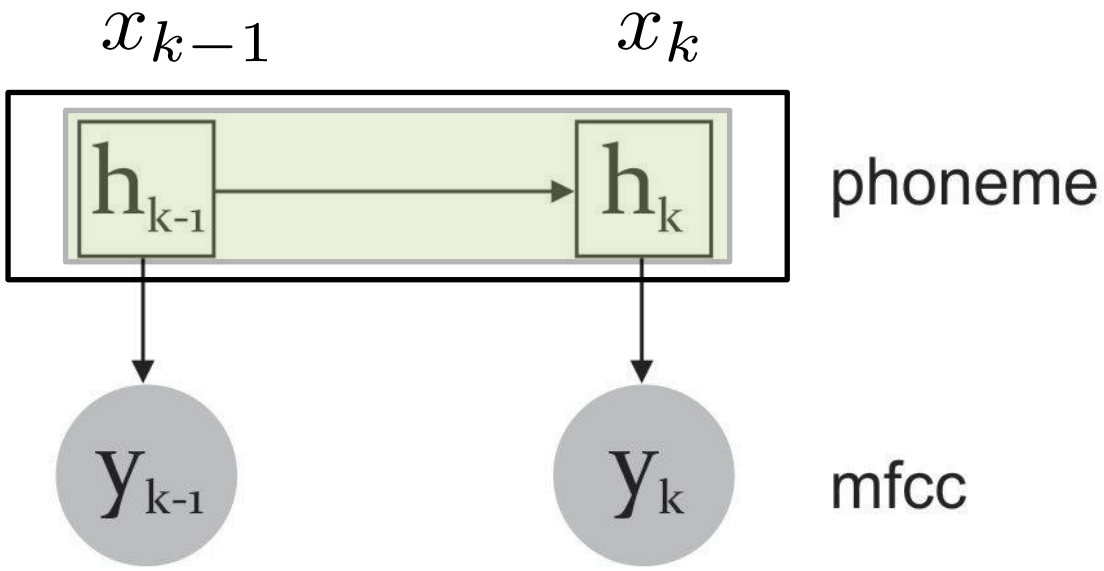


Model components



$$P(x_{1:K}, y_{1:K}) = P(x_0)\Pi_{k=1}^{K} P(x_k|x_{k-1})P(y_k|x_k)$$

Model components

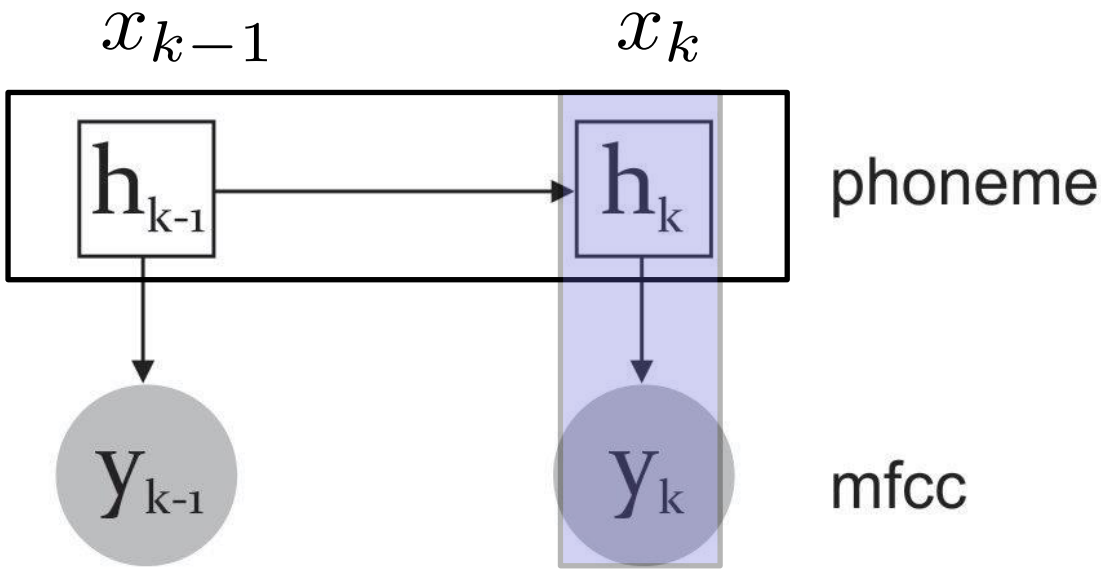


$$P(x_{1:K}, y_{1:K}) = P(x_0)\Pi_{k=1}^{K} P(x_k|x_{k-1})P(y_k|x_k)$$

Transition model

Sec 3.3.4

Model components



$$P(x_{1:K}, y_{1:K}) = P(x_0)\Pi_{k=1}^{K} P(x_k|x_{k-1})P(y_k|x_k)$$

Observation model

Sec 3.3.4

Viterbi decoding

compmusic

Viterbi decoding

$$a_{ij} = P(x_k = j \mid x_{k-1} = i)$$

Sec 3.3.4

Viterbi decoding

$$a_{ij} = P(x_k = j \mid x_{k-1} = i)$$

$$b_j(O_k) = P(y_k = O_k \mid x_k = j)$$

Viterbi decoding

$$a_{ij} = P(x_k = j \mid x_{k-1} = i)$$

$$b_j(O_k) = P(y_k = O_k \mid x_k = j)$$

$$\delta_k(j) = \max_{i \in (j,\, j-1)} \delta_{k-1}(i)\, a_{ij}\, b_j(O_k)$$ (Rabiner, 1989)

Viterbi decoding

$$a_{ij} = P(x_k = j \mid x_{k-1} = i)$$

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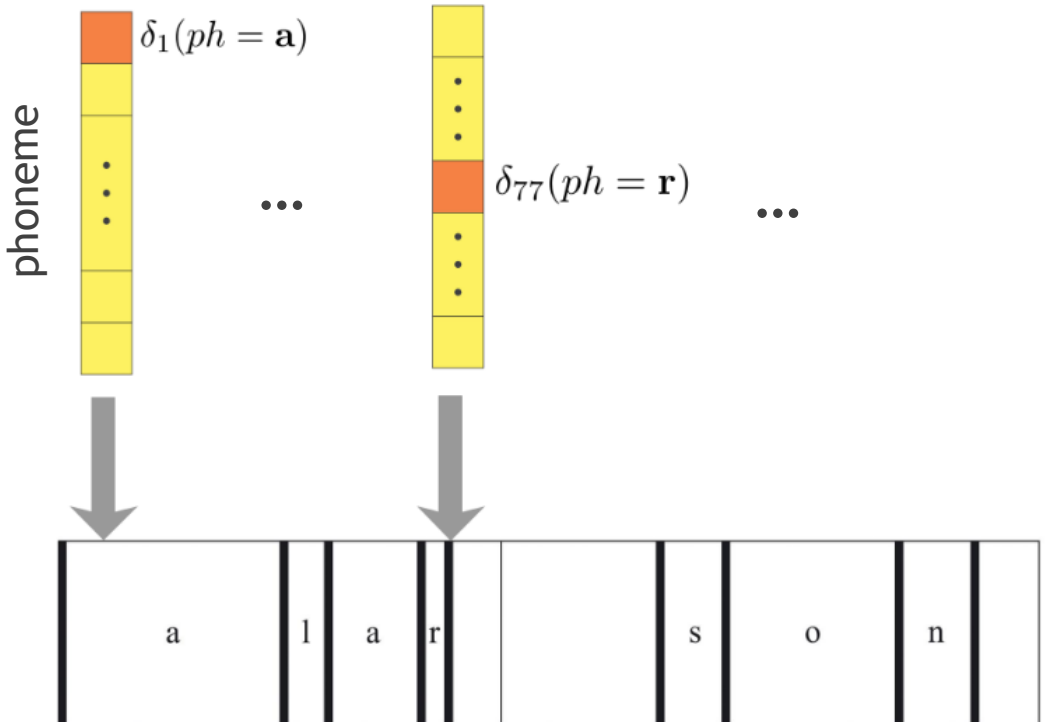
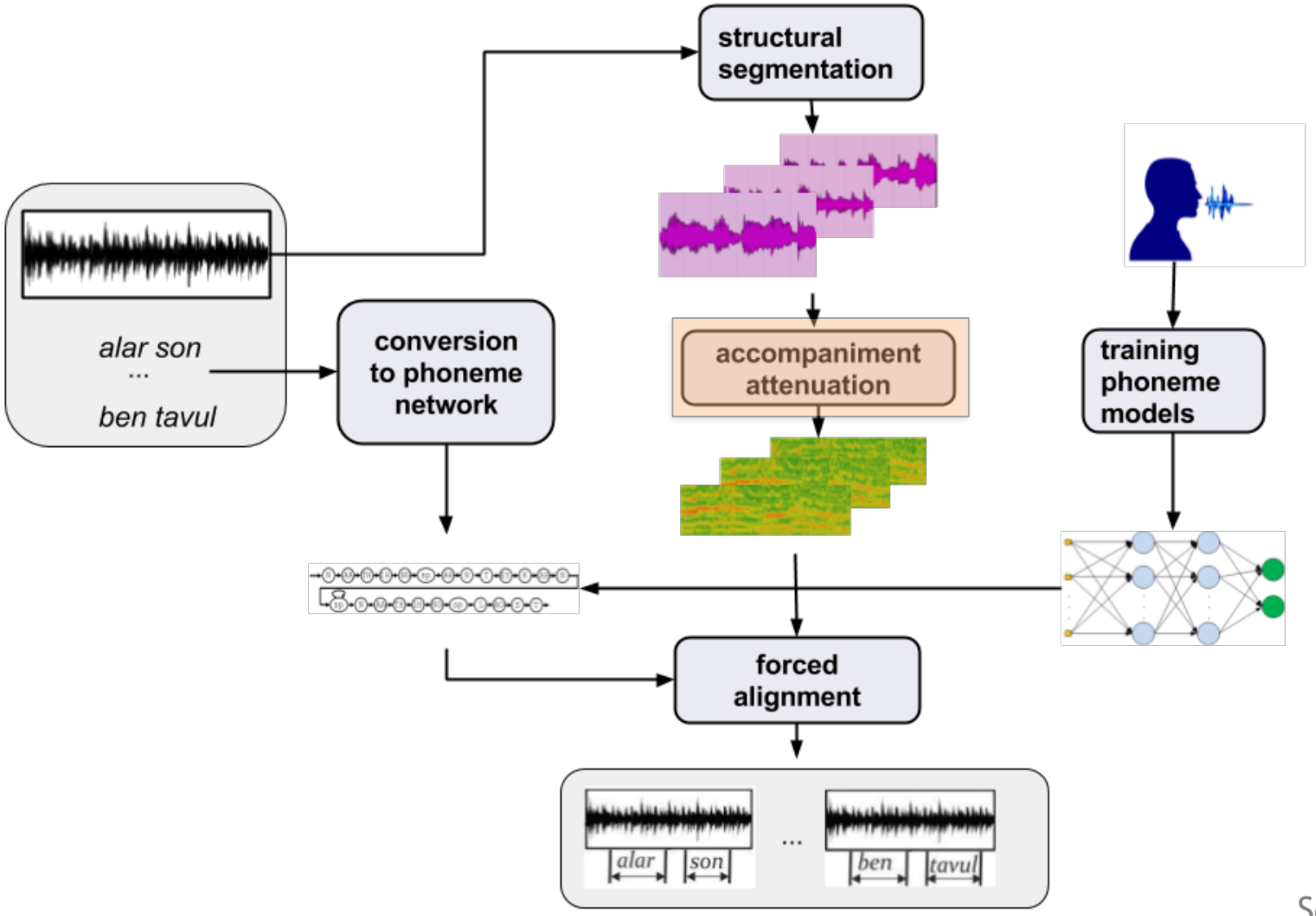


Accompaniment attenuation

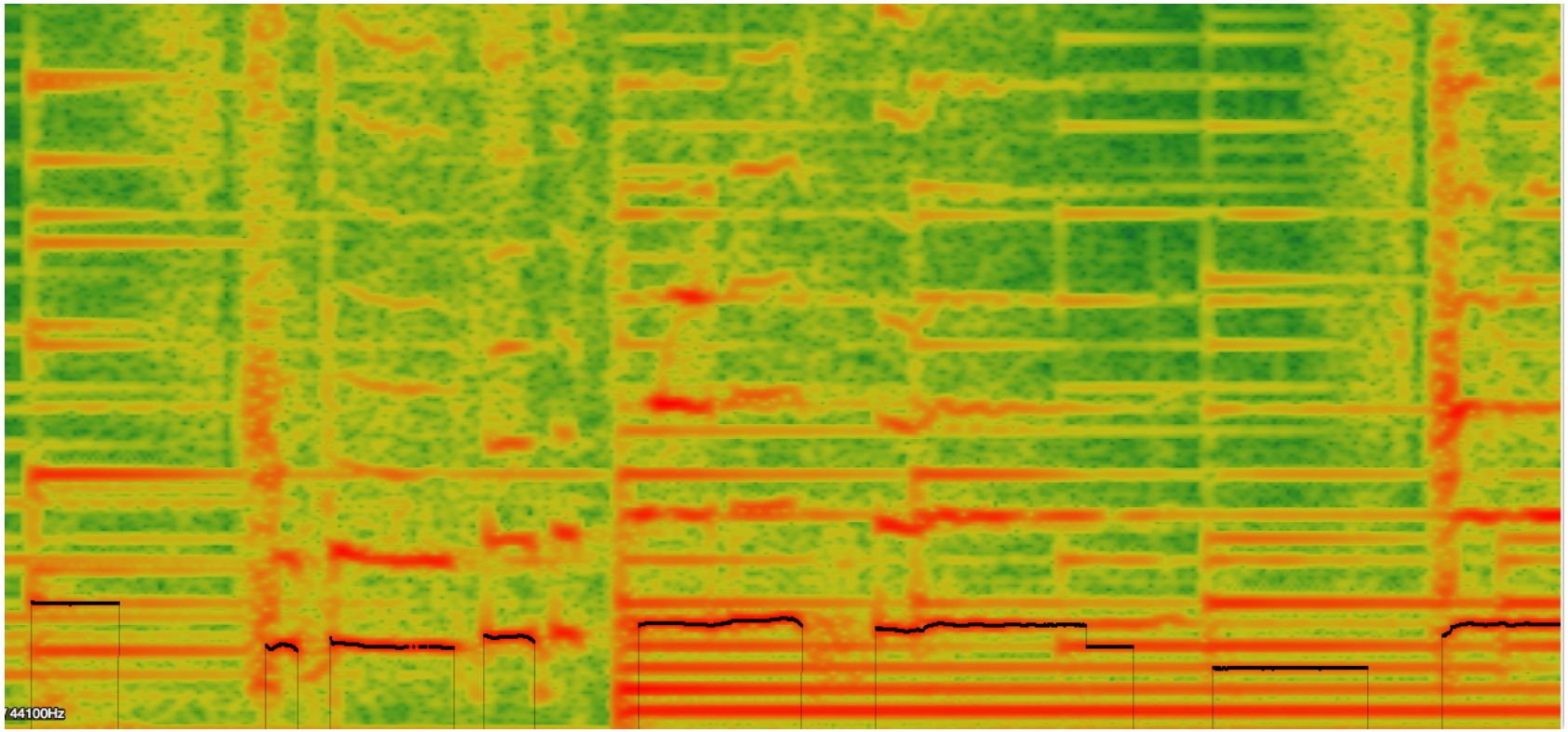


Sec 3.3.2

Accompaniment attenuation

1. Extract fundamental frequency

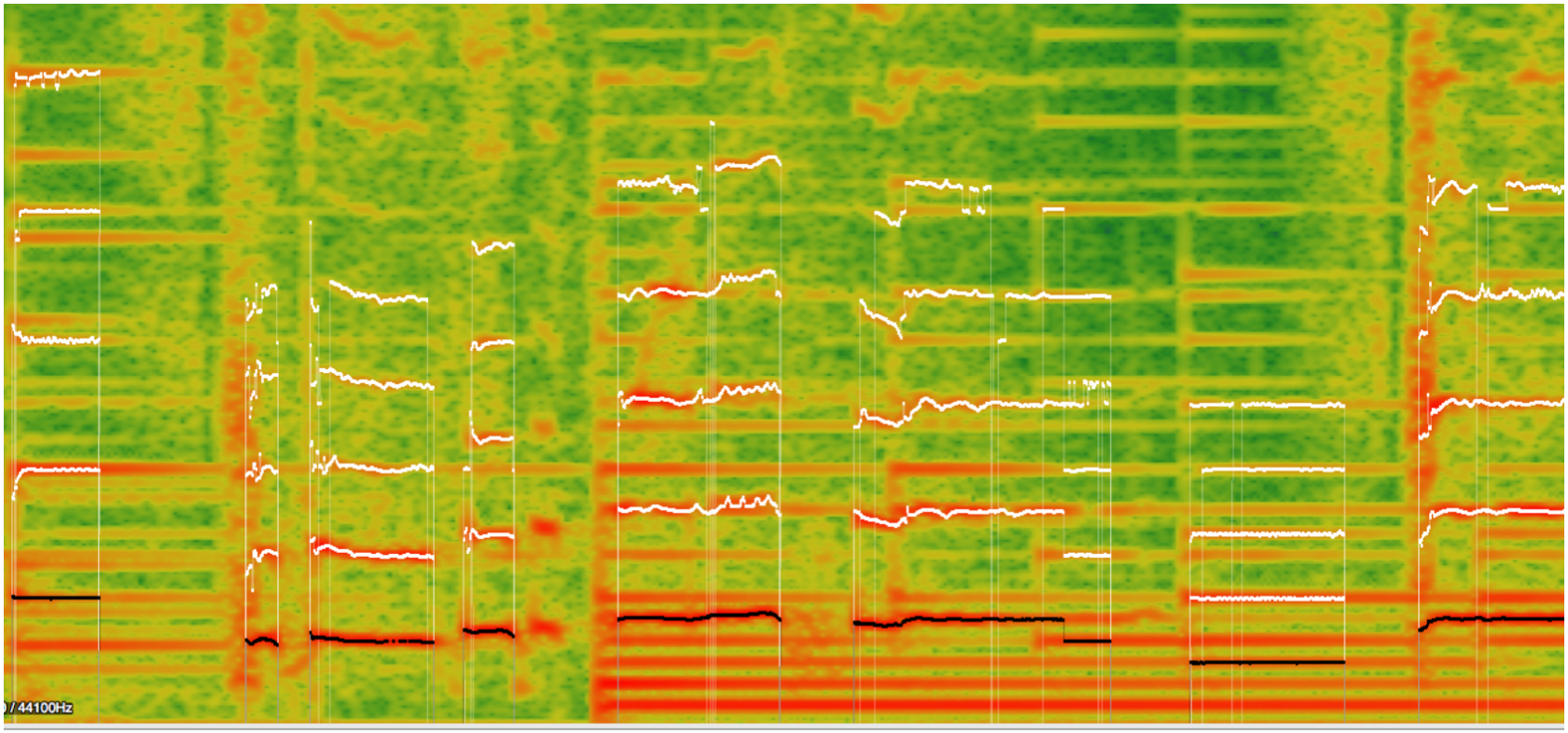
   OTMM-tailored predominant melody (Atlı et al., 2014)



Accompaniment attenuation

2. Extract harmonic partials

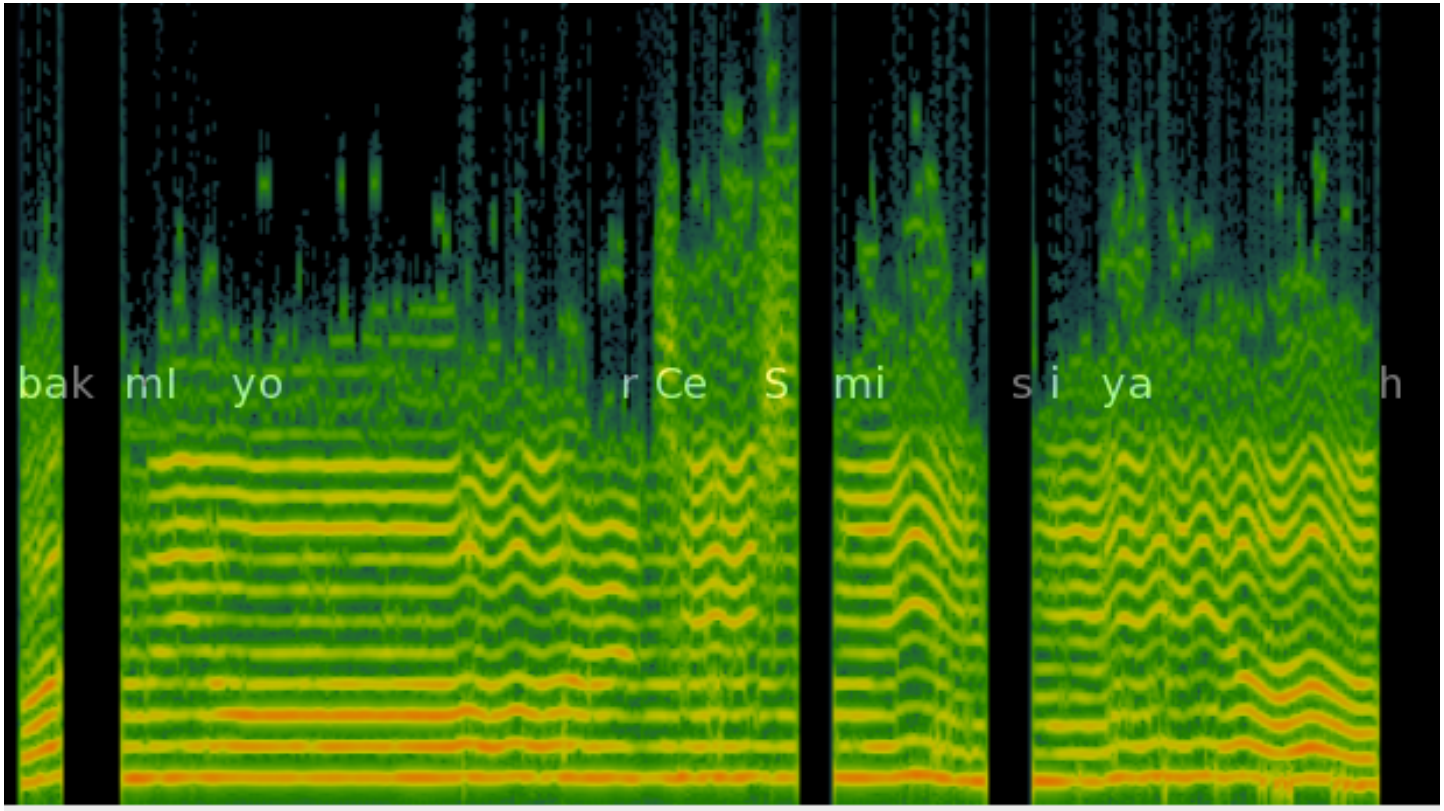
harmonic model (Serra, 1989)



Accompaniment attenuation

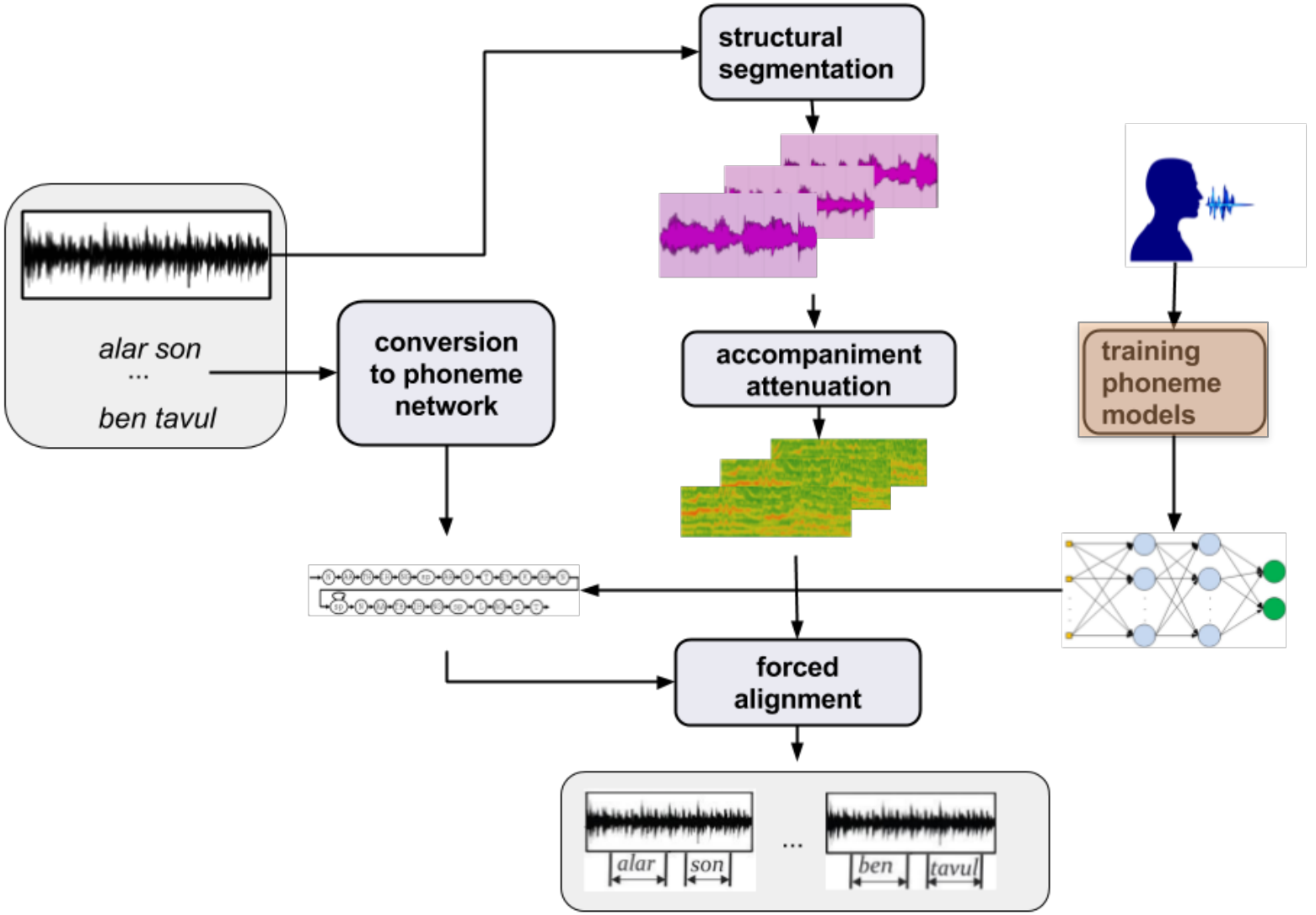
3. Resynthesize harmonic partials

overlapp-add synthesis (Serra, 1989)



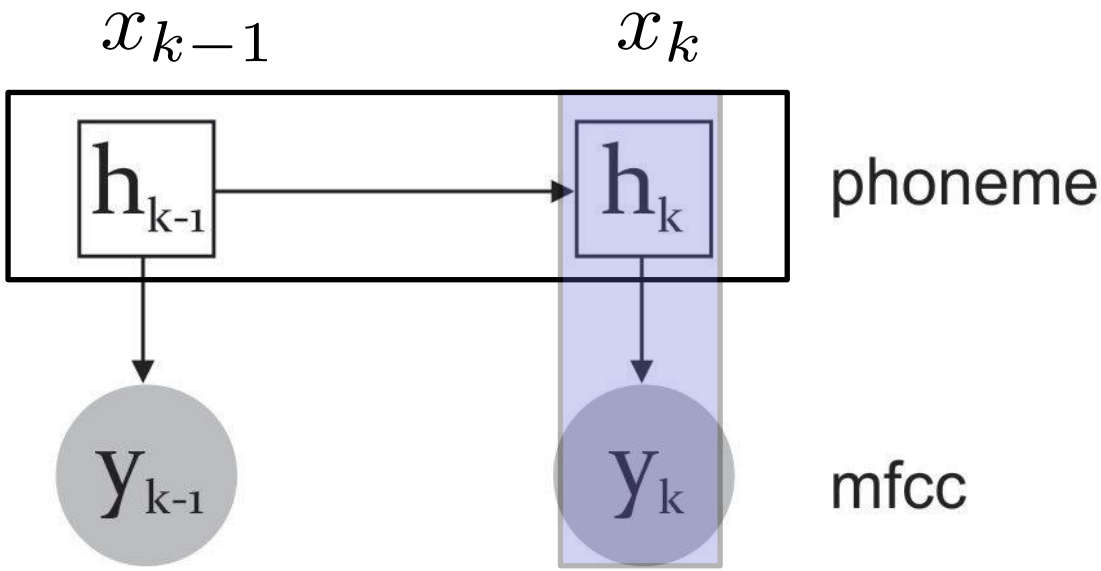
Sec 3.3.2

Training phoneme models



Sec 3.4

Training phoneme models



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Observation model

Sec 3.4

Training phoneme models

- GMMs with MFCCs
  - on Turkish speech
  - 9 mixtures

Training phoneme models

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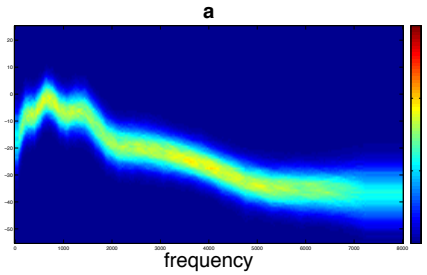
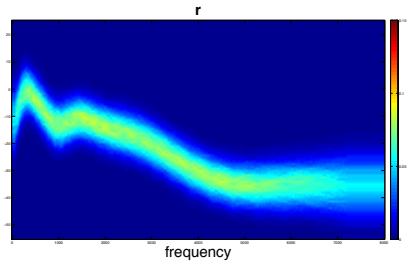
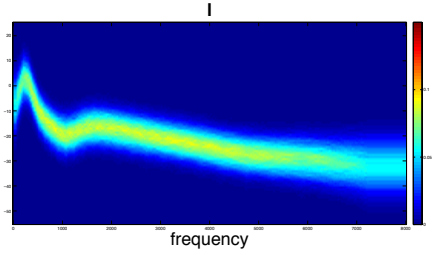
  - on Turkish speech
  - 9 mixtures



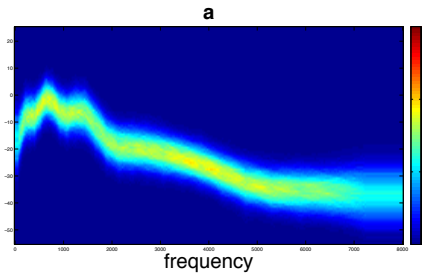


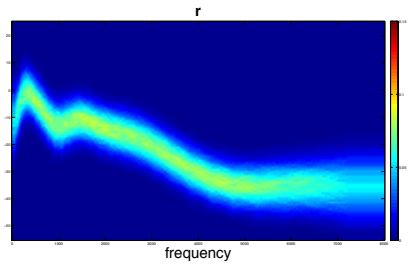


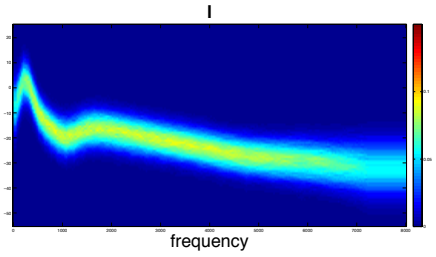
Training phoneme models

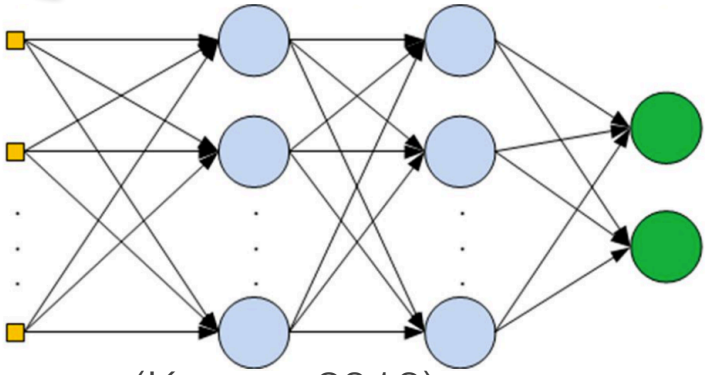
- GMMs with MFCCs
  - on Turkish speech
  - 9 mixtures

- MLP with MFCCs
  - on English a cappella signing
  - 1024-850-1024 neurons









(Kruspe 2016)

Training phoneme models

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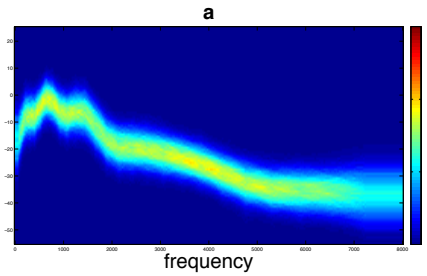
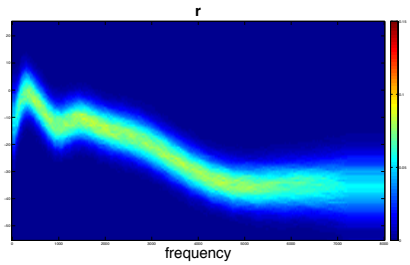
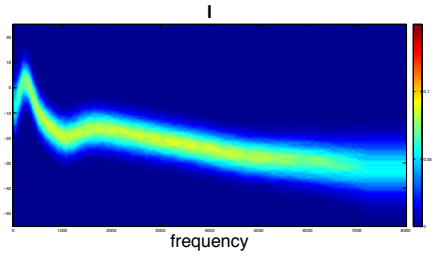
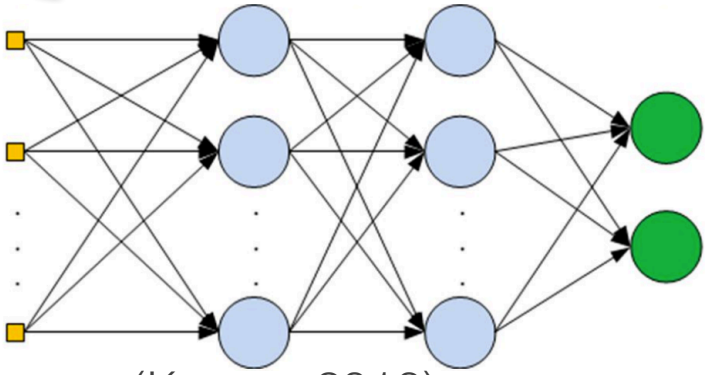
  - 9 mixtures

- MLP with MFCCs
  - on English a cappella signing
  - 1024-850-1024 neurons









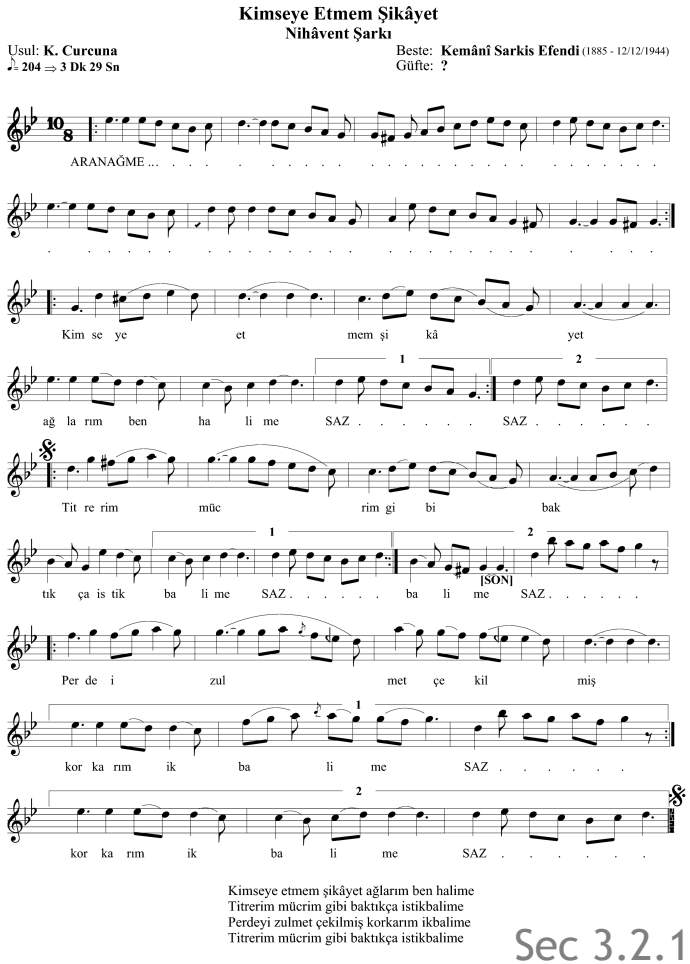
(Kruspe 2016)

- mapping Turkish phonemes to English ones (MLP-DirectM)

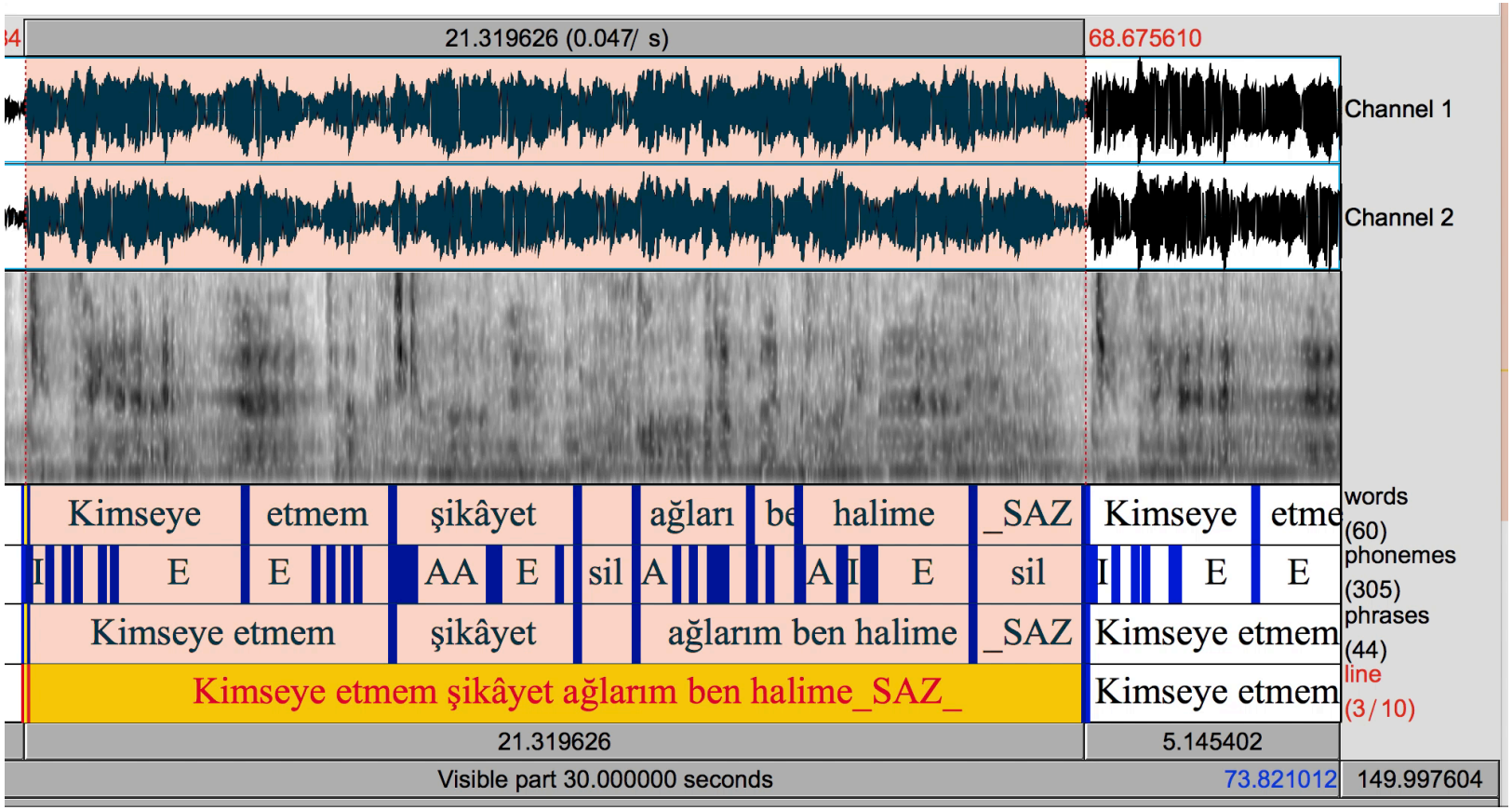
Sec 3.4

Multi-instrumental lyrics OTMM dataset

- 13 recordings from the şarkı form (19 minutes)
- Music scores with section annotations
- Annotations of lyrics phrases

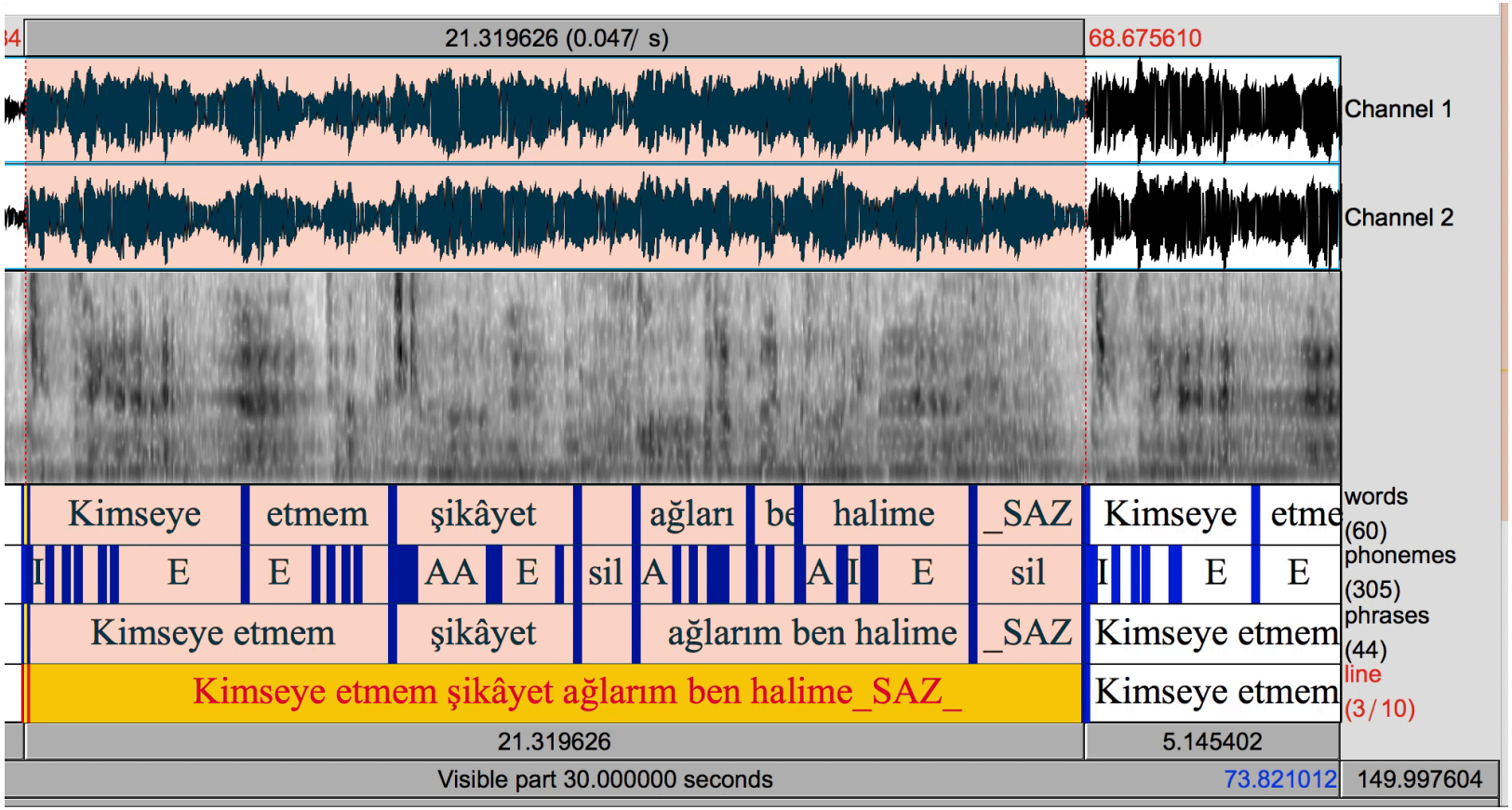


Multi-instrumental lyrics OTMM dataset



http://compmusic.upf.edu/turkish-sarki

Multi-instrumental lyrics OTMM dataset



http://compmusic.upf.edu/turkish-sarki

A cappella lyrics OTMM dataset

compmusic

http://compmusic.upf.edu/turkish-makam-acapella-sections-dataset

Sec 3.2.2

A cappella lyrics OTMM dataset

- A cappella versions recorded in-sync with the original

http://compmusic.upf.edu/turkish-makam-acapella-sections-dataset

A cappella lyrics OTMM dataset

- A cappella versions recorded in-sync with the original

http://compmusic.upf.edu/turkish-makam-acapella-sections-dataset

Experiments

acoustic model	data	AA	AH	accuracy	error
GMMs	a cappella	-	-	70.2	1.14
MLP-DirectM	a cappella	-	-	79.2	0.57
GMMs	multi-instrumental	N	-	59.1	2.15
GMMs	multi-instrumental	Y	N	63.2	1.98
GMMs	multi-instrumental	Y	Y	67.5	1.26
Mesaros	multi-instrumental	-	-	-	1.4
Fujihara	multi-instrumental	-	-	85.2	-

Dzhambazov, Georgi, Sertan Şentürk, and Xavier Serra (2014). Automatic lyrics-to-audio alignment in classical Turkish music. In 4th International Workshop on Folk Music Analysis (FMA 2014)

Sec 3.5

Experiments

acoustic model	data	AA	AH	accuracy	error
GMMs	a cappella	-	-	70.2	1.14
MLP-DirectM	a cappella	-	-	79.2	0.57
GMMs	multi-instrumental	N	-	59.1	2.15
GMMs	multi-instrumental	Y	N	63.2	1.98
GMMs	multi-instrumental	Y	Y	67.5	1.26
Mesaros	multi-instrumental	-	-	-	1.4
Fujihara	multi-instrumental	-	-	85.2	-

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Sec 3.5

Experiments

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MLP-DirectM	a cappella	-	-	79.2	0.57
GMMs	multi-instrumental	N	-	59.1	2.15
GMMs	multi-instrumental	Y	N	63.2	1.98
GMMs	multi-instrumental	Y	Y	67.5	1.26
Mesaros	multi-instrumental	-	-	-	1.4
Fujihara	multi-instrumental	-	-	85.2	-

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Sec 3.5

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Sec 3.5

Outline

- Setting the stage
  - Introduction (Chapter 1)
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- Main
  - Lyrics-duration aware lyrics-to-audio alignment (Chapter 4)
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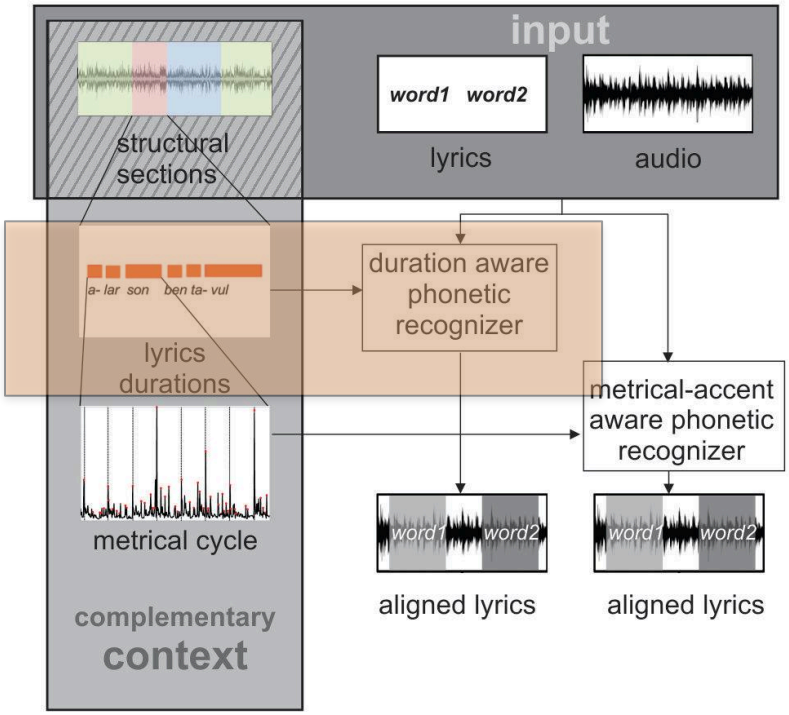
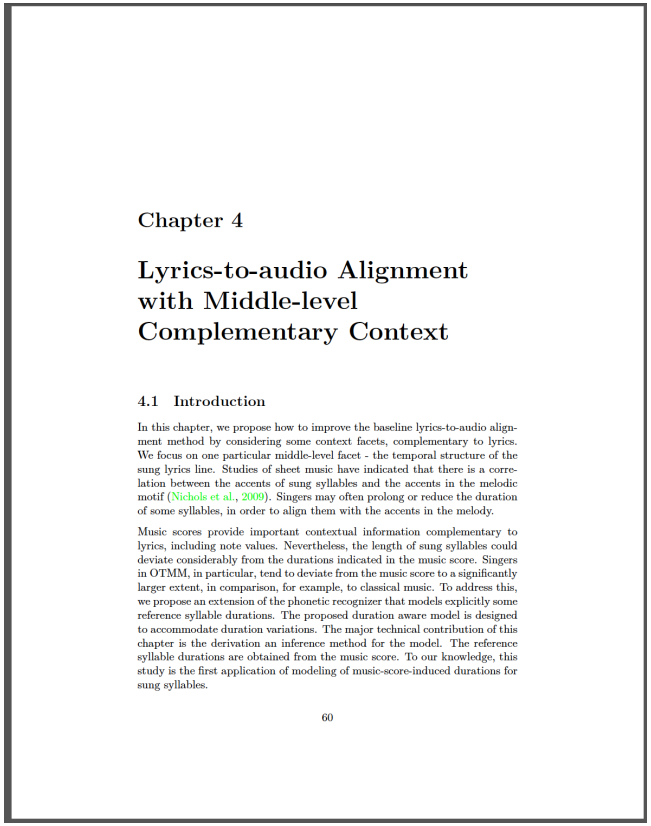
Chapter 4
Lyrics-to-audio Alignment with Middle-level Complementary Context





Chapter 4

Lyrics-to-audio Alignment with Middle-level Complementary Context

4.1 Introduction

In this chapter, we propose how to improve the baseline lyrics-to-audio alignment method by considering some context facets, complementary to lyrics. We focus on one particular middle-level facet - the temporal structure of the sung lyrics line. Studies of sheet music have indicated that there is a correlation between the accents of sung syllables and the accents in the melodic motif (Nichols et al., 2009). Singers may often prolong or reduce the duration of some syllables, in order to align them with the accents in the melody.

Music scores provide important contextual information complementary to lyrics, including note values. Nevertheless, the length of sung syllables could deviate considerably from the durations indicated in the music score. Singers in OTMM, in particular, tend to deviate from the music score to a significantly larger extent, in comparison, for example, to classical music. To address this, we propose an extension of the phonetic recognizer that models explicitly some reference syllable durations. The proposed duration aware model is designed to accommodate duration variations. The major technical contribution of this chapter is the derivation an inference method for the model. The reference syllable durations are obtained from the music score. To our knowledge, this study is the first application of modeling of music-score-induced durations for sung syllables.

60

Context: Syllable durations within a lyrics line

Chapter 4 outline

- 4.3 Duration aware probabilistic model
- 4.4 Durations derived from music score (on OTMM)
- 4.5 Durations derived from music principles (on jingju)

Waiting time distribution

$$P_i(d) = (1 - a_{ij})^d$$

exponential distribution

Waiting time distribution

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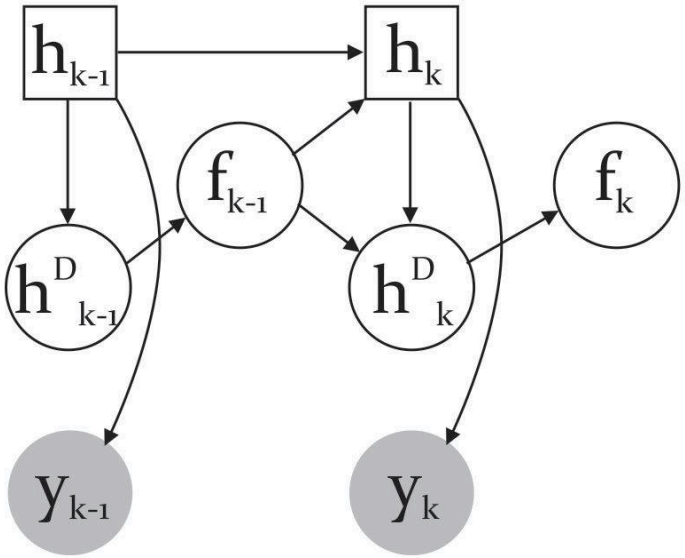
exponential distribution

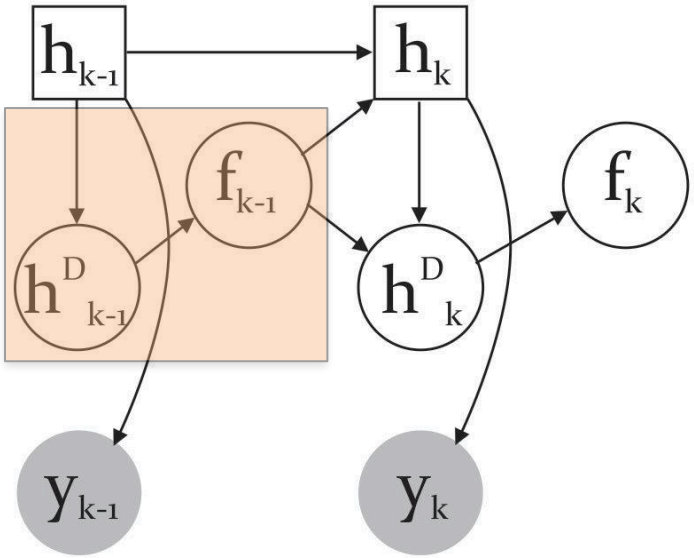
Model components



(Murphy, 2002)

Sec 4.3

Model components



phoneme

binary indicator

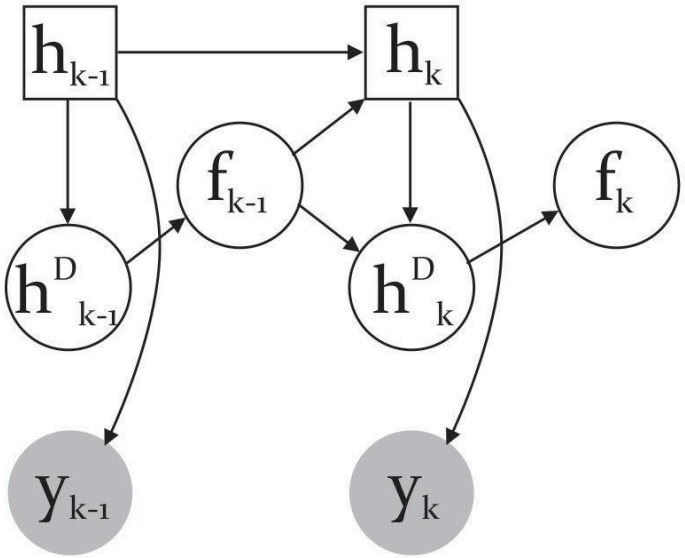
phoneme duration

mfcc

(Murphy, 2002)

Sec 4.3

Model components



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Sec 4.3

Viterbi decoding

$$\delta_k(j) = \max_{i \in (j,\, j-1)} \delta_{k-1}(i)\, a_{ij}\, b_j(O_k)$$

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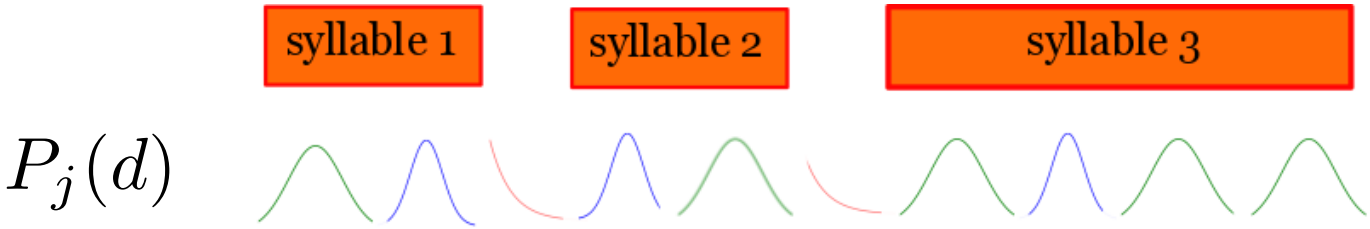
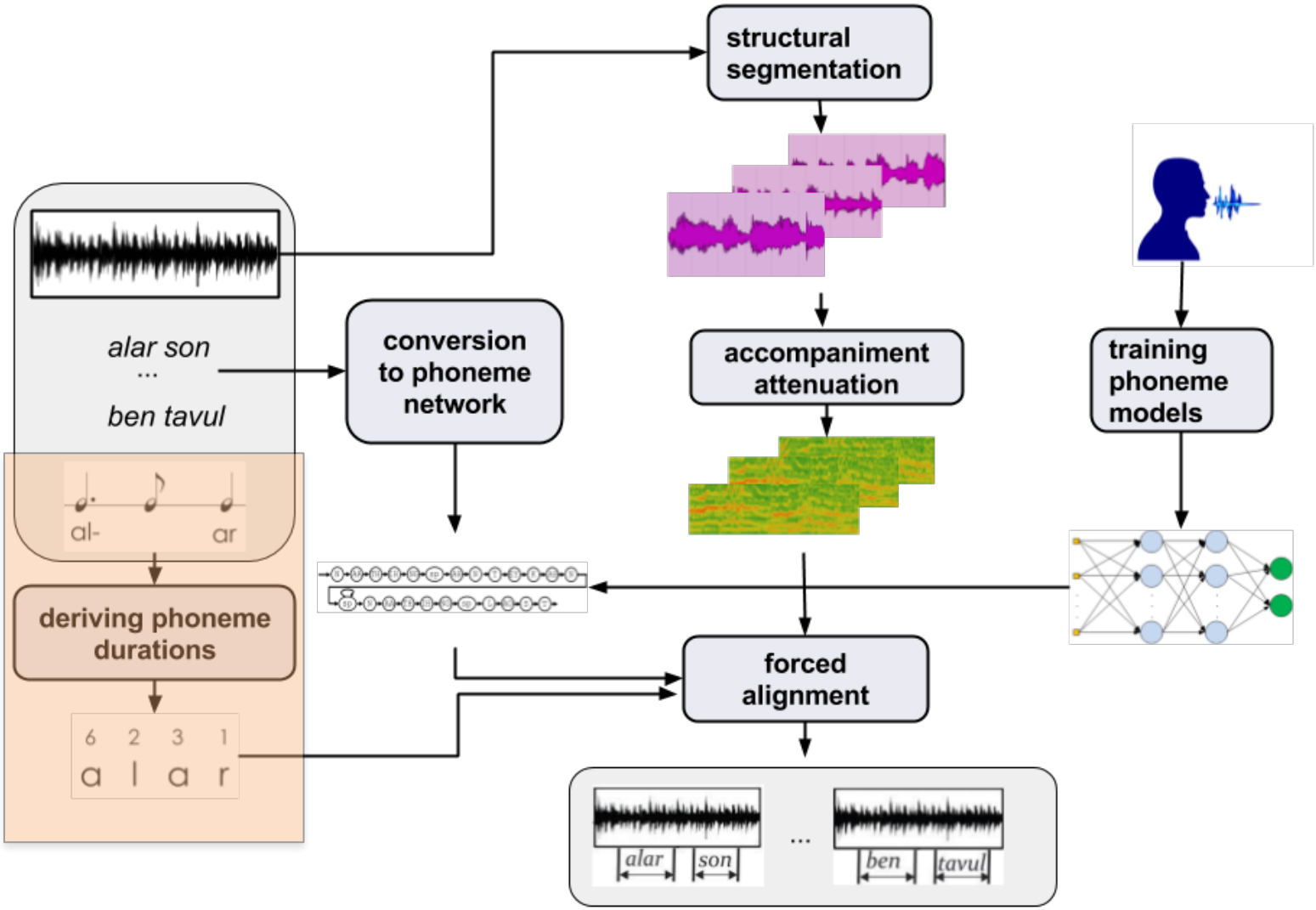
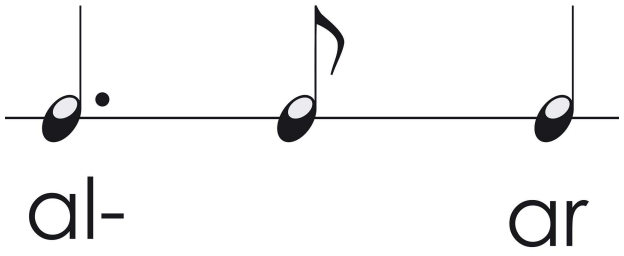


Chapter 4.4
Durations derived from music score



Deriving phoneme durations



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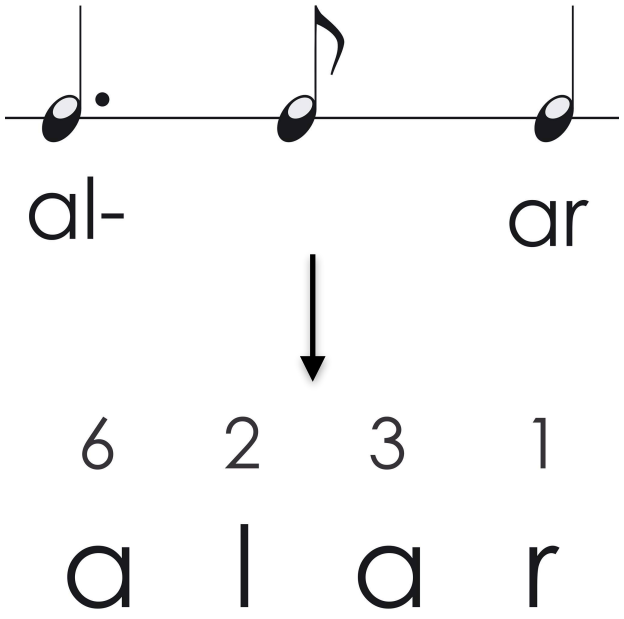

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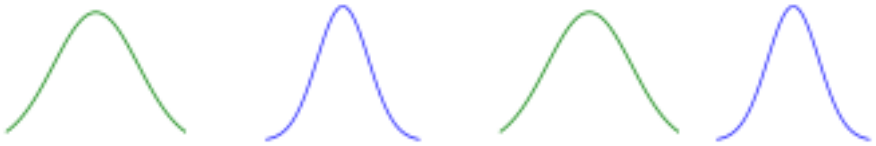
6 2 3 1

a l a r



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duration aware GMM	a cappella OTMM	90.04	0.26
baseline GMM	multi-instrumental OTMM	67.46	1.26
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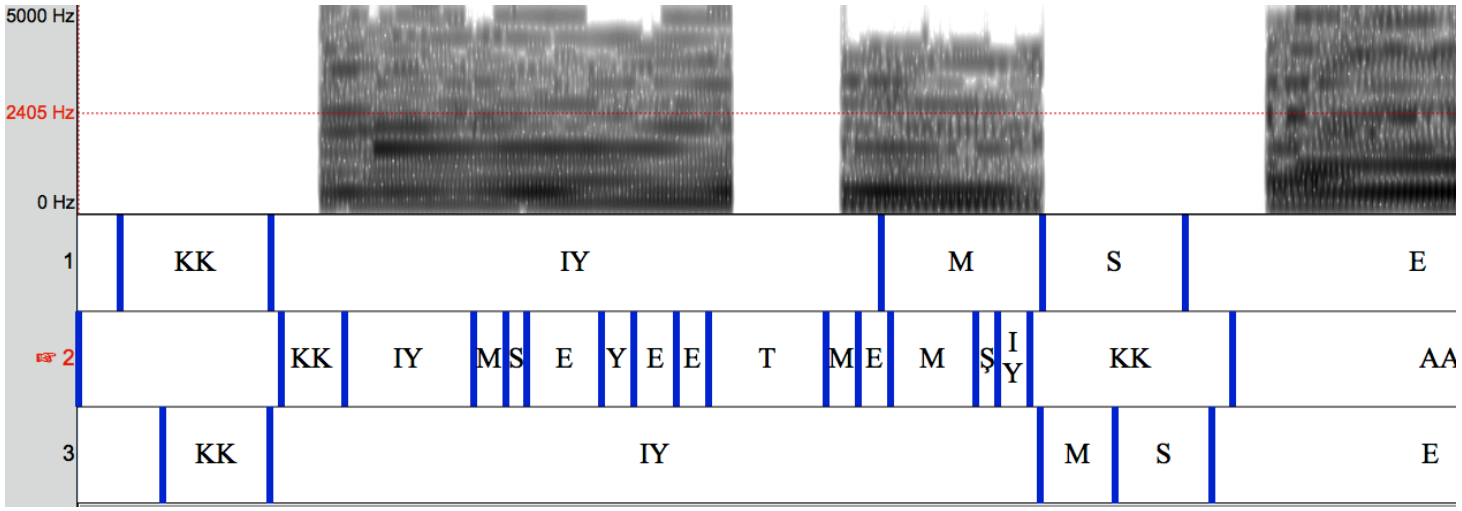

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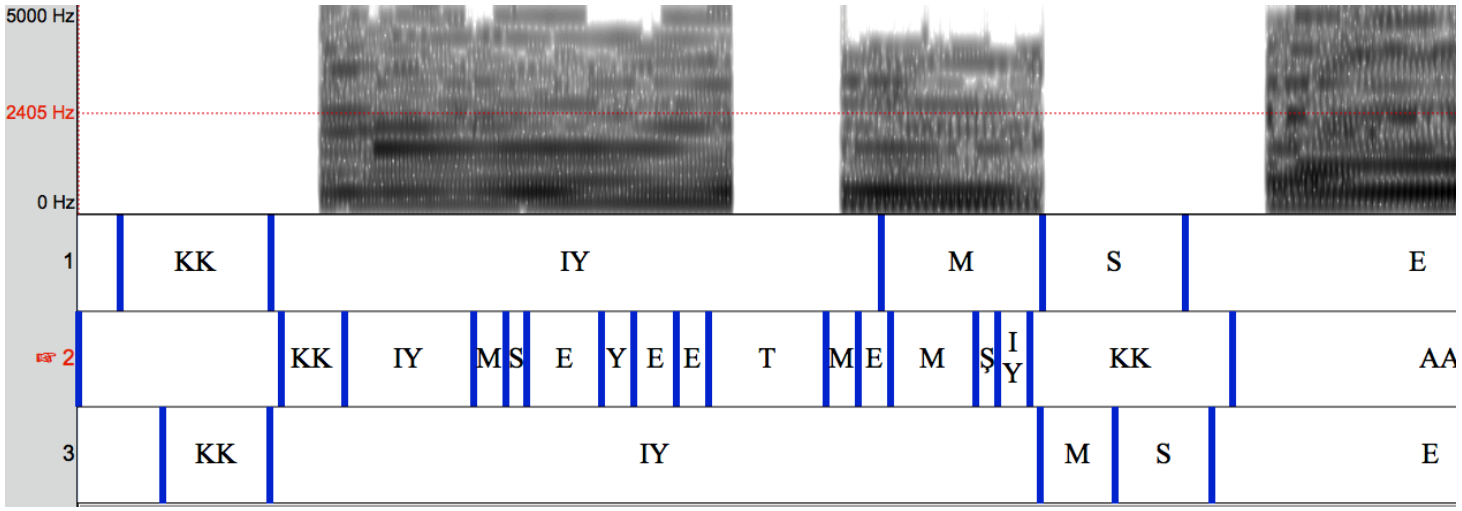

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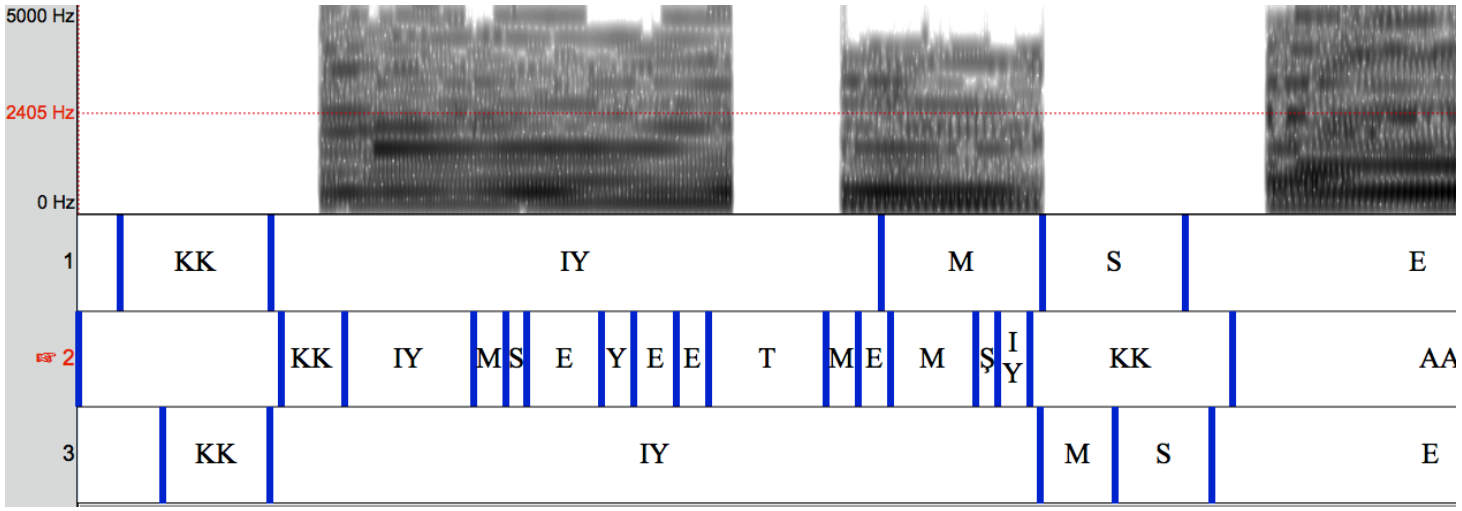

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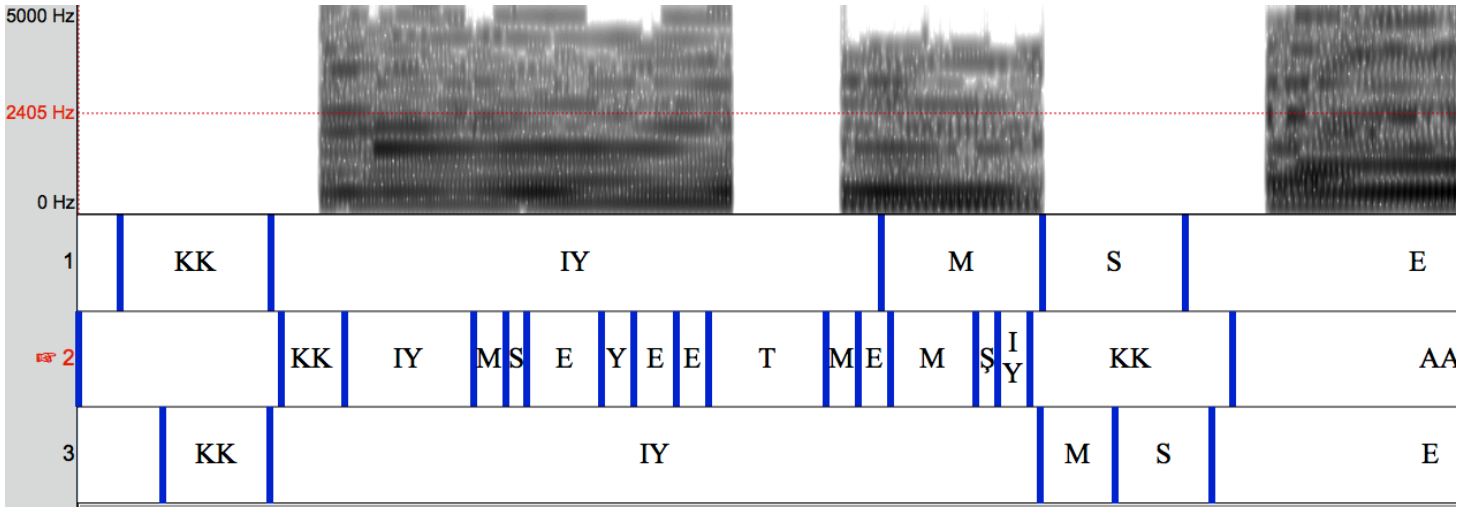

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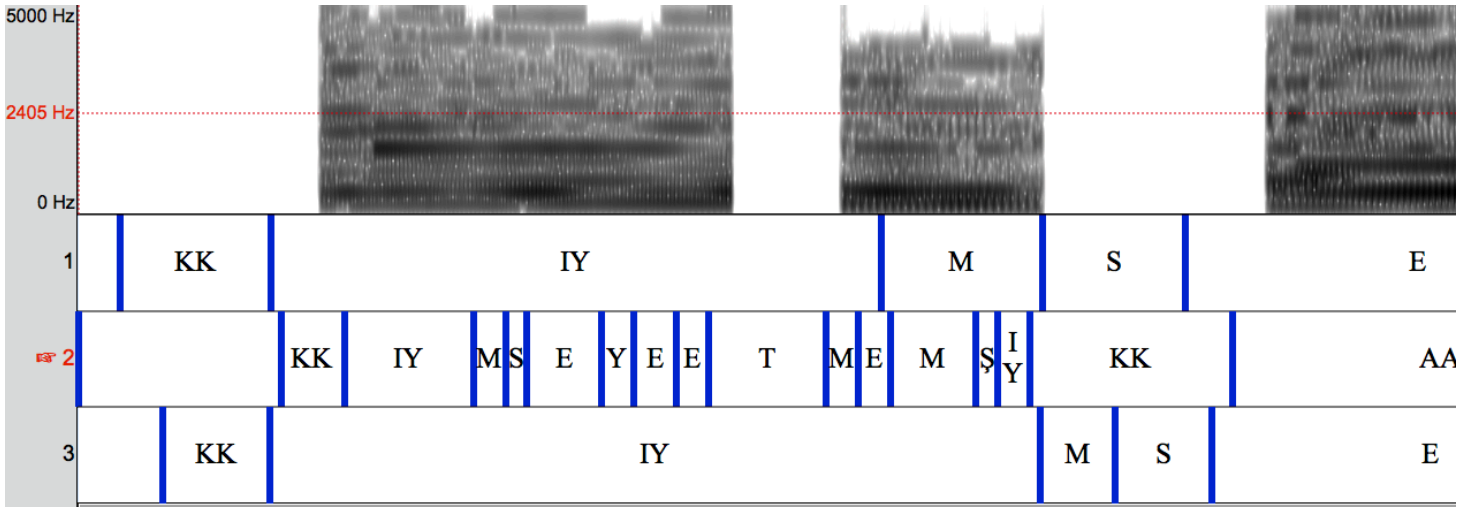

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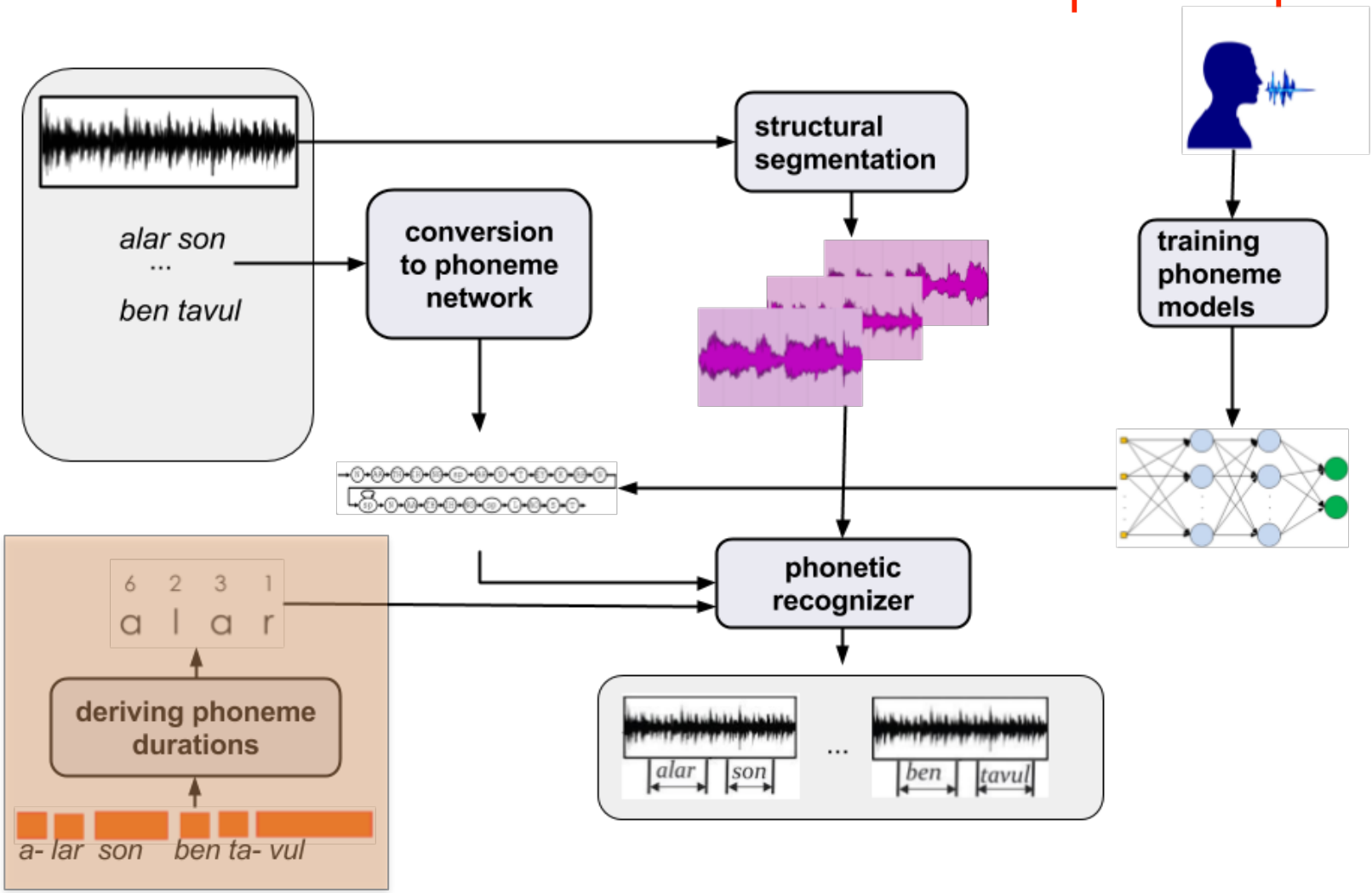
Sec 4.4

Chapter 4.5
Durations derived from music principles



Introduction to jingju

- Unique singing style
- Language based on Mandarin
- Different role types

dan

laosheng

Jingju-specific principles

- Lyrics: have poetic structure

Jingju-specific principles

- Lyrics: have poetic structure

玉堂春含悲泪忙往前进，

想起了当年事好不伤情！

每日里在院中缠头似锦，

到如今只落得罪衣罪裙。

Jingju-specific principles

- Lyrics: have poetic structure

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- Usually 3 dou in a lyrics line

到 如　今　只 落　　得　　罪 衣 罪　　裙

dou　　*dou*　　*dou*

Jingju-specific principles

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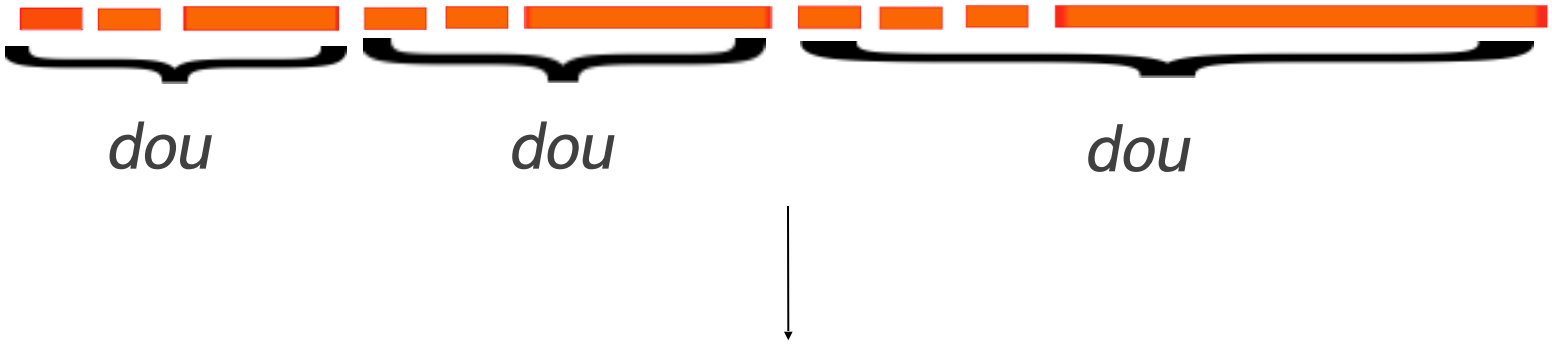
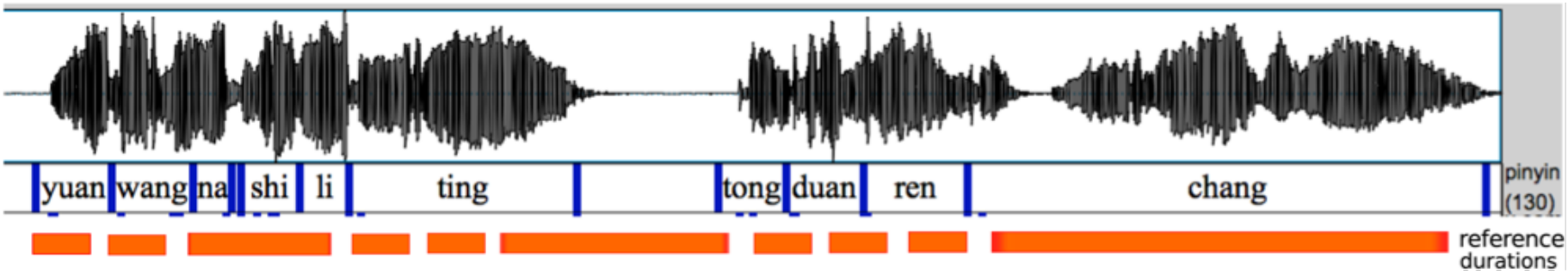
到 如　今　只 落　　得　　罪 衣 罪　　裙

dou　　*dou*　　*dou*

- Long last syllable

Deriving phoneme durations





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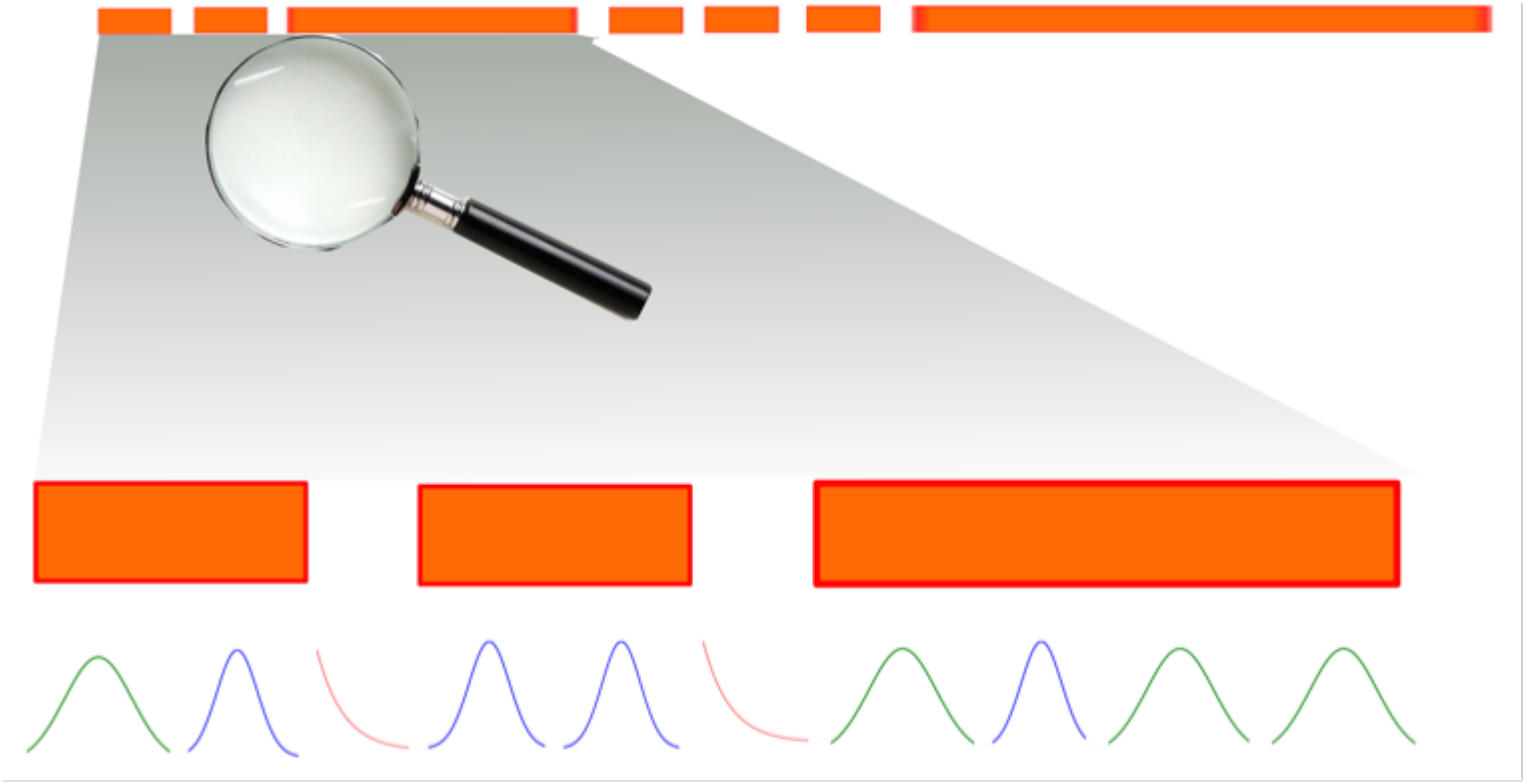
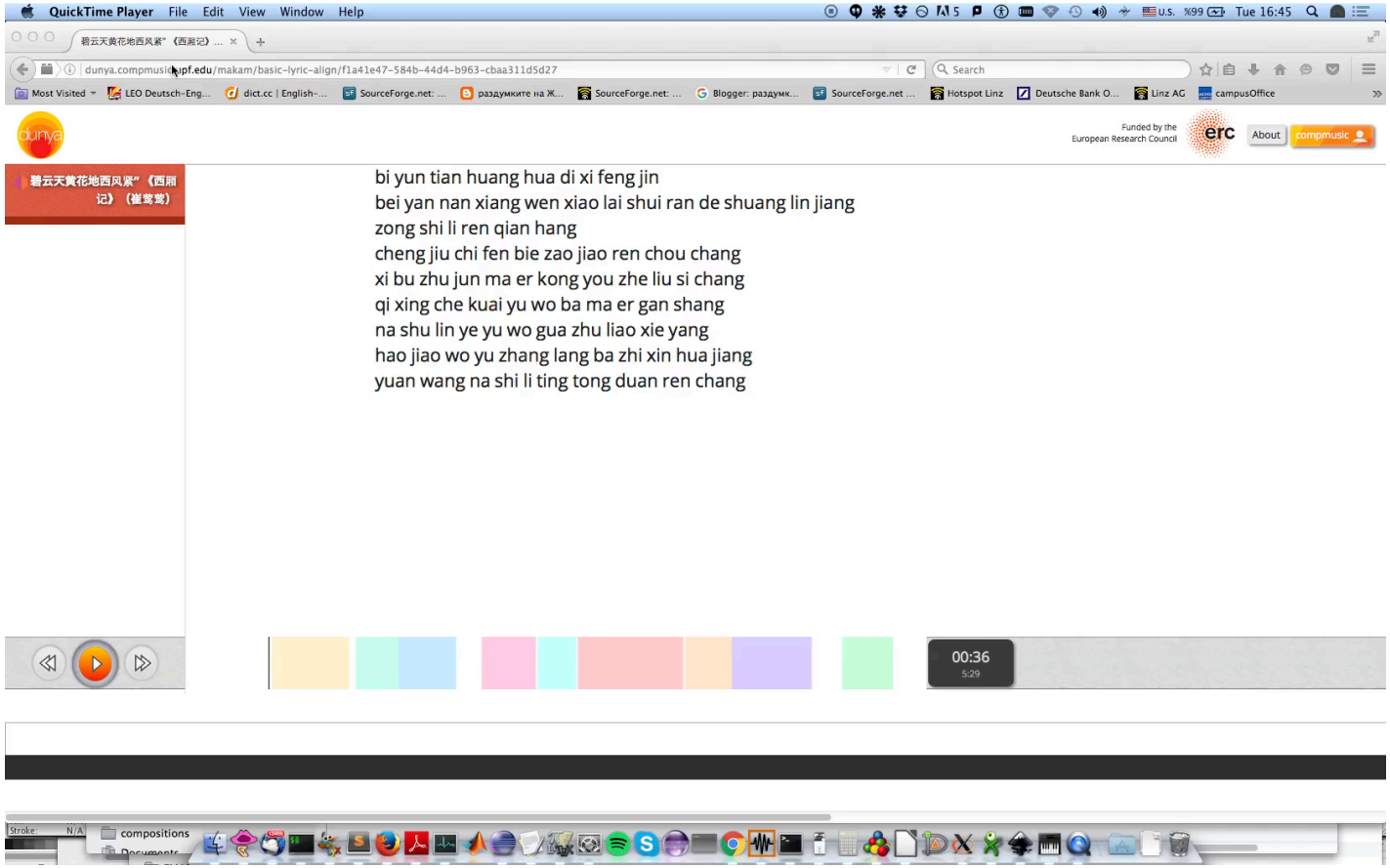


A cappella lyrics jingju dataset

- 15 arias of dan role type (80 minutes)
- A cappella is separated manually



http://compmusic.upf.edu/node/286

Sec 3.2.4

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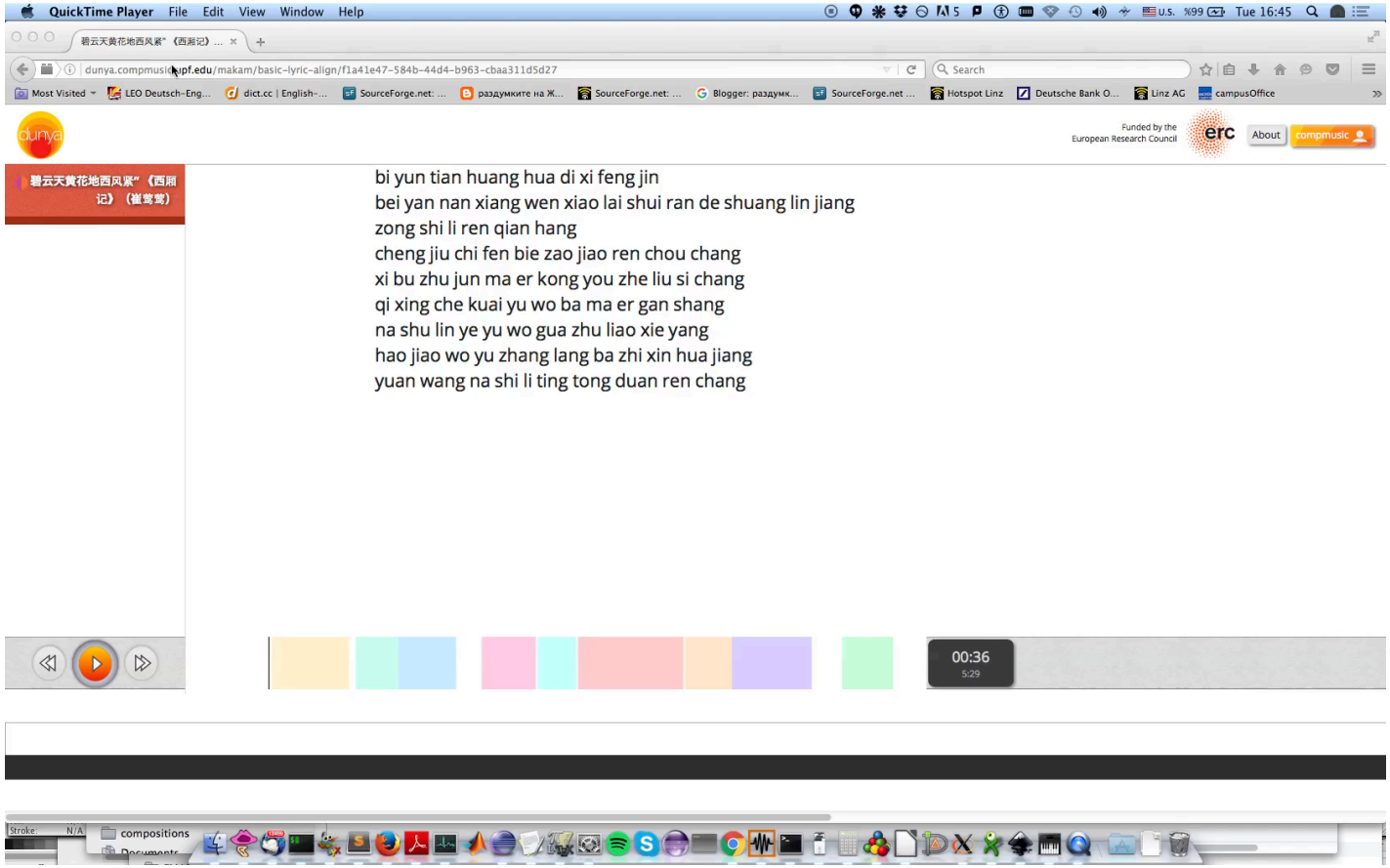

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Sec 3.2.4

Experiments

- Experiment 0: duration aware with oracle phonemes

	oracle	baseline	duration aware
average	98.5	56.6	89.9
median per sentence	98.3	75.2	92.3

Dzhambazov, Georgi, Yile Yang, Rafael Caro Repetto, and Xavier Serra (2016). Automatic alignment of long syllables in a cappella Beijing opera. In 6th International Workshop on Folk Music Analysis (FMA 2016)

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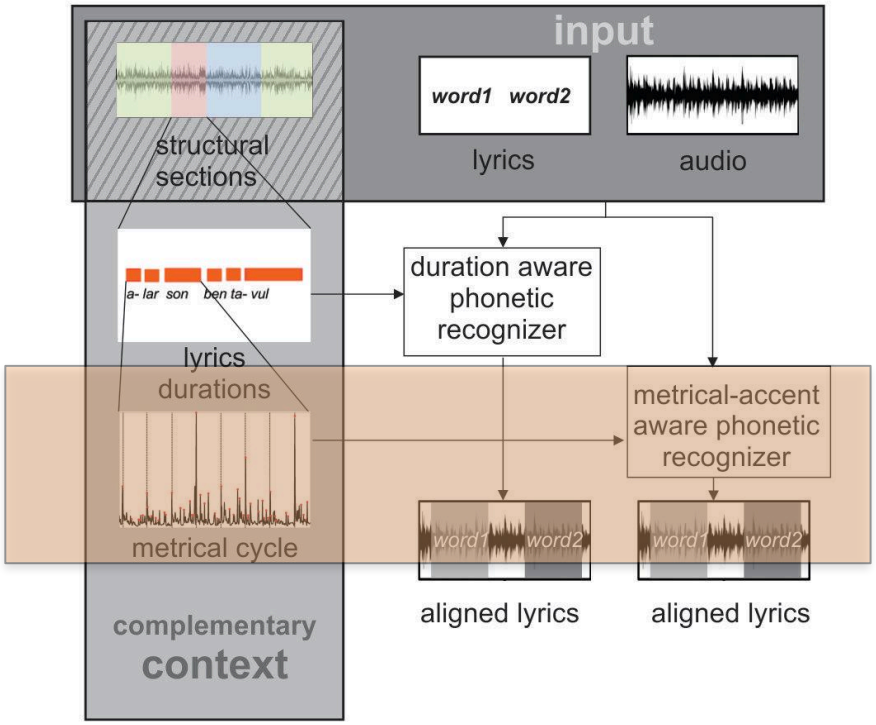
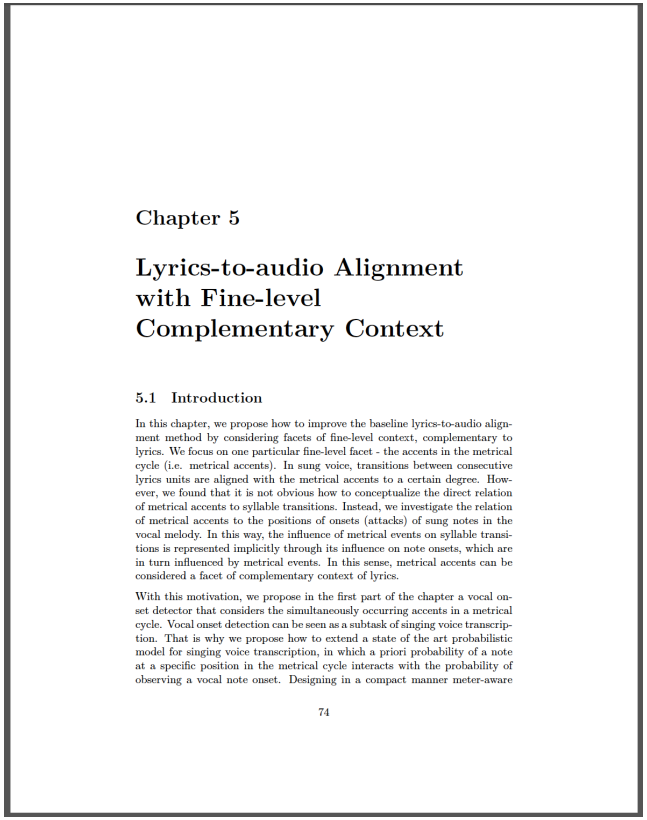
- Conclusion (Chapter 6) and Applications (Appendix)

Chapter 5: Lyrics-to-audio Alignment with Fine-level Complementary Context



Context: Accents within a metrical cycle



Chapter 5

Lyrics-to-audio Alignment with Fine-level Complementary Context

5.1 Introduction

In this chapter, we propose how to improve the baseline lyrics-to-audio alignment method by considering facets of fine-level context, complementary to lyrics. We focus on one particular fine-level facet - the accents in the metrical cycle (i.e. metrical accents). In sung voice, transitions between consecutive lyrics units are aligned with the metrical accents to a certain degree. However, we found that it is not obvious how to conceptualize the direct relation of metrical accents to syllable transitions. Instead, we investigate the relation of metrical accents to the positions of onsets (attacks) of sung notes in the vocal melody. In this way, the influence of metrical events on syllable transitions is represented implicitly through its influence on note onsets, which are in turn influenced by metrical events. In this sense, metrical accents can be considered a facet of complementary context of lyrics.

With this motivation, we propose in the first part of the chapter a vocal onset detector that considers the simultaneously occurring accents in a metrical cycle. Vocal onset detection can be seen as a subtask of singing voice transcription. That is why we propose how to extend a state of the art probabilistic model for singing voice transcription, in which a priori probability of a note at a specific position in the metrical cycle interacts with the probability of observing a vocal note onset. Designing in a compact manner meter-aware

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Chapter 5 outline

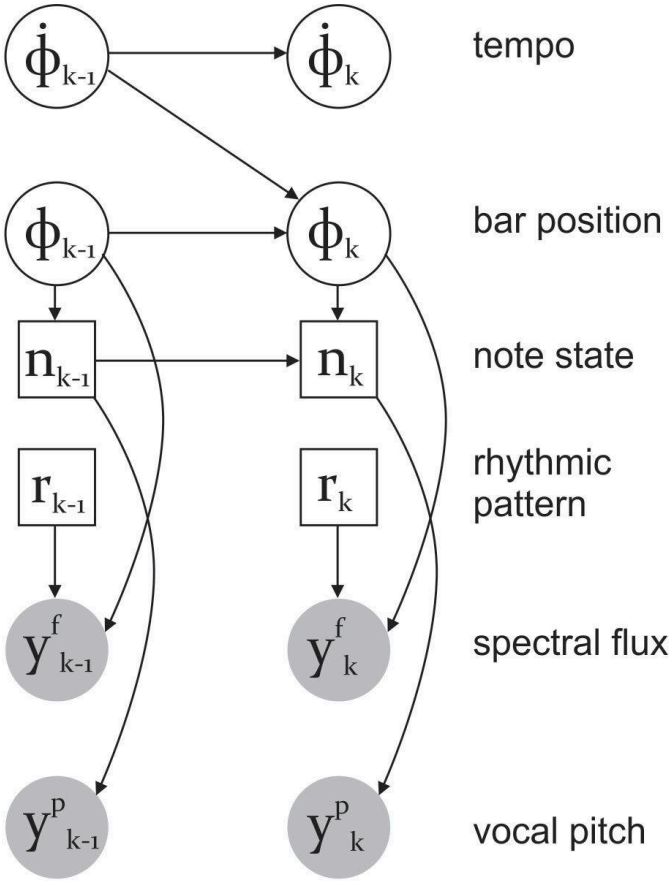
- Metrical-accent aware vocal note onset detection (5.3)
- Vocal-onset aware lyrics-to-audio alignment (5.4)

Chapter 5.3
Metrical-accent aware vocal onset detection

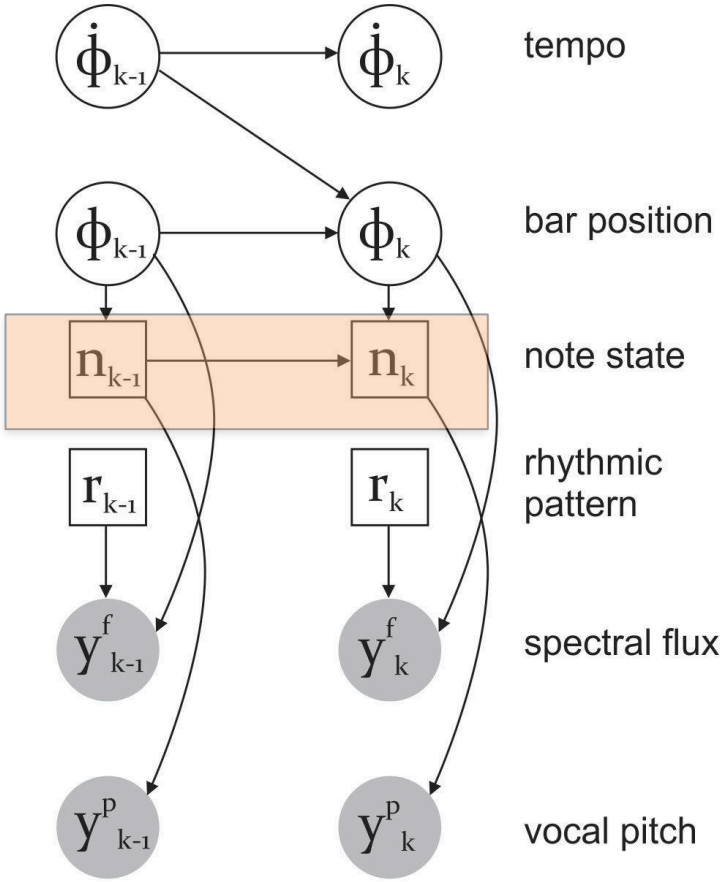
compmusic

- Vocal note events co-occur with accents in a metrical cycle (Holzapfel 2014)
  - OTMM has well pronounced metrical accents

Model components



Model components



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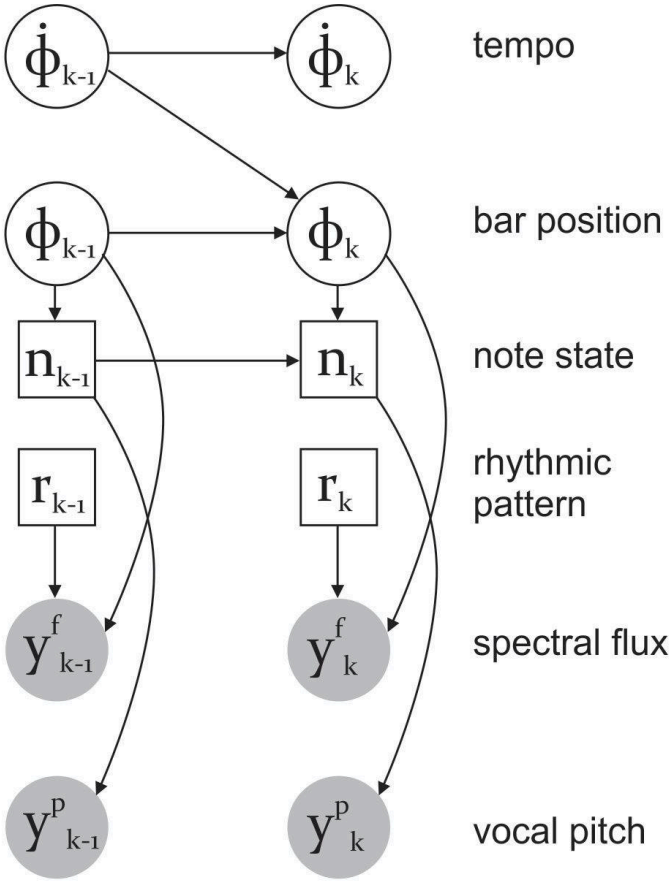
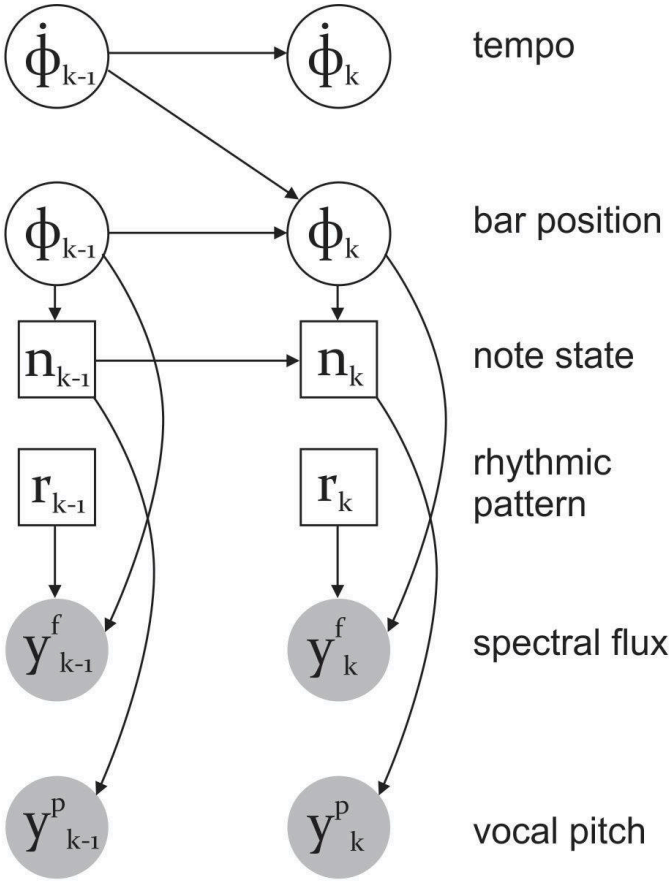


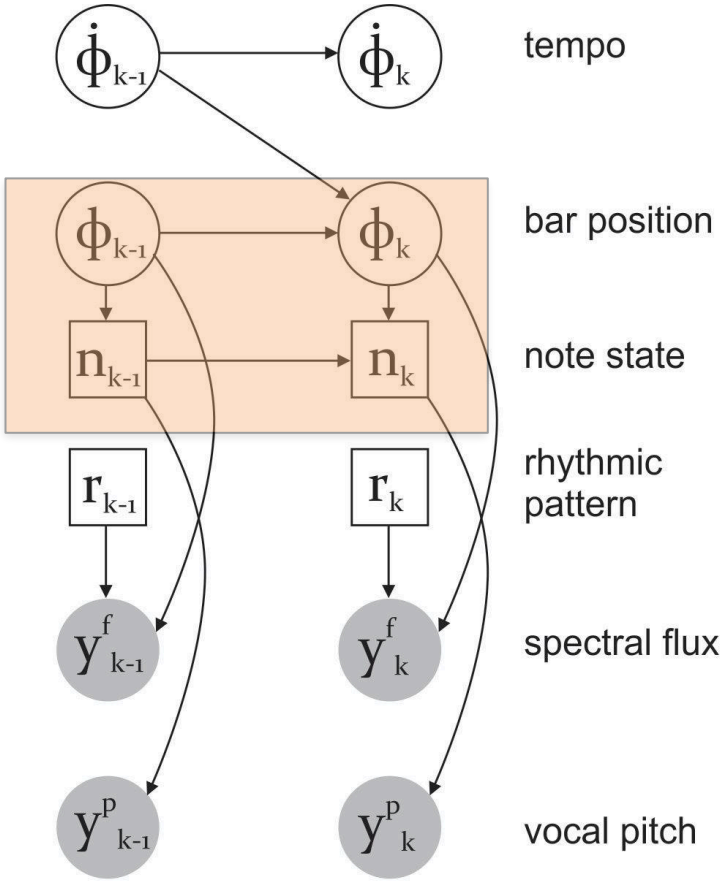
Model components



Goal: track simultaneously bar position and vocal note state

Sec 5.3

Model components



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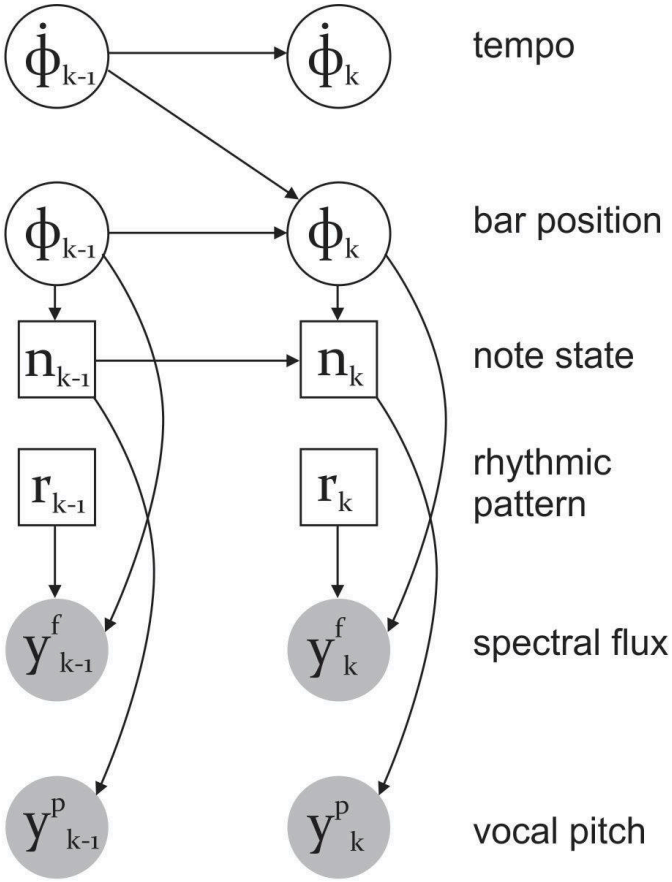
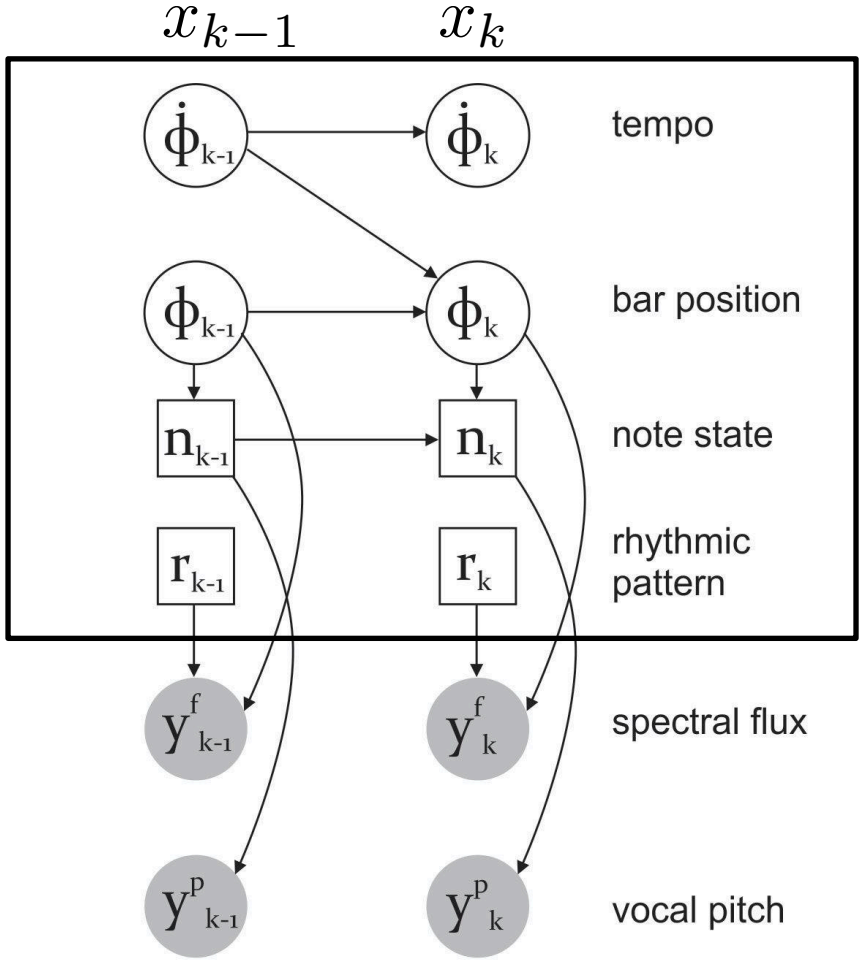
Transition model



(Krebs et al., 2015)

Transition model



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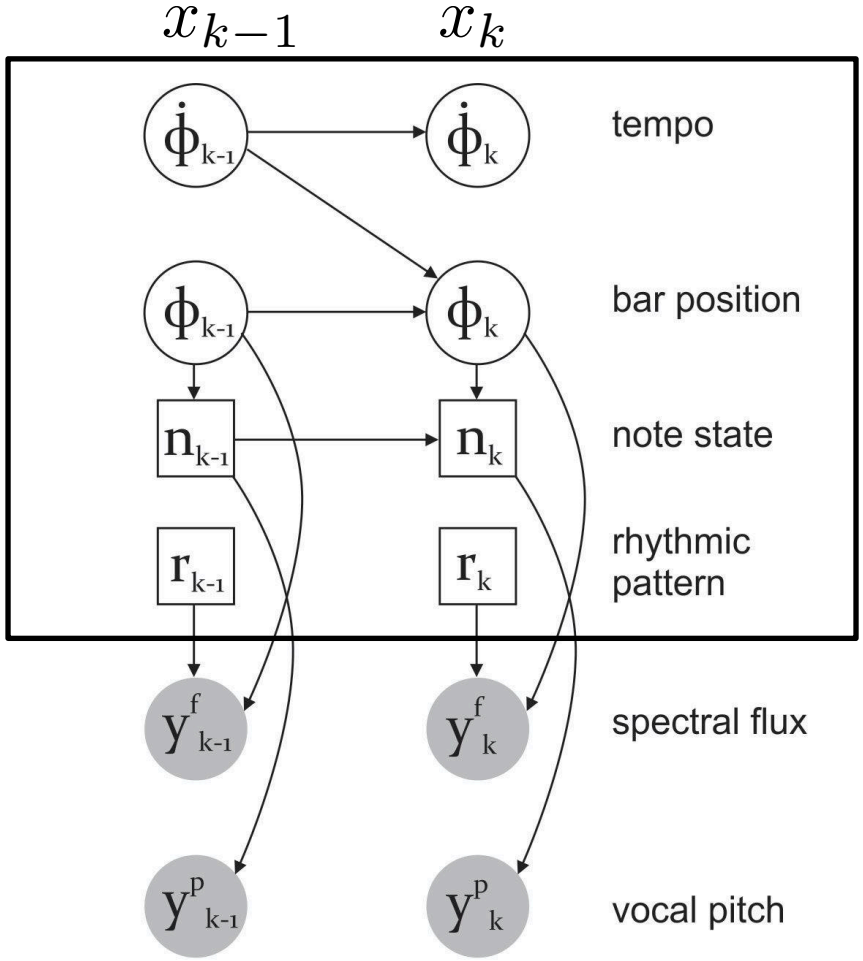
Transition model

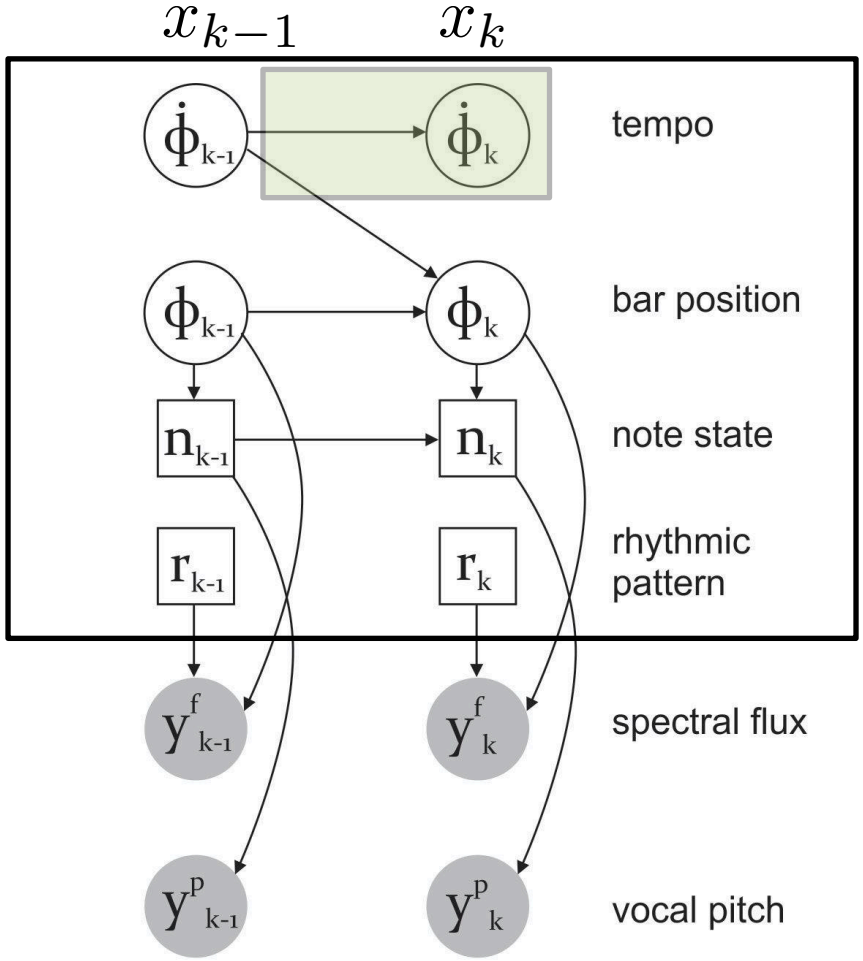


(Krebs et al., 2015)

$$P(x_k|x_{k-1}) = P(\dot{\phi}_k|\dot{\phi}_{k-1}) \times P(\phi_k|\phi_{k-1}, \dot{\phi}_{k-1}) \times P(n_k|n_{k-1}, \phi_k)$$

Sec 5.3

Transition model



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Sec 5.3

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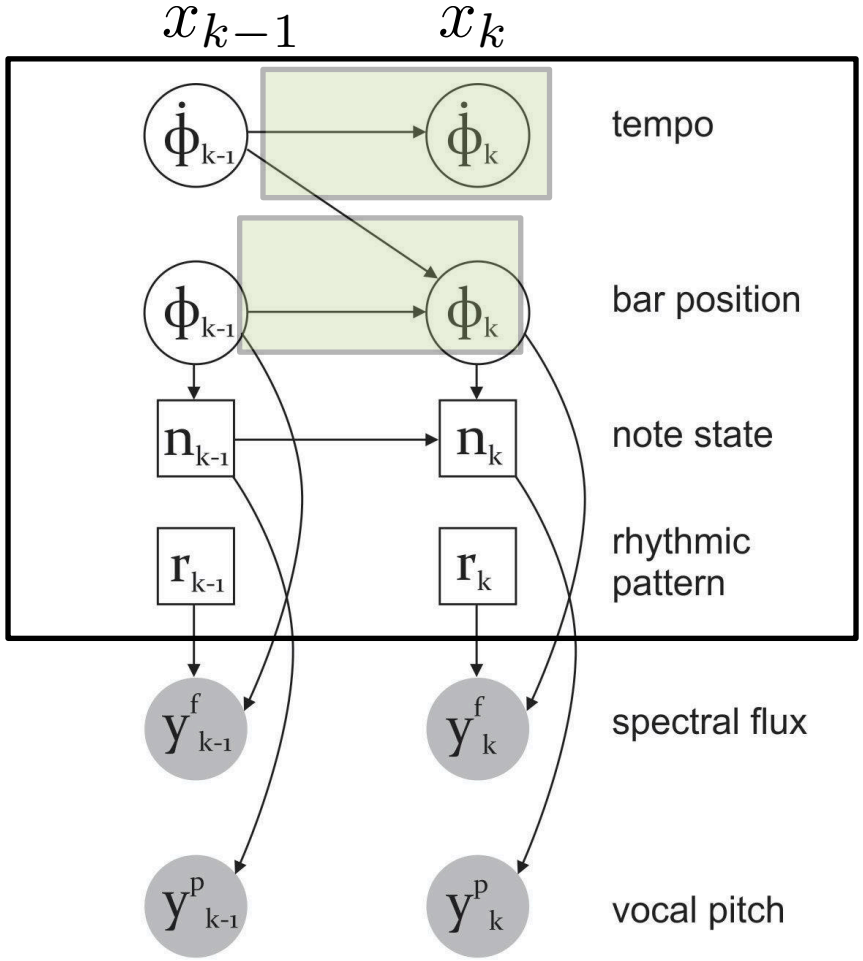

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Sec 5.3

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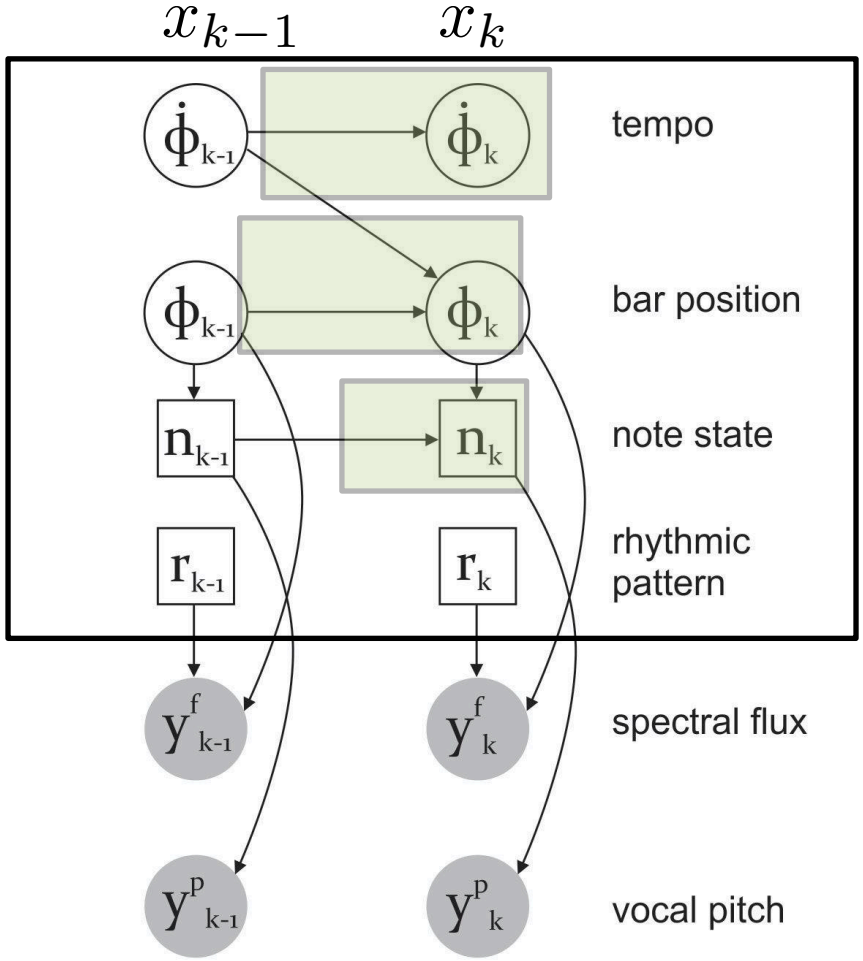

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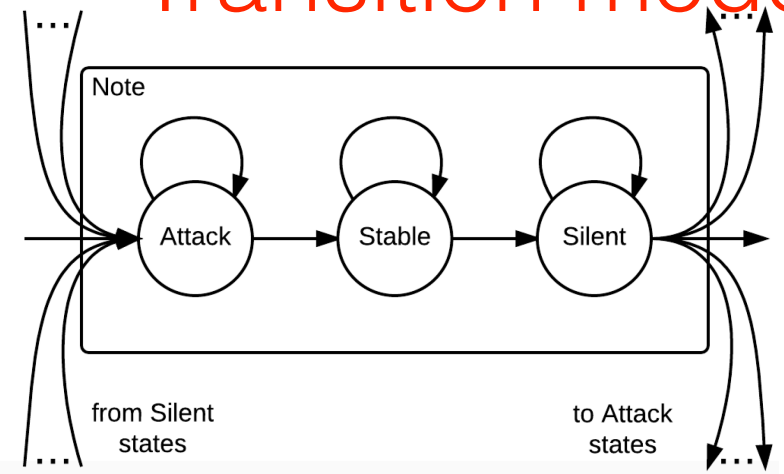
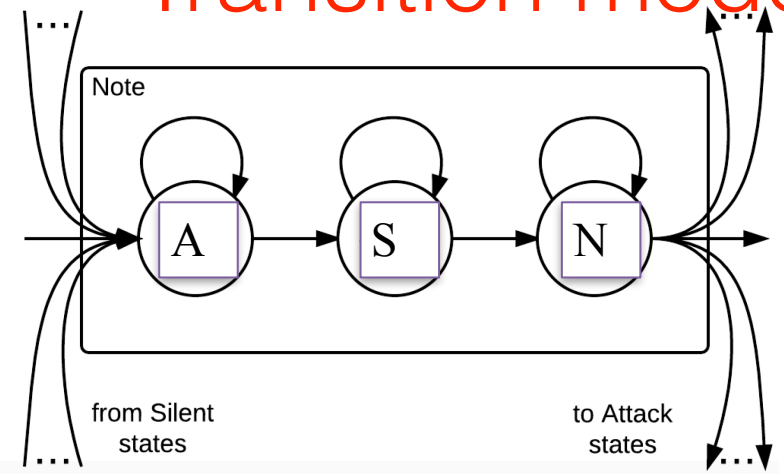
Transition model



compmusic

Transition model



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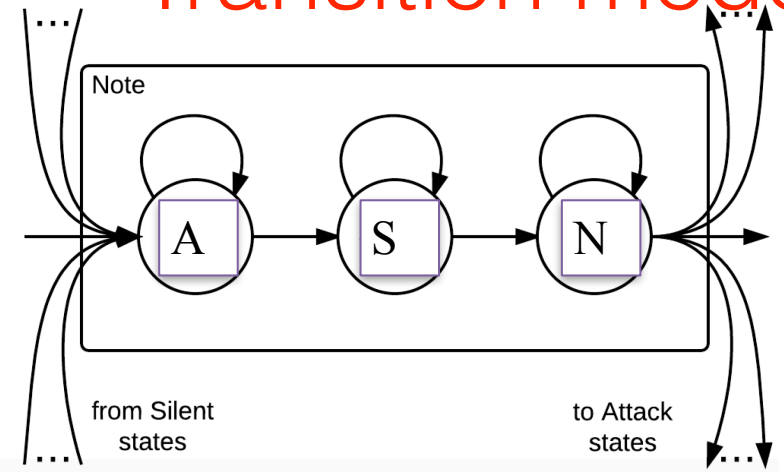
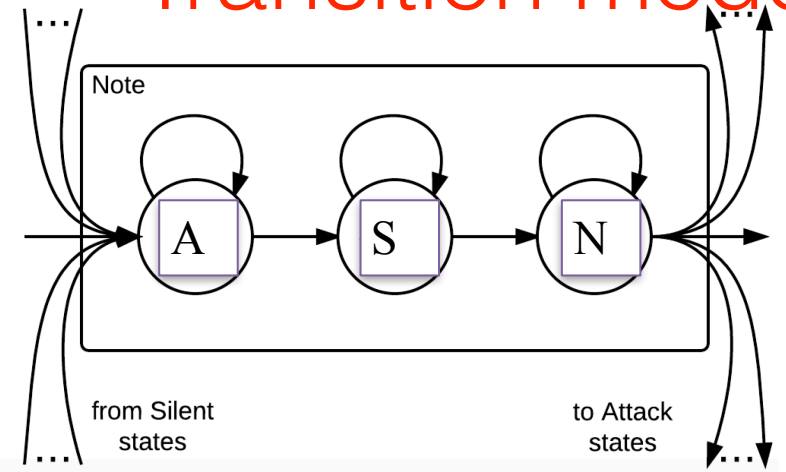
Transition model



$$p(n_k|n_{k-1}) = \begin{cases} P_{N_i A_j}, & n_{k-1} = N_i \quad n_k = A_j \\ 1 - \sum_i P_{N_i A_j}, & n_{k-1} = n_k = N_i \\ 1 - c_A, & n_{k-1} = A_i \quad n_k = S_j \\ c_A, & n_{k-1} = n_k = A_i \\ 1 - c_S & n_{k=1} = S_i \quad n_k = N_j \\ c_S, & n_{k-1} = n_k = S_i \\ 0 & else \end{cases}$$

(Mauch et al., 2015)

Transition model



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(Mauch et al., 2015)

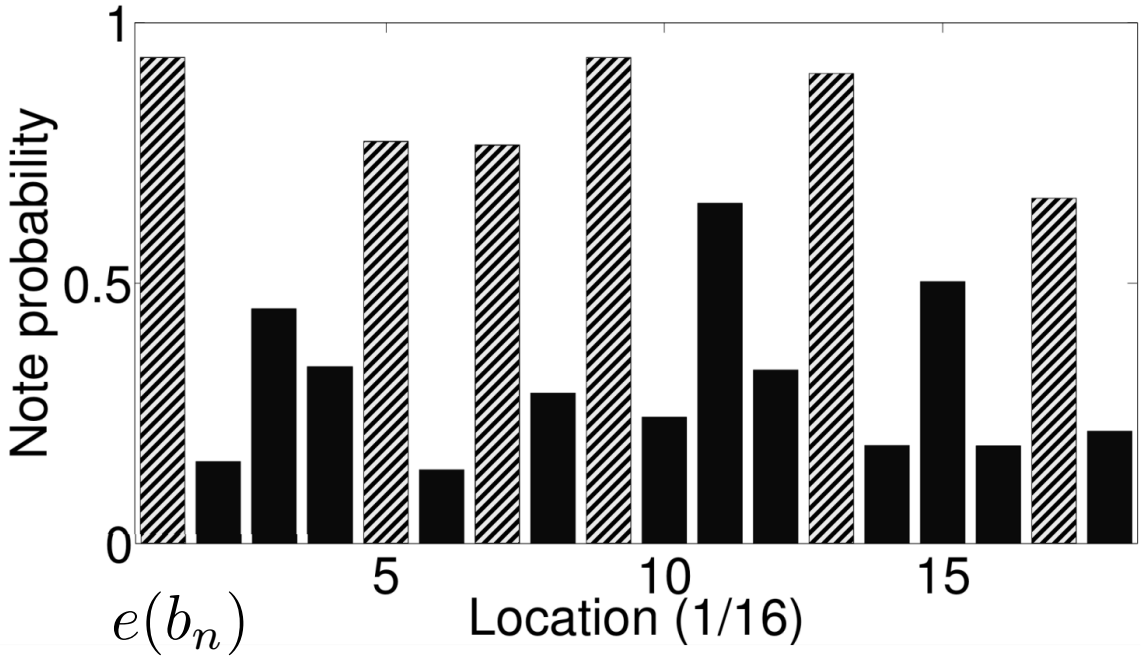
$$p(n_k|n_{k-1}, \phi_k) = \begin{cases} P_{N_i A_j} \Theta(\phi_k), & n_{k-1} = N_i \quad n_k = A_j \\ 1 - \Theta(\phi_k) \sum_i P_{N_i A_j}, & n_{k-1} = n_k = N_i \\ \dots \end{cases}$$

Sec 5.3

Transition model

$$\Theta(\phi_k) = \begin{cases} q.\, e(b_n), & \phi_k := b_n \\ 1 & else \end{cases}$$

$e(b_n)$: note probability within a metrical cycle



(Holzapfel, 2014)

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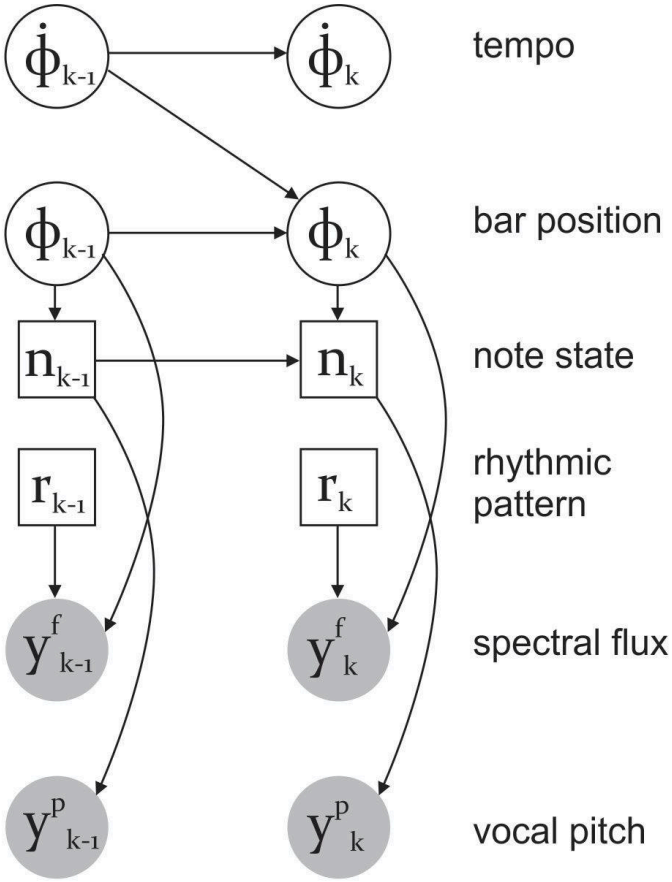
Observation model



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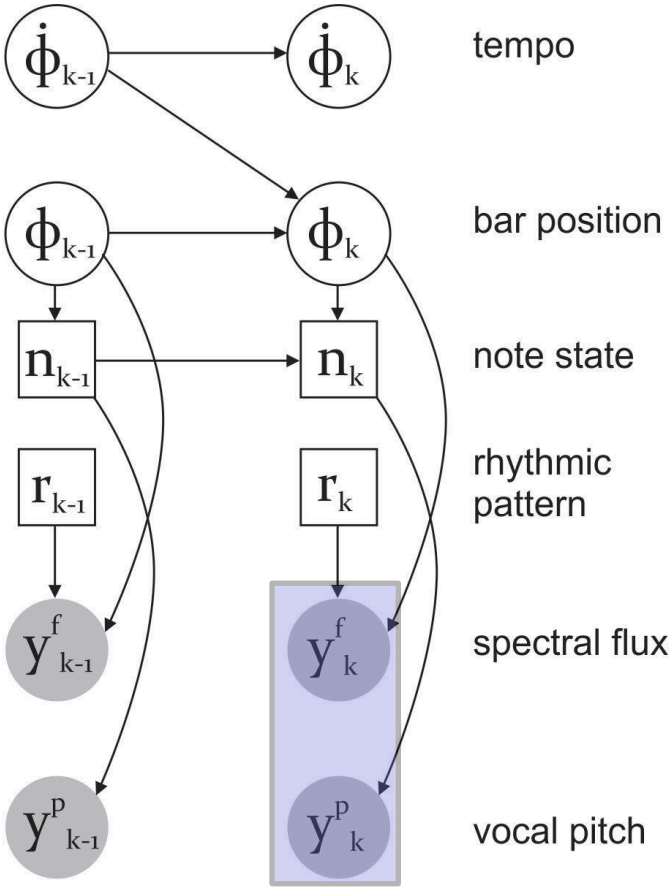
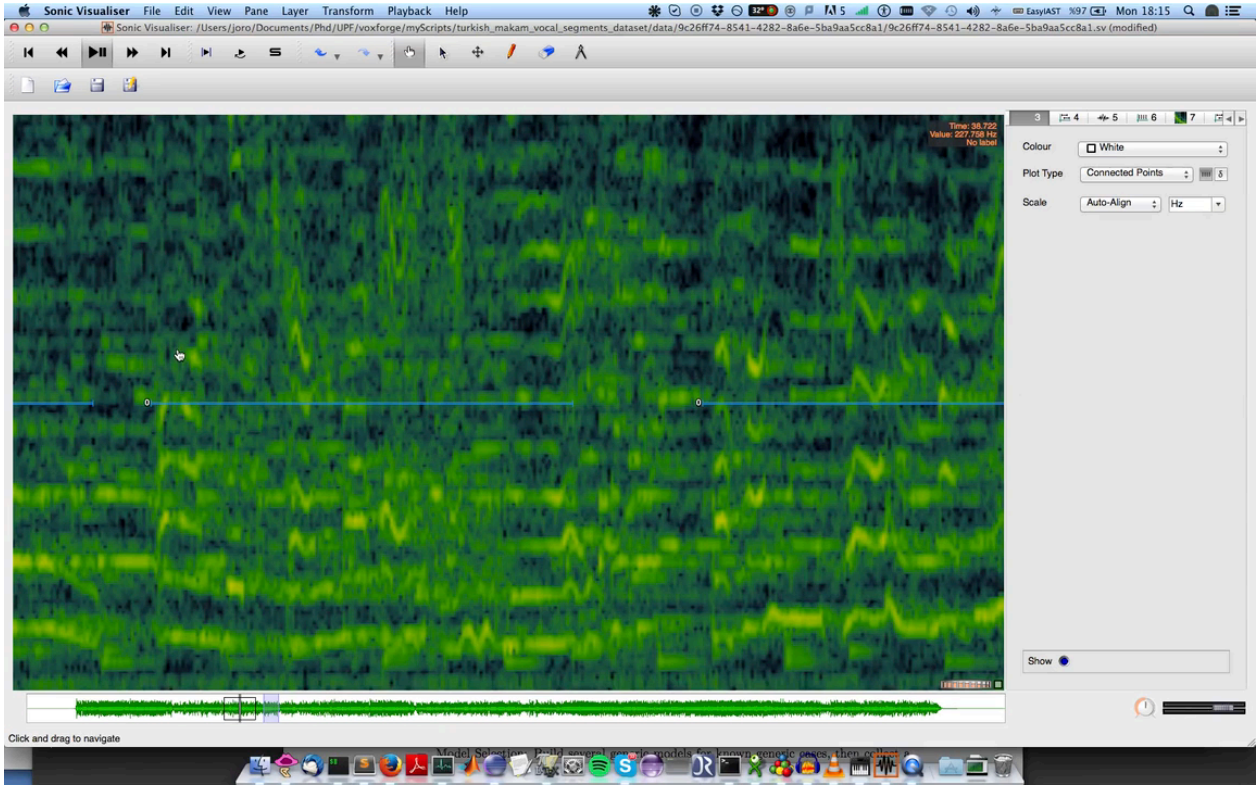


$$P(y_k^f, y_k^p | x_k) = P(y_k^f | \phi_k, r_k) P(y_k^p | n_k)$$

Multi-instrumental vocal onsets OTMM dataset

- Annotations on beats + vocal onsets
- 5 1-minute recordings from two meter types



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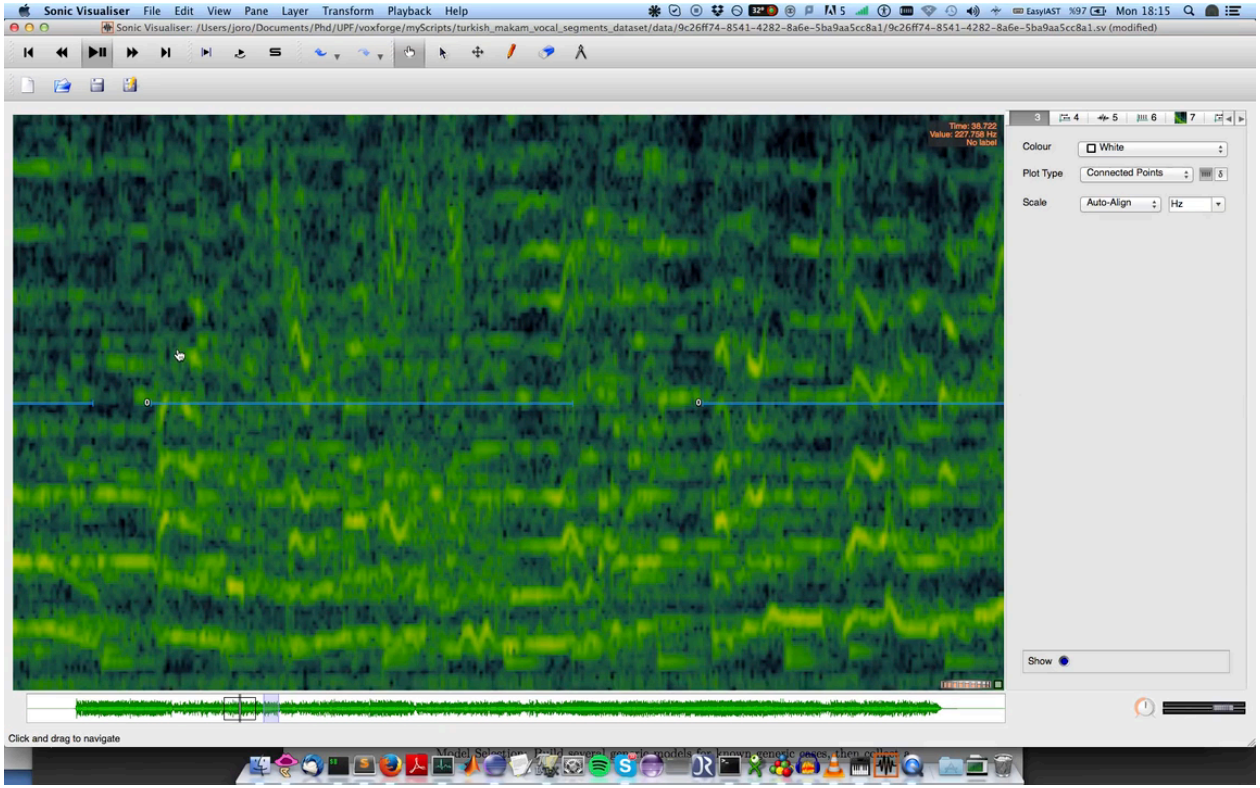

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Experiments

- Experiment 1 (Ex-1): manually annotated beats

meter		beat Fmeas	P	R	Fmeas
düyek	Mauch	-	33.1	31.6	31.6
	Ex-1	-	40.4	39.5	39.0
	Ex-2	86.4	37.8	36.1	36.1
aksak	Mauch	-	42.1	36.9	37.9
	Ex-1	-	48.4	39.1	43.0
	Ex-2	72.9	45.0	39.0	40.3

Dzhambazov, Georgi, Andre Holzapfel, Ajay Srinivasamurthy and Xavier Serra (2017). Metrical-accent aware vocal onset detection. In18th International Society for Music Information Retrieval Conference (ISMIR 2017)

Sec 5.3

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Sec 5.3

Experiments

- Experiment 1 (Ex-1): manually annotated beats
- Experiment 2 (Ex-2): simultaneous bar-position and vocal onset

meter		beat Fmeas	P	R	Fmeas
düyek	Mauch	-	33.1	31.6	31.6
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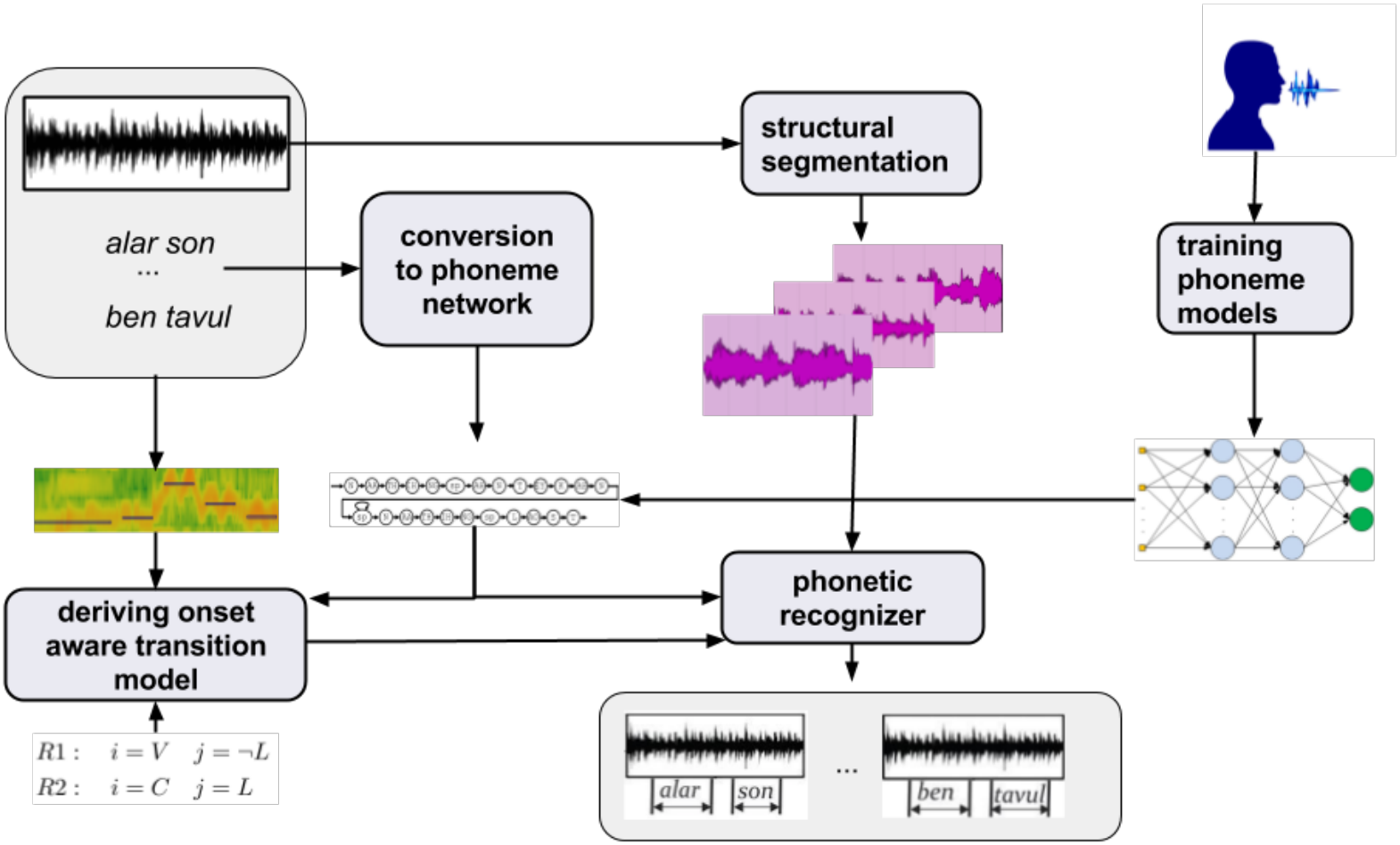
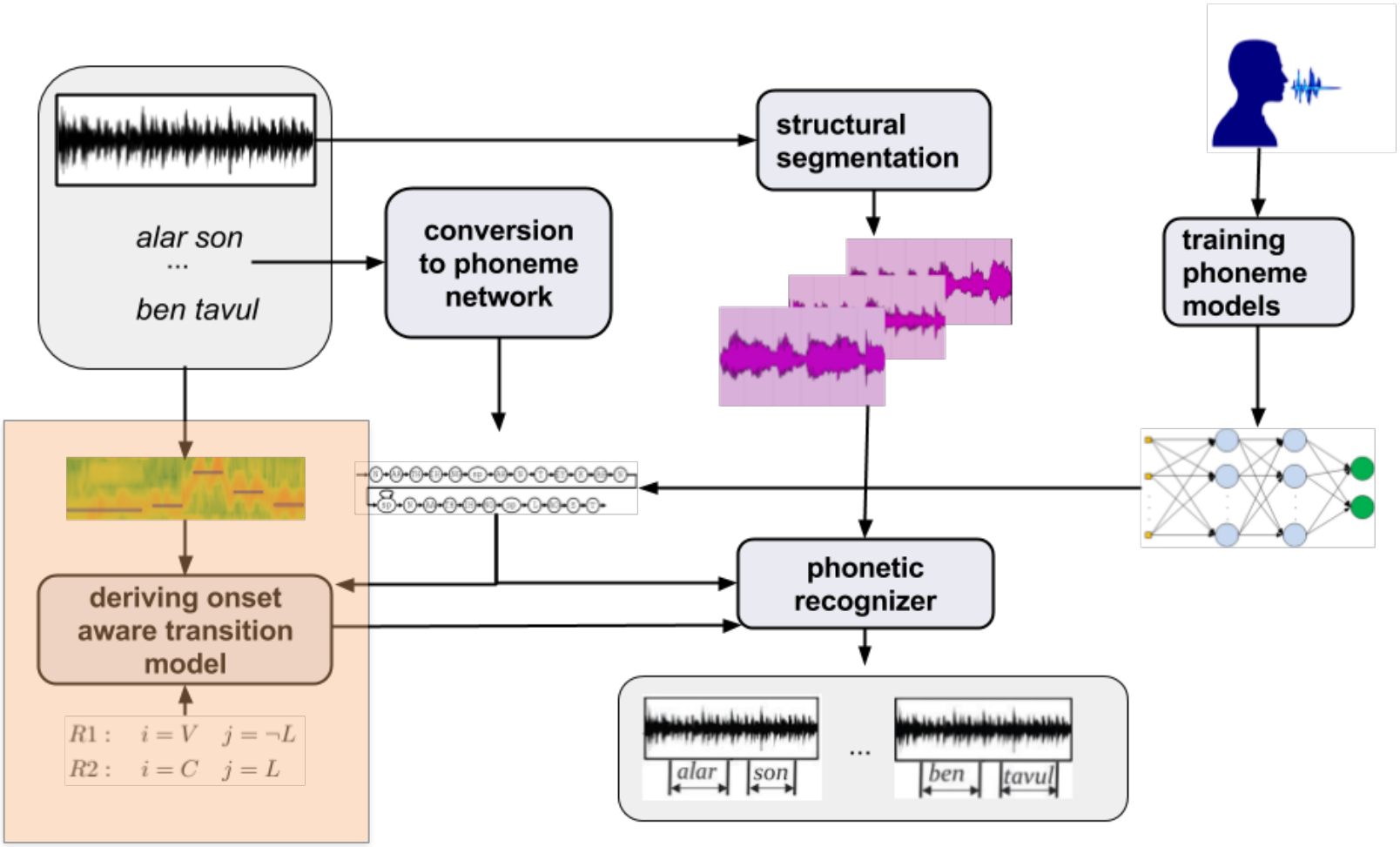
Sec 5.3

Chapter 5.4
Onset aware lyrics-to-audio alignment

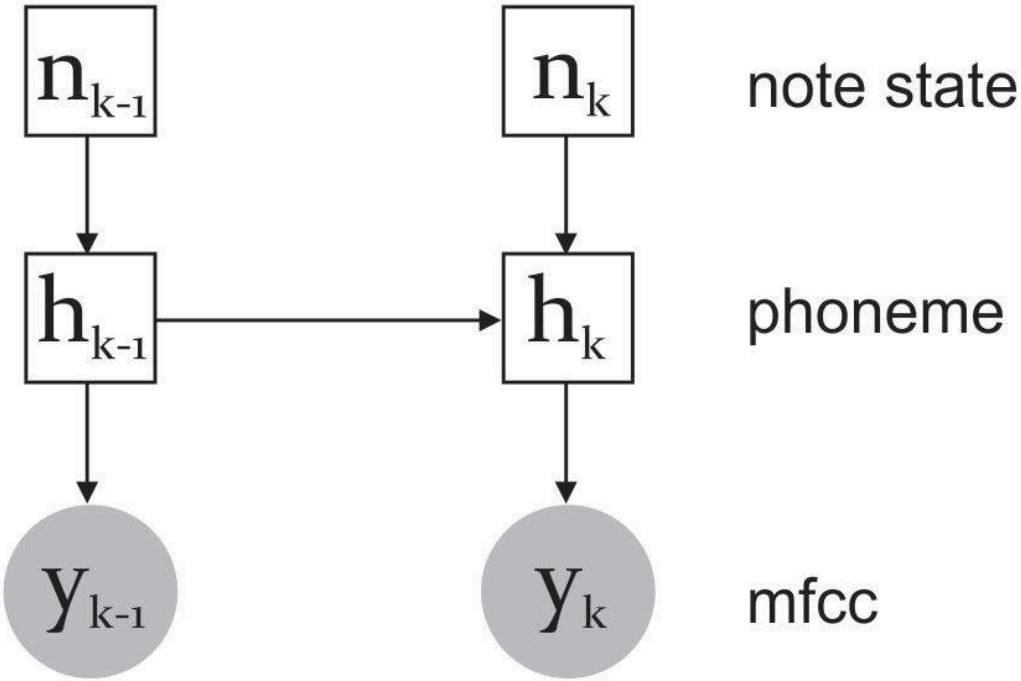


Chapter 5.4
Onset aware lyrics-to-audio alignment



Model components

- Syllable boundaries coincide with segments of vocal notes (e.g. note onsets) (Sundberg 2006)



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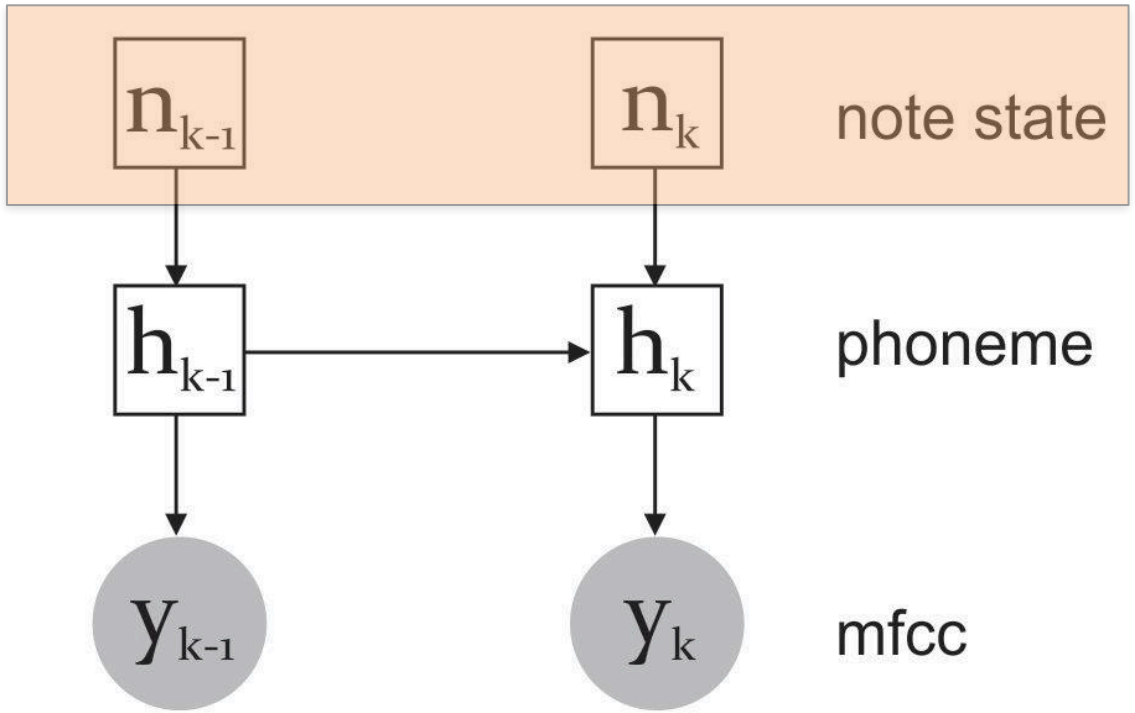


Phoneme transition rules

compmusic

$$\text{R1: } i_t = V \quad i_{t+1} = C \backslash L$$
$$\text{R2: } i_t = C \backslash L \quad i_{t+1} = V \,\text{or}\, L \;^{*}$$
$$\text{R3: } i_t = V \quad i_{t+1} = C$$

} inter-syllable

} intra-syllable

C: consonant
V: vowel
L: liquid (L,M,N) or semivowel (Y)

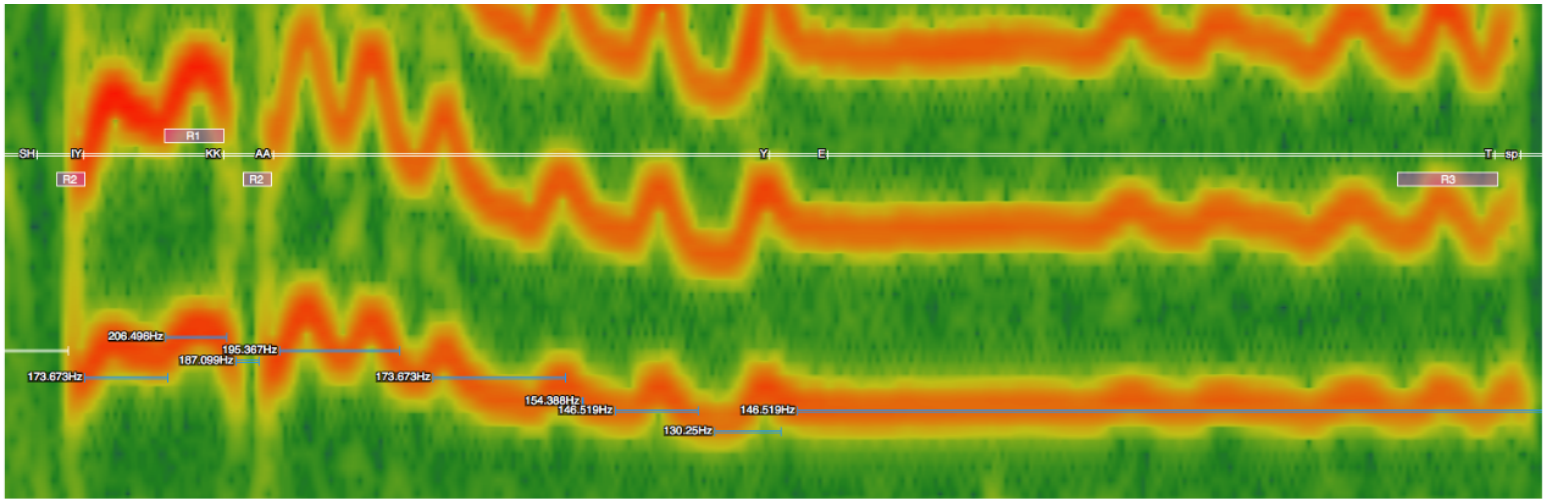
Transition model

$$a_{ij}(k) = \begin{cases} a_{ij} - g(k, k'), & R1 \text{ or } R3 \\ a_{ij} + g(k, k'), & R2 \\ a_{ij}, & else \end{cases}$$

- Variable-time transitions
  - modified at the presence of adjacent note onsets at time k'
  - unaffected otherwise

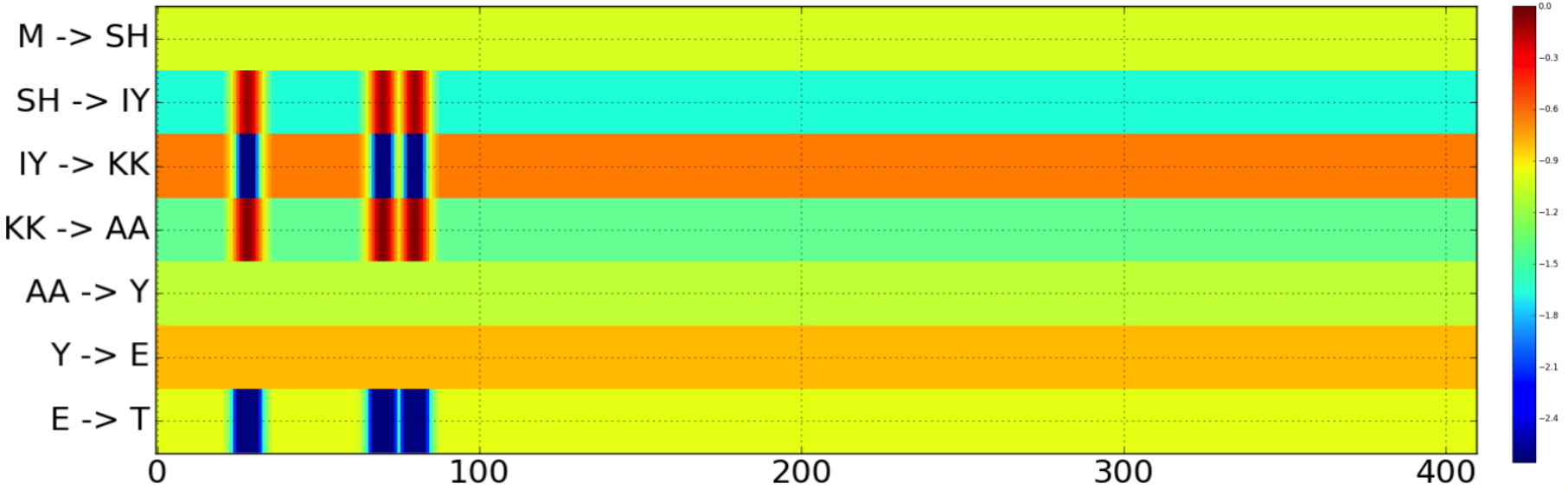
$g(k, k')$: normal distribution centered at k'

Transition model



a_{ij}

$g(t, t')$



Viterbi decoding

$$\delta_k(j) = \max_{i \in (j,\, j-1)} \delta_{k-1}(i)\, a_{ij}\, b_j(O_k)$$

- Decoding with one hidden variable
- Vocal onset detection as a preprocessing step

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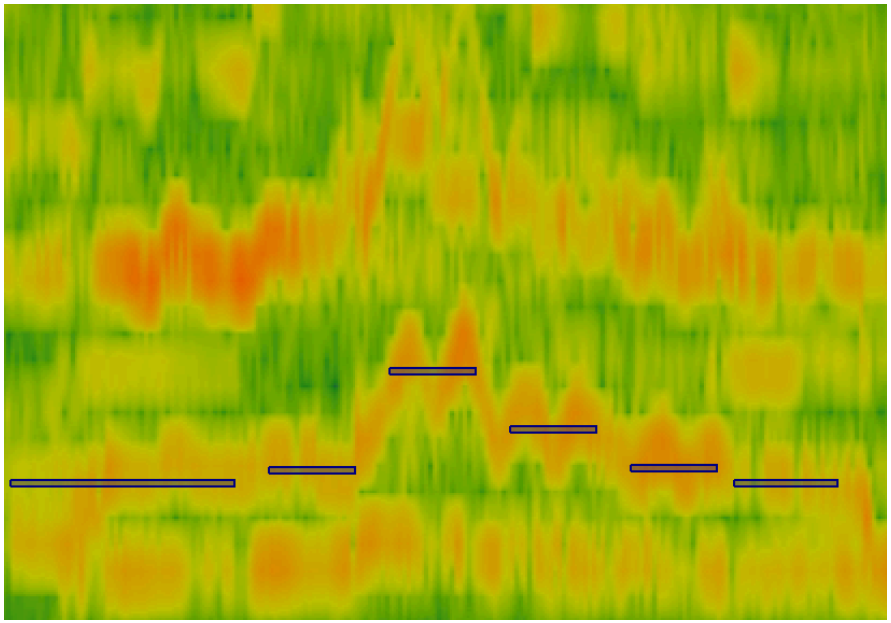
- Decoding with one hidden variable
- Vocal onset detection as a preprocessing step

A cappella lyrics OTMM dataset

- 6 complete recordings (10 minutes) selected from the Multi-instrumental lyrics OTMM dataset
- added annotations of vocal onsets



Experiments

- Experiment 1: oracle (manually annotated) onsets

HMM	onset-aware HMM	
	automatic onsets	oracle onsets
79.2	81.7	82.5

Dzhambazov, Georgi, Ajay Srinivasamurthy, Sertan Şentürk, and Xavier Serra (2016). On the use of note onsets for improved lyrics-to-audio alignment in Turkish makam music. In 17th International Society for Music Information Retrieval Conference (ISMIR 2016)

Sec 5.4

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Sec 5.4

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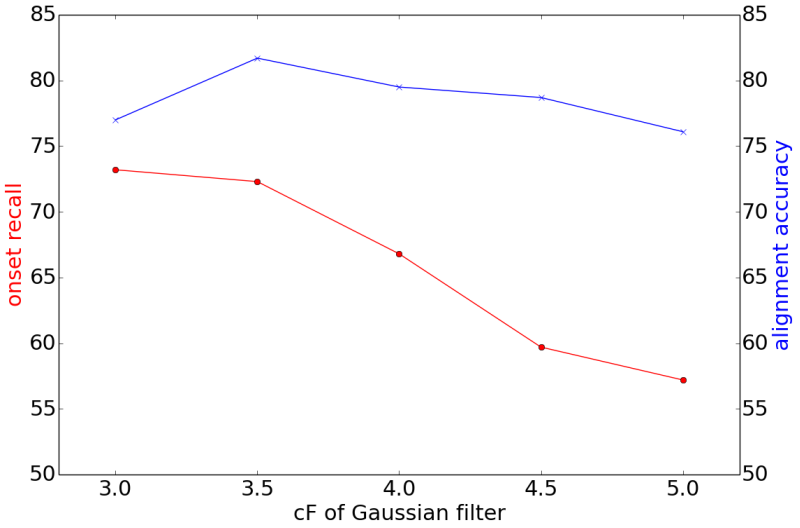
- Experiment 2: onsets detected with Flamenco singing voice transcription algorithm (Kroher, 2016)



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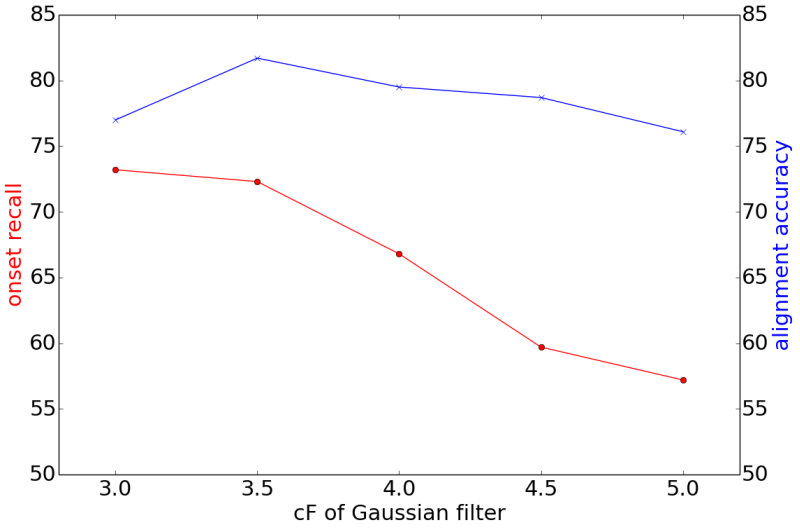
Dzhambazov, Georgi, Ajay Srinivasamurthy, Sertan Şentürk, and Xavier Serra (2016). On the use of note onsets for improved lyrics-to-audio alignment in Turkish makam music. In 17th International Society for Music Information Retrieval Conference (ISMIR 2016)

Sec 5.4

Experiments

- Experiment 1: oracle (manually annotated) onsets
- Experiment 2: onsets detected with Flamenco singing voice transcription algorithm (Kroher, 2016)



HMM	onset-aware HMM	
	automatic onsets	oracle onsets
79.2	81.7	82.5

Dzhambazov, Georgi, Ajay Srinivasamurthy, Sertan Şentürk, and Xavier Serra (2016). On the use of note onsets for improved lyrics-to-audio alignment in Turkish makam music. In 17th International Society for Music Information Retrieval Conference (ISMIR 2016)

Sec 5.4

Outline

- Setting the stage
  - Introduction (Chapter 1)
  - Background (Chapter 2)
  - Baseline lyrics-to-audio alignment (Chapter 3)
- Main
  - Lyrics-duration aware lyrics-to-audio alignment (Chapter 4)
  - Metrical-accent aware lyrics-to-audio alignment (Chapter 5)
- Conclusion (Chapter 6) and Applications (Appendix)

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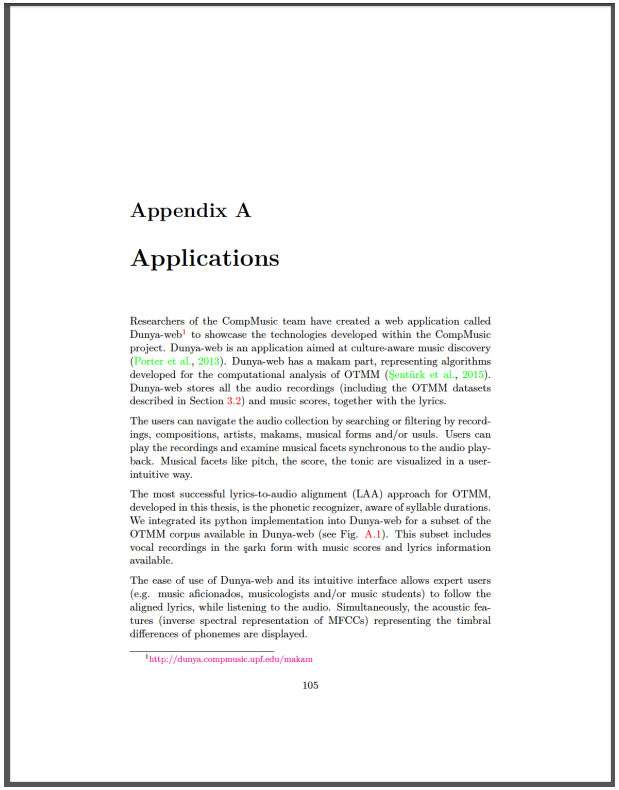
Appendix
Applications



Appendix A

Applications

Researchers of the CompMusic team have created a web application called Dunya-web[1] to showcase the technologies developed within the CompMusic project. Dunya-web is an application aimed at culture-aware music discovery (Porter et al., 2013). Dunya-web has a makam part, representing algorithms developed for the computational analysis of OTMM (Şentürk et al., 2015). Dunya-web stores all the audio recordings (including the OTMM datasets described in Section 3.2) and music scores, together with the lyrics.

The users can navigate the audio collection by searching or filtering by recordings, compositions, artists, makams, musical forms and/or usuls. Users can play the recordings and examine musical facets synchronous to the audio playback. Musical facets like pitch, the score, the tonic are visualized in a user-intuitive way.

The most successful lyrics-to-audio alignment (LAA) approach for OTMM, developed in this thesis, is the phonetic recognizer, aware of syllable durations. We integrated its python implementation into Dunya-web for a subset of the OTMM corpus available in Dunya-web (see Fig. A.1). This subset includes vocal recordings in the şarkı form with music scores and lyrics information available.

The ease of use of Dunya-web and its intuitive interface allows expert users (e.g. music aficionados, musicologists and/or music students) to follow the aligned lyrics, while listening to the audio. Simultaneously, the acoustic features (inverse spectral representation of MFCCs) representing the timbral differences of phonemes are displayed.

[1] http://dunya.compmusic.upf.edu/makam

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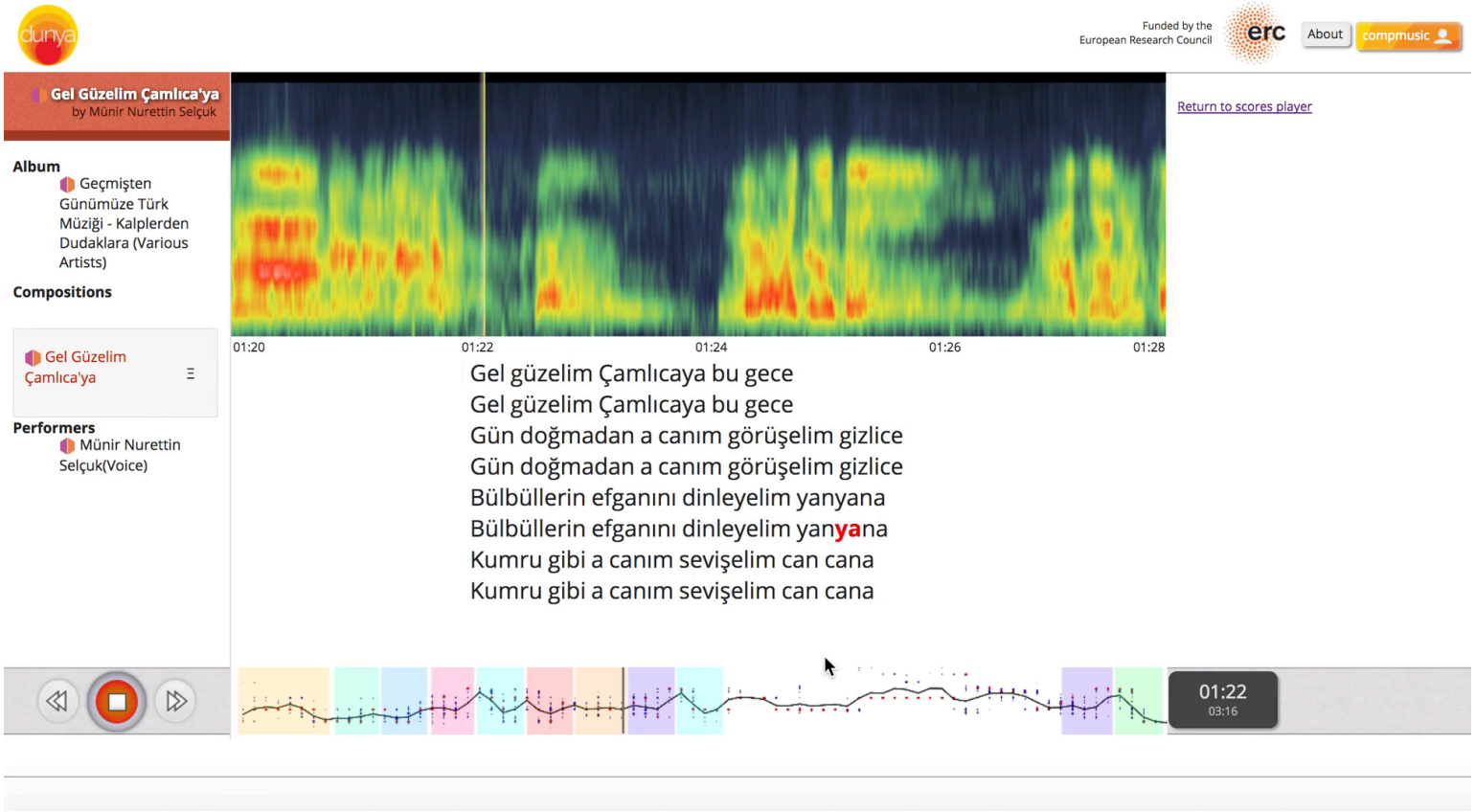
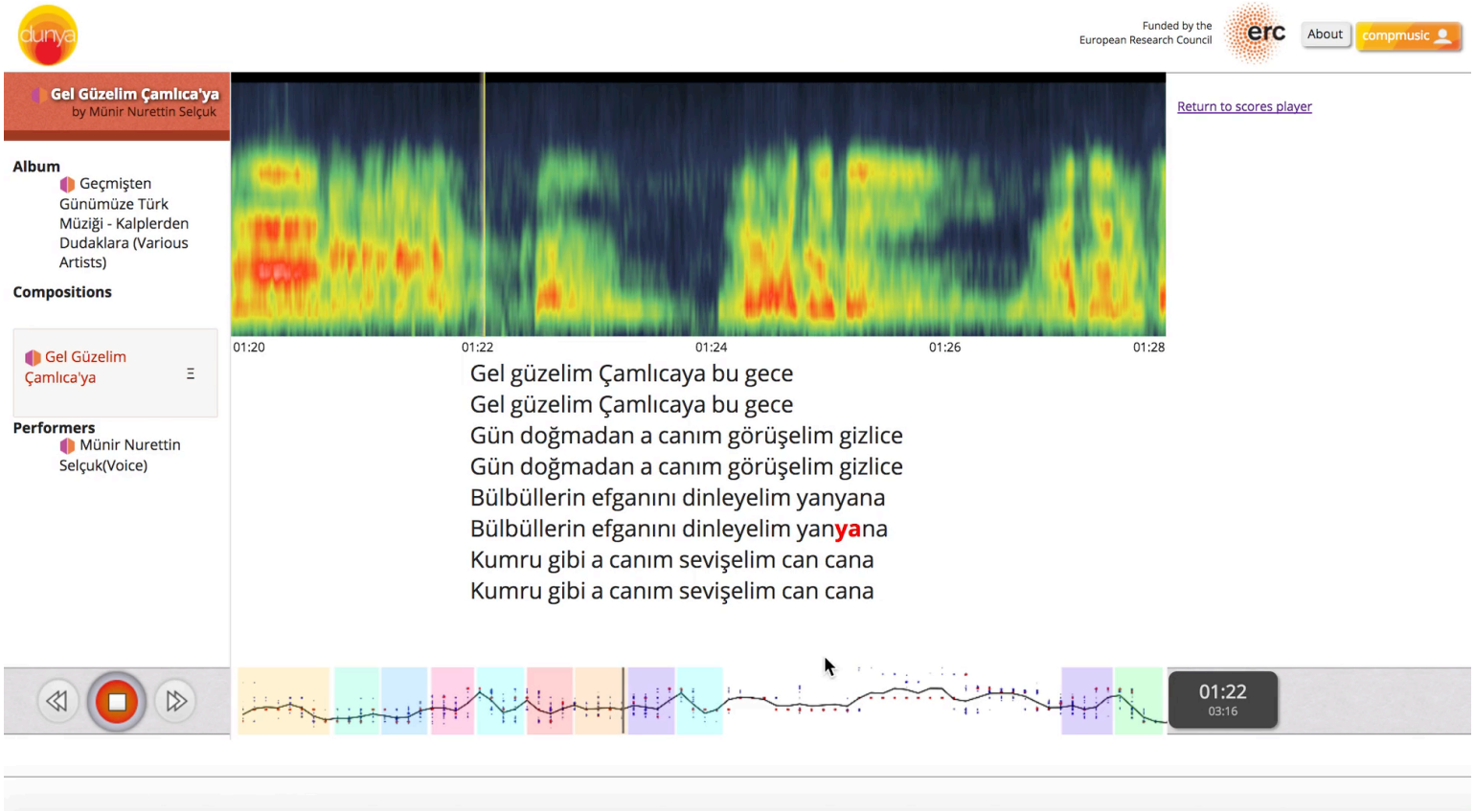
Dunya-web



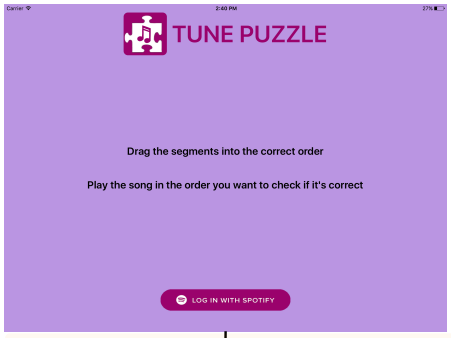
http://dunya.compmusic.upf.edu/makam/

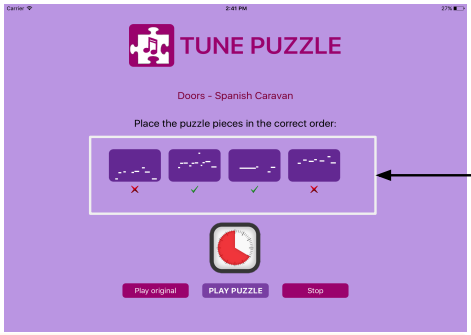
Dunya-web

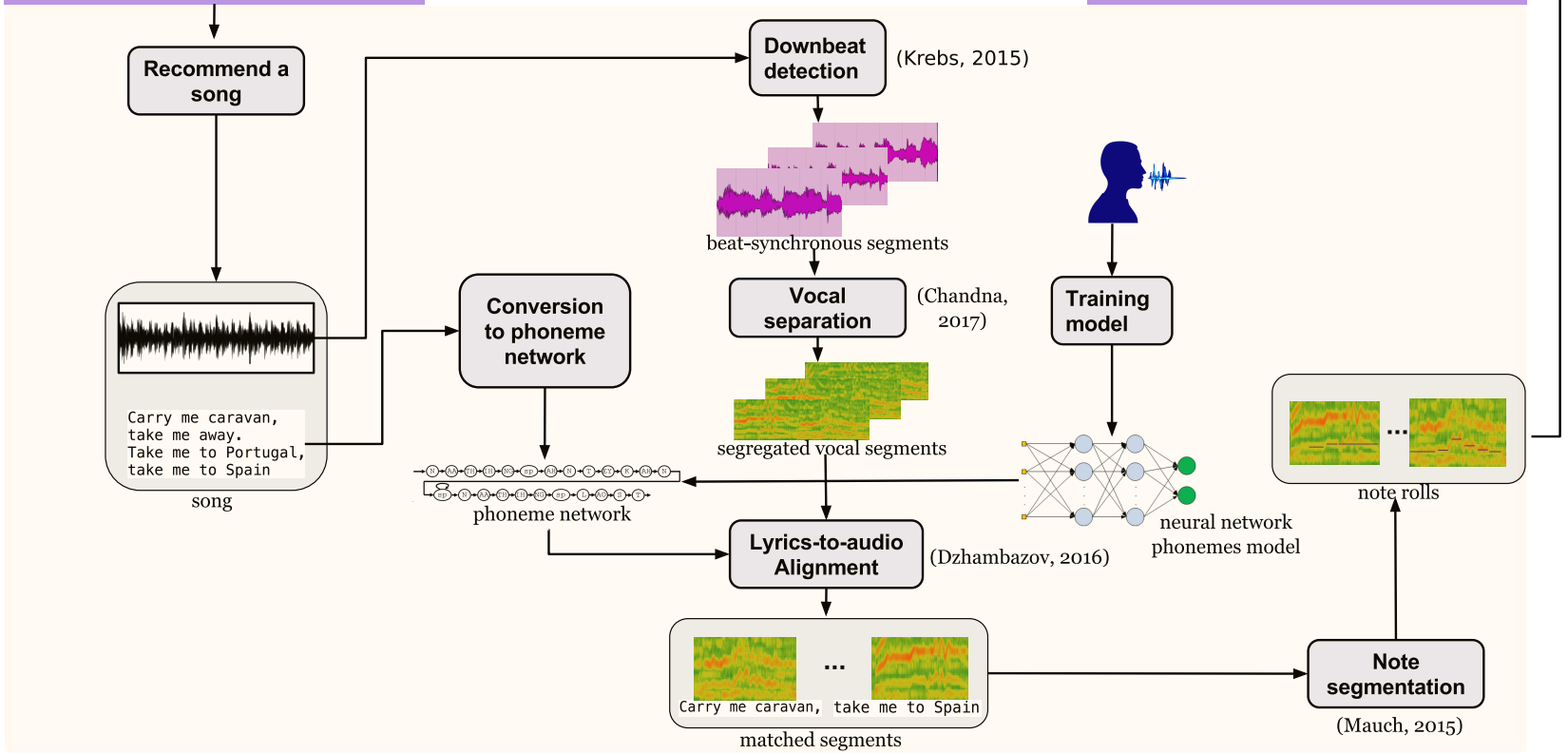


http://dunya.compmusic.upf.edu/makam/

Tune puzzle


TUNE PUZZLE
Drag the segments into the correct order
Play the song in the order you want to check if it's correct
LOG IN WITH SPOTIFY


TUNE PUZZLE
Doors - Spanish Caravan
Place the puzzle pieces in the correct order:
Play original
PLAY PUZZLE
Stop


Recommend a song
Downbeat detection
(Krebs, 2015)
beat-synchronous segments
Vocal separation
(Chandna, 2017)
Training model
Conversion to phoneme network
Carry me caravan,
take me away.
Take me to Portugal,
take me to Spain
song
segregated vocal segments
phoneme network
neural network phonemes model
note rolls
Lyrics-to-audio Alignment
(Dzhambazov, 2016)
Carry me caravan, take me to Spain
matched segments
Note segmentation
(Mauch, 2015)

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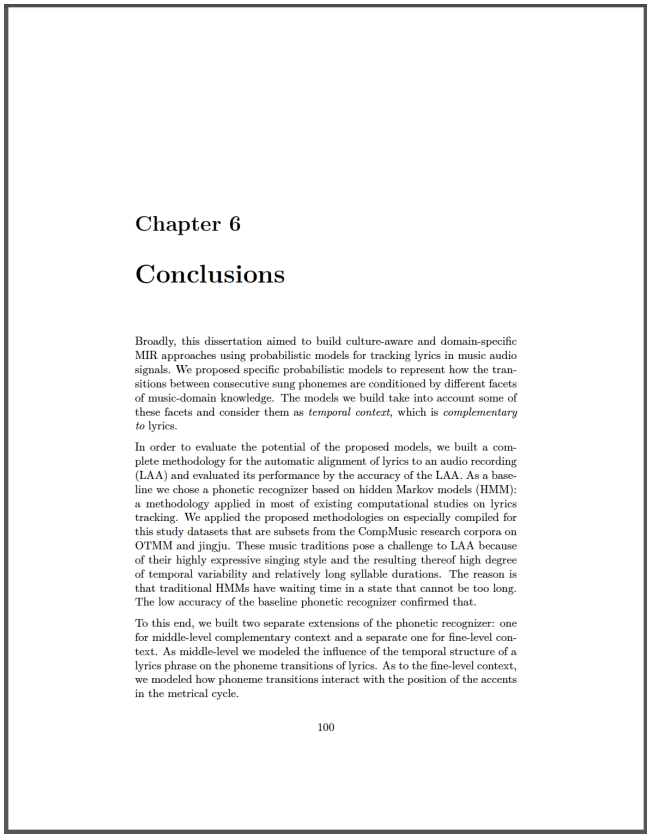
Chapter 6
Conclusions



Chapter 6

Conclusions

Broadly, this dissertation aimed to build culture-aware and domain-specific MIR approaches using probabilistic models for tracking lyrics in music audio signals. We proposed specific probabilistic models to represent how the transitions between consecutive sung phonemes are conditioned by different facets of music-domain knowledge. The models we build take into account some of these facets and consider them as *temporal context*, which is *complementary to* lyrics.

In order to evaluate the potential of the proposed models, we built a complete methodology for the automatic alignment of lyrics to an audio recording (LAA) and evaluated its performance by the accuracy of the LAA. As a baseline we chose a phonetic recognizer based on hidden Markov models (HMM): a methodology applied in most of existing computational studies on lyrics tracking. We applied the proposed methodologies on especially compiled for this study datasets that are subsets from the CompMusic research corpora on OTMM and jingju. These music traditions pose a challenge to LAA because of their highly expressive singing style and the resulting thereof high degree of temporal variability and relatively long syllable durations. The reason is that traditional HMMs have waiting time in a state that cannot be too long. The low accuracy of the baseline phonetic recognizer confirmed that.

To this end, we built two separate extensions of the phonetic recognizer: one for middle-level complementary context and a separate one for fine-level context. As middle-level we modeled the influence of the temporal structure of a lyrics phrase on the phoneme transitions of lyrics. As to the fine-level context, we modeled how phoneme transitions interact with the position of the accents in the metrical cycle.

Importance of complementary context

- Duration aware alignment
  - biggest contribution model
  - dependent on music scores
- Metrical-accents improve vocal onsets detection
- Onset aware alignment
  - onset aware phoneme transition rules improve alignment
  - improvement is not substantial
  - note onsets approached by glides in OTMM

Scientific Contributions

- Conceptualize the interaction of phoneme transitions to complementary music knowledge as DBN
- Proposed several implementation simplifications of decoding in DBN
- Duration aware model beneficial in different music traditions

Other contributions

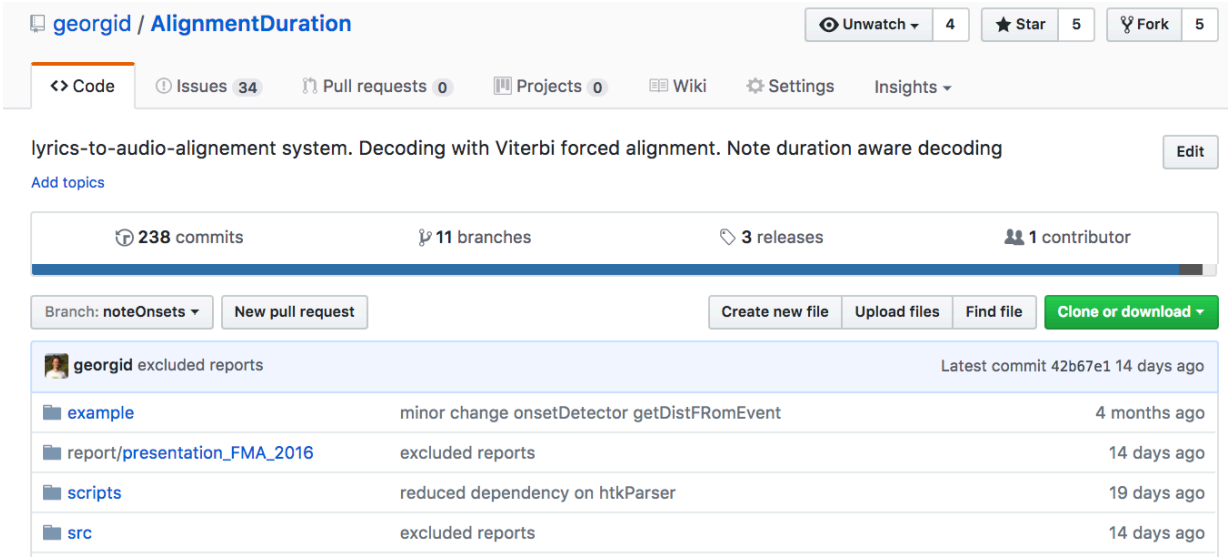
- Compiled several datasets of OTMM and jingju with annotations of different music facets
- Alignment with duration aware model implemented in Dunya-web
  - enriched music listening
  - tracking singing techniques
- MFCC extraction in *Essentia*

Reproducibility

- In python with few dependencies

  (Essentia and sms-tools)

- The first open reproducible system for automatically aligning lyrics



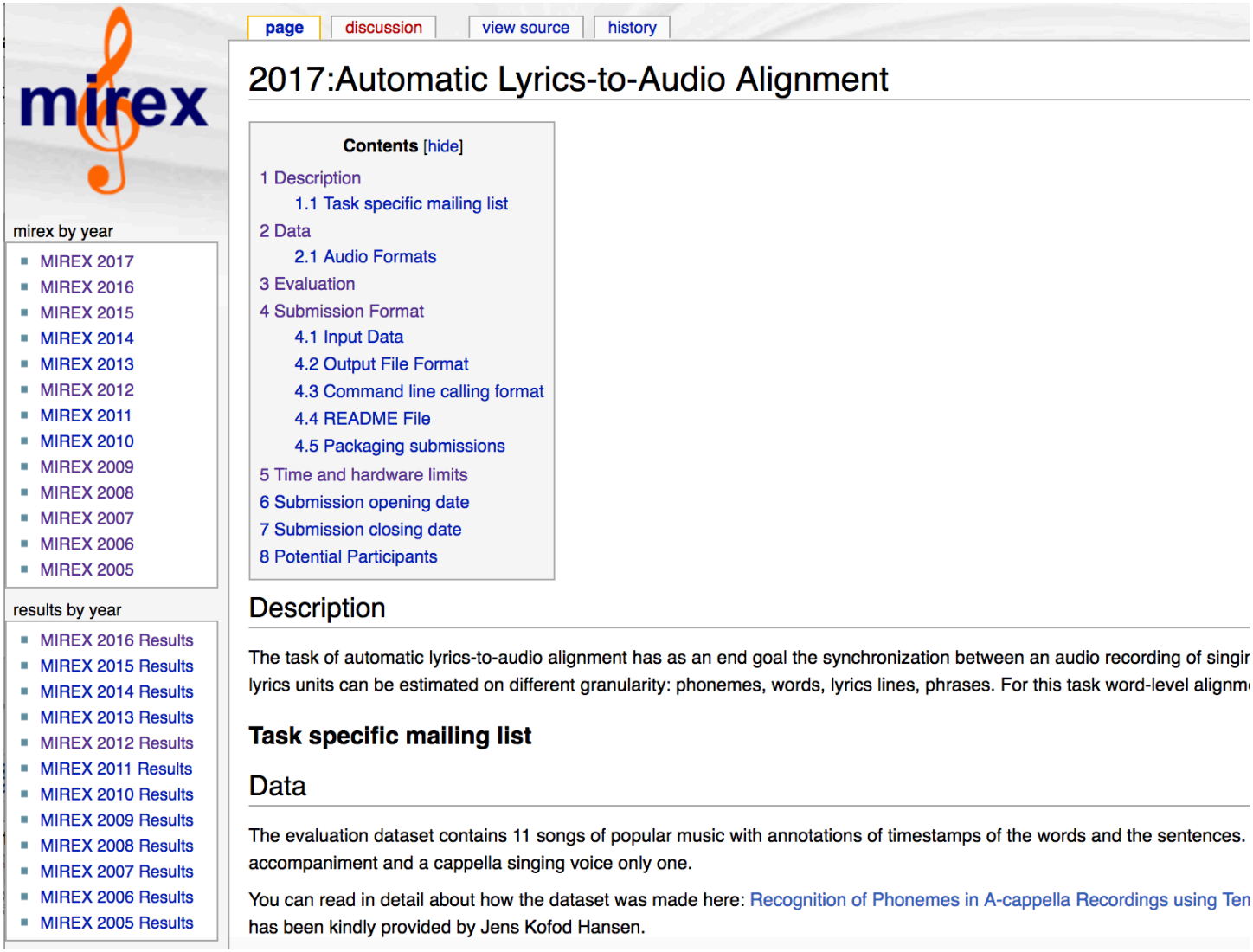
github.com/georgid/AlignmentDuration

Future directions

- Combine the duration aware and the metrical-accent aware models into one
- Explore other music music context facets (e.g. vibrato)
- Generalize the proposed models to other musics with principles similar to these of OTMM and jingju
- Vocal activity detection to replace structural segmentation

MIREX Lyrics-to-Audio Alignment

compmusic



mirex

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2017:Automatic Lyrics-to-Audio Alignment

mirex by year

- MIREX 2017
- MIREX 2016
- MIREX 2015
- MIREX 2014
- MIREX 2013
- MIREX 2012
- MIREX 2011
- MIREX 2010
- MIREX 2009
- MIREX 2008
- MIREX 2007
- MIREX 2006
- MIREX 2005

results by year

- MIREX 2016 Results
- MIREX 2015 Results
- MIREX 2014 Results
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- MIREX 2010 Results
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- MIREX 2008 Results
- MIREX 2007 Results
- MIREX 2006 Results
- MIREX 2005 Results

Contents [hide]

Description

The task of automatic lyrics-to-audio alignment has as an end goal the synchronization between an audio recording of singir lyrics units can be estimated on different granularity: phonemes, words, lyrics lines, phrases. For this task word-level alignm

Task specific mailing list

Data

The evaluation dataset contains 11 songs of popular music with annotations of timestamps of the words and the sentences. accompaniment and a cappella singing voice only one.

You can read in detail about how the dataset was made here: Recognition of Phonemes in A-cappella Recordings using Ten has been kindly provided by Jens Kofod Hansen.

Knowledge-based Probabilistic Modeling for Tracking Lyrics in Music Audio Signals

28 June 2017, PhD defense

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