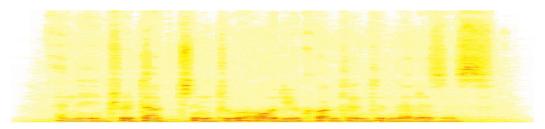
# Introduction to Audio Content Analysis

Module 5.8: Chord Detection

#### alexander lerch





# introduction

overview



### corresponding textbook section

Chapter 5 — Tonal Analysis: pp. 125–127

#### lecture content

- musical chords and harmony
- sample chord detection
- Hidden Markov Models (HMMs) and the Viterbi algorithm

### learning objectives

- name basic chords and describe the concept of chord inversions
- discuss commonalities and differences between chord & key detection
- discuss the usefulness of HMMs for chord detection
- explain the Viterbi algorithm with an example



# introduction

overview

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- simultaneous use of several pitches ⇒ chords
- usually constructed of (major/minor) thirds



- note
  - chord type independent of pitch doubling, pitch order
  - same label for keys and chords

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- note:
  - chord type independent of pitch doubling, pitch order
  - same label for keys and chords

- most common: root note is lowest note
- otherwise: chord inversion



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• key and tonal context define chord's harmonic function

- examples:
  - tonic: chord on 1st scale degree (tonal center)
  - dominant: chord on 5th scale degree (often moves to tonic)
  - **subdominant**: chord on 4th scale degree
  - . . . .

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introduction: key vs. chord detection

### commonalities

- chords are octave independent ⇒ pitch chroma sufficient
- process flow: pitch chroma extraction + classification

#### differences

- time frame for pitch chroma calculation
- templates
- number of templates/chords
- many results per song (time series)

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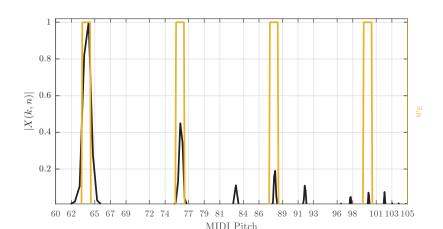
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# pitch chroma introduction

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- pitch class distribution: 12-dimensional vector
- map all pitch class bands in all octaves to one

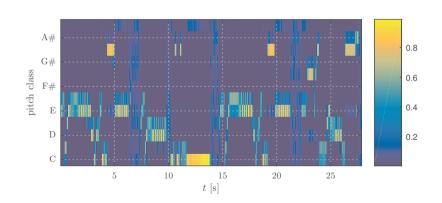




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# pitch chroma introduction

# Georgia Center for Music Technology

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### pitch chroma properties

- no octave information
  - no differentiation between prime and octave
  - no info on inversion
- robust, timbre-independent representation





- similar to key detection we can simply compare an extracted pitch chroma with a template
  - simplest possible template and distance: linear transformation example C major:  $\Gamma(0,j) = [1/3,0,0,0,1/3,0,0,1/3,0,0,0,0]$
  - ⇒ instantaneous chord likelihood:

$$\psi(c,n) = \sum_{j=0}^{11} \Gamma(c,j) \cdot \nu(j,n)$$

# chord detection chord progression 1/2



apply musical knowledge to increase the result's robustness and accuracy:

- different probabilities for different chord progressions (similar to key modulations),
   e.g.
  - cadences: I-IV-V-I
  - sequences: circle progression
- ⇒ model for *chord progression probabilities* 
  - analytical model based on music theory
    - circle of fifths (?!)
    - key profile correlation (?!)
  - empirical model based on data
    - annotate audio
    - symbolic score

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# chord detection chord progression 2/2

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what properties do chord progression probabilities depend on



# chord detection chord progression 2/2

### what properties do chord progression probabilities depend on



- musical key
- larger musical context (model order)
- style
- tempo/length??

**HMMs** 

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- two possible states E, A
- transition probabilities to other state(s) and to self
- sum of transition probabilities equals 1

hidden markov model: variables



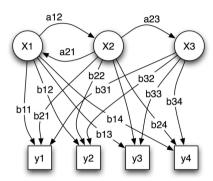
- states: unknown/hidden
- transition probability:
   probability of transitioning from one state to the other
- observations: measureable time series
- emission probability: probability of a state given an observation
- start probability: probability of the initial state

**HMMs** 0000000 Georgia

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# chord detection

hidden markov model: variables



- X: states
- y: possible observations
- a: state transition probabilities
- b: emission probabilities

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hidden markov model: example (WP) 1/2

#### scenario

- doctor diagnoses fever by how patients feel
- patient may feel normal, dizzy, or cold
- patient visits multiple days in a row

what are the states and observations in this case



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hidden markov model: example (WP) 1/2

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#### states

- healthy
- fever

### observations:

- normal
- cold
- dizzy

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hidden markov model: example (WP) 2/2

start probabilities (initial state assumption)

healthy: 0.6fever: 0.4

• emission probabilities (prob of obs given state)

• healthy: normal 0.5, cold 0.4, dizzy 0.1

• fever: : normal 0.1, cold 0.3, dizzy 0.6

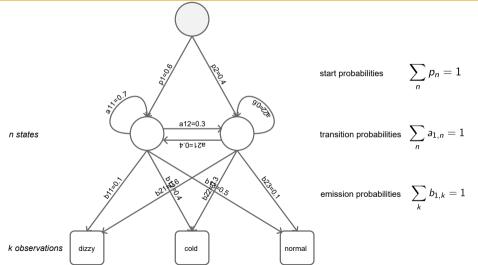
transition probabilities

• healthy: healthy 0.7, fever 0.3

• fever: : healthy 0.4, fever 0.6

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hidden markov model: example (WP) 2/2

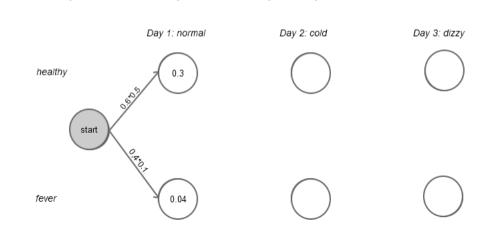


hidden markov model: example (WP) 2/2

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### three observations:

 $\mathsf{Day}\ 1\ \mathit{normal} \to \mathsf{Day}\ 2\ \mathit{cold} \to \mathsf{Day}\ 3\ \mathit{dizzy}$ 

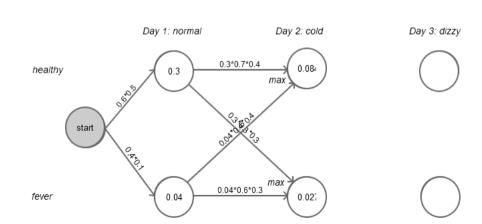


hidden markov model: example (WP) 2/2

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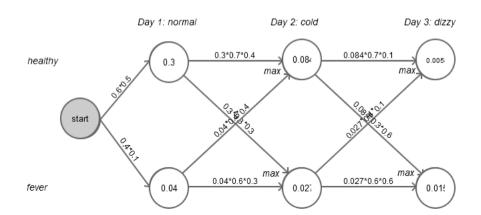


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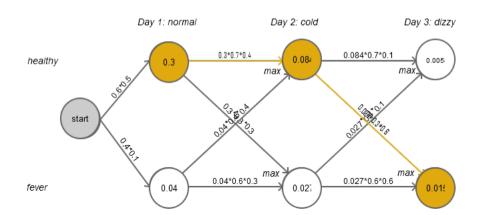


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# chord detection HMMs for chord detection

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- - ullet states o chords
  - observations → pitch chroma
  - ullet emission probability o trained with pitch chroma
  - ullet transition probability o trained from dataset
  - ullet start probability o chord statistics (style dependent?)

### summary

#### lecture content



### chords

- combination of three or more pitches
- usually stacked thirds
- can be inverted

#### chord detection

- processing steps
  - pitch chroma extraction
  - template matching
  - chord transition model

### Viterbi algorithm

- find globally optimal path through state space
- estimate state sequence with
  - emission probabilities
  - transition probabilities

