Introduction to Audio Content Analysis

Module 5.8: Chord Detection

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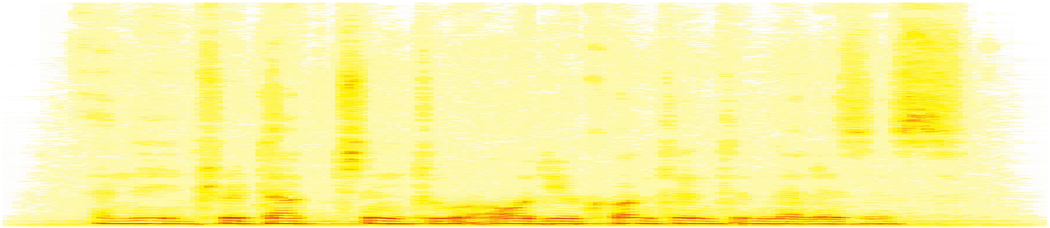

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introduction
overview

corresponding textbook section

Chapter 5 — Tonal Analysis: pp. 125–127

- **lecture content**
  - musical chords and harmony
  - baseline 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

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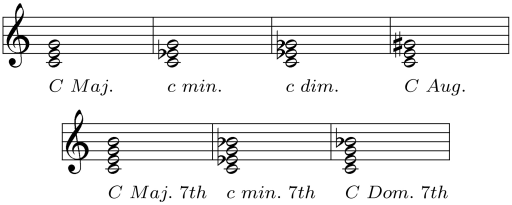
musical pitch
chords

- 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

musical pitch

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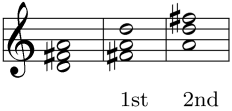
musical pitch
chord inversion

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



musical pitch

harmony

- 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
  - ...

chord detection

introduction: key vs. chord detection

- **commonalities**
  - chords are octave independent $\Rightarrow$ 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)

chord detection

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pitch chroma
introduction

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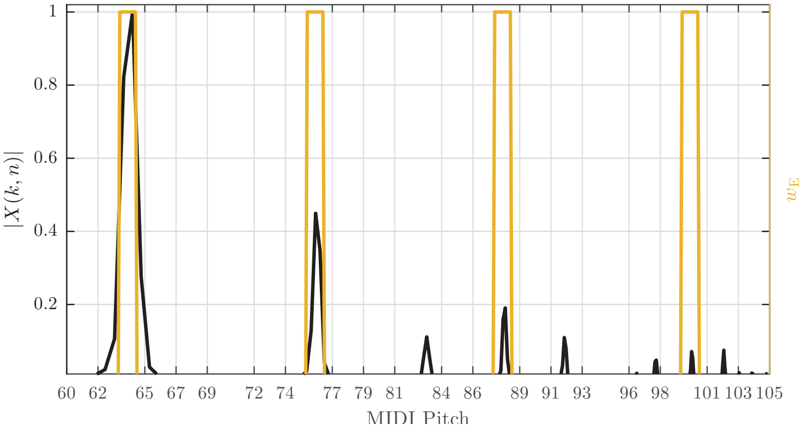
- pitch class distribution: 12-dimensional vector
- map all pitch class bands in all octaves to one



matlab source: matlab/displayPitchChromaGrouping.m

pitch chroma
introduction

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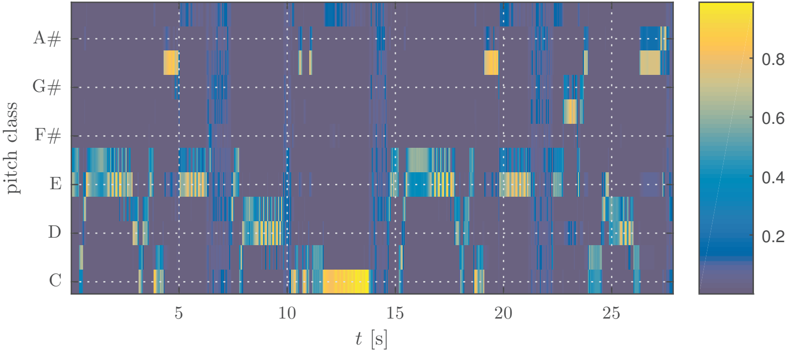

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pitch chroma
introduction

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

pitch chroma properties

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

chord detection

chord template

- 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: $\Gamma(0,j) = [1/3, 0, 0, 0, 1/3, 0, 0, 1/3, 0, 0, 0, 0]$

$\Rightarrow$ 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*

1. *analytical model* based on music theory
   - circle of fifths (?!)
   - key profile correlation (?!)
2. *empirical model* based on data
   - annotate audio
   - symbolic score

chord detection

chord progression 1/2

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chord detection

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chord detection
chord progression 2/2

what properties do chord progression probabilities depend on

chord detection
chord progression 2/2

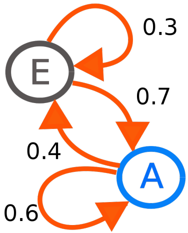
what properties do chord progression probabilities depend on

?

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

chord detection

markov chain



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

https://commons.wikimedia.org/wiki/File:Markovkate_01.svg

chord detection
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

chord detection
hidden markov model: variables

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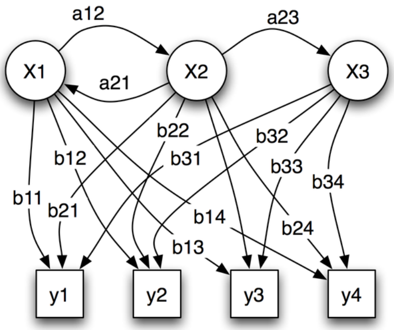

- X: states
- y: possible observations
- a: state transition probabilities
- b: emission probabilities

https://en.wikipedia.org/wiki/File:HiddenMarkovModel.svg

chord detection
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

chord detection

hidden markov model: example (WP) 1/2

- **scenario**
  - doctor diagnoses fever by how patients feel
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what are the states and observations in this case

?

- **states**
  - *healthy*
  - *fever*
- **observations**:
  - *normal*
  - *cold*
  - *dizzy*

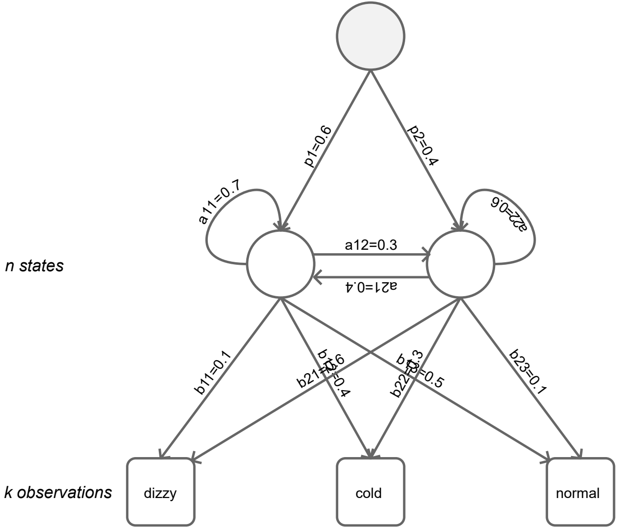
chord detection

hidden markov model: example (WP) 2/2

- **start probabilities** (initial state assumption)
  - *healthy*: 0.6
  - *fever*: 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

chord detection

hidden markov model: example (WP) 2/2



start probabilities $\sum_n p_n = 1$

transition probabilities $\sum_n a_{1,n} = 1$

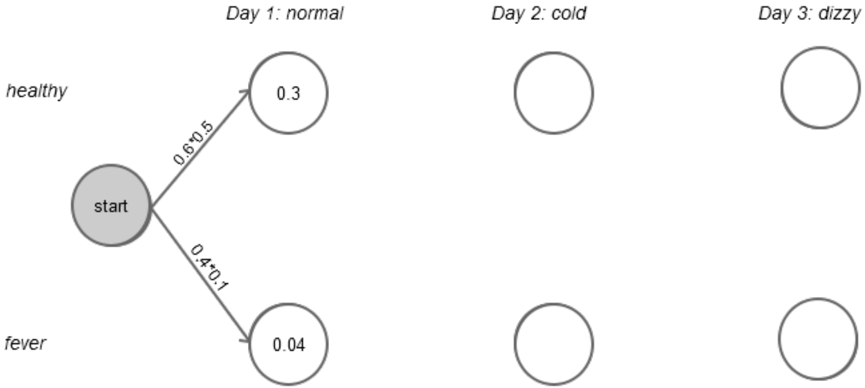
emission probabilities $\sum_k b_{1,k} = 1$

chord detection

hidden markov model: example (WP) 2/2

three observations:

Day 1 *normal* → Day 2 *cold* → Day 3 *dizzy*



chord detection
hidden markov model: example (WP) 2/2

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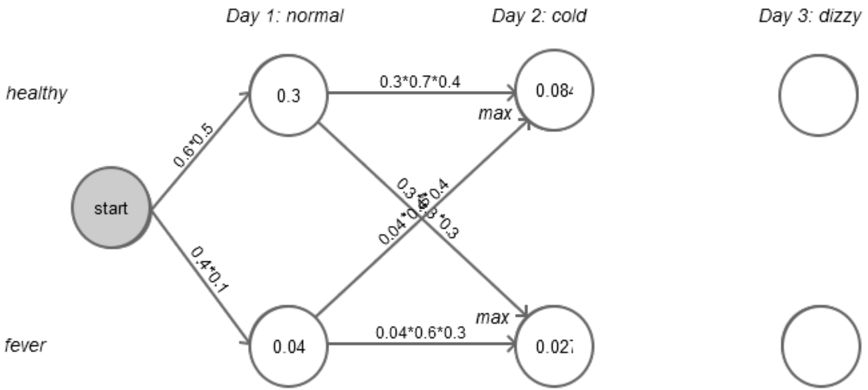

chord detection

hidden markov model: example (WP) 2/2

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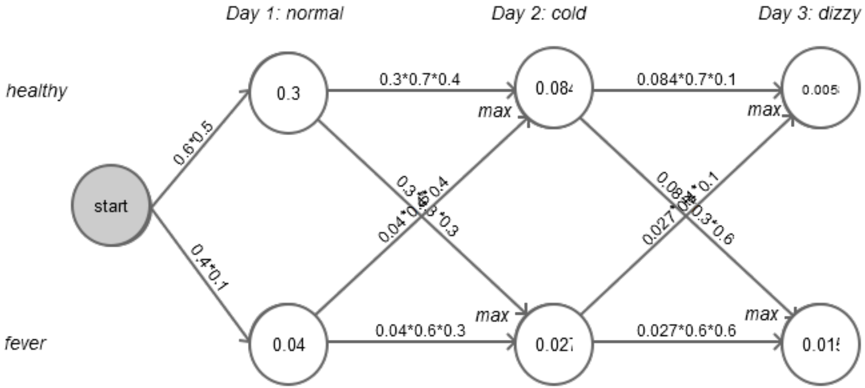

chord detection

hidden markov model: example (WP) 2/2

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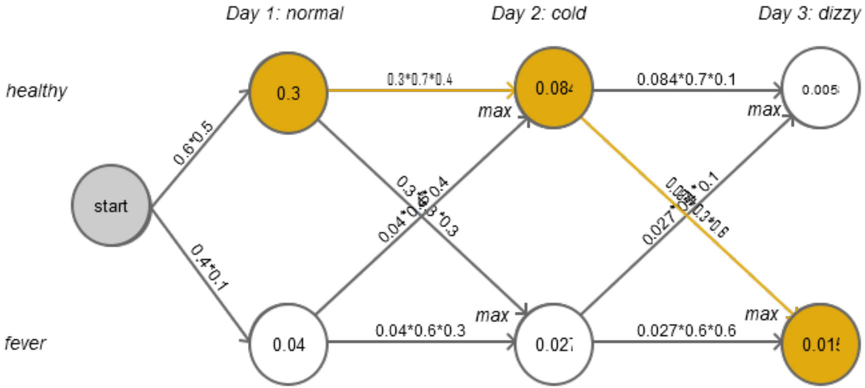

chord detection

HMMs for chord detection

- states $\rightarrow$ chords
- observations $\rightarrow$ pitch chroma
- emission probability $\rightarrow$ trained with pitch chroma
- transition probability $\rightarrow$ trained from dataset
- start probability $\rightarrow$ 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