

## Introduction to Audio Content Analysis

module 7.6: chord detection

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# introduction overview



### corresponding textbook section

section 7.6

#### 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



module 7.6: chord detection  $1 \ / \ 1$ 

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module 7.6: chord detection  $1 \ / \ 1$ 

- 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

module 7.6: chord detection 2/19



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chords ●○○



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

chords ○●○



# musical pitch



- 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
  - . . .

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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introduction: key vs. chord detection



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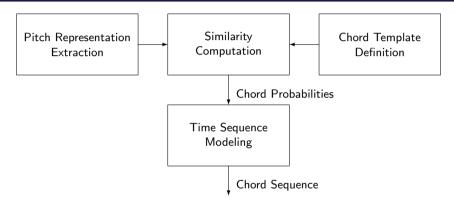
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# chord detection introduction: overview



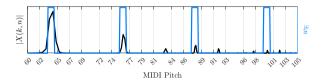


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# pitch chroma introduction

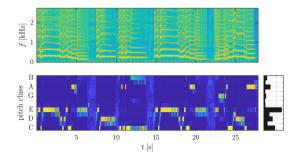


- pitch class distribution: 12-dimensional vector
- map all pitch class bands in all octaves to one



■ map all pitch class bands in all octaves to one





# 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

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# chord detection chord template

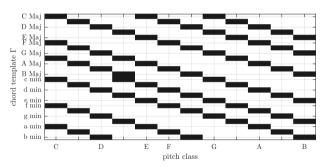
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- compare extracted pitch chroma with template
  - simplest possible template and distance: linear transformation example — C major:

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

⇒ 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:

- probabilities for different chord progressions (similar to key modulations), e.g.
  - cadences: I-IV-V-I
  - sequences: circle progression
- $\Rightarrow$  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

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# chord detection chord progression 1/2



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# chord detection chord progression 1/2



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what properties do chord progression probabilities depend on



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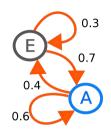
### what properties do chord progression probabilities depend on

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



# chord detection markov chain

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

# chord detection hidden markov model: variables



HMMs

states: unknown/hidden

transition probability: probability of transitioning from one state to the other

observations: measureable time series

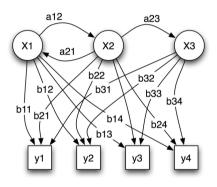
emission probability: probability of an observation given a state

start probability: probability of the initial state

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# chord detection hidden markov model: variables

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

# 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



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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
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#### what are the states and observations in this case

#### states

- healthy
- fever

#### observations:

- normal
- cold
- dizzy



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

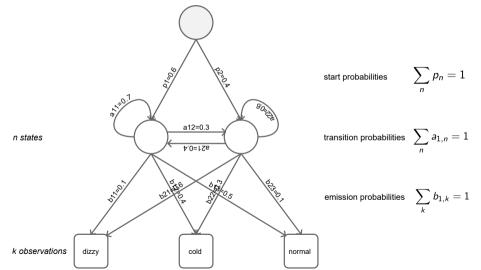
• fever: : healthy 0.4, fever 0.6

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hidden markov model: example (WP) 2/2



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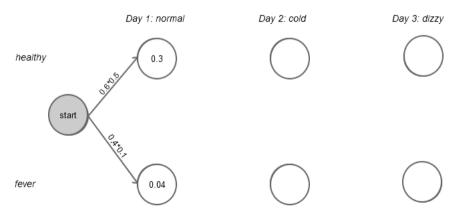
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hidden markov model: example (WP) 2/2



#### three observations:

 $day 1 normal \rightarrow day 2 cold \rightarrow day 3 dizzy$ 



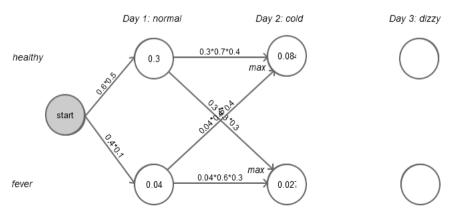
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hidden markov model: example (WP) 2/2



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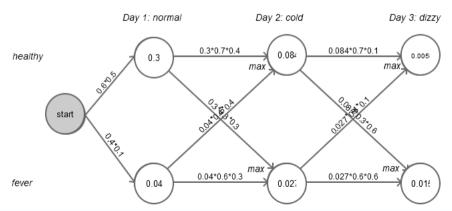
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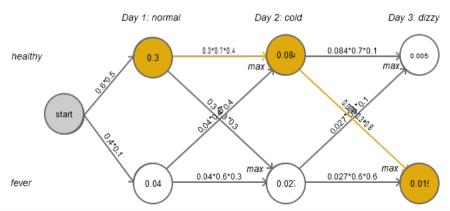
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hidden markov model: example (WP) 2/2

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## chord detection HMMs for chord detection



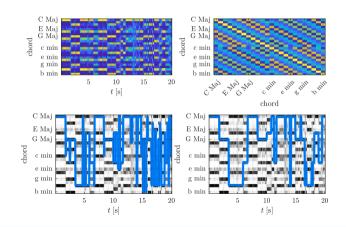
- $\blacksquare$  states  $\rightarrow$  chords
- lacktriangle observations o pitch chroma
- lacktriangledown emission probability o trained with pitch chroma
- lacktriangleright transition probability o trained from dataset
- lacktriangledown start probability o chord statistics (style dependent?)

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# chord detection chord detection example

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## 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



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