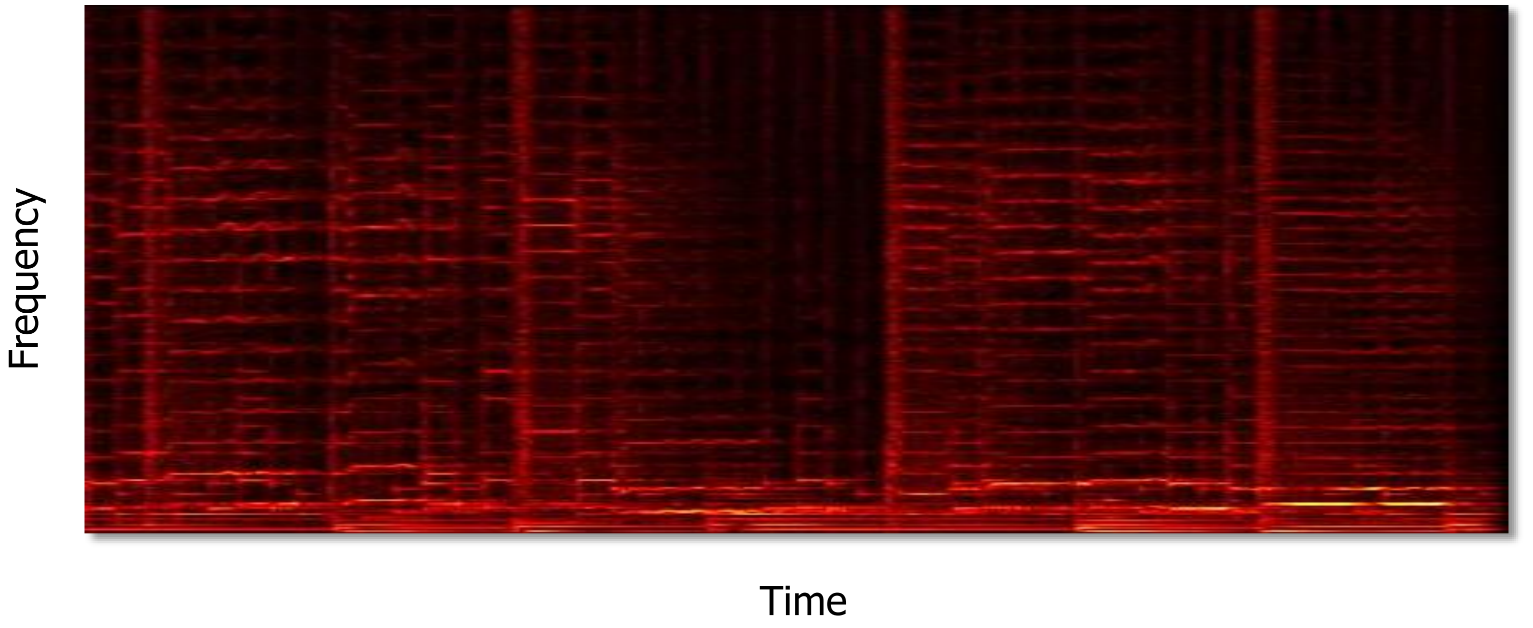
Topic 8

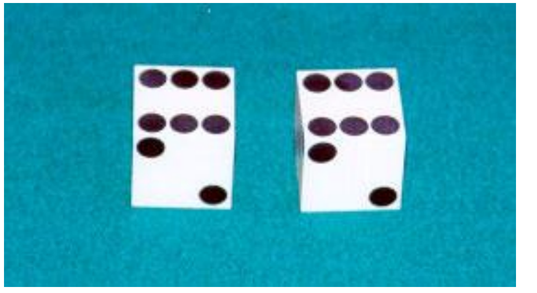
Audio Modeling by
Hidden Markov Models

Structure in Spectrograms

- Spectral structure
- Temporal structure



An HMM Example



- A dishonest casino has two dice:
  - A fair dice

  P(1) = P(2) = P(3) = P(4) = P(5) = P(6) = 1/6
  - A loaded dice

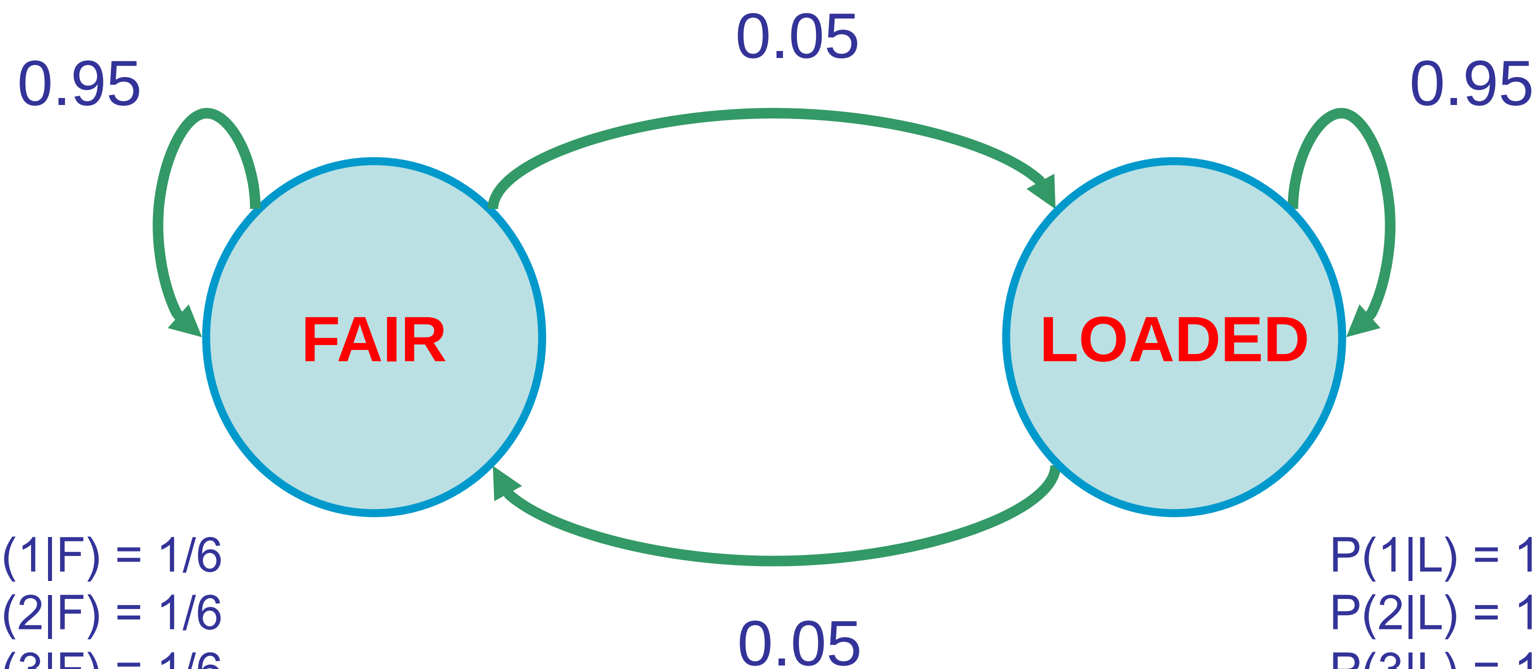
  P(1) = P(2) = P(3) = P(4) = P(5) = 1/10; P(6) = 1/2

- The casino randomly starts with one dice.

- The casino randomly switches the dice once every 20 turns, on average.

My Dishonest Casino Model

P(first dice = F) =0.7; P(first dice = L) = 0.3



P(1|F) = 1/6
P(2|F) = 1/6
P(3|F) = 1/6
P(4|F) = 1/6
P(5|F) = 1/6
P(6|F) = 1/6

P(1|L) = 1/10
P(2|L) = 1/10
P(3|L) = 1/10
P(4|L) = 1/10
P(5|L) = 1/10
P(6|L) = 1/2

Finite-state HMM

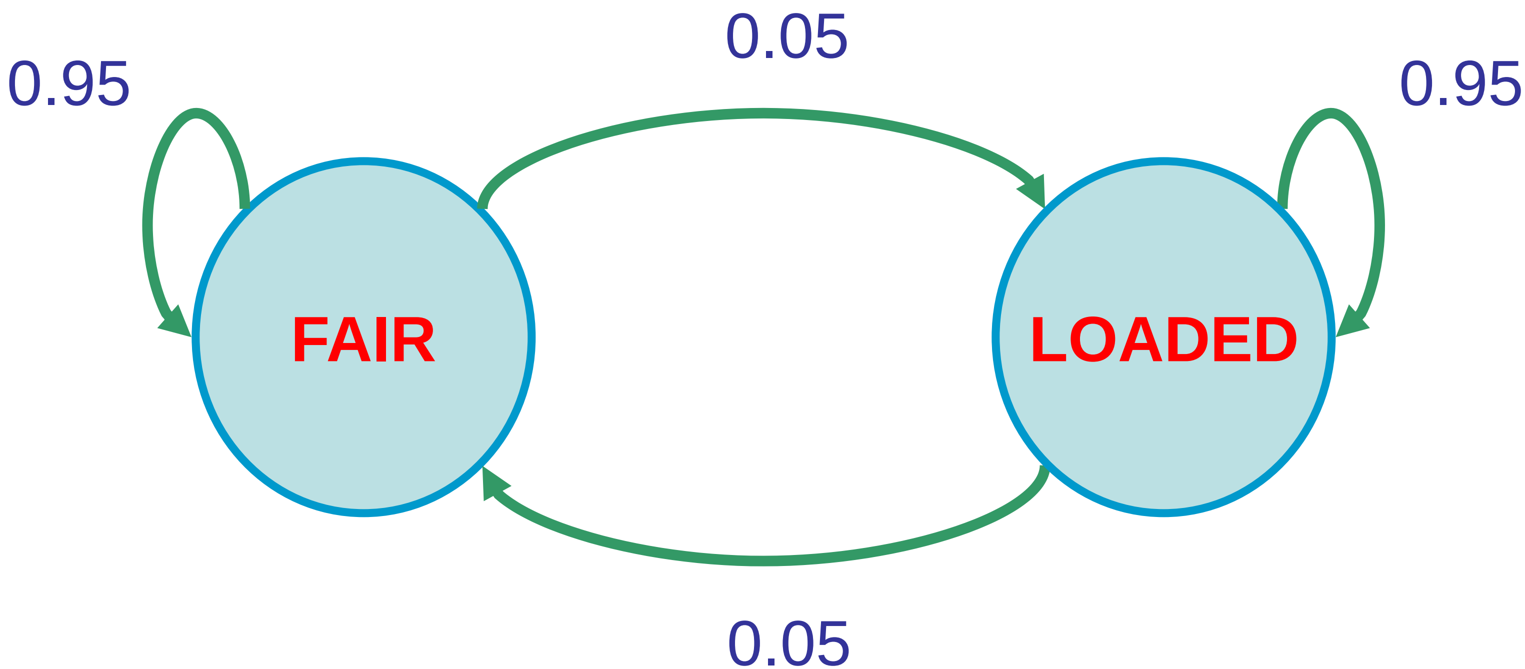
- A finite set of states $\{1, \dots, N\}$
- The initial probability of states $\boldsymbol{\Pi} = \{\pi_1, \dots, \pi_N\}$
  - π_i is the probability of starting with state i.
  - $\sum_i \pi_i = 1$
- State transition probabilities, $\boldsymbol{A} = \{a_{ij}\}$
  - a_{ij} is the probability of going from state i to j
  - $\sum_j a_{ij} = 1$
- An emission (observation) alphabet $\{e_1, \dots, e_M\}$
- Emission probabilities, $\boldsymbol{B} = \{b_{ij}\}$
  - b_{ij} is the probability of observing e_j when at state i
  - $\sum_j b_{ij} = 1$

Markovian Property

- If the current state is known, future states do not depend on previous states.
- I.e., what I'm going to do next depends only on where I am now, NOT on how I got here.
- Memory-less

State Space Representation

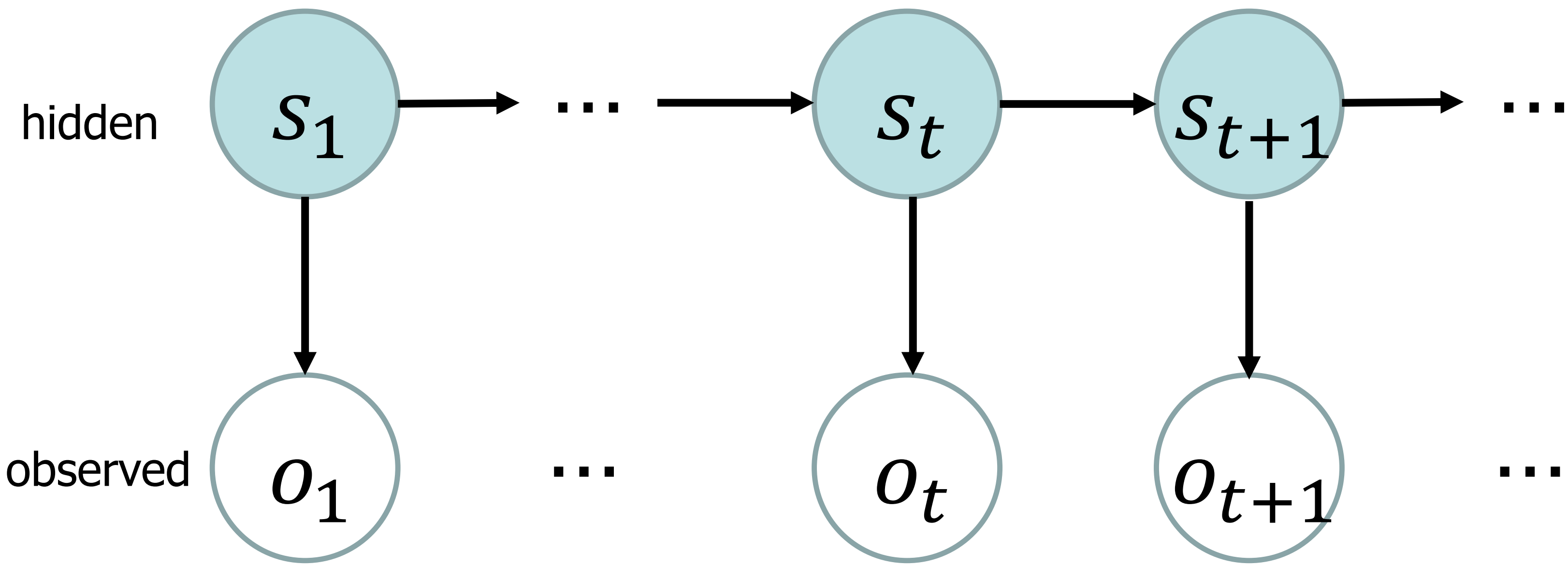
Each node is a state value



Probabilistic Graphical Model Representation

- Let s_t be the state at time t, $t = 1, \dots, T$.
  - s_t takes values of $\{1, \dots, N\}$
- Let o_t be the observation at time t.
  - o_t takes values of $\{e_1, \dots, e_M\}$

Each node is a random variable

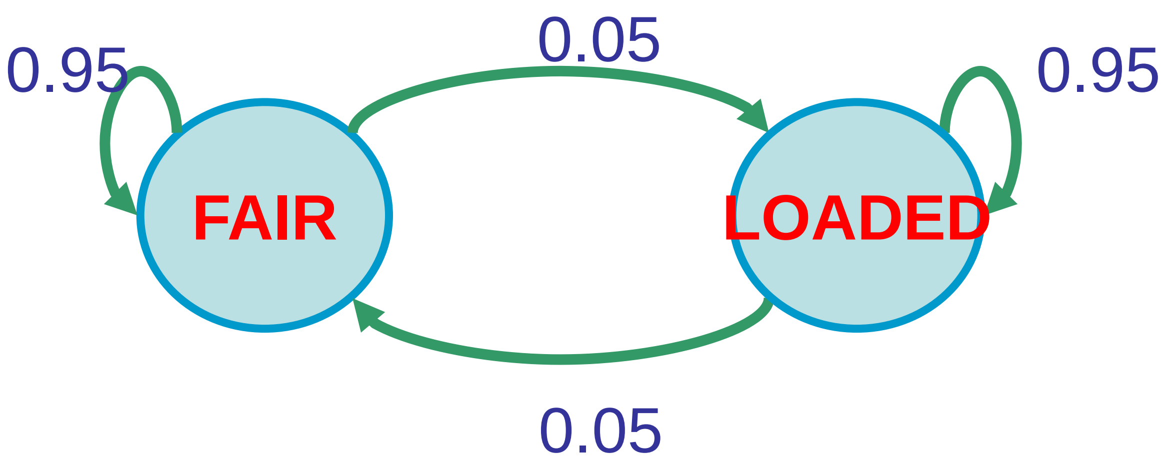


My Dishonest Casino Model

- The states (i.e., which dice is used) are hidden.
- We only observe a sequence of rolls, say

  O = (3, 6, 5, 1, 6, 6, 3, 6)

- If the fair dice is red and the loaded dice is blue, then the states are not hidden anymore.

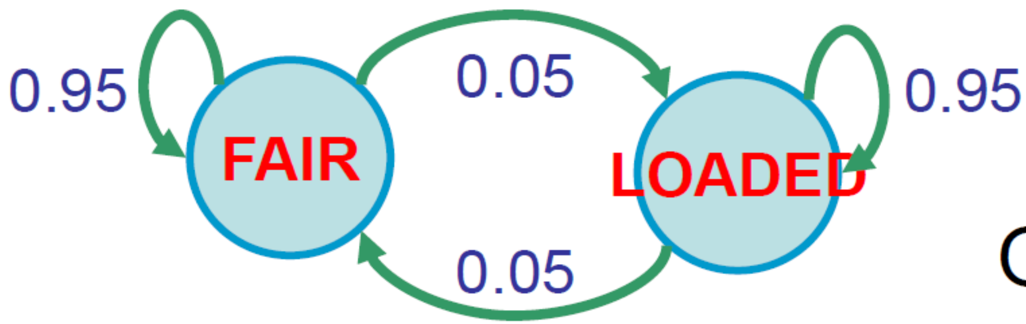


Key Problems for HMM

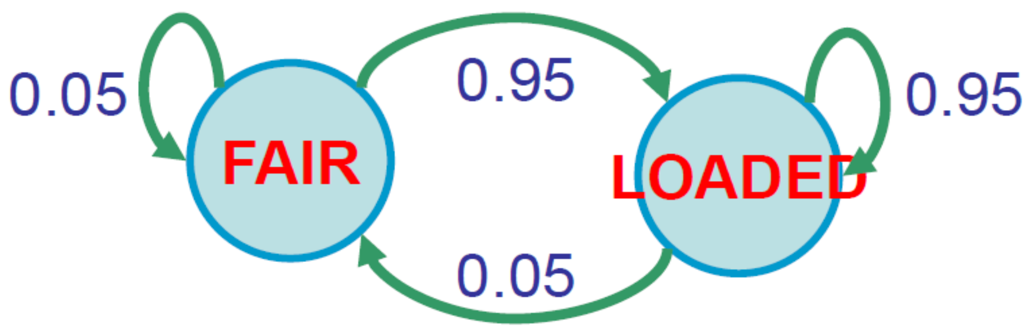
- Given: observation sequence $O = (o_1, \dots, o_T)$, and HMM model $\lambda = < \boldsymbol{\Pi}, \boldsymbol{A}, \boldsymbol{B} >$
- 1) Evaluation
  - What is the probability of the observation sequence, $P(O; \lambda)$, given the model λ? Also called the likelihood of model to explain the observation.
- 2) Decoding
  - What sequence of states $S = (s_1, \dots, s_T)$ best explains the observation, i.e., maximizes $P(O, S; \lambda)$?
- 3) Learning
  - Which model $\lambda = < \boldsymbol{\Pi}, \boldsymbol{A}, \boldsymbol{B} >$ can maximize $P(O; \lambda)$?

Evaluation

- Given observation O and HMM $\lambda = < \boldsymbol{\Pi}, \boldsymbol{A}, \boldsymbol{B} >$, evaluate $P(O; \lambda)$
- Helps choose the best HMM model



O = 1,6,6,2,6,3,6,6



Naïve way to calculate $P(O;\lambda)$

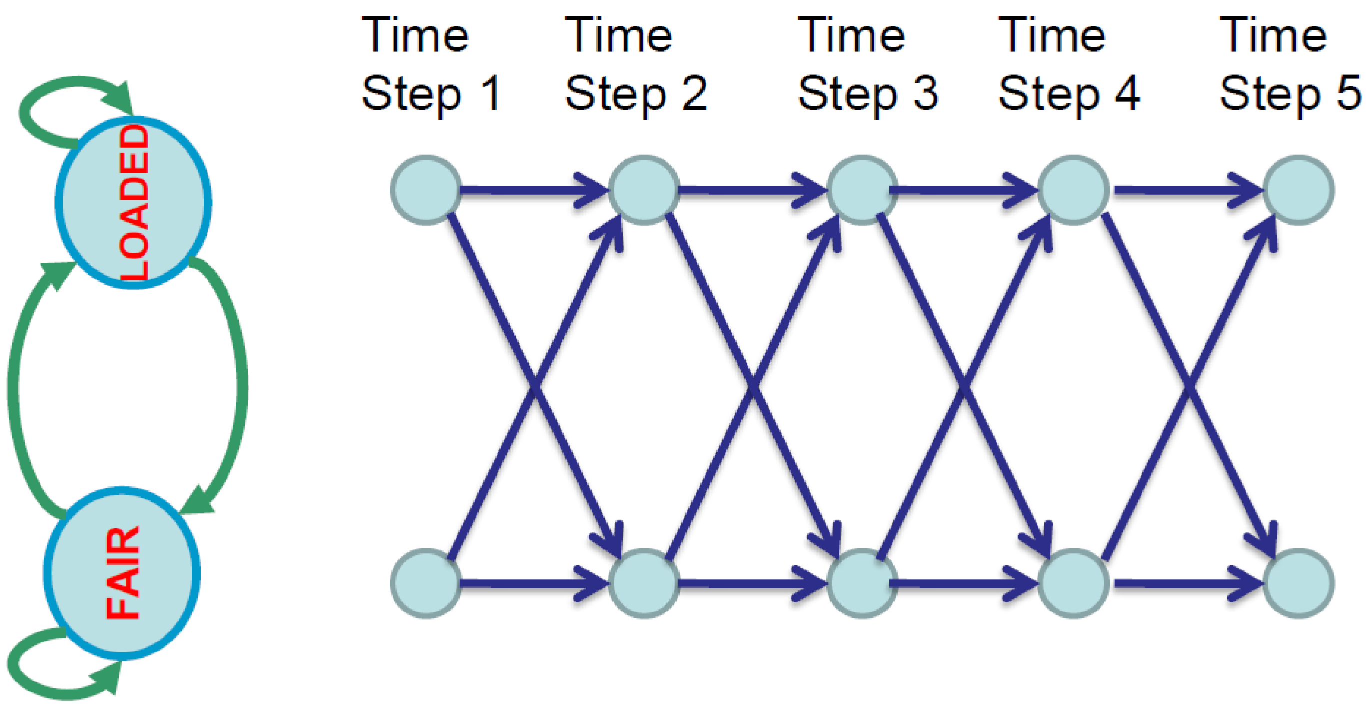
$$P(O;\lambda) = \sum_{\text{all possible state sequences S}} P(O,S;\lambda)$$

- How many possible sequences?
  - Sequence length $= T$; state space size $= N$
  - N^T

- Too slow, often intractable!
- We use the forward algorithm: $O(N^2T)$

The Forward Algorithm

- Idea: Build a trellis that captures all paths through the model so we can reuse probabilities from shared path segments.



The Idea in Math

$$P(O_{1:T}) = \sum_{s_T} \boxed{P(O_{1:T}, s_T)}$$

Recursion!

$$= \sum_{s_T} \sum_{s_{T-1}} P(O_{1:T-1}, o_T, s_T, s_{T-1})$$

$$= \sum_{s_T} \sum_{s_{T-1}} \boxed{P(O_{1:T-1}, s_{T-1})} P(s_T | s_{T-1}) P(o_T | s_T)$$

Transition probability

Emission probability

The Forward Algorithm

- We compute it by induction
- Let $\alpha_t(j) = P(O_{1:t}, s_t = j)$
  - Initialization: $\alpha_1(j) = \pi_j P(o_1|s_1 = j)$, for $j = 1, \dots N$
  - (equivalently: $\alpha_1(j) = \pi_j b_{jo_1}$, for $j = 1, \dots N$)
  - Induction: for $t = 2, \dots, T$ and $j = 1, \dots, N$

$$\alpha_t(j) = \left[\sum_{i=1}^{N} \alpha_{t-1}(i) a_{ij}\right] b_{jo_t}$$

  - Termination: $P(O;\ \lambda) = \sum_{j=1}^{N} \alpha_T(j)$

Decoding

- Given observation $O = (o_1, \dots, o_T)$ and an HMM model $\lambda = < \boldsymbol{\Pi}, \boldsymbol{A}, \boldsymbol{B} >$, find the state sequence $S = (s_1, \dots, s_T)$ that best explains the observation, i.e., maximizes $P(O, S)$.

- Naïve algorithm
  - Try all possible sequences and choose the best one
  - Too many possible sequences: N^T
- Viterbi algorithm
  - Reuse probabilities from shared paths
  - $O(N^2 T)$

The Idea in Math

- Very similar to the forward algorithm

$$
\begin{aligned}
&\max_{S_{1:T}} \boxed{P(O_{1:T}, S_{1:T})} \\
&= \max_{S_{1:T}} P(o_T, s_T | O_{1:T-1}, S_{1:T-1})\, P(O_{1:T-1}, S_{1:T-1}) \\
&= \max_{S_{1:T}} P(o_T, s_T | s_{T-1}) P(O_{1:T-1}, S_{1:T-1}) \\
&= \max_{s_T} P(o_T | s_T) \max_{S_{1:T-1}} P(s_T | s_{T-1}) \boxed{P(O_{1:T-1}, S_{1:T-1})}
\end{aligned}
$$

Recursion!

Emission probability

Transition probability

The Viterbi Algorithm

- Let $v_t(j) = \max_{s_{1:t-1}} P(O_{1:t}, s_{1:t-1}, s_t = j)$

- Initialization: $v_1(j) = \pi_j P(o_1 | s_1 = j)$, for $j = 1, \dots N$
  - (equivalently: $v_1(j) = \pi_j b_{j o_1}$, for $j = 1, \dots N$)

  - Induction: for $t = 2, \dots, T$ and $j = 1, \dots, N$

$$v_t(j) = \left[\max_i v_{t-1}(i) a_{ij}\right] b_{j o_t}$$

$$prev_t(j) = \arg\max_i v_{t-1}(i) a_{ij}$$

  - Termination: $P(O, S; \lambda) = \max_j v_T(j)$
  - Trace back from $\arg\max_j v_T(j)$ to get the best path

Learning

- Given observation $O = (o_1, \dots, o_T)$, what are the best parameters of an HMM model $\lambda = < \boldsymbol{\Pi}, \boldsymbol{A}, \boldsymbol{B} >$ that can maximize $P(O;\ \lambda)$?

- The parameters $\lambda = < \boldsymbol{\Pi}, \boldsymbol{A}, \boldsymbol{B} >$ are unknown
- The hidden states $S = (s_1, \dots, s_T)$ are unknown

- Baum-Welch algorithm
  - EM algorithm!

Continuous Observations

- In the previous slides, we assumed a discrete emission (observation) alphabet $\{e_1, \ldots, e_M\}$.

- What if the observation alphabet is continuous, e.g., real-valued?
- How do we represent emission probabilities $\boldsymbol{B}$?

- Parameterized model $p(o_t | s_t)$

Audio Modeling by HMMs

- Speech recognition
  - States: phonemes
  - Observation: MFCC features of audio frames

  - Transition probabilities: phonemes transition
  - Emission probabilities: phoneme -> audio spectrum

  - Recognition: decoding states from observed audio frames

Audio Modeling by HMMs

- Chord recognition
  - States: chords
  - Observation: some feature rep's of audio spectra

  - Transition probabilities: chord progression
  - Emission probabilities: chord -> audio spectrum

  - Recognition: decoding chord labels from observed audio frames

Audio Modeling by HMMs

- Refining pitch detection results
  - States: pitch candidates (e.g., all discretized freq. between 65Hz-370Hz)
  - Observation: audio spectra
  - Transition probabilities: pitches tend to change smoothly
  - Emission probabilities: the likelihood of each pitch candidate, P(audio frame | pitch candidate)
  - Refinement: decoding pitches from observation

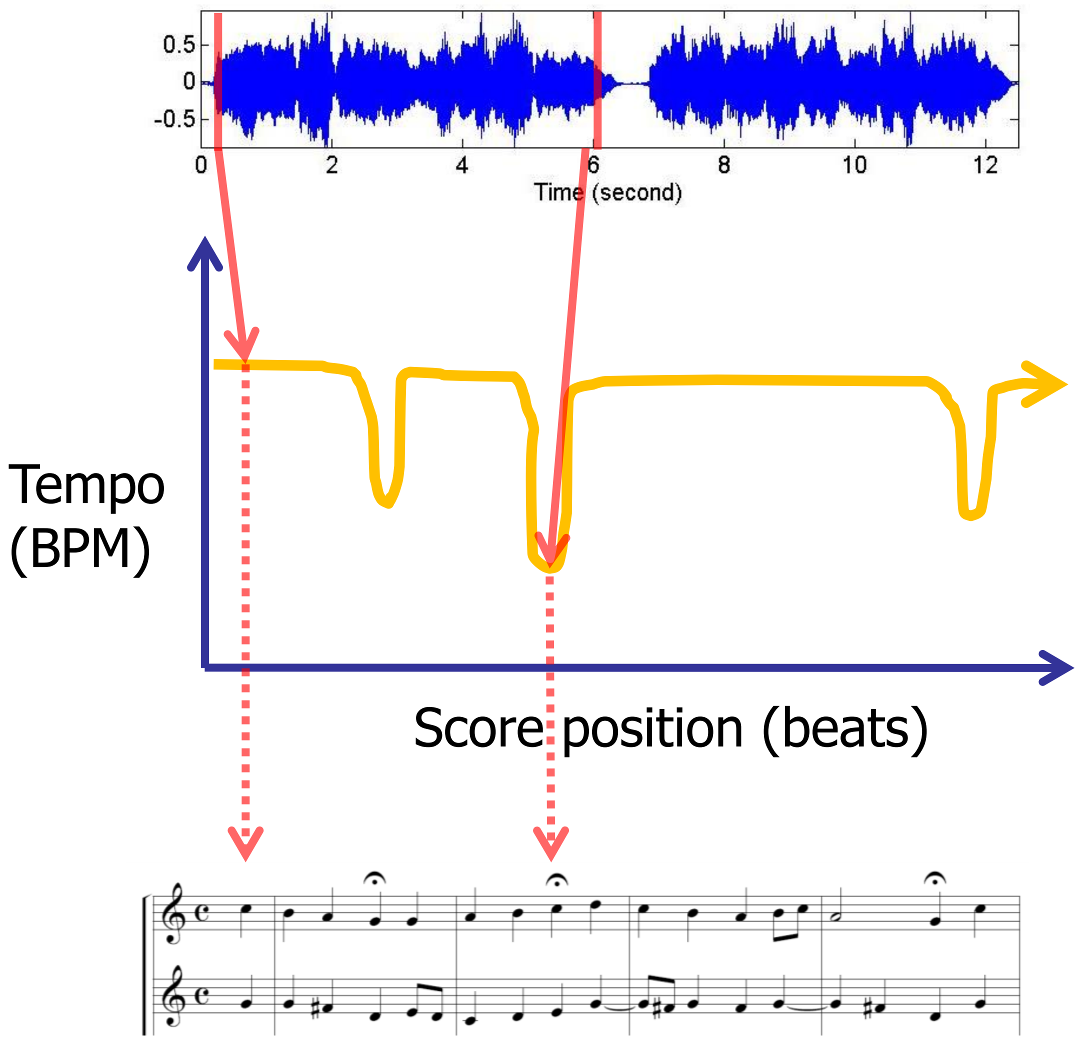
Infinite-state HMM

- There are infinitely many states, also called hidden Markov process.

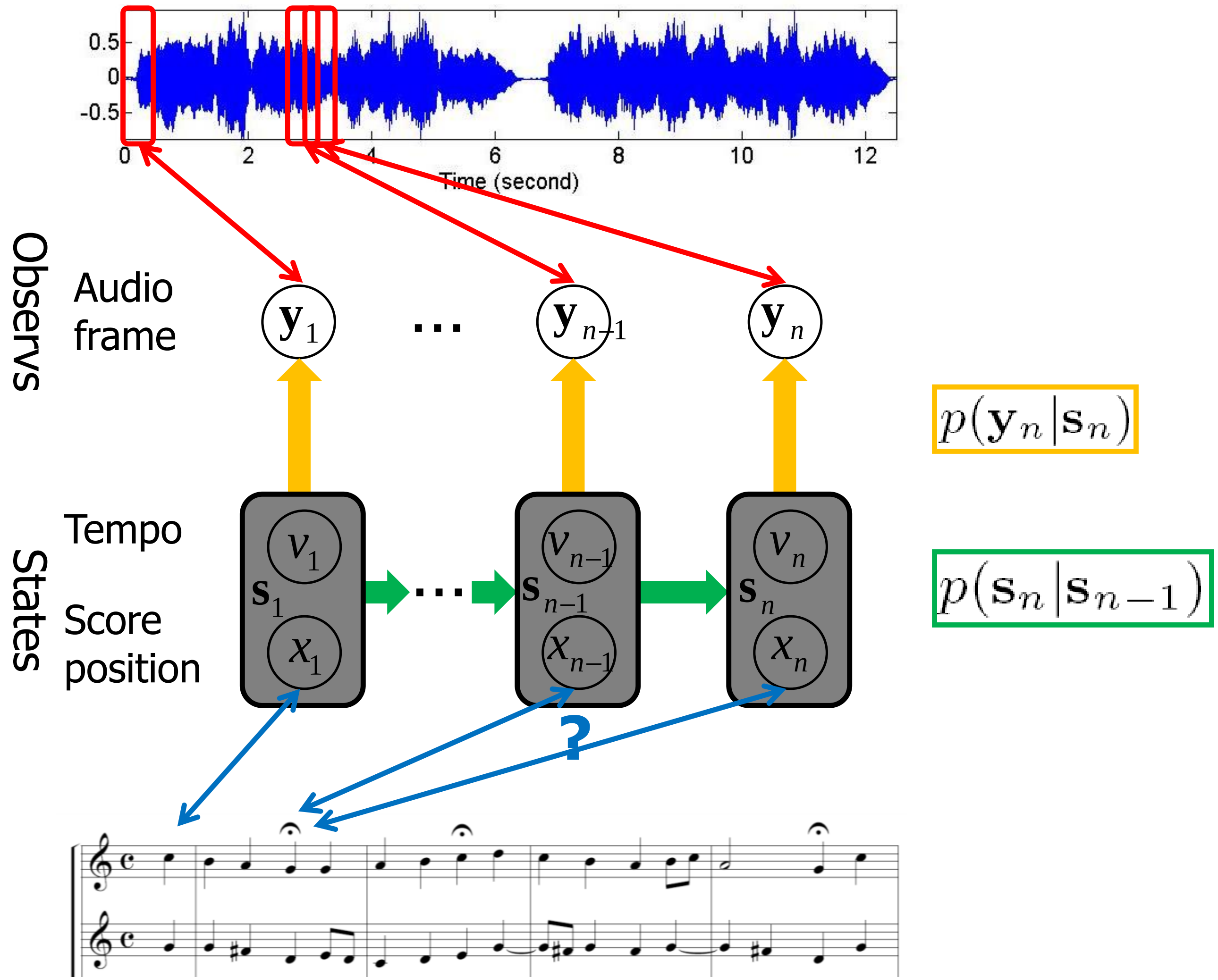
- Summations over states in finite-state HMMs become to integrations over states.

- When the states are high-dimensional, integration is not easy.
  - Use Monte Carlo methods instead

An Example: Audio-score Alignment



An Example: Audio-score Alignment



Inference by particle filtering

Hidden Markov Process

Limitations of HMM

- Only models short-time dependencies
  - Audio signals can have longer dependencies, e.g., rhythmic structure
  - Higher-order HMM
- Only one sequence of states
  - Audio with multiple sound sources?
  - Factorial HMM
- Generative model
  - May not be ideal for some tasks
  - Conditional Random Field (CRF)