Hidden Markov Model

INTELLIGENT SYSTEMS FOR PATTERN RECOGNITION (ISPR)

DAVIDE BACCIU – DIPARTIMENTO DI INFORMATICA - UNIVERSITA’ DI PISA

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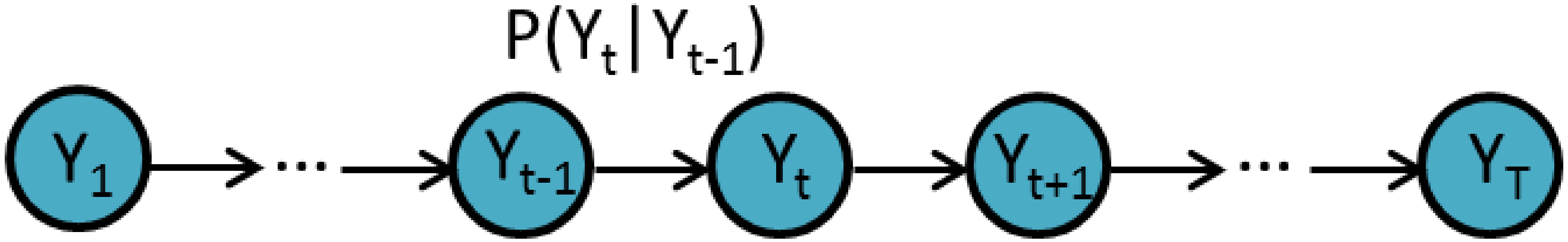
Lecture Plan (Part I, II, III)

- A probabilistic model for sequences: Hidden Markov Models (HMMs)
- Exact inference on a chain with observed and unobserved variables
  - Sum-product message passing example
  - Max-product message passing example
- Using inference to learn: the Expectation-Maximization algorithm for HMMs
- Graphical models with varying structure: Dynamic Bayesian Networks

Part I

Introduction to HMM

Sequences

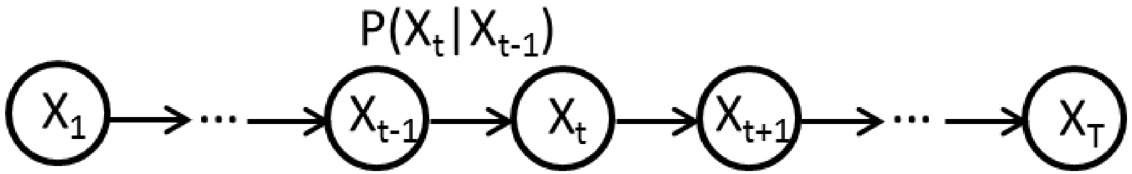


- A sequence $\boldsymbol{y}$ is a collection of observations y_t where t represent the position of the element according to a (complete) order (e.g. time)
- Reference population is a set of i.i.d sequences $\boldsymbol{y}^1, \ldots, \boldsymbol{y}^N$
- Different sequences $\boldsymbol{y}^1, \ldots, \boldsymbol{y}^N$ generally have different lengths $\boldsymbol{T}^1, \ldots, \boldsymbol{T}^N$

Markov Chain

First-Order Markov Chain

Directed graphical model for sequences s.t. element X_t only depends on its predecessor in the sequence



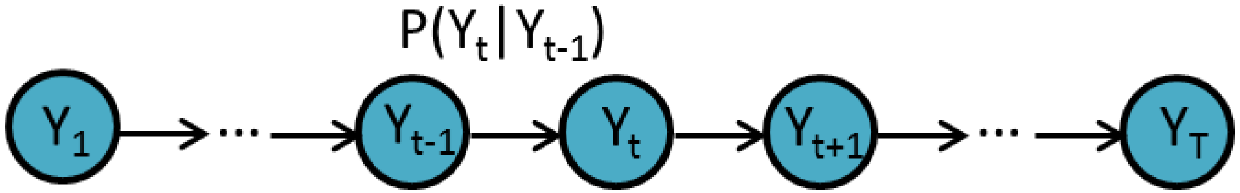
- Joint probability factorizes as

$$P(\boldsymbol{X}) = P(X_1, \dots, X_T) = P(X_1) \prod_{t=2}^{T} P(X_t | X_{t-1})$$

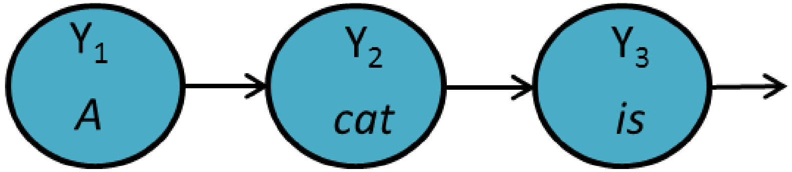
- $P(X_t|X_{t-1})$ is the transition distribution; $P(X_1)$ is the prior distribution
- General form: an L-th order Markov chain is such that X_t depends on L predecessors

Observed Markov Chains

Can we use a Markov chain to model the relationship between observed elements in a sequence?



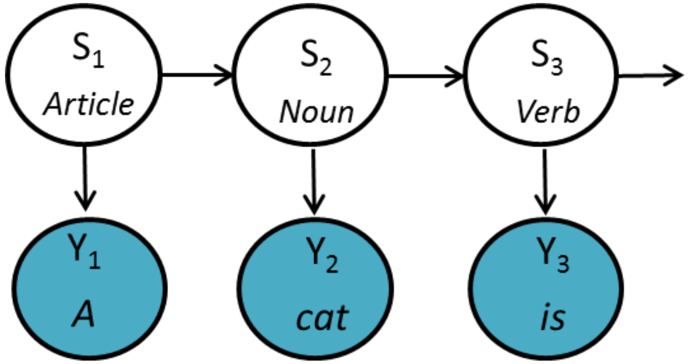
Of course yes, but..



Does it make sense to represent $P(is|cat)$?

Hidden Markov Model (HMM) (I)

Stochastic process where transition dynamics is disentangled from observations generated by the process



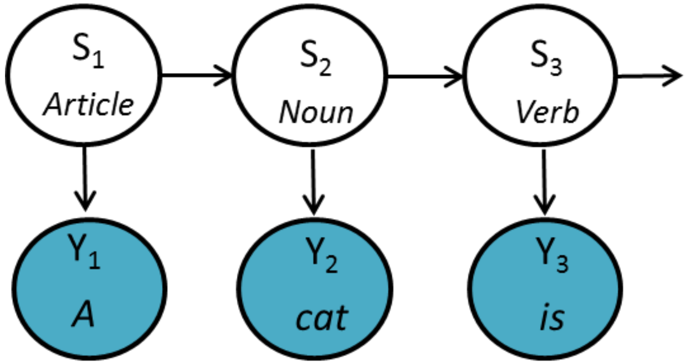
State transition is an unobserved (hidden/latent) process characterized by the hidden state variables S_t

- S_t are often discrete with value in $\{1, \ldots, C\}$
- Multinomial state transition and prior probability (stationarity assumption)

$$A_{ij} = P(S_t = i | S_{t-1} = j) \text{ and } \pi_i = P(S_1 = i)$$

Hidden Markov Model (HMM) (II)

Stochastic process where transition dynamics is disentangled from observations generated by the process



Observations are generated by the emission distribution

$$b_i(y_t) = P(Y_t = y_t \,|S_t \; = \; i)$$

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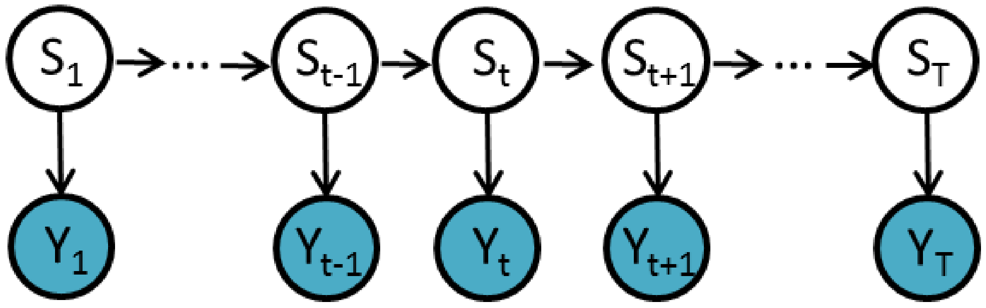
HMM Joint Probability Factorization

Discrete-state HMMs are parameterized by $\theta = (\pi, A, B)$ and the finite number of hidden states C

- State transition and prior distribution A and π
- Emission distribution B (or its parameters)

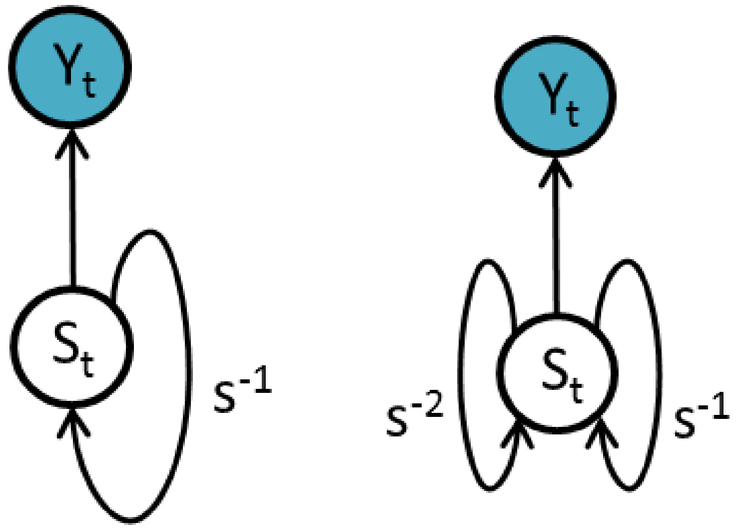


$$P(\boldsymbol{Y} = \boldsymbol{y}) = \sum_{\boldsymbol{s}} P(\boldsymbol{Y} = \boldsymbol{y}, \boldsymbol{S} = \boldsymbol{s})$$

$$= \sum_{s_1,\ldots,s_T} \left\{ P(S_1 = s_1) P(Y_1 = y_1 | S_1 = s_1) \prod_{t=2}^{T} P(S_t = s_t | S_{t-1} = s_{t-1}) P(Y_t = y_t | S_t = s_t) \right\}$$

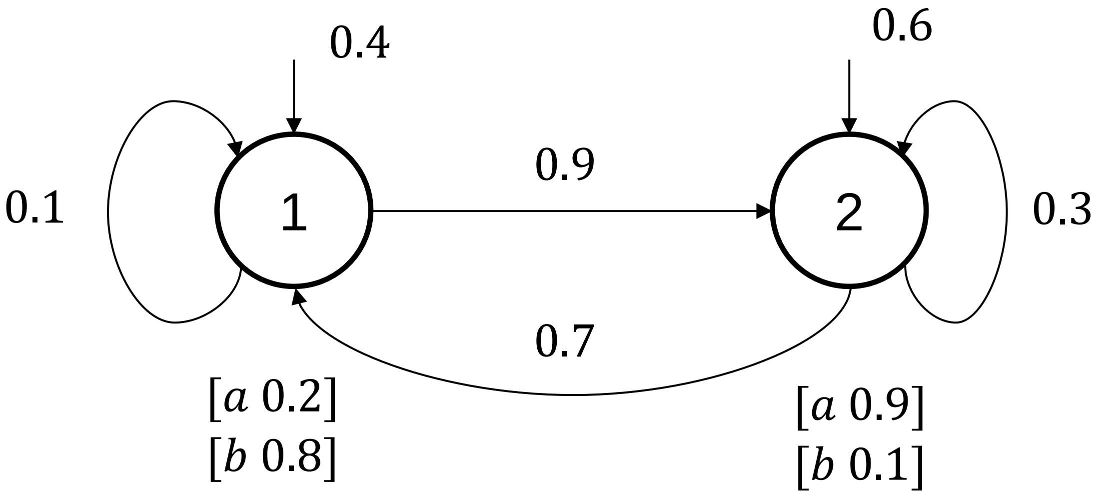
HMMs as a Recursive Model

A graphical framework describing how contextual information is recursively encoded by both probabilistic and neural models



- Indicates that the hidden state S_t at time t is dependent on context information from
  - The previous timestep s^{-1}
  - Two timesteps earlier s^{-2}
  - ...
- When applying the recursive model to a sequence (unfolding), it generates the corresponding directed graphical model

HMMs as Automata



Can be generalized to transducers

3 Notable Inference Problems

Definition (Smoothing)

Given a model θ and an observed sequence $\boldsymbol{y}$, determine the distribution of the hidden state at time t $P(S_t|\boldsymbol{Y} = \boldsymbol{y}, \theta)$

Definition (Learning)

Given a dataset of N observed sequences $\mathcal{D} = \{\boldsymbol{y}^1, \dots, \boldsymbol{y}^N\}$ and the number of hidden states C, find the parameters π, A and B that maximize the probability of model $\theta = \{\pi, A, B\}$ having generated the sequences in $\mathcal{D}$

Definition (Optimal State Assignment)

Given a model θ and an observed sequence $\boldsymbol{y}$, find an optimal state assignment $\boldsymbol{s} = s_1^*, \dots, s_T^*$ for the hidden Markov chain

Part II

Forward-Backward Algorithm and parameter estimation

Forward-Backward Algorithm

Smoothing - How do we determine the posterior $P(S_t = i|\boldsymbol{y})$?

Exploit factorization

$$P(S_t = i|\boldsymbol{y}) \propto P(S_t = i, \boldsymbol{y}) = P(S_t = i, \boldsymbol{Y}_{1:t}, \boldsymbol{Y}_{t+1:T})$$

$$= P(S_t = i, \boldsymbol{Y}_{1:t})P(\boldsymbol{Y}_{t+1:T}|S_t = i) = \alpha_t(i)\beta_t(i)$$

α-term computed as part of forward recursion ($\alpha_1(i) = b_i(y_1)\pi_i$)

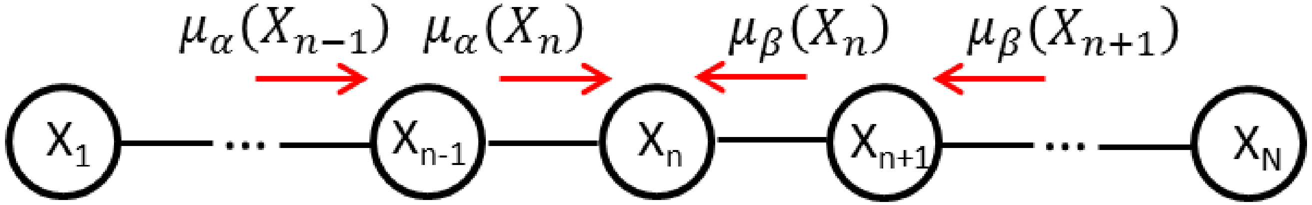
$$\alpha_t(i) = P(S_t = i, \boldsymbol{Y}_{1:t}) = b_i(y_t)\sum_{j=1}^{C} A_{ij}\alpha_{t-1}(j)$$

β-term computed as part of backward recursion ($\beta_T(i) = 1, \forall i$)

$$\beta_t(j) = P(\boldsymbol{Y}_{t+1:T}|S_t = j) = \sum_{i=1}^{C} b_i(y_{t+1})\beta_{t+1}(i)A_{ij}$$

Sum-Product Message Passing

The Forward-Backward algorithm is an example of a sum-product message passing algorithm



A general approach to *efficiently* perform exact inference in graphical models

- $\alpha_t \equiv \mu_\alpha(X_n)$ → forward message

$$\underbrace{\mu_\alpha(X_n)}_{\alpha_t(i)} = \sum_{\underbrace{X_{n-1}}_{\sum_{j=1}^{C}}} \underbrace{\psi(X_{n-1}, X_n)}_{b_i(y_t)A_{ij}} \underbrace{\mu_\alpha(X_{n-1})}_{\alpha_{t-1}(j)}$$

Sum-Product Message Passing

The Forward-Backward algorithm is an example of a sum-product message passing algorithm

A general approach to *efficiently* perform exact inference in graphical models

- $\alpha_t \equiv \mu_\alpha(X_n)$ → forward message
- $\beta_t \equiv \mu_\beta(X_n)$ → backward message

$$\underbrace{\mu_\beta(X_n)}_{\beta_t(j)} = \sum_{\underbrace{X_{n+1}}_{\sum_{i=1}^{C}}} \underbrace{\psi(X_n, X_{n+1})}_{b_i\,(y_{t+1}) A_{ij}} \underbrace{\mu_\beta(X_{n+1})}_{\beta_{t+1}(i)}$$

Learning in HMM

Learning HMM parameters $\theta = (\pi, A, B)$ by maximum likelihood

$$\mathcal{L}(\theta) = \log \prod_{n=1}^{N} P(\boldsymbol{Y}^n|\theta) = \log \prod_{n=1}^{N} \left\{ \sum_{s_1^n,\dots,s_{T_n}^n} P(S_1^n)P(Y_1^n|S_1^n) \prod_{t=2}^{T_n} P(S_t^n|S_{t-1}^n)P(Y_t^n|S_t^n) \right\}$$

- How can we deal with the unobserved random variables S_t^n and the nasty summation in the $\log$?
- Expectation-Maximization algorithm
  - Maximization of the complete likelihood $\mathcal{L}_c(\theta)$
  - Completed with indicator variables

$$z_{ti}^n = \begin{cases} 1 & \text{if } n\text{–th chain is in state } i \text{ at time } t \\ & 0 \text{ otherwise} \end{cases}$$

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Complete HMM Likelihood

Introduce indicator variables in $L(\theta)$ together with model parameters $\theta = (\pi, A, B)$

$$\mathcal{L}_c(\theta) = \log P(\mathcal{Y}, \mathcal{Z}|\theta) = \log \prod_{n=1}^{N} \left\{ \prod_{i=1}^{C} [P(S_1 = i) P(Y_1^n | S_1 = i)]^{z_{1i}^n} \right.$$

$$\left. \prod_{t=2}^{T_n} \prod_{i,j=1}^{C} P(S_t = i | S_{t-1} = j)^{z_{ti}^n z_{(t-1)j}^n} P(Y_t^n | S_t = i)^{z_{ti}^n} \right\}$$

$$= \sum_{n=1}^{N} \left\{ \sum_{i=1}^{C} z_{1i}^n \log \pi_i + \sum_{t=2}^{T_n} \sum_{i,j=1}^{C} z_{ti}^n z_{(t-1)j}^n \log A_{ij} + \sum_{t=1}^{T_n} \sum_{i=1}^{C} z_{ti}^n \log b_i(y_t^n) \right\}$$

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Expectation-Maximization

A 2-step iterative algorithm for the maximization of complete likelihood $\mathcal{L}_c(\theta)$ w.r.t. model parameters θ

E-Step: Given the current estimate of the model parameters $\theta^{(t)}$, compute

$$Q^{(k+1)}\left(\theta \middle| \theta^{(k)}\right) = E_{\mathcal{Z}|Y,\theta^{(t)}}\left[\log P(\mathcal{Y}, \mathcal{Z}|\theta)\right]$$

M-Step: Find the new estimate of the model parameters

$$\theta^{(k+1)} = \arg\max_{\theta} Q^{(k+1)}(\theta|\theta^{(k)})$$

Iterate 2 steps until $\left|\mathcal{L}_c(\theta)^{k+1} - \mathcal{L}_c(\theta)^{k}\right| < \epsilon$ (or stop if maximum number of iterations is reached)

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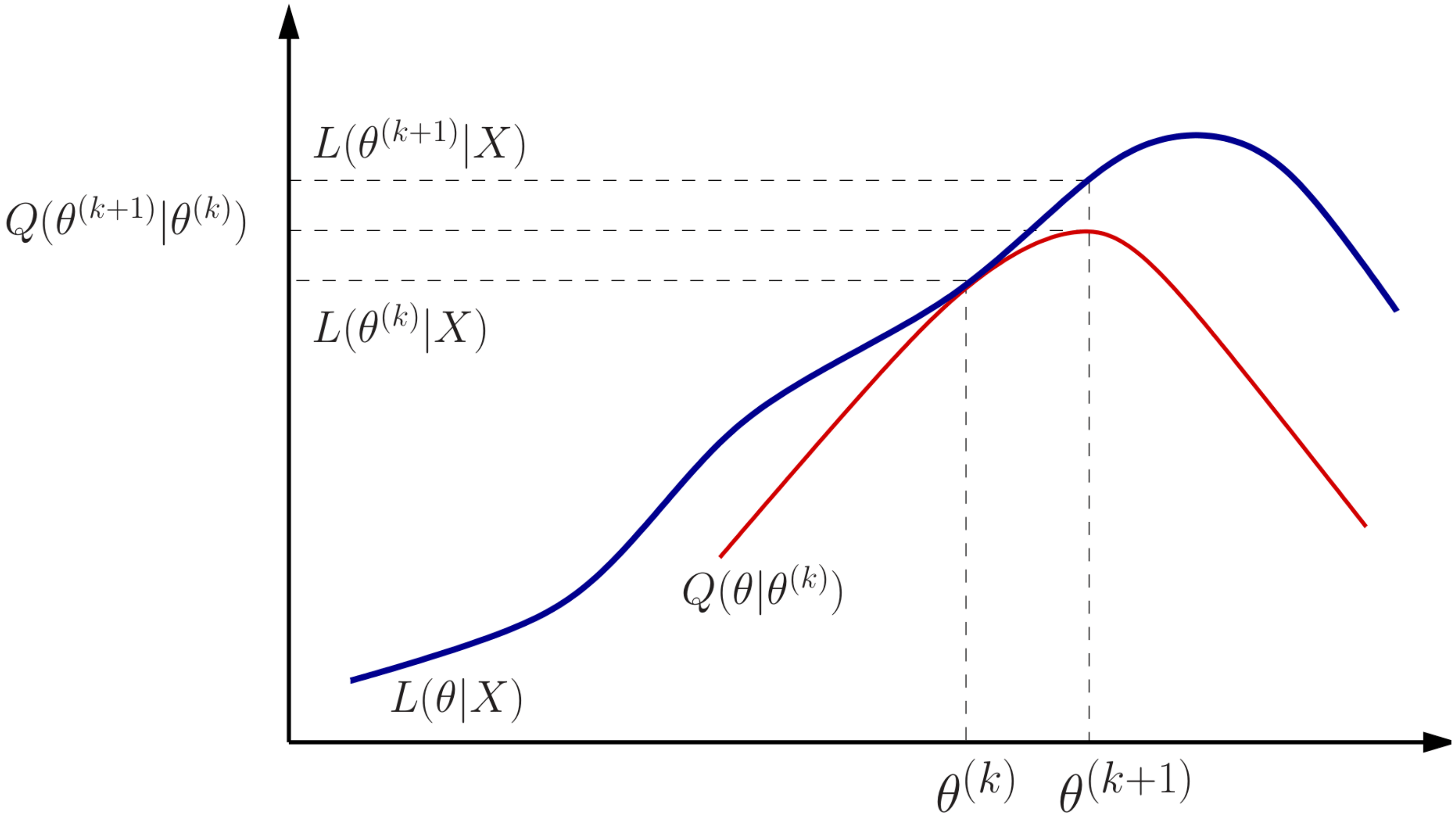
EM Graphically



E-Step (I)

Compute the expectation of the complete log-likelihood w.r.t indicator variables z_{ti}^n assuming (estimated) parameters $\theta^k = (\pi^k, A^k, B^k)$ fixed at iteration k (i.e. constants)

$$Q^{(k+1)}\left(\theta|\theta^{(k)}\right) = E_{\mathcal{Z}|Y,\theta^{(k)}}\left[\log P(Y, \mathcal{Z}|\theta)\right]$$

Expectation w.r.t a (discrete) random variable z is

$$E_z[Z] = \sum_z z \cdot P(Z = z)$$

To compute the conditional expectation $Q^{(t+1)}\left(\theta|\theta^{(t)}\right)$ for the complete HMM log-likelihood we need to estimate

$$E_{\mathcal{Z}|\boldsymbol{Y},\theta^{(k)}}[z_{ti}] = P(S_t = i|\boldsymbol{y})$$

$$E_{\mathcal{Z}|\boldsymbol{Y},\theta^{(k)}}\left[z_{ti} z_{(t-1)j}\right] = P(S_t = i, S_{t-1} = j|\boldsymbol{Y})$$

E-Step (II)

We know how to compute the posteriors by the forward-backward algorithm!

$$\gamma_t(i) = P(S_t = i|\boldsymbol{Y}) = \frac{\alpha_t(i)\beta_t(i)}{\sum_{j=1}^{C} \alpha_t(j)\beta_t(j)}$$

$$\gamma_{t,t-1}(i,j) = P(S_t = i, S_{t-1} = j|\boldsymbol{Y}) = \frac{\alpha_{t-1}(j)A_{ij}b_i(y_t)\beta_t(i)}{\sum_{m,l=1}^{C} \alpha_{t-1}(m)A_{lm}b_l(y_t)\beta_t(l)}$$

M-Step (I)

Solve the optimization problem

$$\theta^{(k+1)} = \arg\max_{\theta} Q^{(k+1)}(\theta|\theta^{(k)})$$

using the information computed at the E-Step (the posteriors).

How?

As usual

$$\frac{\partial Q^{(k+1)}(\theta|\theta^{(k)})}{\partial \theta}$$

where $\theta = (\pi, A, B)$ are now variables.

Attention

Parameters can be distributions $\Rightarrow$ need to preserve sum-to-one constraints (Lagrange Multipliers)

M-Step (II)

State distributions

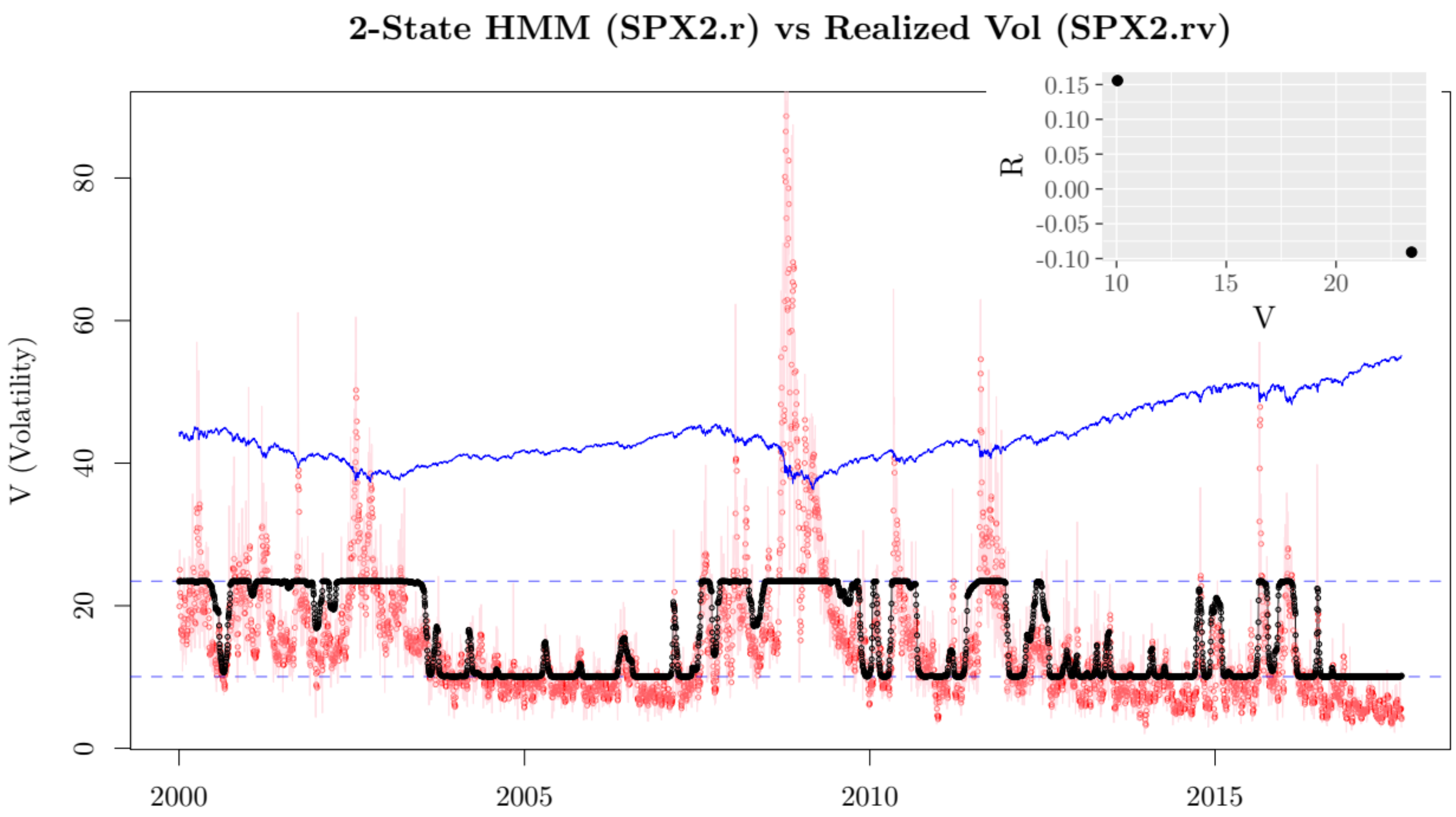
$$A_{ij} = \frac{\sum_{n=1}^{N} \sum_{t=2}^{T^n} \gamma_{t,t-1}^{n}(i,j)}{\sum_{n=1}^{N} \sum_{t=2}^{T^n} \gamma_{t-1}^{n}(j)} \quad \text{and} \quad \pi_i = \frac{\sum_{n=1}^{N} \gamma_1^n(i)}{N}$$

Emission distribution (multinomial)

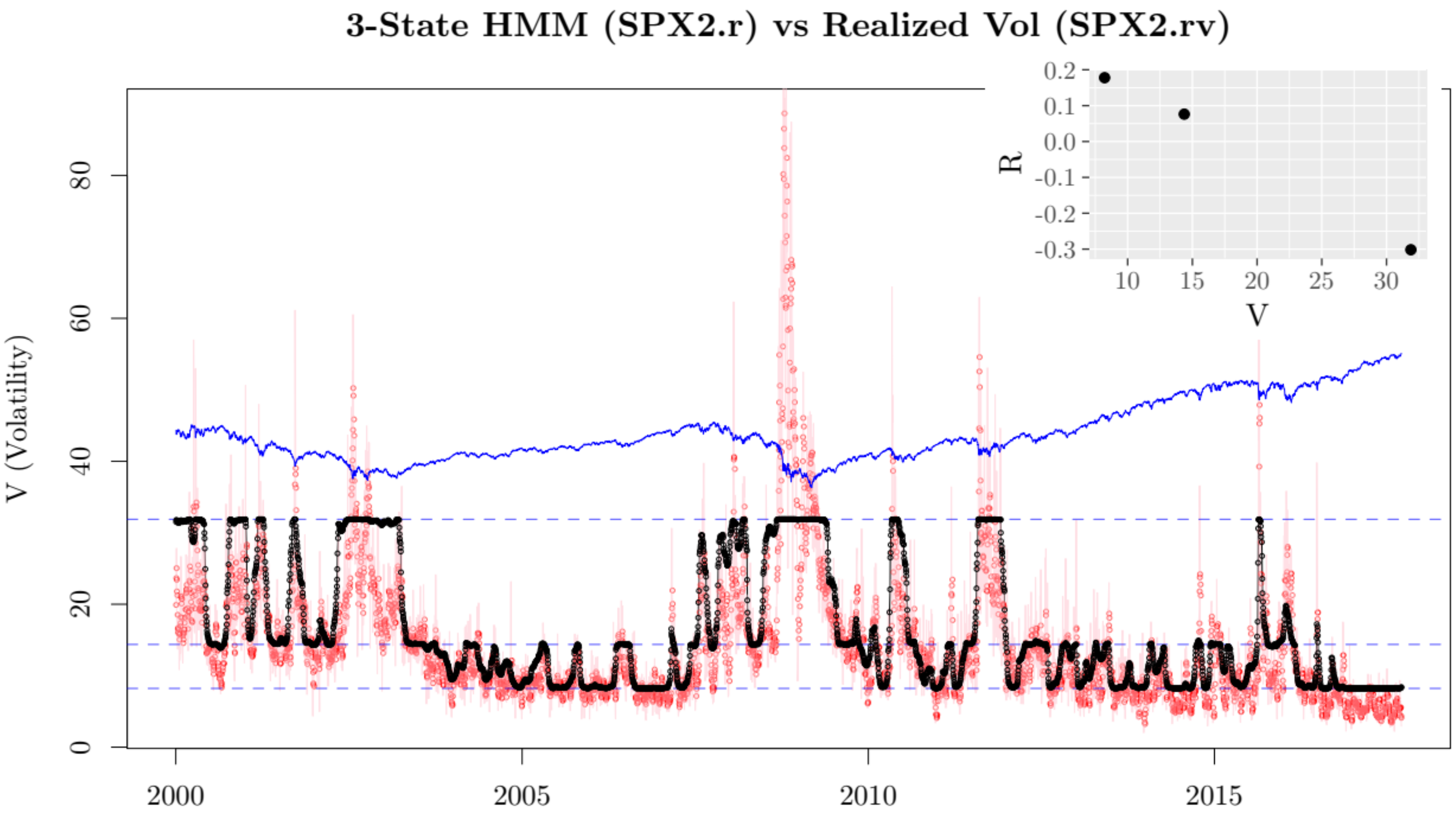
$$B_{ki} = \frac{\sum_{n=1}^{N} \sum_{t=1}^{T_n} \gamma_t^n(i) \delta(y_t = h)}{\sum_{n=1}^{N} \sum_{t=1}^{T_n} \gamma_t^n(i)}$$

where $\delta(\cdot)$ is the indicator function for emission symbols h

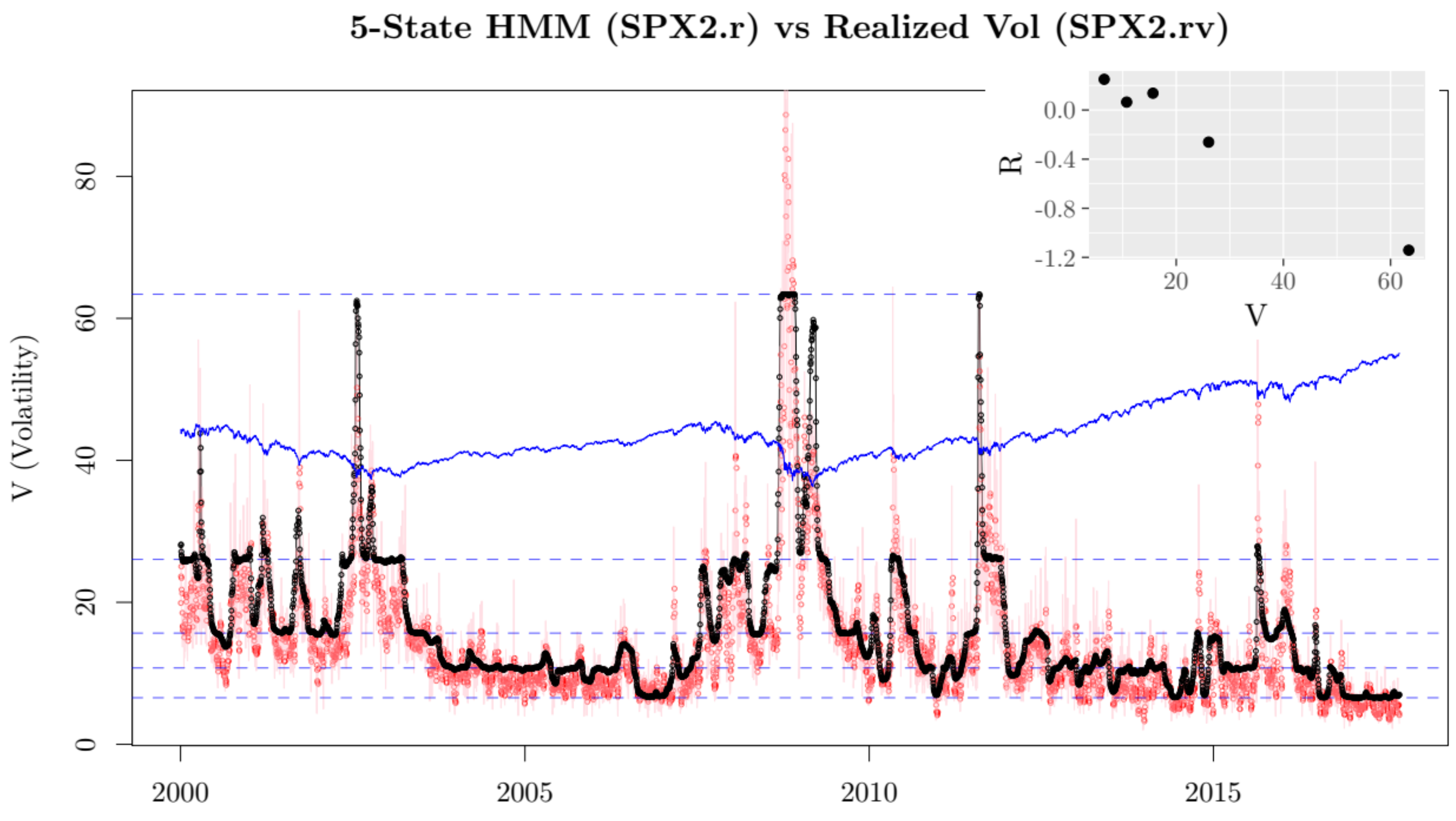
HMM in PR - Regime Detection



HMM in PR - Regime Detection



HMM in PR - Regime Detection



Part III

Viterbi Algorithm and advanced models

Decoding Problem

- Find the optimal hidden state assignment $\boldsymbol{s} = s_1^*, \dots, s_T^*$ for an observed sequence $\boldsymbol{y}$ given a trained HMM
- No unique interpretation of the problem
  - Identify the single hidden states s_t that maximize the posterior

$$s_t^* = \arg\max_{i=1,\dots,C} P(S_t = i|Y)$$

  - Find the most likely joint hidden state assignment

$$\boldsymbol{s}^* = \arg\max_{\boldsymbol{s}} P(\boldsymbol{Y}, \boldsymbol{S} = \boldsymbol{s})$$

- The last problem is addressed by the Viterbi algorithm

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Viterbi Algorithm

An efficient dynamic programming algorithm based on a backward-forward recursion

An example of a **max-product message passing** algorithm

Recursive backward term

$$\epsilon(s_{t-1}) = \max_{s_t} P(Y_t|S_t = s_t)\, P(S_t = s_t|S_{t-1} = s_{t-1})\epsilon(s_t),$$

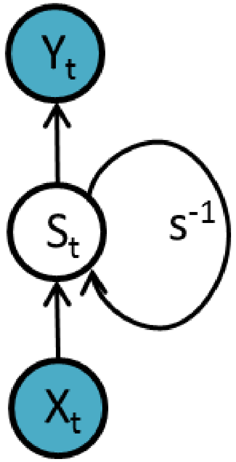
Root optimal state

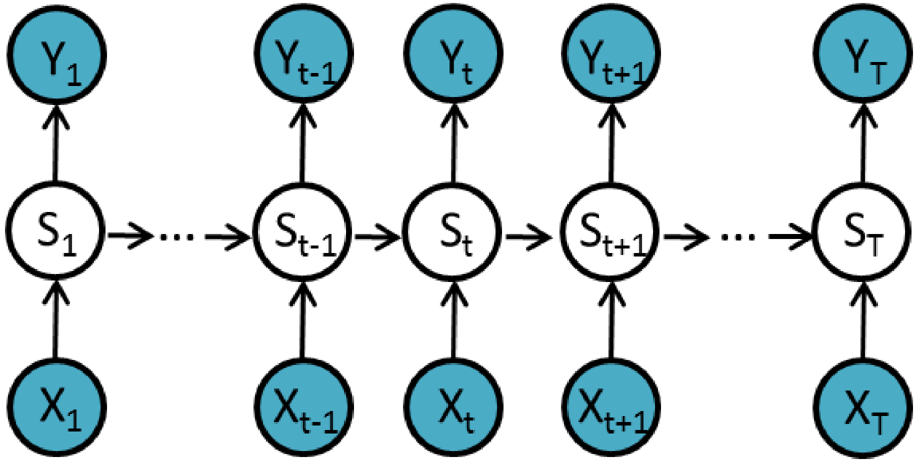
$$s_1^* = \arg\max_{s} P(Y_t|S_1 = s)\, P(S_1 = s)\epsilon(s).$$

Recursive forward optimal state

$$s_t^* = \arg\max_{s} P(Y_t|S_t = s)\, P(S_t = s|S_{t-1} = s_{t-1}^*)\epsilon(s).$$

Input-Output Hidden Markov Models

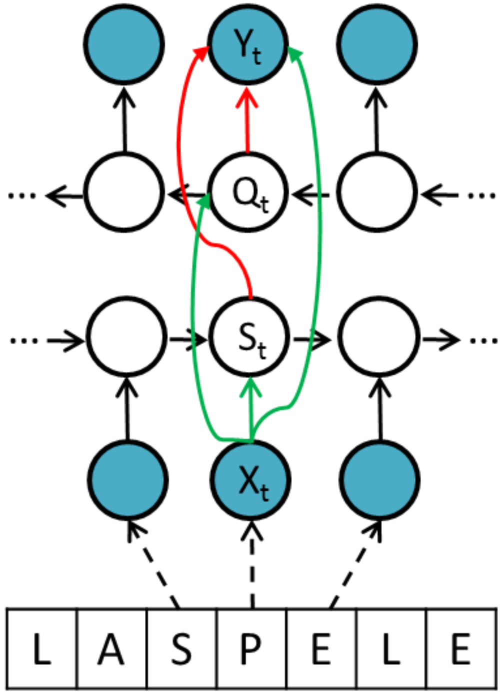




- Translate an input sequence into an output sequence (transduction)
- State transition and emissions depend on input observations (input-driven)
- Recursive model highlights analogy with recurrent neural networks

Bidirectional Input-driven Models

Remove causality assumption that current observation does not depend on the future and homogeneity assumption that an state transition is not dependent on the position in the sequence

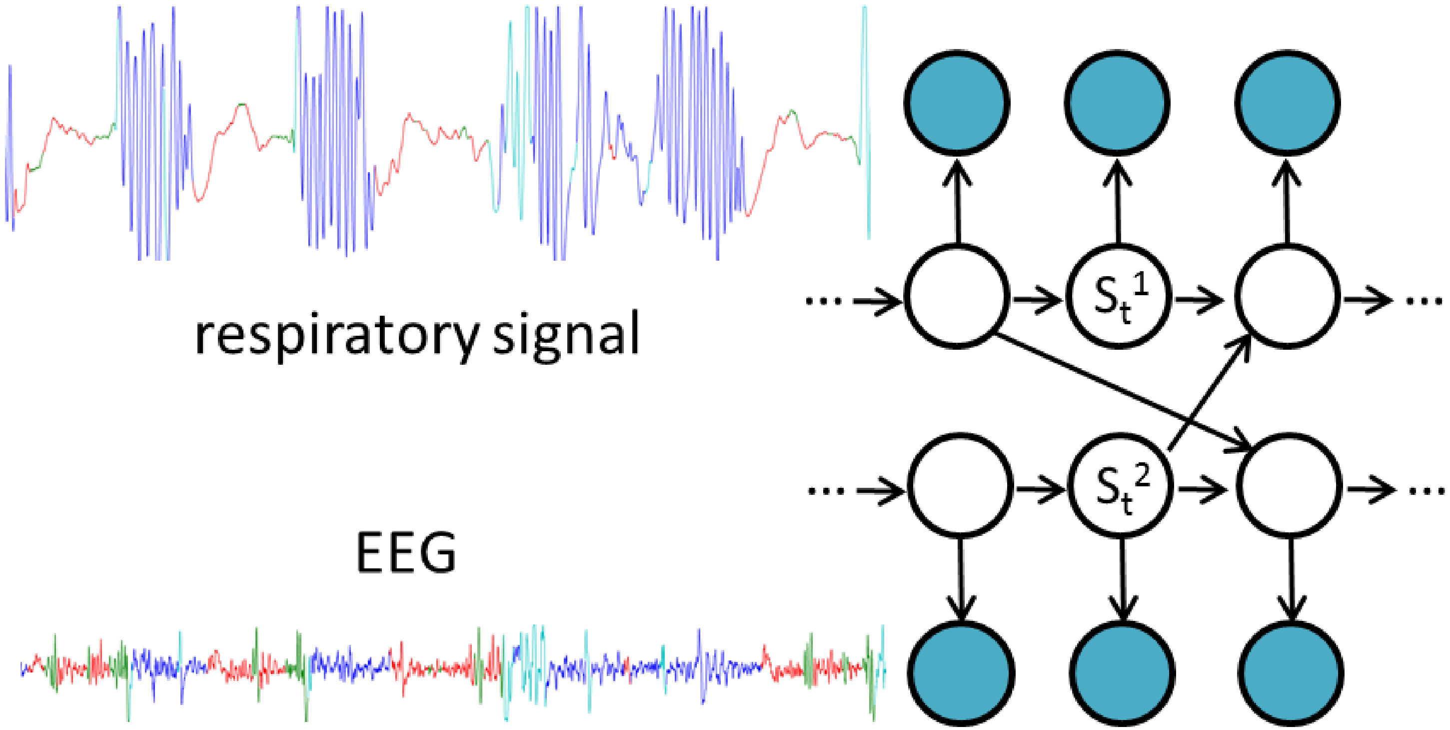


- Structure and function of a region of DNA and protein sequences may depend on upstream and downstream information

- Hidden state transition distribution changes with the amino-acid sequence being fed in input

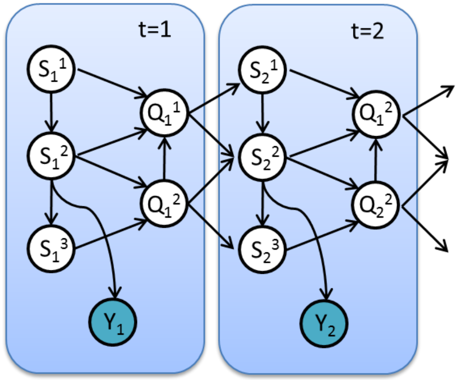
Coupled HMM

Describing interacting processes whose observations follow different dynamics while the underlying generative processes are interlaced

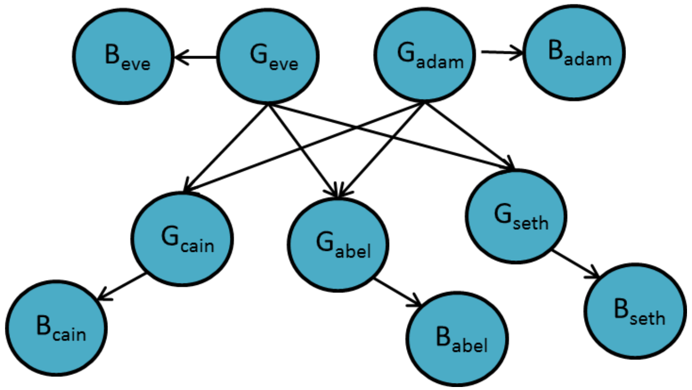


Dynamic Bayesian Networks

HMMs are a specific case of a class of directed models that represent dynamic processes and data with changing connectivity template



Hierarchical HMM



Structure changing information

Dynamic Bayesian Networks (DBN)

Graphical models whose structure changes to represent evolution across time and/or between different samples

HMM in Matlab

An official implementation by Mathworks available as a set of **inference** and **learning** functions

Estimate distributions (based on initial guess)

```
%Initial distribution guess
tg = rand (N,N); %Random init
tg = tg . /repmat (sum( tg , 2 ) ,[ 1 N] ); %Normalize
… %Similarly for eg
[ test , eest ] = hmmtrain ( seq , tg , eg );
```

Estimate posterior states

```
pstates = hmmdecode( seq , test , eest )
```

Estimate Viterbi states

```
vstates = hmmviterbi ( seq , test , eest )
```

Sample a sequence from the model

```
[ seq , st at e s ] = hmmgenerate ( len , t e st , ee st )
```

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HMM in Python

- hmmlearn - The official scikit-like implementation of HMM
  - 3 classes depending on emission type: `MultinomialHMM`, `GaussianHMM`, and `GMMHMM`

```
from hmmlearn . hmm import GaussianHMM
. . .
# Create an HMM and fit it to data X
model = GaussianHMM ( n_components = 4 , covariance_type = "diag" , n_iter = 1000 ) . fit (X)
# Decode the optimal sequence of internal hidden state ( Viterbi )
hidden_states = model . predict ( X )
# Generate new samples ( visible, hidden )
X1 , Z1 = model . sample ( 500 )
```

- hmms 0.1 - A scalable implementation for both discrete and continuous-time HMMs

Take Home Messages

- Hidden Markov Models
  - Hidden states used to realize an unobserved generative process for sequential data
  - A mixture model where selection of the next component is regulated by the transition distribution
  - Hidden states summarize (cluster) information on subsequences in the data
- Inference in HMMS
  - Forward-backward - Hidden state posterior estimation
  - Expectation-Maximization - HMM parameter learning
  - Viterbi - Most likely hidden state sequence
- Dynamic Bayesian Networks
  - A graphical model whose structure changes to reflect information with variable size and connectivity patterns
  - Suitable for modeling structured data (sequences, tree, ...)

Next Lecture/Lectures

Markov Random Fields

- Learning in undirected graphical models
- Introduction to message passing algorithms
- Conditional random fields
- Pattern recognition applications