# Probabilistic Graphical Models and Hidden Markov Models

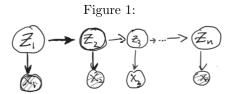
Math189R: Mathematics of Big Data

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April 13, 2020

# 1 Hidden Markov Models (HMM)

### 1.1 Structure of Model



#### Attributes of Figure 1:

$$z_i =$$
"Hidden" variables, (1)

$$x_i = \text{"Observed" data},$$
 (2)

$$z_1, z_2, ..., z_n \in \{1, 2, ..., m\},$$
 (3)

$$x_1, x_2, ..., x_n : X(\text{discrete}, \mathbb{R}, \mathbb{R}^n, ...).$$
 (4)

**Key:** The joint probability factorizes in the following way:

$$p(z_1, z_2, ..., z_n, x_1, x_2, ..., x_n) = p(z_1)p(x_1 \mid z_1)\prod_{k=2}^n p(z_k \mid z_{k-1})p(x_k \mid z_k), \quad (5)$$

$$p(z_1): \Pi(i), \tag{6}$$

$$p(x_1 \mid z_1) : \Sigma_{z_1}(x_1), \tag{7}$$

$$p(z_k \mid z_{k-1}) : \Pi(z_{k-1}, z_k), \tag{8}$$

$$p(x_k \mid z_k) : \mathbf{\Sigma}_{z_k}(x_k). \tag{9}$$

Model:

$$p(z_1, z_2, ..., z_n) = \pi(i) \sum_{z_1} (x_1) \pi_{k=2}^n T(z_{k-1}, z_k) \sum_{z_k} (x_k).$$
 (10)

#### Parameters of the Model:

- Transition Probability:  $T_{(i,j)} = p(z_{k+1} = j \mid z_k = i)$ , where  $i, j \in \{1, 2, ..., m\}$ .
- Emission Probability:
  - Discrete Case (pmf):  $\Sigma_i(x) = p(x_k = x \mid z_k = i)$ .
  - Continuous Case (pdf):  $\Sigma_i(x) = p(x \mid z_k = i)$ .
- Initial Probability Distribution:  $\Pi(i) = p(z_1 = i)$ .

## 1.2 Forward and Backward Algorithm (F/B)

**Goal:** Compute  $p(z_k \mid x)$ , where  $x = (x_1, ..., x_n)$ . We assume the probabilities  $p(x_k \mid z_k), p(z_k, z_{k-1}), p(z_1)$  are known.

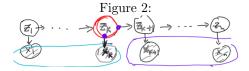
Notation:

$$x_{i:j} = (x_i, x_{i+1}, ..., x_j), \tag{11}$$

$$x_{k+1,n} = (x_{k+1}, ..., x_n). (12)$$

#### Method:

- Forward Algorithm: Compute  $p(z_k, x_{1:k})$  for all  $k \in \{1, 2, ..., n\}$ .
- Backward Algorithm: Compute  $p(x_{k+1:n} \mid z_k)$  for all  $k \in \{1, 2, ..., n-1\}$ .



We have the following probability relationships:

$$p(z_k \mid x) \propto p(z_K, x) = p(z_k, x_{1:k}, x_{k+1:n}),$$
 (13)

$$= p(x_{k+1,n}, z_k, x_{1:k}), \tag{14}$$

$$= p(x_{k+1,n} \mid z_k) p(z_k, x_{1:k}). \tag{15}$$

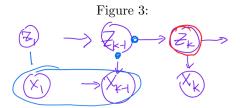
#### **Equation:**

$$p(z_k \mid x) \propto p(x_{k+1:n} \mid z_k)p(z_k, x_{1:k}), \text{ where}$$
 (16)

$$p(x_{k+1:n} \mid z_k)$$
: Backward Part (17)

$$p(z_k, x_{1:k})$$
: Forward Part. (18)

Forward Algorithm: Trick for Hidden Markov Model We will employ a trick to yield the final equation for the forward algorithm.



We use the following relationships:

$$\alpha_k(z_k) = p(z_k, x_{1:k}) \tag{19}$$

$$= \sum_{z_{k-1}=1}^{m} p(z_k, z_{k-1}, x_{1:k})$$
 (20)

$$= \sum_{z_{k-1}}^{m} p(x_k \mid z_k) p(z_k, z_{k-1}, x_{1:k-1}), \text{ where}$$
 (21)

$$p(z_k, z_{k-1}) = p(x_k, z_k, z_k - 1, x_{1,k-1}),$$
(22)

$$p(z_k, z_{k-1}, x_{1:k-1}) = p(z_k \mid z_{k-1})p(z_{k-1}, x_{1:k-1}), \text{ and}$$
 (23)

$$p(z_{k-1}, x_{1:k-1}) = \alpha_{k-1}(z_{k-1}). \tag{24}$$

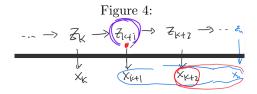
Finally, we have:

$$\alpha_k(z_k) = \sum_{z_{k-1}}^m p(x_k \mid z_k) p(z_k \mid z_{k-1}) \alpha_{k-1}(z_{k-1})$$
(25)

so we can compute  $\alpha_1, \alpha_2, ..., \alpha_n$  by:

$$\alpha_k(z_k) = p(z_k, x_{1:k}) \text{ for all } k.$$
(26)

Backward Algorithm: Trick for Hidden Markov Model We still have  $x_1, x_2, ..., x_n$ . Our goal is to compute  $p(x_{k+1:n} \mid z_k)$  for all  $k \in \{1, 2, ..., m-1\}$  and  $z_k \in \{1, 2, ..., m\}$ .



We use the following relationships:

$$\beta_k(z_k) = p(x_{k+1,n} \mid z_k) \tag{27}$$

$$= \sum_{z_{k+1}=1}^{m} p(x_{k+1,n}, z_{k+1} \mid z_k)$$
 (28)

$$= \sum_{z_{k+1}=1}^{m} p(x_{k+1:n}, z_{k+1}) p(x_{k+1} \mid z_{k+1}) p(z_{k+1} \mid z_k), \text{ where}$$

(29)

$$p(x_{k+1:n}, z_{k+1}) = \beta_{k+1}(z_{k+1}), \tag{30}$$

$$p(x_{k+1} \mid z_{k+1})$$
: Emission Probability (known), (31)

$$p(z_{k+1} \mid z_k)$$
: Transition Probability (known). (32)

We arrive at the recursive formula:

$$\beta_n(z_n) = 1 \tag{33}$$

$$\beta_k(z_k) = \sum_{z_{k+1}=1}^m \beta_{k+1}(z_{k+1}) p(x_{k+1} \mid z_{k+1}) p(z_{k+1} \mid z_k)$$
 (34)

for all 
$$k \in \{1, 2, ..., n-1\}$$
. (35)