

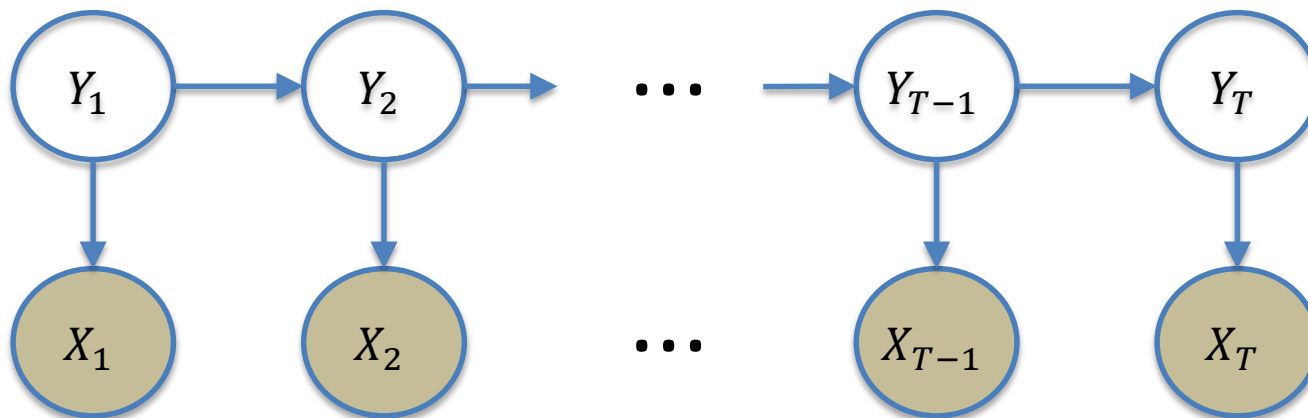
CS 6347

Lecture 15

Expectation Maximization

- **Latent or hidden variables** in the model are never observed
 - We may or may not be interested in their values, but their existence is crucial to the model
- Some observations in a particular sample may be **missing**
 - Missing information on surveys or medical records (quite common)
 - We may need to model how the variables are missing

Hidden Markov Models



$$p(x_1, \dots, x_T, y_1, \dots, y_T) = p(y_1)p(x_1|y_1) \prod_t p(y_t|y_{t-1})p(x_t|y_t)$$

- X 's are observed variables, Y 's are latent
- Example: X variables correspond sizes of tree growth rings for one year, the Y variables correspond to average temperature

- Data can be missing from the model in many different ways
 - Missing completely at random: the probability that a data item is missing is independent of the observed data and the other missing data
 - Missing at random: the probability that a data item is missing can depend on the observed data
 - Missing not at random: the probability that a data item is missing can depend on the observed data and the other missing data

Handling Missing Data



- Discard all incomplete observations
 - Can introduce bias
- Imputation: actual values are substituted for missing values so that all of the data is fully observed
 - E.g., find the most probable assignments for the missing data and substitute them in (not possible if the model is unknown)
 - Use the sample mean/mode
- Explicitly model the missing data
 - For example, could expand the state space
 - The most sensible solution, but may be non-trivial if we don't know how/why the data is missing

- Add additional binary variable m_i to the model for each possible observed variable x_i that indicates whether or not that variable is observed

$$p(x_{obs}, x_{mis}, m) = p(m|x_{obs}, x_{mis})p(x_{obs}, x_{mis})$$

- Add additional binary variable m_i to the model for each possible observed variable x_i that indicates whether or not that variable is observed

$$p(x_{obs}, x_{mis}, m) = \underbrace{p(m|x_{obs}, x_{mis})}_{\text{Explicit model of the missing data (missing not at random)}} p(x_{obs}, x_{mis})$$

**Explicit model of the missing data
(missing not at random)**

- Add additional binary variable m_i to the model for each possible observed variable x_i that indicates whether or not that variable is observed

$$p(x_{obs}, x_{mis}, m) = \underbrace{p(m|x_{obs})}_{\text{Missing at random}} p(x_{obs}, x_{mis})$$

**Missing at
random**

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**Missing
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**Missing
completely at
random**

**How can you model latent
variables in this framework?**

- In order to design learning algorithms for models with missing data, we will make two assumptions
 - The data is missing at random
 - The model parameters corresponding to the missing data (δ) are separate from the model parameters of the observed data (θ)
- That is

$$p(x_{obs}, m | \theta, \delta) = p(m | x_{obs}, \delta) p(x_{obs} | \theta)$$

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- Under the previous assumptions, the log-likelihood of samples $(x^1, m^1), \dots, (x^K, m^K)$ is equal to

$$l(\theta, \delta) = \sum_{k=1}^K \log p(m^k | x_{obs}^k, \delta) + \sum_{k=1}^K \log \sum_{x_{mis_k}} p(x_{obs_k}^k, x_{mis_k} | \theta)$$

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$$l(\theta, \delta) = \underbrace{\sum_{k=1}^K \log p(m^k | x_{obs}^k, \delta)}_{\text{separable in } \delta} + \underbrace{\sum_{k=1}^K \log \sum_{x_{mis_k}} p(x_{obs_k}^k, x_{mis_k} | \theta)}_{\text{separable in } \theta}$$

Separable in θ and δ , so if we don't care about δ , then we only have to maximize the second term over θ

$$l(\theta) = \sum_{k=1}^K \log \sum_{x_{mis_k}} p(x_{obs_k}^k, x_{mis_k} | \theta)$$

- This is NOT a concave function of θ
 - In the worst case, could have a different local maximum for each possible value of the missing data
 - No longer have a closed form solution, even in the case of Bayesian networks

Expectation Maximization



- The expectation-maximization algorithm (EM) is a method to find a local maximum of the log-likelihood with missing data
- Basic idea:

$$\begin{aligned}l(\theta) &= \sum_{k=1}^K \log \sum_{x_{mis_k}} p(x_{obs_k}^k, x_{mis_k} | \theta) \\ &= \sum_{k=1}^K \log \sum_{x_{mis_k}} q_k(x_{mis_k}) \cdot \frac{p(x_{obs_k}^k, x_{mis_k} | \theta)}{q_k(x_{mis_k})} \\ &\geq \sum_{k=1}^K \sum_{x_{mis_k}} q_k(x_{mis_k}) \log \frac{p(x_{obs_k}^k, x_{mis_k} | \theta)}{q_k(x_{mis_k})}\end{aligned}$$

Expectation Maximization



$$F(q, \theta) \equiv \sum_{k=1}^K \sum_{x_{mis_k}} q_k(x_{mis_k}) \log \frac{p(x_{obs_k}^k, x_{mis_k} | \theta)}{q_k(x_{mis_k})}$$

- Maximizing F is equivalent to the maximizing the log-likelihood
- Could maximize it using coordinate ascent

$$q^{t+1} = \arg \max_{q_1, \dots, q_K} F(q, \theta^t)$$

$$\theta^{t+1} = \arg \max_{\theta} F(q^{t+1}, \theta)$$

$$\sum_{x_{mis_k}} q_k(x_{mis_k}) \log \frac{p(x_{obs_k}^k, x_{mis_k} | \theta)}{q_k(x_{mis_k})}$$

- This is just $-d(q_k || p(x_{obs_k}^k, \cdot | \theta))$
- Maximized when $q_k(x_{mis_k}) = p(x_{mis_k} | x_{obs_k}^k, \theta)$
- Can reformulate the EM algorithm as

$$\theta^{t+1} = \operatorname{argmax}_{\theta} \sum_{k=1}^K \sum_{x_{mis_k}} p(x_{mis_k} | x_{obs_k}^k, \theta^t) \log p(x_{obs_k}^k, x_{mis_k} | \theta)$$

- Recall that MLE for Bayesian networks without latent variables yielded

$$\theta_{x_i|x_{\text{parents}(i)}} = \frac{N_{x_i, x_{\text{parents}(i)}}}{\sum_{x'_i} N_{x'_i, x_{\text{parents}(i)}}}$$

- Let's suppose that we are given observations from a Bayesian network in which one of the variables is hidden
 - What do the iterations of the EM algorithm look like?

(on board)