

$$p(\theta | D) \propto p(D | \theta) p(\theta)$$

→ max, θ_{MLE}

Supervised learning:

$$\bar{x} \in X \rightarrow y \in Y$$

$p(y | \bar{x})?$

$$p(y | \bar{x}, \bar{w}) = \mathcal{N}(y | \bar{w}^T \bar{x}, \sigma^2)$$

Discriminative

$$p(y | \bar{x})$$

~~$$p(\bar{x}, y) = p(y | \bar{x}) p(\bar{x})$$~~

Log. regr.:

$$p(y | \bar{x}, \bar{w}) = \sigma(\bar{w}^T \bar{x})$$

Generative

$$p(\bar{x}, y)$$

$$p(y | \bar{x}) = \frac{p(\bar{x}, y)}{p(\bar{x})} \propto p(\bar{x}, y)$$

LDA/QDA

$$p(\bar{x} | C_1) = \mathcal{N}(\bar{x} | \mu_1, \Sigma_1)$$

$$p(\bar{x} | C_2) = \mathcal{N}(\bar{x} | \mu_2, \Sigma_2)$$

$$p(\bar{x}, y) = p(y) p(\bar{x} | y)$$

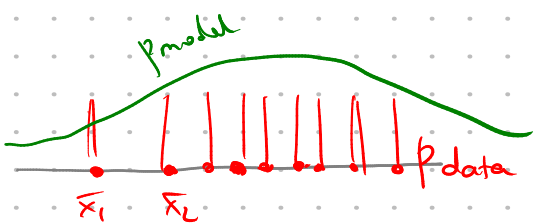
$$p(\bar{x})$$

$$D = \{\bar{x}_1, \dots, \bar{x}_N\}$$

$$p_{\text{model}}(\bar{x} | \bar{\theta})$$

$$\bar{\theta}_{ML} = \underset{\bar{\theta}}{\text{argmax}} \prod_{\bar{x} \in D} p_{\text{model}}(\bar{x} | \bar{\theta})$$

$$\bar{\theta}_{MAP} = \text{---} \text{---} \text{---} - p(\bar{\theta})$$



$$\bar{\theta}^* = \underset{\bar{\theta}}{\text{argmin}} KL(p_{\text{data}} || p_{\text{model}}) =$$

$$= \underset{\bar{\theta}}{\text{argmin}} \int p_{\text{data}}(\bar{x}) \cdot \log \frac{p_{\text{data}}(\bar{x})}{p_{\text{model}}(\bar{x})} d\bar{x} =$$

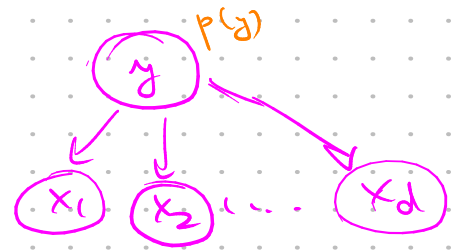
$$= \underset{\bar{\theta}}{\text{argmin}} \sum_{\bar{x} \in D} \frac{1}{N} \cdot (\log \frac{1}{N} - \log p_{\text{model}}(\bar{x}))$$

$$= \underset{\bar{\theta}}{\text{argmax}} \sum_{\bar{x} \in D} \log p_{\text{model}}(\bar{x}) = \bar{\theta}_{ML}$$

Naive Bayes

$$p(y|\bar{x})$$

$$p(\bar{x}|y) = p(y) \cdot \prod_{i=1}^d p(x_i|y)$$



$$y \in \{1, \dots, K\}, \quad x_i \in \{1, \dots, M\}$$

$$\theta_k = p(y=k); \quad \theta_{imk} = p(x_i=m|y=k)$$

$$\bar{\theta} = \{ \theta_1, \dots, \theta_K, \theta_{imk}, i=1, \dots, d, m=1, \dots, M, k=1, \dots, K \}$$

$$\hat{\theta}_k = \frac{\# \{y=k\} + 1}{N + K} \quad \Bigg| \quad \hat{\theta}_{imk} = \frac{\# \{m \text{ appears } i\text{-th in } y=k\} + 1}{\# \{ \text{zeros with } i\text{-th in } y=k\} + M}$$

$$p(D|\bar{\theta}) = \prod_{n=1}^N \left(p(y_n) \prod_{i=1}^d p(x_{ni}|y_n) \right) =$$

$$= \prod_{n=1}^N \prod_{k=1}^K \left(p(y_n=k) \prod_i p(x_{ni}|y_n=k) \right) \quad [y=k]$$

$$= \prod_{n=1}^N \prod_{k=1}^K \left(\theta_k \cdot \prod_{i=1}^d \prod_{m=1}^M p(x_{ni}=m|y_n=k) \right) \quad [x_{ni}=m] \quad [y_n=k]$$

$$= \prod_{n=1}^N \prod_{k=1}^K \left(\theta_k \prod_{i=1}^d \prod_{m=1}^M \theta_{imk} \right) \quad [x_{ni}=m] \quad [y_n=k]$$

$\theta_k \rightarrow \text{max}$

$$\sum_{k=1}^K \frac{\# [y_n=k] \cdot \theta_k}{\sum \theta_k = 1}$$

$$\log p(D|\bar{\theta}) = \sum_{n=1}^N \sum_{k=1}^K \# [y_n=k] \cdot \theta_k +$$

$$+ \sum_{n=1}^N \sum_{k=1}^K \sum_{i=1}^d \sum_{m=1}^M \# [y_n=k] \cdot \# [x_{ni}=m] \theta_{imk} \quad \rightarrow \text{max } \bar{\theta}$$

$$\ll \sum_k \sum_i \left[\sum_m \# [y_n=k, x_{ni}=m] \theta_{imk} \right]$$

$$\log p(D|\theta) = \sum_{k=1}^K \underbrace{f_k(D)}_{\text{count}} \theta_k + \sum_k \sum_i \sum_m \underbrace{f_{imk}(D)}_{\text{count}} \cdot \theta_{imk}$$

$$f_k(D) = \#[y_n = k]$$

$$f_{imk}(D) = \#[y_n = k, x_{ni} = m]$$

Logistic regression

$$p(y=k | \bar{x}, \bar{\theta}) = \frac{e^{\bar{\theta}_k^T \bar{x}}}{\sum_s e^{\bar{\theta}_s^T \bar{x}}} = \frac{1}{z(\bar{x})} \cdot e^{\sum_{i=1}^d \theta_{ki} x_i}$$

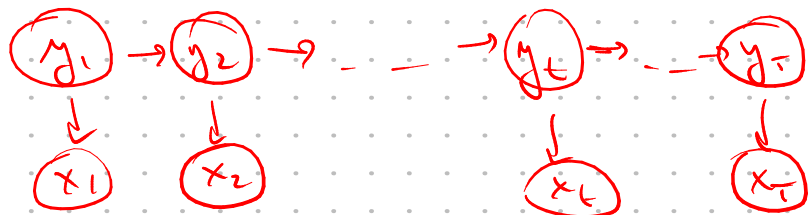
$$p(D|\bar{\theta}) = \prod_{n=1}^N p(y_n | \bar{x}_n, \bar{\theta}) = \prod_{n=1}^N \left(\frac{1}{z(\bar{x}_n)} \cdot e^{\sum_{i=1}^d \theta_{ki} x_{ni}} \right) \quad [y_n = k]$$

$$\log p(D|\bar{\theta}) = \underbrace{-\sum_{n=1}^N \log z(\bar{x}_n)}_{\text{const}} + \sum_{n=1}^N \sum_{i=1}^d [y_n = k] \underbrace{x_{ni} \theta_{ki}}_{\substack{\text{необязательно} \\ \text{применяется}}} \quad \varphi(\bar{x}_n)$$

Generative - discriminative pair

HMM

$$p(\bar{x}, \bar{y}) = p(y_1) p(x_1 | y_1) \dots$$



$$p(y_2 | y_1) p(x_2 | y_2) p(y_3 | y_2) \dots p(y_T | y_{T-1}) p(x_T | y_T)$$

~~θ_{ij}~~ ~~$f_j(k)$~~

$$\log p(D|\theta) = \sum_n \log p(\bar{x}_n, \bar{y}_n | \theta) =$$

$$= \sum_{n=1}^N \log p(\underline{y}_n) + \sum_{n=1}^N \sum_{t=1}^{T-1} \log p(y_{n,t+1} | y_{n,t}) + \sum_{n=1}^N \sum_{t=1}^T \log p(x_{n,t} | y_{n,t})$$

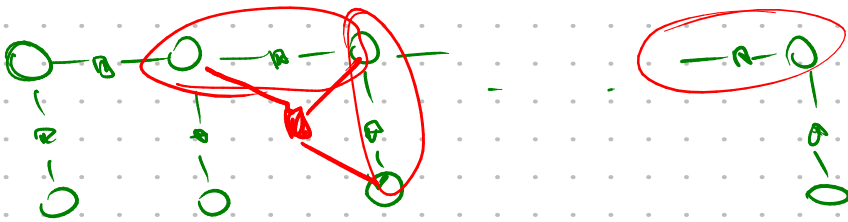
$$y_t = 1, \dots, M, \quad x_t = 1, \dots, K$$

$$= \sum_{n=1}^N \sum_{i=1}^M \underbrace{\left(\log p(y_{nt}=i) \right)}_{\theta_i} \mathbb{1}_{[y_{nt}=i]} + \sum_n \sum_{t=1}^{T-1} \sum_{i=1}^M \sum_{j=1}^M \underbrace{\left(\log p(y_{n,t+1}=j | y_{n,t}=i) \right)}_{\theta_{ij}} \mathbb{1}_{[y_{n,t}=i]} \mathbb{1}_{[y_{n,t+1}=j]} + \sum_n \sum_t \sum_{i=1}^M \sum_{k=1}^K \underbrace{\left(\log p(x_{nt}=k | y_{nt}=i) \right)}_{\theta_{ik}} \mathbb{1}_{[y_{nt}=i]} \mathbb{1}_{[x_{nt}=k]}$$

$$\log p(D|\theta) = \sum_i \left[\sum_n \mathbb{1}_{[y_{nt}=i]} \right] \theta_i + \sum_{i,j} \left[\sum_n \sum_{t=1}^{T-1} \mathbb{1}_{[y_{n,t}=i]} \mathbb{1}_{[y_{n,t+1}=j]} \right] \theta_{ij} + \sum_i \sum_k \left[\sum_n \sum_t \mathbb{1}_{[y_{nt}=i]} \mathbb{1}_{[x_{nt}=k]} \right] \theta_{ik} \xrightarrow{\text{max}} \theta$$

Conditional random field, CRF

$$p(\bar{y} | \bar{x})$$



$$\log p(D|\theta) = \sum_n \left[\sum_i f_i(y_{nt}) \theta_i + \sum_{i,j} \left[\sum_t f(y_{nt}, y_{n,t+1}) \right] \theta_{ij} + \sum_i \sum_k \left[\sum_t f(y_{nt}, x_{nt}) \right] \theta_{ik} \right] + \text{const}$$

$$\sum_{i,j,k} \sum_t f(y_{t-1}, y_t, x_t) \theta_{ijk}$$



$$f(y_t, y_{t+1}, x)$$

