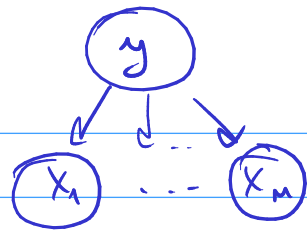


Naive Bayes classifier (Idiot's Bayes)

попозагаюуаа / generative

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

$$\bar{x} = (x_1, x_2, \dots, x_M) \rightsquigarrow y \in \{c_1, \dots, c_K\}$$



$$p(\bar{x}) \quad p(\bar{x}, y) = p(y) p(\bar{x}|y) = p(y) \prod_{i=1}^M p(x_i|y)$$

лог. пер.

$$p(y=c_k|\bar{x}) \propto e^{\bar{w}_k^T \bar{x}} = e^{w_{k1}x_1} e^{w_{k2}x_2} \dots e^{w_{kM}x_M}$$

дискриминативная

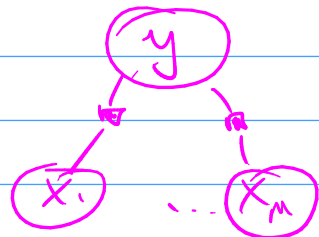
$$p(y|\bar{x})$$

$$\frac{e^{\bar{w}_k^T \bar{x}}}{\sum_l e^{\bar{w}_l^T \bar{x}}}$$

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

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

generative-discriminative pair

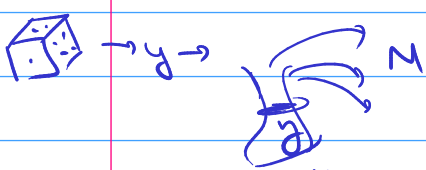


$$p(\bar{x}, y) = p(y) \prod_{i=1}^M p(x_i|y)$$

x_i - tokens
bag-of-words / n-grams / tokens

$y \in \{ \text{справа, левая, нулевая} \}$

Multinomial NB



$$p(y, d) = p(y) \cdot \prod_{j=1}^{N_d} p(w_j|y)$$

$$p(y=c_k) = \pi_k$$

$$p(w_j|y=c_k) = \varphi_{w_j, k}$$

$$\pi_k = \frac{\sum_d [y=c_k]}{D}$$

$$\varphi_{wk} = \frac{1 + \sum_d \sum_{j=1}^{N_d} [y=c_k][w_j=w]}{|V| + \sum_d \sum_{j=1}^{N_d} [y=c_k]}$$

Multivariate NB



$$p(y, d) = p(y) \cdot \prod_{i=1}^V p(w_i \in d|y)$$

$$p(w|y=c_k) = \frac{1 + \sum_d [y=c_k][w \in d]}{2 + \sum_d [y=c_k]}$$

Красочный реп NB

EM-алгоритм:

$$D = \{d_1, \dots, d_N\}$$

t - topic

$$Z = \{\bar{z}_1, \dots, \bar{z}_N\}$$

$$\bar{z}_d = (\dots, z_{td}, \dots)$$

$$z_{td} = [d \in t]$$

$$p(D, Z | \pi_t, \varphi_{wt}) =$$

$$= \prod_{d \in D} \prod_{t=1}^T \left(\pi_t \cdot \prod_{w \in d} \varphi_{wt}^{z_{td}} \right)$$

$$p(D | \bar{\pi}, \bar{\Phi}) \xrightarrow{\lambda} \max$$

$$Q(\lambda, \lambda^{(m)}) = E_{Z | \lambda^{(m)}} [\ln p(D, Z | \lambda)] \xrightarrow{\lambda} \max$$

$$Q(\lambda, \lambda^{(m)}) = E_Z \left[\sum_d \sum_t \bar{z}_{td} (\ln \pi_t + \sum_w \ln \varphi_{wt}) \right] =$$

$$= \sum_d \sum_t \left(E_{Z | \lambda^{(m)}} [z_{td}] \cdot \left(\ln \pi_t + \sum_{j=1}^{N_d} \ln \varphi_{w_j, t} \right) \right) \xrightarrow{\pi, \Phi} \max$$

$$\Phi = \left(\varphi_{wt} \right)_{t, w}$$

$$p(t | d, \lambda^{(m)}) = \frac{p(d, t | \lambda^{(m)})}{p(d | \lambda^{(m)})} =$$

$$Q(\lambda, \lambda^{(m)}) = \sum_t \pi_t \left(\sum_d E[z_{td}] \right) +$$

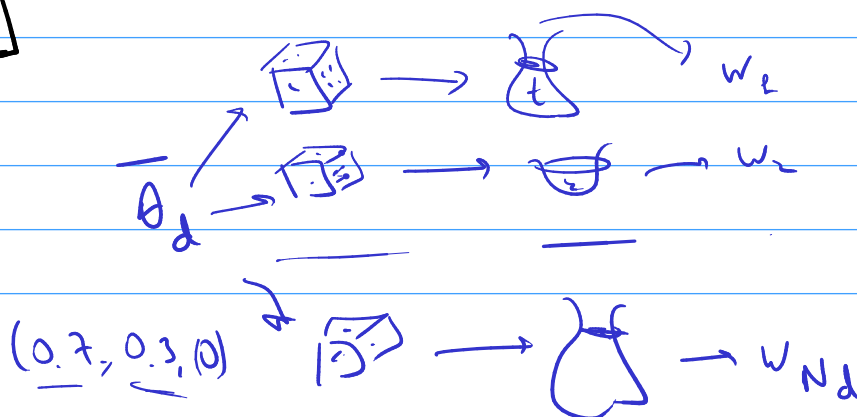
$$+ \sum_t \sum_{w \in V} \ln \varphi_{wt} \cdot \left(\sum_d \sum_{j: w_j = w} E[z_{td}] \right)$$

$$= \frac{\pi_t^{(m)} \cdot \prod_{w \in d} \varphi_{wt}^{(m)}}{\sum_s \pi_s^{(m)} \prod_{w \in d} \varphi_{ws}^{(m)}}$$

$$\pi_t = \frac{\sum_d E[z_{td}]}{D}, \quad \varphi_{wt} = \frac{\sum_d \#\{w \in d\} \cdot E[z_{td}]}{\sum_d N_d \cdot E[z_{td}]}$$

Topic modeling

t	1 ... T
w	1 ... V
d	1 ... N



$$\underline{\Phi} = \mathbf{W} \begin{pmatrix} 1^t \\ \varphi_{wt} \\ 1 \end{pmatrix} \quad \underline{\Theta} = \begin{pmatrix} \theta_{td} \\ \vdots \\ d \end{pmatrix}$$

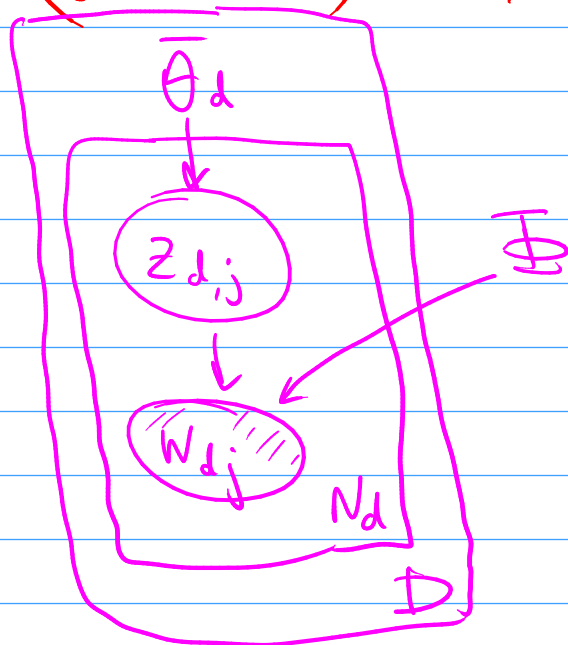
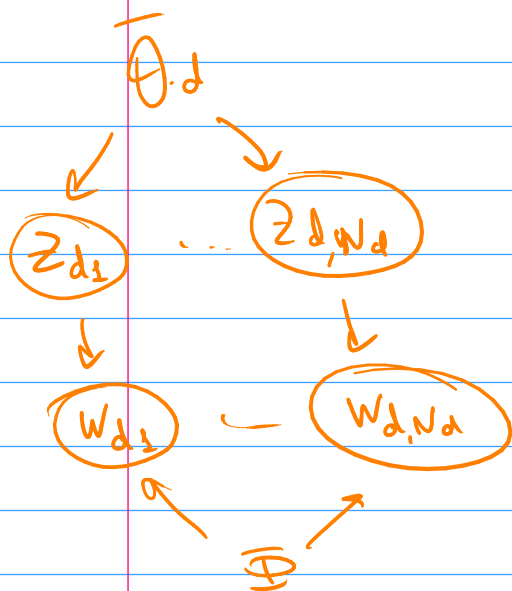
$V \times T \quad T \times N$

$$\begin{aligned} p(\mathbf{W} | \mathbf{d}) &= \prod_{t=1}^T p(\mathbf{w}_t | \mathbf{d}) = \\ &= \prod_{t=1}^T \underbrace{p(t | \mathbf{d}) p(\mathbf{w}_t | t)} \\ &= \sum_{t=1}^T \theta_{td} p_{wt} \end{aligned}$$

$$p(\mathbf{D} | \underline{\Phi}, \underline{\Theta}) = \prod_{d \in \mathbf{D}} p(d | \underline{\Phi}, \underline{\Theta}) =$$

$$= \prod_{d \in \mathbf{D}} \prod_{j=1}^{N_d} p(\mathbf{w}_j | d, \underline{\Phi}, \underline{\Theta}) =$$

$$= \prod_d \prod_{j=1}^{N_d} \left(\prod_{t=1}^T \theta_{td} \varphi_{w_j, t} \right) \xrightarrow{\underline{\Phi}, \underline{\Theta}} \max$$



$$\bar{z}_{dj} = (\dots z_{djt} \dots)$$

$$z_{djt} = [w_{dj} \in t]$$

$$p(\mathbf{W}, \mathbf{Z} | \underline{\Theta}, \underline{\Phi}) = \prod_{d \in \mathbf{D}} \prod_{j=1}^{N_d} \prod_{t=1}^T \left(\theta_{td} \varphi_{w_{dj}, t} \right) \xrightarrow{\underline{\Theta}, \underline{\Phi}} \max$$

$$Q(\lambda, \lambda^{(m)}) = \mathbb{E}_{\mathbf{Z} | \lambda^{(m)}} [\ln p(\mathbf{W}, \mathbf{Z} | \lambda)] =$$

$$= \sum_d \sum_{j=1}^{N_d} \sum_{t=1}^T \mathbb{E}[z_{djt}] (\ln \theta_{td} + \ln \varphi_{w_{dj}, t})$$

$$\underline{\text{E-var}}: \mathbb{E}[z_{djt}] = p(t | w_j, d) = \frac{p(d, t, w_j)}{p(d, w_j)} = \frac{\theta_{td} \varphi_{wt}^{(m)}}{\sum_s \theta_{sd} \varphi_{ws}^{(m)}}$$

$$Q(x, x^{(n)}) = \sum_d \sum_t \left[\ln \theta_{td} \cdot \left(\sum_{j=1}^{N_d} \underbrace{\mathbb{E}[z_{dj}]}_{\sum_w n_{dwt}} \right) + \sum_{w=1}^V \sum_{t=1}^T \ln \varphi_{wt} \left(\sum_d \sum_{j=1}^{N_d} [w_{dj}=w] \cdot \mathbb{E}[z_{dj}] \right) \right]$$

$$n_{dwt} = \mathbb{E}[\#\{w \in t \text{ to } d\}] = \sum_{j=1}^{N_d} [w_{dj}=w] \mathbb{E}[z_{dj}]$$

$$\theta_{td} = \frac{\sum_{w=1}^V n_{dwt}}{N_d}$$

$$\varphi_{wt} = \frac{\sum_d n_{dwt}}{\sum_d \sum_w n_{dwt}}$$

LSA
latent semantic analysis

PLSI
prob. lat sem. indexing

$$V \begin{pmatrix} | \\ \varphi_{wt} \\ | \end{pmatrix}_T \cdot \begin{pmatrix} | \\ \theta_{td} \\ | \end{pmatrix}_D^T \approx \begin{pmatrix} | \\ \text{circled } \text{dot} \\ | \end{pmatrix}_V^W$$

D

ARTM - K. Bogachuk

$$\boxed{\sum_t \varphi_{wt} \theta_{td}}$$

$$p(D|\Theta, \Xi) \cdot p(\Theta, \Xi)$$

$$\ln p(D|\Theta, \Xi) + \sum_i \lambda_i R_i(\Theta, \Xi) \rightarrow \max$$

$$n_{*wt} = \left[\sum_d n_{dwt} + \varphi_{wt} \frac{\partial R}{\partial \varphi_{wt}} \right]_+$$

$$\sum_{t,s} KL(\bar{\varphi}_t \| \bar{\varphi}_s)$$

$$KL(\bar{\varphi}_t \| \text{Unif}) \rightarrow \max$$

$$n_{d*t} = \left[\sum_w n_{dwt} + \theta_{td} \frac{\partial R}{\partial \theta_{td}} \right]_+$$

$$KL(\bar{\varphi}_t \| \text{Unif}) \rightarrow \min$$

fix Ξ

- napahegion

$$p(w, z, \Theta) = \prod_{j=1}^D p(\bar{\Theta}_j) \left(\prod_{j=1}^D \prod_{n=1}^{N_d} \prod_{t=1}^T [z_{jn}=t] \cdot \theta_{jt} \varphi_{w_{jn}, t} \right)$$

$$q(z, \Theta | \dots) = \prod_{j=1}^D \left(q(\bar{\Theta}_j) \prod_{n=1}^{N_d} q(z_{jn}) \right)$$

$$L(q) = E_q \left[\frac{\log p(w, z, \Theta)}{q(z, \Theta)} \right] = \int \log p(-) q dz d\Theta - \int \log q(-) q dz d\Theta$$

$$L(q_j) = \int \left[\log p(\bar{w}_j, \bar{z}_j, \bar{\Theta}_j | \Xi, \alpha, \beta) - \log q_j(\bar{z}_j, \bar{\Theta}_j) \right] q_j(\bar{z}_j, \bar{\Theta}_j) dz d\Theta$$

$$L(q_j) = E_q \left[\log p(\bar{\Theta}_j) + \log p(\bar{z}_j | \bar{\Theta}_j) + \log p(\bar{w}_j | \bar{z}_j) - \log q_j(\bar{z}_j) - \log q_j(\bar{\Theta}_j) \right]$$

$$E_q [\log p(\bar{\Theta}_j | \alpha)] = E_q [\log \text{Dir}(\bar{\Theta}_j | \alpha)] = \left[q_j(\bar{\Theta}_j) = \text{Dir}(\bar{\Theta}_j | \bar{x}_j) \right]$$

$$= E_{\text{Dir}(\bar{\Theta}_j | \bar{x}_j)} \left[\log \prod_{jt} \theta_{jt}^{\alpha_t - 1} + \text{const} \right]$$

$$= \log \Gamma(\sum \alpha_t) - \sum \log \Gamma(\alpha_t)$$

$$+ \sum_t (\alpha_t - 1) (\psi(\bar{x}_{jt}) - \psi(\sum_s \bar{x}_{js}))$$

$$q_j(\bar{z}_j) = \prod_n q_j(z_{jn}) =$$

$$= \prod_n \text{Mult}(z_{jn} | \bar{\pi}_j)$$

$$= \prod_n \prod_j \pi_{jt}^{[z_{jn}=t]}$$

digamma

$$\psi(x) = \frac{\partial \log \Gamma(x)}{\partial x}$$

$$E_q [\log p(\bar{z}_j | \bar{\Theta}_j)] = E_q \left[\sum_n \sum_t [z_{jn}=t] \log \theta_{jt} \right] =$$

$$= \sum_n \sum_t E_q [z_{jn}=t] \cdot E_q [\log \theta_{jt}] =$$

$$= \sum_r \sum_t \pi_{jt} \left(\psi(x_{jt}) - \psi\left(\sum_s x_{js}\right) \right)$$

$$h(\bar{x}_j, \bar{\pi}_j) = (1) + (2) + (3) - (4) - (5) \xrightarrow{\bar{x}, \bar{\pi}} \max$$

LDA : EM no \mathbb{D}, z

- E-was $KL(q_j \parallel p_j) \xrightarrow{\delta_j, \pi_j} \min_{\text{pure. } \mathbb{H}}$ $\text{gib } \text{best } j$

- M-Was: $\varphi_{ES} \propto \dots$

zjut α -

$$q(z, \odot, \mathbb{E}) = q(z, \odot) \cdot \prod_t q_t(\varphi_t)$$

Gibbs sampling

$$\mathbb{I}, \mathbb{Q} \sim p(\mathbb{I}, \mathbb{Q} | W, \alpha, \beta)$$

Collapsed Gibbs sampling

Collapsed Gibbs sampling

$p(\bar{z}_{j^n} | \bar{z}_{-j^n}, w, \alpha, \beta) =$

$$= \int p(\bar{z}_{j_n}, \Phi, \Theta | z_{j_n}, W, \alpha, \beta) d\Phi d\Theta$$

$$\theta_{td} = \frac{n_{td}}{n_d}, \quad \varphi_{st} = \frac{n_{st}}{n_t}$$

