

1) Naive Bayes

$$p(d|\underline{c}) = \prod_{w \in d} p(w|c) \quad - \text{bag of words}$$

2) Unsupervised NB

EM: $p(w|c) = \varphi_{wc}$

$E: z_d = p(c|d)$

$M: \varphi_{wc} = \frac{\#\{w \in d, d \in c\}}{\sum_{w'} \#\{w' \in c\}}$

3) pLSI $\theta_{td} = p(t|d)$

ARTM

$\varphi_{wt} = p(w|t)$

$p(d|\Theta, \Phi) = \prod_{w \in d} p(w|d, \Theta, \Phi) =$

$$p(d|\Theta, \Phi) = \prod_d \prod_{w \in d} \sum_t \theta_{td} \varphi_{wt}$$

$n_{dwt} = \#\{w \in d, w \in t\}$

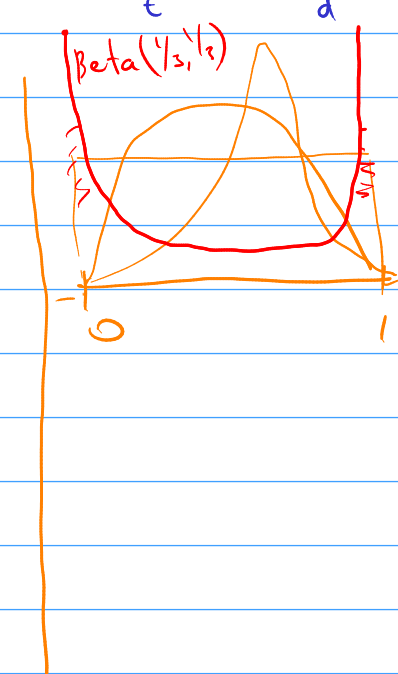
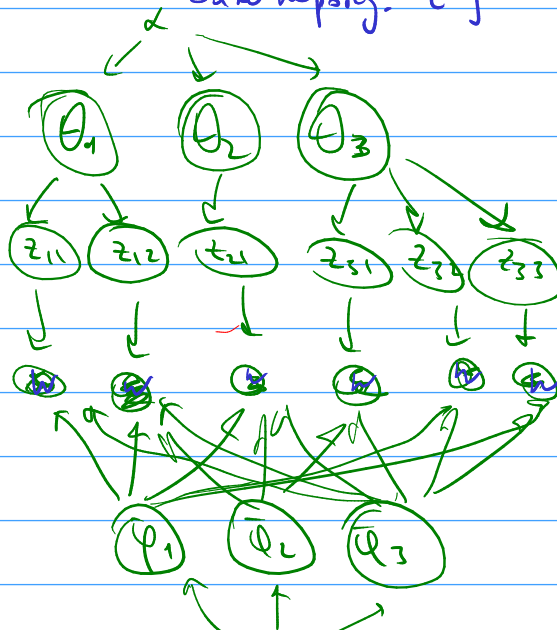
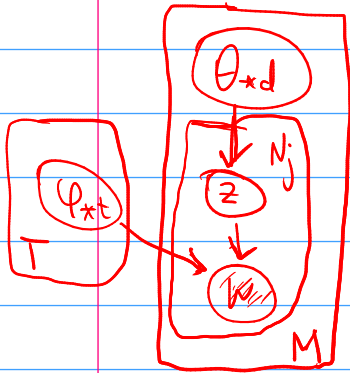
$= \prod_{w \in d} \sum_{t \in T} p(w, t|d, \Theta, \Phi)$

$= \prod_{w \in d} \sum_t \theta_{td} \varphi_{wt}$

4) Latent Dirichlet Allocation LDA

$$w \begin{pmatrix} 1 \\ d \end{pmatrix} \approx w \begin{pmatrix} \Phi \\ t \end{pmatrix} \cdot \begin{pmatrix} \Theta \\ d \end{pmatrix}$$

$[z_{jn} = t] = [w_{jn} \text{ ug } \bar{\theta}_{jt}]$
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$p(W|\Theta, \Phi, \alpha, \beta) \rightarrow \max_{\Theta, \Phi}$

$p(W, \Theta, \Phi | d, \beta) \rightarrow \max_{\Theta, \Phi}$

$\sum_z p(W, z, \Theta, \Phi | d, \beta)$

$$p(W, z, \Theta, \Phi | d, \beta) = p(\Phi | \beta) \cdot \prod_{j=1}^M p(\bar{\theta}_j | d) \cdot \prod_{n=1}^{N_j} p(z_{jn}, w_{jn} | \bar{\theta}_j, \Phi) =$$

$$= \prod_{t=1}^T p(\bar{\varphi}_t | \beta) \cdot \prod_{j=1}^M p(\bar{\theta}_j | d) \cdot \prod_{n=1}^{N_j} p(z_{jn} | \bar{\theta}_j) p(w_{jn} | z_{jn}, \Phi)$$

$p(\bar{\varphi}_t | \beta) = \frac{1}{\text{Dir}(\beta)} \prod_{v=1}^V \varphi_{tv}^{\beta_v - 1}$ $p(\bar{\theta}_j | d) \propto \prod_t \theta_{jt}^{d_{jt} - 1}$ $\theta_{jt} = p(z_{jn} = t)$ $\varphi_{tv} = p(w_{jn} = v | z_{jn} = t)$

$$\log p(W|\alpha, \beta) = \log \int_{\Theta} \int_{\Phi} \sum_z p(W, z, \Theta, \Phi | \alpha, \beta) d\Theta d\Phi =$$

$$= \log \int_{\Theta} \int_{\Phi} \sum_z p(W, z, \Theta, \Phi | \alpha, \beta) \cdot \frac{q(z, \Theta, \Phi)}{q(z, \Theta, \Phi)} d\Theta d\Phi \geq$$

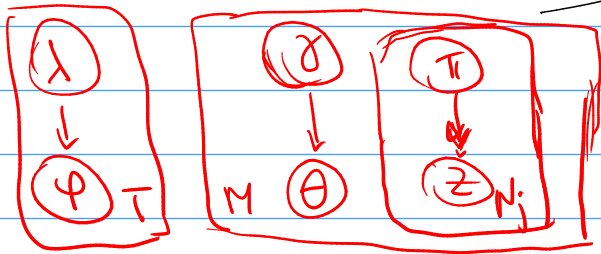
$$\geq \int_{\Theta} \int_{\Phi} \sum_z \log \frac{p(W, z, \Theta, \Phi | \alpha, \beta)}{q(z, \Theta, \Phi)} q(z, \Theta, \Phi) d\Theta d\Phi =$$

$= L(q) \rightarrow \max$
 $KL(q||p) \rightarrow \min$

$$= \int_{\Theta} \int_{\Phi} \sum_z \log \frac{p(z, \Theta, \Phi | W, \alpha, \beta)}{q(z, \Theta, \Phi)} q(z, \Theta, \Phi) d\Theta d\Phi + \log p(W|\alpha, \beta)$$

$$L(q) \rightarrow \max$$

$$q(z, \Theta, \Phi | \Gamma, \Pi, \Lambda) = \left(\prod_{t=1}^T q(\bar{\varphi}_t | \bar{\lambda}_t) \right) \left(\prod_{j=1}^M q_{j\theta}(\bar{\theta}_j | \bar{\delta}_j) \cdot \prod_{n=1}^{N_j} q_{j\pi}(z_{jn} | \bar{\pi}_{jn}) \right)$$



$$q_t(\bar{\varphi}_t | \bar{\lambda}_t) \propto \prod_{\varphi} \varphi^{\lambda_t \varphi - 1}$$

$$q_{j\theta}(\bar{\theta}_j | \bar{\delta}_j) \propto \prod_{\theta} \theta^{\delta_{jt} - 1}$$

$$q_{j\pi}(z_{jn} | \bar{\pi}_{jn}) = \prod_{\pi} \pi^{[z_{jn} = \pi]}$$

1) матрица Φ - напар. матрица

$$q(z, \Theta) \approx p(z, \Theta | W, \Phi, \alpha, \beta)$$

$$KL(q_j || p_j) = \int \sum_{z_j} q(\bar{z}_j, \bar{\theta}_j | \bar{\delta}_j, \bar{\pi}_j) \cdot \log \frac{q(\dots)}{p(\bar{z}_j, \bar{\theta}_j | \bar{w}_j, \Phi, \alpha, \beta)} d\bar{\theta}_j$$

$$h(\bar{\delta}_j, \bar{\pi}_j) = \int \sum_{z_j} \log \frac{p(\bar{w}_j, \bar{z}_j, \bar{\theta}_j | \Phi, \alpha, \beta)}{q(\bar{z}_j, \bar{\theta}_j | \bar{\delta}_j, \bar{\pi}_j)} \cdot q(\bar{z}_j, \bar{\theta}_j | \bar{\delta}_j, \bar{\pi}_j) d\bar{\theta}_j$$

$$= E_q \left[\log p(\bar{w}_j, \bar{z}_j, \bar{\theta}_j | \Phi, \alpha, \beta) \right] - E_q \left[\log q_j \right] =$$

$$= E \left[\log p(\bar{\theta}_j | \alpha) \right] + E \left[\log p(\bar{z}_j | \bar{\theta}_j) \right] + E \left[\log p(\bar{w}_j | \bar{z}_j, \Phi) \right]$$

$$- E \left[\log q(\bar{\theta}_j | \bar{\delta}_j) \right] - E \left[\log q(\bar{z}_j | \bar{\pi}_j) \right]$$

$$E_q[\log p(\bar{\theta}_j | \alpha)] = E_q \left[\log \left(\frac{\Gamma(\sum_t \alpha_t)}{\prod_t \Gamma(\alpha_t)} \prod_t \theta_{jt}^{\alpha_t - 1} \right) \right] =$$

$$= \log \Gamma(\sum_t \alpha_t) - \sum \log \Gamma(\alpha_t) + \sum_{t=1}^T (\alpha_t - 1) E_q[\log \theta_{jt}]$$

$$p(\bar{x} | \bar{\eta}) = h(\bar{x}) e^{\bar{\eta}^T t(\bar{x}) - a(\bar{\eta})}$$

$$\log p(\bar{x} | \bar{\eta}) = \log h(\bar{x}) + \bar{\eta}^T t(\bar{x}) - a(\bar{\eta})$$

$$\log \text{Dir}(\bar{x} | \bar{\alpha}) = \sum_i (\alpha_i - 1) \log x_i - \log B(\bar{\alpha}) = a(\bar{\eta})$$

$t(\bar{x}) = \begin{pmatrix} \log x_1 \\ \vdots \\ \log x_i \end{pmatrix}, \bar{\eta} = \begin{pmatrix} \alpha_1 - 1 \\ \vdots \\ \alpha_i - 1 \end{pmatrix}$

$$\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}(x-\mu)^2} = \left(-\frac{1}{2\sigma^2} x^2 + \frac{1}{\sigma^2} x - \frac{\mu}{2\sigma^2} \right)$$

$t(x) = \begin{pmatrix} -x^2/2 \\ x \end{pmatrix}, \bar{\eta} = \begin{pmatrix} 1/\sigma^2 \\ \mu/\sigma^2 \end{pmatrix}$

$h(x) = \frac{1}{\sqrt{2\pi\sigma^2}}, a(\bar{\eta}) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{\mu^2}{2\sigma^2}}$

$\begin{pmatrix} \tau \\ \mu\tau \end{pmatrix}$

$$\nabla_{\bar{\eta}} \int h(\bar{x}) e^{\bar{\eta}^T t(\bar{x}) - a(\bar{\eta})} d\bar{x} = 0$$

$$\int h(\bar{x}) e^{\bar{\eta}^T t(\bar{x}) - a(\bar{\eta})} \cdot (t(\bar{x}) - \nabla_{\bar{\eta}} a(\bar{\eta})) d\bar{x} = 0$$

$$\int \underbrace{t(\bar{x}) h(\bar{x}) e^{\bar{\eta}^T t(\bar{x}) - a(\bar{\eta})}}_{p(\bar{x})} d\bar{x} = \int \underbrace{\nabla_{\bar{\eta}} a(\bar{\eta})}_{\leftarrow} h(\bar{x}) e^{\bar{\eta}^T t(\bar{x}) - a(\bar{\eta})} d\bar{x}$$

$$E_{p(\bar{x})}[t_i(\bar{x})] = \frac{\partial a(\bar{\eta})}{\partial \eta_i}$$

$$E_{p(\bar{x})}[t(\bar{x})] = \nabla_{\bar{\eta}} a(\bar{\eta})$$

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

digamma function

$$E_q[\log \theta_{jt}] = \frac{\partial \log B(\bar{\alpha})}{\partial \alpha_t} = \frac{\partial (\sum_t \log \Gamma(\alpha_t) - \log \Gamma(\sum_t \alpha_t))}{\partial \alpha_t}$$

$$E_q[\log \theta_{jt}] = \psi(\alpha_t) - \psi(\sum_s \alpha_{js})$$

$$E_q[\log p(\bar{\theta}_j | \bar{\alpha})] = \log \Gamma(\sum_t \alpha_t) - \sum \log \Gamma(\alpha_t) + \sum_t (\alpha_t - 1) (\psi(\alpha_{jt}) - \psi(\sum_s \alpha_{js})) \quad (1)$$

$$E_q[\log p(\bar{z}_j | \bar{\theta}_j)] = E_q \left[\sum_{n=1}^{N_j} \sum_{t=1}^T [z_{jn} = t] \log \theta_{jt} \right] =$$

$$= \sum_n \sum_t E_q[[z_{jn} = t] \cdot \log \theta_{jt}] = \sum_{n=1}^{N_j} \sum_{t=1}^T \pi_{jnt} (\psi(\alpha_{jt}) - \psi(\sum_s \alpha_{js})) \quad (2)$$

$$E_q[\log p(\bar{w}_j | \bar{z}_j, \Phi)] = E_q\left[\sum_{n=1}^{N_j} \sum_{t=1}^T \sum_{v=1}^V [z_{jnt}=t] [w_{jnt}=v] \log \varphi_{tv}\right] \quad (3)$$

$$= \sum_n \sum_t \sum_v [w_{jnt}=v] \cdot \pi_{jnt} \cdot \log \varphi_{tv}$$

$$E_q[\log q(\theta_j | \delta_j)] = \log \Gamma(\sum_s \delta_{js}) - \sum_t \log \Gamma(\delta_{jt}) + \sum_t (\delta_{jt} - 1) (\psi(\delta_{jt}) - \psi(\sum_s \delta_{js})) \quad (4)$$

$$E_q[\log q(\bar{z}_j | \bar{\pi}_j)] = E_q\left[\sum_n \sum_t [z_{jnt}=t] \log \pi_{jnt}\right] = \sum_{n=1}^{N_j} \sum_{t=1}^T \pi_{jnt} \log \pi_{jnt} \quad (5)$$

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

$\sum_s \pi_{jns} = 1$

$$L(\pi_{jnt}) = \pi_{jnt} (\psi(\delta_{jt}) - \psi(\sum_s \delta_{js})) + \pi_{jnt} \log \varphi_{t, w_{jnt}} - \pi_{jnt} \log \pi_{jnt} + \lambda (\sum_s \pi_{jns} - 1) \quad \xrightarrow{\pi_{jnt}} \max$$

$$\frac{\partial L}{\partial \pi_{jnt}} = \psi(\delta_{jt}) - \psi(\sum_s \delta_{js}) + \log \varphi_{t, w_{jnt}} - \log \pi_{jnt} - 1 + \lambda = 0$$

$$\pi_{jnt} = e^{\psi(\delta_{jt}) - \psi(\sum_s \delta_{js}) + \log \varphi_{t, w_{jnt}} - 1 + \lambda} = e^{\lambda - 1} \cdot e^{\psi(\delta_{jt}) - \psi(\sum_s \delta_{js}) + \log \varphi_{t, w_{jnt}}}$$

$$\pi_{jnt} \propto e^{\psi(\delta_{jt}) - \psi(\sum_s \delta_{js}) + \log \varphi_{t, w_{jnt}}}$$

$$\frac{\partial L}{\partial \delta_{jt}} = (\alpha_t - 1) \cdot \psi'(\delta_{jt}) - \left[\sum_s (\alpha_s - 1) \right] \psi'(\sum_s \delta_{js}) + \sum_n (\pi_{jnt} \psi'(\delta_{jt}) - (\sum_s \pi_{jns}) \psi'(\sum_s \delta_{js}))$$

$$\alpha_t \cancel{=} 1 + \sum_n \pi_{jnt} - \alpha_t \cancel{=} 1$$

$$- (\alpha_t - 1) \psi'(\delta_{jt}) + \left[\sum_s (\alpha_s - 1) \right] \psi'(\sum_s \delta_{js}) =$$

$$= \psi'(\delta_{jt}) \left[\alpha_t + \sum_n \pi_{jnt} - \alpha_t \right] - \psi'(\sum_s \delta_{js}) \cdot \sum_{s=1}^T \left[\alpha_s + \sum_n \pi_{jns} - \alpha_s \right] \quad (=0)$$

\forall_{jt}

$$\delta_{jt} = \alpha_t + \sum_n \pi_{jnt}$$

EM

- E-war: fix Φ , $\pi_{jnt} \propto \dots$, $\delta_{jt} = \dots$
- M-war: fix π_{jnt}, δ_{jt}

$$p_{\text{L0}} \propto \sum_{j=1}^M \sum_{n=1}^{N_j} [w_{jn} = \sigma] \pi_{jnt}$$

Bayes-LDA

$$p(z, \Theta, \Phi | \mathcal{D}, R, W) \approx q(z, \Theta, \Phi)$$

$$\lambda_{\text{L0}} = \beta_{\text{L0}} + \sum_{j=1}^M \sum_{n=1}^{N_j} [w_{jn} = \sigma] \pi_{jnt}$$

$\pi_{jnt} \propto \dots$
 $\delta_{jt} = \dots$
 $\lambda_{\text{L0}} = \dots$