

$$p(X|\theta) \xrightarrow{\theta} \max$$

$$p(X|\theta) = \int p(X, z|\theta) dz$$

$$p(X, z|\theta) = p(X|\theta) p(z|X, \theta)$$

$$\ln p(X|\theta) = \ln p(X, z|\theta) - \ln p(z|X, \theta)$$

$$\ln p(X|\theta) = \mathbb{E}_q [\ln p(X, z|\theta) - \ln p(z|X, \theta)] =$$

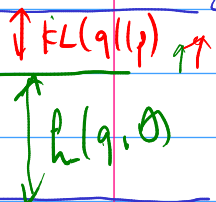
$$\quad \quad \quad \pm \ln q(z)$$

$$= \mathbb{E}_q \left[ \ln \frac{p(X, z|\theta)}{q(z)} - \ln \frac{p(z|X, \theta)}{q(z)} \right]$$

$$\ln p(X|\theta) = \int \ln \frac{p(X, z|\theta)}{q(z)} q(z) dz - \int \ln \frac{p(z|X, \theta)}{q(z)} q(z) dz$$

ELBO

$$\ln p(X|\theta) = \underbrace{\mathbb{E}_q [\ln \frac{p(X, z|\theta)}{q(z)}]}_{\text{ELBO}} + \underbrace{\mathbb{E}_q [\ln \frac{p(z|X, \theta)}{q(z)}]}_{\text{KL}(q(z) \| p(z|X, \theta))}$$



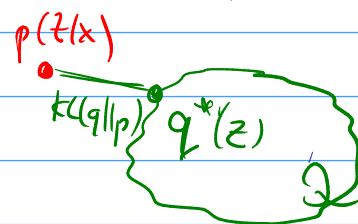
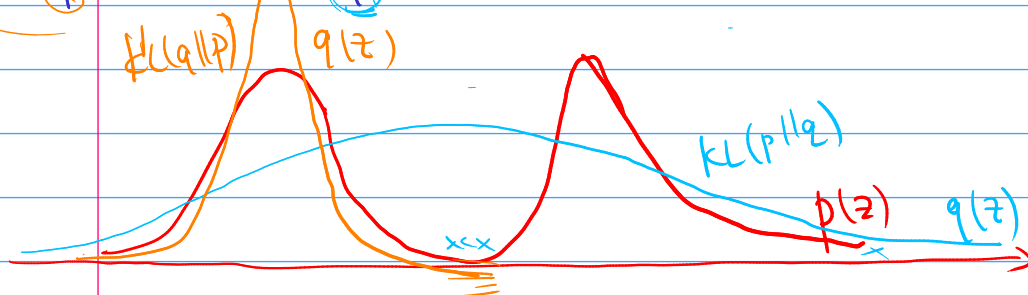
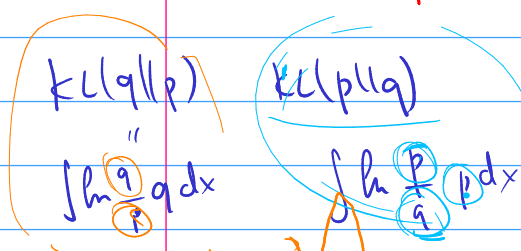
$$\boxed{\text{EM}} \quad \theta^{(m)} \xrightarrow{\max \theta} \theta^{(m+1)} \quad q(z) = p(z|X, \theta^{(m)})$$

Var. approx:

$$\ln p(X) = \mathbb{E}_q [\ln p(X, z)] - \mathbb{E}_q [\ln p(z|X)] =$$

$$= \int \ln \frac{p(X, z)}{q(z)} q(z) dz - \int \ln \frac{p(z|X)}{q(z)} q(z) dz$$

$\xrightarrow{\max}$   $\xrightarrow{\min}$



$$q(z) = \prod_{i=1}^M q_i(z_i), \quad z_1, \dots, z_M = z$$

$$z_i \cap z_j = \emptyset$$

$$\mathbb{E}_q [\ln p(X, z)] = \int \ln \frac{p(X, z)}{q(z)} q(z) dz = \int \ln \frac{p(X, z)}{\prod_i q_i(z_i)} \prod_i q_i(z_i) dz = \int \ln p(X, z) \prod_i q_i(z_i) dz - \sum_{i=1}^M \int \ln q_i(z_i) \prod_i q_i(z_i) dz$$

$$h(q) = \int \ln p(x, z) \prod_i q_i(z_i) dz - \sum_{j=1}^M \int \ln q_j(z_j) q_j(z_j) dz_j$$

$$h(q) \xrightarrow{q_j} \max q_j^*(z_j) = ?$$

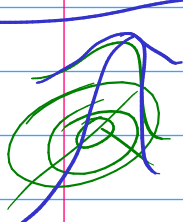
$$\begin{aligned} h(q_j) &= \int q_j(z_j) \left[ \ln p(x, z) \cdot \prod_{i \neq j} q_i(z_i) \right] dz_j - \int \ln q_j \cdot q_j dz_j \\ &= \int \left[ \int \ln p(x, z) \cdot \prod_{i \neq j} q_i(z_i) dz_{-j} \right] q_j(z_j) dz_j - \int q_j \ln q_j dz_j = \end{aligned}$$

$$\begin{aligned} \ln \tilde{p}(x, z_j) &= \int \ln p(x, z) \prod_{i \neq j} q_i(z_i) dz_{-j} + \text{const} \\ &= \int \ln \frac{\tilde{p}(x, z_j)}{q_j(z_j)} q_j(z_j) dz_j \xrightarrow{\max} -KL(q_j \| \tilde{p}) \end{aligned}$$

$$q_j^*(z_j) = \tilde{p}(x, z_j)$$

$$\ln q_j^*(z_j) = \mathbb{E}_{q_{-j}(z_{-j})} [\ln p(x, z)] + \text{const}$$

①



$$p(\bar{z}) = N(\bar{z} | \bar{\mu}, \Sigma) = \frac{1}{(2\pi)^d \sqrt{\det \Sigma}} e^{-\frac{1}{2}(\bar{z} - \bar{\mu})^T \Sigma^{-1} (\bar{z} - \bar{\mu})}$$

$$p(\bar{z}) \approx q(\bar{z}) = q_1(z_1) q_2(z_2)$$

$$\Lambda = \begin{pmatrix} \lambda_{11} & \lambda_{12} \\ \lambda_{12} & \lambda_{22} \end{pmatrix}$$

$$\ln q_1^*(z_1) = \mathbb{E}_{q_2^*(z_2)} [\ln p(\bar{z})] + \text{const}$$

$$\ln q_2^*(z_2) = \mathbb{E}_{q_1^*(z_1)} [\ln p(\bar{z})] + \text{const}$$

$$\begin{aligned} &= \ln 2\pi + \frac{1}{2} \ln \det \Lambda - \frac{1}{2} (\bar{z} - \bar{\mu})^T \Lambda (\bar{z} - \bar{\mu}) \\ &= -\frac{1}{2} \lambda_{11} (z_1 - \mu_1)^2 - \lambda_{12} (z_1 - \mu_1)(z_2 - \mu_2) - \frac{1}{2} \lambda_{22} (z_2 - \mu_2)^2 \end{aligned}$$

$$\begin{aligned} \ln q_1^*(z_1) &= \mathbb{E}_{q_2^*(z_2)} \left[ -\frac{1}{2} \lambda_{11} (z_1 - \mu_1)^2 - \lambda_{12} z_1 (z_2 - \mu_2) \right] + \text{const} \\ &= \mathbb{E}_{q_2^*(z_2)} \left[ -\frac{1}{2} \lambda_{11} z_1^2 + \lambda_{11} \mu_1 z_1 - \frac{1}{2} \lambda_{11} \mu_1^2 - \lambda_{12} z_1 (z_2 - \mu_2) \right] + \text{const} \\ &= -\frac{1}{2} \lambda_{11} z_1^2 + \lambda_{11} \mu_1 z_1 - \lambda_{12} z_1 (\mathbb{E}_{q_2} [z_2] - \mu_2) + \text{const} \\ &\quad - \frac{1}{2} \lambda_{11} (z_1 - \mu_1)^2 \quad \lambda_{11} z_1 (\mu_1 - \frac{\lambda_{12}}{\lambda_{11}} (-)) \end{aligned}$$

$$q_1^*(z_1) = \mathcal{N}(z_1 | \mu_1 - \frac{\lambda_{12}}{\lambda_{11}} (E_{q_2^*}[z_2] - \mu_2), \lambda_{11}^{-1}) = \mathcal{N}(z_1 | \mu_1, \lambda_{11}^{-1})$$

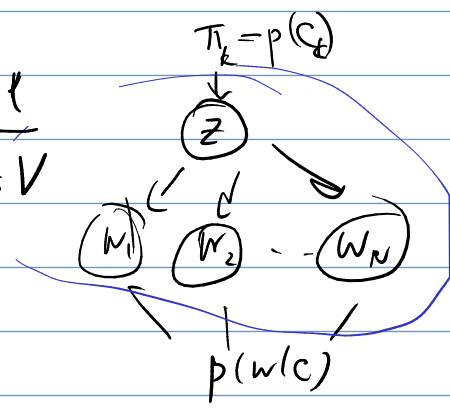
$$q_2^*(z_2) = \mathcal{N}(z_2 | \mu_2 - \frac{\lambda_{12}}{\lambda_{22}} (E_{q_1^*}[z_1] - \mu_1), \lambda_{22}^{-1}) = \mathcal{N}(z_2 | \mu_2, \lambda_{22}^{-1})$$

$$\begin{cases} \mu_1 = \mu_1 - \frac{\lambda_{12}}{\lambda_{11}} (\mu_2 - \mu_2) \\ \mu_2 = \mu_2 - \frac{\lambda_{12}}{\lambda_{22}} (\mu_1 - \mu_1) \end{cases} \quad \mu_1 = \mu_1, \mu_2 = \mu_2$$

Naïve Bayes  $D \quad d_1, d_2, \dots, d_N \quad d_i = \{w_1, \dots, w_N\} \quad y_1, y_2, \dots$   
 Idiot's Bayes  $y_i = k \Leftrightarrow d_i \in C_k$

Multinomial  $p(C|d) \propto p(C) p(d|C) = p(C) \prod_{w \in d} p(w|C)$

$$p(C_k) = \frac{\#\{d \in C_k\}}{\#\{d\}}; \quad p(w|C) = \frac{\#\{w \in d \in C_k\} + 1}{\sum_{w'} \#\{w' \in d \in C_k\} + V}$$



Multivariate

$$p(C|d) \propto p(C) \cdot \prod_{w \in d} p(w|C) \quad (1 - p(w|C))$$

Clustering NB  $p(C|d) \propto p(C) \prod_{w \in d} p(w|C)$

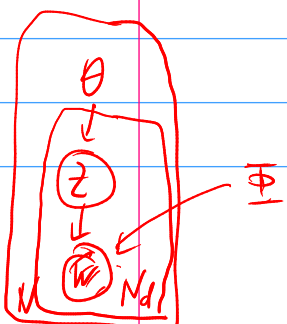
$\bar{z}_d \quad z_{kd} = 1 \Leftrightarrow d \in C_k$

M-var  $\pi_k = \frac{\sum_d z_{kd}}{N}$

$$p(w|C_k) = \frac{\sum_d z_{kd} \cdot n_{dw} + 1}{\sum_d z_{kd} \cdot n_{d+} + V}$$

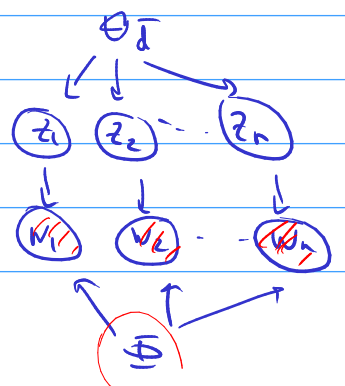
E-var  $z_{kd} \propto \pi_k \cdot \prod_{w \in d} \varphi_{wk}$

Topic Modeling  $d \Leftrightarrow \bar{\theta}_d = (\theta_{td}) \quad \theta_{td} = p(t|d)$   
 pLSI LSA  $\bar{\varphi}_t \quad \varphi_{wt} = p(w|t)$



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

$$= \prod_{d \in D} \prod_{w \in d} \sum_{t=1}^T \theta_{td} \varphi_{wt} \rightarrow \max_{\Theta, \Phi}$$



EM:  $E\text{-var } z_{dtw} = p(t | d, w) = \frac{p(w, t | d)}{p(w | d)} = \frac{\theta_{td} \varphi_{wt}}{\sum_s \theta_{sd} \varphi_{ws}}$   
 $z_{dtw} \propto \theta_{td} \varphi_{wt}$

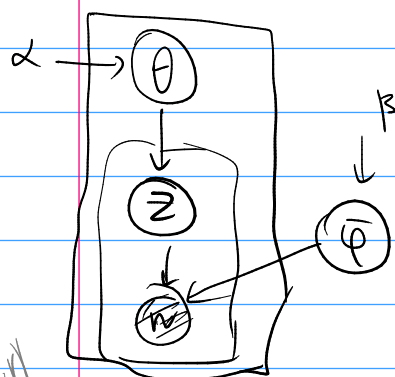
M-var:  $\theta_{td} = \frac{E[\text{count } d \text{ by } t]}{n_d} = \frac{\sum_{w \in d} z_{dtw}}{n_d}$

$\varphi_{wt} = \frac{E[\text{count } w \text{ by } t]}{E[\text{count by } t]} = \frac{\sum_d z_{dtw}}{\sum_d \sum_w z_{dtw}}$

ARTM

$\ln p(W | \Theta, \Phi) - R(\Theta, \Phi) \rightarrow \max$

LDA Latent Dirichlet Allocation



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

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

*(Note: The diagram includes annotations 'Mult' and 'N\_j' above the product terms.)*

$p(\bar{\varphi}_t | \beta) = \text{Dir}(\bar{\varphi}_t | \beta) = \frac{1}{\beta(\beta)} \prod_{v=1}^V \varphi_{tv}^{\beta_v - 1}$

$p(\bar{\theta}_j | \alpha) \propto \prod_{t=1}^T \theta_{jt}^{\alpha_t - 1}$

$= \frac{\Gamma(\sum \beta_v)}{\prod \Gamma(\beta_v)} \prod \varphi_{tv}^{\beta_v - 1}$

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

$KL(q || p) \rightarrow \min$

$\mathcal{L}(q) = \sum_z \log \frac{p(W, z, \Theta, \Phi | \alpha, \beta)}{q(z, \Theta, \Phi)} \rightarrow \max$

$q(z, \Theta, \Phi | \mu, \tau, \pi) = \left( \prod_t q_t(\bar{\varphi}_t | \bar{\lambda}_t) \right) \cdot \prod_{j=1}^M \left[ q_j(\bar{\theta}_j | \bar{\gamma}_j) \cdot \prod_{n=1}^{N_j} q_j(z_{jn} | \bar{\pi}_j) \right]$

*(Note: The diagram includes annotations 'Dir' and 'Mult' below the product terms.)*

Unpooled: fix  $\Phi$   $q(z, \omega | \Gamma, \Pi) \approx p(z, \omega | W, \Phi, \alpha, \beta)$

$$\max_{\Gamma, \Pi} KL(q_j || p_j) = \int_{\Theta} \sum_z q(\bar{z}_j, \bar{\theta}_j | \bar{\gamma}_j, \bar{\pi}_j) \cdot \log \frac{q(\dots)}{p(\bar{z}_j, \bar{\theta}_j | \bar{w}_j, \Phi, \alpha, \beta)} d\theta_j$$

$$\underbrace{L(\bar{\gamma}_j, \bar{\pi}_j)} = \int_{\Theta} \sum_z \log \frac{p(\bar{w}_j, \bar{z}_j, \bar{\theta}_j | \Phi, \alpha, \beta)}{q(\bar{z}_j, \bar{\theta}_j | \bar{\gamma}_j, \bar{\pi}_j)} q(\dots) d\theta_j =$$

$$= E_q[\log p(\bar{w}_j, \bar{z}_j, \bar{\theta}_j | \Phi, \alpha, \beta)] - E_q[\log q(\bar{z}_j, \bar{\theta}_j | \bar{\gamma}_j, \bar{\pi}_j)]$$

$$= \underbrace{E_q[\log p(\bar{\theta}_j | \alpha)]} + E_q[\log p(\bar{z}_j | \bar{\theta}_j)] + \underbrace{E_q[\log p(\bar{w}_j | \bar{z}_j, \Phi)]} - E_q[\log q_j(\bar{\theta}_j | \bar{\gamma}_j)] - E_q[\log q_j(\bar{z}_j | \bar{\pi}_j)] \rightarrow \max$$

$$E_q[\log p(\bar{\theta}_j | \alpha)] = E_q \left[ \log \left( \frac{\Gamma(\sum \alpha_s)}{\prod \Gamma(\alpha_s)} \prod_{t=1}^T \theta_{jt}^{\alpha_t - 1} \right) \right] =$$

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

$$E_{\text{Dir}(\bar{x} | \bar{\gamma})} [\log x_i] = \psi(\gamma_i) - \psi(\sum_j \gamma_j), \quad \psi(x) = \frac{\partial \log \Gamma(x)}{\partial x}$$

$$= \log \Gamma(\sum \alpha_s) - \sum \log \Gamma(\alpha_s) + \sum_t (\alpha_t - 1) (\psi(\gamma_{jt}) - \psi(\sum_s \gamma_{js}))$$

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

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

$$\left[ \begin{array}{l} \pi_{jnt} \propto e^{\log \varphi_{t, w_{jn}} + \psi(\gamma_{jt}) - \psi(\sum_s \gamma_{js})} \\ \gamma_{jt} = \alpha_t + \sum_{n=1}^{N_j} \pi_{jnt} \end{array} \right] \quad \left| \quad \varphi_{tv} \propto \sum_{j=1}^M \sum_{n=1}^{N_j} [w_{jn} = v] \pi_{jnt}$$

