Weekly Report IV

Donglai Wei

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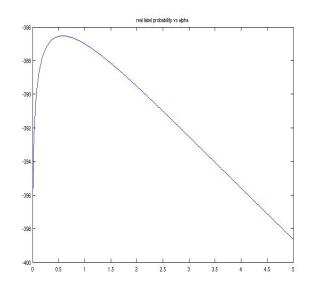
0)Understanding Concentration parameter

I)DPmixture

Concentration parameter: α $\mathcal{F}([z]) = \sum_{c=1}^{K} \left[\frac{DN_c}{2} log \pi + \frac{D}{2} log \frac{\xi_c}{\xi_0} log det(B_c) - \frac{\eta_0}{2} log det(B_0) - log \frac{\Gamma_D(\frac{\eta_c}{2})}{\Gamma_D(\frac{\eta_0}{2})} \right] - log(\Gamma(N_c)) - log \alpha \right] + log \frac{\Gamma(N+\alpha)}{\Gamma(\alpha)}$

a)

Given Ground Truth of z^* , $\mathcal{F}([z^*])$ is a function of α : $\frac{\partial \mathcal{F}([z^*])}{\partial \alpha} = \Psi(N+\alpha) - \Psi(\alpha) - \frac{K}{\alpha}$



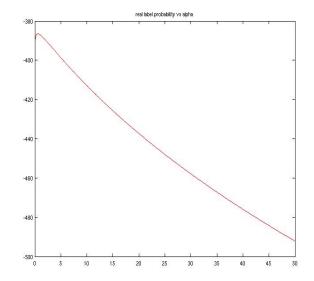


Figure 1: domain:0-5

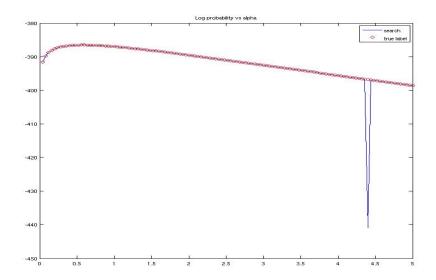
Figure 2: domain:0-50

b)

Given $\alpha, \mathcal{F}([z])$ = $(Likelihood\ term) \sum_{c=1}^{K} \left[\frac{DN_c}{2} log\pi + \frac{D}{2} log \frac{\xi_c}{\xi_0} logdet(B_c) - \frac{\eta_0}{2} logdet(B_0) - log \frac{\Gamma_D(\frac{\eta_c}{2})}{\Gamma_D(\frac{\eta_0}{2})} \right]$

 $(Allocation\ term) - \sum_{c=1}^{K} [log(\Gamma(N_c)) + log\alpha]$

 $(Constant\ term) + log \tfrac{\Gamma(N+\alpha)}{\Gamma(\alpha)}$



II) HDP(multinomial)

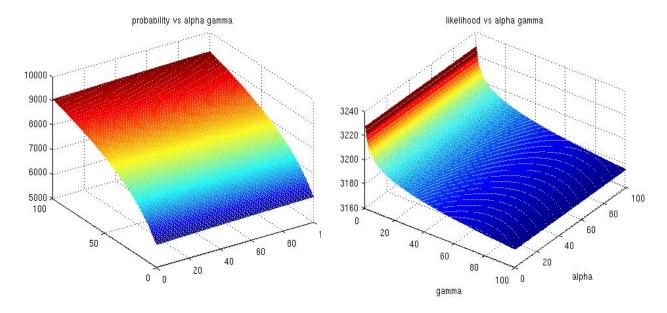


Figure 3: Log-probability

Figure 4: Likelihood term

1)Normal-Inverse Wishart

 $-logp(x|z,\lambda)$

$$\begin{split} &(\text{Likelihood}) \sum_{k=1}^{K} [\frac{Dn_{-k}}{2}log\pi + \frac{D}{2}log\frac{\xi_{k}}{\xi_{0}} + \frac{\eta_{k}}{2}logdet(B_{k}) - \frac{\eta_{0}}{2}logdet(B_{0}) - log\frac{\Gamma_{D}(\frac{\eta_{k}}{2})}{\Gamma_{D}(\frac{\eta_{0}}{2})}] \\ &+ \\ &(\text{Allocation:}) \underline{\sum_{j=1}^{J} \sum_{t=1}^{m_{j}} [\frac{1}{m_{j}}log\frac{\Gamma(n_{j,t}+\alpha)}{\Gamma(\alpha)} - log(\Gamma(n_{jt,t}) - log\alpha] + \sum_{k=1}^{K} [\frac{1}{K}log\frac{\Gamma(T+\gamma)}{\Gamma(\gamma)} - log(\Gamma(m_{,k}) - log\gamma]}] \\ &= \\ &(\text{t-term}) \sum_{j=1}^{J} \sum_{t=1}^{m_{j}} [\frac{1}{m_{j,t}}log\frac{\Gamma(n_{j,t}+\alpha)}{\Gamma(\alpha)} - log(\Gamma(n_{jt,t}) - log\alpha + \frac{1}{Jm_{j,t}}log\frac{\Gamma(T+\gamma)}{\Gamma(\gamma)}] \\ &+ (\text{k-term}) \sum_{k=1}^{K} [\frac{n_{-k}D}{2}log\pi + \frac{D}{2}log\frac{\xi_{k}}{\xi_{0}} + \frac{\eta_{k}}{2}logdet(B_{k}) - \frac{\eta_{0}}{2}logdet(B_{0}) - log\frac{\Gamma_{D}(\frac{\eta_{k}}{2})}{\Gamma_{D}(\frac{\eta_{k}}{2})} - \frac{log(\Gamma(m_{,k}) - log\gamma)}{log(\Gamma(m_{,k}) - log\gamma)}] \\ &= \\ &(\text{DP mixture of } z_{ji}) \sum_{k=1}^{K} [\frac{n_{-k}D}{2}log\pi + \frac{D}{2}log\frac{\xi_{k}}{\xi_{0}} + \frac{\eta_{k}}{2}logdet(B_{k}) - \frac{\eta_{0}}{2}logdet(B_{0}) - log\frac{\Gamma_{D}(\frac{\eta_{k}}{2})}{\Gamma_{D}(\frac{\eta_{0}}{2})} - log(\Gamma(n_{,k})) - log\gamma) \\ &- (\text{m term}) \sum_{k=1}^{K} log[\frac{\Pi_{j=1}^{J}(\Gamma(n_{j,k})}{\Gamma(n_{,k})}] - log\frac{\Pi_{k=1}^{K}\Gamma(m_{,k})}{\Gamma(T+\gamma)} - Tlog(\alpha) \\ &+ (\text{constant}) \sum_{j=1}^{J} log\frac{\Gamma(n_{j,k}+\alpha)}{\Gamma(\alpha)} + log\Gamma(\gamma) \\ &\text{where:} \\ &\xi_{k} = \xi_{0} + n_{-k} \\ &m_{k} = \frac{n_{-k}\vec{x}(s_{j+j+1}=k) + \xi_{0}m_{0}}{\xi_{k}}} \\ &\eta_{0} = n_{-k} \\ &B_{k} = B_{0} + n_{-k}S_{k} + \frac{n_{-k}\xi_{0}}{\xi_{k}}(\vec{x}(k_{j+j+1}=k) - m_{0})(\vec{x}(k_{j+j+1}=k) - m_{0})^{T} \\ &S_{k} : sample covariance \\ \end{cases}$$

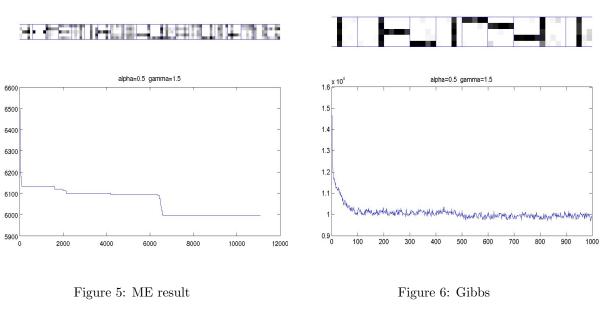
2) Dirichlet-Multinomial

W:
number of unique words $n^w_{\ k} \text{number of occurence of word w in dish k}$

$$\begin{split} &-logp(x|z,\lambda) \\ &= \\ &(\text{Likelihood}) \sum_{k=1}^{K} [log(\frac{\Gamma(n_{..k}+W\phi_0)}{\Gamma(W\phi_0)}) + \sum_{w=1}^{W} log(\frac{\Gamma(\phi_0)}{\Gamma(\phi_0+n_{..k}^w)})] \\ &+ \\ &(\text{Allocation:}) \underline{\sum_{j=1}^{J} \sum_{t=1}^{m_{j.}} [\frac{1}{m_{j.}} log\frac{\Gamma(n_{j..}+\alpha)}{\Gamma(\alpha)} - log(\Gamma(n_{jt.}) - log\alpha] + \sum_{k=1}^{K} [\frac{1}{K} log\frac{\Gamma(T+\gamma)}{\Gamma(\gamma)} - log(\Gamma(m_{.k}) - log\gamma])]} \\ &= \\ &(\text{t-term}) \underline{log} \frac{\Gamma(T+\gamma)}{\Gamma(\gamma)} + \sum_{j=1}^{J} \{log\frac{\Gamma(n_{j..}+\alpha)}{\Gamma(\alpha)} - \sum_{t=1}^{m_{j.}} [log(\Gamma(n_{jt.}) + log\alpha]]\} \\ &+ (\text{k-term}) \sum_{k=1}^{K} [log(\frac{\Gamma(n_{..k}+W\phi_0)}{\Gamma(W\phi_0)}) + log(\Pi_{w=1}^{W} \frac{\Gamma(\phi_0)}{\Gamma(\phi_0+n_{..k}^w)}) - \underline{log}(\Gamma(m_{.k}) - log\gamma] \\ &= \\ &(\text{k-term}) + \sum_{k=1}^{K} [log(\frac{\Gamma(n_{..k}+W\phi_0)}{\Gamma(W\phi_0+n_{..k}^w)\Gamma(m_{.k})\Pi_{q=1}^{m_{.k}}\Gamma(n_{q.})})] \\ &(\text{hyper-term}) - Tlog\alpha - Klog\gamma + Klog\frac{\Gamma(\phi_0)^W}{\Gamma(W\phi_0)} + log\Gamma(T+\gamma) \\ &(\text{constant-term}) - log\Gamma(\gamma) + \sum_{j=1}^{J} log\frac{\Gamma(n_{j..}+\alpha)}{\Gamma(\alpha_{j..}+\alpha)} \\ \end{array}$$

Experiment

$$\alpha=0.5, \gamma=1.5$$



ME vs Gibbs ME vs Gibbs ×10 6700 Ground Truth Gibbs 6600 ME 2.5 6500 6400 2 6300 1.5 6200 6100 6000 0.5 5900 2000 10000 1400 4000 6000 8000 12000 500 1000 1500 2000 2500 3000

Figure 7: ME vs Gibbs

Figure 8: ME vs Gibbs

Ground Truth

3500 4000 4500

ME Gibbs