STATS370: Final Project

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1 Introduction

1.1 Description

- Compute quantiles, plot histograms, obtain means, variances and correlation matrix.
- Check convergence of the chain: does the variance of the distribution stabilize? Run two markov chains, how do they compare?
- Hamiltonian: Parameter search. Implement over M, eps, L. See section 3.5 for tuning
- Gibbs: basically show the math
- Metropolis Hasting: choice of candidate distribution. Make sure domain is right for each, could optimize parameters of the candidate distributions
- Importance sampling: TBD

Priors

$$
\begin{aligned}
\theta &= (\sigma^2, \tau, \mu_1, \mu_2, \gamma_1, \gamma_2) \\
p(\sigma^2) &\propto \frac{1}{\sigma^2} \\
p(\tau) &\sim Unif[0,1] \\
p(\mu) &= p(\mu_1, \mu_2) \propto 1 \text{ (improper uniform)} \\
p(\gamma) &= p(\gamma_1, \gamma_2) \propto 1 \text{ (improper uniform)}
\end{aligned}
$$

Gene expression distributions

$$
\begin{aligned}
(y_i | g_i = 1) &\sim N(\mu, \sigma^2 I) \\
(y_i | g_i = 2) &\sim N(\gamma, \sigma^2 I) \\
(y_i | g_i = 3) &\sim N(\frac{1}{2}(\mu + \gamma), \sigma^2 I) \\
(y_i | g_i = 4) &\sim N(\tau\mu + (1-\tau)\gamma, \sigma^2 I)
\end{aligned}
$$

Likelihood

$$\begin{aligned}
L(Y|\theta) &= \prod_{i=1}^{n} p(y_i|\theta), \text{ for } Y = (y_i, \ldots, y_n) \\
&= \prod_{i\in g_1} \frac{1}{\sqrt{2\pi}}((\sigma^2)^2)^{-\frac{1}{2}} \exp[-\frac{1}{2\sigma^2}(y_i-\mu)^T(y_i-\mu)] \times \prod_{i\in g_2} \frac{1}{\sqrt{2\pi}}((\sigma^2)^2)^{-\frac{1}{2}} \exp[-\frac{1}{2\sigma^2}(y_i-\gamma)^T(y_i-\gamma)] \\
&\quad \times \prod_{i\in g_3} \frac{1}{\sqrt{2\pi}}((\sigma^2)^2)^{-\frac{1}{2}} \exp[-\frac{1}{2\sigma^2}(y_i-\frac{1}{2}(\mu+\gamma))^T(y_i-\frac{1}{2}(\mu+\gamma))] \\
&\quad \times \prod_{i\in g_4} \frac{1}{\sqrt{2\pi}}((\sigma^2)^2)^{-\frac{1}{2}} \exp[-\frac{1}{2\sigma^2}(y_i-(\tau\mu+(1-\tau)\gamma))^T(y_i-(\tau\mu+(1-\tau)\gamma))] \\
&= \left(\frac{1}{\sigma^2\sqrt{2\pi}}\right)^n \exp[-\frac{1}{2\sigma^2}(\sum_{i\in g_1}(y_i-\mu)^T(y_i-\mu) + \sum_{i\in g_2}(y_i-\gamma)^T(y_i-\gamma) \\
&\quad + \sum_{i\in g_3}(y_i-\frac{1}{2}(\mu+\gamma))^T(y_i-\frac{1}{2}(\mu+\gamma)) + \sum_{i\in g_4}(y_i-(\tau\mu+(1-\tau)\gamma))^T(y_i-(\tau\mu+(1-\tau)\gamma)))]
\end{aligned}$$

Posterior

$$p(\theta|Y) \propto p(\theta)L(Y|\theta)$$

2 Metropolis Hasting

- Candidate distribution selection, including log-normal for ss with change of varibles transformation
- Grid search for potential parameters within chosen proposal distribution

3 Gibbs sampling

Posterior conditioned on each parameter

$$p(\theta[i]|Y,\theta[-i]) = \frac{p(\theta[i],\theta[-i]|Y)}{p(\theta[-i]|Y)} = f(\theta[i]) \propto p(\theta|Y) \text{ with fixed } \theta[-i], Y$$

Posterior conditional probability of τ

$$
\begin{aligned}
p(\tau|Y,\theta[-\tau]) &\propto p(\theta)L(Y|\theta) \\
&\propto p(\tau)\prod_{i\in g_4}\frac{1}{\sigma^2\sqrt{2\pi}}\exp[-\frac{1}{2\sigma^2}(y_i-(\tau\mu+(1-\tau)\gamma))^T(y_i-(\tau\mu+(1-\tau)\gamma))] \\
&\propto \exp[-\frac{1}{2\sigma^2}\sum_{i\in g_4}(y_i-(\tau\mu+(1-\tau)\gamma))^T(y_i-(\tau\mu+(1-\tau)\gamma))], \text{ for } \tau\in[0,1] \\
&\propto \exp[-\frac{1}{2\sigma^2}\sum_{i\in g_4}(y_i^Ty_i-2y_i^T(\tau\mu+(1-\tau)\gamma)+(\tau\mu+(1-\tau)\gamma)^T(\tau\mu+(1-\tau)\gamma))], \text{ for } \tau\in[0,1] \\
&\propto \exp[-\frac{1}{2\sigma^2}\sum_{i\in g_4}\tau^2(\mu^T\mu-2\mu^T\gamma+\gamma^T\gamma)-2\tau(y_i^T\mu-y_i^T\gamma-\mu^T\gamma+\gamma^T\gamma)], \text{ for } \tau\in[0,1] \\
&\propto \exp[-\frac{1}{2\sigma^2}(n_4\tau^2(\mu-\gamma)^T(\mu-\gamma)-2\tau(\mu-\gamma)^T[\sum_{i\in g_4}(y_i-\gamma), \text{ for } \tau\in[0,1] \\
&\propto \exp\left[-\frac{1}{2}*\frac{n_4(\mu-\gamma)^T(\mu-\gamma)}{\sigma^2}\left(\tau-\frac{(\mu-\gamma)^T(\sum_{i\in g_4}(y_i-\gamma))}{n_4(\mu-\gamma)^T(\mu-\gamma)}\right)^2\right], \text{ for } \tau\in[0,1] \\
&\sim Norm\left(\mu=\frac{(\mu-\gamma)^T(\sum_{i\in g_4}(y_i-\gamma))}{n_4(\mu-\gamma)^T(\mu-\gamma)},\sigma^2=\frac{\sigma^2}{n_4(\mu-\gamma)^T(\mu-\gamma)}\right), \text{ truncated to } [0,1]
\end{aligned}
$$

Posterior conditional probability of σ^2

$$
\begin{aligned}
p(\sigma^2|Y,\theta[-\sigma^2]) \propto& p(\theta)L(Y|\theta)\propto p(\sigma^2)\prod_{i=1}^{n}p(y_i|\theta) \\
\propto&\frac{1}{\sigma^2}*\left(\frac{1}{\sigma^2}\right)^n\exp\left[-\frac{1}{2\sigma^2}M\right], \text{ where } M= \\
&\sum_{i\in g_1}(y_i-\mu)^T(y_i-\mu)+\sum_{i\in g_2}(y_i-\gamma)^T(y_i-\gamma)+\sum_{i\in g_3}(y_i-\frac{1}{2}(\mu+\gamma))^T(y_i-\frac{1}{2}(\mu+\gamma)) \\
&+\sum_{i\in g_4}(y_i-(\tau\mu+(1-\tau)\gamma))^T(y_i-(\tau\mu+(1-\tau)\gamma)) \\
\propto&(\sigma^2)^{-n-1}\exp\left[-\frac{M}{2}\frac{1}{\sigma^2}\right] \\
\sim& InvGamma\left(\alpha=n,\beta=\frac{M}{2}\right)
\end{aligned}
$$

Posterior conditional probability of μ

$$\begin{aligned}
p(\mu|Y,\theta[-\mu]) \propto & p(\theta)L(Y|\theta)\\
& \propto \prod_{i\in g_1}\frac{1}{\sigma^2\sqrt{2\pi}}\exp[-\frac{1}{2\sigma^2}(y_i-\mu)^T(y_i-\mu)] \times \prod_{i\in g_3}\frac{1}{\sigma^2\sqrt{2\pi}}\exp[-\frac{1}{2\sigma^2}(y_i-\frac{1}{2}(\mu+\gamma))^T(y_i-\frac{1}{2}(\mu+\gamma))]\\
& \quad\times \prod_{i\in g_4}\frac{1}{\sigma^2\sqrt{2\pi}}\exp[-\frac{1}{2\sigma^2}(y_i-(\tau\mu+(1-\tau)\gamma))^T(y_i-(\tau\mu+(1-\tau)\gamma))]\\
& \propto \exp[-\frac{1}{2\sigma^2}(n_1\mu^T\mu-2\mu^T\left(\sum_{i\in g_1}y_i\right)-\mu^T\left(\sum_{i\in g_3}y_i\right)+\frac{n_3}{4}\mu^T\mu+\frac{n_3}{2}\mu^T\gamma\\
& \quad -2\tau\mu^T\left(\sum_{i\in g_4}y_i\right)+\tau^2 n_4\mu^T\mu+2\tau(1-\tau)n_4\mu^T\gamma)]\\
& \propto \exp\left[-\frac{1}{2\sigma^2}(n_1+\frac{n_3}{4}+n_4\tau^2)\left(\mu^T\mu-2\mu^T\frac{\sum_{i\in g_1}y_i+\frac{1}{2}\sum_{i\in g_3}y_i+\tau\sum_{i\in g_4}y_i-(\frac{n_3}{4}+n_4\tau(1-\tau))\gamma}{n_1+\frac{n_3}{4}+n_4\tau^2}\right)\right]\\
& \propto \exp\left[-\frac{1}{2\phi^2}(\mu-\psi)^T(\mu-\psi)\right], \text{ where}\\
& \quad \psi=\frac{\sum_{i\in g_1}y_i+\frac{1}{2}\sum_{i\in g_3}y_i+\tau\sum_{i\in g_4}y_i-(\frac{n_3}{4}+n_4\tau(1-\tau))\gamma}{n_1+\frac{n_3}{4}+n_4\tau^2},\ \phi^2=\frac{\sigma^2}{n_1+\frac{n_3}{4}+n_4\tau^2}\\
& \sim N(\mu=\psi,\Sigma=\phi^2 I)
\end{aligned}$$

Posterior conditional probability of γ

By symmetry with posterior conditional probability of μ,

$$\begin{aligned}
p(\gamma|Y,\theta[-\gamma]) \sim & N(\mu=\psi',\Sigma=\phi'^2 I), \text{ where}\\
& \psi'=\frac{\sum_{i\in g_2}y_i+\frac{1}{2}\sum_{i\in g_3}y_i+(1-\tau)\sum_{i\in g_4}y_i-(\frac{n_3}{4}+n_4\tau(1-\tau))\mu}{n_2+\frac{n_3}{4}+n_4(1-\tau)^2},\ \phi'^2=\frac{\sigma^2}{n_2+\frac{n_3}{4}+n_4(1-\tau)^2}
\end{aligned}$$

4 Hamiltonian Monte Carlo

- Boundary constraints using Rollback HMC: https://arxiv.org/pdf/1709.02855.pdf and Reflection HMC: https://people.cs.umass.edu/ domke/papers/2015nips1.pdf

$$\begin{aligned}
H(q,p) = & U(q)+K(p), \text{ Hamiltonian function}\\
& \text{with } U(\cdot), \text{ potential energy, } K(\cdot), \text{ kinetic energy, } q\in\mathbb{R}^k, \text{ position, } p\in\mathbb{R}^k \text{ momentum}\\
& \text{let } U(\theta):=-\log f(\theta), \text{ where } p(\theta|Y)=\frac{1}{C}f(\theta), \text{ and } p\sim N(0,\mathbf{M})
\end{aligned}$$

5 Importance sampling