Summary of Short-term Research Objectives

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1 Model Specification

Let L be a K-dimensional Bernoulli random variable denoting the true state. Consider the general log linear model:

$$f(l;\Theta) = \exp\{\Theta_1^T l + \Theta_2^T u_2 + \ldots + \Theta_K^T u_K - A^*(\Theta)\}$$

where U_k is a $\binom{K}{k} \times 1$ vector of k-way cross-products, $k = 1, \ldots, K$, and $\Theta = (\Theta_1, \ldots, \Theta_K)$ contains the the natural parameters, which is a $(2^K - 1) \times 1$ vector.

Model restrictions, let $\tilde{l} = (l, u_2, \ldots, u_K)^T$, and $S = \sum_{j=1}^K L_j = s$ has some fixed pmf

$$\begin{aligned}
\pi(s) :=& P(S = s) \\
=& \frac{1}{A(\Theta)} \sum_{\tilde{l}:S=s} \exp\{\Theta^T \tilde{l}\}\ , s = 0, 1, \ldots, K \qquad (1)\\
A(\Theta) =& \sum_{\tilde{l}:l\in\{0,1\}^K} \exp\{\Theta^T \tilde{l}\} \qquad (2)
\end{aligned}$$

2 Posterior Distribution

2.1 On sampling $[\mu, \pi | L]$

2.1.1 General model

For General model, $\tilde{L}$ is a square matrix with dimension $J_1 = 2^K - 1$. Recall that

$$A(\Theta) = \frac{1}{\pi(0)}$$

$$\pi(s) = \frac{1}{A(\Theta)} \sum_{\tilde{l}:S=s} \exp\{\Theta^T \tilde{l}\}\ ,\ s = 1, \ldots, K \tag{3}$$

$$\mu_k = \frac{1}{A(\Theta)} \sum_{\tilde{l}:l_k=1} \exp\{\Theta^T \tilde{l}\}\ ,\ k = 1, \ldots, K \tag{4}$$

Define intermediate parameter $\phi_j = \exp(\theta^T \tilde{l}_j) > 0$, $\Theta = (\theta^{(1)}, \theta^{(2)}, \ldots, \theta^{(K)}), j = 1, \ldots, J_1$ and two $K \times J_1$ sub-design matrices B, C, where $B[k, j] = 1(\sum_{s=1}^{K} \tilde{L}[j, s] = k)$, $C[k, j] = \tilde{L}[j, k]$. Thus (3) and (4) become

$$\vec{\phi} > 0 \tag{5}$$

$$B\vec{\phi} = \vec{\pi}/\pi(0) \tag{6}$$

$$C\vec{\phi} = \vec{\mu}/\pi(0) \tag{7}$$

Note that B and C are not independent constraints and should be compatible so that $\binom{B}{C}$ has rank $2K - 1$.

Based on [1][2], we can sample $\vec{\phi}$ from Uniform distribution subject to the above linear constraints efficiently and robustly. Then Θ are the solutions to the linear system (J_1 equations with J_1 unknowns):

$$\tilde{L}\Theta = \log \vec{\phi}$$

Then the posterior distribution of (μ, π) given data L becomes:

$$\begin{aligned} P(\mu, \pi | L) &\propto P(L, \mu, \pi) \\ &\propto \int P(L, \phi, \mu, \pi) d\phi \\ &\propto \int P(L|\phi) P(\phi|\mu, \pi) P(\mu, \pi) d\phi \\ &\approx \sum P(L|\phi_h) P(\pi|\mu) P(\mu) \end{aligned}$$

where $P(L|\phi_h)$ is the log linear model density evaluated at ϕ_h, which is sampled uniformly from the feasible region subject to constrains (5-7).

$P(\mu)$ is a multivariate logit Normal density with mean 0 and standard deviation Σ.

$P(\pi|\mu) = P(\pi_0|\mu) P(\pi_1, .., \pi_K | \pi_0, \alpha)$, where $P(\pi_0|\mu)$ is a uniform density on $(0, 1 - \max(\mu))$ and $P(\pi_1, ..\pi_K | \pi_0, \alpha)$ is a Stick Breaking prior with shape parameter α on $(0, 1 - \pi_0)$.

2.2 Example for $K = 3$ with prior on (μ, π_0)

2.2.1 The Feasible Space

For $K = 3$ with the General Log-linear model, $\Theta = (\theta_1, \theta_2, \theta_3, \theta_{12}, \theta_{13}, \theta_{23}, \theta_{123})^T$
$\Phi = (\phi_1 = \exp{(\theta_1)}, \ldots, \phi_4 = \exp{(\theta_1 + \theta_2 + \theta_{12})}, \ldots, \phi_7 = \exp{(\theta_1 + \theta_2 + \theta_3 + \theta_{12} + \theta_{13} + \theta_{23} + \theta_{123})})^T$
When we made prior assumption on $\vec{\mu} = (\mu_1, \mu_2, \mu_3)^T$ and π_0, the sampling constraints are:

$$\begin{aligned}
\sum_{i=1}^{7} \phi_i =& \frac{1 - \pi_0}{\pi_0} \\
\phi_1 + \phi_4 + \phi_5 + \phi_7 =& \frac{\mu_1}{\pi_0} \\
\phi_2 + \phi_4 + \phi_6 + \phi_7 =& \frac{\mu_2}{\pi_0} \\
\phi_3 + \phi_5 + \phi_6 + \phi_7 =& \frac{\mu_3}{\pi_0} \\
\phi_i \in& (0, \frac{1}{\pi_0} - 1)
\end{aligned}$$

And an implicit assumption is $\mu_k < 1 - \pi_0 \leq \sum_{k=1}^{3} \mu_k$.

By applying row reduction to the augmented matrix of the above 4 equations, we have

$$\begin{pmatrix}
-1 & -1 & -1 & 0 & 0 & 0 & 1 & -\frac{\sum \mu_k + 2\pi_0 - 2}{\pi_0} \\
0 & 1 & 1 & 0 & 0 & 1 & 0 & \frac{\mu_1 + \pi_0 - 1}{\pi_0} \\
1 & 0 & 1 & 0 & 1 & & 0 & \frac{\mu_2 + \pi_0 - 1}{\pi_0} \\
1 & 1 & 0 & 1 & 0 & 0 & 0 & \frac{\mu_3 + \pi_0 - 1}{\pi_0}
\end{pmatrix}$$

Thus let $\phi_1 = u, \phi_2 = v, \phi_3 = w$, the feasible region of Φ is defined by:

$$\begin{pmatrix}
u \\
v \\
w \\
-u - v - \frac{\pi_0 - 1 + \mu_3}{\pi_0} \\
-u - w - \frac{\pi_0 - 1 + \mu_2}{\pi_0} \\
-v - w - \frac{\pi_0 - 1 + \mu_1}{\pi_0} \\
u + v + w + \frac{\sum \mu_k + 2\pi_0 - 2}{\pi_0}
\end{pmatrix} = \begin{pmatrix}
0 \\
0 \\
0 \\
-\frac{\pi_0 - 1 + \mu_3}{\pi_0} \\
-\frac{\pi_0 - 1 + \mu_2}{\pi_0} \\
-\frac{\pi_0 - 1 + \mu_1}{\pi_0} \\
\frac{\sum \mu_k + 2\pi_0 - 2}{\pi_0}
\end{pmatrix} + u \begin{pmatrix} 1 \\ 0 \\ 0 \\ -1 \\ -1 \\ 0 \\ 1 \end{pmatrix} + v \begin{pmatrix} 0 \\ 1 \\ 0 \\ -1 \\ 0 \\ -1 \\ 1 \end{pmatrix} + w \begin{pmatrix} 0 \\ 0 \\ 1 \\ 0 \\ -1 \\ -1 \\ 1 \end{pmatrix}$$

and $\phi_i \in (0, \frac{1}{\pi_0} - 1)$ for $i = 1, \ldots, 7$ (*)

To sample (u, v, w) from its feasible space, we can do as follow: Let $a = max\{\mu_2, \mu_3\}$, $b = max\{\mu_1, \mu_3\}$, $c = max\{\mu_1, \mu_2\}$

1. Sample u from Unif(0, $\frac{1-a-\pi_0}{\pi_0}$).
2. Sample v from Unif(0, $\frac{1-b-\pi_0}{\pi_0}$) .
3. Sample w from Unif(0, $\frac{1-c-\pi_0}{\pi_0}$) .

Then reject all (u, v, w) samples such that the resulted ϕ does not satisfy condition (*). Also note that the Monte Carlo estimate of the sampling density is

$$\frac{1}{\text{AcceptRatio} \times \frac{1-a-\pi_0}{\pi_0} \frac{1-b-\pi_0}{\pi_0} \frac{1-c-\pi_0}{\pi_0}}$$

2.2.2 Sampling the Posterior Distribution

The joint density (without regression):

$$\begin{aligned}
[y, \phi, \mu, \pi_0] =& [y|\phi][\phi|\mu, \pi_0][\mu, \pi_0] \\
[\mu, \pi_0|y] \propto& [\mu, \pi_0, y] \\
=& [\mu, \pi_0] \int [y|\phi][\phi|\mu, \pi_0] \mathrm{d}\phi \\
=& [\mu][\pi_0|\mu] \int [y|\phi][\phi|\mu, \pi_0] \mathrm{d}\phi
\end{aligned}$$

where we set the prior $[\mu]$ to be multivariate logit-normal$(0, 1.6)$, which is approximately uniform at the scale of μ and set $[\pi_0|\mu]$ to be Uniform$(0, max(\mu))$. And we approximate the integral by Monte Carlo Integration that samples from $[\phi|\mu, \pi_0]$, i.e. uniformly from the feasible space of ϕ. Now we can estimate the joint density $[\mu, \pi_0, y]$, therefore we can sample the posterior distribution of (μ, π_0) by Random Walk Metropolis-Hastings algorithm.

For the version 1.0, a symmetric proposal distribution (Gaussian with mean 0) is applied on the logit scale of μ and the original scale of π_0. The standard deviations of the Gaussian proposal distribution can be tuned so that the acceptance rates for all parameters are close to 0.25, suggested by Gelman, Roberts and Gilks (1995).

Application to a toy example

Set data as

```
      [,1] [,2] [,3]
 [1,]    1    0    0
 [2,]    1    0    0
 [3,]    1    0    0
 [4,]    1    0    0
 [5,]    1    0    0
 [6,]    1    0    0
 [7,]    1    0    0
 [8,]    1    0    0
 [9,]    1    0    0
[10,]    1    0    0
[11,]    0    1    0
[12,]    0    1    0
[13,]    0    1    0
[14,]    0    1    0
[15,]    0    1    0
[16,]    0    0    1
[17,]    0    0    1
[18,]    0    0    0
[19,]    0    0    0
[20,]    0    0    0
[21,]    1    1    0
[22,]    1    1    0
[23,]    1    1    0
[24,]    1    1    0
[25,]    1    0    1
```

```
[26,]    1    0    1
[27,]    0    1    1
```

then the MLE of (μ, π_0) is $(0.593, 0.371, 0.185, 0.111)$.

In the MH algorithm, setting the proposal distribution parameter $\Sigma = \text{diag}(1.3, 1.3, 1.6, 0.15)$ leads to acceptance rates $(0.245, 0.281, 0.268, 0.298)$. The following graph shows the sampling chain and the posterior densities.

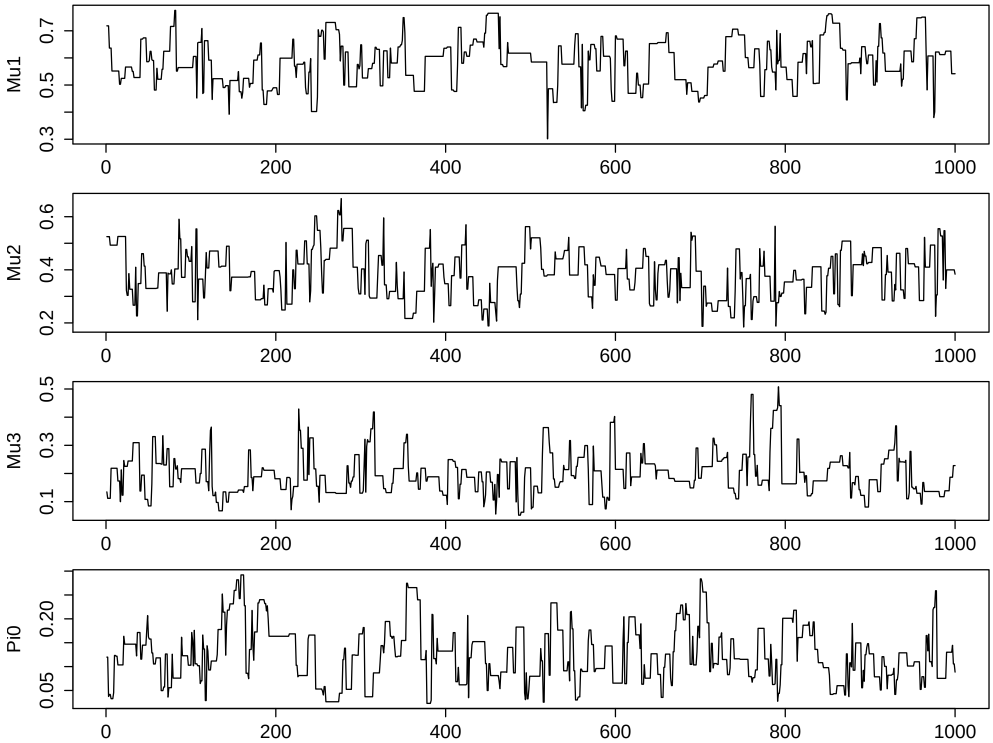

Figure 1: The sampling chains of (μ, π_0)

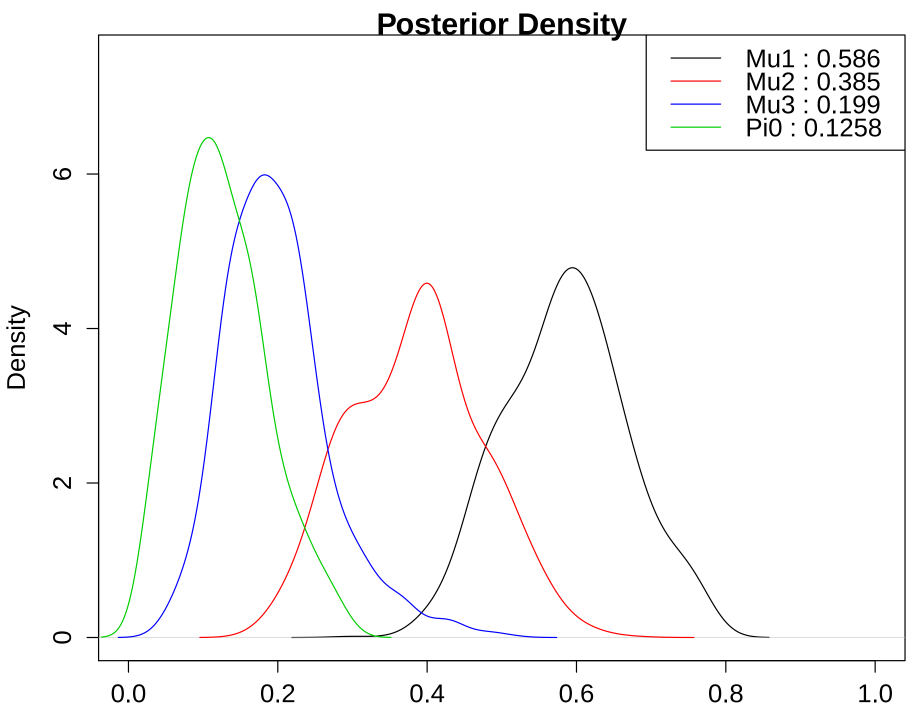

Figure 2: The Posterior density of (μ, π_0) where the legend shows the posterior mean of each parameter

2.3 Example for $K = 3$ with prior on (μ, π)

2.3.1 The Feasible Space

2.3.2 Sampling the Posterior Distribution

Application to a toy example

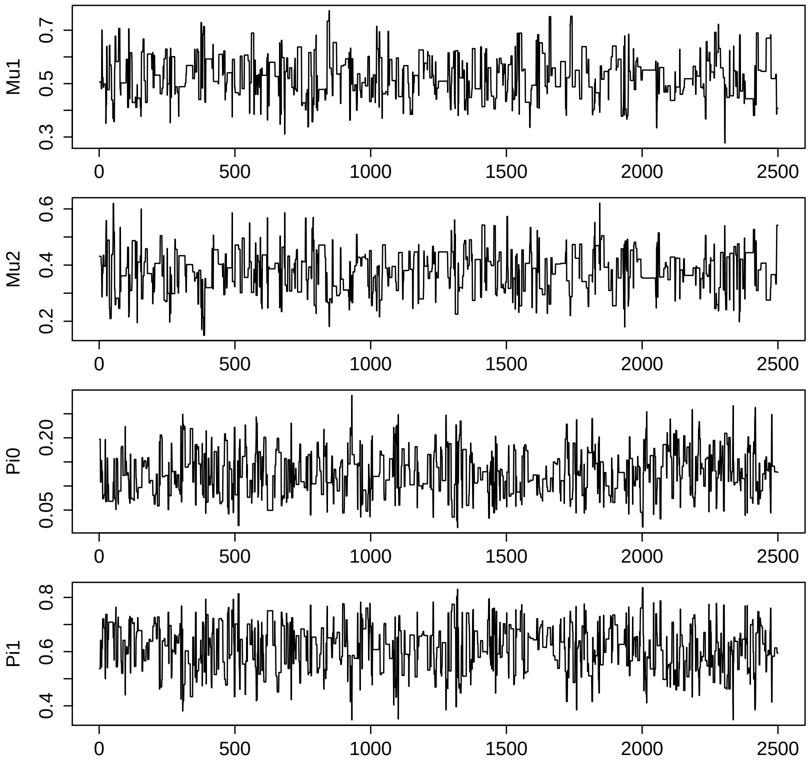

Figure 3: The sampling chains of $(\mu_1, \mu_2, \pi_0, \pi_1)$

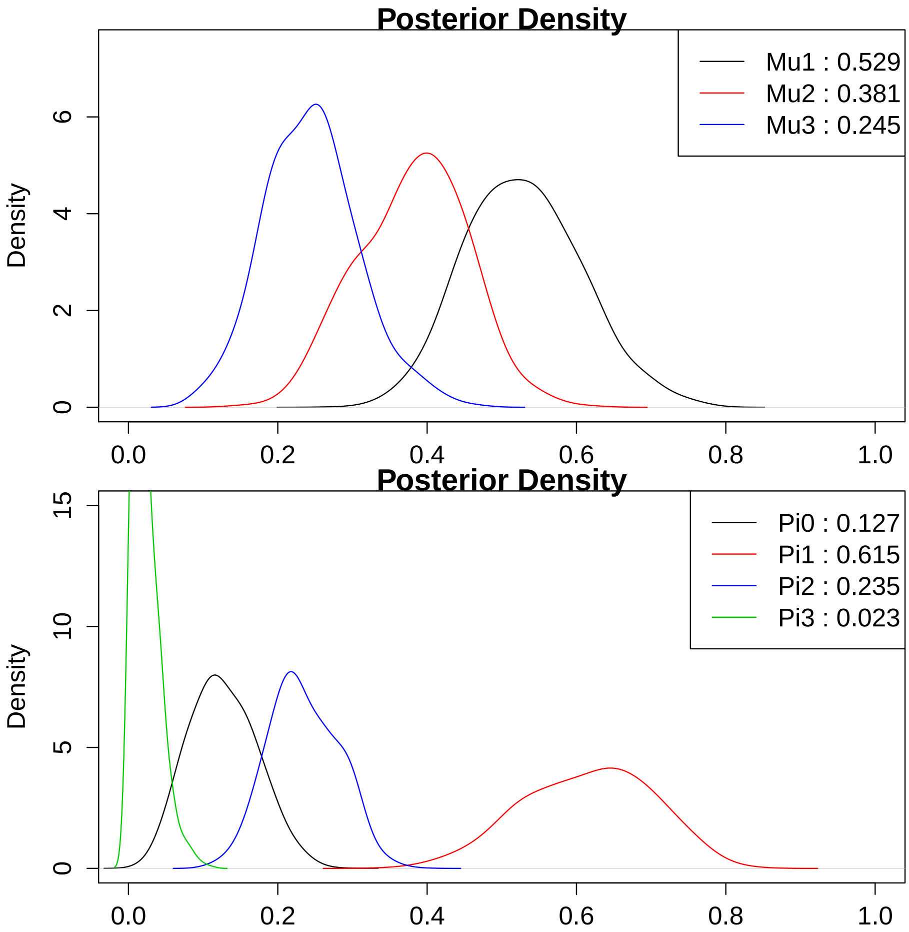

Figure 4: The Posterior density of (μ, π) where the legend shows the posterior mean of each parameter

Reference

1. Smith RL . Efficient Monte-Carlo Procedures for Generating Points Uniformly Dis- tributed over Bounded Regions. Operations Research, 32(6), 12961308 (1984).
2. Van den Meersche, Karel, K. E. R. Soetaert, and D. J. Van Oevelen. ”xsample (): an R function for sampling linear inverse problems.” Journal of Statistical Software 30 (2009).