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

$$\pi(s) := P(S = s) = \frac{1}{A(\Theta)} \sum_{\tilde{l}: S = s} \exp\{\Theta^T \tilde{l}\}, \ s = 0, 1, \dots, K$$
 (1)

$$A(\Theta) = \sum_{\tilde{l}: l \in \{0,1\}^K} \exp\{\Theta^T \tilde{l}\}$$
 (2)

2 Research Objectives

Suppose $\{L_i\}$ are i.i.d random variables with density $P(L_i; \Theta)$ defined above, our goal is to find a re-parameterization from Θ to $(\boldsymbol{\pi}, \boldsymbol{\gamma})$ such that $P(L_i; \Theta) = P(L_i; \boldsymbol{\pi}, \boldsymbol{\gamma})$, where $\boldsymbol{\pi} = (\pi_0, \pi_1, \dots, \pi_s, \dots, \pi_K)^T$, with $\sum_{s=0}^K \pi_s = 1$.

3 Results

3.1 Definition of New Parameters

Using previous notations, with some properly defined γ , we have:

$$P(L_i; \boldsymbol{\pi}, \boldsymbol{\gamma}) = P(L_i, S_i; \boldsymbol{\pi}, \boldsymbol{\gamma})$$

= $P(L_i | S_i; \boldsymbol{\pi}, \boldsymbol{\gamma}) P(S_i; \boldsymbol{\pi}, \boldsymbol{\gamma})$

where $P(L_i|S_i; \boldsymbol{\pi}, \boldsymbol{\gamma}) = P(L_i|S_i; \boldsymbol{\gamma})$ because $1(S_i = s)$ is the sufficient statistic for π_s , furthermore S_i is the sufficient statistic for $\boldsymbol{\pi}$. Also $P(S_i; \boldsymbol{\pi}, \boldsymbol{\gamma}) = \pi_{S_i}$ by definition.

Therefore, we have

$$P(L_i; \boldsymbol{\pi}, \boldsymbol{\gamma}) = P(L_i|S_i; \boldsymbol{\gamma})\pi_{S_i}$$

Then we define the following parameters:

$$\gamma_{j_1,...,j_s} = P(L_{ij_1} = \dots = L_{ij_s} = 1 | S_i = s)$$

$$\gamma = (\gamma_1, \gamma_2, \dots, \gamma_{12}, \dots, \gamma_{1...K})^T, \text{ where } \sum_j \gamma_j = \sum_{j \neq j'} \gamma_{jj'} = \sum_{j \neq j' \neq j''} \gamma_{jj'j''} = \dots = \gamma_{1...K} = 1$$

Therefore $(\boldsymbol{\pi}, \boldsymbol{\gamma})^T$ is a vector of length $2^K + K$ with degrees of freedom $2^K - 1$.

Let $J_i = \{j : L_{ij} = 1\}$. We have,

$$P(L_i; \boldsymbol{\pi}, \boldsymbol{\gamma}) = \gamma_{J_i} \pi_{S_i} \tag{4}$$

The relation between (π, γ) and Θ is defined by equation (2) together with:

$$\gamma_{J_i} = \frac{\exp(\Theta^T \tilde{l}_i)}{\sum_{l:l^T = S_i} \exp(\Theta^T \tilde{l})}$$
 (5)

with $2^K - 1 - K$ degrees of freedom.

Therefore (1), (3) and (5) together define $2^K - 1$ non-linear equations for $2^K - 1$ unknowns. If there exists a unique root for the above non-linear system, then there is a one-to-one mapping between $(\boldsymbol{\pi}, \boldsymbol{\gamma})$ and Θ , which provides the re-parameterization.

3.2 Find the Re-parameterization