# Supplementary Material "Bayesian Subject-Specific Bi-Level Feature Selection Model"

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## 1 Subject-Specific Group-Level Feature Selection Model

As motivated by Xu and Ghosh [1] and Liquet et al. [2], we present here a Bayesian subject-specific group-level feature selection model.

#### 1.1 Model hierarchy

For  $k = 1, \dots, K$  let

• 
$$vec\left(\mathbf{Y}_{J\times n}^{T}\right)|_{nJ\times Jp}^{\mathbf{X}}, \underset{pJ\times 1}{\beta}, \sigma^{2}, \underset{nJ\times nq}{\mathbf{Z}}, \underset{nq\times 1}{\mathbf{b}} \sim$$

$$N_{Jn}\left(\mathbf{X}_{nJ\times Jp}^{\beta} + \mathbf{Z}_{nJ\times nq} \underset{nq\times 1}{\mathbf{b}}, \left(\sigma^{2} \mathbf{I}_{n} \otimes \mathbf{I}_{J}\right)\right),$$

$$\bullet \ vec\left(\mathbf{B}_{k}\atop p_{k}\times J\right)|\sum_{J\times J},\tau_{k}^{2},\pi_{0k}\stackrel{ind.}{\sim} \ \pi_{0k}N_{p_{k}J}\left(\mathbf{0}\atop p_{k}J\times 1},\tau_{k}^{2}\sum_{J\times J}\otimes\mathbf{I}_{p_{k}}\atop p_{k}\times p_{k}\right)+(1-\pi_{0k})\,\delta_{0}\left(vec\left(\mathbf{B}_{k}\atop p_{k}\times J\right)\right),$$

• 
$$\tau_k^2 | \lambda_k^2 \stackrel{ind.}{\sim} Gamma\left(shape = \frac{p_k J + 1}{2}, rate = \frac{\lambda_k^2}{2}\right)$$
,

$$\bullet \ \ \underset{J\times J}{\boldsymbol{\Sigma}} | d, \ \underset{J\times J}{\mathbf{Q}} \sim \ Inverse \ Wishart \left( df = d, scale = \underset{J\times J}{\mathbf{Q}} \right),$$

- $\pi_{0k}|\theta_{\beta} \stackrel{iid}{\sim} Bernoulli(\theta_{\beta}),$
- $\theta_{\beta}|a,b \sim Beta(a,b)$ ,
- $\sigma^2 | \alpha, \gamma \stackrel{ind.}{\sim} Inverse \ Gamma \ (shape = \alpha, scale = \gamma),$
- $\lambda_k^2 | r, \delta \stackrel{ind.}{\sim} Gamma (shape = r, rate = \delta),$

• 
$$\mathbf{b}_{na \times 1} | \mathbf{G}_{a \times a} \sim N_{nq} \left( \mathbf{0}_{na \times 1}, \mathbf{I}_{n \times n} \otimes \mathbf{G}_{a \times a} \right)$$
, and

• 
$$\mathbf{G}_{q \times q} | \nu_o, \mathbf{C_0}_{q \times q} \sim Inverse \ Wishart \left( df = \nu_o, scale = \mathbf{C_0}_{q \times q} \right).$$

#### 1.2 Gibbs sampler

Let

$$\bullet \ \, \underset{Jp_k \times Jp_k}{\boldsymbol{\Sigma}_k} \equiv \left[ \tau_k^2 \underset{Jp_k \times nJ}{\mathbf{X}_k^T} \underset{nJ \times Jp_k}{\mathbf{X}_k} + \sigma^2 \Biggl( \underset{J \times J}{\boldsymbol{\Sigma}} \otimes \underset{p_k \times p_k}{\mathbf{I}_{p_k}} \right)^{-1} \right],$$

$$\bullet \ \ \mathbf{z}_{k} \\ J_{n\times 1} \equiv vec\left(\mathbf{Y}^{T}\right) - \left(\mathbf{X}_{\neg k} \ vec\left(\mathbf{B}_{\neg k} \\ p_{\neg k} \times J\right) + \mathbf{Z} \mathbf{b} \\ p_{\neg k} \times J\right),$$

$$\bullet \ \ \mathop{\mathbf{r}}_{Jn\times 1} \equiv vec\left(\mathbf{Y}^{T}\right) - \left(\mathbf{X} \underset{nJ\times Jp}{\beta} + \mathbf{Z} \underset{nJ\times nq}{\mathbf{b}} \right),$$

$$\bullet \ \ \underset{nq \times nq}{\boldsymbol{\Sigma_b}} \equiv \left[ \mathbf{Z}^T \mathbf{Z} \\ {}_{nq \times nJ} \mathbf{Z}_{nJ \times nq} + \sigma^2 \bigg( \mathbf{I}_n \otimes \mathbf{G} \\ {}_{n \times n} \boldsymbol{S}_{q \times q} \bigg)^{-1} \right],$$

• 
$$\mathbf{r_b}_{Jn \times 1} \equiv vec\left(\mathbf{Y}_{J \times n}^T\right) - \mathbf{X}_{nJ \times Jp} \frac{\beta}{p_J \times 1}$$

• 
$$f_k \equiv \mathbf{z}_k^T \mathbf{X}_k \mathbf{\Sigma}_{h}^{-1} \mathbf{X}_k^T \mathbf{z}_k$$
, and  $\mathbf{z}_k \mathbf{Z}_{h}^T \mathbf{z}_k \mathbf{Z}_{h}^T$ , and

$$\bullet \ \eta_k^2 \equiv \frac{1}{\tau_k^2}.$$

Then, the full-conditional posterior distributions for our subject-specific group-level feature selection model Gibbs sampler are given below:

• 
$$vec\left(\mathbf{B}_{k}\right)|rest \overset{ind.}{\sim} \pi_{0k}N_{p_{k}J}\left(\tau_{k}^{2}\sum_{k}^{-1}\mathbf{X}_{k}^{T}\mathbf{z}_{k},\sigma^{2}\tau_{k}^{2}\sum_{jp_{k}\times Jp_{k}}^{-1}\right) + (1-\pi_{0k})\delta_{0}\left(vec\left(\mathbf{B}_{k}\right)\right),$$

$$\bullet \ \eta_k^2|rest \overset{ind.}{\sim} \left\{ \begin{aligned} &Inverse\ Gaussian \left( \left( \frac{\lambda_k^2}{tr \left( \mathbf{B}_k \sum\limits_{J \times J} -1 \mathbf{B}_k^T \\ p_k \times J \xrightarrow{J \times J} \mathbf{J} \times p_k \right)} \right)^{\frac{1}{2}}, \lambda_k^2 \right) & if\ \pi_{0k} = 1 \\ &Inverse\ Gamma \left( shape = \frac{p_k J + 1}{2}, scale = \frac{\lambda_k^2}{2} \right) & if\ \pi_{0k} = 0 \end{aligned} \right.$$

• 
$$\sum_{J \times J} |rest \sim Inverse \ Wishart \left( df = d + \sum_{k=1}^{K} \pi_{0k} p_k, scale = \mathbf{B}_{J \times p}^T diag \left( \frac{1}{\tau_k^2} \mathbf{I}_{p_k} \right) \mathbf{B}_{p \times J} + \mathbf{Q}_{J \times J} \right)$$

$$\bullet \ \pi_{0k}|rest \overset{ind.}{\sim} \ Bernoulli \left( \frac{\theta_{\beta}\left(\sigma^{2}\right)^{\frac{Jp_{k}}{2}} \det\left(\sum\limits_{J \times J} \otimes \mathbf{I}_{p_{k}}\right)^{-\frac{1}{2}} \exp\left\{\frac{\tau_{k}^{2}}{2\sigma^{2}}f_{k}\right\} \det\left(\sum\limits_{Jp_{k} \times Jp_{k}}\right)^{\frac{1}{2}}}{\left(1-\theta\right) + \theta_{\beta}\left(\sigma^{2}\right)^{\frac{Jp_{k}}{2}} \det\left(\sum\limits_{J \times J} \otimes \mathbf{I}_{p_{k}}\right)^{-\frac{1}{2}} \exp\left\{\frac{\tau_{k}^{2}}{2\sigma^{2}}f_{k}\right\} \det\left(\sum\limits_{Jp_{k} \times Jp_{k}}\right)^{\frac{1}{2}}}\right),$$

• 
$$\theta_{\beta}|rest \sim Beta\left(a + \sum_{k=1}^{K} \pi_{0k}, b + K - \sum_{k=1}^{K} \pi_{0k}\right)$$
,

• 
$$\sigma^2 | rest \sim Inverse \ Gamma \left( shape = \frac{nJ}{2} + \alpha, scale = \frac{\mathbf{r}^T \quad \mathbf{r}}{2} + \gamma \right)$$

• 
$$\lambda_k^2 | rest \stackrel{ind.}{\sim} Gamma \left( shape = \frac{p_k J + 1}{2} + r, rate = \frac{\tau_k^2}{2} + \delta \right),$$

• 
$$\mathbf{b}_{nq \times 1} | rest \sim N_{nq} \left( \sum_{\mathbf{b}}^{-1} \mathbf{Z}^T \mathbf{r}_{\mathbf{b}}, \sigma^2 \sum_{\mathbf{b}}^{-1} \right)$$
, and

• 
$$\mathbf{G}_{q \times q} | rest \sim Inverse \ Wishart \left( df = n + \nu_o, scale = \sum_{i=1}^n \mathbf{b}_i \ \mathbf{b}_i^T + \mathbf{C_0} \right).$$

## 2 Alzheimer's Disease Neuroimaging Initiative (ADNI) Feature Data

Below is a table 1 detailing all of the p = 44 features we used for our applied analysis.

## Bibliography

- [1] Xiaofan Xu and Malay Ghosh. Bayesian Variable Selection and Estimation for Group Lasso. *Bayesian Analysis*, 10(4):909–936, 2015.
- [2] Benoit Liquet, Kerrie Mengersen, Anthony Pettitt, and Matthew Sutton. Bayesian variable selection regression of multivariate responses for group data. *Bayesian Analysis*, 12(4):1039–1067, 2017.

| Feature $(l)$             | Feature Group $(k)$    | $p_k$ | Feature Description  |
|---------------------------|------------------------|-------|--|
| ABETA                     | CSF biomarkers         | 2     | Amyloid beta peptide   |
| TAU                       | CSF biomarkers         | 2     | Total tau protein  |
| Age                       | Demographics           | 5     | Age  |
| Education                 | Demographics           | 5     | Education level (in years)   |
| Sex                       | Demographics           | 5     | Sex (female vs. male)  |
| Race                      | Demographics           | 5     | Race (white vs. other)   |
| Marriage                  | Demographics           | 5     | Marital status (married vs. other)   |
| MCI                       | Neurological diagnoses | 2     | MCI vs. cognitively normal diagnosis   |
| Dementia                  | Neurological diagnoses | 2     | Dementia vs. cognitively normal diagnosis  |
| APOE4 1                   | Genetic markers        | 2     | 1 vs. $0$ APOE- $\epsilon 4$ alleles   |
| APOE4 2                   | Genetic markers        | 2     | 2 vs. 0 APOE- $\epsilon 4$ alleles   |
| Hippocampus               | MRI measurements       | 7     | Volumetric quantification of the hippocampus   |
| Ventricles                | MRI measurements       | 7     | Volumetric quantification of the ventricles  |
| Whole Brain               | MRI measurements       | 7     | Volumetric quantification of the whole brain   |
| Entorhinal                | MRI measurements       | 7     | Volumetric quantification of the entorhinal cortex   |
| Fusiform                  | MRI measurements       | 7     | Volumetric quantification of the fusiform gyrus  |
| MidTemp                   | MRI measurements       | 7     | Volumetric quantification of the middle temporal gyrus   |
| ICV                       | MRI measurements       | 7     | Intracerebral volume   |
| MOCA                      | NP assessments/ECog    | 24    | Montreal Cognitive Assessment  |
| CDRSB                     | NP assessments/ECog    | 24    | Clinical Dementia Rating sum of boxes  |
| ADAS11                    | NP assessments/ECog    | 24    | Alzheimer's Disease Assessment Subscale (11 task version)                                      |
| ADASQ4                    | NP assessments/ECog    | 24    | Alzheimer's Disease Assessment Cognitive Delayed Recall Task                                   |
| MMSE                      | NP assessments/ECog    | 24    | Mini-Mental State Examination  |
| RAVLT Learning            | NP assessments/ECog    | 24    | Rey's Auditory Verbal Learning Test Learning   |
| RAVLT Forgetting          | NP assessments/ECog    | 24    | Rey's Auditory Verbal Learning Test Forgetting   |
| RAVLT Percent Forgetting  | NP assessments/ECog    | 24    | Rey's Auditory Verbal Learning Test Percent Forgetting   |
| FAQ                       | NP assessments/ECog    | 24    | Functional Assessment Questionnaire  |
| LDELTOTAL                 | NP assessments/ECog    | 24    | Logical Memory – Delayed Recall  |
| TRABSCOR                  | NP assessments/ECog    | 24    | Trail Making B Digit Symbol Substitution Test of the Wechsler Adult Intelligence Scale–Revised |
| ECog Pt Memory            | NP assessments/ECog    | 24    | ECog Participant Memory  |
| ECog Pt Language          | NP assessments/ECog    | 24    | ECog Participant Language  |
| ECog Pt Visuospatial      | NP assessments/ECog    | 24    | ECog Participant Visuospatial Abilities  |
| ECog Pt Planning          | NP assessments/ECog    | 24    | ECog Participant Planning  |
| ECog Pt Organization      | NP assessments/ECog    | 24    | ECog Participant Organization  |
| ECog Pt Divided Attention | NP assessments/ECog    | 24    | ECog Participant Divided Attention   |
| ECog Pt Total             | NP assessments/ECog    | 24    | Average ECog Participant Score   |
| ECog SP Memory            | NP assessments/ECog    | 24    | ECog Study Partner Assessment of Memory  |
| ECog SP Language          | NP assessments/ECog    | 24    | ECog Study Partner Assessment of Language  |
| ECog SP Visuospatial      | NP assessments/ECog    | 24    | ECog Study Partner Assessment of Visuospatial Abilities  |
| ECog SP Planning          | NP assessments/ECog    | 24    | ECog Study Partner Assessment of Planning  |
| ECog SP Organization      | NP assessments/ECog    | 24    | ECog Study Partner Assessment of Organization  |
| ECog SP Divided Attention | NP assessments/ECog    | 24    | ECog Study Partner Assessment of Divided Attention   |
| FDG                       | PET measurements       | 2     | Average FDG PET of the angular, temporal, and posterior cingulate                              |
| AV45                      | PET measurements       | 2     | Average Florbetapir F 18 PET of THE whole cerebellum   |

Table 1: Baseline feature data from the ADNI; we consider a total of p=44 features partitioned into K=7 feature groups. **Abbreviations**: **MCI**: mild cognitive impairment, **APOE**: Apolipoprotein E, **NP**: neuropsychological, **ECog**: Everyday Cognition, and **FDG**: Fluorodeoxyglucose.