

Variable Selection with Sum of Single Effects Model (SuSiE)

- Uses the technique of *sum of single effects* regression
 - The *single effects* model assumes that exactly one of the predictors has a nonzero coefficient
 - Single-effect model: $1 \times p$ vector $\beta = \beta\gamma$ has exactly one nonzero element, where $\gamma \sim \text{Mult}(1, \pi)$, $\beta \sim N_1(0, \sigma_0^2)$
- **Sum of single effects model:**
 - Introduce L single-effect vectors $\beta_l = \beta_l\gamma_l$, where $\gamma_l \sim \text{Mult}(1, \pi)$, $\beta_l \sim N_1(0, \sigma_{0l}^2)$
 - Then $\beta = \sum_{l=1}^L \beta_l$ gives the sum
 - $L \ll p$ gives standard BVSR
- Approximately equivalent to BVSR, but with two computational advantages
 - Deterministic algorithm for approximate posterior distributions \rightarrow *variational method*
 - Simple calculation of credible sets
 - *Credible set* of level ρ is a subset of variables with probability ρ or greater of containing at least one effect variable (useful for quantifying uncertainty in which variables to select)
- Given $\beta_1, \dots, \beta_{L-1}$, estimating β_L reduces to fitting a single effects model
 - Leads to an iterative algorithm the estimates β_l with a single effects model given the current estimates for other $\beta_{l'}, l' \neq l$
 - Effect of predictor j is $\beta^{(j)} = \sum_{l=1}^L \beta_{lj}$
- Model is robust to large L
 - If L is overstated, the uncertainty in the model spreads out extra effects among the covariates and makes little difference overall
 - Key signals remain the same
- **Iterative Bayesian Stepwise Selection (IBSS)**
 - Essentially a variational method
 - Relies on fact (above) that given $\beta_1, \dots, \beta_{L-1}$, estimating β_L reduces to fitting a single effects model
 - Requires that we initialize number of effects L and hyperparameters, and initialize posterior means
 - Then cycle through each effect vector and estimate it given the others, continue recycling through until convergence criterion satisfied
 - Result: gives an approximation of the posterior of each effect vector
 - **Scales linearly with data size**