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On a quest to find a more modern variable selection method within the Bayesian framework, here is presented the somewhat more recently adapted version of the Shotgun Stochastic Search (SSS) algorithm.
The SSS algorithm, introduced by Hans et al. [-@Hans2007], is designed to efficiently navigate high-dimensional model spaces in regression settings with a large number of candidate predictors, where $p \gg n$. Its primary objective is to swiftly pinpoint regions with high posterior probabilities and ascertain the maximum a posteriori (MAP) model. To achieve this, the algorithm amalgamates sparsity-inducing priors promoting parsimony, temperature control akin to that used in global optimisation algorithms like simulated annealing [@Vecchi1983], and screening techniques resembling Iterative Sure Independence Screening [@Fan2008]. Furthermore, SSS exploits parallel computation to enhance performance on cluster computers. The MAP model, denoted $\hat{k}$, is formally defined as:

$$\hat{k} = \arg\max_{k \in \Gamma^*} \{\pi(k|y)\}, \tag{1}$$

where Γ^* represents the set of models that are assigned non-zero prior probability. In its quest to traverse large model spaces and pinpoint global maxima efficiently, SSS algorithm defines $\mathrm{nbd}(k) = \{\Gamma^+, \Gamma^-, \Gamma^0\}$, where $\Gamma^+ = \{k \cup \{j\} : j \in k^c\}$, $\Gamma^- = \{k \setminus \{j\} : j \in k\}$, and $\Gamma^0 = \{[k \setminus \{j\}] \cup \{l\} : l \in k^c, j \in k\}$. The *SSS* algorithm proceeds as follows:

1. Select an initial model $k^{(1)}$.
2. For $i = 1$ to $i = N - 1$:
   - Compute $\pi(k|y)$ for all $k \in \mathrm{nbd}(k^{(i)})$.
   - Sample k^+, k^-, and k^0 from Γ^+, Γ^-, and Γ^0, respectively, with probabilities proportional to $\pi(k|y)$.
   - Sample $k^{(i+1)}$ from $\{k^+, k^-, k^0\}$, with probability proportional to $\{\pi(k^+|y), \pi(k^-|y), \pi(k^0|y)\}$.

The MAP model is determined as the model with the highest unnormalised posterior probability among those models searched by SSS.