Posterior computation for BART

- In order to generate the posterior for f, we sample the structure of all the trees $\mathcal{T}_h$, for $h = 1, \ldots, H$;
  the values of all leaves μ_{hn} for $n \in \mathcal{L}_h$ within tree h;
  and, the error variance σ^2
- Additionally, with the sparsity prior, there are samples of the vector of splitting variable selection probabilities $[s_1, \ldots, s_P]$ and, when the sparsity parameter is random, samples of θ
- The leaf and variance parameters are sampled from the posterior using Gibbs sampling
- Since the priors on these parameters are conjugate, the Gibbs conditionals are specified analytically
- The leaves, μ_{hn}, are drawn from a Normal conditional density
- The error variance, σ^2, is drawn from a scaled inverse Chi-square conditional (equivalent to inverse Gamma)

Posterior computation for BART

- Drawing a tree from the posterior requires a Metropolis-within-Gibbs sampling scheme, i.e., a Metropolis-Hastings (MH) step within Gibbs sampling
- For single-tree models, four different proposals are defined in Chipman George 1998 *JASA*
- The complementary BIRTH/DEATH proposals are essential (the others are CHANGE and SWAP which are optional)
- This is only one of several schemes that have been proposed; see Pratola 2016 *Bayesian Analysis*
- For programming simplicity, the **BART/BART3** package only implements BIRTH and DEATH with equal probability
- BIRTH selects a leaf and turns it into a branch: a new variable and cut-point with two leaves "born" as its descendants
- DEATH selects a branch leading to two terminal leaves and "kills" the branch by replacing it with a single leaf

Posterior computation for BART: the BIRTH proposal

- we present the acceptance probability for a BIRTH proposal
- a DEATH proposal is the reversible inverse of a BIRTH
- The algorithm assumes a fixed discrete set of possible split values for each x_j denoted by c_{jk}
- the leaf values, μ_{hn}, are integrated out so this search in tree space is over a large discrete set of possibilities
- At the mth MCMC step, let $\mathcal{T}_h^m$ denote the current state of tree h while $\mathcal{T}_h^*$ denotes the tree proposal
- $\mathcal{T}_h^*$ are identical $\mathcal{T}_h^m$ except that one terminal leaf of $\mathcal{T}_h^m$ is replaced by a branch of $\mathcal{T}_h^*$ with two terminal leaves

Posterior computation for BART: the BIRTH proposal

- The proposed tree is accepted with the following probability:

$$\pi_{\text{BIRTH}} = \min\left(1, \frac{[\mathcal{T}_h^*|y]}{[\mathcal{T}_h^m|y]}\frac{[\mathcal{T}_h^m|\mathcal{T}_h^*]}{[\mathcal{T}_h^*|\mathcal{T}_h^m]}\right)$$

- $[\mathcal{T}_h^*|\mathcal{T}_h^m]$ is the probability of proposing $\mathcal{T}_h^*$ (a BIRTH) given current state $\mathcal{T}_h^m$
- while $[\mathcal{T}_h^m|\mathcal{T}_h^*]$ is the reverse the probability of proposing $\mathcal{T}_h^m$ (a DEATH) given $\mathcal{T}_h^*$
- Now we delve into the calculations for $[\mathcal{T}_h^*|y]$ and $[\mathcal{T}_h^m|y]$

Posterior computation for BART: the BIRTH proposal

- First, we describe the likelihood contribution to the posterior
- Let $\boldsymbol{y_n}$ denote the partition of $\boldsymbol{y}$ corresponding to the leaf node $\boldsymbol{n}$ given the tree $\boldsymbol{\mathcal{T}_h}$
- Because the leaf values are a priori conditionally independent, we have $[\boldsymbol{y}|\boldsymbol{\mathcal{T}_h}] = \prod_{\boldsymbol{n}} [\boldsymbol{y_n}|\boldsymbol{\mathcal{T}_h}]$ where $[\boldsymbol{y_n}|\boldsymbol{\mathcal{T}_h}] = \int [\boldsymbol{\mu_n}] [\boldsymbol{y_n}|\boldsymbol{\mathcal{T}_h}, \boldsymbol{\mu_n}] \, \mathrm{d}\boldsymbol{\mu_n}$ (we will return to this later)
- After cancellation of terms in the ratio $\frac{[\boldsymbol{\mathcal{T}_h^*}|\boldsymbol{y}]}{[\boldsymbol{\mathcal{T}_h^m}|\boldsymbol{y}]}$ we have the likelihood contributions

$$\frac{[\boldsymbol{y}_{\mathrm{L}}, \boldsymbol{y}_{\mathrm{R}}|\boldsymbol{\mathcal{T}_h^*}]}{[\boldsymbol{y_n}|\boldsymbol{\mathcal{T}_h^m}]} = \frac{[\boldsymbol{y}_{\mathrm{L}}|\boldsymbol{\mathcal{T}_h^*}] \, [\boldsymbol{y}_{\mathrm{R}}|\boldsymbol{\mathcal{T}_h^*}]}{[\boldsymbol{y_n}|\boldsymbol{\mathcal{T}_h^m}]}$$

$\boldsymbol{y}_{\mathbf{L}}$: partition for the newborn left leaf node
$\boldsymbol{y}_{\mathbf{R}}$: partition for the newborn right leaf node

Posterior computation for BART

- Similarly, the terms that the prior contributes to the posterior ratio often cancel since there is only one area where the trees differ: either a terminal leaf or a penultimate branch
- Therefore, the prior contribution to $\frac{[\mathcal{T}_h^* | y]}{[\mathcal{T}_h^m | y]}$ is

$$\frac{\mathrm{P}[\psi_n = 1]\,\mathrm{P}[\psi_l = 0]\,\mathrm{P}[\psi_r = 0]\, s_j}{\mathrm{P}[\psi_n = 0]} =$$

$$\frac{\alpha(d(n)+1)^{-\beta}\left[1-\alpha(d(n)+2)^{-\beta}\right]^2 s_j}{1-\alpha(d(n)+1)^{-\beta}}$$

- $\mathrm{P}[\psi_n]$ is the branch regularity prior
  s_j is the splitting variable selection probability
  n is the chosen leaf node in tree $\mathcal{T}_h^m$
  $l = 2n$ is the newborn left leaf node in tree $\mathcal{T}_h^*$
  $r = 2n + 1$ is the newborn right leaf node in tree $\mathcal{T}_h^*$

Posterior computation for BART

- Finally, the ratio $\frac{[\mathcal{T}_h^m | \mathcal{T}_h^*]}{[\mathcal{T}_h^* | \mathcal{T}_h^m]}$ is

$$\frac{[\mathbf{DEATH} | \mathcal{T}_h^*] \, [n | \mathcal{T}_h^*]}{[\mathbf{BIRTH} | \mathcal{T}_h^m] \, [n | \mathcal{T}_h^m] \, s_j}$$

- $[n | \mathcal{T}_h]$ is the probability of choosing node n given tree $\mathcal{T}_h$
- N.B. s_j appears in both the numerator and denominator of the acceptance probability $\pi_{\mathbf{BIRTH}}$, therefore, canceling which is mathematically convenient

Posterior computation for weighted BART

$$y_i = f(x_i) + \epsilon_i \text{ where } f \overset{\text{prior}}{\sim} \text{BART}$$
$$\epsilon_i \sim \mathrm{N}\left(0,\ w_i{}^2\sigma^2\right)$$

BART variant	Weights	Comment
Homoskedastic	$w_i = 1$	*Chipman, George et al. 2010*
Weighted		Non-trivial known weights (circa 2015)
Heteroskedastic	$w_i = s(x_i)$	$s^2 \overset{\text{prior}}{\sim} \text{HBART}$ *Pratola, Chipman et al. 2020*

- Until now, we have not dwelled on BART variants
- From here on, we will focus on weighted BART
- This development extends the homoskedastic variant and naturally incorporates heteroskedastic BART

Posterior computation for weighted BART: BIRTH

- Based on the centered data: $y_i = \tilde{y}_i - \mu$
- Given that the nth leaf only depends on $(y_{i'}, w_{i'})$ where $i' = 1, \ldots, m_n$

$$w_n = \sum_{i'} w_{i'} = w_L + w_R \qquad \xi_n = \sum_{i'} w_{i'} y_{i'} = \xi_L + \xi_R$$

$$\mu_{hl} \overset{\text{prior}}{\sim} \mathrm{N}\left(0,\ \sigma_0^2\right) \qquad \sigma_0^2 = \frac{\tau^2}{4H\kappa^2}$$

$$\begin{aligned}
[y_n|\mathcal{T}_h] &= \int [\mu_n]\,[y_n|\mathcal{T}_h, \mu_n]\,\mathrm{d}\mu_n \\
&\propto \omega_n \exp\left(0.5\sigma_0^2 \xi_n^2 \omega_n^2\right) & \omega_n &= (\sigma_0^2 w_n + 1)^{-0.5} \\
[y_L|\mathcal{T}_h] &\propto \omega_L \exp\left(0.5\sigma_0^2 \xi_L^2 \omega_L^2\right) & \omega_L &= (\sigma_0^2 w_L + 1)^{-0.5} \\
[y_R|\mathcal{T}_h] &\propto \omega_R \exp\left(0.5\sigma_0^2 \xi_R^2 \omega_R^2\right) & \omega_R &= (\sigma_0^2 w_R + 1)^{-0.5}
\end{aligned}$$

Posterior computation for weighted BART: BIRTH

- After cancellation of terms in the ratio $\frac{[\mathcal{T}_h^*|y]}{[\mathcal{T}_h^m|y]}$ we have the likelihood contributions

$$\frac{[y_{\mathrm{L}}, y_{\mathrm{R}}|\mathcal{T}_h^*]}{[y_n|\mathcal{T}_h^m]} = \frac{[y_{\mathrm{L}}|\mathcal{T}_h^*]\,[y_{\mathrm{R}}|\mathcal{T}_h^*]}{[y_n|\mathcal{T}_h^m]}$$
$$= \omega_L \omega_R \omega_n^{-1} \exp 0.5\sigma_0^2 \left(\xi_L^2\omega_L^2 + \xi_R^2\omega_R^2 - \xi_n^2\omega_n^2\right)$$

Posterior computation for weighted BART: the leaves

- Based on the centered data: $y_i = \tilde{y}_i - \mu$
- Given $\mathcal{T}_h$, suppose that the lth leaf, μ_{hl}, only depends on $(y_{i'}, w_{i'})$ where $i' = 1, \dots, m_{hl}$
- Define the residuals, $z_{i'}$, due to everything except $(\mathcal{T}_h, \mathcal{M}_h)$

$$z_{i'} = y_{i'} - \sum_{h' \neq h} g(x_{i'}; \mathcal{T}_{h'}, \mathcal{M}_{h'})$$

$$\sim \mathrm{N}\left(\mu_{hl},\ w_{i'}^2 \sigma^2\right)$$

$$\bar{z}_{\cdot} = \mathrm{N}\left(\mu_{hl},\ \eta_{hl}^{-1}\right) \qquad \eta_{hl}^{-1} = \frac{\sigma^2}{m_{hl}^2} \sum_{i'} w_{i'}^2$$

$$\mu_{hl} \overset{\text{prior}}{\sim} \mathrm{N}\left(0,\ \eta_0^{-1}\right) \qquad \eta_0^{-1} = \frac{\tau^2}{4H\kappa^2}$$

$$\mu_{hl} | (\mathcal{T}_h, y) \sim \mathrm{N}\left(\frac{\eta_{hl} m_{hl} \bar{z}_{\cdot}}{\eta_0 + \eta_{hl} m_{hl}},\ \frac{1}{\eta_0 + \eta_{hl} m_{hl}}\right)$$

Posterior computation for BART: uncertainty intervals

- Suppose that we want to estimate f at some value x whether from the training or testing
- The standard Bayesian estimate is $\hat{f}(x) = M^{-1} \sum_m f_m(x)$
- Construct a Bayesian $(1-\alpha) \times 100\%$ credible interval from the $\alpha/2$ and the $1-\alpha/2$ quantiles of the posterior
- $(f_{(\alpha/2)}(x), f_{(1-\alpha/2)}(x))$
- Construct a Bayesian $(1-\alpha) \times 100\%$ prediction interval
- Generate $\tilde{y}$ from the predictive distribution: $\tilde{y}_m \sim \mathrm{N}\big(f_m(x),\ \sigma_m^2\big)$
- Select the $\alpha/2$ and the $1-\alpha/2$ quantiles of $\tilde{y}$
- $(\tilde{y}_{(\alpha/2)}, \tilde{y}_{(1-\alpha/2)})$