Implementation Notes

Issues

- Under setting 1 and 2: 5% and 10% quantiles are a bit low as compared to the data points. Similarly, 90% and 95% quantiles are a bit high as compared to the data points. I think the reason is, $K \sim Normal$ and `mainly` because $G_0 = unif(0,1)$. Should we use $G_0 \equiv unif(a_0, b_0)$ with $0 < a_0 < b_0 < 1$? eg, $a_0 = max(0, min(y) - \sigma_0)$ and $b_0 = min(1, max(y) + \sigma_0)$? `ToDo`
- Sure bugs in logprior and loglikelihood functions. `ToDo`
- Uniform for both kernel K and centering dist G_0. For this, should we take $G_0 \equiv unif(c, 1-c)$ for $K(y \mid z) \equiv unif(z-c, z+c)$ in order to ensure $y \in [0,1]$? Also, $z_i \in [y_i - c, y_i + c]$. `ToDo`
- Choice of β prior? using $N(\mu_\beta, \Sigma_\beta)$ with hyperparameter estimates coming from spglm (also, we can get that from classical glm), how about diffuse priors eg $N(0, 1000 * I_p)$? `ToDo`
- Problem in *thetaStart* `Fix` set to NULL. `Done`

Major Problems

- No $\tilde{z}$ in between 0.2 - 0.5, which is giving absurd quantile jump for lower ages (< 50 months). is this due to: only 9% y is less than 0.5, so do we need to be more restrictive in that region on constructing our priors? very small $\hat{\sigma}_i$ in $K(y_i \mid z_i, \hat{\sigma}_i)$? or, better to put prior on σ_i? how about normal for K with small $\hat{\sigma}_i$? it would automatically restrict $z \in [0,1]$. `Fixed` using $\hat{\sigma}_i = \hat{\sigma} = 0.001$ (best if used 0.0005, median(se($\hat{\mu}$)) is 0.005, with min(se($\hat{\mu}$)) is 0.002)
- `NA` in probability vector: in z_sampler function. This is is happening when $\tilde{J}_\ell$ is very small, then problem of numerical stability! `Fixed` using prob $\leftarrow$ log(prob) then prob $\leftarrow$ exp(prob - max(prob))

Keep an eye on

- y versus $\hat{y}$ (why fit is generally bad below 0.5?) Ans: y observations less than 0.5 are sparse (only 9%)

Notes

- current implementation time 1 sec per MCMC iteration
- `iSpline` overfits, `ns` is better

Results (`.rds` files)

- *..without_monotonicity0150pm*: `ns`, $M = 15$, $\alpha = 10$, K & $G_0 = 1$, $\hat{\sigma}_i = 0.01$ (setting 1)
- *..without_monotonicity0232pm*: `ns`, $M = 20$, $\alpha = 10$, $K = 1$, $G_0 = 6 = unif(0, 1)$, $\hat{\sigma}_i = 0.05$ (setting 2)
- *MCMC_output3*: `ns`, $M = 20$, $\alpha = 1$, $K(\cdot \mid z) = unif(z - 0.25, z + 0.25)1_{[0,1]}(\cdot)$, $G_0 = 6 = unif(0, 1)$ (setting 3) `ToDo`

Uniform Kernel K

Quantile for $K(\cdot \mid z) = unif(z - c, z + c)1_{[0,1]}(\cdot)$:

$$
\begin{aligned}
q_\alpha(x) = \frac{\alpha + B_x}{A_x}, \text{ with } A_x &= \sum_{\ell=1}^{L} \frac{p_{\ell,x}}{min(1, z_\ell + c) - max(0, z_\ell - c)} \text{ and} \\
B_x &= \sum_{\ell=1}^{L} \frac{p_{\ell,x} * max(0, z_\ell - c)}{min(1, z_\ell + c) - max(0, z_\ell - c)}, \text{ where} \\
p_{\ell,x} &= \frac{\exp(\theta_x z_\ell) J_\ell}{\sum_{r=1}^{L} \exp(\theta_x z_r) J_r}
\end{aligned}
$$

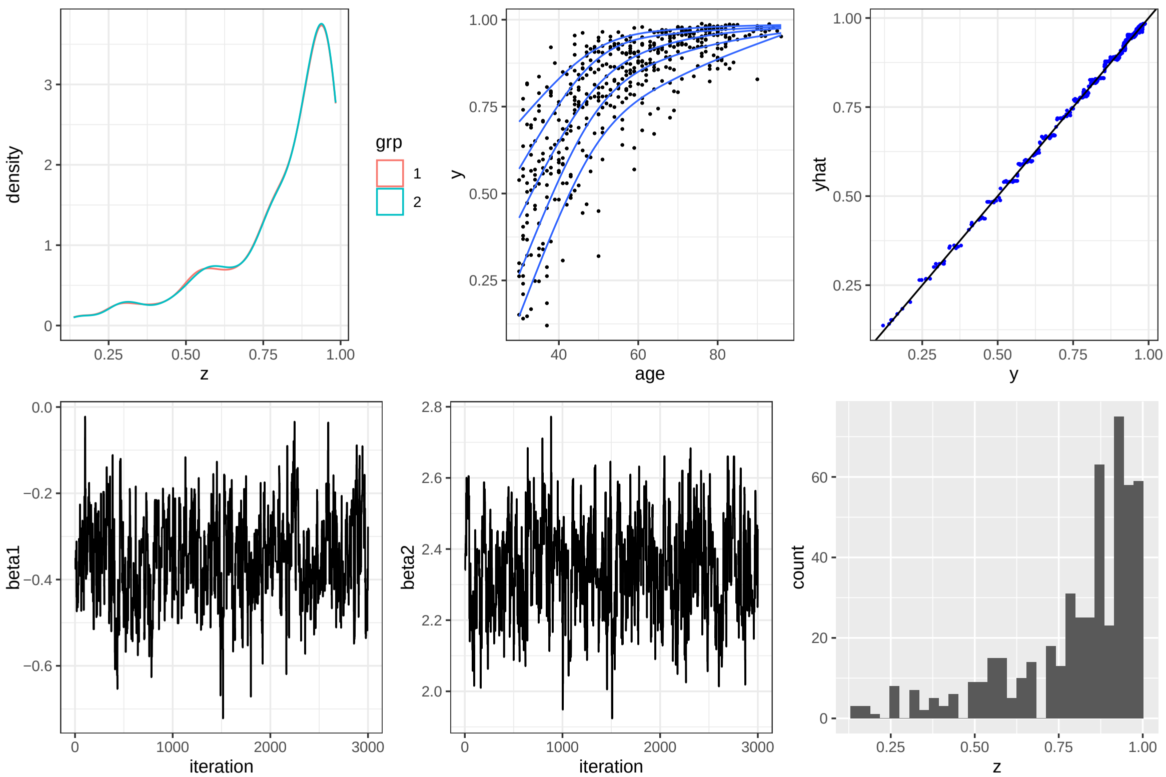

Figure 1: MCMC diagnostics

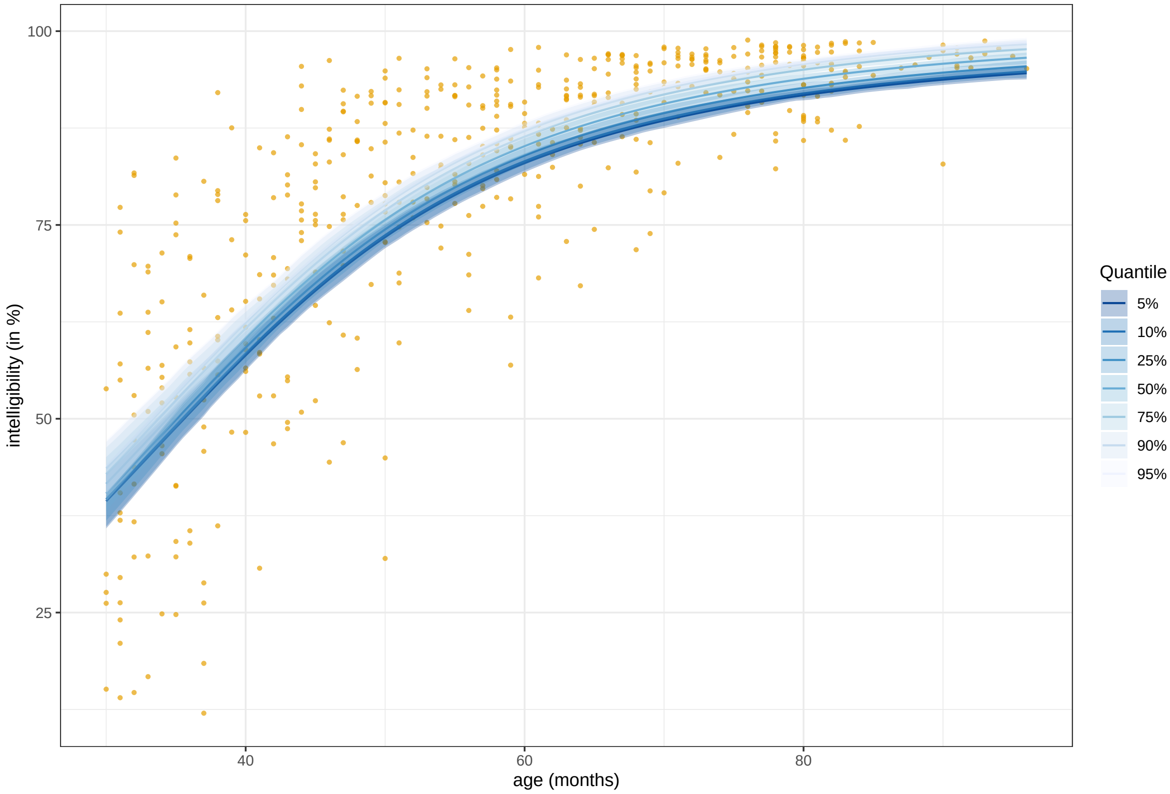

Figure 2: Quantiles and Uncertainties