Chapter 1

Appendix

he eror term in the by Gelman *et al.* (2017) proposed definition of the R^2 is defined as $\mathrm{Var}(\sum_{i=1}^{n} e_n^s)$. I think we could also use $\sum(y - \hat{y}^s)^2/(n-1)$ as an estimate for the error. For the maximum likelihood estimate $\mathrm{Var}(y_i - \hat{y}_i) = \sum(y_i - \hat{y}_i)^2/(n-1)$. This is because the mean of the residuals is 0. When samples of the posterior parameters are used, the mean of the residuals is not excatly zero. $\mathrm{Var}(y_i - \hat{y}_i) = \sum(y_i - \hat{y}_i)^2/(n-1)$ is than a little bit bigger than $\mathrm{Var}(y_i - \hat{y}_i)$. In practice the values should only differ by a very small amount. We do not expect the errors to have a systematic bias. However, the residuals are just a sample of the error. The mean of the residuals must not be excatly 0 when the samples of the posteriors are used for the regression coefficients.

Bibliography

Gelman, A., Goodrich, B., Gabry, J., and Ali, I. (2017). R squared for Bayesian regression models *. Technical report. 1