Today's big idea in data science

Laplace's big idea (1810). Central Limit Theorem.

The sum of many individual stochastic processes, each of which could come from any of a variety of distributions, tends to a normal distribution. (Extending De Moivre who showed the same for binomial processes in 1733). McElreath Ch 4.

Language for describing models

e.g. a linear model $y_i \sim \text{Normal}(\mu_i, \sigma)$ $\mu_i = \beta_0 + \beta_1 x_i$ $\beta_0 \sim \text{Normal}(178,100)$ $\beta_1 \sim \text{Normal}(0,10)$ $\sigma \sim \text{Uniform}(0,50)$

Mean model

In the book:

$$y_i \sim \text{Normal}(\mu, \sigma)$$

 $\mu \sim \text{Normal}(178,100)$
 $\sigma \sim \text{Uniform}(0,50)$

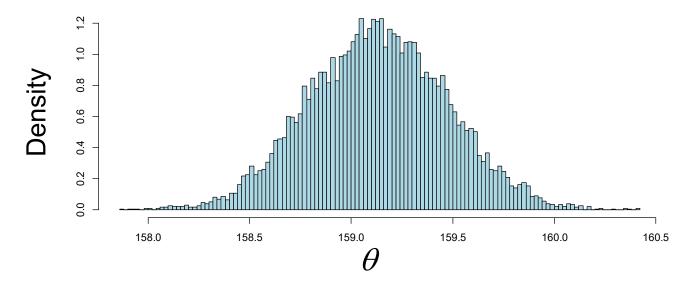
Alternative:

$$y_i \sim \text{Normal}(\mu_i, \sigma)$$

 $\mu_i = \beta_0$
 $\beta_0 \sim \text{Normal}(178,100)$
 $\sigma \sim \text{Uniform}(0,50)$

Thus, the mean is a special case of the linear model

Histogram is the posterior distribution

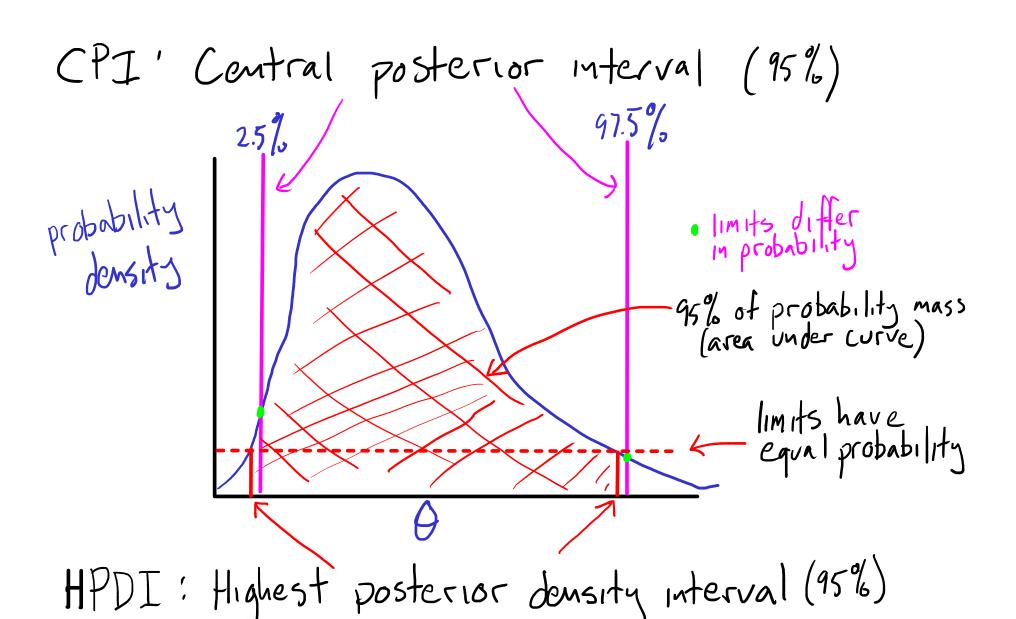


 Obtain all our inferences (means, credible intervals, prediction intervals) from the posterior samples

 Credible intervals are probabilities for model quantities (e.g. parameters or the average relationship)

Credible intervals

- Plausibility intervals
- HPDI vs CPI



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- What do you think about 89% intervals?

- You can derive quantities (e.g. height at weight 50 kg) from the posterior samples
- Correlation among parameters can be obtained from the posterior samples
- Flat priors correspond to non-Bayesian approaches. Useful but there often better alternatives

- Polynomials: nonlinear models that are linear in the parameters
- Centering can help the training algorithm converge
- Standardizing allows you to compare predictors on a common scale

My recommendations: points of departure

- Plot histograms instead of densities
- Credible intervals usually make the most sense (most coherent) compared to central posterior intervals
 - calculate HPDI
 - unless CPI is more stable estimate of HPDI
- Don't use the quadratic approximation (also called Laplacian approximation)
 - always use MCMC