Rapid-fire bayes intro

29 Nov 2024

inference

- typically based on *marginal distributions* (integrate over nuisance variables)
- $$P(\theta_1|y) = \iint P(\theta_1, \theta_2, \dots |y)\, d\theta_2 \dots d\theta_n)$$
- can also look at bivariate distributions etc.
- can propagate distributions to any derived quantity, e.g. model predictions: we have a sample of θ values, so compute $f(\theta)$ and get the full posterior distribution

summary statistics

- location: mode vs mean vs median
- interval/region: highest posterior density vs quantiles
- for *symmetric unimodal* distributions, all equivalent
- criteria:
  - scale-independence
  - robustness
  - Bayesian coherence

priors

- nothing is 'uninformative'
- scale dependence (continuous), aggregation dependence (categorical)
- e.g. log-uniform vs uniform, logit-normal with wide variance
- we usually assume independence, which can make trouble
  - e.g. U(0,1) × U(0,1) for baseline and treatment effect; what if we change fom `~1 + ttt` to `~0 + ttt` (i.e. treatment mean parameterization)?

- uniform priors are dicey ("Cromwell's rule")
- **prior predictive simulations**

prior rules of thumb

- think about a reasonable range for the parameter (L, U)
- consider a (univariate) Gaussian prior
- $±2 SD ≈95% range
- mean = $(L+U)/2$; SD $\approx (U-L)/4$
- could make tails fatter
    - t, Cauchy
- ... or thinner
    - power-exponential priors
- easier/more universal for log/logit-scales
- e.g. consider a proportional range from (0.001x to 1000x) $\to (-3,3) \times \ln(10) = (-6.9, 6.9) \to$ SD $= 6.9/2 = 3.45$