Previously on MA40189:

- the Jeffreys prior

$$f(\theta) \propto det(I(\theta))^{\frac{1}{2}}$$

where $I(\theta)$ is the Fisher information matrix,

$$\begin{aligned}(I(\theta))_{ij} &= E\left\{\frac{\partial}{\partial\theta_i}\log f(x\,|\,\theta)\frac{\partial}{\partial\theta_j}\log f(x\,|\,\theta)\,\middle|\,\theta\right\} \\ &= -E\left\{\frac{\partial^2}{\partial\theta_i\partial\theta_j}\log f(x\,|\,\theta)\,\middle|\,\theta\right\}\end{aligned}$$

Today on MA40189:

- invariance of Jeffreys' prior: $\phi = g(\theta)$ same answer if
  1. find $f_\phi(\phi)$ by transforming $f_\theta(\theta)$
  2. find $f_\phi(\phi) \propto det(I(\phi))^{\frac{1}{2}}$
- final remarks about noninformative priors
  - Jeffreys' prior depends upon the form of the data and violates the likelihood principle
  - improper priors do not always lead to proper posteriors
- Bayesian computation: calculate posterior summaries from distributions $f(\theta\,|\,x) = cg(\theta)$ which are
  - mathematically complex
  - often high dimensional