

Previously on MA40189:

- posterior $f(\theta | x) = cg(\theta)$ where $g(\theta) \propto f(x | \theta)f(\theta)$
- worked with tractable distributions and identified c by recognising $g(\theta)$ as a **kernel** of a familiar parametric family
- final remarks about noninformative priors
 - Jeffreys' prior depends upon the form of the data and violates the **likelihood principle**

Today on MA40189:

- final remarks about noninformative priors (concluded)
 - 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
- **Normal approximation** about the **mode** $\tilde{\theta}$
- $\theta | x \sim N(\tilde{\theta}, I^{-1}(\tilde{\theta} | x))$ where $I(\theta | x)$ is the **observed information**,

$$I(\theta | x) = -\frac{\partial^2}{\partial \theta^2} \log f(\theta | x)$$