

# Bayesian Models

A Quick Review...

Frequentist Approach

$$\operatorname{argmax}_{\theta} P(x|\theta)$$

Bayesian Approach

$$\operatorname{argmax}_{\theta} \underbrace{P(\theta|x)}_{\text{posterior}}$$

In Bayesian models, we take the Bayesian approach to estimating parameters.

$$\hat{\theta} = \operatorname{argmax}_{\theta} P(\theta|x) = \operatorname{argmax}_{\theta} \frac{P(x|\theta)P(\theta)}{P(x)}$$

$$= \operatorname{argmax}_{\theta} \underbrace{P(x|\theta)}_{\text{likelihood}} \underbrace{P(\theta)}_{\text{prior}}$$

Posterior Mean  
 $E[\theta|x]$

Reason for using a prior: computational convergence

$$P(\theta|x) = \frac{P(x|\theta)P(\theta)}{P(x)} \quad \left\{ \int P(x|\theta)P(\theta)d\theta \right.$$

If we don't assume a distribution over  $\theta$ s, we must integrate over all possible prior distributions.



If we choose a prior, the integral in the denominator becomes tractable

$$\therefore P(\theta|x) \propto P(x|\theta)P(\theta)$$

How do I choose a prior?

Typically, the posterior and the prior are from the same family of distributions.

A prior is a conjugate prior for a given likelihood distribution if the resulting posterior has the same form as the prior.

Example: Poisson-Gamma Conjugacy

Poisson:  
Likelihood

$$P(x|\theta) = \frac{e^{-n\lambda} \lambda^{\sum x_i}}{\prod_{i=1}^n x_i!} = P(x|\lambda)$$

Gamma:  
Prior

$$P(\theta) = \frac{\beta^\alpha}{\Gamma(\alpha)} \lambda^{\alpha-1} e^{-\beta\lambda} = P(\lambda|\alpha, \beta)$$

$$P(x|\theta)P(\theta) = \left( \frac{e^{-n\lambda} \lambda^{\sum x_i}}{\prod_{i=1}^n x_i!} \right) \left( \frac{\beta^\alpha}{\Gamma(\alpha)} \lambda^{\alpha-1} e^{-\beta\lambda} \right)$$

$$= \frac{\beta^\alpha \lambda^{\sum x_i + \alpha - 1} e^{-\lambda(n+\beta)}}{\prod_{i=1}^n x_i! \Gamma(\alpha)} \propto \frac{(n+\beta)^\alpha \lambda^{\sum x_i + \alpha - 1} e^{-\lambda(n+\beta)}}{\Gamma(\sum x_i + \alpha)}$$

↑  
proportional to

$$= \text{Gamma}(\sum x_i + \alpha, n+\beta) \rightarrow P(\theta|x)$$