A Brief Intro to Bayesian Inference

Thomas Bayes (c. 1701 – 1761)

$$P(A \mid B) = \frac{P(B \mid A)P(A)}{P(B)}$$

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Tossing a Coin, Again

- Suppose the coin came up Heads 65 times and Tails 35 times. Is the coin fair?
- Model: $P(heads) = \theta$
- Log-likelihood: $\log P(data|\theta) = 65 \log \theta + 35 \log(1 - \theta)$
  - Maximized at $\theta = .65$
- But would you conclude that the coin really is not fair?

Prior Distributions

- We can encode out beliefs about what the values of the parameters could be using $P(\theta)$
- Using Bayes' rule, we have

likelihood

Prior

$$P(\theta = \theta_0|\text{data}) = \frac{\mathrm{P}(\theta{=}\theta_0,data)}{P(data)} = \frac{P(data|\theta = \theta_0)P(\theta{=}\theta_0)}{P(data)}$$

$$= \sum_{\theta_1} P(data|\,\theta = \theta_1)\,P(\theta = \theta_1)$$

Maximum a-posteriori (MAP)

- Maximize the *posterior probability* of the parameter:

$$argmax_{\theta_0} \frac{P(data|\theta = \theta_0)P(\theta=\theta_0)}{P(data)}$$

$$= argmax_{\theta_0} P(data|\theta = \theta_0)P(\theta = \theta_0)$$

$$= argmax_{\theta_0} \log P(data|\theta = \theta_0) + \log P(\theta = \theta_0)$$

- The posterior of probability is the product of the prior and the data likelihood
- Represents the *updated* belief about the parameter, given the observed data

Aside: Bayesian Inference is a Powerful Idea

- You can think about anything like that. You have your prior belief $P(\theta)$, and you observe some new data. Now your belief about θ *must be* proportional to $P(\theta)P(data|\theta)$
  - But only if you are 100% sure that the likelihood function is correct!
  - Recall that the likelihood function is your model of the world – it represents knowledge about how the data is generated for given values of θ
  - Where do you get your original prior beliefs anyway?
- Arguably, makes more sense than Maximum Likelihood

Back to the Coin

- (In Python)