

Homework 6: Frequentists vs Bayesians

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DO NOT POLLUTE! AVOID PRINTING, OR PRINT 2-SIDED MULTIPAGE.**Problem 6.1. Frequentist (MLE)**

To find the MLE of p^* , we first start with the likelihood function:

$$\mathbb{P}(p^*) = \prod_{i=1}^n (p^{x_i} (1-p)^{1-x_i})$$

Then we take the log of the likelihood function:

$$\log(\mathbb{P}(p^*)) = \log p \sum_{i=1}^n x_i + \log(1-p) \sum_{i=1}^n (1-x_i)$$

Using our optimization 101 technique, we get the derivative and set it equal to zero:

$$p_{MLE} = \frac{1}{n} \sum_{i=1}^n x_i$$

Which we recognize to just be the mean.

Problem 6.2. Bayesian (MAP)

We use our MAP formula $p_{MAP} = \arg \max_p \mathbb{P}(X|p)$ as our starting point. Using Bayes Rule, we can rearrange it as such:

$$p_{MAP} = \arg \max_p \frac{\mathbb{P}(X|p)\mathbb{P}(p)}{\mathbb{P}(X)}$$

Since we're maximizing for p , we can ignore the $\mathbb{P}(X)$ term as it doesn't depend on p :

$$p_{MAP} = \arg \max_p \mathbb{P}(X|p)\mathbb{P}(p)$$

This is very similar to our MLE statement above, with the exception of our prior term $\mathbb{P}(p)$ which we're assuming is information gathered about a previous event. Notably, if there is no prior information, our MAP estimate is equal to our MLE.

Given our prior $\mathbb{P}(p)$ being modeled as $Beta(\alpha, \beta)$, we can show our prior below:

$$\mathbb{P}(p) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} p^{\alpha-1} (1-p)^{\beta-1}$$

Using the prior information, the likelihood of our data (we'll say $X = [x_1, x_2, \dots, x_N]^T$) can be written as:

$$\mathbb{P}(X|p) = p^{\sum_{i=1}^N x_i} (1-p)^{N - \sum_{i=1}^N x_i} = p^{1^T X} (1-p)^{N - 1^T X}$$

Simplifying and matching with the form of a Beta distribution, we find our MAP estimator to be:

$$\hat{p}_{MAP} = \frac{\sum_{i=1}^N x_i + \alpha - 1}{N + \alpha + \beta - 2}$$

Problem 6.3

(a)

(b)

Problem 6.4

(a)

(b)

Problem 6.5