

Problem Set 1 Solutions

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QUESTION ONE

1 Gamma Prior for Poisson Distribution

The Poisson likelihood function for a sample y_1, \dots, y_n is:

$$\begin{aligned} L(\theta|y_1, \dots, y_n) &= \prod_{i=1}^n \frac{\theta^{y_i} e^{-\theta}}{y_i!} \\ &= \theta^{\sum y_i} e^{-n\theta} \prod_{i=1}^n \frac{1}{y_i!} \end{aligned}$$

The prior distribution is assumed to be Gamma:

$$p(\theta) = \frac{\beta^\alpha}{\Gamma(\alpha)} \theta^{\alpha-1} e^{-\beta\theta}$$

The posterior is proportional to:

$$\begin{aligned} p(\theta|y_1, \dots, y_n) &\propto L(\theta|y_1, \dots, y_n)p(\theta) \\ &\propto \theta^{\sum y_i} e^{-n\theta} \times \theta^{\alpha-1} e^{-\beta\theta} \\ &\propto \theta^{(\alpha+\sum y_i)-1} e^{-(\beta+n)\theta} \end{aligned}$$

Since this matches the form of a Gamma distribution:

$$\theta|y_1, \dots, y_n \sim G(\alpha + \sum y_i, \beta + n)$$

Thus, the Gamma distribution is a conjugate prior for the Poisson likelihood.

2 Maximum Likelihood Estimation (MLE)

The log-likelihood function for the Poisson distribution is:

$$\log L(\theta) = \sum_{i=1}^n [y_i \log \theta - \theta - \log(y_i!)]$$

Taking the derivative with respect to θ and setting it to zero:

$$\frac{d}{d\theta} \sum y_i \log \theta - n\theta = \frac{\sum y_i}{\theta} - n = 0$$

Solving for θ :

$$\hat{\theta} = \frac{\sum y_i}{n} = \bar{y}$$

Thus, the MLE for θ is \bar{y} .

3 Posterior Mean as a Weighted Average

From the conjugate prior result, the posterior mean is:

$$E[\theta|y] = \frac{\alpha + \sum y_i}{\beta + n}$$

Rewriting it:

$$\begin{aligned} E[\theta|y] &= \frac{\alpha}{\beta + n} + \frac{\sum y_i}{\beta + n} \\ &= \left(\frac{\beta}{\beta + n} \right) \frac{\alpha}{\beta} + \left(\frac{n}{\beta + n} \right) \bar{y} \end{aligned}$$

This expresses the posterior mean as a weighted average of the prior mean $\frac{\alpha}{\beta}$ and the MLE \bar{y} .

4 Effect of Increasing Sample Size

As $n \rightarrow \infty$, the weight on the prior mean $\frac{\beta}{\beta+n}$ approaches 0, while the weight on the MLE $\frac{n}{\beta+n}$ approaches 1. This means the influence of the prior diminishes as the sample size increases, making the posterior distribution more dependent on the observed data

QUESTION TWO

5 Posterior Distribution for θ_1

The Dirichlet prior is:

$$(\theta_1, \dots, \theta_6) \sim \text{Dir}(2, 2, 2, 2, 2, 2)$$

Using the data from the table:

5.1 For $n = 100$

$$\begin{aligned}\theta_1 | \text{data} &\sim \text{Beta}(19 + 2, 100 - 19 + 10) \\ &= \text{Beta}(21, 91)\end{aligned}$$

5.2 For $n = 1000$

$$\begin{aligned}\theta_1 | \text{data} &\sim \text{Beta}(190 + 2, 1000 - 190 + 10) \\ &= \text{Beta}(192, 820)\end{aligned}$$

6 Comparison of Posterior Distributions

The figure below shows the posterior distributions for θ_1 using both sample sizes.

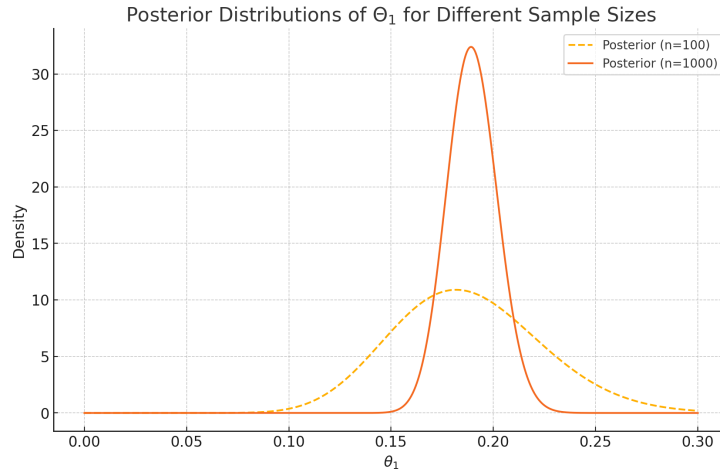


Figure 1: Posterior distributions for different sample sizes

Observations:

- The posterior distribution with $n = 100$ is wider, indicating more uncertainty.
- The posterior with $n = 1000$ is more concentrated around its mean, showing that a larger sample size reduces uncertainty.
- As n increases, the influence of the prior diminishes, and the posterior is more dominated by the data.