



[Lecture 18: Jeffreys Prior and](#)

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> 5. Improper Prior: Example

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Examples

estimations.

$$\pi(p|X_1, \dots, X_n) \propto p^{\sum_{i=1}^n X_i} (1-p)^{n - \sum_{i=1}^n X_i} = L_n(X_1, \dots, X_n | p)$$

i.e., the posterior distribution is

$$\text{Beta}\left(1 + \sum_{i=1}^n X_i, 1 + n - \sum_{i=1}^n X_i\right)$$

► If $\pi(\theta) = 1, \forall \theta \in \mathbb{R}$ and given $X_1, \dots, X_n | \theta \stackrel{i.i.d.}{\sim} \mathcal{N}(\theta, 1)$:

$$\pi(\theta|X_1, \dots, X_n) \propto \exp\left(-\frac{1}{2} \sum_{i=1}^n (X_i - \theta)^2\right)$$

i.e., the posterior distribution is

$$\mathcal{N}\left(\bar{X}_n, \frac{1}{n}\right)$$

▶ 10:22 / 10:22

▶ 1.50x



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Gaussian Prior on Gaussian Observations

2/2 points (graded)

Let X_1, X_2, \dots, X_n be random variables; which are i.i.d., conditional on θ , and such that,

$$p(X_i|\theta) = N(\theta, 1),$$

where $p(X_i|\theta)$ is the conditional density of X_i given θ . Furthermore, we assume the prior $\pi(\theta) \sim N(\mu, 1)$. Let

$$\pi(\theta|X_1, \dots, X_n) \sim N(\alpha, \beta^2).$$

Find, α and β^2 .

- $\alpha =$

☒ $\frac{1}{n+1}((\sum_{i=1}^n X_i) + \mu)$

☐ $\frac{1}{n}(\sum_{i=1}^n X_i + \mu)$

☐ $\frac{1}{n+1}(\sum_{i=1}^n X_i) + \mu$

☐ $\frac{1}{n}(\sum_{i=1}^n X_i)$



- $\beta^2 =$

☒ $\frac{1}{n+1}$

☐ $\frac{1}{n}$

☐ $\frac{\mu}{n}$

$$\frac{\mu}{n+1}$$



Solution:

We begin by recalling that,

$$\begin{aligned}\pi(\theta|X_1, \dots, X_n) &\propto p_n(X_1, \dots, X_n|\theta) \pi(\theta) \\ &\propto \exp\left(-\frac{1}{2} \sum_{i=1}^n (X_i - \theta)^2\right) \exp\left(-\frac{1}{2}(\theta - \mu)^2\right).\end{aligned}$$

We now study the last quantity, keeping in mind that, Gaussian distribution is a conjugate prior of itself; hence, we expect the resulting distribution to be a Gaussian. For this, we need to arrive at a formula of the form,

$$\exp\left(-\frac{1}{2} \sum_{i=1}^n (X_i - \theta)^2\right) \exp\left(-\frac{1}{2}(\theta - \mu)^2\right) \propto \exp\left(-\frac{1}{2\beta^2}(\theta - \alpha)^2\right).$$

Now, we begin doing the algebra, after removing exp's from both sides.

$$\begin{aligned}&-\frac{1}{2} \sum_{i=1}^n (X_i - \theta)^2 - \frac{1}{2}(\theta - \mu)^2 \\ &= -\frac{1}{2} \left((n+1)\theta^2 - 2\theta \left(\sum_{i=1}^n X_i + \mu \right) \right) + C \\ &= -\frac{n+1}{2} \left(\theta^2 - 2\theta \frac{[\sum_{i=1}^n X_i] + \mu}{n+1} \right) + C \\ &= -\frac{1}{2(n+1)^{-1}} (\theta - \alpha)^2 + C',\end{aligned}$$

where C and C' 's are constants; and,

$$\alpha = \frac{1}{n+1} \left(\left[\sum_{i=1}^n X_i \right] + \mu \right) \quad \text{and} \quad \beta^2 = \frac{1}{n+1}.$$

This is, essentially, the same formula as derived in the lecture, except that n is replaced with $n + 1$ (since we have a prior now), and the summation also takes μ into account. In a sense, you may view this as, $n + 1$ observations, where the first n are X_1, \dots, X_n and the last one is from $N(\mu, 1)$.

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i Answers are displayed within the problem

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💬 If you are stuck on this one, consider referencing Lecture 15 from 6.431x
It discusses recognizing normal PDFs and their mean and variance when they are represented in perhaps a less familiar fashion.

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