

### 3. Choosing a Prior

#### Choosing a Prior

Examples

► If  $p \sim \mathcal{U}(0, 1)$  and given  $p$ ,  $X_1, \dots, X_n \stackrel{i.i.d.}{\sim} \text{Ber}(p)$ :

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

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  $X_1, \dots, X_n | \theta \stackrel{i.i.d.}{\sim} \mathcal{N}(\theta, 1)$ :

$$\pi(\theta|X_1, \dots, X_n) \propto \exp$$

i.e., the posterior distribution is

to p.

So it's the joint distribution of the  $x_i$ .

So if I were to integral-- integrate this with respect to the  $x_i$ , I would certainly get 1.

But what I'm interested in is integrating with respect to  $p$ .

So there's no reason why this thing should integrate to 1.

And so the coefficient of proportionality we have is just the integral of the log likelihood with respect

to  $p$ .

► 9:32 / 9:32

► 1.0x

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### Uniform Priors: True or False

1/1 point (graded)

Select from the following statements the **true** ones for uniform priors. (In this question, we also allow **improper** priors.)

☐ They can be defined only on parameter sets  $\Theta$  with a finite number of possible values.

☐ They should integrate to 1 (or if the distribution is discrete; should sum to 1)

☒ They reflect an equal belief in each possible hypothesis. ✓

☒ The maximum a-posteriori and maximum likelihood estimators when using such a prior would always be the same. ✓



#### Solution:

- The first choice is false. As discussed in the lecture, they can be defined on infinite sets or even non-discrete distributions with an uncountably infinite number of possible parameter values.
- The second choice is also false. If  $\pi(\cdot)$  is improper, then it will definitely not integrate to 1 by definition.
- The third choice is correct. A uniform prior reflects an "equal" belief in each of the possible hypothesis.

- The last choice is also correct. Recall that the maximum-a-posterior estimator maximizes  $\pi(\theta|X_1, \dots, X_n)$  while the maximum likelihood estimator maximizes  $L_n(X_1, \dots, X_n|\theta)$ , both taken as functions of  $\theta$ . By Bayes' rule, we have that

$$\pi(\theta|X_1, \dots, X_n) \propto L_n(X_1, \dots, X_n|\theta) \pi(\theta) \propto L_n(X_1, \dots, X_n|\theta),$$

where the first proportionality is due to Bayes' rule and the second proportionality is due to  $\pi(\cdot)$  being uniform. The two statistics, when taken as a function of  $\theta$ , are therefore identical up to a constant of proportionality. Hence, while the maximum values might be different, the value of  $\theta$  attaining the maximum for both quantities are the same.

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You have used 3 of 3 attempts

**i** Answers are displayed within the problem

Beta Distribution: True or False

1/1 point (graded)  
One specific prior discussed in the previous lecture is the Beta distribution, which was then demonstrated in a scenario with a Bernoulli statistical model. **Which of the following statements is/are true about the Beta distribution**, written as **Beta** ( $\alpha, \beta$ )  $\propto p^{\alpha-1}(1 - p)^{\beta-1}$ ?

- ☒ The Beta distribution is very suited to models where our parameter represents a probability due to its support being  $[0, 1]$ .
- ☐ The Beta distribution is very suited to models where our parameter represents a probability due to its maximum always being close to  $\frac{1}{2}$ .
- ☒ The Beta distribution is very suited to models where our parameter represents a probability because multiplying it by  $p$  or  $1 - p$  simply involves incrementing the respective parameter.



Solution:

The first and third statements are correct.

- **The first statement is correct.** The Beta distribution indeed has support on the interval  $[0, 1]$ , which is also the range of possible probabilities. Thus, using the Beta distribution to model possible parameters  $p$  would allow us to exactly cover the feasible range.
- **The second statement is incorrect.** The Beta family of distributions is very flexible and does not constrain us to symmetric shapes (which happens if we instead use a Gaussian prior). Indeed, if you recall the calculation of modes from the previous lecture, the mode can be at **0** or **1** for certain special cases. In the general case  $\alpha > 1, \beta > 1$ , the mode is at  $\frac{\alpha-1}{\alpha+\beta-2}$ , which could range anywhere in  $(0, 1)$  depending on  $\alpha$  and  $\beta$ .
- **The third statement is correct.** Mathematically, it is easy to see that multiplying the PDF of a Beta distribution by  $p$  or  $1 - p$  increments the  $\alpha$  or  $\beta$  coefficient, respectively, by 1. In practical terms, it is very common in statistical applications, as you've seen in the previous lecture, to multiply the likelihood function by either  $p$  or  $1 - p$  depending on the outcome of a binary trial.

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Discussion

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