

9. Bayes' Formula with the Beta Distribution

Application: Bernoulli Experiment with the Beta Prior

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Bernoulli experiment with a Beta prior

In the Kiss example:

- ▶ $p \sim \text{Beta}(a, a)$:

$$\pi(p) \propto p^{a-1}(1-p)^{a-1}, p \in (0, 1)$$

- ▶ Given p , $X_1, \dots, X_n \stackrel{i.i.d.}{\sim} \text{Bernoulli}(p)$ so
 $L_n(X_1, \dots, X_n | p) =$

- ▶ Hence,

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

- ▶ The posterior distribution is

(Caption will be displayed when you start playing the video.)

12/20

So in the Kiss example, I'm going to have p. I'm going to assume that the prior I have on p is this beta with twice the same parameter. I don't want to have to play with too many parameters, so I'm going to take a beta with parameters of a and a.

So I know that the PDF is up to this beta



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Posterior Update : A Concrete Example

2/2 points (graded)

You are playing a computer game, where at each step you either succeed with probability θ or fail with probability $1 - \theta$. Assume that the outcomes of the games are independent. Based on previous knowledge, you select a prior $\pi(\theta) \sim \text{Beta}(a, b)$.

Assume that you play this game for **12** rounds, with **7** successes and **5** failures. Find the posterior distribution $\pi(\theta | X_1, \dots, X_{12})$.

It is known that the posterior is a Beta distribution, so you just need to state the parameters a' and b' below (the primes simply indicate that these parameters are the updated versions of aforementioned a, b).

$a' =$

a+7

✓ Answer: a+7

$a + 7$

$b' =$

b+5

✓ Answer: b+5

$b + 5$

[STANDARD NOTATION](#)

Solution:

- Note that if we interpret $X_i = 1$ for a success and $X_i = 0$ for a failure, the experiment simply is an instance of i.i.d. Bernoulli trials. $L_n(X_1, \dots, X_n | \theta)$ therefore computes as

$$p_n(X_1, \dots, X_n | \theta) = \theta^{\sum_{i=1}^n X_i} (1 - \theta)^{n - \sum_{i=1}^n X_i}.$$

- Using the update rule for the Beta prior discussed in lecture,

$$\begin{aligned} \pi(\theta | X_1, \dots, X_n) &\propto p_n(X_1, \dots, X_n | \theta) \pi(\theta) \\ &\propto \theta^{a-1} (1 - \theta)^{b-1} \theta^{\sum_{i=1}^n X_i} (1 - \theta)^{n - \sum_{i=1}^n X_i} \\ &\propto \theta^{a + \sum_{i=1}^n X_i - 1} (1 - \theta)^{b + n - \sum_{i=1}^n X_i - 1}. \end{aligned}$$

Therefore, the updated versions are

$$a' = a + \sum_{i=1}^n X_i = a + 7,$$

and

$$b' = b + n - \sum_{i=1}^n X_i = b + 5.$$

Thus,

$$\pi(\theta | X_1, \dots, X_{12}) \sim \text{Beta}(a + 7, b + 5).$$

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You have used 1 of 3 attempts

 Answers are displayed within the problem

Advantages of Bayesian View

0/1 point (graded)

Which one of the following statements below illustrates the advantages of Bayesian view over the frequentist approach?

- ☐ The Bayesian approach gives statisticians some freedom to reflect prior belief. 
- ☒ The Bayesian approach is computationally more tractable. 
- ☐ An estimator that takes the maximum of the posterior distribution obtained via Bayes rule is strictly closer to the actual parameter than the maximum likelihood estimator.

Solution:

The first choice is the correct answer.

- The main power of Bayesian approach comes from the fact that, designer can reflect the prior information in terms of a cleverly-engineered prior distribution.
- The second statement is false. Bayesian approach is actually computationally more expensive: normalizing the posterior distribution (via Bayes' rule) involves computing an integral in the denominator which might not have a simple solution.
- The third item is also false. A counterexample is that the maximum a-posteriori and maximum likelihood are actually the same if one has a uniform prior.