

# The Effect of the Prior On Our Posterior Inference

- With a beta(3,1) prior, our posterior mean was \_\_\_\_\_
- Suppose we had used a beta(12,4) prior (same prior mean, but \_\_\_\_\_ prior variance = \_\_\_\_\_).
- In that case, the posterior mean would be \_\_\_\_\_
  
- When we have \_\_\_\_\_ prior certainty, our Bayesian estimate comes closer to the prior mean than when we have \_\_\_\_\_ prior certainty.
- What if we used a beta(3,2) prior (having prior mean \_\_\_\_\_)?
- Our Bayesian estimate would be \_\_\_\_\_

Prior

Prior Mean

MLE

Posterior Mean

- As the prior mean shifts, the posterior mean shifts with it somewhat.
- Note: With large samples, the sample estimate dominates and the effect of the prior is relatively minor.

Fact: The Bayes estimator of any function  $\tau(\theta)$  of  $\theta$  can be found by the posterior expected value of  $\tau(\theta)$ :

Example 1 again: Find the Bayesian estimator of  $V(Y_i) = p(1-p)$ .

Example 2: Let  $Y_1, \dots, Y_n$  be iid r.v.'s  
with pdf

$$f(y) = \begin{cases} \theta e^{-\theta y} & \text{if } y > 0 \\ 0 & \text{elsewhere} \end{cases}$$

where  $\theta > 0$ . Note this is \_\_\_\_\_  
distribution with mean

- Consider a prior distribution for  $\theta$

Then

- We recognize this as the kernel of a density.
- So  $g^*(\theta | y_1, \dots, y_n)$  is
- The Bayesian estimator of  $\theta$  is
- The form of this makes sense since  $\theta$  is

Theorem: If  $U$  is a sufficient statistic for  $\theta$ , then a Bayes estimator of  $\theta$  is a function of  $U$ .

Proof:

- Therefore we can find the posterior for  $\theta$  using the conditional distribution of  $U$  given  $\theta$ .

Example 3:  $Y_1, \dots, Y_n \stackrel{iid}{\sim} N(\mu, \sigma^2)$  where  $\mu$  is unknown and  $\sigma^2$  is known.

Consider a  $N(\eta, \delta^2)$  prior for  $\mu$ .

Find the posterior distribution for  $\mu$ .

- This is the kernel of a \_\_\_\_\_  
density with mean  
and variance

- So the posterior for  $\mu$  must have  
this distribution.



- We see the Bayes estimator is the posterior mean

which is a weighted average of the \_\_\_\_\_ and the \_\_\_\_\_.

Note: The Bayes estimator here is \_\_\_\_\_ (recall that

- However, it is \_\_\_\_\_ since the bias  $\rightarrow 0$  and its variance  $\rightarrow 0$  as  $n \rightarrow \infty$ .

- Many Bayesian estimators are \_\_\_\_\_ but \_\_\_\_\_.

Application: An Army recruiting staff gives intelligence tests to its recruits, and the scores are known to be normally distributed with variance  $15^2 = 225$ . The staff will estimate the mean score for next year's set of recruits using the scores of a small sample of next year's group. The staff believes the mean score will be around 100, and is 95% sure the mean score will be between 90 and 110.

- Based on the \_\_\_\_\_, the prior for  $\mu$  will have standard deviation

⇒

- The sample of 30 recruits yields scores with  $\sum y_i = 2850$ . So

- The posterior for  $\mu$  is \_\_\_\_\_ with mean



and variance

- We see the Bayes estimate (posterior mean) of  $\mu$  is between the prior mean of  $\mu$  and the sample mean of  $\mu$ .
- Also, the posterior variance is \_\_\_\_\_ than the prior variance, so we have \_\_\_\_\_ certainty about  $\mu$  after examining the sample.

### Noninformative Priors

- Sometimes we can use the Bayesian approach even when we have no subjective prior knowledge about the target parameter.
- We may use a noninformative (objective) prior.
- In Example 1, what is a natural noninformative prior about  $p$ ?

- In Example 3 (the normal model), a noninformative prior for  $\mu$  is

which is not even a proper density!

- It is OK if the prior is improper as long as the resulting posterior is a proper pdf.

Note:

- This is a \_\_\_\_\_, so the posterior for  $\mu$  is

- In this case, the Bayesian posterior inference will mirror the classical inference about  $\mu$  based on  $\bar{y}$ .