

# Homework 3

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- Course: STAT638, 2022 Fall

Do the following exercises in Hoff: 3.8, 3.9, 3.14.

In [Exercise 3.9](#), you should be able to avoid “brute-force” integration by exploiting the fact that the Galenshore distribution is a proper distribution, meaning that the density of the Galenshore( $a, b$ ) distribution integrates to one for any  $a, b > 0$ .

For [3.14\(b\)](#), note that  $p_U(\theta)$  is proportional to the density of a known distribution.

Please note that while there are only 3 problems in this assignment, some of them are fairly challenging. So please don't wait too long to get started on this assignment.

- Deadline: Sept. 27, 12:01pm

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## Computational Environment Setup

### Third-party libraries

```
%matplotlib inline
import sys # system information
import matplotlib # plotting
import scipy # scientific computing
import pandas as pd # data managing
from scipy.special import comb
from scipy import stats as st
from scipy.special import gamma
import numpy as np
import matplotlib.pyplot as plt
```

```
# Matplotlib setting
plt.rcParams['text.usetex'] = True
matplotlib.rcParams['figure.dpi']= 300
```

## Version

```
print(sys.version)
print(matplotlib.__version__)
print(scipy.__version__)
print(np.__version__)
print(pd.__version__)
```

```
3.8.12 (default, Oct 22 2021, 18:39:35)
[Clang 13.0.0 (clang-1300.0.29.3)]
3.3.1
1.5.2
1.19.1
1.1.1
```

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## Problem 3.8

Coins: Diaconis and Ylvisaker (1985) suggest that coins spun on a flat surface display long-run frequencies of heads that vary from coin to coin. About 20% of the coins behave symmetrically, whereas the remaining coins tend to give frequencies of  $\frac{1}{3}$  or  $\frac{2}{3}$ .

Let  $\theta$  be the probability of tossing head.<sup>1</sup>

### (a)

Based on the observations of Diaconis and Ylvisaker (1985), use an appropriate mixture of beta distributions as a prior distribution for  $\theta$ , the long-run frequency of heads for a particular coin. Plot your prior.

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<sup>1</sup>This solution is referred to the lecture note about mixture priors. URL: <http://www.mas.ncl.ac.uk/~nmf16/teaching/mas3301/week11.pdf>

$$p(\theta) = 0.2 \times \text{Beta}(3, 3) + 0.4 \times \text{Beta}(2, 4) + 0.4 \times \text{Beta}(4, 2)$$

The distribution is shown in Figure 1.

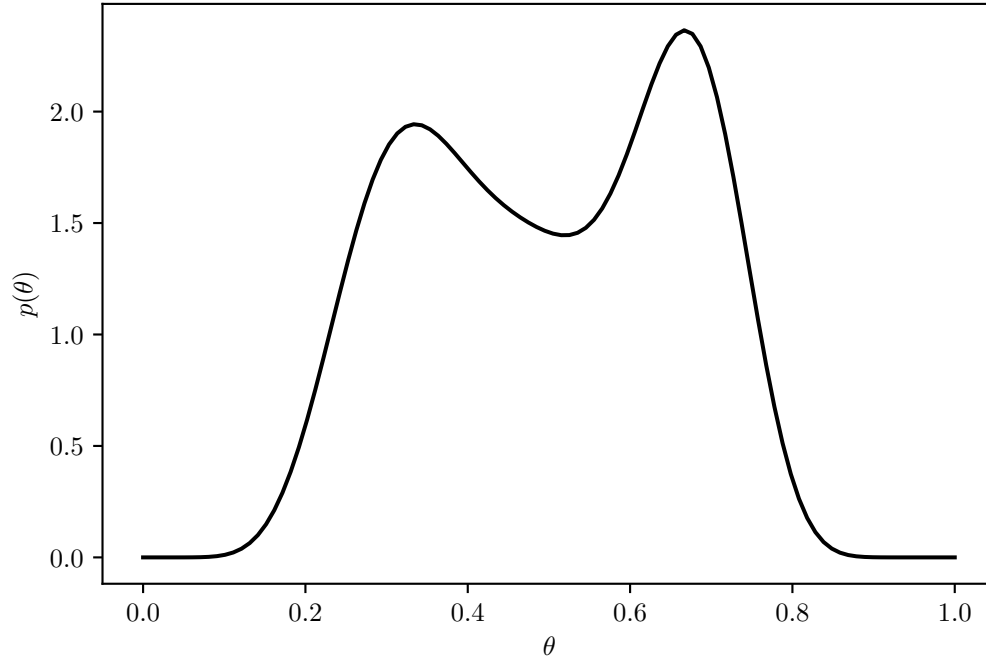


Figure 1: Designed mixture prior.

**(b)**

Choose a single coin and spin it at least 50 times. Record the number of heads obtained. Report the year and denomination of the coin.

Let  $n > 50$  be the number of flips, and  $x$  be the number of heads obtained.

- $n$
- $x$
- $n-x$

**(c)**

Compute your posterior for  $\theta$ , based on the information obtained in (b)

(d)

Repeat (b) and (c) for a different coin, but possibly using a prior for  $\theta$  that includes some information from the first coin. Your choice of a new prior may be informal, but needs to be justified. How the results from the first experiment influence your prior for the  $\theta$  of the second coin may depend on whether or not the two coins have the same denomination, have a similar year, etc. Report the year and denomination of this coin.

### Problem 3.9

Galenshore distribution: An unknown quantity  $Y$  has a Galenshore( $\alpha, \theta$ ) distribution if its density is given by

$$p(y) = \frac{2}{\Gamma(a)} \theta^{2a} y^{2a-1} e^{-\theta^2 y^2}$$

for  $y > 0$ ,  $\theta > 0$  and  $a > 0$ . Assume for now that  $a$  is known. For this density,

$$E[Y] = \frac{\Gamma(a + \frac{1}{2})}{\theta \Gamma(a)}, \quad E[Y^2] = \frac{a}{\theta^2}$$

(a)

Identify a class of conjugate prior densities for  $\theta$ . Plot a few members of this class of densities.

(b)

Let  $Y_1, \dots, Y_n \sim i.i.d.$  Galenshore( $a, \theta$ ). Find the posterior distribution of  $\theta$  given  $Y_1, \dots, Y_n$ , using a prior from your conjugate class.

(c)

Write down  $\frac{p(\theta_a | Y_1, \dots, Y_n)}{p(\theta_b | Y_1, \dots, Y_n)}$  and simplify. Identify a sufficient statistics.

(d)

Determine  $E[\theta | y_1, \dots, y_n]$ .

(e)

Determine the form of the posterior predictive density  $y(\tilde{y}|y_1, \dots, y_n)$ .

### Problem 3.14

Unit information prior: Let  $Y_1, \dots, Y_n \sim i.i.d. p(y|\theta)$ . Having observed the values  $Y_1 = y_1, \dots, Y_n = y_n$ , the *log likelihood* is given by  $l(\theta|y) = \sum \log p(y_i|\theta)$ , and the value  $\hat{\theta}$  of  $\theta$  that maximize  $l(\theta|y)$  is called the *maximum likelihood estimator*. The negative of the curvature of the log-likelihood,  $J(\theta) = -\frac{\partial^2 l}{\partial \theta^2}$ , describes the precision of the MLE  $\hat{\theta}$  and is called the *observed Fisher information*. For situations in which it is difficult to quantify prior information in terms of a probability distribution, some have suggested that the “prior” distribution be based on the likelihood, for example, by centering the prior distribution around the MLE  $\hat{\theta}$ . To deal with the fact that the MLE is not really prior information, the curvature of the prior is chosen so that it has only “one  $n$ th” as much information as the likelihood, so that  $-\frac{\partial^2 \log p(\theta)}{\partial \theta^2} = \frac{J(\hat{\theta})}{n}$ . Such a prior is called a *unit information prior* (Kass and Wasserman, 1995; Kass and Raftery, 1995), as it has as much information as the average amount of information from a single observation. The unit information prior is not really a prior distribution, as it is computed from the observed data. However, it can be roughly viewed as the prior information of someone with weak but accurate prior information.

(a)

Let  $Y_1, \dots, Y_n \sim i.i.d.$  binary ( $\theta$ ). Obtain the MLE  $\hat{\theta}$  and  $\frac{J(\hat{\theta})}{n}$ .

(b)

Find a probability density  $p_U(\theta)$  such that  $\log p_U(\theta) = \frac{l(\theta|y)}{n} + c$ , where  $c$  is a constant that does not depend on  $\theta$ . Compute the information  $-\frac{\partial^2 \log p_U(\theta)}{\partial \theta^2}$  of this density.

(c)

Obtain a probability density for  $\theta$  that is proportional to  $p_U(\theta) \times p(y_1, \dots, y_n|\theta)$ . Can this be considered a posterior distribution for  $\theta$ ?

**(d)**

Repeat (a), (b) and (c) but with  $p(y|\theta)$  being the Poisson distribution.

Diaconis, Persi, and Donald Ylvisaker. 1985. “Quantifying Prior Opinion, Bayesian Statistics. Vol. 2.” North Holland Amsterdam: