

Exercise 2

Junsong Tang

junsong.tang@stat.ubc.ca

1 define a Bayesian model

1. The unknown quantity is the value of p , and the data is the observed value of Y_i 's.
- 2.

$$X \sim \rho, \rho = (\rho_k)_{k=1}^K$$

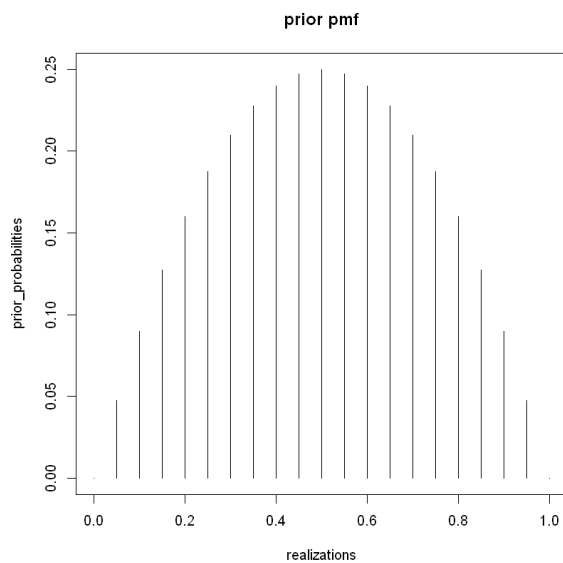
$$Y|X \sim \text{Bernoulli}(X)$$

2 posterior and point estimates

```

1 prior_probabilities = NULL
2 realizations = NULL
3 for (k in (0 : K)) {
4   prior_probabilities = c(prior_probabilities, (k/K)*(1-k/K))
5   realizations = c(realizations, k/K)
6 }
7 prior_probabilities
8 realizations
9 plot(realizations, prior_probabilities, type="h", main = "prior pmf")
10

```



```

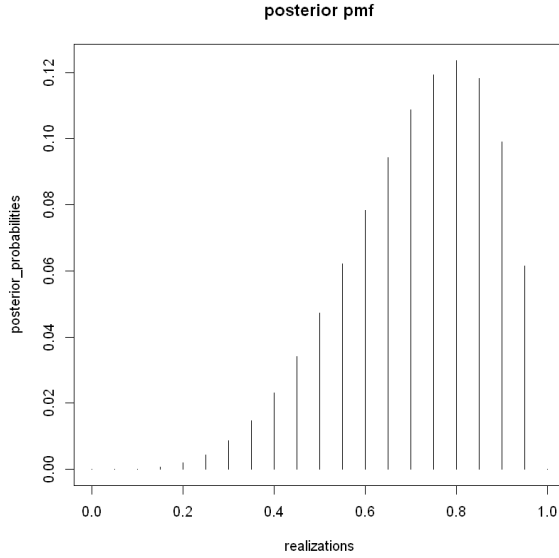
2. posterior_probabilities = NULL
   Z = 0
   for (k in (0 : K)) {
4     # likelihood = P(X = k/K) * P(Y = (1,1,1) | X = k/K)
5     likelihood = realizations[k+1]**3 * prior_probabilities[k+1]
6     Z = Z + likelihood
7     posterior_probabilities = c(posterior_probabilities, likelihood)
8   }

```

```

9     posterior_probabilities = posterior_probabilities / Z
10    posterior_probabilities
11    plot(realizations, posterior_probabilities, type = "h", main = "posterior pmf")
12

```



3. From the plot, we can see the posterior mode is at $X = 0.8$

```

41    # posterior mean
2     m = 0
3     for (k in (0 : K)) {
4         x = realizations[k+1]
5         pi_k = posterior_probabilities[k+1]
6         m = m + x * pi_k
7     }
8     m #0.712497759455099
9

```

3 Bayes action

1. Set the money unit into $\$M$

$$\begin{aligned}
 L(a, Y_4) &= \mathbf{1}_{a=0} \cdot \$0 + \mathbf{1}_{a=1; Y_4=1} \cdot \$2 + \mathbf{1}_{a=1; Y_4=0} \cdot (\$2 - \$100) \\
 &= 2\mathbf{1}_{a=1; Y_4=1} - 98\mathbf{1}_{a=1; Y_4=0}
 \end{aligned}$$

2. By LOTUS,

$$\begin{aligned}
 \mathcal{L}(a) &= \mathbb{E}[L(a, Y_4) | Y_{1:3} = (1, 1, 1)] \\
 &= \sum_{y_4 \in \{0, 1\}} L(a, Y_4 = y_4) \cdot \mathbb{P}(Y_4 = y_4 | Y_{1:3} = (1, 1, 1)) \\
 &= 2\mathbf{1}_{a=1} \cdot \mathbb{P}(Y_4 = 1 | Y_{1:3} = (1, 1, 1)) - 98\mathbf{1}_{a=1} \cdot \mathbb{P}(Y_4 = 0 | Y_{1:3} = (1, 1, 1)) \\
 &= 2\mathbf{1}_{a=1} \cdot p - 98\mathbf{1}_{a=1} \cdot (1 - p); \text{ where } p := \mathbb{P}(Y_4 = 1 | Y_{1:3} = (1, 1, 1))
 \end{aligned}$$

3. Plug in the value of p that has been computed in q2(4), then we have $\mathcal{L}(a) = -26.75\mathbf{1}_{a=1}$, so $\mathcal{L}(1) < \mathcal{L}(0)$, meaning we need to buy insurance.

However, if $\mathcal{L}(0) < \mathcal{L}(1) \Rightarrow (2p - 98(1 - p)) > 0 \Rightarrow p > 0.98$, then we don't need to buy insurance for the posterior at least 98%.

4 Challenges

```

11 # challenge question
12 # signature: posteriors, threshold -> index set
13 # overall complexity:
14 # time:  $O(n \log n + 2n)$ 
15 # space:  $O(n)$ 
16
17 highest_prob_set = function(posterior_probabilities, alpha) {
18   n = length(posterior_probabilities)
19   # create hashmap that maps prob -> index
20   # time complexity  $O(n)$  and space complexity  $O(n)$ 
21   dict = c()
22   for (i in (1:n)) {
23     # set k-v pair as (prob, index)
24     p = posterior_probabilities[i]
25     dict[as.character(p)] = i
26   }
27   # sort complexity:  $O(n \log n)$ 
28   posterior_probabilities = sort(posterior_probabilities, decreasing = TRUE)
29
30   # linear search complexity:  $O(n)$ 
31   j = 1
32   sum = 0
33   hps = NULL
34   while (j <= n && sum < alpha) {
35     p = posterior_probabilities[j]
36     hps = c(hps, dict[as.character(p)])
37     j = j + 1
38     sum = sum + p
39   }
40
41   return (hps)
42 }
43
44 print(highest_prob_set(posterior_probabilities = posterior_probabilities, alpha=0.75))
45 # 17, 16, 18, 15, 19, 14, 13, 12

```