MS2505: Bayesian Statistics Course Project

December 17, 2024

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1 Setup

- Describe the data and the analysis problem.
- Choose and describe the modeling approach (e.g., non-hierarchical or hierarchical model).
- Justify your prior choice.
- Perform posterior predictive checks.

1.1 Analysis problem

1.2 Data Selection

Describe the data and the analysis problem.

The dataset selected is a datasets containing a list of emails, as well as a label marking each email as "spam" or "ham" (spam or not spam). The first 10 rows of the dataset looks as follows:

Table 1

mail_data.csv dataset first 10 rows

Category	Message
ham	"Go until jurong point, crazy Available only in bugis n great
	world la e buffet Cine there got amore wat"
ham	Ok lar Joking wif u oni
spam	Free entry in 2 a wkly comp to win FA Cup final tkts 21st
	May 2005. Text FA to 87121 to receive entry question(std txt
	rate)T&C's apply 08452810075over18's
ham	U dun say so early hor U c already then say
ham	"Nah I don't think he goes to usf, he lives around here though"
spam	"FreeMsg Hey there darling it's been 3 week's now and no word
	back! I'd like some fun you up for it still? To ok! XxX std chgs to
	send, £1.50 to rcv"
ham	Even my brother is not like to speak with me. They treat me like
	aids patent.
ham	As per your request 'Melle Melle (Oru Minnaminunginte Nurungu
	Vettam)' has been set as your callertune for all Callers. Press *9 to
	copy your friends Callertune
•••	

Then, using a Python script, the labels were converted to 1 if it was "spam" and 0 if it was "ham", for easier analysis.

1.3 Model

- Choose and describe the modeling approach (e.g., non-hierarchical or hierarchical model).
- Justify your prior choice.

The model chosen was a binomial likelihood model with a beta prior. As the goal is to analyse the probability of an email being spam, the fallout will be binary (either it is spam or it is not). Hence, a binomial likelihood, where I want to find the parameter θ in a dataset of fixed size with a set number of "successes" and "fails" (spam and ham), is appropriate.

Additionally, as I do not have any prior knowledge in regards to this distribution, a non-informative prior is the most suited option, and as Beta(1,1) is a common prior used with binomial likelihood functions, I chose it for this problem.

1.4 Prior checks

```
Perform posterior predictive checks.
```

2 Results

Include diagnostics to assess model convergence and adequacy.

3 Discussion

Discuss results, problems encountered, and possible improvements.

A R Code

Listing 1 Project R code

```
# Load required libraries
  library(bayesplot)
  library(rstanarm)
  library(ggplot2)
  library(brms)
6
   # Set a global random seed for reproducibility
  set.seed(123)
   # Create the directory if it doesn't exist
10
   if (!dir.exists("Project/logs")) {
11
       dir.create("Project/logs", recursive = TRUE)
12
13
  # Create the directory for figures if it doesn't exist
15
  if (!dir.exists("figures")) {
16
       dir.create("figures", recursive = TRUE)
17
   }
18
19
  # Specify the log file path
20
  log_file <- "Project/logs/R_output.log"</pre>
21
22
  # Open the sink to redirect output
23
  sink(log_file)
24
25
```

```
# Read the data
  mail_data <- read.csv("Project/data/mail_data_bin.csv")</pre>
27
28
  # Set metadata
29
  alpha_prior <- 1</pre>
30
  beta_prior <- 1</pre>
  total_emails <- nrow(mail_data)</pre>
32
  spam_count <- sum(mail_data$Category == 1)</pre>
33
  ham_count <- sum(mail_data$Category == 0)</pre>
34
35
  # Fit the model with a vague prior
  fit_prior <- brm(</pre>
37
       Category ~ 1,
38
       data = mail_data,
39
       family = bernoulli(),
40
       prior = prior(beta(1, 1),
41
           class = "Intercept"
42
43
44
45
  # Prior predictive check
46
47
  pdf("figures/prior_predictive_check.pdf")
  pp_check(fit_prior, type = "hist") +
       ggtitle ("Prior Predictive Check for Email Spam Model")
49
  dev.off()
50
51
  # Fit a robust model with a more informative prior
52
  fit_robust <- brm(
53
       Category ~ 1,
54
       data = mail_data,
55
       family = bernoulli(),
56
       prior = prior(beta(2, 2), class = "Intercept")
57
58
59
  # Posterior predictive check
  pdf("figures/posterior_predictive_check.pdf")
61
  pp_check(fit_robust, type = "dens_overlay") +
62
       ggtitle("Posterior Predictive Check for Robust Email Spam Model")
63
  dev.off()
64
65
  # Compute posterior parameters for P(spam)
  alpha_post <- alpha_prior + spam_count</pre>
67
  beta_post <- beta_prior + ham_count</pre>
68
69
  # Posterior probability of an email being spam
70
  posterior_spam <- alpha_post / (alpha_post + beta_post)</pre>
71
72
  # Print results
73
  cat("Prior: Beta(", alpha_prior, ",", beta_prior, ")\n")
74
75 cat("Spam Count:", spam_count, "\n")
  cat("Ham Count:", ham_count, "\n")
```

```
cat("Posterior: Beta(", alpha_post, ",", beta_post, ")\n")
   cat("P(spam):", posterior_spam, "\n")
78
79
   # Posterior Predictive Checking
80
   cat ("\n--- Posterior Predictive Checking ---\n")
81
   # Simulate posterior predictive samples
83
   num_samples <- 1000</pre>
84
   posterior_samples <- rbeta(num_samples, alpha_post, beta_post)</pre>
85
86
   observed_counts <- spam_count / total_emails
   # Generate density overlay
89
  y <- rep(observed_counts, num_samples)</pre>
90
   yrep <- matrix(posterior_samples, nrow = num_samples)</pre>
91
92
   # Save density overlay plot
93
   # pdf("../figures/ppc_density_overlay.pdf")
94
   # ppc_dens_overlay(y = y, yrep = yrep) +
95
        ggtitle ("Posterior Predictive Check: Density Overlay")
96
   # dev.off()
97
98
   # Generate and save histogram of posterior samples
   pdf("figures/ppc_histogram.pdf")
100
  hist (posterior_samples,
101
       breaks = 30, col = "blue", border = "white",
102
       main = "Posterior Predictive Distribution", xlab = "P(spam)"
103
104
   dev.off()
105
106
   # Sensitivity Analysis
107
   cat("\n--- Sensitivity Analysis ---\n")
108
   sensitivity_results <- data.frame()</pre>
109
   alpha_values <- seq(0.5, 2, by = 0.5)
110
   beta_values <- seq(0.5, 2, by = 0.5)
111
112
   for (alpha in alpha_values) {
113
       for (beta in beta_values) {
114
            alpha_post_temp <- alpha + spam_count</pre>
115
            beta_post_temp <- beta + ham_count
116
            posterior_temp <- alpha_post_temp / (alpha_post_temp +</pre>
117
               beta_post_temp)
            sensitivity_results <- rbind(</pre>
118
                sensitivity_results,
119
                data.frame(alpha, beta, posterior_temp)
120
            )
121
122
       }
123
124
  # Display the sensitivity analysis results
125
  cat("Sensitivity Analysis Results:\n")
```

```
print(sensitivity_results)
127
128
   # Save sensitivity results to CSV
129
   write.csv(sensitivity_results,
130
       "Project/logs/sensitivity_analysis.csv",
131
       row.names = FALSE
132
133
134
   # Flush the output and close the sink
135
  flush.console()
136
  sink()
```