Complete the following tasks. Show your work/code where applicable. Assemble your work into one PDF document and upload the PDF back into our Canvas page.

1. (*Bayes Rules!* Exercise 9.9) **(How humid is too humid: model building)** Throughout this chapter, we explored how bike ridership fluctuates with temperature. But what about humidity? In the next exercises, you will explore the Normal regression model of `rides` (Y) by `humidity` (X) using the bikes dataset. Based on past bikeshare analyses, suppose we have the following prior understanding of this relationship:

   - On an average humidity day, there are typically around 5000 riders, though this average could be somewhere between 1000 and 9000.
   - Ridership tends to decrease as humidity increases. Specifically, for every one percentage point increase in humidity level, ridership tends to decrease by 10 rides, though this average decrease could be anywhere between 0 and 20.
   - Ridership is only weakly related to humidity. At any given humidity, ridership will tend to vary with a large standard deviation of 2000 rides.

   (a) Tune the Normal regression model to match our prior understanding. Use careful notation to write out the complete Bayesian structure of this model.

   (b) To explore our combined prior understanding of the model parameters, simulate the Normal regression prior model with 5 chains run for 8000 iterations each. HINT: You can use the same `stan_glm()` syntax that you would use to simulate the posterior, but include `prior_PD = TRUE`.

2. (*Bayes Rules!* Exercise 9.10) **(How humid is too humid: data)** With the priors in place, let's examine the data.

   (a) Plot and discuss the observed relationship between ridership and humidity in the `bikes` data.

   (b) Does simple Normal regression seem to be a reasonable approach to modeling this relationship? Explain.

3. (*Bayes Rules!* Exercise 9.11) **(How humid is too humid: posterior simulation)** We can now simulate our posterior model of the relationship between ridership and humidity, a balance between our prior understanding and the data.

   (a) Use `stan_glm()` to simulate the Normal regression posterior model. Do so with 5 chains run for 8000 iterations each. HINT: You can either do this from scratch or `update()` your prior simulation from Exercise 9.9 using `prior_PD = FALSE`.

   (b) Perform and discuss some MCMC diagnostics to determine whether or not we can "trust" these simulation results.

4. (*Bayes Rules!* Exercise 9.12) **(How humid: posterior interpretation)** Finally, let's dig deeper into our posterior understanding of the relationship between ridership and humidity.

   (a) Provide a `tidy()` summary of your posterior model, including 95% credible intervals.

   (b) Interpret the posterior median value of the σ parameter.

   (c) Interpret the 95% posterior credible interval for the humidity coefficient, β_1. Do we have ample posterior evidence that there's a negative association between ridership and humidity? Explain.

5. (*Bayes Rules!* Exercise 9.13) **(How humid is too humid: prediction)** Tomorrow is supposed to be 90% humidity in Washington, D.C. What levels of ridership should we expect?

   (a) Without using the `posterior_predict()` shortcut function, simulate two posterior models and compute an 80% credible interval for each:

   - the posterior model for the typical number of riders on 90% humidity days; and
   - the posterior predictive model for the number of riders tomorrow.

   (b) Using the `posterior_predict()` shortcut function, calculate and interpret an 80% posterior prediction interval for the number of riders tomorrow.

6. (*Bayes Rules!* Exercise 10.13) **(Getting started with coffee ratings)** Before doing any modeling, let's get to know the `coffee_ratings` data.

   (a) The `coffee_ratings` data includes ratings and features of 1339 different batches of beans grown on 571 different farms. Explain why using this data to model ratings (`total_cup_points`) by `aroma` or `aftertaste` likely violates the independence assumption of the Bayesian linear regression model. HINT: Check out the `head()` of the dataset. NOTE: use the `R` code from the textbook (and consider removing the outlier).

7. (*Bayes Rules!* Exercise 10.14) **(Coffee ratings: model it)** In this exercise you will build a Bayesian Normal regression model of a coffee bean's rating (Y) by its aroma grade (X) with $\mu = \beta_0 + \beta_1 X$. In doing so, assume that our only prior understanding is that the average cup of coffee has a 75-point rating, though this might be anywhere between 55 and 95. Beyond that, utilize weakly informative priors.

   (a) Plot and discuss the relationship between a coffee's rating (`total_cup_points`) and its `aroma` grade (the higher the better).

   (b) Use `stan_glm()` to simulate the Normal regression posterior model.

   (c) Provide numerical posterior summaries for the `aroma` coefficient β_1.

   (d) Interpret the posterior median of β_1.

(e) Do you have significant posterior evidence that, the better a coffee bean's aroma, the higher its rating tends to be? Explain.

8. (*Bayes Rules!* Exercise 10.15) **(Coffee ratings: Is it wrong?)** Before putting too much stock into your regression analysis, step back and consider whether it's wrong.

   (a) Use `pp_check()` to implement a posterior predictive check.

   (b) Putting this together, do you think that assumptions 2 and 3 of the Normal regression model are reasonable? Explain.

9. (*Bayes Rules!* Exercise 10.17) **Coffee ratings: Are the posterior predictions accurate?)**

   (a) Use `prediction_summary_cv()` to obtain 10-fold cross-validated measurements of our model's posterior predictive quality.

   (b) Interpret each of the four cross-validated metrics reported in part a.

10. (*Bayes Rules!* Exercise 10.19) **Coffee ratings: Now with aftertaste)** Aroma isn't the only possible predictor of a coffee bean's rating. What if, instead, we were to predict rating by a bean's aftertaste? In exploring this relationship, continue to utilize the same prior models.

   (a) Use `stan_glm()` to simulate the Normal regression posterior model of `total_cup_points` by aftertaste.

   (b) Produce a quick plot to determine whether this model is wrong.

   (c) Obtain 10-fold cross-validated measurements of this model's posterior predictive quality.

   (d) Putting it all together, if you could only pick one predictor of coffee bean ratings, would it be `aroma` or `aftertaste`? Why?