# Problem Set 2

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```
# Load Data
data("Howell1", package = "rethinking")
data <- subset(Howell1, age <= 13)</pre>
```

Simulate data based on dataset and knowledge of the world

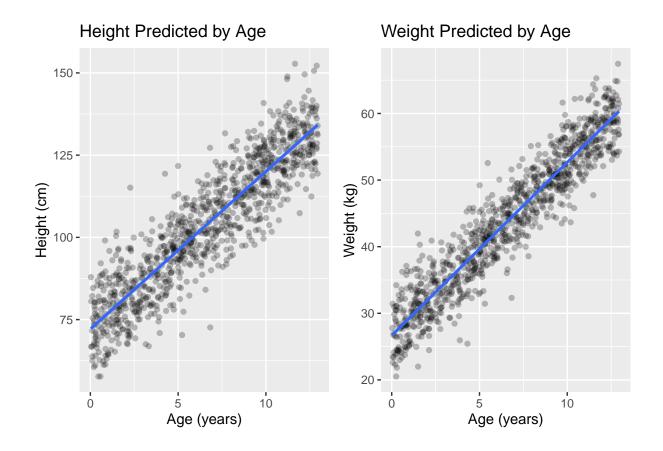
```
# Fit models to extract parameters
weight_age_model <- lm(weight ~ age, data = data)</pre>
height_age_model <- lm(height ~ age, data = data)
weight_height_model <- lm(weight ~ height, data = data)</pre>
# Extract coefficients
weight_rate <- coef(weight_age_model)["age"] # Weight increase per year</pre>
weight_intercept <- coef(weight_age_model)["(Intercept)"] # Weight at age 0</pre>
height_rate <- coef(height_age_model)["age"] # Height increase per year
height_intercept <- coef(height_age_model)["(Intercept)"] # Height at age 0
weight_by_height <- coef(weight_height_model)["height"] # Weight per cm</pre>
# Extract standard deviations for noise
weight_std <- sigma(weight_age_model) # Residual SD for weight</pre>
height_std <- sigma(height_age_model) # Residual SD for height
# Generative simulation for children under 13
sim_child_data <- function(n = 100,
                          seed = 213,
                          height intercept,
                          height std,
                          height_rate,
                          weight_intercept,
                          weight_std,
                          weight_rate,
                          weight_by_height) {
  set.seed(seed)
  # Generate ages (uniform distribution of children under 13)
  age <- runif(n, 0, 13)
  # Generate height based on age
  height <- height_intercept + height_rate * age + rnorm(n, 0, height_std)
```

#### Plot synthetic data

```
# Plot relationships
p1 <- ggplot(child_data, aes(x = age, y = height)) +
    geom_point(alpha=0.25) +
    geom_smooth(method = "lm") +
    labs(title = "Height Predicted by Age", x = "Age (years)", y = "Height (cm)")

p2 <- ggplot(child_data, aes(x = age, y = weight)) +
    geom_point(alpha=0.25) +
    geom_smooth(method = "lm") +
    labs(title = "Weight Predicted by Age", x = "Age (years)", y = "Weight (kg)")

p1 + p2</pre>
```



### Mathematical Model of weight as a function of age

```
# LaTeX refused to knit
# weight_i ~ normal(mu_i, sigma)
# mu_i = a + b * age_i

# Where:
# weight_i = individual weight observation
# age_i = individual age observation
# a = intercept (weight at age 0)
# b = slope (weight gain per year)
# sigma = residual standard deviation
```

## Extracting prior from simulated data

```
# Extract parameters from the simulation
analyze_sim_params <- function(sim_data) {
    # Fit a simple linear model
    model <- lm(weight ~ age, data = sim_data)

# Extract parameters
intercept <- coef(model)[1]</pre>
```

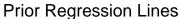
```
slope <- coef(model)[2]</pre>
  sigma <- sigma(model)</pre>
  # Print results
  cat("From simulation:\n")
  cat("Intercept:", round(intercept, 2), "kg\n")
  cat("Slope:", round(slope, 2), "kg/year\n")
  cat("Residual SD:", round(sigma, 2), "kg\n\n")
  # Suggest priors
  cat("Suggested priors:\n")
  cat("prior(normal(", round(intercept, 1), ", ", max(1, round(intercept/5, 1)),
      "), class = \"Intercept\")\n", sep="")
  cat("prior(normal(", round(slope, 1), ", ", max(0.5, round(slope/4, 1)),
      "), class = \"b\")\n", sep="")
  cat("prior(exponential(", round(1/sigma, 2), "), class = \"sigma\")\n", sep="")
  # Return values
  return(list(intercept = intercept, slope = slope, sigma = sigma))
}
# Analyze simulated data
sim_params <- analyze_sim_params(child_data)</pre>
## From simulation:
## Intercept: 26.67 kg
## Slope: 2.6 kg/year
## Residual SD: 3.37 kg
##
## Suggested priors:
## prior(normal(26.7, 5.3), class = "Intercept")
## prior(normal(2.6, 0.6), class = "b")
## prior(exponential(0.3), class = "sigma")
# Set priors for model
priors <- c(</pre>
  prior(normal(26.7, 5.3), class = "Intercept"),
  prior(normal(2.6, 0.6), class = "b"),
  prior(exponential(.3), class = "sigma")
# Fit the model
weight_model <- brm(</pre>
 formula = weight ~ age,
  data = data,
 family = gaussian(),
 prior = priors,
  chains = 2,
  iter = 2000,
  warmup = 500,
  seed = 213,
```

```
## Running "C:/PROGRA~1/R/R-44~1.3/bin/x64/Rcmd.exe" SHLIB foo.c
## using C compiler: 'gcc.exe (GCC) 13.3.0'
## gcc -I"C:/PROGRA~1/R/R-44~1.3/include" -DNDEBUG -I"C:/Users/hssla/AppData/Local/R/win-library/4.4
## cc1.exe: warning: command-line option '-std=c++14' is valid for C++/ObjC++ but not for C
## In file included from C:/Users/hssla/AppData/Local/R/win-library/4.4/RcppEigen/include/Eigen/Core:19
                    from C:/Users/hssla/AppData/Local/R/win-library/4.4/RcppEigen/include/Eigen/Dense:1
##
##
                    from C:/Users/hssla/AppData/Local/R/win-library/4.4/StanHeaders/include/stan/math/p
                    from <command-line>:
##
## C:/Users/hssla/AppData/Local/R/win-library/4.4/RcppEigen/include/Eigen/src/Core/util/Macros.h:679:10
     679 | #include <cmath>
##
##
         ## compilation terminated.
## make: *** [C:/PROGRA~1/R/R-44~1.3/etc/x64/Makeconf:289: foo.o] Error 1
## SAMPLING FOR MODEL 'anon_model' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0.000104 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would take 1.04 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration: 1 / 2000 [ 0%]
                                           (Warmup)
## Chain 1: Iteration: 200 / 2000 [ 10%]
                                           (Warmup)
## Chain 1: Iteration: 400 / 2000 [ 20%]
                                           (Warmup)
## Chain 1: Iteration: 501 / 2000 [ 25%]
                                           (Sampling)
## Chain 1: Iteration: 700 / 2000 [ 35%]
                                           (Sampling)
## Chain 1: Iteration: 900 / 2000 [ 45%]
                                           (Sampling)
## Chain 1: Iteration: 1100 / 2000 [ 55%]
                                           (Sampling)
## Chain 1: Iteration: 1300 / 2000 [ 65%]
                                           (Sampling)
## Chain 1: Iteration: 1500 / 2000 [ 75%]
                                           (Sampling)
## Chain 1: Iteration: 1700 / 2000 [ 85%]
                                           (Sampling)
## Chain 1: Iteration: 1900 / 2000 [ 95%]
                                           (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%]
                                           (Sampling)
## Chain 1:
## Chain 1: Elapsed Time: 0.028 seconds (Warm-up)
## Chain 1:
                           0.038 seconds (Sampling)
## Chain 1:
                           0.066 seconds (Total)
## Chain 1:
## SAMPLING FOR MODEL 'anon_model' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 7e-06 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would take 0.07 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:
                       1 / 2000 [ 0%]
                                           (Warmup)
## Chain 2: Iteration: 200 / 2000 [ 10%]
                                           (Warmup)
## Chain 2: Iteration: 400 / 2000 [ 20%]
                                           (Warmup)
## Chain 2: Iteration: 501 / 2000 [ 25%]
                                           (Sampling)
## Chain 2: Iteration: 700 / 2000 [ 35%]
                                           (Sampling)
## Chain 2: Iteration: 900 / 2000 [ 45%]
                                           (Sampling)
## Chain 2: Iteration: 1100 / 2000 [ 55%]
                                           (Sampling)
```

```
## Chain 2: Iteration: 1300 / 2000 [ 65%]
                                            (Sampling)
## Chain 2: Iteration: 1500 / 2000 [ 75%]
                                           (Sampling)
## Chain 2: Iteration: 1700 / 2000 [ 85%]
                                            (Sampling)
## Chain 2: Iteration: 1900 / 2000 [ 95%]
                                            (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%]
                                           (Sampling)
## Chain 2:
## Chain 2: Elapsed Time: 0.024 seconds (Warm-up)
## Chain 2:
                           0.052 seconds (Sampling)
## Chain 2:
                           0.076 seconds (Total)
## Chain 2:
```

#### Plot Results of prior and posterior linear fits

```
# Grabbing prior lines
n lines <- 50
alpha samples <- rnorm(n lines, 5.2, 1) # Using the prior mean and SD
beta_samples <- rnorm(n_lines, 2.2, 0.6) # Using the prior mean and SD
# Create a grid of ages
age_grid <- seq(0, 13, length.out = 100)
# Create plot data for prior lines
prior lines data <- data.frame()</pre>
for (i in 1:n_lines) {
  line_data <- data.frame(</pre>
    age = age_grid,
    weight = alpha_samples[i] + beta_samples[i] * age_grid,
    line_id = i
  prior_lines_data <- rbind(prior_lines_data, line_data)</pre>
# Plot prior lines WITH data points
prior_plot <- ggplot() +</pre>
  geom_line(data = prior_lines_data, aes(x = age, y = weight, group = line_id), alpha = 0.2) +
  geom_point(data = data, aes(x = age, y = weight), alpha = 0.1) + # Added data points
  labs(title = "Prior Regression Lines",
       x = \text{"Age (years)"}, y = \text{"Weight (kg)"}) +
  ylim(0, 50)
# For posterior lines - extract posterior samples directly
posterior_samples <- as.data.frame(weight_model)</pre>
n_posterior <- min(n_lines, nrow(posterior_samples))</pre>
sample_indices <- sample(1:nrow(posterior_samples), n_posterior)</pre>
# Create plot data for posterior lines
posterior_lines_data <- data.frame()</pre>
for (i in 1:n_posterior) {
  idx <- sample_indices[i]</pre>
  intercept <- posterior_samples$b_Intercept[idx]</pre>
  slope <- posterior_samples$b_age[idx]</pre>
```



# Posterior Regression Lines with Da

