Homework 5

2.1(d), 2.2(c)

- Posterior predictive check
  - Sample 200 posterior draws $(\mu_i^{(b)}, \sigma^{(b)}), b = 1, ..., 200$
  - For each set of posterior draws, we can sample predicted datasets $Y_{pred}^{(b)}$, from $N(\mu_i^{(b)}, \sigma^{(b)})$
  - You can use `dens()` in the `rethinking` package to create density plots. For more information you can type `rethinking::dens()` in the console window.

?rethinking::dens()

2.2(e)

- Under the model specified, we can write out expressions for APD:

$$\text{APD}_{yx} = \beta_1 + 2\beta_2 \mathbb{E}[X_i] = \beta_1 + 2\beta_2 \mu_x$$

Placing a prior on μ_x, essentially we treat APD as a function of model parameters, and we can thus generate posterior draws based on the fitted model.

- You can introduce the parameter `mu_x` in your jags code, and then extract posterior samples of β_1, β_2 and μ_x, this allows you to generate posterior draws of APD.

2.2(f)

The goal is to estimate $\mathbb{E}[X_i]$ using Bayesian Bootstrap. We do the similar thing we just covered – sample weights, take weighted mean based on X, repeat M times if you have M posterior samples. The posterior draws is

$$\text{APD}_{yx}^{(m)} = \beta_1^{(m)} + 2\beta_2^{(m)} \mu_x^{(m)}$$

where $\mu_x^{(m)}$ is the Bootstrap sample.

3.1

As the three questions are similar in spirit, I will go through the first one instead.

- Choose the set of confounders you want to control – X_1 is a confounder, X_2 is a mediator, adjust for X_1
  - There is a cool package called `dagitty` that allows you to check your reasoning. See some examples here: http://dagitty.net/primer/.
- For full interaction model we need to consider all main and interaction effects – D, X_1, DX_1 for our case.
- Write out $E[Y \mid D = 1, X]$ and $E[Y \mid D = 0, X]$, use what we learned in Bayesian Bootstrapping to generate ATE posterior draws