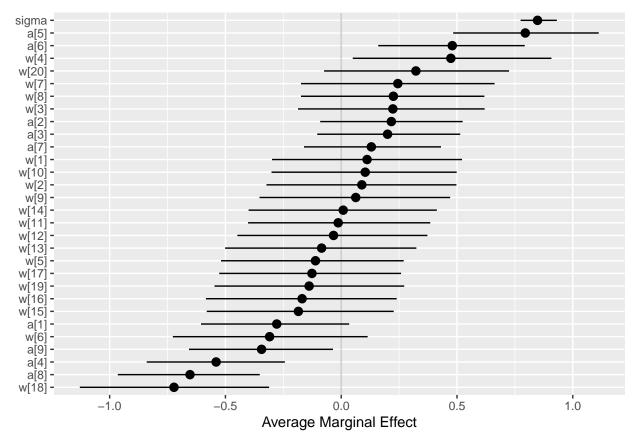
Homework 5

Question 7E1

```
data(Wines2012)
d <- Wines2012
dat list <- list(</pre>
    S = standardize(d$score),
    jid = as.integer(d$judge),
    wid = as.integer(d$wine) )
m1 <- ulam(
    alist(
        S ~ dnorm( mu , sigma ),
        mu <- a[jid] + w[wid],</pre>
        a[jid] \sim dnorm(0,0.5),
        w[wid] \sim dnorm(0,0.5),
        sigma ~ dexp(1)
    ), data=dat_list , chains=4 , cores=4 , cmdstan=TRUE )
## This is cmdstanr version 0.4.0.9000
## - Online documentation and vignettes at mc-stan.org/cmdstanr
## - CmdStan path set to: C:/Users/Public/.cmdstanr/cmdstan-2.26.1
## - Use set_cmdstan_path() to change the path
## Running MCMC with 4 parallel chains, with 1 thread(s) per chain...
## Chain 1 Iteration:
                         1 / 1000 [ 0%]
                                           (Warmup)
## Chain 1 Iteration: 100 / 1000 [ 10%]
                                           (Warmup)
## Chain 1 Iteration: 200 / 1000 [ 20%]
                                           (Warmup)
## Chain 1 Iteration: 300 / 1000 [ 30%]
                                           (Warmup)
## Chain 1 Iteration: 400 / 1000 [ 40%]
                                           (Warmup)
## Chain 1 Iteration: 500 / 1000 [ 50%]
                                           (Warmup)
## Chain 1 Iteration: 501 / 1000 [ 50%]
                                           (Sampling)
## Chain 1 Iteration: 600 / 1000 [ 60%]
                                           (Sampling)
## Chain 1 Iteration: 700 / 1000 [ 70%]
                                           (Sampling)
## Chain 1 Iteration: 800 / 1000 [ 80%]
                                           (Sampling)
## Chain 1 Iteration: 900 / 1000 [ 90%]
                                           (Sampling)
## Chain 1 Iteration: 1000 / 1000 [100%]
                                           (Sampling)
## Chain 2 Iteration:
                         1 / 1000 [ 0%]
                                           (Warmup)
## Chain 2 Iteration: 100 / 1000 [ 10%]
                                           (Warmup)
## Chain 2 Iteration: 200 / 1000 [ 20%]
                                           (Warmup)
## Chain 2 Iteration: 300 / 1000 [ 30%]
                                           (Warmup)
## Chain 2 Iteration: 400 / 1000 [ 40%]
                                           (Warmup)
## Chain 2 Iteration: 500 / 1000 [ 50%]
                                           (Warmup)
## Chain 2 Iteration: 501 / 1000 [ 50%]
                                           (Sampling)
## Chain 2 Iteration: 600 / 1000 [ 60%]
                                           (Sampling)
```

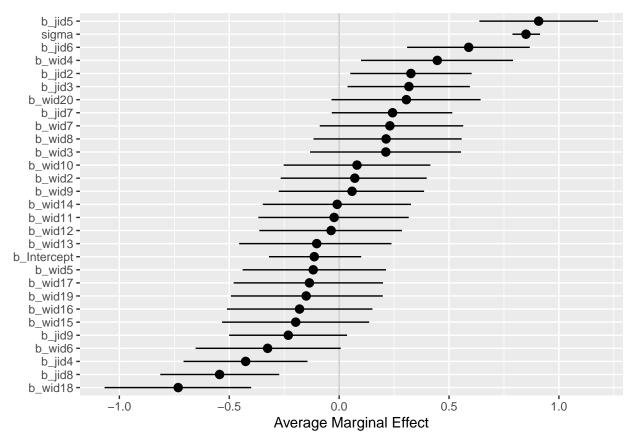
```
## Chain 2 Iteration: 700 / 1000 [ 70%]
                                           (Sampling)
## Chain 2 Iteration: 800 / 1000 [ 80%]
                                           (Sampling)
## Chain 2 Iteration: 900 / 1000 [ 90%]
                                           (Sampling)
## Chain 2 Iteration: 1000 / 1000 [100%]
                                            (Sampling)
## Chain 3 Iteration:
                         1 / 1000 [ 0%]
                                           (Warmup)
## Chain 3 Iteration: 100 / 1000 [ 10%]
                                           (Warmup)
## Chain 3 Iteration: 200 / 1000 [ 20%]
                                           (Warmup)
## Chain 3 Iteration: 300 / 1000 [ 30%]
                                           (Warmup)
## Chain 3 Iteration: 400 / 1000 [ 40%]
                                           (Warmup)
## Chain 3 Iteration: 500 / 1000 [ 50%]
                                           (Warmup)
## Chain 3 Iteration: 501 / 1000 [ 50%]
                                           (Sampling)
## Chain 3 Iteration: 600 / 1000 [ 60%]
                                           (Sampling)
## Chain 3 Iteration: 700 / 1000 [ 70%]
                                           (Sampling)
## Chain 3 Iteration: 800 / 1000 [ 80%]
                                           (Sampling)
## Chain 3 Iteration: 900 / 1000 [ 90%]
                                           (Sampling)
## Chain 3 Iteration: 1000 / 1000 [100%]
                                            (Sampling)
## Chain 1 finished in 0.4 seconds.
## Chain 2 finished in 0.4 seconds.
## Chain 3 finished in 0.4 seconds.
                         1 / 1000 [
## Chain 4 Iteration:
                                           (Warmup)
## Chain 4 Iteration: 100 / 1000 [ 10%]
                                           (Warmup)
## Chain 4 Iteration: 200 / 1000 [ 20%]
                                           (Warmup)
## Chain 4 Iteration: 300 / 1000 [ 30%]
                                           (Warmup)
## Chain 4 Iteration: 400 / 1000 [ 40%]
                                           (Warmup)
## Chain 4 Iteration: 500 / 1000 [ 50%]
                                           (Warmup)
## Chain 4 Iteration: 501 / 1000 [ 50%]
                                           (Sampling)
## Chain 4 Iteration: 600 / 1000 [ 60%]
                                           (Sampling)
## Chain 4 Iteration: 700 / 1000 [ 70%]
                                           (Sampling)
## Chain 4 Iteration: 800 / 1000 [ 80%]
                                           (Sampling)
## Chain 4 Iteration: 900 / 1000 [ 90%]
                                           (Sampling)
## Chain 4 Iteration: 1000 / 1000 [100%]
                                            (Sampling)
## Chain 4 finished in 0.4 seconds.
##
## All 4 chains finished successfully.
## Mean chain execution time: 0.4 seconds.
## Total execution time: 16.3 seconds.
coef <- precis(m1,2)</pre>
coef$name <- row.names(coef)</pre>
coef
##
                                          5.5%
                                                     94.5%
                                                              n_{eff}
                                                                         Rhat4
                                                                                name
                 mean
                               sd
## a[1]
         -0.278369941 0.19836766 -0.60551121
                                                0.03429281 2079.139 0.9991343
                                                                                a[1]
## a[2]
          0.216456486 0.19622297 -0.09082728
                                                0.52435759 2580.321 0.9998527
                                                                                a[2]
## a[3]
          0.200104305 0.19163527 -0.10369016
                                                0.51390049 1821.868 0.9996002
                                                                                a[3]
         -0.540226716 0.18488197 -0.83991140
                                              -0.24324385 1972.856 0.9991558
                                                                                a[4]
## a[4]
## a[5]
          0.794841525 0.19553095
                                   0.48345563
                                                1.11202335 1903.142 0.9998754
                                                                                a[5]
## a[6]
          0.479505035 0.19477978
                                  0.15969242
                                                0.79251526 2007.390 0.9987834
                                                                                a[6]
## a[7]
          0.130030896 0.18793104 -0.16076955
                                                0.43075139 1935.802 1.0002912
                                                                                a[7]
         -0.653030769 0.19541151 -0.96473514 -0.35189402 2215.136 0.9998671
## a[8]
                                                                                a[8]
## a[9]
         -0.343943575 0.19326402 -0.65744228
                                               -0.03563197 1897.402 1.0007348
                                                                                a[9]
## w[1]
          0.111629041 0.26026794 -0.29871574
                                                0.52174931 2311.686 0.9997940
                                                                                w[1]
## w[2]
          0.088988940 0.26034975 -0.32282386
                                                0.49735867 2741.550 0.9995385
                                                                                w[2]
## w[3]
          0.223028366 0.25216970 -0.18659805
                                                0.61938039 2275.948 0.9995122
                                                                                w[3]
## w[4]
          0.473399408 0.26792422 0.04980580
                                                0.90771546 2497.025 1.0000725
                                                                                w[4]
```

```
-0.111224528 0.25303616 -0.51899946
                                              0.26981864 2405.535 1.0026407
        -0.309337632 0.26901595 -0.72713600
                                              0.11418881 2280.077 0.9997239
                                                                              w[6]
## w[6]
          0.244371052 0.26050774 -0.17376595
                                               0.66235622 3115.295 0.9994760
                                                                              w[7]
          0.225154236 0.24632094 -0.17381744
                                              0.61822779 2786.631 0.9986483
## w[8]
                                                                              w[8]
## w[9]
          0.062779795 0.25884105 -0.35297428
                                               0.47045297 2129.454 0.9992560
                                                                              w[9]
## w[10] 0.103594078 0.25329866 -0.30096901
                                              0.49853992 2698.399 1.0001735 w[10]
## w[11] -0.013161483 0.24385493 -0.40231350
                                               0.38447709 2336.517 1.0000985 w[11]
## w[12] -0.033202015 0.25659890 -0.44852738
                                              0.37208707 2524.656 0.9993038 w[12]
## w[13] -0.084641074 0.25924034 -0.50152080
                                              0.32446323 2675.612 1.0000929 w[13]
                                              0.41305019 2831.435 0.9986902 w[14]
## w[14] 0.008565749 0.25394390 -0.40011122
## w[15] -0.185004878 0.25334865 -0.58059889
                                              0.22674283 2429.259 0.9989091 w[15]
## w[16] -0.168949156 0.25602021 -0.58449120
                                              0.23952499 2670.744 1.0012947 w[16]
## w[17] -0.126470609 0.24569248 -0.52689845
                                              0.25829822 2231.416 1.0016168 w[17]
## w[18] -0.722159481 0.26316874 -1.12877660 -0.31140707 2809.579 0.9998947 w[18]
## w[19] -0.138577934 0.25534883 -0.54717580
                                              0.27202568 3020.121 0.9990070 w[19]
## w[20] 0.322422653 0.24935615 -0.07407082
                                               0.72463585 2653.750 0.9995331 w[20]
                                              0.93116847 2457.926 0.9994926 sigma
## sigma 0.847624633 0.05008081 0.77453753
p <- ggplot(data = coef, aes(x = reorder(name, mean),</pre>
                              y = mean, ymin = 5.5\%, ymax = 94.5\%)
p + geom_hline(yintercept = 0, color = "gray80") +
    geom_pointrange() + coord_flip() +
    labs(x = NULL, y = "Average Marginal Effect")
```



```
d2 <- as.data.frame(dat_list) %>%
mutate(jid=as.factor(jid)) %>%
```

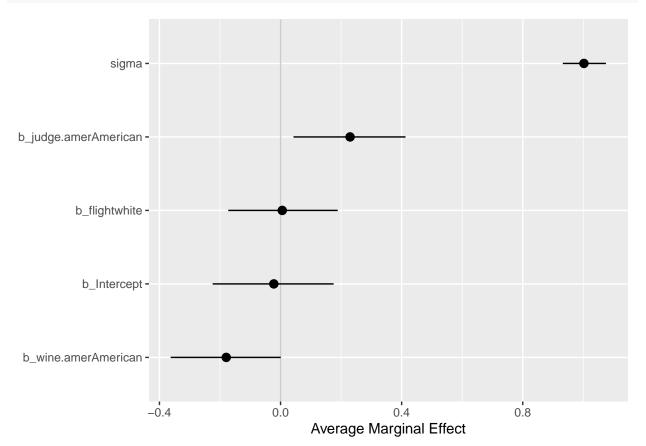
```
mutate(wid=as.factor(wid))
head(d2)
##
               S jid wid
## 1 -1.57660412
                        1
## 2 -0.45045832
                        3
## 3 -0.07507639
                        5
## 4 0.30030555
                        7
## 5 -2.32736799
                        9
## 6 -0.45045832
                      11
df <- as.data.frame(posterior_summary(m1, probs = c(0.1, 0.9))) %>% filter(Estimate > -10)
df$name <- row.names(df)</pre>
p <- ggplot(data = df, aes(x = reorder(name, Estimate ),</pre>
                               y = Estimate , ymin = Q10, ymax = Q90))
p + geom_hline(yintercept = 0, color = "gray80") +
    geom_pointrange() + coord_flip() +
    labs(x = NULL, y = "Average Marginal Effect")
```



```
d3 <- d %>%
  mutate(wine.amer=factor(wine.amer, labels=c('French', 'American')) ) %>%
  mutate(judge.amer=factor(judge.amer, labels=c('French', 'American') )) %>%
  mutate(score=standardize(score)) %>%
  select(score, flight, wine.amer, judge.amer)
```

head(d3)

```
##
           score flight wine.amer judge.amer
## 1 -1.57660412 white American
                                      French
                                      French
## 2 - 0.45045832 white American
## 3 -0.07507639
                                      French
                  white
                           French
## 4 0.30030555
                  white
                           French
                                      French
## 5 -2.32736799 white American
                                      French
## 6 -0.45045832 white American
                                      French
df <- as.data.frame(posterior_summary(m3, probs = c(0.1, 0.9))) %>% filter(Estimate > -10)
df$name <- row.names(df)</pre>
p \leftarrow ggplot(data = df, aes(x = reorder(name, Estimate)),
                              y = Estimate , ymin = Q10, ymax = Q90))
p + geom_hline(yintercept = 0, color = "gray80") +
    geom_pointrange() + coord_flip() +
    labs(x = NULL, y = "Average Marginal Effect")
```



```
d3s <- d %>%
  mutate(S=standardize(score)) %>%
  mutate(wid= wine.amer + 1L) %>%
  mutate(jid= judge.amer + 1L) %>%
  rowwise %>%
  mutate(fid =ifelse(flight == 'white', 2L, 1L)) %>%
```

```
select(S, wid , jid, fid)
head(d3s)
## # A tibble: 6 x 4
## # Rowwise:
       S wid jid fid
##
     <dbl> <int> <int> <int>
## 1 -1.58
              2 1
## 2 -0.450
              2
                    1
## 3 -0.0751
                           2
              1
                    1
## 4 0.300
              1
                           2
                    1
                    1
                           2
## 5 -2.33
               2
## 6 -0.450
              2
                    1
                           2
row_labels = c("FFR", "FFW", "FAR", "FAW", "AFR", "AFW", "AAR", "AAW")
mcode <- "
data {
 vector[180] S;
 int fid[180];
 int jid[180];
 int wid[180];
}
parameters {
real w[2,2,2];
 real<lower=0> sigma;
model{
vector[180] mu;
 sigma ~ exponential(1);
 for (i in 1:2)
   for (j in 1:2)
    for (k in 1:2)
       w[i,j,k] ~ normal(0, 0.5);
   for (i in 1:180) {
     mu[i] = w[wid[i], jid[i], fid[i]];
   S ~ normal(mu, sigma);
}
m3s <- stan(model_code = mcode, data=d3s, cores=4)</pre>
row_labels = c("FFR", "FFW", "FAR", "FAW", "AFR", "AFW", "AAR", "AAW")
```

```
results <- precis(m3s, 3, pars='w')
row.names(results) <- row_labels
head(results)</pre>
```

```
## FFR 0.20278341 0.2216720 -0.15009120 0.55797080 7082.610 0.9995729  
## FFW -0.30805499 0.2270568 -0.67608717 0.04764032 6761.877 0.9999312  
## FAR 0.26732628 0.1991237 -0.05047396 0.58758671 7459.715 0.9998276  
## FAW 0.16473986 0.1970029 -0.14452314 0.47897919 7925.183 0.9991866  
## AFR -0.36076719 0.1878611 -0.66209213 -0.06414612 8047.008 0.9994777  
## AFW 0.03847544 0.1863493 -0.26443879 0.33234038 7081.129 0.9991524
```