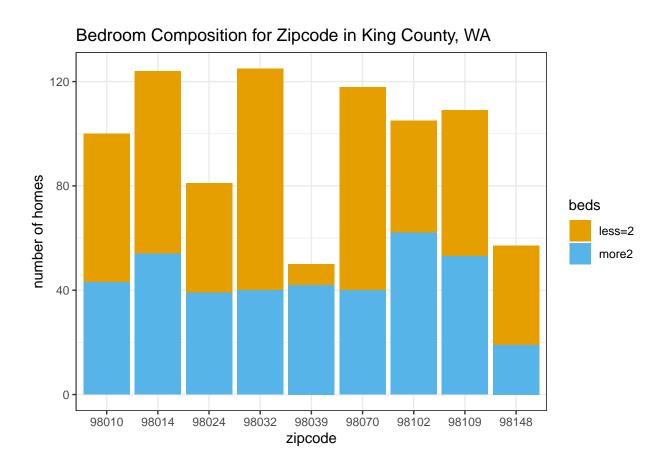
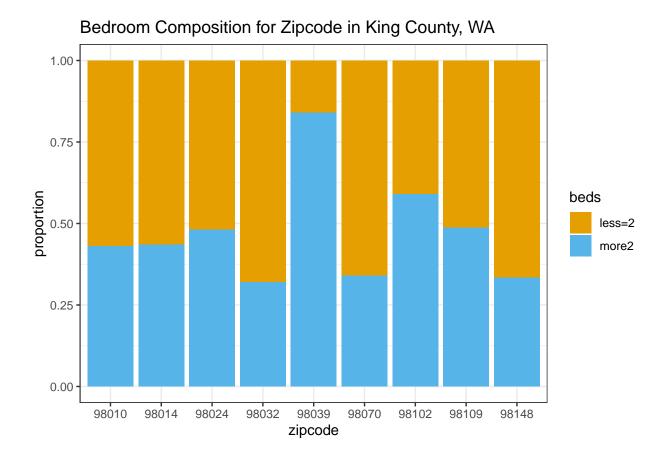
Hierarchical GLMs





Hierarchical GLMs

```
glm1 <- glm(cbind(more2,lessequal2) ~ 1, data = seattle, family = binomial)</pre>
display(glm1)
## glm(formula = cbind(more2, lessequal2) ~ 1, family = binomial,
##
       data = seattle)
##
               coef.est coef.se
## (Intercept) -0.20
                         0.07
## ---
##
   n = 869, k = 1
    residual deviance = 1196.4, null deviance = 1196.4 (difference = 0.0)
invlogit(coef(glm1))
## (Intercept)
    0.4510932
stan1 <- stan_glm(cbind(more2,lessequal2) ~ 1, data = seattle, family = binomial, refresh = 0)</pre>
print(stan1)
## stan_glm
## family:
                  binomial [logit]
## formula:
                  cbind(more2, lessequal2) ~ 1
## observations: 869
## predictors:
##
               Median MAD_SD
## (Intercept) -0.2
                     0.1
##
## * For help interpreting the printed output see ?print.stanreg
## * For info on the priors used see ?prior_summary.stanreg
invlogit(coef(stan1))
## (Intercept)
    0.4511562
##
seattle %>% summarise(freq = mean(more2))
## # A tibble: 1 x 1
##
     freq
##
     <dbl>
## 1 0.451
```

```
glmer1 <- stan_glmer(cbind(more2,lessequal2) ~ 1 + (1 | zipcode),</pre>
                     data = seattle, family = binomial, refresh = 0)
print(glmer1)
## stan_glmer
## family:
                  binomial [logit]
## formula:
                  cbind(more2, lessequal2) ~ 1 + (1 | zipcode)
## observations: 869
## -----
##
               Median MAD SD
## (Intercept) -0.1
                     0.2
##
## Error terms:
## Groups Name
                        Std.Dev.
## zipcode (Intercept) 0.75
## Num. levels: zipcode 9
##
## -----
## * For help interpreting the printed output see ?print.stanreg
## * For info on the priors used see ?prior_summary.stanreg
fixef(glmer1)
## (Intercept)
## -0.1027465
ranef(glmer1)
## $zipcode
         (Intercept)
## 98010 -0.16656036
## 98014 -0.14945066
## 98024 0.01306696
## 98032 -0.60303269
## 98039 1.34142591
## 98070 -0.51789418
## 98102 0.41693212
## 98109 0.04043826
## 98148 -0.50169135
## with conditional variances for "zipcode"
coef(glmer1)
## $zipcode
         (Intercept)
## 98010 -0.26930690
## 98014 -0.25219720
## 98024 -0.08967958
## 98032 -0.70577923
## 98039 1.23867937
## 98070 -0.62064073
## 98102 0.31418558
## 98109 -0.06230828
## 98148 -0.60443789
##
```

```
## attr(,"class")
## [1] "coef.mer"
seattle %>% group_by(zipcode) %>% summarise(freq = mean(more2), n = n()) %>%
 ungroup() %>%
 bind_cols(tibble(glmer_est = invlogit(coef(glmer1)$zipcode[[1]]))
## # A tibble: 9 x 4
    zipcode freq
                      n glmer_est
##
    <fct>
            <dbl> <int>
                            <dbl>
## 1 98010
           0.43
                    100
                            0.433
## 2 98014
           0.435
                    124
                            0.437
## 3 98024
           0.481
                    81
                            0.478
## 4 98032
           0.32
                    125
                            0.331
## 5 98039
            0.84
                            0.775
                     50
## 6 98070
            0.339
                    118
                            0.350
## 7 98102
            0.590
                    105
                            0.578
## 8 98109
           0.486
                    109
                            0.484
## 9 98148
           0.333
                     57
                            0.353
```

```
glmer2 <- stan_glmer(cbind(more2,lessequal2) ~ scale_sqft + (1 + scale_sqft | zipcode),</pre>
                data = seattle, family = binomial, refresh = 0)
print(glmer2)
## stan_glmer
## family:
                 binomial [logit]
## formula:
                  cbind(more2, lessequal2) ~ scale_sqft + (1 + scale_sqft | zipcode)
## observations: 869
## -----
##
              Median MAD SD
## (Intercept) 0.0
                     0.1
## scale_sqft 2.6
##
## Error terms:
## Groups Name
                        Std.Dev. Corr
  zipcode (Intercept) 0.36
##
           scale_sqft 0.73
                                -0.41
## Num. levels: zipcode 9
##
## * For help interpreting the printed output see ?print.stanreg
## * For info on the priors used see ?prior_summary.stanreg
fixef(glmer2)
## (Intercept) scale_sqft
## 0.008075054 2.562810019
ranef(glmer2)
## $zipcode
         (Intercept) scale_sqft
## 98010 -0.19355120 0.32465085
## 98014 -0.11171548 0.37711644
## 98024 -0.09345333 0.30622201
## 98032 -0.05358081 -0.08713374
## 98039 0.01501471 -0.01143682
## 98070 -0.22437035 0.27526049
## 98102 0.43709917 -1.20124400
## 98109 0.13083105 -0.30786904
## 98148 0.06550678 0.25440726
##
## with conditional variances for "zipcode"
coef(glmer2)
## $zipcode
##
         (Intercept) scale_sqft
## 98010 -0.18547615
                     2.887461
## 98014 -0.10364042
                      2.939926
## 98024 -0.08537828
                       2.869032
## 98032 -0.04550575
                      2.475676
## 98039 0.02308976
                     2.551373
## 98070 -0.21629529
                     2.838071
## 98102 0.44517422
                      1.361566
## 98109 0.13890610
                      2.254941
```

```
## 98148 0.07358183 2.817217
##
## attr(,"class")
## [1] "coef.mer"
```

Stan

```
data {
  int<lower=1> D;
  int<lower=0> N;
 int<lower=1> L;
  int<lower=0,upper=1> y[N];
  int<lower=1,upper=L> 11[N];
 row_vector[D] x[N];
parameters {
  real mu[D];
 real<lower=0> sigma[D];
  vector[D] beta[L];
}
model {
 for (d in 1:D) {
    mu[d] ~ normal(0, 100);
   for (1 in 1:L)
     beta[1,d] ~ normal(mu[d], sigma[d]);
  }
 for (n in 1:N)
    y[n] ~ bernoulli(inv_logit(x[n] * beta[ll[n]]));
```