MA684_homework_08

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Getting to know stan

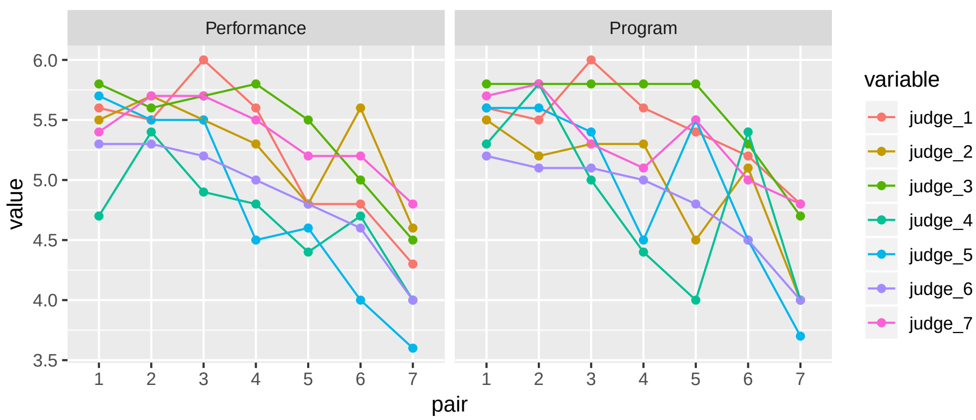
Read through the tutorial on Stan https://github.com/stan-dev/rstan/wiki/RStan-Getting-Started

- Explore Stan website and Stan reference manual and try to connect them with Gelman and Hill 16 - 17.

Data analysis

Using stan:

The folder olympics has seven judges' ratings of seven figure skaters (on two criteria: "technical merit" and "artistic impression") from the 1932 Winter Olympics. Take a look at http://www.stat.columbia.edu/~gelman/arm/examples/olympics/olympics1932.txt




```
##    Program Performance pair   Judge
## 1:     5.6         5.6    1 judge_1
## 2:     5.5         5.5    1 judge_2
## 3:     5.8         5.8    1 judge_3
## 4:     5.3         4.7    1 judge_4
## 5:     5.6         5.7    1 judge_5
## 6:     5.2         5.3    1 judge_6
```

use stan to fit a non-nested multilevel model (varying across skaters and judges) for the technical merit ratings.

$$y_i \sim N(\mu + \gamma_{j[i]} + \delta_{k[i]}, \sigma_y^2), \text{ for } i = 1, \ldots, n \quad (1)$$
$$\gamma_j \sim N(0, \sigma_\gamma^2) j = 1, \ldots, 7 \quad (2)$$
$$\delta_k \sim N(0, \sigma_\delta^2) k = 1, \ldots, 7 \quad (3)$$

https://github.com/stan-dev/example-models/blob/master/ARM/Ch.17/17.3_flight_simulator.stan https://github.com/stan-dev/example-models/blob/master/ARM/Ch.17/17.3_non-nested_models.R

```
fit_program<-lmer(Program~1+(1|pair) +  (1|Judge),olympics_long)
```

```
dataList.1 <- list(N=49, n_judges=7, n_pairs=7,  judge=as.integer(olympics_long$Judge), pair=as.integer

skating_stan<-"
data {
  int<lower=0> N;
  int<lower=0> n_judges;
  int<lower=0> n_pairs;
  int<lower=0,upper=n_judges> judge[N];
  int<lower=0,upper=n_pairs> pair[N];
  vector[N] y;
}
parameters {
  real<lower=0> sigma;
  real<lower=0> sigma_gamma;
  real<lower=0> sigma_delta;
  vector[n_judges] gamma;
  vector[n_pairs] delta;
  real mu;
}
model {
  vector[N] y_hat;

  sigma ~ uniform(0, 100);
  sigma_gamma ~ uniform(0, 100);
  sigma_delta ~ uniform(0, 100);

  mu ~ normal(0, 100);

  gamma ~ normal(0, sigma_gamma);
  delta ~ normal(0, sigma_delta);

  for (i in 1:N)
    y_hat[i] = mu + gamma[judge[i]] + delta[pair[i]];
  y ~ normal(y_hat, sigma);
}
"
```

pilots <- read.table ("http://www.stat.columbia.edu/~gelman/arm/examples/pilots/pilots.dat", header=TRUE)

flight_simulator.sf1 <- stan(model_code=skating_stan , data=dataList.1, iter=2000, chains=4)

Multilevel logistic regression

The folder `speed.dating` contains data from an experiment on a few hundred students that randomly assigned each participant to 10 short dates with participants of the opposite sex (Fisman et al., 2006). For each date, each person recorded several subjective numerical ratings of the other person (attractiveness, compatibility, and some other characteristics) and also wrote down whether he or she would like to meet the other person again. Label $y_{ij} = 1$ if person i is interested in seeing person j again 0 otherwise. And $r_{ij1}, \ldots, r_{ij6}$ as person i's numerical ratings of person j on the dimensions of attractiveness, compatibility, and so forth. Please look at http://www.stat.columbia.edu/~gelman/arm/examples/speed.dating/Speed%20Dating%20Data%20Key.doc for details.

```r
dating<-fread("http://www.stat.columbia.edu/~gelman/arm/examples/speed.dating/Speed%20Dating%20Data.csv
dating_pooled <- glm(match~attr_o +sinc_o +intel_o +fun_o +amb_o +shar_o,data=dating,family=binomial)
dating_pooled <- glmer(match~gender + attr_o +sinc_o +intel_o +fun_o +amb_o +shar_o+(1|iid)+(1|pid),data
```

```
## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control
## $checkConv, : Model failed to converge with max|grad| = 0.676505 (tol =
## 0.001, component 1)
```

1. Fit a classical logistic regression predicting $Pr(y_{ij} = 1)$ given person i's 6 ratings of person j. Discuss the importance of attractiveness, compatibility, and so forth in this predictive model.

```r
model1 <- glm(match ~ attr_o + sinc_o + fun_o + amb_o + intel_o + shar_o, data = dating,
              family = binomial)
summary(model1)
```

```
##
## Call:
## glm(formula = match ~ attr_o + sinc_o + fun_o + amb_o + intel_o +
##     shar_o, family = binomial, data = dating)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.5300  -0.6362  -0.4420  -0.2381   3.1808
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -5.62091    0.21859 -25.714  < 2e-16 ***
## attr_o       0.22047    0.02388   9.233  < 2e-16 ***
## sinc_o      -0.01996    0.03067  -0.651   0.5152
## fun_o        0.25315    0.02922   8.665  < 2e-16 ***
## amb_o       -0.12099    0.02838  -4.264 2.01e-05 ***
## intel_o      0.07176    0.03716   1.931   0.0535 .
## shar_o       0.21225    0.02209   9.608  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 6466.6  on 7030  degrees of freedom
## Residual deviance: 5611.0  on 7024  degrees of freedom
##   (1347 observations deleted due to missingness)
## AIC: 5625
##
## Number of Fisher Scoring iterations: 5
```

From the fitted model, $Logodds(match = 1) = -5.62 + 0.22attr_o - 0.02sinc_o + 0.25fun_o - 0.12amb_o + 0.07intel_o + 0.21shar_o$ Therefore, a unit increase in attractiveness will lead to an increase of $\frac{0.22}{4} = 0.055$ or 5.5% in the willingness to have another date.

Similarly, a unit increase in sincerity decreases the willingness to have another date by $\frac{0.02}{4} = 0.005$ or 0.5%. But this coefficient is not statistically significant at two standard errors and hence may not be influential in switching the willingness for another date from 1 to 0.

One unit increase in humor increases the willingness for another date by $\frac{0.25}{4} = 0.0625$ or 6.25%.

One unit increase in ambition decreases the willingness for another date by $\frac{0.12}{4} = 0.03$ or 3%.

A unit increase in intelligence increases the willingness to have another date by $\frac{0.07}{4} = 0.0175$ or 1.75%.

One unit increase in shared interest increases the willingness to have anotehr date by $\frac{0.21}{4} = 0.0525$ or 5.25%.

2. Expand this model to allow varying intercepts for the persons making the evaluation; that is, some people are more likely than others to want to meet someone again. Discuss the fitted model.

```r
model2 <- glmer(match ~ scale(attr_o) + scale(sinc_o) + scale(fun_o) + scale(amb_o) + scale(intel_o) + s
              family = binomial)
```

```
## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control
## $checkConv, : Model failed to converge with max|grad| = 0.119726 (tol =
## 0.001, component 1)
```

```
## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, : Model is nearly unide
##  - Rescale variables?
```

```r
summary(model2)
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: binomial  ( logit )
## Formula:
## match ~ scale(attr_o) + scale(sinc_o) + scale(fun_o) + scale(amb_o) +
##     scale(intel_o) + scale(shar_o) + gender + (1 | iid)
##    Data: dating
##
##      AIC      BIC   logLik deviance df.resid
##   5543.2   5605.0  -2762.6   5525.2     7022
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.7459 -0.4453 -0.2877 -0.1454 10.3718
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  iid    (Intercept) 0.4294   0.6553
## Number of obs: 7031, groups:  iid, 551
##
## Fixed effects:
##                  Estimate Std. Error  z value Pr(>|z|)
## (Intercept)    -2.1320649  0.0006220 -3427.62   <2e-16 ***
## scale(attr_o)   0.4605811  0.0006553   702.88   <2e-16 ***
## scale(sinc_o)  -0.0249443  0.0006216   -40.13   <2e-16 ***
## scale(fun_o)    0.5132471  0.0006217   825.56   <2e-16 ***
## scale(amb_o)   -0.2352678  0.0006420  -366.45   <2e-16 ***
## scale(intel_o)  0.1087984  0.0006420   169.46   <2e-16 ***
## scale(shar_o)   0.4845416  0.0006217   779.39   <2e-16 ***
## gender          0.1542607  0.0006554   235.38   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) scl(t_) scl(sn_) scl(f_) scl(m_) scl(n_) scl(sh_)
## scale(ttr_)  0.000
```

```
## scale(snc_)  0.000  0.000
## scale(fun_)  0.000  0.000   0.000
## scale(amb_)  0.000  0.000   0.000    0.000
## scale(ntl_)  0.000  0.000   0.000    0.000  -0.250
## scale(shr_)  0.000  0.000   0.000    0.000   0.000   0.000
## gender       0.000  0.200   0.000    0.000   0.000   0.000   0.000
## convergence code: 0
## Model failed to converge with max|grad| = 0.119726 (tol = 0.001, component 1)
## Model is nearly unidentifiable: very large eigenvalue
##  - Rescale variables?
```

Fixed Effects: $logodds(match = 1) = -2.13 + 0.46attr_o - 0.02sinc_o + 0.51fun_o - 0.23amb_o + 0.11intel_o + 0.48shar_o + 0.15gender$ one unit increase in attractiveness increases the willingness to have another date by $\frac{0.46}{4} = 0.115$ or 11.5%.

one unit increase in sincerity decreases the willingness for another date by $\frac{0.02}{4} = 0.005$ or 0.5%.

a unit increase in humor increases the willingness to have another date by $\frac{0.51}{4} = 0.1275$ or 12.75%.

one unit increase in ambition decreases the willingness to have another date by $\frac{0.23}{4} = 0.0575$ or 5.75%.

one unit increase in intelligence increases the willingness for another date by $\frac{0.11}{4} = 0.0275$ 0r 2.75%.

a unit increase in shared interest increases the willingness to have another date by $\frac{0.48}{4} = 0.12$ or 12%.

Compared to a female dating partner, a male partner is $\frac{0.15}{4} = 0.0375$ or 3.75% more likely to have another date.

Random Effects: For person 1: $logodds(match = 1) = -1.64 + 0.46attr_o - 0.02sinc_o + 0.51fun_o - 0.23amb_o + 0.11intel_o + 0.48shar_o + 0.15gender$

For person 2: $logodds(match = 1) = -2.13 + 0.46attr_o - 0.02sinc_o + 0.51fun_o - 0.23amb_o + 0.11intel_o + 0.48shar_o + 0.15gender$

For person 3: $logodds(match = 1) = -2.54 + 0.46attr_o - 0.02sinc_o + 0.51fun_o - 0.23amb_o + 0.11intel_o + 0.48shar_o + 0.15gender$

For person 4: $logodds(match = 1) = -2.24 + 0.46attr_o - 0.02sinc_o + 0.51fun_o - 0.23amb_o + 0.11intel_o + 0.48shar_o + 0.15gender$

3. Expand further to allow varying intercepts for the persons being rated. Discuss the fitted model.

```r
model3 <- glmer(match ~ scale(attr_o) + scale(sinc_o) + scale(fun_o) + scale(amb_o) + scale(intel_o) + s
```

```
## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control
## $checkConv, : Model failed to converge with max|grad| = 0.185818 (tol =
## 0.001, component 1)
```

```r
summary(model3)
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: binomial  ( logit )
## Formula:
## match ~ scale(attr_o) + scale(sinc_o) + scale(fun_o) + scale(amb_o) +
##     scale(intel_o) + scale(shar_o) + gender + (1 | iid) + (1 |      pid)
##    Data: dating
##
##      AIC      BIC   logLik deviance df.resid
##   5257.6   5326.1  -2618.8   5237.6     7021
```

```
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.7829 -0.3827 -0.2194 -0.0917  9.1667
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  iid    (Intercept) 0.5932   0.7702
##  pid    (Intercept) 1.2592   1.1222
## Number of obs: 7031, groups:  iid, 551; pid, 537
##
## Fixed effects:
##                Estimate Std. Error z value Pr(>|z|)
## (Intercept)    -2.53935    0.11740 -21.629  < 2e-16 ***
## scale(attr_o)   0.63782    0.06373  10.008  < 2e-16 ***
## scale(sinc_o)   0.03540    0.06785   0.522   0.6019
## scale(fun_o)    0.57774    0.07099   8.138 4.02e-16 ***
## scale(amb_o)   -0.16654    0.06466  -2.576   0.0100 *
## scale(intel_o)  0.17128    0.07359   2.327   0.0199 *
## scale(shar_o)   0.58891    0.06158   9.564  < 2e-16 ***
## gender          0.17340    0.14943   1.160   0.2459
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) scl(t_) scl(sn_) scl(f_) scl(m_) scl(n_) scl(sh_)
## scale(ttr_) -0.221
## scale(snc_) -0.049 -0.064
## scale(fun_) -0.140 -0.220  -0.123
## scale(amb_)  0.072 -0.051   0.011   -0.168
## scale(ntl_) -0.009 -0.024  -0.438   -0.098  -0.334
## scale(shr_) -0.139 -0.072  -0.057   -0.234  -0.159  -0.020
## gender      -0.647  0.093   0.037    0.009  -0.070  -0.044   0.004
## convergence code: 0
## Model failed to converge with max|grad| = 0.185818 (tol = 0.001, component 1)
```

All the coefficients estimates, except the ones for sincerity and gender, seem to be significant at two standard errors.

4. You will now fit some models that allow the coefficients for attractiveness, compatibility, and the other attributes to vary by person. Fit a no-pooling model: for each person i, fit a logistic regression to the data y_{ij} for the 10 persons j whom he or she rated, using as predictors the 6 ratings $r_{ij1}, \dots, r_{ij6}$. (Hint: with 10 data points and 6 predictors, this model is difficult to fit. You will need to simplify it in some way to get reasonable fits.)

5. Fit a multilevel model, allowing the intercept and the coefficients for the 6 ratings to vary by the rater i.

```r
model5 <- glm(match ~ (1 + attr_o + sinc_o + fun_o + amb_o + intel_o + shar_o | iid) +
              attr_o + sinc_o + fun_o + amb_o + intel_o + shar_o, data = dating,
              family = binomial)
summary(model5)
```

```
##
## Call:
## glm(formula = match ~ (1 + attr_o + sinc_o + fun_o + amb_o +
```

```
##     intel_o + shar_o | iid) + attr_o + sinc_o + fun_o + amb_o +
##     intel_o + shar_o, family = binomial, data = dating)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.5300  -0.6362  -0.4420  -0.2381   3.1808
##
## Coefficients: (1 not defined because of singularities)
##                                                                   Estimate
## (Intercept)                                                       -5.62091
## 1 + attr_o + sinc_o + fun_o + amb_o + intel_o + shar_o | iidTRUE        NA
## attr_o                                                             0.22047
## sinc_o                                                            -0.01996
## fun_o                                                              0.25315
## amb_o                                                             -0.12099
## intel_o                                                            0.07176
## shar_o                                                             0.21225
##                                                                   Std. Error
## (Intercept)                                                          0.21859
## 1 + attr_o + sinc_o + fun_o + amb_o + intel_o + shar_o | iidTRUE          NA
## attr_o                                                               0.02388
## sinc_o                                                               0.03067
## fun_o                                                                0.02922
## amb_o                                                                0.02838
## intel_o                                                              0.03716
## shar_o                                                               0.02209
##                                                                   z value
## (Intercept)                                                       -25.714
## 1 + attr_o + sinc_o + fun_o + amb_o + intel_o + shar_o | iidTRUE       NA
## attr_o                                                              9.233
## sinc_o                                                             -0.651
## fun_o                                                               8.665
## amb_o                                                              -4.264
## intel_o                                                             1.931
## shar_o                                                              9.608
##                                                                   Pr(>|z|)
## (Intercept)                                                        < 2e-16
## 1 + attr_o + sinc_o + fun_o + amb_o + intel_o + shar_o | iidTRUE        NA
## attr_o                                                             < 2e-16
## sinc_o                                                              0.5152
## fun_o                                                              < 2e-16
## amb_o                                                             2.01e-05
## intel_o                                                             0.0535
## shar_o                                                             < 2e-16
##
## (Intercept)                                                       ***
## 1 + attr_o + sinc_o + fun_o + amb_o + intel_o + shar_o | iidTRUE
## attr_o                                                            ***
## sinc_o
## fun_o                                                             ***
## amb_o                                                             ***
## intel_o                                                           .
## shar_o                                                            ***
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 6466.6  on 7030  degrees of freedom
## Residual deviance: 5611.0  on 7024  degrees of freedom
##   (1347 observations deleted due to missingness)
## AIC: 5625
##
## Number of Fisher Scoring iterations: 5
```

6. Compare the inferences from the multilevel model in (5) to the no-pooling model in (4) and the complete-pooling model from part (1) of the previous exercise.

```
anova(model1, model4, model5)
```

```
## Analysis of Deviance Table
##
## Model 1: match ~ attr_o + sinc_o + fun_o + amb_o + intel_o + shar_o
## Model 2: match ~ attr_o + sinc_o + fun_o + amb_o + intel_o + shar_o +
##     factor(iid) - 1
## Model 3: match ~ (1 + attr_o + sinc_o + fun_o + amb_o + intel_o + shar_o |
##     iid) + attr_o + sinc_o + fun_o + amb_o + intel_o + shar_o
##   Resid. Df Resid. Dev   Df Deviance
## 1      7024     5611.0
## 2      6474      779.8  550   4831.2
## 3      7024     5611.0 -550  -4831.2
```

The AICs of the three models do not differ much from each other. Model 4 seems to be slightly better than the otehr two.