Load necessary packages

```
library(easypackages)
libraries('tidyverse', 'data.table', 'reshape2', 'ggpubr', 'lmerTest',
          'reghelper', 'car', 'lattice', 'sjstats', 'sjPlot', 'gridExtra',
          'stargazer', 'lavaan', 'semPlot', 'psych', 'grid')
theme_set(theme_classic(base_size = 12)) # set font size for ggplot
```

Scoring/cleaning functions

```
Read.Score <- function(file){
  # read master E-CLASS file and calculate total scores on student and expert questions
  dt <- fread(file)

  # columns with students responses end in a (student Qs) or b (expert Qs)...get those
  answers.cols <- names(dt)[grep('(a|b)$', names(dt))]

  # correct answers marked as 5, incorrect as 1, and neutral as 0...map to +/- 1 and 0
  dt[, (answers.cols) := lapply(.SD, function(x) case_when(x == 5 ~ 1,
                                                          x == 1 ~ -1,
                                                          TRUE ~ 0)),
     .SDcols = answers.cols]
  df <- dt[, -c('q40a', 'q40b')] # q40 was a filter question, no part of scoring

  # sum student/expert scores
  df$student.score <- rowSums(df %>% select(grep("a$", names(.))))
  df$expert.score <- rowSums(df %>% select(grep("b$", names(.))))

  return(df)
}
```

Read, score, and match

```
# read course information survey (CIS) and pre/post survey data
cis.df <- read.csv('C:/Users/Cole/Documents/GRA_Summer2020/eclass-public-analysis/anon_cis_CW.csv')
pre.df <- Read.Score('C:/Users/Cole/Documents/GRA_Summer2020/eclass-public-analysis/anon_pre.csv')

# join CIS on presurvey
cis.pre.df <- right_join(cis.df, pre.df, by = c('pre_survey_id' = 'survey_id'),
                         suffix = c('.CIS', '.pre'))
```

```
## Warning: Column `pre_survey_id`/`survey_id` joining factor and character
## vector, coercing into character vector
```

```r
post.df <- Read.Score('C:/Users/Cole/Documents/GRA_Summer2020/eclass-public-analysis/anon_post.csv')

# join presurveys (with CIS) on postsurveys...full join keeps unmatched surveys
full.df <- full_join(cis.pre.df, post.df, by = c('post_survey_id' = 'survey_id',
                                                  'anon_student_id'),
                     suffix = c('.pre', '.post'))
```

```
## Warning: Column `post_survey_id`/`survey_id` joining factor and character
## vector, coercing into character vector
```

```r
# mutate lab type and course level info from CIS
full.df <- full.df %>%
    mutate(Lab.type = case_when(
      Q33 == 'Reinforce physics concepts.' ~ 'Concepts-based',
      Q33 == 'Both about equally.' ~ 'Mixed',
      Q33 == 'Develop lab skills.' ~ 'Skills-based',
      TRUE ~ NA_character_
    ),
    Course.level = case_when(
      Q18 == 'Beyond the first year lab' ~ 'BFY',
      Q27 == 'Calculus-based' ~ 'FY.Calc',
      Q27 == 'Algebra-based' ~ 'FY.Alg',
      TRUE ~ NA_character_
    ))

full.df <- data.table(full.df)[, `:=`(N.students = .N,
                                      pre.rate = sum(!is.na(student.score.pre))/.N,
                                      post.rate = sum(!is.na(student.score.post))/.N),
                               .(ResponseId.CIS)] %>%
  data.frame()

# remove whole classes without type and/or level information
complete.df <- full.df %>%
  filter(!is.na(Lab.type) & !is.na(Course.level) & (pre.rate > 0) &
           (post.rate > 0))

# get matched dataset
df.matched <- complete.df %>%
  filter(!is.na(student.score.pre) & !is.na(student.score.post))

data.frame(N.student.records = unlist(lapply(list(full.df, complete.df, df.matched),
                                             function(x) nrow(x))),
           N.students = unlist(lapply(list(full.df, complete.df, df.matched),
                                      function(x) length(unique(x[,
                                                                  'anon_student_id'])))),
           N.classes = unlist(lapply(list(full.df, complete.df, df.matched),
                                     function(x) length(unique(x[, 'ResponseId.CIS'])))),
           N.institutions = unlist(lapply(list(full.df, complete.df, df.matched),
                                          function(x) length(unique(x[,
                                                                      'anon_university_id'])))), row.na
```

```
##                N.student.records N.students N.classes N.institutions
```

```
## full dataset               49124      43081       491            112
## course info                30026      26721       380             96
## matched                    18308      16490       380             96
```

```r
# Breakdown of institution type, course level, and lab type
table(df.matched[!duplicated(df.matched$anon_university_id),]$Q15, exclude = NULL)
```

```
##
##                                                2 year college
##                               0                             4
##                  4 year college Master's granting institution
##                              46                             8
##       PhD granting institution
##                              38
```

```r
table(df.matched[!duplicated(df.matched$ResponseId.CIS),]$Course.level, exclude = NULL)
```

```
##
##      BFY  FY.Alg FY.Calc
##      150      80     150
```

```r
table(df.matched[!duplicated(df.matched$ResponseId.CIS),]$Lab.type, exclude = NULL)
```

```
##
## Concepts-based          Mixed   Skills-based
##             55            203            122
```

Data processing

```r
# replace declared major with intended major in cases where students intend to switch
df.matched[is.na(df.matched$Q48) | (df.matched$Q48 == 0),
'Q48'] <- df.matched[is.na(df.matched$Q48) | (df.matched$Q48 == 0), 'Q47']

# mutate and combine categories
df.matched <- df.matched %>%
  mutate(Major = case_when(
    Q48 == 1 ~ 'Physics',
    Q48 == 2 ~ 'Chemistry',
    Q48 == 3 ~ 'Biochemistry',
    Q48 == 4 ~ 'Biology',
    Q48 == 5 ~ 'Engineering',
    Q48 == 6 ~ 'Engineering Physics',
    Q48 == 7 ~ 'Astronomy',
    Q48 == 8 ~ 'Astrophysics',
    Q48 == 9 ~ 'Geology/geophysics',
    Q48 == 10 ~ 'Math/applied math',
    Q48 == 11 ~ 'Computer science',
    Q48 == 12 ~ 'Physiology',
    Q48 == 13 ~ 'Other science',
```

```
    Q48 == 14 ~ 'Non-science',
    Q48 == 15 ~ 'Open/undeclared',
    TRUE ~ 'Unknown'
  ),
  Gender = case_when(
    Q54 == 1 ~ 'Woman',
    Q54 == 2 ~ 'Man',
    Q54 == 3 ~ 'Other',
    TRUE ~ 'Unknown'
  )) %>%
  mutate(Major = case_when(
    (Major == 'Physics') | (Major == 'Engineering Physics') | (Major == 'Astronomy') |
      (Major == 'Astrophysics') ~ 'Physics',
    (Major == 'Chemistry') | (Major == 'Biochemistry') | (Major == 'Biology') |
      (Major == 'Physiology') ~ 'Chem.LifeSci',
    Major == 'Engineering' ~ 'Engineering',
    (Major == 'Math/applied math') | (Major == 'Computer science') ~ 'Math.CS',
    (Major == 'Geology/geophysics') | (Major == 'Other science') ~ 'OtherSci',
    Major == 'Non-science' ~ 'NonSci',
    Major == 'Open/undeclared' ~ 'Undeclared',
    Major == 'Unknown' ~ 'Unknown',
    TRUE ~ NA_character_
  )) %>% # set reference levels for factors...important for regressions
  mutate(Major = relevel(as.factor(Major), ref = 'Physics'),
         Gender = relevel(as.factor(Gender), ref = 'Man'),
         Lab.type = relevel(as.factor(Lab.type), ref = 'Concepts-based'),
         Course.level = relevel(as.factor(Course.level), ref = 'FY.Alg'))

# rename race columns
new.race.cols <- c('Race.ethnicity.Other', 'Race.ethnicity.Black',
                   'Race.ethnicity.Hispanic', 'Race.ethnicity.Asian',
                   'Race.ethnicity.White', 'Race.ethnicity.Unknown',
                   'Race.ethnicity.AmInd', 'Race.ethnicity.NatHawaii')
setnames(df.matched, old = c('Q52_7', 'Q52_3', 'Q52_4', 'Q52_2', 'Q52_6',
                             'race_unknown', 'Q52_5', 'Q52_1'), new =
           new.race.cols)

# fill all NAs with zero and set factors to binary
df.matched[is.na(df.matched)] <- 0
df.matched[new.race.cols] <- lapply(df.matched[new.race.cols], factor,
                                    levels = c(0, 1))
```

Demographic breakdowns

```
Race.ethnicity.cols <- names(df.matched)[names(df.matched) %like% 'Race']
Race.ethnicity.table <- function(df, Lab.type = FALSE){
  # race/ethnicity variables are not independent...this function calculates tables
  # for each of those variables
  if(Lab.type){
    for(col in Race.ethnicity.cols){
      print(col)
```

```r
      print(table(df[, col], df$Lab.type))
    }
  } else {
    for(col in Race.ethnicity.cols){
      print(col)
      print(table(df[, col]))
    }
  }
}

# get demographic breakdowns across lab type
table(df.matched$Gender)
```

```
##
##     Man   Other Unknown   Woman
##   10507     201     431    7169
```

```r
Race.ethnicity.table(df.matched)
```

```
## [1] "Race.ethnicity.NatHawaii"
##
##     0     1
## 18137   171
## [1] "Race.ethnicity.Asian"
##
##     0     1
## 13919  4389
## [1] "Race.ethnicity.Black"
##
##     0     1
## 17185  1123
## [1] "Race.ethnicity.Hispanic"
##
##     0     1
## 16716  1592
## [1] "Race.ethnicity.AmInd"
##
##     0     1
## 18148   160
## [1] "Race.ethnicity.White"
##
##     0     1
##  7614 10694
## [1] "Race.ethnicity.Other"
##
##     0     1
## 17841   467
## [1] "Race.ethnicity.Unknown"
##
##     0     1
## 17095  1213
```

```r
table(df.matched$Lab.goal)
```

```
## < table of extent 0 >
```

```r
table(df.matched$Gender, df.matched$Lab.type)
```

```
##
##           Concepts-based Mixed Skills-based
##   Man               1661  5999         2847
##   Other               31   109           61
##   Unknown             93   254           84
##   Woman             1519  3909         1741
```

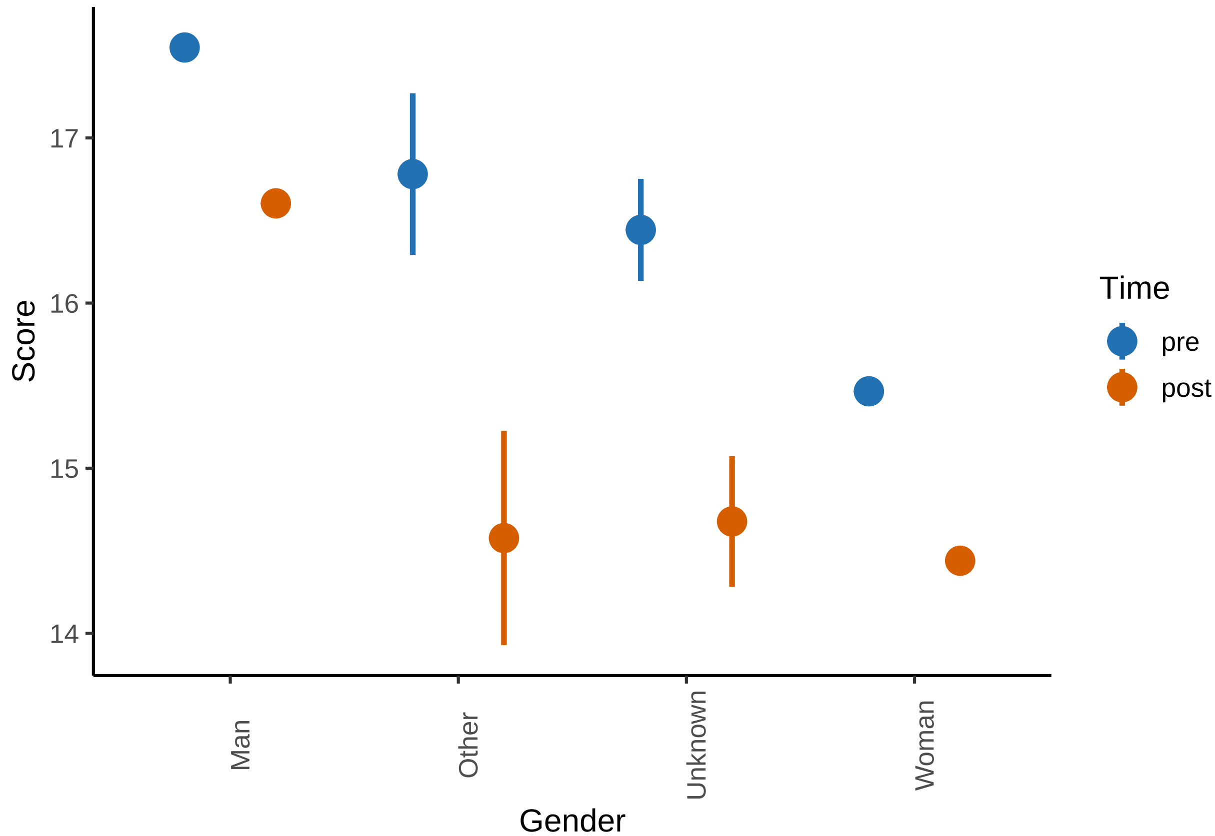
```r
Race.ethnicity.table(df.matched, Lab.type = TRUE)
```

```
## [1] "Race.ethnicity.NatHawaii"
##
##     Concepts-based Mixed Skills-based
##   0           3277 10163         4697
##   1             27   108           36
## [1] "Race.ethnicity.Asian"
##
##     Concepts-based Mixed Skills-based
##   0           2682  7411         3826
##   1            622  2860          907
## [1] "Race.ethnicity.Black"
##
##     Concepts-based Mixed Skills-based
##   0           2761  9813         4611
##   1            543   458          122
## [1] "Race.ethnicity.Hispanic"
##
##     Concepts-based Mixed Skills-based
##   0           3017  9396         4303
##   1            287   875          430
## [1] "Race.ethnicity.AmInd"
##
##     Concepts-based Mixed Skills-based
##   0           3286 10152         4710
##   1             18   119           23
## [1] "Race.ethnicity.White"
##
##     Concepts-based Mixed Skills-based
##   0           1501  4465         1648
##   1           1803  5806         3085
## [1] "Race.ethnicity.Other"
##
##     Concepts-based Mixed Skills-based
##   0           3227  9988         4626
##   1             77   283          107
## [1] "Race.ethnicity.Unknown"
```

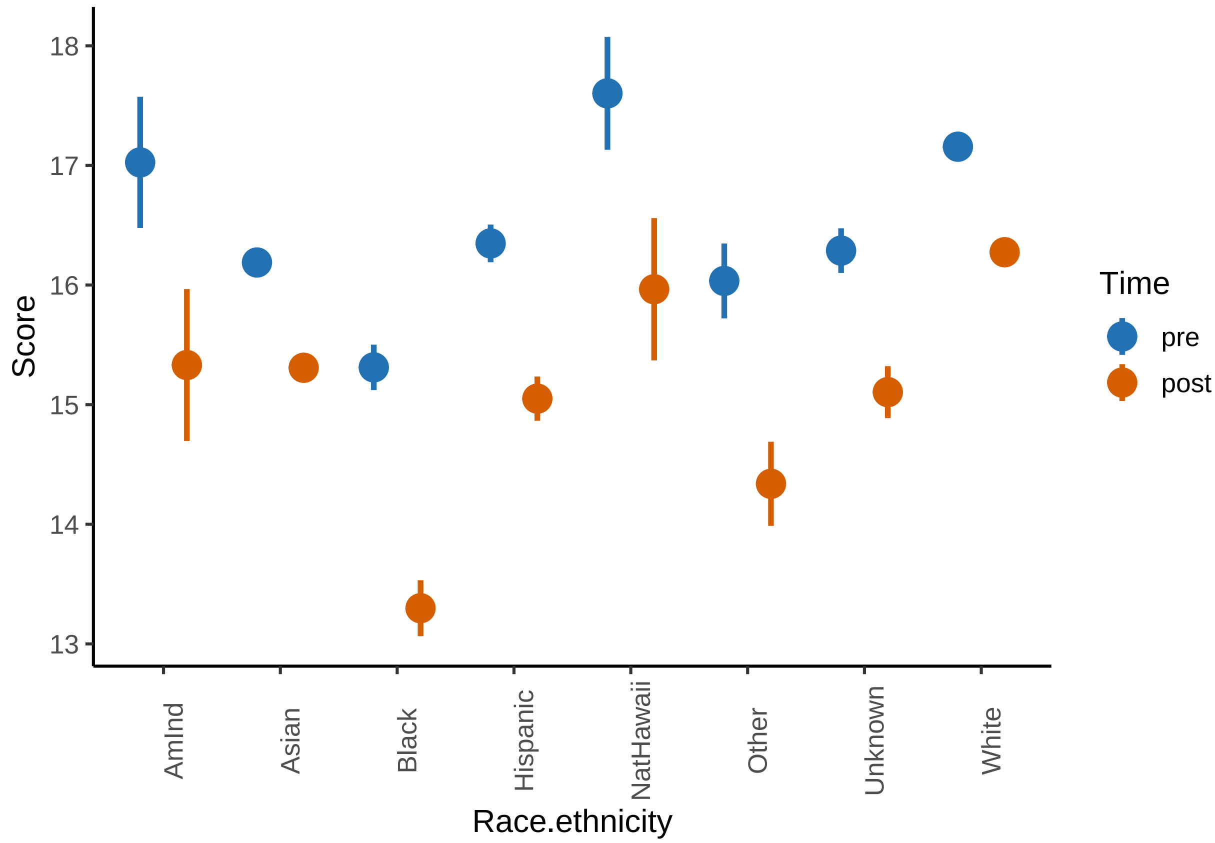
```
##
##     Concepts-based Mixed Skills-based
##   0           3101  9594        4400
##   1            203   677         333
```

Descriptive statistics

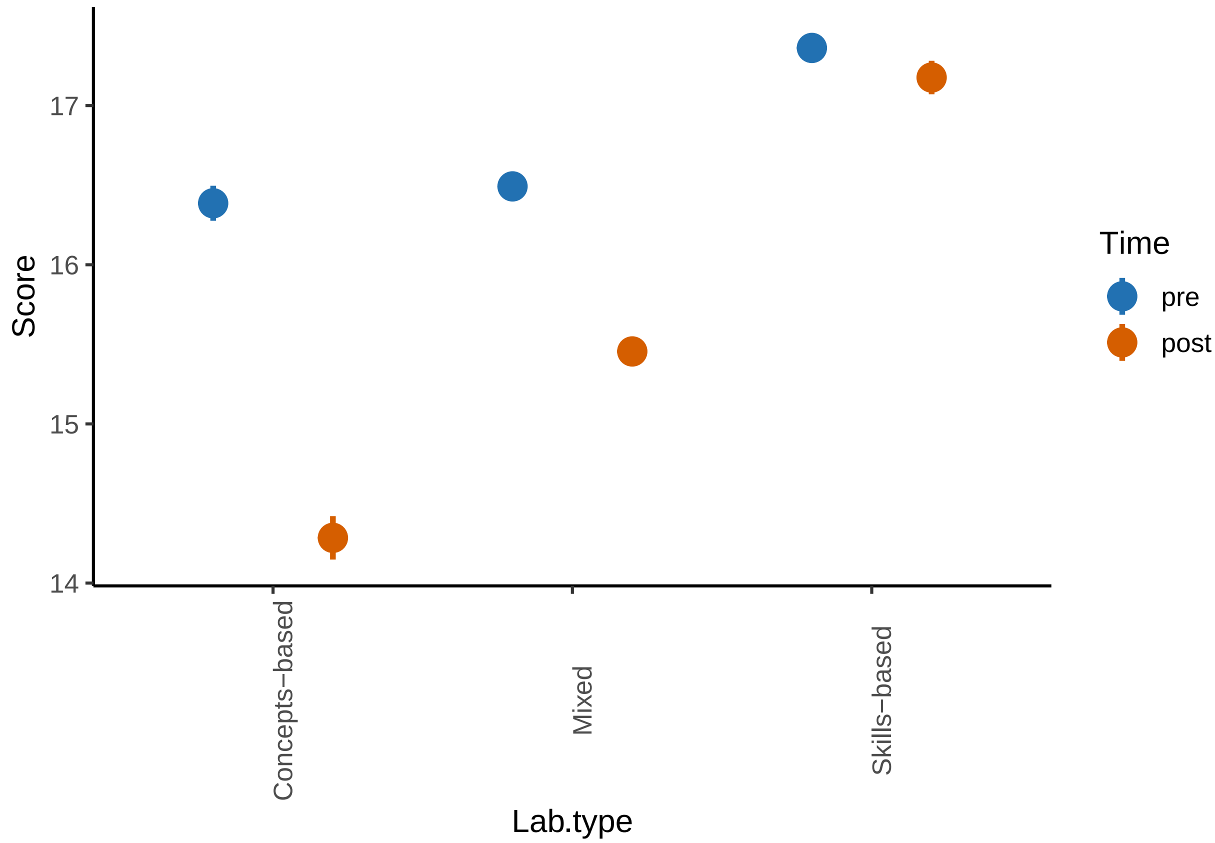
```r
plot.pre.post <- function(df, var){
  # plot pre-post score shifts on overall student scores
  if(var == 'Race.ethnicity'){
    # race/ethnicity variables aren't independent, so we melt twice...first to put
    # pre-post scores in long form
    df.long <- reshape2::melt(df.matched, id.vars = new.race.cols,
                              measure.vars = c('student.score.pre',
                                               'student.score.post'),
                              variable.name = 'Time', value.name = 'Score') %>%
      # ...then again to put race/ethnicity in long form
      reshape2::melt(., measure.vars = new.race.cols,
                     id.vars = c('Time', 'Score'),
                     variable.name = 'Race.ethnicity') %>%
      filter(value == 1) %>%
      select(Time, Score, Race.ethnicity) %>%
      rowwise() %>% # rowwise split the characters in the column to get labels
      mutate(Race.ethnicity = strsplit(as.character(Race.ethnicity), '\\.')[[1]][3])

  } else {
    # we only need to put the scores in long form since the gender/lab type
    # variables are already long
    df.long <- reshape2::melt(df, measure.vars = c('student.score.pre',
                                                   'student.score.post'),
                              variable.name = 'Time', value.name = 'Score')
  }

  p <- ggplot(df.long, aes_string(x = var, y = 'Score', group = 'Time', color = 'Time'))
  add_summary(p, fun = 'mean_se', group = c('Time')) +
    scale_color_manual(labels = c('pre', 'post'), values = c('#2271B2', '#D55E00')) +
    theme(axis.text.x = element_text(angle = 90))
}

plot.pre.post(df.matched, 'Gender')
```




```
plot.pre.post(df.matched, 'Race.ethnicity')
```




```r
plot.pre.post(df.matched, 'Lab.type')
```



Mixed-effects models

```
# fit null model with random intercepts for class and institution
# this model measures the interclass correlation coefficient (ICC)
mod0 <- lmer(student.score.post ~ (1 | anon_university_id/ResponseId.CIS), df.matched)
r2(mod0)
```

```
##
## R-Squared for (Generalized) Linear (Mixed) Model
##
## Family : gaussian (identity)
## Formula: list(~1 | ResponseId.CIS:anon_university_id, ~1 | anon_university_id) student.score.post ~ 1
##
##    Marginal R2: 0.000
## Conditional R2: 0.101
```

```
# fit model of interest
mod <- lmer(student.score.post ~ student.score.pre + Course.level + Lab.type *
               (Gender + Race.ethnicity.AmInd + Race.ethnicity.NatHawaii +
               Race.ethnicity.Other + Race.ethnicity.Black +
                 Race.ethnicity.Hispanic + Race.ethnicity.Asian +
                 Race.ethnicity.White + Race.ethnicity.Unknown) +
```

```r
             Major + (1 | anon_university_id/ResponseId.CIS), df.matched)
summary(mod)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula:
## student.score.post ~ student.score.pre + Course.level + Lab.type *
##     (Gender + Race.ethnicity.AmInd + Race.ethnicity.NatHawaii +
##         Race.ethnicity.Other + Race.ethnicity.Black + Race.ethnicity.Hispanic +
##         Race.ethnicity.Asian + Race.ethnicity.White + Race.ethnicity.Unknown) +
##     Major + (1 | anon_university_id/ResponseId.CIS)
##    Data: df.matched
##
## REML criterion at convergence: 115552.3
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -6.2857 -0.5271  0.1211  0.6561  3.9853
##
## Random effects:
##  Groups                             Name        Variance Std.Dev.
##  ResponseId.CIS:anon_university_id (Intercept)  0.9756  0.9877
##  anon_university_id                 (Intercept)  0.7128  0.8443
##  Residual                                        31.7741  5.6369
## Number of obs: 18308, groups:
## ResponseId.CIS:anon_university_id, 380; anon_university_id, 96
##
## Fixed effects:
##                                                   Estimate Std. Error
## (Intercept)                                      4.369e+00  5.584e-01
## student.score.pre                                7.106e-01  6.711e-03
## Course.levelBFY                                  5.468e-01  3.078e-01
## Course.levelFY.Calc                             -3.834e-02  2.501e-01
## Lab.typeMixed                                    9.399e-01  5.515e-01
## Lab.typeSkills-based                             1.369e+00  6.390e-01
## GenderOther                                     -2.458e+00  1.044e+00
## GenderUnknown                                   -1.699e+00  6.992e-01
## GenderWoman                                     -1.016e+00  2.086e-01
## Race.ethnicity.AmInd1                           -1.076e+00  1.343e+00
## Race.ethnicity.NatHawaii1                       -1.486e+00  1.099e+00
## Race.ethnicity.Other1                           -8.746e-01  7.123e-01
## Race.ethnicity.Black1                           -1.040e-01  4.821e-01
## Race.ethnicity.Hispanic1                        -1.771e-01  4.375e-01
## Race.ethnicity.Asian1                            7.052e-01  4.121e-01
## Race.ethnicity.White1                           -1.423e-02  3.874e-01
## Race.ethnicity.Unknown1                          1.316e-01  6.068e-01
## MajorChem.LifeSci                               -1.495e+00  1.848e-01
## MajorEngineering                                -7.588e-01  1.632e-01
## MajorMath.CS                                    -1.326e+00  1.824e-01
## MajorNonSci                                     -2.232e+00  2.232e-01
## MajorOtherSci                                   -1.274e+00  2.052e-01
## MajorUndeclared                                 -5.733e-01  3.106e-01
## MajorUnknown                                    -1.622e+00  6.854e-01
```

```
## Lab.typeMixed:GenderOther                        1.105e+00  1.182e+00
## Lab.typeSkills-based:GenderOther                 1.325e+00  1.281e+00
## Lab.typeMixed:GenderUnknown                      1.446e+00  8.027e-01
## Lab.typeSkills-based:GenderUnknown               9.816e-01  9.684e-01
## Lab.typeMixed:GenderWoman                        7.591e-01  2.407e-01
## Lab.typeSkills-based:GenderWoman                 1.110e+00  2.760e-01
## Lab.typeMixed:Race.ethnicity.AmInd1              7.251e-01  1.441e+00
## Lab.typeSkills-based:Race.ethnicity.AmInd1       1.957e+00  1.799e+00
## Lab.typeMixed:Race.ethnicity.NatHawaii1          1.080e+00  1.230e+00
## Lab.typeSkills-based:Race.ethnicity.NatHawaii1   2.177e+00  1.458e+00
## Lab.typeMixed:Race.ethnicity.Other1              8.579e-02  8.074e-01
## Lab.typeSkills-based:Race.ethnicity.Other1       4.639e-01  9.457e-01
## Lab.typeMixed:Race.ethnicity.Black1             -8.738e-01  5.768e-01
## Lab.typeSkills-based:Race.ethnicity.Black1       9.578e-02  7.471e-01
## Lab.typeMixed:Race.ethnicity.Hispanic1          -3.528e-01  5.066e-01
## Lab.typeSkills-based:Race.ethnicity.Hispanic1    3.292e-01  5.870e-01
## Lab.typeMixed:Race.ethnicity.Asian1             -4.924e-01  4.672e-01
## Lab.typeSkills-based:Race.ethnicity.Asian1      -6.159e-01  5.517e-01
## Lab.typeMixed:Race.ethnicity.White1              1.047e-01  4.415e-01
## Lab.typeSkills-based:Race.ethnicity.White1       1.236e-01  5.279e-01
## Lab.typeMixed:Race.ethnicity.Unknown1           -2.333e-01  6.909e-01
## Lab.typeSkills-based:Race.ethnicity.Unknown1    -1.138e+00  7.914e-01
##                                                         df t value Pr(>|t|)
## (Intercept)                                      1.085e+03   7.825 1.20e-14
## student.score.pre                                1.826e+04 105.885  < 2e-16
## Course.levelBFY                                  4.244e+02   1.776  0.07640
## Course.levelFY.Calc                              2.727e+02  -0.153  0.87830
## Lab.typeMixed                                    1.601e+03   1.704  0.08851
## Lab.typeSkills-based                             2.000e+03   2.142  0.03229
## GenderOther                                      1.813e+04  -2.355  0.01855
## GenderUnknown                                    1.815e+04  -2.430  0.01513
## GenderWoman                                      1.809e+04  -4.870 1.12e-06
## Race.ethnicity.AmInd1                            1.815e+04  -0.801  0.42286
## Race.ethnicity.NatHawaii1                        1.814e+04  -1.352  0.17645
## Race.ethnicity.Other1                            1.813e+04  -1.228  0.21956
## Race.ethnicity.Black1                            8.586e+03  -0.216  0.82927
## Race.ethnicity.Hispanic1                         1.819e+04  -0.405  0.68566
## Race.ethnicity.Asian1                            1.825e+04   1.711  0.08709
## Race.ethnicity.White1                            1.817e+04  -0.037  0.97069
## Race.ethnicity.Unknown1                          1.815e+04   0.217  0.82828
## MajorChem.LifeSci                                1.326e+04  -8.087 6.67e-16
## MajorEngineering                                 1.537e+04  -4.650 3.34e-06
## MajorMath.CS                                     1.696e+04  -7.269 3.77e-13
## MajorNonSci                                      1.650e+04  -9.996  < 2e-16
## MajorOtherSci                                    1.487e+04  -6.207 5.53e-10
## MajorUndeclared                                  1.813e+04  -1.846  0.06493
## MajorUnknown                                     1.824e+04  -2.367  0.01793
## Lab.typeMixed:GenderOther                        1.815e+04   0.935  0.34981
## Lab.typeSkills-based:GenderOther                 1.818e+04   1.034  0.30114
## Lab.typeMixed:GenderUnknown                      1.819e+04   1.801  0.07171
## Lab.typeSkills-based:GenderUnknown               1.824e+04   1.014  0.31078
## Lab.typeMixed:GenderWoman                        1.800e+04   3.154  0.00161
## Lab.typeSkills-based:GenderWoman                 1.799e+04   4.021 5.82e-05
## Lab.typeMixed:Race.ethnicity.AmInd1              1.814e+04   0.503  0.61497
```

```
## Lab.typeSkills-based:Race.ethnicity.AmInd1      1.817e+04   1.088  0.27660
## Lab.typeMixed:Race.ethnicity.NatHawaii1         1.814e+04   0.878  0.37990
## Lab.typeSkills-based:Race.ethnicity.NatHawaii1  1.816e+04   1.493  0.13544
## Lab.typeMixed:Race.ethnicity.Other1             1.814e+04   0.106  0.91538
## Lab.typeSkills-based:Race.ethnicity.Other1      1.813e+04   0.491  0.62373
## Lab.typeMixed:Race.ethnicity.Black1             1.179e+04  -1.515  0.12982
## Lab.typeSkills-based:Race.ethnicity.Black1      1.533e+04   0.128  0.89798
## Lab.typeMixed:Race.ethnicity.Hispanic1          1.822e+04  -0.697  0.48609
## Lab.typeSkills-based:Race.ethnicity.Hispanic1   1.822e+04   0.561  0.57488
## Lab.typeMixed:Race.ethnicity.Asian1             1.826e+04  -1.054  0.29189
## Lab.typeSkills-based:Race.ethnicity.Asian1      1.826e+04  -1.116  0.26429
## Lab.typeMixed:Race.ethnicity.White1             1.818e+04   0.237  0.81252
## Lab.typeSkills-based:Race.ethnicity.White1      1.820e+04   0.234  0.81487
## Lab.typeMixed:Race.ethnicity.Unknown1           1.823e+04  -0.338  0.73565
## Lab.typeSkills-based:Race.ethnicity.Unknown1    1.793e+04  -1.437  0.15063
##
## (Intercept)                                    ***
## student.score.pre                              ***
## Course.levelBFY                                .
## Course.levelFY.Calc
## Lab.typeMixed                                  .
## Lab.typeSkills-based                           *
## GenderOther                                    *
## GenderUnknown                                  *
## GenderWoman                                    ***
## Race.ethnicity.AmInd1
## Race.ethnicity.NatHawaii1
## Race.ethnicity.Other1
## Race.ethnicity.Black1
## Race.ethnicity.Hispanic1
## Race.ethnicity.Asian1                          .
## Race.ethnicity.White1
## Race.ethnicity.Unknown1
## MajorChem.LifeSci                              ***
## MajorEngineering                               ***
## MajorMath.CS                                   ***
## MajorNonSci                                    ***
## MajorOtherSci                                  ***
## MajorUndeclared                                .
## MajorUnknown                                   *
## Lab.typeMixed:GenderOther
## Lab.typeSkills-based:GenderOther
## Lab.typeMixed:GenderUnknown                    .
## Lab.typeSkills-based:GenderUnknown
## Lab.typeMixed:GenderWoman                      **
## Lab.typeSkills-based:GenderWoman               ***
## Lab.typeMixed:Race.ethnicity.AmInd1
## Lab.typeSkills-based:Race.ethnicity.AmInd1
## Lab.typeMixed:Race.ethnicity.NatHawaii1
## Lab.typeSkills-based:Race.ethnicity.NatHawaii1
## Lab.typeMixed:Race.ethnicity.Other1
## Lab.typeSkills-based:Race.ethnicity.Other1
## Lab.typeMixed:Race.ethnicity.Black1
## Lab.typeSkills-based:Race.ethnicity.Black1
```

```
## Lab.typeMixed:Race.ethnicity.Hispanic1
## Lab.typeSkills-based:Race.ethnicity.Hispanic1
## Lab.typeMixed:Race.ethnicity.Asian1
## Lab.typeSkills-based:Race.ethnicity.Asian1
## Lab.typeMixed:Race.ethnicity.White1
## Lab.typeSkills-based:Race.ethnicity.White1
## Lab.typeMixed:Race.ethnicity.Unknown1
## Lab.typeSkills-based:Race.ethnicity.Unknown1
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

##
## Correlation matrix not shown by default, as p = 46 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it
```

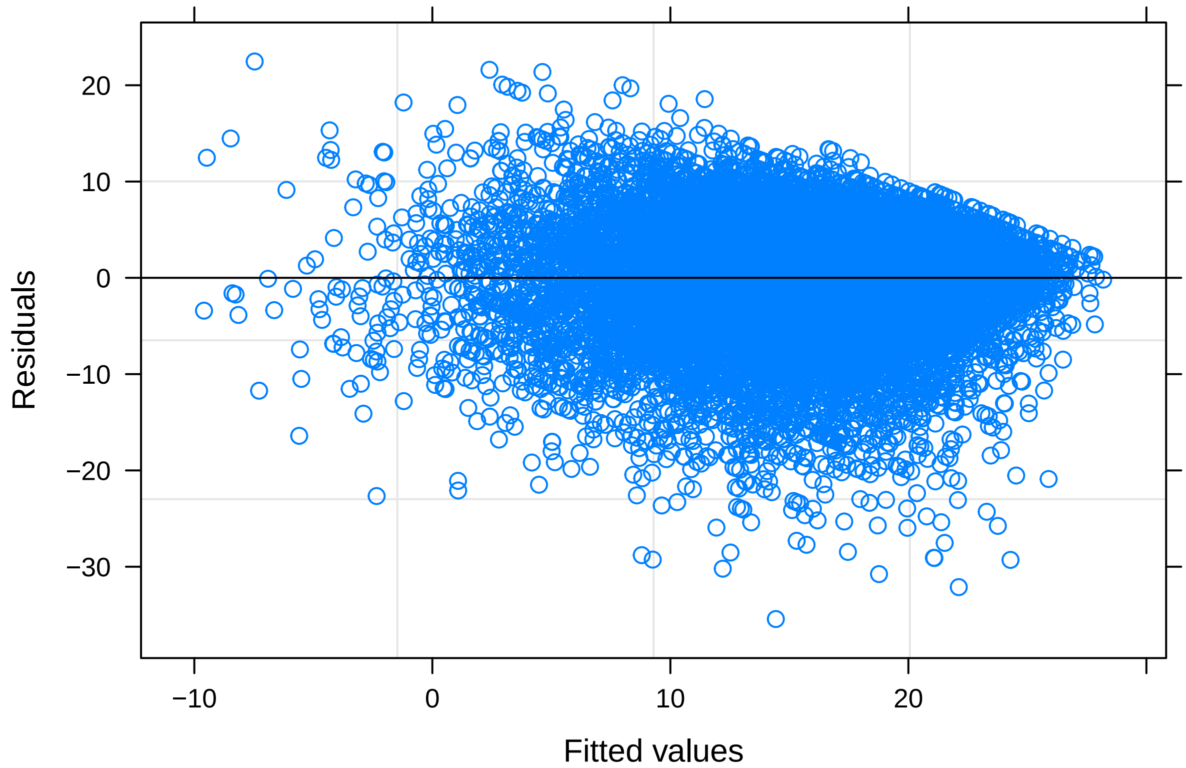
```
# get standardized coefficients, grand-mean-centering continuous variables
noStandard.cols <- c('Lab.type', 'Course.level', 'Major', 'Gender',
                     names(df.matched)[names(df.matched) %like% "Race"])
class(mod) <- "lmerMod"
mod.std <- beta(mod, skip = noStandard.cols)
```

Variance inflation factors and model diagnostics

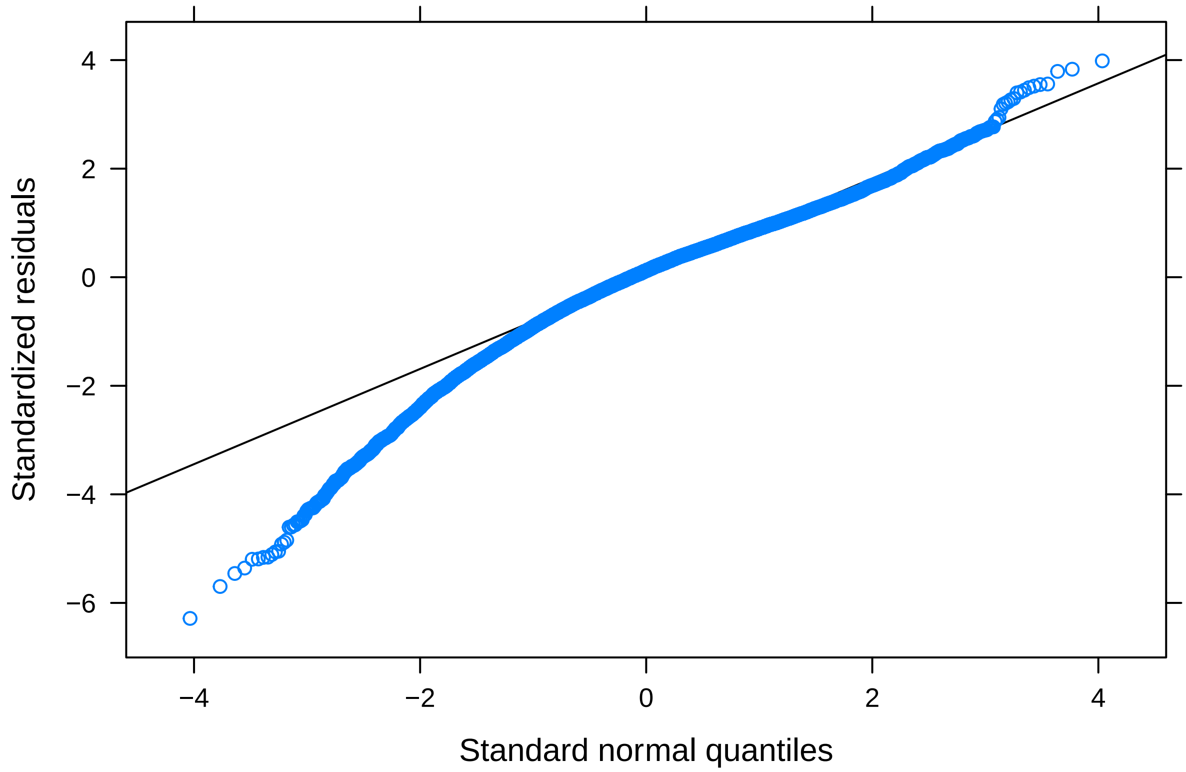
```
# variance inflation factors...ratio of variance in measured parameter compared to model
# with only that parameter
vif(mod)
```

```
##                                         GVIF Df GVIF^(1/(2*Df))
## student.score.pre                   1.030597  1        1.015183
## Course.level                        1.398741  2        1.087513
## Lab.type                           13.043634  2        1.900420
## Gender                            221.342937  3        2.459486
## Race.ethnicity.AmInd                8.900141  1        2.983310
## Race.ethnicity.NatHawaii            6.384736  1        2.526803
## Race.ethnicity.Other                7.193625  1        2.682093
## Race.ethnicity.Black                5.519118  1        2.349280
## Race.ethnicity.Hispanic             8.078261  1        2.842228
## Race.ethnicity.Asian               15.519226  1        3.939445
## Race.ethnicity.White               17.979053  1        4.240171
## Race.ethnicity.Unknown             12.238951  1        3.498421
## Major                               1.411382  7        1.024917
## Lab.type:Gender                   287.353165  6        1.602758
## Lab.type:Race.ethnicity.AmInd       9.096440  2        1.736672
## Lab.type:Race.ethnicity.NatHawaii   6.524229  2        1.598204
## Lab.type:Race.ethnicity.Other       9.137759  2        1.738641
## Lab.type:Race.ethnicity.Black       6.210474  2        1.578633
## Lab.type:Race.ethnicity.Hispanic   13.787500  2        1.926954
## Lab.type:Race.ethnicity.Asian      47.388623  2        2.623726
## Lab.type:Race.ethnicity.White      94.343809  2        3.116581
## Lab.type:Race.ethnicity.Unknown    26.857065  2        2.276484
```

```r
# fitted values versus residuals...should be no trend
plot(mod, xlab = 'Fitted values', ylab = 'Residuals')
```




```r
qqmath(mod) # standardized residuals versus standard quantiles
```



Output stargazer

Marginal effects plots

```
# marginal effects (average effect) of different labs on posttest scores
p1 <- plot_model(mod, type = 'eff', terms = c('Lab.type'), ci.lvl = 0.67)

p1.new <- ggplot(data.frame(p1$data), aes(x = factor(x), y = predicted,
                                          color = factor(x))) +
  geom_point(size = 2) +
  geom_errorbar(aes(ymin = conf.low, ymax = conf.high), size = 1, width = 0,
                position = position_dodge(width = 0.5)) +
  scale_x_discrete(labels = c('Concepts-based', 'Mixed', 'Skills-based')) +
  scale_color_manual(values = c('#e69f00', '#009e74', '#0071b2')) +
  labs(x = 'Lab type', y = 'Predicted E-CLASS posttest scores') +
  theme(axis.text.x = element_text(angle = 40, vjust = 1, hjust = 1),
        legend.position = 'none')

# average over lab type and gender
p2 <- plot_model(mod, type = 'eff', terms = c('Gender', 'Lab.type'), dot.size = 2,
                 line.size = 1, ci.lvl = 0.67, title = '',
                 axis.title = '',
```

```
                 colors = c('#e69f00', '#009e74', '#0071b2'), dodge = 0.5) +
  scale_x_discrete(limits = c("Man", "Non-binary", "Woman", "Unknown")) +
  labs(x = 'Gender', y = '') +
  theme(legend.position = 'top')
```

```
## Scale for 'x' is already present. Adding another scale for 'x', which
## will replace the existing scale.
```

```
p2.new <- p2
p2.new$data$x <- rep(c(1, 2, 4, 3), 3)

get_legend <- function(myggplot){
  # from http://www.sthda.com/english/wiki/wiki.php?id_contents=7930
  tmp <- ggplot_gtable(ggplot_build(myggplot))
  leg <- which(sapply(tmp$grobs, function(x) x$name) == "guide-box")
  legend <- tmp$grobs[[leg]]
  return(legend)
}

leg <- get_legend(p2.new)
p2.new <- p2.new + theme(legend.position = 'none',
                         axis.text.x = element_text(angle = 40, vjust = 1,
                                                    hjust = 1),
                         plot.margin = unit(c(0, 0, 0, -0.5), 'cm'))
```

Race/ethnicity marginal effects plots

```
# average over lab type and race/ethnicity...since race/ethnicity variables are not
# independent, we calculate marginal effects separately for each variable...
p3.native <- plot_model(mod, type = 'eff', terms = c('Race.ethnicity.Other [1]',
                                                     'Lab.type'), ci.lvl = 0.67)
# the [1]s are because effects are estimated for variable = 0 and variable = 1...we only
# want the 1s
df.race.eff <- data.frame(p3.native$data) %>%
  mutate(race.ethnicity = 'Race.ethnicity.Other')
for(race in c(new.race.cols[2:length(new.race.cols)])){
  p3 <- plot_model(mod, type = 'eff', terms = c(paste(race, ' [1]', sep = ''),
                                                'Lab.type'), ci.lvl = 0.67)
  # ...bind results in one dataframe...
  df.race.eff <- rbind(df.race.eff, data.frame(p3$data) %>%
                         mutate(race.ethnicity = race))
}

# ...and clean up the dataframe a little bit
df.race.eff <- df.race.eff %>%
  rowwise() %>%
  mutate(race.ethnicity = strsplit(race.ethnicity, '\\.')[[1]][3]) %>%
  mutate(group = factor(group, levels = c('Concepts-based', 'Mixed',
                                          'Skills-based'),
                        ordered = TRUE),
```

```r
         race.ethnicity = case_when(
           race.ethnicity == 'AmInd' ~ 'American Indian',
           race.ethnicity == 'NatHawaii' ~ 'Native Hawaiian',
           TRUE ~ race.ethnicity))

p3 <- ggplot(df.race.eff, aes(x = factor(race.ethnicity,
                                         levels = c('American Indian', 'Asian',
                                                    'Black', 'Hispanic',
                                                    'Native Hawaiian', 'White',
                                                    'Other', 'Unknown')),
                            y = predicted, group = group, color = group)) +
  geom_point(size = 2, position = position_dodge(width = 0.5)) +
  geom_errorbar(aes(ymin = conf.low, ymax = conf.high), size = 1, width = 0.2,
                position = position_dodge(width = 0.5)) +
  scale_color_manual(values = c('#e69f00', '#009e74', '#0071b2')) +
  labs(x = 'Race/ethnicity', y = '') +
  theme(axis.text.x = element_text(angle = 40, vjust = 1, hjust = 1),
        legend.position = 'none',
        plot.margin = unit(c(0, 0, 0, -0.5), 'cm'))
```

```r
png('Figures/E-CLASS_Labtype_Demos.png', width = 586, height = 363)
grobs = cbind(ggplotGrob(p1.new), ggplotGrob(p2.new), ggplotGrob(p3), size = "first")
grid.arrange(leg, arrangeGrob(grobs), heights = c(1, 10))
dev.off()
```

```
## pdf
##   2
```

Process CIS items

```r
df.matched[, names(df.matched) %like% "Q34|Q35|Q36"] <-
  data.frame(lapply(df.matched[, names(df.matched) %like% "Q34|Q35|Q36"], function(x)
    droplevels(factor(as.vector(x), levels = c('Never', 'Rarely', 'Sometimes',
                                               'Often', 'Always'),
                      ordered = TRUE))))

df.matched[, names(df.matched) %like% "Q34|Q35|Q36"] <- data.frame(lapply(df.matched[, names(df.matched)
```

Run CFA on CIS

```r
mod <- '
  agency =~ Q35_1 + Q35_2 + Q35_3 + Q35_4 + Q35_5 + Q35_6 + Q34_1 + Q34_2 + Q34_3
'

# unique classes only
CIS.df <- unique(df.matched[, names(df.matched) %like% "Q34|Q35|Q36"])
```

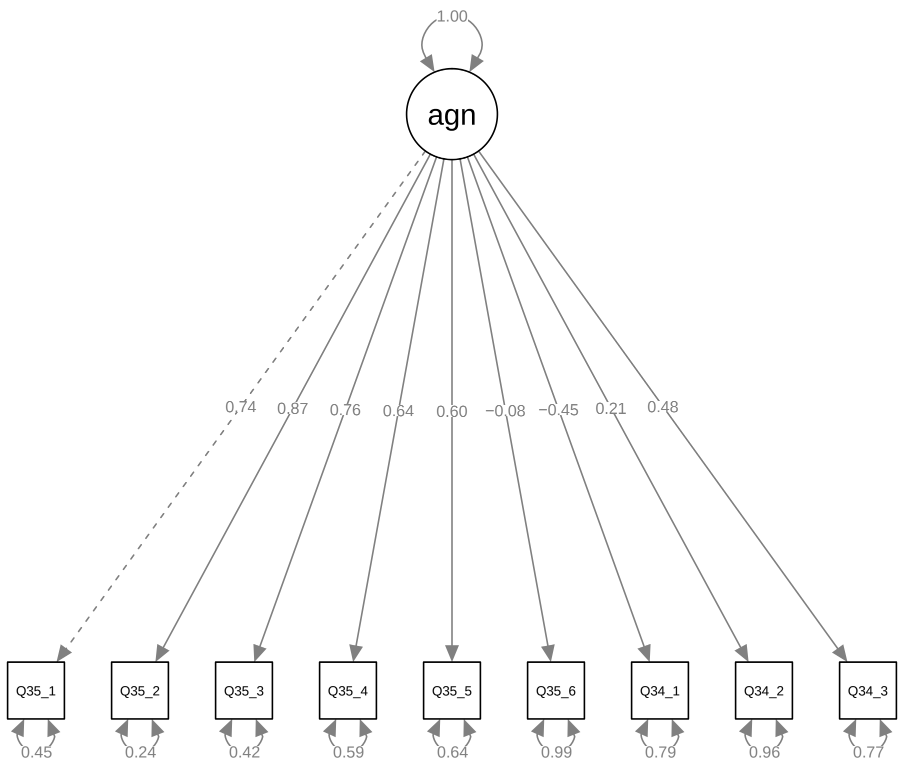
```r
fit <- cfa(mod, CIS.df)
summary(fit, standardized = TRUE, fit.measures = TRUE, modindices = TRUE)
```

```
## lavaan 0.6-3 ended normally after 19 iterations
##
##   Optimization method                           NLMINB
##   Number of free parameters                         18
##
##   Number of observations                           181
##
##   Estimator                                         ML
##   Model Fit Test Statistic                      74.084
##   Degrees of freedom                                27
##   P-value (Chi-square)                           0.000
##
## Model test baseline model:
##
##   Minimum Function Test Statistic              519.118
##   Degrees of freedom                                36
##   P-value                                        0.000
##
## User model versus baseline model:
##
##   Comparative Fit Index (CFI)                    0.903
##   Tucker-Lewis Index (TLI)                       0.870
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)              -2052.249
##   Loglikelihood unrestricted model (H1)      -2015.207
##
##   Number of free parameters                         18
##   Akaike (AIC)                                4140.499
##   Bayesian (BIC)                              4198.072
##   Sample-size adjusted Bayesian (BIC)         4141.064
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.098
##   90 Percent Confidence Interval          0.072  0.125
##   P-value RMSEA <= 0.05                          0.002
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                           0.062
##
## Parameter Estimates:
##
##   Information                                 Expected
##   Information saturated (h1) model          Structured
##   Standard Errors                             Standard
##
## Latent Variables:
```

```
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   agency =~
##     Q35_1             1.000                               0.801    0.742
##     Q35_2             1.233    0.111   11.138    0.000    0.987    0.870
##     Q35_3             1.122    0.113    9.934    0.000    0.899    0.765
##     Q35_4             0.837    0.101    8.304    0.000    0.671    0.643
##     Q35_5             0.750    0.097    7.740    0.000    0.601    0.601
##     Q35_6            -0.073    0.068   -1.075    0.282   -0.058   -0.085
##     Q34_1            -0.517    0.089   -5.804    0.000   -0.414   -0.454
##     Q34_2             0.240    0.090    2.667    0.008    0.192    0.210
##     Q34_3             0.567    0.093    6.100    0.000    0.454    0.476
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Q35_1             0.524    0.066    7.913    0.000    0.524    0.450
##    .Q35_2             0.313    0.057    5.486    0.000    0.313    0.243
##    .Q35_3             0.575    0.075    7.658    0.000    0.575    0.415
##    .Q35_4             0.639    0.074    8.612    0.000    0.639    0.587
##    .Q35_5             0.639    0.073    8.795    0.000    0.639    0.639
##    .Q35_6             0.467    0.049    9.504    0.000    0.467    0.993
##    .Q34_1             0.660    0.072    9.187    0.000    0.660    0.794
##    .Q34_2             0.796    0.084    9.455    0.000    0.796    0.956
##    .Q34_3             0.701    0.077    9.143    0.000    0.701    0.773
##     agency            0.642    0.115    5.555    0.000    1.000    1.000
##
## Modification Indices:
##
##      lhs op   rhs     mi    epc sepc.lv sepc.all sepc.nox
## 20 Q35_1 ~~ Q35_2  0.919  0.053   0.053    0.130    0.130
## 21 Q35_1 ~~ Q35_3  0.453 -0.037  -0.037   -0.068   -0.068
## 22 Q35_1 ~~ Q35_4  0.486 -0.036  -0.036   -0.062   -0.062
## 23 Q35_1 ~~ Q35_5  4.221 -0.104  -0.104   -0.180   -0.180
## 24 Q35_1 ~~ Q35_6  0.128 -0.014  -0.014   -0.029   -0.029
## 25 Q35_1 ~~ Q34_1  1.597  0.062   0.062    0.106    0.106
## 26 Q35_1 ~~ Q34_2  2.511  0.084   0.084    0.129    0.129
## 27 Q35_1 ~~ Q34_3 12.506  0.181   0.181    0.298    0.298
## 28 Q35_2 ~~ Q35_3  0.145  0.023   0.023    0.055    0.055
## 29 Q35_2 ~~ Q35_4  0.729  0.044   0.044    0.099    0.099
## 30 Q35_2 ~~ Q35_5  1.059 -0.051  -0.051   -0.115   -0.115
## 31 Q35_2 ~~ Q35_6  1.004  0.037   0.037    0.097    0.097
## 32 Q35_2 ~~ Q34_1  0.283 -0.025  -0.025   -0.055   -0.055
## 33 Q35_2 ~~ Q34_2  3.397 -0.090  -0.090   -0.180   -0.180
## 34 Q35_2 ~~ Q34_3  2.292 -0.074  -0.074   -0.157   -0.157
## 35 Q35_3 ~~ Q35_4  3.514 -0.104  -0.104   -0.171   -0.171
## 36 Q35_3 ~~ Q35_5  2.536  0.086   0.086    0.142    0.142
## 37 Q35_3 ~~ Q35_6  1.509 -0.052  -0.052   -0.101   -0.101
## 38 Q35_3 ~~ Q34_1  5.323 -0.121  -0.121   -0.197   -0.197
## 39 Q35_3 ~~ Q34_2  1.738  0.074   0.074    0.109    0.109
## 40 Q35_3 ~~ Q34_3  3.593 -0.103  -0.103   -0.163   -0.163
## 41 Q35_4 ~~ Q35_5 10.081  0.168   0.168    0.262    0.262
## 42 Q35_4 ~~ Q35_6  0.038  0.008   0.008    0.015    0.015
## 43 Q35_4 ~~ Q34_1  1.724  0.068   0.068    0.105    0.105
## 44 Q35_4 ~~ Q34_2  0.070  0.015   0.015    0.021    0.021
## 45 Q35_4 ~~ Q34_3  0.026 -0.009  -0.009   -0.013   -0.013
```

```
## 46 Q35_5 ~~ Q35_6  0.353  0.025   0.025    0.046    0.046
## 47 Q35_5 ~~ Q34_1  0.793  0.046   0.046    0.070    0.070
## 48 Q35_5 ~~ Q34_2  0.041 -0.011  -0.011   -0.016   -0.016
## 49 Q35_5 ~~ Q34_3  0.368 -0.032  -0.032   -0.048   -0.048
## 50 Q35_6 ~~ Q34_1  1.172  0.045   0.045    0.082    0.082
## 51 Q35_6 ~~ Q34_2  1.533  0.056   0.056    0.092    0.092
## 52 Q35_6 ~~ Q34_3  0.000  0.001   0.001    0.002    0.002
## 53 Q34_1 ~~ Q34_2 12.534  0.195   0.195    0.269    0.269
## 54 Q34_1 ~~ Q34_3  0.867 -0.049  -0.049   -0.072   -0.072
## 55 Q34_2 ~~ Q34_3  5.862  0.138   0.138    0.184    0.184
```

```r
semPaths(fit, whatLabels = 'std')
```




```r
resid(fit, type = 'cor')
```

```
## $type
## [1] "cor.bollen"
##
## $cov
##       Q35_1  Q35_2  Q35_3  Q35_4  Q35_5  Q35_6  Q34_1  Q34_2  Q34_3
## Q35_1  0.000
## Q35_2  0.013  0.000
## Q35_3 -0.016  0.005  0.000
## Q35_4 -0.022  0.015 -0.056  0.000
## Q35_5 -0.070 -0.020  0.051  0.130  0.000
```

```
## Q35_6 -0.016  0.028 -0.053  0.010  0.034  0.000
## Q34_1  0.050 -0.013 -0.086  0.062  0.044  0.070  0.000
## Q34_2  0.070 -0.050  0.055  0.014 -0.011  0.089  0.225  0.000
## Q34_3  0.137 -0.035 -0.069 -0.007 -0.030  0.001 -0.052  0.151  0.000
```

Run EFA on half of the dataset

```r
set.seed(11)
inds <- sample(seq_len(nrow(CIS.df)), size = nrow(CIS.df)/2)
CIS.train.df <- CIS.df[inds, names(CIS.df) %like% 'Q34|Q35']

CIS.train.df
```

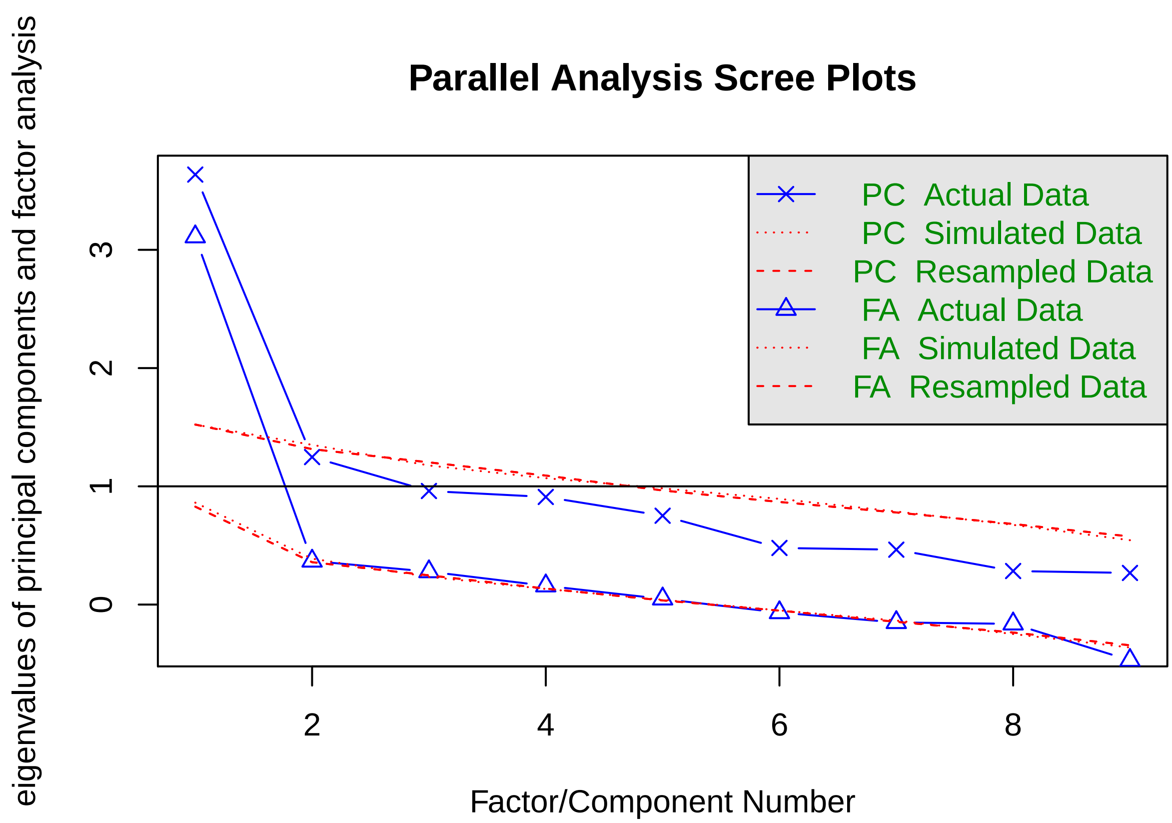
```
##       Q34_1 Q34_2 Q34_3 Q35_1 Q35_2 Q35_3 Q35_4 Q35_5 Q35_6
## 3020      4     4     4     1     3     4     4     5     5
## 1         2     2     4     4     4     5     4     5     5
## 6950      4     3     3     2     3     1     3     2     5
## 49        3     4     5     2     2     2     2     4     5
## 422       4     2     4     3     2     1     3     3     5
## 15483     4     3     3     3     5     1     4     3     5
## 548       4     2     2     1     2     1     2     2     5
## 18087     4     4     3     1     3     1     3     3     5
## 13569     4     3     3     5     5     2     3     3     5
## 779       4     2     2     3     3     1     3     3     5
## 1593      4     4     5     5     4     2     4     4     5
## 4571      4     3     3     1     2     1     1     3     5
## 13612     5     4     4     2     2     1     5     3     5
## 12466     2     4     4     3     5     5     5     4     5
## 9902      4     4     2     1     2     3     3     3     5
## 7437      3     3     4     5     5     3     4     5     5
## 4956      4     4     4     3     2     2     4     4     5
## 3455      3     3     3     2     3     2     3     2     5
## 998       4     2     2     2     2     1     2     3     5
## 4737      3     3     4     3     5     3     4     4     4
## 1725      1     2     5     3     5     5     4     5     5
## 8361      4     4     2     1     2     2     2     3     5
## 3538      4     5     4     1     1     1     1     2     5
## 3525      3     2     3     3     4     3     4     4     5
## 317       4     4     4     3     3     3     3     4     5
## 4655      4     2     3     2     2     2     3     2     4
## 4064      3     3     3     3     3     3     3     3     3
## 17257     4     4     3     1     2     1     3     3     5
## 766       4     3     2     1     3     1     3     4     5
## 4041      2     3     3     3     3     5     3     5     5
## 4722      2     2     4     2     4     2     2     4     5
## 3007      4     3     2     2     3     3     2     3     5
## 13625     5     4     4     4     4     4     3     3     4
## 15868     2     4     3     2     4     4     4     4     5
## 9465      3     4     4     3     3     3     3     5     5
## 6987      3     3     3     2     4     5     3     5     5
## 2793      3     3     4     3     3     3     3     3     5
```

```
## 535        3    3    2    2    3    4    3    5    5
## 2312       5    5    5    5    5    3    3    5    5
## 245        2    4    3    3    4    4    4    5    3
## 2243       3    4    4    4    4    2    4    4    4
## 1692       4    4    3    3    3    4    4    5    3
## 4181       3    3    4    3    3    3    3    3    5
## 6948       2    4    4    3    3    3    3    4    5
## 2905       3    3    3    1    1    1    1    2    5
## 9453       4    4    3    1    4    3    4    4    5
## 6096       5    5    2    3    2    3    4    5    5
## 12         3    3    3    2    4    3    4    5    5
## 4260       4    3    3    1    1    1    1    3    5
## 8620       4    4    3    3    3    2    2    4    4
## 4109       4    4    4    4    4    3    3    3    5
## 14854      4    4    4    2    2    2    3    4    5
## 15066      3    2    4    2    2    3    2    5    5
## 2407       2    2    5    2    3    2    2    3    5
## 1436       4    5    3    1    1    1    1    2    5
## 13694      4    2    2    1    2    1    3    1    5
## 3099       4    3    3    2    1    1    1    3    5
## 8093       4    4    3    2    3    3    4    4    2
## 775        3    3    3    3    3    2    3    3    5
## 4401       4    4    3    2    3    4    3    4    4
## 624        3    3    5    5    5    5    5    5    5
## 11899      5    2    2    1    1    1    3    1    5
## 15273      3    2    3    3    3    3    3    4    3
## 12221      4    4    3    3    4    1    3    4    5
## 6107       2    3    4    4    4    2    3    3    1
## 15928      4    4    4    2    3    1    3    4    4
## 230        3    4    3    2    1    1    4    4    5
## 3534       3    5    4    4    4    4    4    4    3
## 8773       4    4    5    3    4    3    4    4    4
## 4251       3    3    4    2    3    1    2    2    5
## 13439      2    3    4    3    4    3    3    3    5
## 2911       4    2    3    1    3    1    3    4    4
## 8387       4    3    2    1    2    1    3    3    5
## 807        4    5    3    1    1    3    1    2    5
## 8042       4    4    4    4    4    3    3    3    5
## 8647       5    2    3    1    3    1    2    4    5
## 10278      3    4    4    4    4    4    3    3    4
## 12323      3    3    3    2    4    3    3    5    5
## 2316       4    4    3    2    3    2    3    2    5
## 8214       4    2    1    2    2    2    3    3    5
## 204        4    4    2    2    3    2    2    3    5
## 13421      4    4    4    3    4    4    3    3    5
## 16663      3    4    4    3    1    1    4    3    5
## 877        2    3    4    2    4    3    4    3    4
## 4927       4    2    4    2    2    1    2    4    5
## 12485      3    3    4    2    3    2    3    4    5
## 750        5    3    1    1    1    1    3    3    5
## 13449      3    3    3    1    3    1    2    2    5
## 13642      5    5    4    4    5    4    4    5    5
## 9460       4    3    4    1    1    1    2    2    5
```

```r
fa.parallel(CIS.train.df)
```

```
## Warning in fac(r = r, nfactors = nfactors, n.obs = n.obs, rotate =
## rotate, : A loading greater than abs(1) was detected. Examine the loadings
## carefully.

## Warning in fa.stats(r = r, f = f, phi = phi, n.obs = n.obs, np.obs
## = np.obs, : The estimated weights for the factor scores are probably
## incorrect. Try a different factor extraction method.

## Warning in fac(r = r, nfactors = nfactors, n.obs = n.obs, rotate =
## rotate, : An ultra-Heywood case was detected. Examine the results carefully

## Warning in fa.stats(r = r, f = f, phi = phi, n.obs = n.obs, np.obs
## = np.obs, : The estimated weights for the factor scores are probably
## incorrect. Try a different factor extraction method.

## Warning in fa.stats(r = r, f = f, phi = phi, n.obs = n.obs, np.obs
## = np.obs, : The estimated weights for the factor scores are probably
## incorrect. Try a different factor extraction method.

## Warning in fac(r = r, nfactors = nfactors, n.obs = n.obs, rotate =
## rotate, : A loading greater than abs(1) was detected. Examine the loadings
## carefully.

## Warning in fa.stats(r = r, f = f, phi = phi, n.obs = n.obs, np.obs
## = np.obs, : The estimated weights for the factor scores are probably
## incorrect. Try a different factor extraction method.

## Warning in fac(r = r, nfactors = nfactors, n.obs = n.obs, rotate =
## rotate, : An ultra-Heywood case was detected. Examine the results carefully

## Warning in fac(r = r, nfactors = nfactors, n.obs = n.obs, rotate =
## rotate, : A loading greater than abs(1) was detected. Examine the loadings
## carefully.

## Warning in fa.stats(r = r, f = f, phi = phi, n.obs = n.obs, np.obs
## = np.obs, : The estimated weights for the factor scores are probably
## incorrect. Try a different factor extraction method.

## Warning in fac(r = r, nfactors = nfactors, n.obs = n.obs, rotate =
## rotate, : An ultra-Heywood case was detected. Examine the results carefully

## Warning in fac(r = r, nfactors = nfactors, n.obs = n.obs, rotate =
## rotate, : A loading greater than abs(1) was detected. Examine the loadings
## carefully.

## Warning in fa.stats(r = r, f = f, phi = phi, n.obs = n.obs, np.obs
## = np.obs, : The estimated weights for the factor scores are probably
## incorrect. Try a different factor extraction method.
```

```
## Warning in fac(r = r, nfactors = nfactors, n.obs = n.obs, rotate =
## rotate, : An ultra-Heywood case was detected. Examine the results carefully

## Warning in fa.stats(r = r, f = f, phi = phi, n.obs = n.obs, np.obs
## = np.obs, : The estimated weights for the factor scores are probably
## incorrect. Try a different factor extraction method.

## Warning in fac(r = r, nfactors = nfactors, n.obs = n.obs, rotate =
## rotate, : A loading greater than abs(1) was detected. Examine the loadings
## carefully.

## Warning in fa.stats(r = r, f = f, phi = phi, n.obs = n.obs, np.obs
## = np.obs, : The estimated weights for the factor scores are probably
## incorrect. Try a different factor extraction method.

## Warning in fac(r = r, nfactors = nfactors, n.obs = n.obs, rotate =
## rotate, : An ultra-Heywood case was detected. Examine the results carefully
```

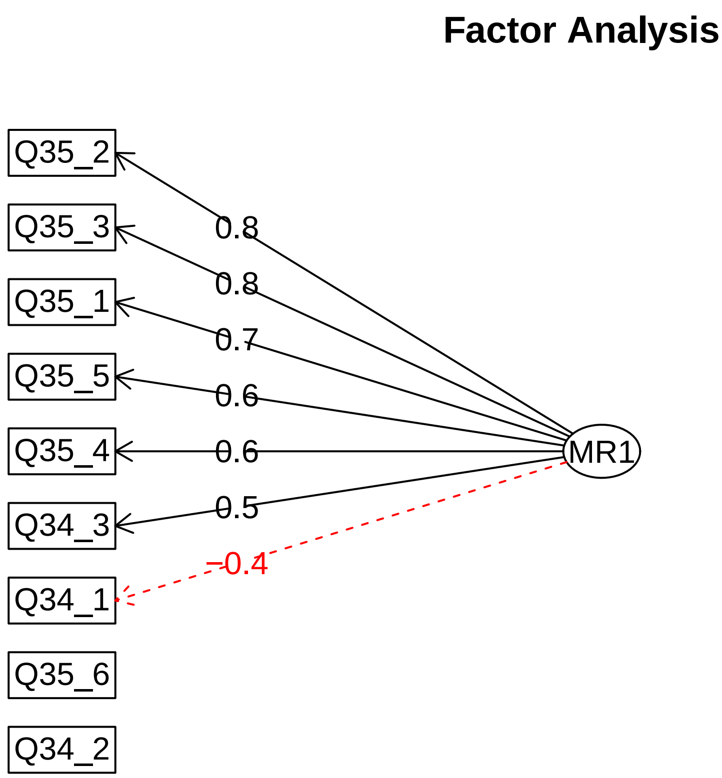



```
## Parallel analysis suggests that the number of factors =  1  and the number of components =  1
```

```
fit1 <- fa(CIS.train.df, 1)
fit1
```

```
## Factor Analysis using method =  minres
## Call: fa(r = CIS.train.df, nfactors = 1)
## Standardized loadings (pattern matrix) based upon correlation matrix
##         MR1    h2   u2 com
## Q34_1 -0.40 0.157 0.84   1
## Q34_2  0.17 0.027 0.97   1
## Q34_3  0.51 0.255 0.74   1
## Q35_1  0.74 0.551 0.45   1
## Q35_2  0.82 0.665 0.33   1
## Q35_3  0.75 0.567 0.43   1
## Q35_4  0.64 0.409 0.59   1
## Q35_5  0.64 0.415 0.58   1
## Q35_6 -0.25 0.063 0.94   1
##
##                 MR1
## SS loadings    3.11
## Proportion Var 0.35
##
## Mean item complexity =  1
## Test of the hypothesis that 1 factor is sufficient.
##
## The degrees of freedom for the null model are  36  and the objective function was  2.99 with Chi Squa
## The degrees of freedom for the model are 27  and the objective function was  0.66
##
## The root mean square of the residuals (RMSR) is  0.08
## The df corrected root mean square of the residuals is  0.1
##
## The harmonic number of observations is  90 with the empirical chi square  46.54  with prob <  0.011
## The total number of observations was  90  with Likelihood Chi Square =  55.65  with prob <  0.00095
##
## Tucker Lewis Index of factoring reliability =  0.824
## RMSEA index =  0.115  and the 90 % confidence intervals are  0.068 0.15
## BIC =  -65.84
## Fit based upon off diagonal values = 0.94
## Measures of factor score adequacy
##                                                    MR1
## Correlation of (regression) scores with factors   0.93
## Multiple R square of scores with factors          0.87
## Minimum correlation of possible factor scores     0.74
```

```r
fa.diagram(fit1)
```




```r
fit2 <- fa(CIS.train.df, 2)
```

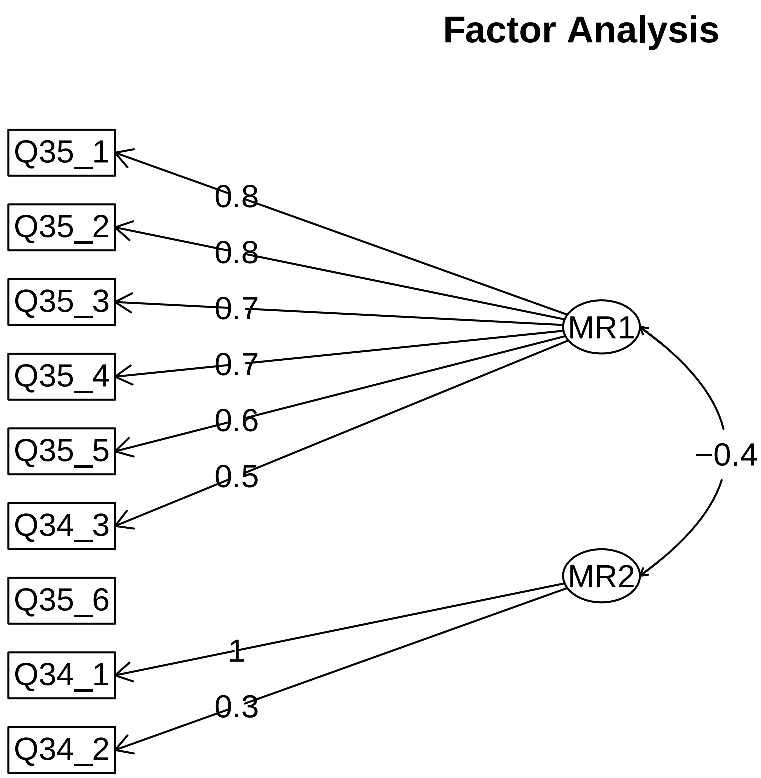
```
## Loading required namespace: GPArotation

## Warning in fa.stats(r = r, f = f, phi = phi, n.obs = n.obs, np.obs
## = np.obs, : The estimated weights for the factor scores are probably
## incorrect. Try a different factor extraction method.

## Warning in fa.stats(r = r, f = f, phi = phi, n.obs = n.obs, np.obs =
## np.obs, : An ultra-Heywood case was detected. Examine the results carefully
```

```r
fit2
```

```
## Factor Analysis using method =  minres
## Call: fa(r = CIS.train.df, nfactors = 2)
## Standardized loadings (pattern matrix) based upon correlation matrix
##         MR1   MR2    h2     u2 com
## Q34_1 -0.02  1.00 1.013 -0.013 1.0
## Q34_2  0.33  0.34 0.148  0.852 2.0
## Q34_3  0.46 -0.10 0.254  0.746 1.1
## Q35_1  0.79  0.08 0.585  0.415 1.0
## Q35_2  0.78 -0.07 0.650  0.350 1.0
## Q35_3  0.69 -0.13 0.557  0.443 1.1
## Q35_4  0.69  0.08 0.438  0.562 1.0
```

```
## Q35_5  0.64 -0.02 0.412  0.588 1.0
## Q35_6 -0.23  0.04 0.062  0.938 1.1
##
##                        MR1  MR2
## SS loadings           2.96 1.16
## Proportion Var        0.33 0.13
## Cumulative Var        0.33 0.46
## Proportion Explained  0.72 0.28
## Cumulative Proportion 0.72 1.00
##
##  With factor correlations of
##       MR1   MR2
## MR1  1.00 -0.35
## MR2 -0.35  1.00
##
## Mean item complexity =  1.1
## Test of the hypothesis that 2 factors are sufficient.
##
## The degrees of freedom for the null model are  36  and the objective function was  2.99 with Chi Squa
## The degrees of freedom for the model are 19  and the objective function was  0.42
##
## The root mean square of the residuals (RMSR) is  0.06
## The df corrected root mean square of the residuals is  0.08
##
## The harmonic number of observations is  90 with the empirical chi square  22.18  with prob <  0.28
## The total number of observations was  90  with Likelihood Chi Square =  35.56  with prob <  0.012
##
## Tucker Lewis Index of factoring reliability =  0.854
## RMSEA index =  0.105  and the 90 % confidence intervals are  0.046 0.149
## BIC =  -49.94
## Fit based upon off diagonal values = 0.97
```

```
fa.diagram(fit2)
```



Run CFA on CIS with new model

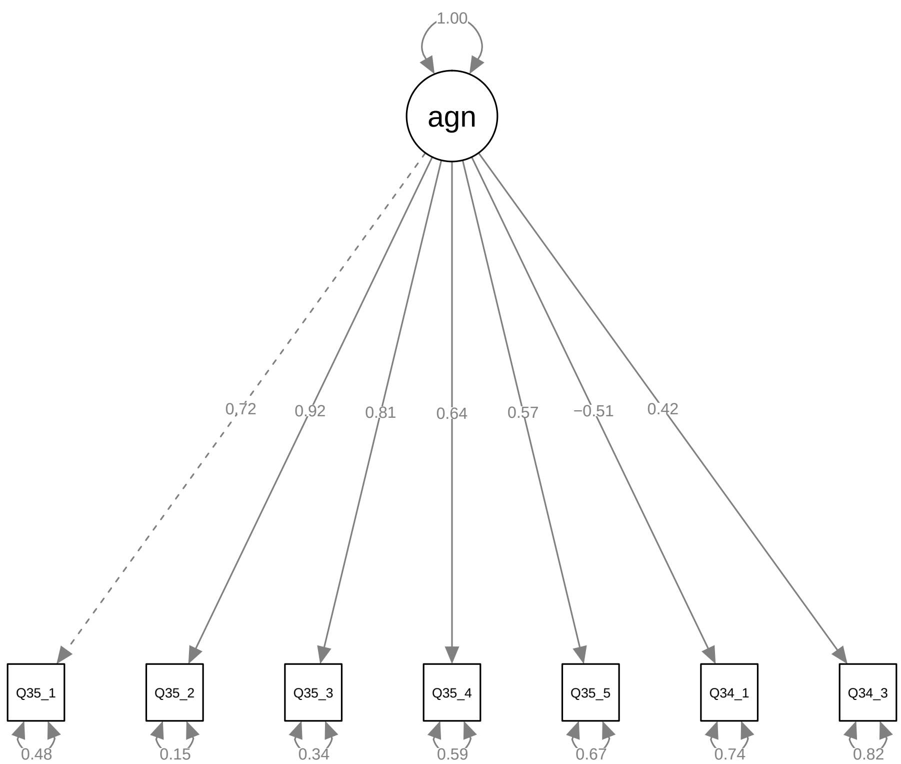
```
mod <- '
  agency =~ Q35_1 + Q35_2 + Q35_3 + Q35_4 + Q35_5 + Q34_1 + Q34_3
'

fit <- cfa(mod, CIS.df[-inds,])
summary(fit, standardized = TRUE, fit.measures = TRUE, modindices = TRUE)
```

```
## lavaan 0.6-3 ended normally after 19 iterations
##
##   Optimization method                           NLMINB
##   Number of free parameters                         14
##
##   Number of observations                            91
##
##   Estimator                                         ML
##   Model Fit Test Statistic                      28.618
##   Degrees of freedom                                14
##   P-value (Chi-square)                           0.012
##
## Model test baseline model:
##
```

```
##   Minimum Function Test Statistic              273.489
##   Degrees of freedom                                21
##   P-value                                        0.000
##
## User model versus baseline model:
##
##   Comparative Fit Index (CFI)                    0.942
##   Tucker-Lewis Index (TLI)                       0.913
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)               -808.259
##   Loglikelihood unrestricted model (H1)       -793.949
##
##   Number of free parameters                         14
##   Akaike (AIC)                                1644.517
##   Bayesian (BIC)                              1679.669
##   Sample-size adjusted Bayesian (BIC)         1635.481
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.107
##   90 Percent Confidence Interval          0.049  0.163
##   P-value RMSEA <= 0.05                          0.053
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                           0.061
##
## Parameter Estimates:
##
##   Information                                 Expected
##   Information saturated (h1) model          Structured
##   Standard Errors                             Standard
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   agency =~
##     Q35_1             1.000                               0.736    0.718
##     Q35_2             1.388    0.169    8.211    0.000    1.021    0.925
##     Q35_3             1.212    0.163    7.445    0.000    0.892    0.813
##     Q35_4             0.990    0.170    5.830    0.000    0.728    0.637
##     Q35_5             0.766    0.146    5.237    0.000    0.564    0.572
##     Q34_1            -0.662    0.143   -4.640    0.000   -0.487   -0.507
##     Q34_3             0.573    0.149    3.851    0.000    0.422    0.421
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Q35_1             0.509    0.085    6.012    0.000    0.509    0.485
##    .Q35_2             0.177    0.062    2.842    0.004    0.177    0.145
##    .Q35_3             0.409    0.077    5.292    0.000    0.409    0.339
##    .Q35_4             0.778    0.124    6.290    0.000    0.778    0.595
##    .Q35_5             0.652    0.102    6.425    0.000    0.652    0.672
##    .Q34_1             0.683    0.105    6.520    0.000    0.683    0.743
```

```
##    .Q34_3             0.823    0.125    6.606    0.000    0.823    0.822
##     agency            0.541    0.142    3.824    0.000    1.000    1.000
##
## Modification Indices:
##
##      lhs op   rhs     mi    epc sepc.lv sepc.all sepc.nox
## 16 Q35_1 ~~ Q35_2  2.593 -0.106  -0.106   -0.353   -0.353
## 17 Q35_1 ~~ Q35_3  2.204  0.094   0.094    0.206    0.206
## 18 Q35_1 ~~ Q35_4  0.134 -0.027  -0.027   -0.043   -0.043
## 19 Q35_1 ~~ Q35_5  1.070 -0.069  -0.069   -0.119   -0.119
## 20 Q35_1 ~~ Q34_1  0.009 -0.006  -0.006   -0.011   -0.011
## 21 Q35_1 ~~ Q34_3  7.361  0.198   0.198    0.305    0.305
## 22 Q35_2 ~~ Q35_3  1.924  0.109   0.109    0.406    0.406
## 23 Q35_2 ~~ Q35_4  0.643  0.057   0.057    0.154    0.154
## 24 Q35_2 ~~ Q35_5  0.062  0.015   0.015    0.045    0.045
## 25 Q35_2 ~~ Q34_1  0.019 -0.008  -0.008   -0.024   -0.024
## 26 Q35_2 ~~ Q34_3  1.967 -0.089  -0.089   -0.234   -0.234
## 27 Q35_3 ~~ Q35_4  6.658 -0.187  -0.187   -0.332   -0.332
## 28 Q35_3 ~~ Q35_5  1.016 -0.065  -0.065   -0.125   -0.125
## 29 Q35_3 ~~ Q34_1  0.679 -0.053  -0.053   -0.100   -0.100
## 30 Q35_3 ~~ Q34_3  1.233 -0.077  -0.077   -0.133   -0.133
## 31 Q35_4 ~~ Q35_5 10.013  0.253   0.253    0.355    0.355
## 32 Q35_4 ~~ Q34_1  0.501  0.057   0.057    0.079    0.079
## 33 Q35_4 ~~ Q34_3  1.487  0.107   0.107    0.134    0.134
## 34 Q35_5 ~~ Q34_1  1.155  0.079   0.079    0.118    0.118
## 35 Q35_5 ~~ Q34_3  0.005 -0.006  -0.006   -0.008   -0.008
## 36 Q34_1 ~~ Q34_3  0.001  0.002   0.002    0.003    0.003
```

```r
semPaths(fit, whatLabels = 'std')
```




```
resid(fit, type = 'cor')
```

```
## $type
## [1] "cor.bollen"
##
## $cov
##       Q35_1  Q35_2  Q35_3  Q35_4  Q35_5  Q34_1  Q34_3
## Q35_1  0.000
## Q35_2 -0.021  0.000
## Q35_3  0.048  0.012  0.000
## Q35_4 -0.018  0.013 -0.099  0.000
## Q35_5 -0.056  0.005 -0.043  0.196  0.000
## Q34_1 -0.006 -0.003 -0.037  0.047  0.076  0.000
## Q34_3  0.167 -0.032 -0.054  0.085 -0.005  0.002  0.000
```

Full SEM

```
df.matched <- df.matched %>%
  mutate(Lab.goal.skills = 1 * (Lab.type == 'Skills-based'),
         Lab.goal.both = 1 * (Lab.type == 'Mixed'),
         Lab.goal.concepts = 1 * (Lab.type == 'Concepts-based'))
```

```r
mod.sem <- '
  level: 1
    student.score.post ~ student.score.pre
  level: 2
    agency =~ Q35_1 + Q35_2 + Q35_3 + Q35_4 + Q35_5 + Q34_1 + Q34_3
    Q35_3 ~~ Q35_4 + Q35_5
    Q35_4 ~~ Q35_5

    agency ~ Lab.goal.skills + Lab.goal.both

    student.score.post ~ agency + Lab.goal.skills + Lab.goal.both
'

fit <- sem(mod.sem, data = df.matched, cluster = "ResponseId.CIS")
summary(fit, standardized = TRUE, fit.measures = TRUE, modindices = TRUE)
```

```
## lavaan 0.6-3 ended normally after 150 iterations
##
##   Optimization method                           NLMINB
##   Number of free parameters                         33
##
##   Number of observations                         18308
##   Number of clusters [ResponseId.CIS]              380
##
##   Estimator                                         ML
##   Model Fit Test Statistic                     115.652
##   Degrees of freedom                                29
##   P-value (Chi-square)                           0.000
##
## Model test baseline model:
##
##   Minimum Function Test Statistic            10569.694
##   Degrees of freedom                                45
##   P-value                                        0.000
##
## User model versus baseline model:
##
##   Comparative Fit Index (CFI)                    0.992
##   Tucker-Lewis Index (TLI)                       0.987
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)            -121854.330
##   Loglikelihood unrestricted model (H1)    -121796.504
##
##   Number of free parameters                         33
##   Akaike (AIC)                              243774.659
##   Bayesian (BIC)                            244032.557
##   Sample-size adjusted Bayesian (BIC)       243927.685
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.013
```

```
##   90 Percent Confidence Interval          0.010  0.015
##   P-value RMSEA <= 0.05                         1.000
##
## Standardized Root Mean Square Residual (corr metric):
##
##   SRMR (within covariance matrix)               0.000
##   SRMR (between covariance matrix)              0.051
##
## Parameter Estimates:
##
##   Information                                Observed
##   Observed information based on               Hessian
##   Standard Errors                            Standard
##
##
## Level 1 [within]:
##
## Regressions:
##                        Estimate  Std.Err  z-value  P(>|z|)   Std.lv
##   student.score.post ~
##     student.scr.pr        0.724    0.008   88.933    0.000    0.724
##   Std.all
##
##     0.641
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .studnt.scr.pst    0.000                               0.000    0.000
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .studnt.scr.pst   32.110    0.339   94.759    0.000   32.110    0.590
##
##
## Level 2 [ResponseId.CIS]:
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   agency =~
##     Q35_1             1.000                               0.850    0.797
##     Q35_2             1.310    0.064   20.324    0.000    1.114    0.916
##     Q35_3             0.971    0.064   15.134    0.000    0.825    0.733
##     Q35_4             1.007    0.065   15.426    0.000    0.856    0.742
##     Q35_5             0.804    0.060   13.354    0.000    0.683    0.661
##     Q34_1            -0.473    0.053   -8.972    0.000   -0.402   -0.465
##     Q34_3             0.429    0.056    7.671    0.000    0.364    0.396
##
## Regressions:
##                        Estimate  Std.Err  z-value  P(>|z|)   Std.lv
##   agency ~
##     Lab.goal.sklls        1.216    0.127    9.544    0.000    1.431
##     Lab.goal.both         0.176    0.112    1.579    0.114    0.207
##   student.score.post ~
##     agency                0.796    0.150    5.291    0.000    0.676
```

```
##     Lab.goal.sklls        1.245    0.344    3.622    0.000    1.245
##     Lab.goal.both         1.277    0.264    4.845    0.000    1.277
##   Std.all
##
##     0.668
##     0.103
##
##     0.424
##     0.364
##     0.399
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##  .Q35_3 ~~
##    .Q35_4            -0.095    0.036   -2.677    0.007   -0.095   -0.161
##    .Q35_5             0.049    0.035    1.411    0.158    0.049    0.083
##  .Q35_4 ~~
##    .Q35_5             0.161    0.037    4.339    0.000    0.161    0.268
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Q35_1             1.655    0.105   15.793    0.000    1.655    1.553
##    .Q35_2             1.936    0.131   14.790    0.000    1.936    1.593
##    .Q35_3             1.661    0.106   15.689    0.000    1.661    1.476
##    .Q35_4             2.246    0.109   20.543    0.000    2.246    1.946
##    .Q35_5             2.950    0.092   32.238    0.000    2.950    2.857
##    .Q34_1             3.803    0.065   58.212    0.000    3.803    4.392
##    .Q34_3             3.053    0.066   46.517    0.000    3.053    3.320
##    .studnt.scr.pst    2.592    0.247   10.484    0.000    2.592    1.624
##    .agency            0.000                               0.000    0.000
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Q35_1             0.414    0.036   11.459    0.000    0.414    0.364
##    .Q35_2             0.236    0.034    6.905    0.000    0.236    0.160
##    .Q35_3             0.585    0.049   11.948    0.000    0.585    0.462
##    .Q35_4             0.600    0.051   11.814    0.000    0.600    0.450
##    .Q35_5             0.600    0.048   12.520    0.000    0.600    0.562
##    .Q34_1             0.588    0.044   13.424    0.000    0.588    0.784
##    .Q34_3             0.713    0.053   13.526    0.000    0.713    0.843
##    .studnt.scr.pst    1.761    0.246    7.160    0.000    1.761    0.691
##    .agency            0.466    0.052    8.877    0.000    0.645    0.645
##
## Modification Indices:
##
##                   lhs op                rhs block group level     mi
## 3   student.score.pre ~~  student.score.pre     1     1     1  0.000
## 4  student.score.post ~1                        1     1     1  0.000
## 5   student.score.pre ~1                        1     1     1  0.000
## 30    Lab.goal.skills ~~    Lab.goal.skills     2     1     2  0.000
## 31    Lab.goal.skills ~~      Lab.goal.both     2     1     2  0.000
## 32      Lab.goal.both ~~      Lab.goal.both     2     1     2  0.000
## 41    Lab.goal.skills ~1                        2     1     2  0.000
## 42      Lab.goal.both ~1                        2     1     2  0.000
```

```
## 44  student.score.pre  ~ student.score.post     1     1     1  0.000
## 45             Q35_1 ~~              Q35_2     2     1     2  1.434
## 46             Q35_1 ~~              Q35_3     2     1     2  1.513
## 47             Q35_1 ~~              Q35_4     2     1     2  0.005
## 48             Q35_1 ~~              Q35_5     2     1     2  0.315
## 49             Q35_1 ~~              Q34_1     2     1     2 15.137
## 50             Q35_1 ~~              Q34_3     2     1     2 15.391
## 51             Q35_1 ~~ student.score.post     2     1     2  5.643
## 52             Q35_2 ~~              Q35_3     2     1     2  1.329
## 53             Q35_2 ~~              Q35_4     2     1     2  0.032
## 54             Q35_2 ~~              Q35_5     2     1     2  0.154
## 55             Q35_2 ~~              Q34_1     2     1     2  0.207
## 56             Q35_2 ~~              Q34_3     2     1     2  7.954
## 57             Q35_2 ~~ student.score.post     2     1     2  3.634
## 58             Q35_3 ~~              Q34_1     2     1     2  7.166
## 59             Q35_3 ~~              Q34_3     2     1     2  0.678
## 60             Q35_3 ~~ student.score.post     2     1     2  3.501
## 61             Q35_4 ~~              Q34_1     2     1     2  2.137
## 62             Q35_4 ~~              Q34_3     2     1     2  2.144
## 63             Q35_4 ~~ student.score.post     2     1     2  5.287
## 64             Q35_5 ~~              Q34_1     2     1     2  0.294
## 65             Q35_5 ~~              Q34_3     2     1     2  0.178
## 66             Q35_5 ~~ student.score.post     2     1     2  1.558
## 67             Q34_1 ~~              Q34_3     2     1     2 10.541
## 68             Q34_1 ~~ student.score.post     2     1     2  0.768
## 69             Q34_3 ~~ student.score.post     2     1     2  6.737
## 71    Lab.goal.skills  ~             agency     2     1     2  0.000
## 72    Lab.goal.skills  ~ student.score.post     2     1     2  0.000
## 73    Lab.goal.skills  ~      Lab.goal.both     2     1     2  0.000
## 74      Lab.goal.both  ~             agency     2     1     2  0.000
## 75      Lab.goal.both  ~ student.score.post     2     1     2  0.000
## 76      Lab.goal.both  ~    Lab.goal.skills     2     1     2  0.000
##       epc sepc.lv sepc.all sepc.nox
## 3   0.000   0.000    0.000    0.000
## 4   0.000   0.000    0.000    0.000
## 5   0.000   0.000    0.000    0.000
## 30  0.000   0.000    0.000    0.000
## 31  0.000   0.000       NA    0.000
## 32  0.000   0.000    0.000    0.000
## 41  0.000   0.000    0.000    0.000
## 42  0.000   0.000    0.000    0.000
## 44  0.000   0.000    0.000    0.000
## 45  0.045   0.045    0.144    0.144
## 46 -0.040  -0.040   -0.082   -0.082
## 47  0.002   0.002    0.004    0.004
## 48 -0.016  -0.016   -0.032   -0.032
## 49  0.110   0.110    0.223    0.223
## 50  0.121   0.121    0.223    0.223
## 51  0.162   0.162    0.190    0.190
## 52  0.045   0.045    0.121    0.121
## 53  0.007   0.007    0.018    0.018
## 54  0.012   0.012    0.033    0.033
## 55 -0.013  -0.013   -0.034   -0.034
## 56 -0.085  -0.085   -0.207   -0.207
```

```
## 57 -0.129  -0.129   -0.199   -0.199
## 58 -0.087  -0.087   -0.148   -0.148
## 59 -0.029  -0.029   -0.045   -0.045
## 60 -0.146  -0.146   -0.144   -0.144
## 61  0.046   0.046    0.077    0.077
## 62 -0.050  -0.050   -0.077   -0.077
## 63  0.174   0.174    0.169    0.169
## 64  0.016   0.016    0.027    0.027
## 65  0.014   0.014    0.021    0.021
## 66  0.090   0.090    0.088    0.088
## 67 -0.110  -0.110   -0.170   -0.170
## 68  0.066   0.066    0.065    0.065
## 69 -0.213  -0.213   -0.190   -0.190
## 71  0.000   0.000    0.000    0.000
## 72  0.000   0.000    0.000    0.000
## 73  0.000   0.000    0.000    0.000
## 74  0.000   0.000    0.000    0.000
## 75  0.000   0.000    0.000    0.000
## 76  0.000   0.000    0.000    0.000
```

```r
standardizedsolution(fit)
```

```
##                   lhs op                rhs est.std    se       z pvalue
## 1  student.score.post  ~  student.score.pre   0.641 0.005 136.988  0.000
## 2  student.score.post ~~ student.score.post   0.590 0.006  98.425  0.000
## 3   student.score.pre ~~  student.score.pre   1.000 0.000      NA     NA
## 4  student.score.post ~1                      0.000 0.000      NA     NA
## 5   student.score.pre ~1                      2.557 0.000      NA     NA
## 6              agency =~              Q35_1   0.797 0.021  37.278  0.000
## 7              agency =~              Q35_2   0.916 0.014  67.600  0.000
## 8              agency =~              Q35_3   0.733 0.027  27.408  0.000
## 9              agency =~              Q35_4   0.742 0.026  28.241  0.000
## 10             agency =~              Q35_5   0.661 0.032  20.796  0.000
## 11             agency =~              Q34_1  -0.465 0.042 -10.952  0.000
## 12             agency =~              Q34_3   0.396 0.046   8.692  0.000
## 13              Q35_3 ~~              Q35_4  -0.161 0.061  -2.636  0.008
## 14              Q35_3 ~~              Q35_5   0.083 0.057   1.450  0.147
## 15              Q35_4 ~~              Q35_5   0.268 0.053   5.064  0.000
## 16             agency  ~    Lab.goal.skills   0.668 0.056  11.842  0.000
## 17             agency  ~      Lab.goal.both   0.103 0.065   1.585  0.113
## 18 student.score.post  ~             agency   0.424 0.075   5.657  0.000
## 19 student.score.post  ~    Lab.goal.skills   0.364 0.099   3.691  0.000
## 20 student.score.post  ~      Lab.goal.both   0.399 0.080   5.020  0.000
## 21              Q35_1 ~~              Q35_1   0.364 0.034  10.674  0.000
## 22              Q35_2 ~~              Q35_2   0.160 0.025   6.444  0.000
## 23              Q35_3 ~~              Q35_3   0.462 0.039  11.775  0.000
## 24              Q35_4 ~~              Q35_4   0.450 0.039  11.556  0.000
## 25              Q35_5 ~~              Q35_5   0.562 0.042  13.368  0.000
## 26              Q34_1 ~~              Q34_1   0.784 0.039  19.900  0.000
## 27              Q34_3 ~~              Q34_3   0.843 0.036  23.316  0.000
## 28 student.score.post ~~ student.score.post   0.691 0.056  12.353  0.000
## 29             agency ~~             agency   0.645 0.039  16.501  0.000
## 30    Lab.goal.skills ~~    Lab.goal.skills   1.000 0.000      NA     NA
## 31    Lab.goal.skills ~~      Lab.goal.both  -0.736 0.000      NA     NA
```

```
## 32      Lab.goal.both ~~      Lab.goal.both   1.000 0.000      NA     NA
## 33             Q35_1 ~1                       1.553 0.125  12.450  0.000
## 34             Q35_2 ~1                       1.593 0.133  11.968  0.000
## 35             Q35_3 ~1                       1.476 0.119  12.369  0.000
## 36             Q35_4 ~1                       1.946 0.131  14.816  0.000
## 37             Q35_5 ~1                       2.857 0.152  18.788  0.000
## 38             Q34_1 ~1                       4.392 0.159  27.625  0.000
## 39             Q34_3 ~1                       3.320 0.153  21.759  0.000
## 40 student.score.post ~1                      1.624 0.201   8.064  0.000
## 41    Lab.goal.skills ~1                      0.688 0.000      NA     NA
## 42      Lab.goal.both ~1                      1.071 0.000      NA     NA
## 43            agency ~1                       0.000 0.000      NA     NA
##    ci.lower ci.upper
## 1     0.631    0.650
## 2     0.578    0.601
## 3     1.000    1.000
## 4     0.000    0.000
## 5     2.557    2.557
## 6     0.755    0.839
## 7     0.890    0.943
## 8     0.681    0.786
## 9     0.690    0.793
## 10    0.599    0.724
## 11   -0.548   -0.381
## 12    0.307    0.486
## 13   -0.280   -0.041
## 14   -0.029    0.196
## 15    0.164    0.372
## 16    0.557    0.779
## 17   -0.024    0.231
## 18    0.277    0.571
## 19    0.171    0.557
## 20    0.243    0.555
## 21    0.297    0.431
## 22    0.111    0.209
## 23    0.385    0.539
## 24    0.374    0.526
## 25    0.480    0.645
## 26    0.707    0.861
## 27    0.772    0.914
## 28    0.582    0.801
## 29    0.568    0.722
## 30    1.000    1.000
## 31   -0.736   -0.736
## 32    1.000    1.000
## 33    1.308    1.797
## 34    1.332    1.854
## 35    1.242    1.710
## 36    1.689    2.204
## 37    2.559    3.155
## 38    4.080    4.703
## 39    3.021    3.619
## 40    1.229    2.019
## 41    0.688    0.688
```

```
## 42    1.071    1.071
## 43    0.000    0.000
```

```r
resid(fit, type = 'cor')
```

```
## $within
## $within$type
## [1] "cor.bollen"
##
## $within$cov
##                    stdnt.scr.ps stdnt.scr.pr
## student.score.post 0
## student.score.pre  0            0
##
## $within$mean
## student.score.post  student.score.pre
##             -1.589              0.000
##
##
## $ResponseId.CIS
## $ResponseId.CIS$type
## [1] "cor.bollen"
##
## $ResponseId.CIS$cov
##                    Q35_1  Q35_2  Q35_3  Q35_4  Q35_5  Q34_1  Q34_3  stdn..
## Q35_1               0.000
## Q35_2               0.006  0.000
## Q35_3              -0.021  0.008  0.000
## Q35_4               0.001  0.001  0.000  0.000
## Q35_5              -0.013  0.005  0.000  0.000  0.000
## Q34_1               0.096 -0.006 -0.082  0.060  0.025  0.000
## Q34_3               0.101 -0.037 -0.016 -0.038 -0.001 -0.133  0.000
## student.score.post  0.043 -0.073 -0.094  0.143  0.079  0.009 -0.136  0.000
## Lab.goal.skills    -0.001 -0.007 -0.024  0.003 -0.012 -0.103  0.061 -0.008
## Lab.goal.both      -0.038 -0.008  0.057  0.036  0.027  0.036 -0.063  0.016
##                    Lb.gl.s Lb.gl.b
## Q35_1
## Q35_2
## Q35_3
## Q35_4
## Q35_5
## Q34_1
## Q34_3
## student.score.post
## Lab.goal.skills     0.000
## Lab.goal.both       0.000   0.000
##
## $ResponseId.CIS$mean
##              Q35_1              Q35_2              Q35_3
##              0.000              0.000              0.000
##              Q35_4              Q35_5              Q34_1
##              0.000              0.000              0.000
##              Q34_3 student.score.post    Lab.goal.skills
##              0.000              7.171              0.000
```

```
##      Lab.goal.both
##              0.000
```