Load necessary packages

```
library(easypackages)
libraries('tidyverse', 'data.table', 'reshape2', 'ggpubr', 'lmerTest',
          'reghelper', 'car', 'lattice', 'sjstats', 'sjPlot', 'gridExtra',
          'stargazer', 'lavaan', 'semPlot', 'psych', 'grid', 'semTools')
theme_set(theme_classic(base_size = 12)) # set font size for ggplot
source('C:/Users/Cole/Documents/GitHub/PLIC/Processing-Scripts/PLIC_DataProcessing.R')
```

Read and match

```
full.df <- fread('C:/Users/Cole/Documents/DATA/PLIC_DATA/Collective_Surveys/Complete/Complete_Concat_Co
  filter(Survey_x == 'C' | Survey_y == 'C')

# Remove FR scores
full.df[full.df$Survey_x == 'F', 'PreScores'] <- NA_real_
full.df[full.df$Survey_y == 'F', 'PostScores'] <- NA_real_

print('Total # of students in dataset...')
```

```
## [1] "Total # of students in dataset..."
```

```
length(unique(full.df$anon_student_id))
```

```
## [1] 9752
```

```
print('Total # of student records in dataset...')
```

```
## [1] "Total # of student records in dataset..."
```

```
nrow(full.df)
```

```
## [1] 10889
```

```
print('Total # of institutions in dataset..')
```

```
## [1] "Total # of institutions in dataset.."
```

```
length(unique(full.df$anon_institution_id))
```

```
## [1] 46
```

```
print('Total # of courses in dataset...')
```

```
## [1] "Total # of courses in dataset..."
```

```r
length(unique(full.df$anon_course_id))
```

```
## [1] 77
```

```r
print('Total # of classes in dataset...')
```

```
## [1] "Total # of classes in dataset..."
```

```r
length(unique(full.df$Class_ID))
```

```
## [1] 119
```

```r
# Remove whole classes without goal and/or level information or that were only administered at pre or p
full.df <- data.table(full.df)[, `:=`(N.students = .N,
                                      pre.rate = sum(Survey_x == 'C')/.N,
                                      post.rate = sum(Survey_y == 'C')/.N),
                               .(Class_ID)]

full.df <- full.df %>%
  filter(!is.na(Lab_level) & !is.na(Lab_purpose) & (Lab_purpose != '') &
           (pre.rate > 0) & (post.rate > 0))

print('remaining # of students in dataset...')
```

```
## [1] "remaining # of students in dataset..."
```

```r
length(unique(full.df$anon_student_id))
```

```
## [1] 8352
```

```r
print('remaining # of student records in dataset...')
```

```
## [1] "remaining # of student records in dataset..."
```

```r
nrow(full.df)
```

```
## [1] 8822
```

```r
print('remaining # of institutions in dataset..')
```

```
## [1] "remaining # of institutions in dataset.."
```

```r
length(unique(full.df$anon_institution_id))
```

```
## [1] 35
```

```r
print('remaining # of courses in dataset...')
```

```
## [1] "remaining # of courses in dataset..."
```

```r
length(unique(full.df$anon_course_id))
```

```
## [1] 60
```

```r
print('remaining # of classes in dataset...')
```

```
## [1] "remaining # of classes in dataset..."
```

```r
length(unique(full.df$Class_ID))
```

```
## [1] 87
```

```r
df.matched <- full.df %>%
  filter(!is.na(PreScores) & !is.na(PostScores))

print('# of students in matched dataset...')
```

```
## [1] "# of students in matched dataset..."
```

```r
length(unique(df.matched$anon_student_id))
```

```
## [1] 4600
```

```r
print('# of student records in matched dataset...')
```

```
## [1] "# of student records in matched dataset..."
```

```r
nrow(df.matched)
```

```
## [1] 4758
```

```r
print('# of institutions in matched dataset..')
```

```
## [1] "# of institutions in matched dataset.."
```

```r
length(unique(df.matched$anon_institution_id))
```

```
## [1] 35
```

```r
print('# of courses in matched dataset...')
```

```
## [1] "# of courses in matched dataset..."
```

```r
length(unique(df.matched$anon_course_id))
```

```
## [1] 60
```

```r
print('# of classes in matched dataset...')
```

```
## [1] "# of classes in matched dataset..."
```

```r
length(unique(df.matched$Class_ID))
```

```
## [1] 87
```

```r
table(df.matched[!duplicated(df.matched$anon_institution_id),
                 ]$Institution_type, exclude = NULL)
```

```
##
##              4 year college Masters granting institution
##                          14                            2
##     PhD granting institution
##                          19
```

```r
table(df.matched[!duplicated(df.matched$anon_course_id),]$Lab_level,
      exclude = NULL)
```

```
##
##   Intro-Algebra Intro-Calculus         Junior         Senior      Sophomore
##               7             33              9              4              7
```

```r
table(df.matched[!duplicated(df.matched$Class_ID),]$Lab_level, exclude = NULL)
```

```
##
##   Intro-Algebra Intro-Calculus         Junior         Senior      Sophomore
##               9             51             11              7              9
```

```r
table(df.matched[!duplicated(df.matched$anon_course_id),]$Lab_purpose,
      exclude = NULL)
```

```
##
## Both about equally Develop lab skills Reinforce concepts
##                 19                 31                 10
```

```
table(df.matched[!duplicated(df.matched$Class_ID),]$Lab_purpose, exclude = NULL)
```

```
##
## Both about equally Develop lab skills Reinforce concepts
##                 25                 44                 18
```

Data processing

```
# Creates new gender/race/major columns
df.matched <- Collapse.vars(df.matched) %>%
  mutate(Lab_level = relevel(as.factor(case_when(
    Lab_level == 'Intro-Algebra' ~ 'FY-Algebra',
    Lab_level == 'Intro-Calculus' ~ 'FY-Calculus',
    (Lab_level == 'Sophomore') | (Lab_level == 'Junior') |
      (Lab_level == 'Senior') ~ 'BFY',
    TRUE ~ NA_character_
  )), ref= 'FY-Algebra'),
  Lab_purpose = relevel(as.factor(case_when(
    Lab_purpose == 'Reinforce concepts' ~ 'Concepts-based',
    Lab_purpose == 'Both about equally' ~ 'Mixed',
    Lab_purpose == 'Develop lab skills' ~ 'Skills-based')), ref = 'Concepts-based'))


df.matched[is.na(df.matched)] <- 0
df.matched[names(df.matched) %like% "Race"] <-
  lapply(df.matched[names(df.matched) %like% "Race"], factor, levels = c(1, 0))
df.matched[names(df.matched) %like% "Race"] <-
  lapply(df.matched[names(df.matched) %like% "Race"], relevel, ref = '0')
```

Demographic breakdowns

```
table(df.matched$Gender)
```

```
##
##        Man Non-binary    Unknown      Woman
##       2673         55         30       2000
```

```
Race.ethnicity.table(df.matched, normalize = FALSE)
```

```
## [1] "Race.ethnicity.AmInd"
##
##    0    1
## 4697   61
## [1] "Race.ethnicity.Asian"
##
##    0    1
```

```
## 3314 1444
## [1] "Race.ethnicity.Black"
##
##    0    1
## 4538  220
## [1] "Race.ethnicity.Hispanic"
##
##    0    1
## 4303  455
## [1] "Race.ethnicity.NatHawaii"
##
##    0    1
## 4728   30
## [1] "Race.ethnicity.White"
##
##    0    1
## 1893 2865
## [1] "Race.ethnicity.Other"
##
##    0    1
## 4602  156
## [1] "Race.ethnicity.unknown"
##
##    0    1
## 4758    0
```

```
table(df.matched$Major)
```

```
##
##       Physics   Engineering         Other Other science       Unknown
##           894          2017           360          1389            98
```

```
table(df.matched$Lab_purpose)
```

```
##
## Concepts-based          Mixed   Skills-based
##           1838            783           2137
```

```
table(df.matched$Gender, df.matched$Lab_purpose)
```

```
##
##               Concepts-based Mixed Skills-based
##   Man                   1065   441         1167
##   Non-binary              11    14           30
##   Unknown                  9     5           16
##   Woman                  753   323          924
```

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

```
## [1] "Race.ethnicity.AmInd"
##
```

```
##     Concepts-based Mixed Skills-based
##   0           1816   772         2109
##   1             22    11           28
## [1] "Race.ethnicity.Asian"
##
##     Concepts-based Mixed Skills-based
##   0           1174   626         1514
##   1            664   157          623
## [1] "Race.ethnicity.Black"
##
##     Concepts-based Mixed Skills-based
##   0           1787   744         2007
##   1             51    39          130
## [1] "Race.ethnicity.Hispanic"
##
##     Concepts-based Mixed Skills-based
##   0           1697   711         1895
##   1            141    72          242
## [1] "Race.ethnicity.NatHawaii"
##
##     Concepts-based Mixed Skills-based
##   0           1828   775         2125
##   1             10     8           12
## [1] "Race.ethnicity.White"
##
##     Concepts-based Mixed Skills-based
##   0            775   251          867
##   1           1063   532         1270
## [1] "Race.ethnicity.Other"
##
##     Concepts-based Mixed Skills-based
##   0           1787   746         2069
##   1             51    37           68
## [1] "Race.ethnicity.unknown"
##
##     Concepts-based Mixed Skills-based
##   0           1838   783         2137
##   1              0     0            0
```

```r
table(df.matched$Major, df.matched$Lab_purpose)
```

```
##
##                 Concepts-based Mixed Skills-based
##   Physics                  150   177          567
##   Engineering             1391    73          553
##   Other                     45   103          212
##   Other science            213   416          760
##   Unknown                   39    14           45
```

```r
chisq.test(df.matched[!duplicated(df.matched$Class_ID), 'Lab_purpose'],
           df.matched[!duplicated(df.matched$Class_ID), 'Lab_level'])
```

```
## Warning in chisq.test(df.matched[!duplicated(df.matched$Class_ID),
## "Lab_purpose"], : Chi-squared approximation may be incorrect
```

```
##
##  Pearson's Chi-squared test
##
## data:  df.matched[!duplicated(df.matched$Class_ID), "Lab_purpose"] and df.matched[!duplicated(df.mat
## X-squared = 13.466, df = 4, p-value = 0.009209
```

```
summary(aov(PreScores ~ Lab_purpose, df.matched))
```

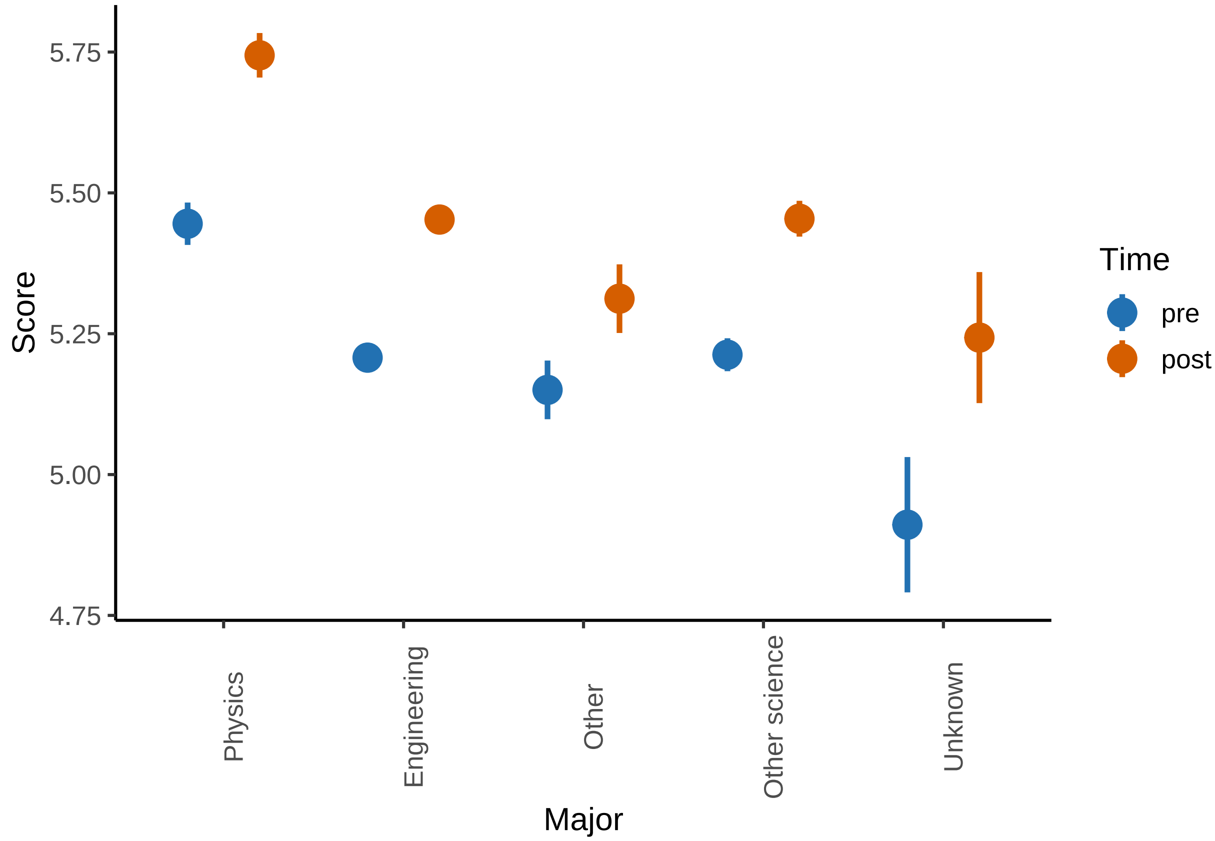
```
##               Df Sum Sq Mean Sq F value  Pr(>F)
## Lab_purpose    2     12   5.902   4.866 0.00774 **
## Residuals   4755   5768   1.213
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Descriptive statistics

```
plot.pre.post <- function(df, var){
  if(var == 'Race.ethnicity'){
    print(colSums(sapply(df[, names(df) %like% "Race"],
                         function (x) as.numeric(as.character(x)))))

    df.long <- reshape2::melt(df.matched,
                              id.vars = names(df)[names(df) %like% "Race"],
                              measure.vars = c('PreScores', 'PostScores'),
                              variable.name = 'Time', value.name = 'Score') %>%
      reshape2::melt(., measure.vars = names(df)[names(df) %like% "Race"],
                     id.vars = c('Time', 'Score'),
                     variable.name = 'Race.ethnicity') %>%
      filter(value == 1) %>%
      select(Time, Score, Race.ethnicity) %>%
      rowwise() %>%
      mutate(Race.ethnicity = strsplit(as.character(Race.ethnicity),
                                       '\\.')[[1]][3])

  } else {
    print(table(df[, var]))
    df.long <- reshape2::melt(df, measure.vars = c('PreScores', 'PostScores'),
                              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, 'Major')
```

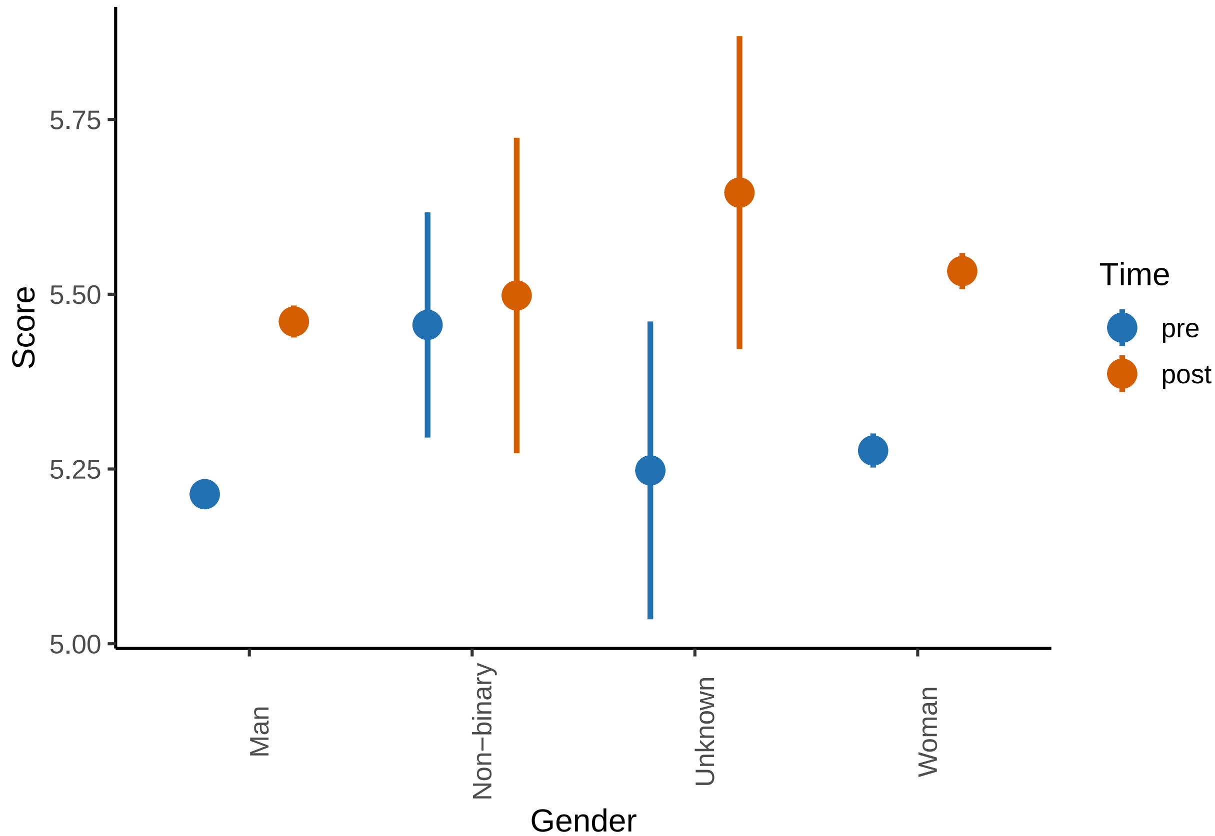
```
##
```

```
##        Physics    Engineering          Other Other science        Unknown
##            894           2017            360          1389             98
```



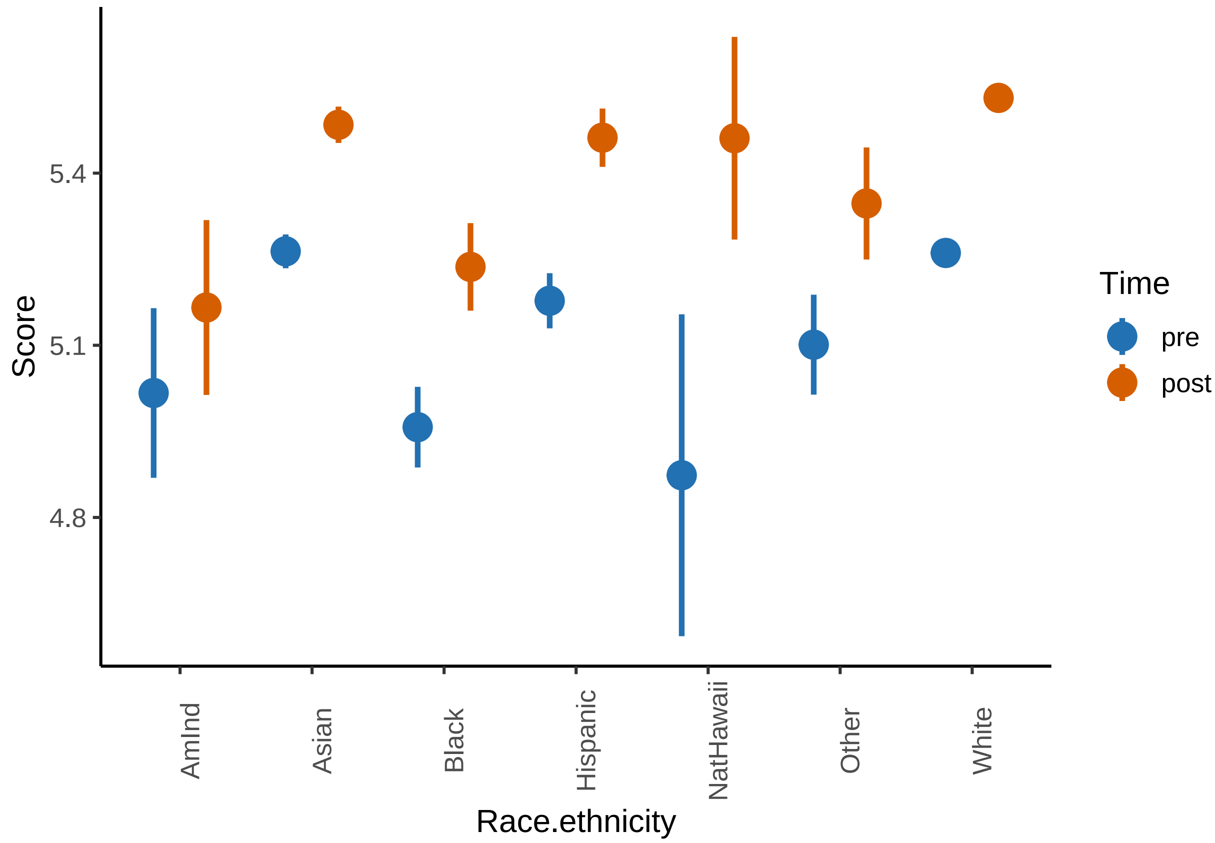

```r
plot.pre.post(df.matched, 'Gender')
```

```
##
##         Man Non-binary    Unknown       Woman
##        2673         55         30        2000
```



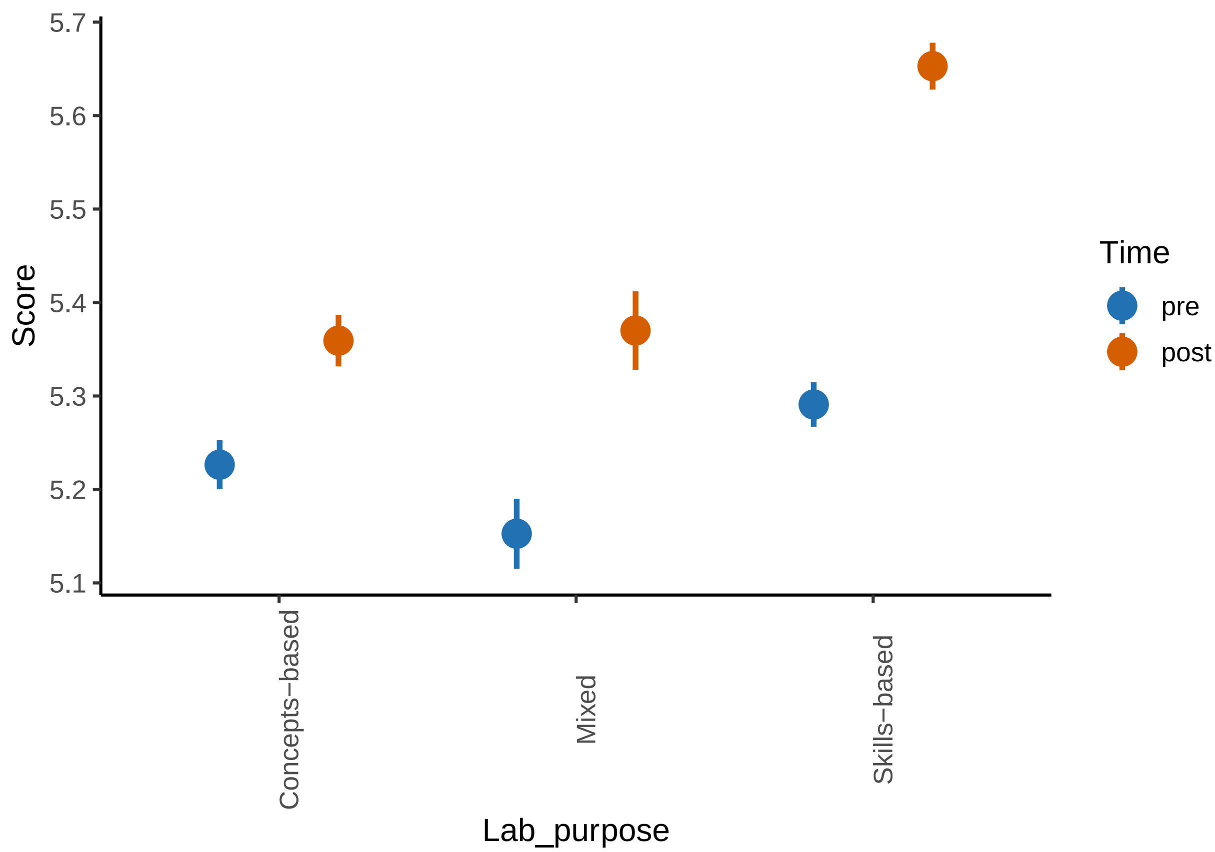

```r
plot.pre.post(df.matched, 'Race.ethnicity')
```

```
##     Race.ethnicity.AmInd     Race.ethnicity.Asian     Race.ethnicity.Black
##                       61                     1444                      220
##  Race.ethnicity.Hispanic Race.ethnicity.NatHawaii     Race.ethnicity.White
##                      455                       30                     2865
##     Race.ethnicity.Other   Race.ethnicity.unknown
##                      156                        0
```




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

```
##
## Concepts-based          Mixed   Skills-based
##           1838            783           2137
```



Mixed-effects models

```
mod0 <- lmer(PostScores ~ (1 | anon_institution_id/Class_ID), df.matched)
r2(mod0)
```

```
##
## R-Squared for (Generalized) Linear (Mixed) Model
##
## Family : gaussian (identity)
## Formula: list(~1 | Class_ID:anon_institution_id, ~1 | anon_institution_id) PostScores ~ 1 NA
##
##    Marginal R2: 0.000
## Conditional R2: 0.112
```

```
mod <- lmer(PostScores ~ PreScores + Lab_level + Major +
              Lab_purpose * (Gender + Race.ethnicity.AmInd +
                               Race.ethnicity.Asian + Race.ethnicity.Black +
                               Race.ethnicity.Hispanic +
                               Race.ethnicity.NatHawaii + Race.ethnicity.White +
                               Race.ethnicity.Other) +
              (1 | anon_institution_id/Class_ID), df.matched)
summary(mod)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula:
## PostScores ~ PreScores + Lab_level + Major + Lab_purpose * (Gender +
##     Race.ethnicity.AmInd + Race.ethnicity.Asian + Race.ethnicity.Black +
##     Race.ethnicity.Hispanic + Race.ethnicity.NatHawaii + Race.ethnicity.White +
##     Race.ethnicity.Other) + (1 | anon_institution_id/Class_ID)
##    Data: df.matched
##
## REML criterion at convergence: 14341.2
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -5.1759 -0.5959  0.0549  0.6696  2.9284
##
## Random effects:
##  Groups                       Name        Variance Std.Dev.
##  Class_ID:anon_institution_id (Intercept) 0.006831 0.08265
##  anon_institution_id          (Intercept) 0.060572 0.24611
##  Residual                                 1.164689 1.07921
## Number of obs: 4758, groups:
## Class_ID:anon_institution_id, 87; anon_institution_id, 35
##
## Fixed effects:
##                                                 Estimate Std. Error
## (Intercept)                                    3.372e+00  1.728e-01
## PreScores                                      3.055e-01  1.470e-02
## Lab_levelBFY                                   5.131e-01  1.171e-01
## Lab_levelFY-Calculus                           2.970e-01  9.514e-02
## MajorEngineering                              -1.248e-01  5.700e-02
## MajorOther                                    -1.382e-01  7.618e-02
## MajorOther science                             3.192e-03  5.974e-02
## MajorUnknown                                  -1.796e-01  1.212e-01
## Lab_purposeMixed                              -7.124e-02  1.799e-01
## Lab_purposeSkills-based                        2.217e-01  1.325e-01
## GenderNon-binary                               2.906e-01  3.321e-01
## GenderUnknown                                  1.393e-01  3.689e-01
## GenderWoman                                    4.327e-02  5.342e-02
## Race.ethnicity.AmInd1                          1.638e-01  2.355e-01
## Race.ethnicity.Asian1                         -8.433e-02  8.967e-02
## Race.ethnicity.Black1                         -2.268e-01  1.663e-01
## Race.ethnicity.Hispanic1                      -5.074e-02  1.021e-01
## Race.ethnicity.NatHawaii1                      1.514e-01  3.474e-01
## Race.ethnicity.White1                          4.793e-02  8.756e-02
## Race.ethnicity.Other1                         -3.470e-01  1.564e-01
## Lab_purposeMixed:GenderNon-binary             -4.998e-01  4.477e-01
## Lab_purposeSkills-based:GenderNon-binary      -4.423e-01  3.880e-01
## Lab_purposeMixed:GenderUnknown                -1.817e-01  6.182e-01
## Lab_purposeSkills-based:GenderUnknown          9.864e-02  4.612e-01
## Lab_purposeMixed:GenderWoman                   8.270e-02  1.014e-01
## Lab_purposeSkills-based:GenderWoman           -4.319e-02  7.303e-02
## Lab_purposeMixed:Race.ethnicity.AmInd1        -5.261e-01  4.108e-01
## Lab_purposeSkills-based:Race.ethnicity.AmInd1 -6.863e-01  3.136e-01
## Lab_purposeMixed:Race.ethnicity.Asian1         8.012e-02  1.652e-01
```

```
## Lab_purposeSkills-based:Race.ethnicity.Asian1      3.729e-02  1.203e-01
## Lab_purposeMixed:Race.ethnicity.Black1             8.817e-02  2.596e-01
## Lab_purposeSkills-based:Race.ethnicity.Black1      2.577e-03  2.003e-01
## Lab_purposeMixed:Race.ethnicity.Hispanic1          1.331e-01  1.897e-01
## Lab_purposeSkills-based:Race.ethnicity.Hispanic1   3.737e-02  1.312e-01
## Lab_purposeMixed:Race.ethnicity.NatHawaii1         2.653e-01  5.233e-01
## Lab_purposeSkills-based:Race.ethnicity.NatHawaii1 -2.596e-01  4.702e-01
## Lab_purposeMixed:Race.ethnicity.White1             2.407e-01  1.560e-01
## Lab_purposeSkills-based:Race.ethnicity.White1      8.873e-02  1.153e-01
## Lab_purposeMixed:Race.ethnicity.Other1             2.311e-01  2.458e-01
## Lab_purposeSkills-based:Race.ethnicity.Other1      4.695e-01  2.070e-01
##                                                           df t value
## (Intercept)                                        2.361e+02  19.510
## PreScores                                          4.670e+03  20.780
## Lab_levelBFY                                       9.428e+01   4.380
## Lab_levelFY-Calculus                               4.507e+01   3.122
## MajorEngineering                                   7.710e+02  -2.190
## MajorOther                                         2.741e+03  -1.815
## MajorOther science                                 1.642e+03   0.053
## MajorUnknown                                       4.379e+03  -1.481
## Lab_purposeMixed                                   6.182e+02  -0.396
## Lab_purposeSkills-based                            3.350e+02   1.673
## GenderNon-binary                                   4.677e+03   0.875
## GenderUnknown                                      4.676e+03   0.377
## GenderWoman                                        4.623e+03   0.810
## Race.ethnicity.AmInd1                              4.681e+03   0.695
## Race.ethnicity.Asian1                              4.696e+03  -0.940
## Race.ethnicity.Black1                              4.684e+03  -1.364
## Race.ethnicity.Hispanic1                           4.688e+03  -0.497
## Race.ethnicity.NatHawaii1                          4.677e+03   0.436
## Race.ethnicity.White1                              4.697e+03   0.547
## Race.ethnicity.Other1                              4.682e+03  -2.219
## Lab_purposeMixed:GenderNon-binary                  4.693e+03  -1.116
## Lab_purposeSkills-based:GenderNon-binary           4.693e+03  -1.140
## Lab_purposeMixed:GenderUnknown                     4.703e+03  -0.294
## Lab_purposeSkills-based:GenderUnknown              4.685e+03   0.214
## Lab_purposeMixed:GenderWoman                       3.873e+03   0.816
## Lab_purposeSkills-based:GenderWoman                4.260e+03  -0.591
## Lab_purposeMixed:Race.ethnicity.AmInd1             4.697e+03  -1.281
## Lab_purposeSkills-based:Race.ethnicity.AmInd1      4.688e+03  -2.188
## Lab_purposeMixed:Race.ethnicity.Asian1             4.666e+03   0.485
## Lab_purposeSkills-based:Race.ethnicity.Asian1      4.709e+03   0.310
## Lab_purposeMixed:Race.ethnicity.Black1             4.716e+03   0.340
## Lab_purposeSkills-based:Race.ethnicity.Black1      4.697e+03   0.013
## Lab_purposeMixed:Race.ethnicity.Hispanic1          4.524e+03   0.702
## Lab_purposeSkills-based:Race.ethnicity.Hispanic1   4.707e+03   0.285
## Lab_purposeMixed:Race.ethnicity.NatHawaii1         4.701e+03   0.507
## Lab_purposeSkills-based:Race.ethnicity.NatHawaii1  4.711e+03  -0.552
## Lab_purposeMixed:Race.ethnicity.White1             4.690e+03   1.543
## Lab_purposeSkills-based:Race.ethnicity.White1      4.710e+03   0.770
## Lab_purposeMixed:Race.ethnicity.Other1             4.704e+03   0.940
## Lab_purposeSkills-based:Race.ethnicity.Other1      4.705e+03   2.268
##                                                   Pr(>|t|)
## (Intercept)                                        < 2e-16 ***
```

```
## PreScores                                               < 2e-16 ***
## Lab_levelBFY                                           3.07e-05 ***
## Lab_levelFY-Calculus                                    0.00314 **
## MajorEngineering                                        0.02880 *
## MajorOther                                              0.06968 .
## MajorOther science                                      0.95740
## MajorUnknown                                            0.13861
## Lab_purposeMixed                                        0.69223
## Lab_purposeSkills-based                                 0.09524 .
## GenderNon-binary                                        0.38165
## GenderUnknown                                           0.70584
## GenderWoman                                             0.41792
## Race.ethnicity.AmInd1                                   0.48683
## Race.ethnicity.Asian1                                   0.34705
## Race.ethnicity.Black1                                   0.17259
## Race.ethnicity.Hispanic1                                0.61916
## Race.ethnicity.NatHawaii1                               0.66298
## Race.ethnicity.White1                                   0.58410
## Race.ethnicity.Other1                                   0.02655 *
## Lab_purposeMixed:GenderNon-binary                       0.26427
## Lab_purposeSkills-based:GenderNon-binary                0.25433
## Lab_purposeMixed:GenderUnknown                          0.76883
## Lab_purposeSkills-based:GenderUnknown                   0.83066
## Lab_purposeMixed:GenderWoman                            0.41458
## Lab_purposeSkills-based:GenderWoman                     0.55432
## Lab_purposeMixed:Race.ethnicity.AmInd1                  0.20033
## Lab_purposeSkills-based:Race.ethnicity.AmInd1           0.02870 *
## Lab_purposeMixed:Race.ethnicity.Asian1                  0.62780
## Lab_purposeSkills-based:Race.ethnicity.Asian1           0.75652
## Lab_purposeMixed:Race.ethnicity.Black1                  0.73417
## Lab_purposeSkills-based:Race.ethnicity.Black1           0.98973
## Lab_purposeMixed:Race.ethnicity.Hispanic1               0.48295
## Lab_purposeSkills-based:Race.ethnicity.Hispanic1        0.77574
## Lab_purposeMixed:Race.ethnicity.NatHawaii1              0.61218
## Lab_purposeSkills-based:Race.ethnicity.NatHawaii1       0.58087
## Lab_purposeMixed:Race.ethnicity.White1                  0.12291
## Lab_purposeSkills-based:Race.ethnicity.White1           0.44159
## Lab_purposeMixed:Race.ethnicity.Other1                  0.34722
## Lab_purposeSkills-based:Race.ethnicity.Other1           0.02339 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Correlation matrix not shown by default, as p = 40 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it
```

```
r2(mod)
```

```
##
## R-Squared for (Generalized) Linear (Mixed) Model
##
## Family : gaussian (identity)
```

```
## Formula: list(~1 | Class_ID:anon_institution_id, ~1 | anon_institution_id) PostScores ~ PreScores + L
##
##    Marginal R2: 0.126
## Conditional R2: 0.174
```

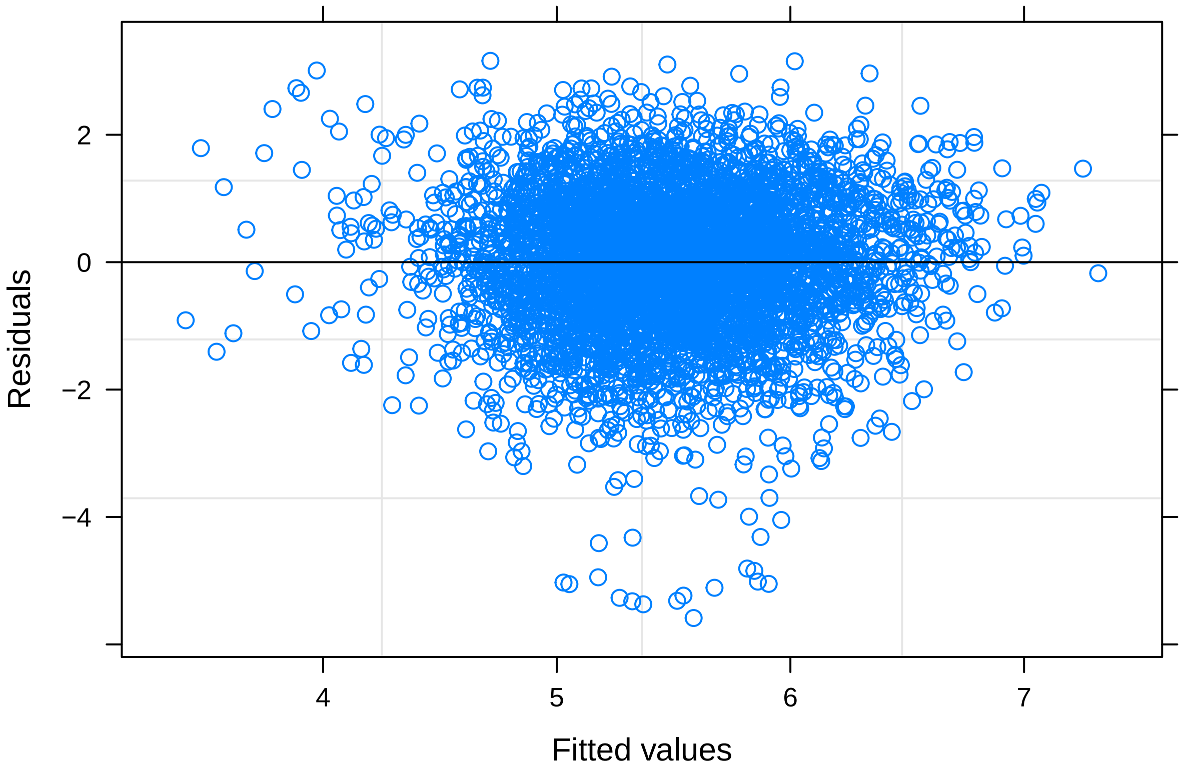
```r
noStandard.cols <- c('Lab_purpose', 'Lab_level', 'Major', 'Gender',
                     names(df.matched)[names(df.matched) %like% "Race"])
class(mod) <- "lmerMod"
mod.std <- beta(mod, skip = noStandard.cols)
```

Variance inflation factors and model diagnostics

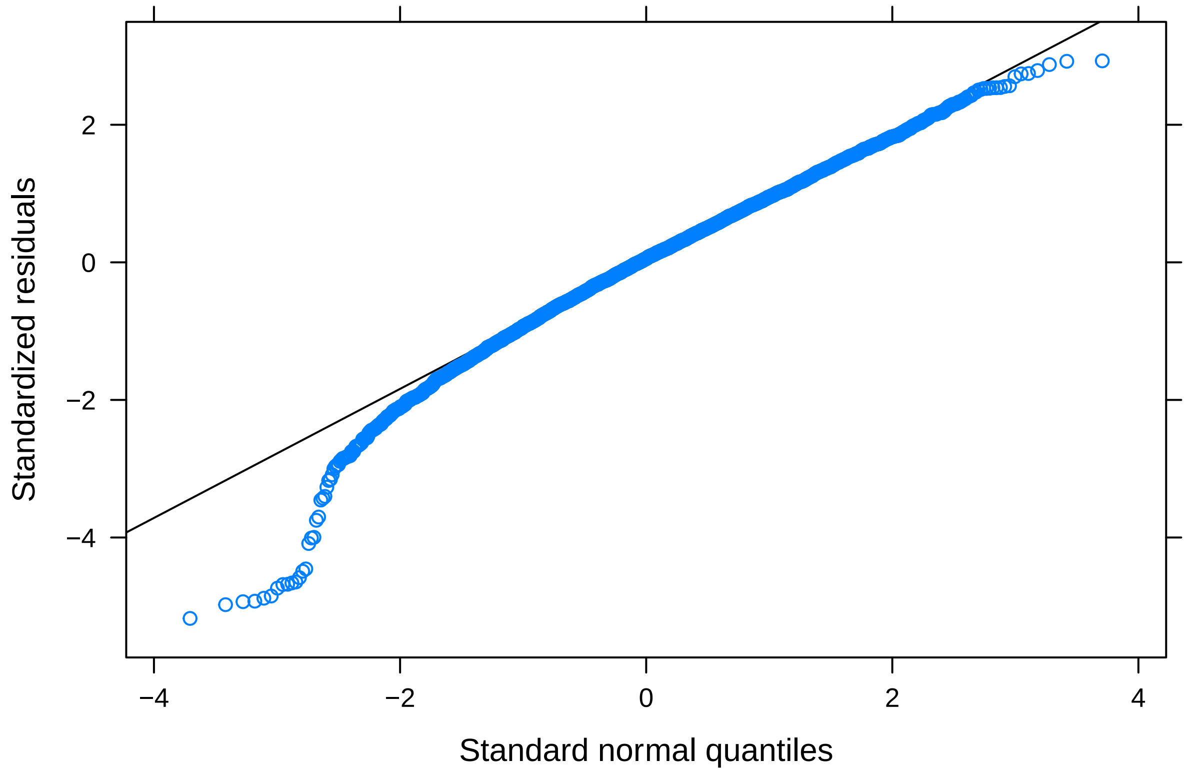
```r
vif(mod)
```

```
##                                           GVIF Df GVIF^(1/(2*Df))
## PreScores                             1.025262  1        1.012552
## Lab_level                             1.597465  2        1.124237
## Major                                 1.644084  4        1.064120
## Lab_purpose                          20.790838  2        2.135345
## Gender                               45.354873  3        1.888443
## Race.ethnicity.AmInd                  2.845063  1        1.686732
## Race.ethnicity.Asian                  6.037630  1        2.457159
## Race.ethnicity.Black                  4.827676  1        2.197197
## Race.ethnicity.Hispanic               3.560880  1        1.887029
## Race.ethnicity.NatHawaii              3.052031  1        1.747006
## Race.ethnicity.White                  6.479295  1        2.545446
## Race.ethnicity.Other                  3.105610  1        1.762274
## Lab_purpose:Gender                   67.147602  6        1.419883
## Lab_purpose:Race.ethnicity.AmInd      2.949712  2        1.310524
## Lab_purpose:Race.ethnicity.Asian     11.348591  2        1.835420
## Lab_purpose:Race.ethnicity.Black      6.131812  2        1.573610
## Lab_purpose:Race.ethnicity.Hispanic   5.007494  2        1.495909
## Lab_purpose:Race.ethnicity.NatHawaii  3.141087  2        1.331282
## Lab_purpose:Race.ethnicity.White     29.400664  2        2.328570
## Lab_purpose:Race.ethnicity.Other      3.283730  2        1.346145
```

```r
plot(mod, xlab = 'Fitted values', ylab = 'Residuals')
```




```
qqmath(mod)
```



Output stargazer

Marginal effects plots

```
# Main effect of lab goal
p1 <- plot_model(mod, type = 'eff', terms = 'Lab_purpose', 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 PLIC posttest scores') +
  theme(axis.text.x = element_text(angle = 40, vjust = 1, hjust = 1),
        legend.position = 'none')

# Effects of gender across lab goal
p2 <- plot_model(mod, type = 'eff', terms = c('Gender', 'Lab_purpose'),
                 dot.size = 2,
                 line.size = 1, ci.lvl = 0.67, title = '',
```

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

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

```r
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

```r
p3.other <- plot_model(mod, type = 'eff', terms = c('Race.ethnicity.Other [1]',
                                                    'Lab_purpose'),
                       ci.lvl = 0.67)
df.race.eff <- data.frame(p3.other$data) %>%
  mutate(race.ethnicity = 'Race.ethnicity.Other')
for(race in c('Race.ethnicity.AmInd', 'Race.ethnicity.Asian',
              'Race.ethnicity.Black', 'Race.ethnicity.Hispanic',
              'Race.ethnicity.NatHawaii', 'Race.ethnicity.White')){
  p3 <- plot_model(mod, type = 'eff', terms = c(paste(race, ' [1]', sep = ''),
                                               'Lab_purpose'), ci.lvl = 0.67)
  df.race.eff <- rbind(df.race.eff, data.frame(p3$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),
         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')),
                        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'))
```

```
png('Figures/PLIC_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

```
df.matched[, names(df.matched) %like% "Q28|Q29|Q31"] <-
  data.frame(lapply(df.matched[, names(df.matched) %like% "Q28|Q29|Q31"],
                    function(x) droplevels(factor(as.vector(x),
                                                  levels = c('1', '2', '3', '4',
                                                             '5'),
                                                  ordered = TRUE))))

df.matched[, names(df.matched) %like% "Q28|Q29|Q31"] <- data.frame(lapply(df.matched[, names(df.matched)
                                                                          function(x) as.numeric(x)))
```

Run CFA on CIS

```
mod <- '
  agency =~ Q29_1 + Q29_2 + Q29_3 + Q29_4 + Q29_5 + Q29_6 + Q28_1 + Q28_2 + Q28_3
'

# unique classes only
CIS.df <- unique(df.matched[, names(df.matched) %like% "Q28|Q29|Q31"])
```

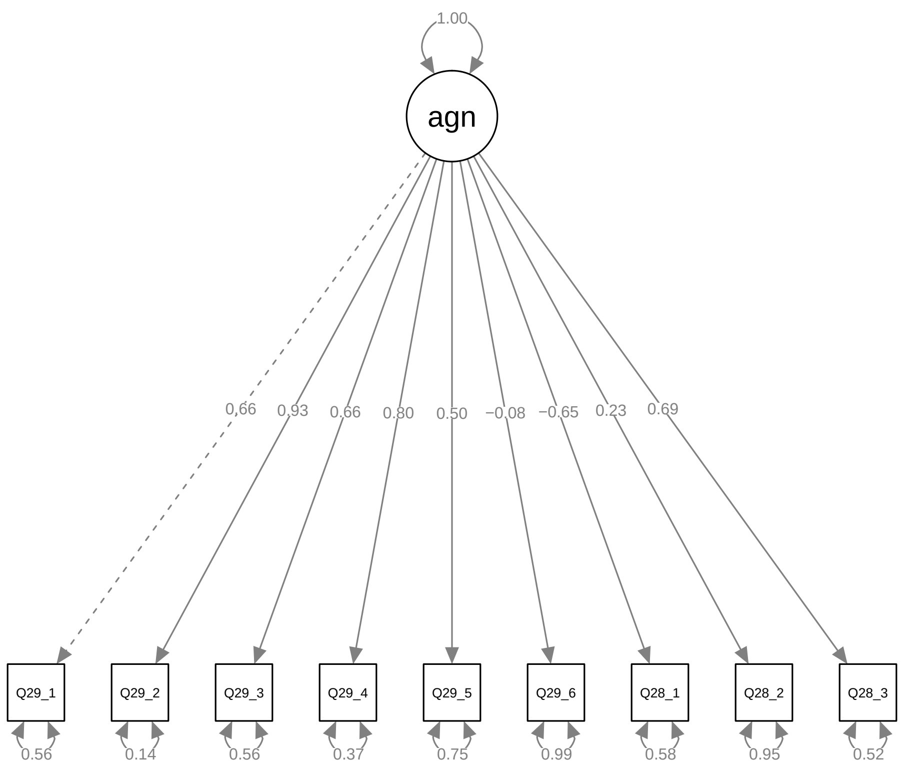
```r
fit <- cfa(mod, CIS.df)
summary(fit, standardized = TRUE, fit.measures = TRUE, modindices = TRUE)
```

```
## lavaan 0.6-3 ended normally after 22 iterations
##
##   Optimization method                           NLMINB
##   Number of free parameters                         18
##
##   Number of observations                            60
##
##   Estimator                                         ML
##   Model Fit Test Statistic                      47.951
##   Degrees of freedom                                27
##   P-value (Chi-square)                           0.008
##
## Model test baseline model:
##
##   Minimum Function Test Statistic              236.962
##   Degrees of freedom                                36
##   P-value                                        0.000
##
## User model versus baseline model:
##
##   Comparative Fit Index (CFI)                    0.896
##   Tucker-Lewis Index (TLI)                       0.861
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)               -645.065
##   Loglikelihood unrestricted model (H1)       -621.089
##
##   Number of free parameters                         18
##   Akaike (AIC)                                1326.129
##   Bayesian (BIC)                              1363.828
##   Sample-size adjusted Bayesian (BIC)         1307.213
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.114
##   90 Percent Confidence Interval          0.058  0.165
##   P-value RMSEA <= 0.05                          0.034
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                           0.073
##
## 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 =~
##     Q29_1             1.000                               0.605    0.661
##     Q29_2             1.621    0.271    5.992    0.000    0.981    0.928
##     Q29_3             1.249    0.271    4.604    0.000    0.756    0.661
##     Q29_4             1.495    0.277    5.393    0.000    0.904    0.796
##     Q29_5             0.836    0.232    3.599    0.000    0.506    0.503
##     Q29_6            -0.085    0.151   -0.562    0.574   -0.051   -0.076
##     Q28_1            -1.023    0.226   -4.518    0.000   -0.619   -0.647
##     Q28_2             0.325    0.192    1.693    0.090    0.197    0.230
##     Q28_3             1.047    0.218    4.793    0.000    0.633    0.693
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Q29_1             0.470    0.092    5.090    0.000    0.470    0.562
##    .Q29_2             0.155    0.064    2.436    0.015    0.155    0.139
##    .Q29_3             0.735    0.144    5.090    0.000    0.735    0.563
##    .Q29_4             0.472    0.104    4.555    0.000    0.472    0.366
##    .Q29_5             0.754    0.142    5.313    0.000    0.754    0.747
##    .Q29_6             0.460    0.084    5.474    0.000    0.460    0.994
##    .Q28_1             0.531    0.104    5.120    0.000    0.531    0.581
##    .Q28_2             0.694    0.127    5.451    0.000    0.694    0.947
##    .Q28_3             0.435    0.087    5.014    0.000    0.435    0.520
##     agency            0.366    0.131    2.798    0.005    1.000    1.000
##
## Modification Indices:
##
##      lhs op   rhs    mi    epc sepc.lv sepc.all sepc.nox
## 20 Q29_1 ~~ Q29_2 1.244 -0.069  -0.069   -0.256   -0.256
## 21 Q29_1 ~~ Q29_3 0.003 -0.005  -0.005   -0.008   -0.008
## 22 Q29_1 ~~ Q29_4 3.132  0.127   0.127    0.270    0.270
## 23 Q29_1 ~~ Q29_5 0.004 -0.005  -0.005   -0.009   -0.009
## 24 Q29_1 ~~ Q29_6 0.958  0.061   0.061    0.131    0.131
## 25 Q29_1 ~~ Q28_1 3.648  0.134   0.134    0.268    0.268
## 26 Q29_1 ~~ Q28_2 0.326  0.044   0.044    0.077    0.077
## 27 Q29_1 ~~ Q28_3 1.607  0.082   0.082    0.181    0.181
## 28 Q29_2 ~~ Q29_3 0.002 -0.004  -0.004   -0.011   -0.011
## 29 Q29_2 ~~ Q29_4 0.956  0.079   0.079    0.291    0.291
## 30 Q29_2 ~~ Q29_5 0.012 -0.008  -0.008   -0.022   -0.022
## 31 Q29_2 ~~ Q29_6 1.582  0.064   0.064    0.239    0.239
## 32 Q29_2 ~~ Q28_1 2.868 -0.110  -0.110   -0.383   -0.383
## 33 Q29_2 ~~ Q28_2 0.886 -0.059  -0.059   -0.181   -0.181
## 34 Q29_2 ~~ Q28_3 1.113 -0.065  -0.065   -0.252   -0.252
## 35 Q29_3 ~~ Q29_4 4.732 -0.195  -0.195   -0.331   -0.331
## 36 Q29_3 ~~ Q29_5 6.657  0.262   0.262    0.353    0.353
## 37 Q29_3 ~~ Q29_6 0.159  0.031   0.031    0.053    0.053
## 38 Q29_3 ~~ Q28_1 2.289 -0.133  -0.133   -0.212   -0.212
## 39 Q29_3 ~~ Q28_2 0.125  0.034   0.034    0.047    0.047
## 40 Q29_3 ~~ Q28_3 0.017 -0.011  -0.011   -0.019   -0.019
## 41 Q29_4 ~~ Q29_5 0.248  0.043   0.043    0.072    0.072
## 42 Q29_4 ~~ Q29_6 5.234 -0.149  -0.149   -0.321   -0.321
## 43 Q29_4 ~~ Q28_1 4.310  0.157   0.157    0.314    0.314
## 44 Q29_4 ~~ Q28_2 2.582  0.129   0.129    0.226    0.226
## 45 Q29_4 ~~ Q28_3 0.001 -0.002  -0.002   -0.004   -0.004
```

```
## 46 Q29_5 ~~ Q29_6 0.178  0.033   0.033    0.055    0.055
## 47 Q29_5 ~~ Q28_1 2.288  0.130   0.130    0.206    0.206
## 48 Q29_5 ~~ Q28_2 2.010 -0.135  -0.135   -0.186   -0.186
## 49 Q29_5 ~~ Q28_3 1.073 -0.082  -0.082   -0.143   -0.143
## 50 Q29_6 ~~ Q28_1 0.381  0.041   0.041    0.082    0.082
## 51 Q29_6 ~~ Q28_2 0.810 -0.066  -0.066   -0.117   -0.117
## 52 Q29_6 ~~ Q28_3 0.003 -0.003  -0.003   -0.007   -0.007
## 53 Q28_1 ~~ Q28_2 0.497  0.057   0.057    0.094    0.094
## 54 Q28_1 ~~ Q28_3 1.870 -0.093  -0.093   -0.194   -0.194
## 55 Q28_2 ~~ Q28_3 0.035  0.014   0.014    0.025    0.025
```

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




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

```
## $type
## [1] "cor.bollen"
##
## $cov
##        Q29_1  Q29_2  Q29_3  Q29_4  Q29_5  Q29_6  Q28_1  Q28_2  Q28_3
## Q29_1  0.000
## Q29_2 -0.023  0.000
## Q29_3 -0.004 -0.001  0.000
## Q29_4  0.088  0.012 -0.108  0.000
## Q29_5 -0.005 -0.003  0.204  0.030  0.000
```

```
## Q29_6  0.091  0.041  0.037 -0.164  0.046  0.000
## Q28_1  0.130 -0.035 -0.103  0.105  0.122  0.059  0.000
## Q28_2  0.052 -0.030  0.032  0.112 -0.151 -0.112  0.065  0.000
## Q28_3  0.080 -0.020 -0.008 -0.001 -0.078 -0.005 -0.088  0.016  0.000
```

Run EFA on half of the dataset

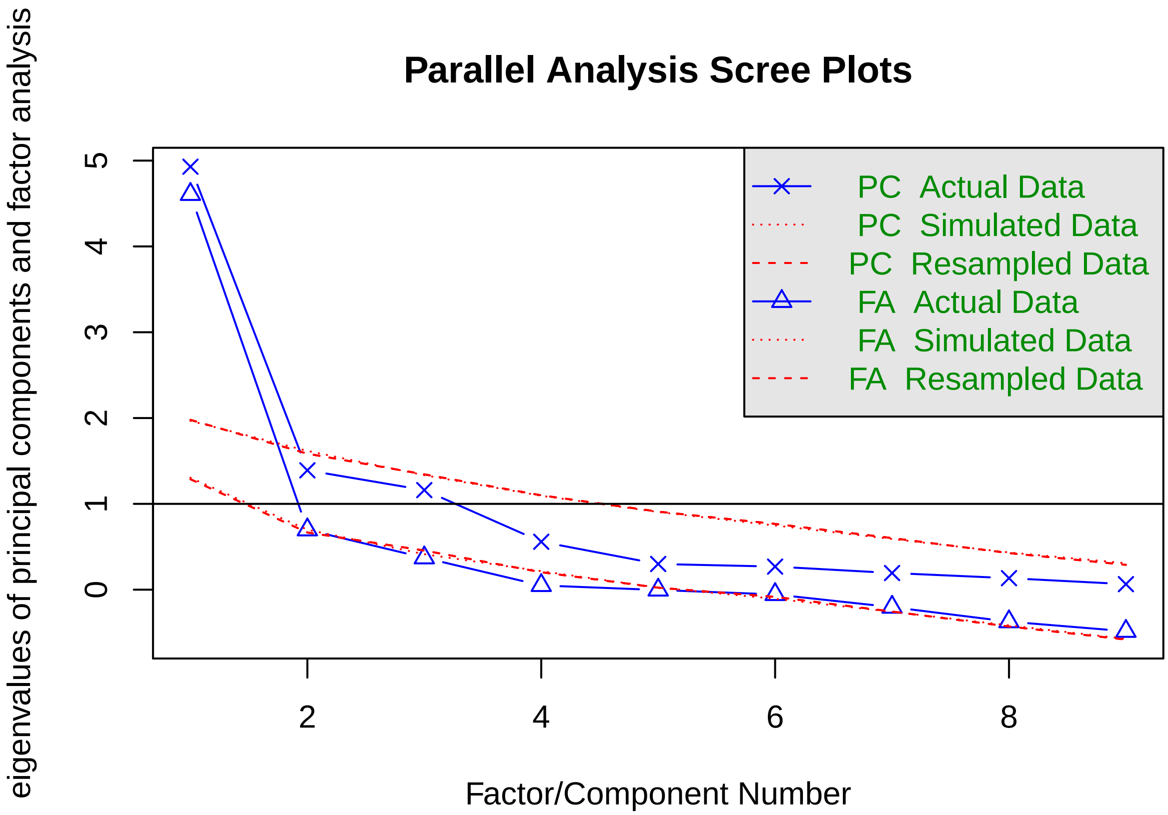
```r
set.seed(11)
inds <- sample(seq_len(nrow(CIS.df)), size = nrow(CIS.df)/2)
CIS.train.df <- CIS.df[inds, names(CIS.df) %like% 'Q28|Q29']

CIS.train.df
```

```
##      Q28_1 Q28_2 Q28_3 Q29_1 Q29_2 Q29_3 Q29_4 Q29_5 Q29_6
## 573      2     2     4     4     4     5     4     4     4
## 1        4     2     2     1     2     1     2     2     4
## 1965     4     4     3     2     3     3     3     2     4
## 4714     5     5     3     3     3     2     5     4     2
## 155      4     1     2     1     2     1     2     2     4
## 4606     4     2     3     2     4     2     4     3     4
## 210      4     2     2     2     2     1     3     2     4
## 377      3     3     3     1     3     2     2     1     4
## 3958     4     3     3     3     3     2     4     4     4
## 224      3     2     3     2     3     1     2     3     4
## 229      4     3     2     1     2     1     1     1     4
## 985      3     3     4     3     4     3     4     3     4
## 3895     4     3     2     2     3     1     3     1     4
## 3751     3     2     4     3     3     2     4     3     4
## 2562     4     4     2     1     1     1     1     1     4
## 1022     2     4     4     3     4     3     5     1     2
## 4545     3     2     3     4     4     3     4     3     4
## 348      4     3     3     3     3     3     3     2     4
## 4566     4     4     3     2     3     3     4     3     4
## 966      3     3     4     4     4     4     4     4     4
## 4562     4     4     3     3     3     1     4     3     4
## 1027     2     4     4     2     4     4     4     2     2
## 344      4     4     3     2     2     2     2     2     4
## 343      5     2     1     2     2     2     2     2     4
## 77       5     2     3     2     2     1     2     2     4
## 4716     2     2     4     3     3     3     3     2     2
## 3607     3     3     4     3     4     4     4     3     4
## 4644     3     4     4     4     5     4     5     4     4
## 4616     4     4     4     3     4     3     5     4     4
## 3492     4     4     2     1     1     1     1     2     4
```

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

```
## 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.
```



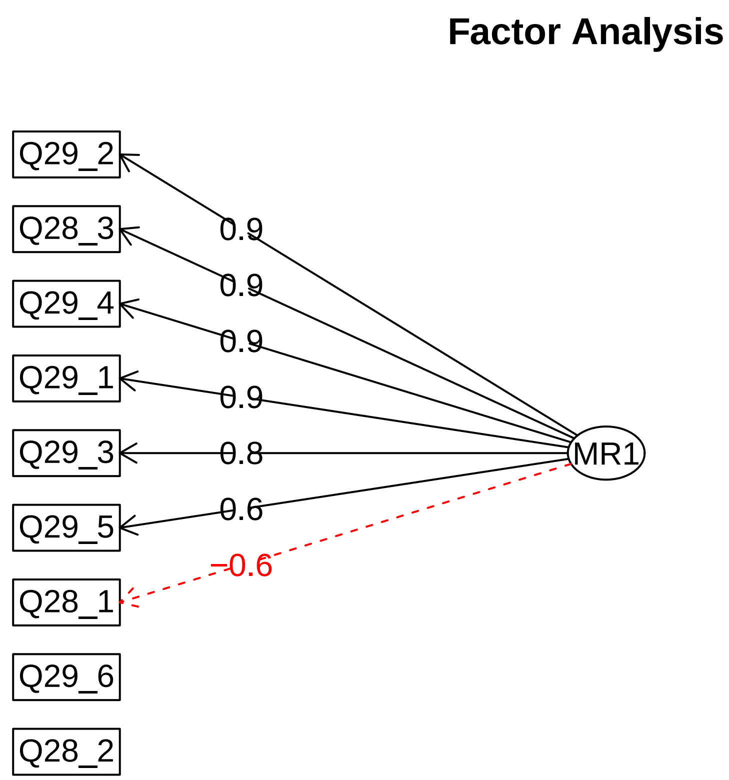

```
## Parallel analysis suggests that the number of factors =  1  and the number of components =  1
```

```r
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
## Q28_1 -0.56 0.319 0.68   1
## Q28_2  0.18 0.032 0.97   1
## Q28_3  0.88 0.782 0.22   1
## Q29_1  0.85 0.724 0.28   1
## Q29_2  0.92 0.848 0.15   1
## Q29_3  0.84 0.699 0.30   1
## Q29_4  0.87 0.758 0.24   1
## Q29_5  0.60 0.361 0.64   1
## Q29_6 -0.29 0.084 0.92   1
##
##                 MR1
```

```
## SS loadings    4.61
## Proportion Var 0.51
##
## 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  7.42 with Chi Squa
## The degrees of freedom for the model are 27  and the objective function was  2.2
##
## The root mean square of the residuals (RMSR) is  0.12
## The df corrected root mean square of the residuals is  0.14
##
## The harmonic number of observations is  30 with the empirical chi square  31.36  with prob <  0.26
## The total number of observations was  30  with Likelihood Chi Square =  53.82  with prob <  0.0016
##
## Tucker Lewis Index of factoring reliability =  0.755
## RMSEA index =  0.217  and the 90 % confidence intervals are  0.111 0.257
## BIC =  -38.01
## Fit based upon off diagonal values = 0.95
## Measures of factor score adequacy
##                                                    MR1
## Correlation of (regression) scores with factors   0.98
## Multiple R square of scores with factors          0.97
## Minimum correlation of possible factor scores     0.93
```

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



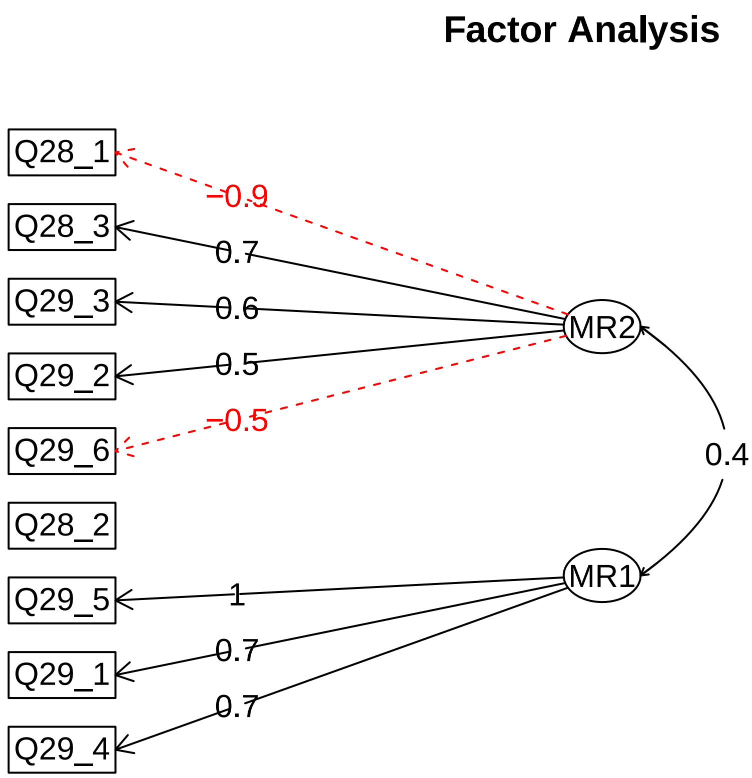
```r
fit2 <- fa(CIS.train.df, 2)
```

```
## Loading required namespace: GPArotation
```

```r
fit2
```

```
## Factor Analysis using method =  minres
## Call: fa(r = CIS.train.df, nfactors = 2)
## Standardized loadings (pattern matrix) based upon correlation matrix
##         MR2  MR1    h2   u2 com
## Q28_1 -0.90 0.19 0.688 0.31 1.1
## Q28_2  0.13 0.07 0.032 0.97 1.5
## Q28_3  0.72 0.32 0.823 0.18 1.4
## Q29_1  0.29 0.72 0.785 0.21 1.3
## Q29_2  0.55 0.52 0.824 0.18 2.0
## Q29_3  0.61 0.36 0.704 0.30 1.6
## Q29_4  0.36 0.66 0.778 0.22 1.6
## Q29_5 -0.19 0.97 0.812 0.19 1.1
## Q29_6 -0.54 0.20 0.238 0.76 1.3
##
##                        MR2  MR1
## SS loadings           2.89 2.80
## Proportion Var        0.32 0.31
## Cumulative Var        0.32 0.63
## Proportion Explained  0.51 0.49
## Cumulative Proportion 0.51 1.00
##
##  With factor correlations of
##      MR2  MR1
## MR2 1.00 0.44
## MR1 0.44 1.00
##
## Mean item complexity =  1.4
## Test of the hypothesis that 2 factors are sufficient.
##
## The degrees of freedom for the null model are  36  and the objective function was  7.42 with Chi Squa
## The degrees of freedom for the model are 19  and the objective function was  1.27
##
## The root mean square of the residuals (RMSR) is  0.07
## The df corrected root mean square of the residuals is  0.1
##
## The harmonic number of observations is  30 with the empirical chi square  11.33  with prob <  0.91
## The total number of observations was  30  with Likelihood Chi Square =  30.17  with prob <  0.05
##
## Tucker Lewis Index of factoring reliability =  0.85
## RMSEA index =  0.179  and the 90 % confidence intervals are  0.005 0.234
## BIC =  -34.46
## Fit based upon off diagonal values = 0.98
## Measures of factor score adequacy
##                                                    MR2  MR1
## Correlation of (regression) scores with factors   0.95 0.96
## Multiple R square of scores with factors          0.91 0.92
## Minimum correlation of possible factor scores     0.82 0.85
```

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



Run CFA on CIS with new model

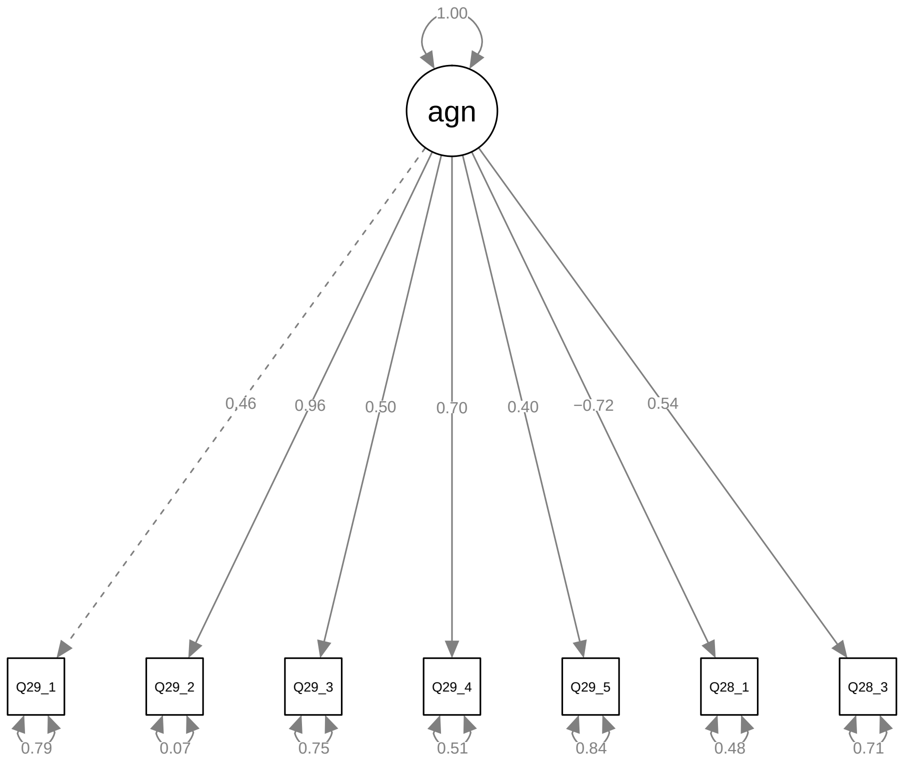
```r
mod <- '
  agency =~ Q29_1 + Q29_2 + Q29_3 + Q29_4 + Q29_5 + Q28_1 + Q28_3
'

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

```
## lavaan 0.6-3 ended normally after 30 iterations
##
##   Optimization method                           NLMINB
##   Number of free parameters                         14
##
##   Number of observations                            30
##
##   Estimator                                         ML
##   Model Fit Test Statistic                      18.550
##   Degrees of freedom                                14
##   P-value (Chi-square)                           0.183
```

```
##
## Model test baseline model:
##
##   Minimum Function Test Statistic               86.129
##   Degrees of freedom                                21
##   P-value                                        0.000
##
## User model versus baseline model:
##
##   Comparative Fit Index (CFI)                    0.930
##   Tucker-Lewis Index (TLI)                       0.895
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)               -268.881
##   Loglikelihood unrestricted model (H1)       -259.606
##
##   Number of free parameters                         14
##   Akaike (AIC)                                 565.762
##   Bayesian (BIC)                               585.379
##   Sample-size adjusted Bayesian (BIC)          541.790
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.104
##   90 Percent Confidence Interval          0.000  0.218
##   P-value RMSEA <= 0.05                          0.243
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                           0.110
##
## 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 =~
##     Q29_1             1.000                               0.395    0.459
##     Q29_2             2.784    1.053    2.644    0.008    1.099    0.964
##     Q29_3             1.417    0.693    2.046    0.041    0.559    0.500
##     Q29_4             1.832    0.755    2.428    0.015    0.723    0.700
##     Q29_5             1.032    0.580    1.781    0.075    0.407    0.403
##     Q28_1            -1.911    0.777   -2.460    0.014   -0.754   -0.723
##     Q28_3             1.340    0.627    2.138    0.033    0.529    0.540
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Q29_1             0.583    0.153    3.800    0.000    0.583    0.789
##    .Q29_2             0.091    0.131    0.698    0.485    0.091    0.070
##    .Q29_3             0.937    0.248    3.779    0.000    0.937    0.750
```

```
##    .Q29_4             0.544    0.155    3.517    0.000    0.544    0.510
##    .Q29_5             0.856    0.224    3.822    0.000    0.856    0.838
##    .Q28_1             0.520    0.151    3.450    0.001    0.520    0.478
##    .Q28_3             0.680    0.181    3.753    0.000    0.680    0.708
##     agency            0.156    0.121    1.289    0.197    1.000    1.000
##
## Modification Indices:
##
##      lhs op   rhs    mi    epc sepc.lv sepc.all sepc.nox
## 16 Q29_1 ~~ Q29_2 0.100  0.034   0.034    0.149    0.149
## 17 Q29_1 ~~ Q29_3 0.289 -0.075  -0.075   -0.101   -0.101
## 18 Q29_1 ~~ Q29_4 0.247  0.054   0.054    0.097    0.097
## 19 Q29_1 ~~ Q29_5 2.624 -0.213  -0.213   -0.301   -0.301
## 20 Q29_1 ~~ Q28_1 0.649  0.087   0.087    0.158    0.158
## 21 Q29_1 ~~ Q28_3 2.004  0.168   0.168    0.266    0.266
## 22 Q29_2 ~~ Q29_3 0.010  0.014   0.014    0.048    0.048
## 23 Q29_2 ~~ Q29_4 0.242  0.075   0.075    0.338    0.338
## 24 Q29_2 ~~ Q29_5 0.151  0.049   0.049    0.175    0.175
## 25 Q29_2 ~~ Q28_1 0.429  0.105   0.105    0.482    0.482
## 26 Q29_2 ~~ Q28_3 0.238 -0.061  -0.061   -0.247   -0.247
## 27 Q29_3 ~~ Q29_4 2.846 -0.236  -0.236   -0.331   -0.331
## 28 Q29_3 ~~ Q29_5 7.518  0.458   0.458    0.512    0.512
## 29 Q29_3 ~~ Q28_1 0.903 -0.132  -0.132   -0.188   -0.188
## 30 Q29_3 ~~ Q28_3 0.464 -0.103  -0.103   -0.129   -0.129
## 31 Q29_4 ~~ Q29_5 0.641 -0.105  -0.105   -0.154   -0.154
## 32 Q29_4 ~~ Q28_1 0.072 -0.032  -0.032   -0.060   -0.060
## 33 Q29_4 ~~ Q28_3 0.247  0.060   0.060    0.099    0.099
## 34 Q29_5 ~~ Q28_1 0.017 -0.017  -0.017   -0.026   -0.026
## 35 Q29_5 ~~ Q28_3 1.199 -0.157  -0.157   -0.205   -0.205
## 36 Q28_1 ~~ Q28_3 0.121 -0.042  -0.042   -0.070   -0.070
```

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




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

```
## $type
## [1] "cor.bollen"
##
## $cov
##       Q29_1  Q29_2  Q29_3  Q29_4  Q29_5  Q28_1  Q28_3
## Q29_1  0.000
## Q29_2  0.005  0.000
## Q29_3 -0.074  0.002  0.000
## Q29_4  0.054  0.005 -0.177  0.000
## Q29_5 -0.236  0.007  0.388 -0.091  0.000
## Q28_1  0.084  0.005 -0.096 -0.020 -0.014  0.000
## Q28_3  0.187 -0.007 -0.088  0.050 -0.150 -0.034  0.000
```

SEM with fixed measurement model

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

```r
mod.sem <- '
  level: 1
    PostScores ~ PreScores
  level: 2
    agency =~ Q29_1 + Q29_2 + Q29_3 + Q29_4 + Q29_5 + Q28_1 + Q28_3
    Q29_3 ~~ Q29_4 + Q29_5
    Q29_4 ~~ Q29_5

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

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

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

```
## lavaan 0.6-3 ended normally after 169 iterations
##
##   Optimization method                           NLMINB
##   Number of free parameters                         33
##
##   Number of observations                          4758
##   Number of clusters [Class_ID]                     87
##
##   Estimator                                         ML
##   Model Fit Test Statistic                     111.748
##   Degrees of freedom                                29
##   P-value (Chi-square)                           0.000
##
## Model test baseline model:
##
##   Minimum Function Test Statistic              859.028
##   Degrees of freedom                                45
##   P-value                                        0.000
##
## User model versus baseline model:
##
##   Comparative Fit Index (CFI)                    0.898
##   Tucker-Lewis Index (TLI)                       0.842
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)             -15175.055
##   Loglikelihood unrestricted model (H1)     -15119.182
##
##   Number of free parameters                         33
##   Akaike (AIC)                               30416.111
##   Bayesian (BIC)                             30629.541
##   Sample-size adjusted Bayesian (BIC)        30524.679
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.024
```

```
##   90 Percent Confidence Interval          0.020  0.029
##   P-value RMSEA <= 0.05                          1.000
##
## Standardized Root Mean Square Residual (corr metric):
##
##   SRMR (within covariance matrix)                0.001
##   SRMR (between covariance matrix)               0.099
##
## 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  Std.all
##   PostScores ~
##     PreScores         0.321    0.076    4.230    0.000    0.321    0.311
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .PostScores        0.000                               0.000    0.000
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .PostScores        1.171    0.024   48.159    0.000    1.171    0.904
##
##
## Level 2 [Class_ID]:
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   agency =~
##     Q29_1             1.000                               0.579    0.624
##     Q29_2             1.556    0.240    6.477    0.000    0.902    0.860
##     Q29_3             1.421    0.257    5.519    0.000    0.823    0.713
##     Q29_4             1.718    0.263    6.538    0.000    0.995    0.874
##     Q29_5             0.691    0.215    3.213    0.001    0.401    0.383
##     Q28_1            -1.208    0.221   -5.474    0.000   -0.700   -0.696
##     Q28_3             1.230    0.205    5.988    0.000    0.712    0.768
##
## Regressions:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   agency ~
##     Lab.goal.sklls    1.186    0.191    6.196    0.000    2.047    1.024
##     Lab.goal.both     0.557    0.139    4.014    0.000    0.961    0.435
##   PostScores ~
##     agency           -0.068    0.150   -0.452    0.651   -0.039   -0.123
##     Lab.goal.sklls    0.318    0.210    1.518    0.129    0.318    0.501
##     Lab.goal.both    -0.064    0.140   -0.458    0.647   -0.064   -0.091
##
```

```
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##  .Q29_3 ~~
##    .Q29_4            -0.222    0.064   -3.465    0.001   -0.222   -0.496
##    .Q29_5             0.289    0.098    2.944    0.003    0.289    0.369
##  .Q29_4 ~~
##    .Q29_5             0.023    0.072    0.325    0.745    0.023    0.044
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Q29_1             1.389    0.155    8.937    0.000    1.389    1.496
##    .Q29_2             1.748    0.160   10.905    0.000    1.748    1.668
##    .Q29_3             1.277    0.194    6.586    0.000    1.277    1.106
##    .Q29_4             1.729    0.177    9.795    0.000    1.729    1.518
##    .Q29_5             1.900    0.189   10.034    0.000    1.900    1.816
##    .Q28_1             4.274    0.165   25.919    0.000    4.274    4.251
##    .Q28_3             2.180    0.148   14.718    0.000    2.180    2.351
##    .PostScores        3.743    0.221   16.913    0.000    3.743   11.781
##    .agency            0.000                               0.000    0.000
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Q29_1             0.527    0.083    6.322    0.000    0.527    0.611
##    .Q29_2             0.286    0.055    5.205    0.000    0.286    0.260
##    .Q29_3             0.655    0.114    5.758    0.000    0.655    0.492
##    .Q29_4             0.307    0.071    4.315    0.000    0.307    0.237
##    .Q29_5             0.935    0.145    6.431    0.000    0.935    0.853
##    .Q28_1             0.521    0.087    5.965    0.000    0.521    0.516
##    .Q28_3             0.353    0.062    5.695    0.000    0.353    0.410
##    .PostScores        0.077    0.024    3.188    0.001    0.077    0.764
##    .agency            0.112    0.037    3.017    0.003    0.335    0.335
##
## Modification Indices:
##
##                lhs op              rhs block group level    mi    epc
## 3        PreScores ~~        PreScores     1     1     1 0.000  0.000
## 4       PostScores ~1                      1     1     1 0.000  0.000
## 5        PreScores ~1                      1     1     1 0.000  0.000
## 30 Lab.goal.skills ~~ Lab.goal.skills     2     1     2 0.000  0.000
## 31 Lab.goal.skills ~~    Lab.goal.both     2     1     2 0.000  0.000
## 32   Lab.goal.both ~~    Lab.goal.both     2     1     2 0.000  0.000
## 41 Lab.goal.skills ~1                      2     1     2 0.000  0.000
## 42   Lab.goal.both ~1                      2     1     2 0.000  0.000
## 44       PreScores  ~       PostScores     1     1     1 0.000  0.000
## 45           Q29_1 ~~            Q29_2     2     1     2 0.031 -0.008
## 46           Q29_1 ~~            Q29_3     2     1     2 0.450 -0.043
## 47           Q29_1 ~~            Q29_4     2     1     2 1.904  0.074
## 48           Q29_1 ~~            Q29_5     2     1     2 0.043 -0.015
## 49           Q29_1 ~~            Q28_1     2     1     2 2.731  0.098
## 50           Q29_1 ~~            Q28_3     2     1     2 2.258  0.075
## 51           Q29_1 ~~       PostScores     2     1     2 0.806 -0.026
## 52           Q29_2 ~~            Q29_3     2     1     2 0.003  0.003
## 53           Q29_2 ~~            Q29_4     2     1     2 0.366  0.034
## 54           Q29_2 ~~            Q29_5     2     1     2 5.605  0.150
```

```
## 55           Q29_2 ~~           Q28_1     2     1     2  3.881 -0.097
## 56           Q29_2 ~~           Q28_3     2     1     2  0.115  0.014
## 57           Q29_2 ~~      PostScores     2     1     2  3.392 -0.043
## 58           Q29_3 ~~           Q28_1     2     1     2  0.038 -0.013
## 59           Q29_3 ~~           Q28_3     2     1     2  4.831 -0.125
## 60           Q29_3 ~~      PostScores     2     1     2  1.272 -0.035
## 61           Q29_4 ~~           Q28_1     2     1     2  5.536  0.131
## 62           Q29_4 ~~           Q28_3     2     1     2  3.392 -0.091
## 63           Q29_4 ~~      PostScores     2     1     2 15.126  0.103
## 64           Q29_5 ~~           Q28_1     2     1     2  5.769  0.174
## 65           Q29_5 ~~           Q28_3     2     1     2  0.120 -0.021
## 66           Q29_5 ~~      PostScores     2     1     2  1.786  0.046
## 67           Q28_1 ~~           Q28_3     2     1     2  6.369 -0.127
## 68           Q28_1 ~~      PostScores     2     1     2  2.663  0.048
## 69           Q28_3 ~~      PostScores     2     1     2  0.032 -0.004
## 71 Lab.goal.skills  ~          agency     2     1     2  0.000  0.000
## 72 Lab.goal.skills  ~      PostScores     2     1     2  0.000  0.000
## 73 Lab.goal.skills  ~   Lab.goal.both     2     1     2  0.000  0.000
## 74   Lab.goal.both  ~          agency     2     1     2  0.000  0.000
## 75   Lab.goal.both  ~      PostScores     2     1     2  0.000  0.000
## 76   Lab.goal.both  ~ Lab.goal.skills     2     1     2  0.000  0.000
##    sepc.lv sepc.all sepc.nox
## 3    0.000    0.000    0.000
## 4    0.000    0.000    0.000
## 5    0.000    0.000    0.000
## 30   0.000    0.000    0.000
## 31   0.000       NA    0.000
## 32   0.000    0.000    0.000
## 41   0.000    0.000    0.000
## 42   0.000    0.000    0.000
## 44   0.000    0.000    0.000
## 45  -0.008   -0.022   -0.022
## 46  -0.043   -0.072   -0.072
## 47   0.074    0.183    0.183
## 48  -0.015   -0.021   -0.021
## 49   0.098    0.187    0.187
## 50   0.075    0.174    0.174
## 51  -0.026   -0.131   -0.131
## 52   0.003    0.008    0.008
## 53   0.034    0.115    0.115
## 54   0.150    0.290    0.290
## 55  -0.097   -0.251   -0.251
## 56   0.014    0.045    0.045
## 57  -0.043   -0.292   -0.292
## 58  -0.013   -0.022   -0.022
## 59  -0.125   -0.260   -0.260
## 60  -0.035   -0.156   -0.156
## 61   0.131    0.327    0.327
## 62  -0.091   -0.277   -0.277
## 63   0.103    0.667    0.667
## 64   0.174    0.250    0.250
## 65  -0.021   -0.037   -0.037
## 66   0.046    0.173    0.173
## 67  -0.127   -0.297   -0.297
```

```
## 68   0.048    0.240    0.240
## 69  -0.004   -0.027   -0.027
## 71   0.000    0.000    0.000
## 72   0.000    0.000    0.000
## 73   0.000    0.000    0.000
## 74   0.000    0.000    0.000
## 75   0.000    0.000    0.000
## 76   0.000    0.000    0.000
```

```
standardizedsolution(fit)
```

```
##                lhs op              rhs est.std    se       z pvalue
## 1       PostScores  ~        PreScores   0.311 0.066   4.693  0.000
## 2       PostScores ~~       PostScores   0.904 0.041  21.992  0.000
## 3        PreScores ~~        PreScores   1.000 0.000      NA     NA
## 4       PostScores ~1                    0.000 0.000      NA     NA
## 5        PreScores ~1                    4.757 0.000      NA     NA
## 6           agency =~            Q29_1   0.624 0.066   9.395  0.000
## 7           agency =~            Q29_2   0.860 0.031  27.632  0.000
## 8           agency =~            Q29_3   0.713 0.058  12.379  0.000
## 9           agency =~            Q29_4   0.874 0.033  26.368  0.000
## 10          agency =~            Q29_5   0.383 0.098   3.912  0.000
## 11          agency =~            Q28_1  -0.696 0.059 -11.877  0.000
## 12          agency =~            Q28_3   0.768 0.047  16.233  0.000
## 13           Q29_3 ~~            Q29_4  -0.496 0.141  -3.524  0.000
## 14           Q29_3 ~~            Q29_5   0.369 0.100   3.707  0.000
## 15           Q29_4 ~~            Q29_5   0.044 0.133   0.329  0.742
## 16          agency  ~ Lab.goal.skills   1.024 0.050  20.550  0.000
## 17          agency  ~   Lab.goal.both   0.435 0.084   5.165  0.000
## 18      PostScores  ~           agency  -0.123 0.271  -0.455  0.649
## 19      PostScores  ~ Lab.goal.skills   0.501 0.323   1.550  0.121
## 20      PostScores  ~   Lab.goal.both  -0.091 0.197  -0.463  0.643
## 21           Q29_1 ~~            Q29_1   0.611 0.083   7.375  0.000
## 22           Q29_2 ~~            Q29_2   0.260 0.054   4.858  0.000
## 23           Q29_3 ~~            Q29_3   0.492 0.082   5.985  0.000
## 24           Q29_4 ~~            Q29_4   0.237 0.058   4.087  0.000
## 25           Q29_5 ~~            Q29_5   0.853 0.075  11.391  0.000
## 26           Q28_1 ~~            Q28_1   0.516 0.082   6.324  0.000
## 27           Q28_3 ~~            Q28_3   0.410 0.073   5.640  0.000
## 28      PostScores ~~       PostScores   0.764 0.113   6.762  0.000
## 29          agency ~~           agency   0.335 0.056   5.959  0.000
## 30 Lab.goal.skills ~~ Lab.goal.skills   1.000 0.000      NA     NA
## 31 Lab.goal.skills ~~   Lab.goal.both  -0.642 0.000      NA     NA
## 32   Lab.goal.both ~~   Lab.goal.both   1.000 0.000      NA     NA
## 33           Q29_1 ~1                    1.496 0.247   6.063  0.000
## 34           Q29_2 ~1                    1.668 0.240   6.957  0.000
## 35           Q29_3 ~1                    1.106 0.224   4.938  0.000
## 36           Q29_4 ~1                    1.518 0.231   6.560  0.000
## 37           Q29_5 ~1                    1.816 0.265   6.842  0.000
## 38           Q28_1 ~1                    4.251 0.244  17.427  0.000
## 39           Q28_3 ~1                    2.351 0.292   8.041  0.000
## 40      PostScores ~1                   11.781 1.494   7.886  0.000
## 41 Lab.goal.skills ~1                    1.012 0.000      NA     NA
## 42   Lab.goal.both ~1                    0.635 0.000      NA     NA
```

```
## 43          agency ~1                    0.000 0.000      NA     NA
##    ci.lower ci.upper
## 1      0.181    0.440
## 2      0.823    0.984
## 3      1.000    1.000
## 4      0.000    0.000
## 5      4.757    4.757
## 6      0.494    0.754
## 7      0.799    0.921
## 8      0.600    0.826
## 9      0.809    0.939
## 10     0.191    0.575
## 11    -0.811   -0.581
## 12     0.675    0.861
## 13    -0.772   -0.220
## 14     0.174    0.564
## 15    -0.216    0.303
## 16     0.926    1.121
## 17     0.270    0.600
## 18    -0.655    0.408
## 19    -0.132    1.135
## 20    -0.478    0.295
## 21     0.449    0.773
## 22     0.155    0.365
## 23     0.331    0.653
## 24     0.123    0.350
## 25     0.707    1.000
## 26     0.356    0.676
## 27     0.268    0.552
## 28     0.542    0.985
## 29     0.225    0.445
## 30     1.000    1.000
## 31    -0.642   -0.642
## 32     1.000    1.000
## 33     1.012    1.979
## 34     1.198    2.138
## 35     0.667    1.545
## 36     1.064    1.971
## 37     1.295    2.336
## 38     3.773    4.729
## 39     1.778    2.924
## 40     8.853   14.709
## 41     1.012    1.012
## 42     0.635    0.635
## 43     0.000    0.000
```

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

```
## $within
## $within$type
## [1] "cor.bollen"
##
## $within$cov
##            PstScr PrScrs
```

```
## PostScores  0.000
## PreScores  -0.002  0.000
##
## $within$mean
## PostScores  PreScores
##     -1.367      0.000
##
##
## $Class_ID
## $Class_ID$type
## [1] "cor.bollen"
##
## $Class_ID$cov
##                  Q29_1  Q29_2  Q29_3  Q29_4  Q29_5  Q28_1  Q28_3  PstScr
## Q29_1             0.000
## Q29_2            -0.006  0.000
## Q29_3            -0.076  0.024  0.000
## Q29_4             0.058  0.011  0.000  0.000
## Q29_5            -0.032  0.106  0.000  0.000  0.000
## Q28_1             0.094 -0.065 -0.009  0.075  0.177  0.000
## Q28_3             0.075  0.010 -0.071 -0.011 -0.072 -0.113  0.000
## PostScores       -0.123 -0.167 -0.285  0.347  0.053  0.185 -0.042  0.000
## Lab.goal.skills -0.107 -0.069 -0.026  0.046 -0.059 -0.001  0.047 -0.109
## Lab.goal.both     0.173  0.015  0.139 -0.070  0.191  0.024 -0.072  0.129
##                  Lb.gl.s Lb.gl.b
## Q29_1
## Q29_2
## Q29_3
## Q29_4
## Q29_5
## Q28_1
## Q28_3
## PostScores
## Lab.goal.skills  0.000
## Lab.goal.both    0.000   0.000
##
## $Class_ID$mean
##           Q29_1           Q29_2           Q29_3           Q29_4
##           0.000           0.000           0.000           0.000
##           Q29_5           Q28_1           Q28_3      PostScores
##           0.000           0.000           0.000           4.923
## Lab.goal.skills   Lab.goal.both
##           0.000           0.000
```

Check null model

```
nullRMSEA(fit)
```

```
## The baseline model's RMSEA = 0.06575585
##
## CFI, TLI, and other incremental fit indices may not be very informative because the baseline model's
```