Chi Squared

Instructions

The data comes from the faculty salary example.

There are three variables: sex (sex of professor) 1 = male 2 = female rank (rank of professor) 1 = full professor 2 = associate professor 3 = assistant professor 4 = instructor level (type of program that professor teaches in) 1 = doctoral program 2 = masters program

```
library(pacman) #Package used to load all packages using p_load(); will install missing packages
```

```
## Warning: package 'pacman' was built under R version 3.5.3
```

```
p_load(vcd, MASS, jmv, gmodels)
# jmv and gmodels used for chi-squared
# vcd, MASS used for loglinear
```

Load your data

```
dat <- read.csv("https://www.dropbox.com/s/w2bcd0c2n7qgwzz/Salary-1.csv?dl=1")
head(dat)
```

```
##   sex rank level
## 1   1    1     1
## 2   1    1     1
## 3   1    1     1
## 4   1    1     1
## 5   2    1     1
## 6   2    1     1
```

While this part isn't necessary it will make this entire demo easier to read. You are relabeling the levels of each variable.

```
dat$sex <- factor(dat$sex, levels = c(1,2), labels = c("Male", "Female"))
dat$rank <- factor(dat$rank, levels = c(1,2,3,4), labels = c("Full", "Associate", "Assistant", "Instruc
dat$level <- factor(dat$level, levels = c(1,2), labels = c("Doctorate", "Masters"))
head(dat)
```

```
##      sex rank     level
## 1   Male Full Doctorate
## 2   Male Full Doctorate
## 3   Male Full Doctorate
## 4   Male Full Doctorate
## 5 Female Full Doctorate
## 6 Female Full Doctorate
```

Goodness of Fit

Observed Frequencies for each variable.

```
sex <- table(dat$sex)
sex
```

```
##
##   Male Female
```

```
##   2803   1839
```

```r
rank <- table(dat$rank)
rank
```

```
##
##       Full  Associate  Assistant Instructor
##       2032       1311       1215         84
```

```r
level <- table(dat$level)
level
```

```
##
## Doctorate   Masters
##      3848       794
```

```r
## uses descriptives from jmv library - it is mas cute

desc <- descriptives(data = dat,
                     vars = c('sex', 'rank', 'level'),
                     freq = TRUE)
desc
```

```
##
##  DESCRIPTIVES
##
##  Descriptives
##  ------------------------------------
##                sex     rank    level
##  ------------------------------------
##    N          4642     4642     4642
##    Missing       0        0        0
##    Mean
##    Median
##    Minimum
##    Maximum
##  ------------------------------------
##
##
##  FREQUENCIES
##
##  Frequencies of sex
##  --------------------------------------------------
##    Levels    Counts    % of Total    Cumulative %
##  --------------------------------------------------
##    Male        2803          60.4            60.4
##    Female      1839          39.6           100.0
##  --------------------------------------------------
##
##
##  Frequencies of rank
##  ------------------------------------------------------
##    Levels        Counts    % of Total    Cumulative %
##  ------------------------------------------------------
##    Full            2032          43.8            43.8
##    Associate       1311          28.2            72.0
##    Assistant       1215          26.2            98.2
```

```
##    Instructor        84           1.8          100.0
##  ------------------------------------------------------
##
##
##  Frequencies of level
##  -----------------------------------------------------
##    Levels       Counts    % of Total    Cumulative %
##  -----------------------------------------------------
##    Doctorate      3848          82.9            82.9
##    Masters         794          17.1           100.0
##  -----------------------------------------------------
```

Assumptions - 1. Adequate expected cell counts - 5 or more in 2 x 2 or 5 or more in 80% of cells for larger table - Otherwise, Fisher's test - 2. Independence of Observations - otherwise McNemar's test of dependent proportions

Chi Squared Test Goodness of fit (testing if all frequencies are equal)

```r
# HO = equal proportions in each category; Ha = unequal proportions in each category
# Chi-square = Sum[(Observed - Expected)^2/Expected]
# df = # of categories - 1
jmv::propTestN(data = dat,
               var = 'sex',
               expected = TRUE,
               ratio = c(1,1))
```

```
##
##  PROPORTION TEST (N OUTCOMES)
##
##  Proportions
##  ---------------------------------------------
##    Level                 Count    Proportion
##  ---------------------------------------------
##    Male      Observed     2803         0.604
##              Expected     2321         0.500
##
##    Female    Observed     1839         0.396
##              Expected     2321         0.500
##  ---------------------------------------------
##
##
##  <U+03C7>² Goodness of Fit
##  -----------------------
##    <U+03C7>²     df    p
##  -----------------------
##    200     1    < .001
##  -----------------------
```

```r
jmv::propTestN(data = dat,
               var = 'rank',
               expected = TRUE,
               ratio = c(1,1,1,1))
```

```
##
##  PROPORTION TEST (N OUTCOMES)
##
##  Proportions
```

```
## -------------------------------------------------
##   Level                       Count    Proportion
## -------------------------------------------------
##   Full          Observed      2032        0.4377
##                 Expected      1160         0.250
##
##   Associate     Observed      1311        0.2824
##                 Expected      1160         0.250
##
##   Assistant     Observed      1215        0.2617
##                 Expected      1160         0.250
##
##   Instructor    Observed        84        0.0181
##                 Expected      1160         0.250
## -------------------------------------------------
##
##
## <U+03C7>² Goodness of Fit
## ------------------------
##   <U+03C7>²      df    p
## ------------------------
##   1675     3    < .001
## ------------------------
```

```
jmv::propTestN(data = dat,
               var = 'level',
               expected = TRUE,
               ratio = c(1,1))
```

```
##
## PROPORTION TEST (N OUTCOMES)
##
## Proportions
## ------------------------------------------------
##   Level                      Count    Proportion
## ------------------------------------------------
##   Doctorate    Observed      3848          0.829
##                Expected      2321          0.500
##
##   Masters      Observed       794          0.171
##                Expected      2321          0.500
## ------------------------------------------------
##
##
## <U+03C7>² Goodness of Fit
## ------------------------
##   <U+03C7>²      df    p
## ------------------------
##   2009     1    < .001
## ------------------------
```

However, what if we expected the proportions to be a little different. For example, based on an educated guess:

44% full Professors,
28% Associate Professors,
26% Assistant Professors,
2% Instructors

How does it compare to the Chi-square where all levels were expected to have equal proportions?

```
# H0 = baseline model proportions; Ha = significantly different than baseline model proportions
jmv::propTestN(data = dat,
               var = 'rank',
               expected = TRUE,
               ratio = c(.44, .28, .26, .02))
```

```
##
##  PROPORTION TEST (N OUTCOMES)
##
##  Proportions
##  -------------------------------------------------
##    Level                      Count    Proportion
##  -------------------------------------------------
##    Full          Observed     2032        0.4377
##                  Expected     2042        0.4400
##
##    Associate     Observed     1311        0.2824
##                  Expected     1300        0.2800
##
##    Assistant     Observed     1215        0.2617
##                  Expected     1207        0.2600
##
##    Instructor    Observed       84        0.0181
##                  Expected       93        0.0200
##  -------------------------------------------------
##
##
##  <U+03C7>² Goodness of Fit
##  -----------------------
##    <U+03C7>²      df    p
##  -----------------------
##    1.05     3    0.790
##  -----------------------
```

Chi-square Test of Independence

Ha: Is sex dependent upon rank? Is there a relationship between sex and rank?

We have a *new* effect size here (Cramer's V), what does it mean in the context of these results?

```r
# Chi-square = Sum[(Observed - Expected)^2/Expected]
# Expected = [(# of row entries for cel)/(# total entries)] * (# of column entries for cel)
# Expected indicates expected values for each category if there is no relationship between two categori
# df = (# rows - 1) * (# columns - 1)
# Cramer's V - small = .1; medium = .3, large = .5; discrepancy between observed and expected scores
jmv::contTables(dat = dat,
                rows = 'sex',
                cols = 'rank',
                exp = TRUE,
                phiCra = TRUE)
```

```
##
##  CONTINGENCY TABLES
##
##  Contingency Tables
##  -------------------------------------------------------------------------------
##    sex                  Full    Associate    Assistant    Instructor    Total
##  -------------------------------------------------------------------------------
##    Male      Observed    1474          711          583            35     2803
##              Expected    1227          792          734          50.7
##
##    Female    Observed     558          600          632            49     1839
##              Expected     805          519          481          33.3
##
##    Total     Observed    2032         1311         1215            84     4642
##              Expected    2032         1311         1215          84.0
##  -------------------------------------------------------------------------------
##
##
##  <U+03C7>² Tests
##  -------------------------------
##          Value    df    p
##  -------------------------------
##    <U+03C7>²      237     3    < .001
##    N      4642
##  -------------------------------
##
##
##  Nominal
##  ----------------------------
##                       Value
##  ----------------------------
##    Phi-coefficient      NaN
##    Cramer's V         0.226
##  ----------------------------
```

```r
# report APA, magnitude of effect (Cramer's V), direction of effect example (more or less than expected
```

Chi-square Test of Independence

Is level dependent upon sex? Is there a relationship between level and sex?

```r
jmv::contTables(dat = dat,
                rows = 'sex',
```

```
               cols = 'level',
               exp = TRUE,
               phiCra = TRUE)
```

```
##
##  CONTINGENCY TABLES
##
##  Contingency Tables
##  -------------------------------------------------------
##    sex                     Doctorate    Masters    Total
##  -------------------------------------------------------
##    Male      Observed           2332        471     2803
##              Expected           2324        479
##
##    Female    Observed           1516        323     1839
##              Expected           1524        315
##
##    Total     Observed           3848        794     4642
##              Expected           3848        794
##  -------------------------------------------------------
##
##
##  <U+03C7>² Tests
##  ------------------------------
##          Value    df    p
##  ------------------------------
##    <U+03C7>²    0.453     1    0.501
##    N      4642
##  ------------------------------
##
##
##  Nominal
##  ------------------------------
##                       Value
##  ------------------------------
##    Phi-coefficient    0.00988
##    Cramer's V         0.00988
##  ------------------------------
```

Chi-square Test of Independence

How about for rank and level?

```
jmv::contTables(dat = dat,
               rows = 'rank',
               cols = 'level',
               exp = TRUE,
               phiCra = TRUE)
```

```
##
##  CONTINGENCY TABLES
##
##  Contingency Tables
##  -----------------------------------------------------------
```

```
##    rank                      Doctorate    Masters    Total
##  -----------------------------------------------------------
##    Full          Observed         1722        310     2032
##                  Expected       1684.4      347.6
##
##    Associate     Observed         1089        222     1311
##                  Expected       1086.8      224.2
##
##    Assistant     Observed          971        244     1215
##                  Expected       1007.2      207.8
##
##    Instructor    Observed           66         18       84
##                  Expected         69.6       14.4
##
##    Total         Observed         3848        794     4642
##                  Expected       3848.0      794.0
##  -----------------------------------------------------------
##
##
##  <U+03C7>² Tests
##  ------------------------------
##          Value    df    p
##  ------------------------------
##    <U+03C7>²     13.6     3    0.003
##    N      4642
##  ------------------------------
##
##
##  Nominal
##  -----------------------------
##                       Value
##  -----------------------------
##    Phi-coefficient       NaN
##    Cramer's V         0.0542
##  -----------------------------
```

What happens if we take this a step further...

What if our research question asks: is there a three-way contingency (sex x rank x level)? df1 = # cells for sex - 1 = 2 - 1 = 1 df2 = # cells for rank - 1 = 4 - 1 = 3 df3 = # cells for level - 1 = 2 -1 = 1 N = number of cells in table (2 x 4 x 2) - df1 - df2 - df3 df = N - 1 = 10

Three way contingency test require *log-linear modeling*.
Start with the independence model and end with the saturated model.

Evidence for model fit: non-significant chi-square value - no discrepancy between observed and expected values under the null model

Model 1, There are no relationships among the variables.

```
# overall model test
# 2 x 4 x 2 contingency table
# Observed = mytable
# Expected = loglm
```

```r
# Expected = Expected frequencies in 2 x 4 x 2 table if there are no relationships

# Null hypothesis means that expected frequencies satisfy our model of expected values
# Alternative Hypothesis means that difference between expected and observed frequencies is significant

mytable<- xtabs(~dat$sex + dat$rank + dat$level) # table of observed values
model1 <- loglm(~dat$sex + dat$rank + dat$level, mytable)
mytable
```

```
## , , dat$level = Doctorate
##
##         dat$rank
## dat$sex  Full Associate Assistant Instructor
##   Male   1251       591       464         26
##   Female  471       498       507         40
##
## , , dat$level = Masters
##
##         dat$rank
## dat$sex  Full Associate Assistant Instructor
##   Male    223       120       119          9
##   Female   87       102       125          9
```

```r
summary(model1)
```

```
## Formula:
## ~dat$sex + dat$rank + dat$level
## attr(,"variables")
## list(dat$sex, dat$rank, dat$level)
## attr(,"factors")
##           dat$sex dat$rank dat$level
## dat$sex         1        0         0
## dat$rank        0        1         0
## dat$level       0        0         1
## attr(,"term.labels")
## [1] "dat$sex"   "dat$rank"  "dat$level"
## attr(,"order")
## [1] 1 1 1
## attr(,"intercept")
## [1] 1
## attr(,"response")
## [1] 0
## attr(,".Environment")
## <environment: R_GlobalEnv>
##
## Statistics:
##                       X^2 df P(> X^2)
## Likelihood Ratio 254.4448 10        0
## Pearson          251.2707 10        0
```

Model 2: Rank and Sex are *independent* but Rank/Level are related and Sex/Level are *related*.

```r
model2 <- loglm(~(dat$rank+dat$sex)*dat$level, mytable)
summary(model2)
```

```
## Formula:
```

```
## ~(dat$rank + dat$sex) * dat$level
## attr(,"variables")
## list(dat$rank, dat$sex, dat$level)
## attr(,"factors")
##           dat$rank dat$sex dat$level dat$rank:dat$level dat$sex:dat$level
## dat$rank         1       0         0                  1                 0
## dat$sex          0       1         0                  0                 1
## dat$level        0       0         1                  1                 1
## attr(,"term.labels")
## [1] "dat$rank"           "dat$sex"            "dat$level"
## [4] "dat$rank:dat$level" "dat$sex:dat$level"
## attr(,"order")
## [1] 1 1 1 2 2
## attr(,"intercept")
## [1] 1
## attr(,"response")
## [1] 0
## attr(,".Environment")
## <environment: R_GlobalEnv>
##
## Statistics:
##                       X^2 df P(> X^2)
## Likelihood Ratio 240.6000  6        0
## Pearson          237.0755  6        0
```

Model 3: *All two-way* relationships

```
model3 <- loglm(~dat$rank*dat$level + dat$level*dat$sex + dat$rank*dat$sex, mytable)
summary(model3)
```

```
## Formula:
## ~dat$rank * dat$level + dat$level * dat$sex + dat$rank * dat$sex
## attr(,"variables")
## list(dat$rank, dat$level, dat$sex)
## attr(,"factors")
##           dat$rank dat$level dat$sex dat$rank:dat$level dat$level:dat$sex
## dat$rank         1         0       0                  1                 0
## dat$level        0         1       0                  1                 1
## dat$sex          0         0       1                  0                 1
##           dat$rank:dat$sex
## dat$rank                 1
## dat$level                0
## dat$sex                  1
## attr(,"term.labels")
## [1] "dat$rank"           "dat$level"          "dat$sex"
## [4] "dat$rank:dat$level" "dat$level:dat$sex"  "dat$rank:dat$sex"
## attr(,"order")
## [1] 1 1 1 2 2 2
## attr(,"intercept")
## [1] 1
## attr(,"response")
## [1] 0
## attr(,".Environment")
## <environment: R_GlobalEnv>
##
```

```
## Statistics:
##                         X^2 df  P(> X^2)
## Likelihood Ratio 0.7852340  3 0.8529955
## Pearson          0.7916546  3 0.8514621
```

Model 4: All two-way relationships *and the three-way* relationship

```r
#saturated model or "overfit model
# this takes us one step past parsimony
# this means that the three-way relationship does not add to the model

# i.e. Chi-squared is zero
# e.g., no degrees of freedom
model4 <- loglm(~dat$rank*dat$level*dat$sex, mytable)
summary(model4)
```

```
## Formula:
## ~dat$rank * dat$level * dat$sex
## attr(,"variables")
## list(dat$rank, dat$level, dat$sex)
## attr(,"factors")
##           dat$rank dat$level dat$sex dat$rank:dat$level dat$rank:dat$sex
## dat$rank         1         0       0                  1                1
## dat$level        0         1       0                  1                0
## dat$sex          0         0       1                  0                1
##           dat$level:dat$sex dat$rank:dat$level:dat$sex
## dat$rank                  0                          1
## dat$level                 1                          1
## dat$sex                   1                          1
## attr(,"term.labels")
## [1] "dat$rank"                   "dat$level"
## [3] "dat$sex"                    "dat$rank:dat$level"
## [5] "dat$rank:dat$sex"           "dat$level:dat$sex"
## [7] "dat$rank:dat$level:dat$sex"
## attr(,"order")
## [1] 1 1 1 2 2 2 3
## attr(,"intercept")
## [1] 1
## attr(,"response")
## [1] 0
## attr(,".Environment")
## <environment: R_GlobalEnv>
##
## Statistics:
##                  X^2 df P(> X^2)
## Likelihood Ratio   0  0        1
## Pearson            0  0        1
```

Compare Models

```r
stats::anova(model1,model2,model3, model4)
```

```
## LR tests for hierarchical log-linear models
##
## Model 1:
##  ~dat$sex + dat$rank + dat$level
```

```
## Model 2:
##  ~(dat$rank + dat$sex) * dat$level
## Model 3:
##  ~dat$rank * dat$level + dat$level * dat$sex + dat$rank * dat$sex
## Model 4:
##  ~dat$rank * dat$level * dat$sex
##
##             Deviance df Delta(Dev) Delta(df) P(> Delta(Dev)
## Model 1   254.444762 10
## Model 2   240.600036  6  13.844726         4        0.00781
## Model 3     0.785234  3 239.814802         3        0.00000
## Model 4     0.000000  0   0.785234         3        0.85300
## Saturated   0.000000  0   0.000000         0        1.00000
```

```
#Delta(Dev) is a chi-squared difference test between models
#once difference is no longer significant, the first model is likely parsimonious fit
```

The JMV way produces a cleaner output, but there are some drawbacks. Overall, it's good to know multiple ways but see which may be best for your analyses or purpose(s). For now, stick with loglm function.

```
# note the similarities between 'Deviance' values and the model comparison stats with the loglm output.
# the top table output is unknown - so look it up

jmv::logLinear(
  data = dat,
  counts = NULL,
  factors = c('sex', 'rank', 'level'),
  blocks = list(
    list(
      'sex', 'rank', 'level'),
    list(
      c('sex', 'level'),
      c('rank', 'level')),
    list(
      c('sex', 'rank')),
    list(
      c('sex', 'rank', 'level'))),
  refLevels = list(
    list(
      var = 'sex',
      ref = 'Male'),
    list(
      var = 'rank',
      ref = 'Full'),
    list(
      var = 'level',
      ref = 'Doctorate')),
  modelTest = TRUE)
```

```
##
##  LOG-LINEAR REGRESSION
##
##  Model Fit Measures
##  --------------------------------------------------------------
##    Model    Deviance    AIC    R²-McF    <U+03C7>²      df    p
##  --------------------------------------------------------------
```

```
##       1     254.445    374     0.948    4656     5    < .001
##       2     240.600    369     0.951    4669     9    < .001
##       3       0.785    135     1.000    4909    12    < .001
##       4    2.80e-13    140     1.000    4910    15    < .001
##  --------------------------------------------------------------
##
##
##  Model Comparisons
##  --------------------------------------------------
##    Model         Model    <U+03C7>²         df    p
##  --------------------------------------------------
##       1    -        2     13.845     4     0.008
##       2    -        3    239.815     3    < .001
##       3    -        4      0.785     3     0.853
##  --------------------------------------------------
##
##
##  MODEL SPECIFIC RESULTS
##
##  MODEL 1
##
##  Model Coefficients
##  ----------------------------------------------------------------
##    Predictor              Estimate    SE        Z        p
##  ----------------------------------------------------------------
##    Intercept                 6.925    0.0260    266.0    < .001
##    sex:
##    Female - Male            -0.421    0.0300    -14.0    < .001
##    rank:
##    Associate - Full         -0.438    0.0354    -12.4    < .001
##    Assistant - Full         -0.514    0.0363    -14.2    < .001
##    Instructor - Full        -3.186    0.1113    -28.6    < .001
##    level:
##    Masters - Doctorate      -1.578    0.0390    -40.5    < .001
##  ----------------------------------------------------------------
##
##
##  MODEL 2
##
##  Model Coefficients
##  ----------------------------------------------------------------------------------------
##    Predictor                                  Estimate    SE        Z          p
##  ----------------------------------------------------------------------------------------
##    Intercept                                    6.9504    0.0274    253.851    < .001
##    sex:
##    Female - Male                               -0.4307    0.0330    -13.053    < .001
##    rank:
##    Associate - Full                            -0.4582    0.0387    -11.835    < .001
##    Assistant - Full                            -0.5729    0.0401    -14.276    < .001
##    Instructor - Full                           -3.2616    0.1254    -26.004    < .001
##    level:
##    Masters - Doctorate                         -1.7361    0.0696    -24.956    < .001
##    sex:level:
##    (Female - Male):(Masters - Doctorate)        0.0534    0.0794      0.673     0.501
```

```
##   rank:level:
##   (Associate - Full):(Masters - Doctorate)      0.1243    0.0961      1.294     0.196
##   (Assistant - Full):(Masters - Doctorate)      0.3335    0.0945      3.528    < .001
##   (Instructor - Full):(Masters - Doctorate)     0.4154    0.2730      1.522     0.128
## ---------------------------------------------------------------------------------------
##
##
## MODEL 3
##
## Model Coefficients
## ----------------------------------------------------------------------------------------
##   Predictor                                    Estimate    SE        Z           p
## ----------------------------------------------------------------------------------------
##   Intercept                                     7.12988    0.0279    255.4574    < .001
##   sex:
##   Female - Male                                -0.97021    0.0512    -18.9376    < .001
##   rank:
##   Associate - Full                             -0.74933    0.0484    -15.4948    < .001
##   Assistant - Full                             -0.98667    0.0521    -18.9290    < .001
##   Instructor - Full                            -3.81665    0.1807    -21.1208    < .001
##   level:
##   Masters - Doctorate                          -1.71257    0.0656    -26.1009    < .001
##   sex:level:
##   (Female - Male):(Masters - Doctorate)        -0.00766    0.0816     -0.0938     0.925
##   rank:level:
##   (Associate - Full):(Masters - Doctorate)      0.12573    0.0972      1.2933     0.196
##   (Assistant - Full):(Masters - Doctorate)      0.33539    0.0966      3.4711    < .001
##   (Instructor - Full):(Masters - Doctorate)     0.41775    0.2741      1.5239     0.128
##   sex:rank:
##   (Female - Male):(Associate - Full)            0.80176    0.0745     10.7664    < .001
##   (Female - Male):(Assistant - Full)            1.05245    0.0761     13.8385    < .001
##   (Female - Male):(Instructor - Full)           1.30832    0.2269      5.7665    < .001
## ----------------------------------------------------------------------------------------
##
##
## MODEL 4
##
## Model Coefficients
## --------------------------------------------------------------------------------------------------------
##   Predictor                                                   Estimate    SE        Z          p
## --------------------------------------------------------------------------------------------------------
##   Intercept                                                     7.1317    0.0283    252.244    < .
##   sex:
##   Female - Male                                                -0.9768    0.0541    -18.070    < .
##   rank:
##   Associate - Full                                             -0.7499    0.0499    -15.023    < .
##   Assistant - Full                                             -0.9918    0.0544    -18.247    < .
##   Instructor - Full                                            -3.8736    0.1981    -19.549    < .
##   level:
##   Masters - Doctorate                                          -1.7245    0.0727    -23.725    < .
##   sex:level:
##   (Female - Male):(Masters - Doctorate)                         0.0356    0.1375      0.259     0.
##   rank:level:
##   (Associate - Full):(Masters - Doctorate)                      0.1302    0.1237      1.052     0.
```

```
##    (Assistant - Full):(Masters - Doctorate)                         0.3638    0.1259      2.890     0.0
##    (Instructor - Full):(Masters - Doctorate)                        0.6637    0.3935      1.686     0.0
##    sex:rank:
##    (Female - Male):(Associate - Full)                               0.8056    0.0814      9.900    < .0
##    (Female - Male):(Assistant - Full)                               1.0655    0.0840     12.689    < .0
##    (Female - Male):(Instructor - Full)                              1.4076    0.2577      5.463    < .0
##    sex:rank:level:
##    (Female - Male):(Associate - Full):(Masters - Doctorate)        -0.0269    0.2018     -0.133     0.8
##    (Female - Male):(Assistant - Full):(Masters - Doctorate)        -0.0750    0.1986     -0.378     0.7
##    (Female - Male):(Instructor - Full):(Masters - Doctorate)       -0.4664    0.5519     -0.845     0.3
## ------------------------------------------------------------------------------------------------------
```