Lab 2

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January 30, 2018

Loading in packages

```
library(tidyverse)
library(car)
library(QuantPsyc)
library(stats)
library(lmSupport)
library(papaja)
```

Creating the dataset

```
student <- seq(1:12)
exam <- c(100,72,84,41,69,74,95,94,81,83,65,61)
attend <- c(13,15,10,5,9,9,12,9,10,11,2,8)
gpa <- c(3.4,3.9,3.4,2.3,3.0,2.6,4.0,3.9,2.9,3.4,2.2,3.8)
class <- data.frame (student,exam,attend,gpa)
```

Q1a

```
attendgpa <-lm(exam~attend, data = class)
summary(attendgpa)
```

```
##
## Call:
## lm(formula = exam ~ attend, data = class)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -22.592  -7.622   2.230  10.379  18.642
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   48.885     12.029   4.064  0.00227 **
## attend         2.941      1.205   2.440  0.03484 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 13.79 on 10 degrees of freedom
## Multiple R-squared:  0.3732, Adjusted R-squared:  0.3105
## F-statistic: 5.955 on 1 and 10 DF,  p-value: 0.03484
```

I would tell the professor that attendence significantly predicts exam scores $R^2 = 0.3732$, $F(1,10) = 5.95$, $p < .05$

Q1b

```
examgpa <- lm(exam~gpa, data = class)
summary(examgpa)
```

```
##
## Call:
## lm(formula = exam ~ gpa, data = class)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -24.260  -6.706   4.552   7.138  20.865
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   27.076     22.247   1.217   0.2515
## gpa           15.312      6.763   2.264   0.0471 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 14.17 on 10 degrees of freedom
## Multiple R-squared:  0.3389, Adjusted R-squared:  0.2728
## F-statistic: 5.125 on 1 and 10 DF,  p-value: 0.04705
```

I would tell the professor that GPA scores significantly predicts exam scores $R^2 = 0.3389$, $F(1,10) = 5.125$, $p < .05$

Q1c

```
examscoresattend <- lm(exam~gpa+attend, data = class)
summary(examscoresattend)
```

```
##
## Call:
## lm(formula = exam ~ gpa + attend, data = class)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -20.386  -8.050   4.042   8.335  15.273
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   33.798     22.993   1.470    0.176
## gpa            7.650      9.858   0.776    0.458
## attend         1.917      1.805   1.062    0.316
##
## Residual standard error: 14.07 on 9 degrees of freedom
## Multiple R-squared:  0.4125, Adjusted R-squared:  0.282
## F-statistic:  3.16 on 2 and 9 DF,  p-value: 0.0913
```

I would tell the professors that GPA scores with attendence do not significantly predict exam scores $R^2 = 0.4126$, $F(2,9) = 3.16$, $p = 0.09$

Q1d

```
cor.test(class$gpa,class$attend)
```

```
##
##  Pearson's product-moment correlation
##
## data:  class$gpa and class$attend
## t = 3.394, df = 10, p-value = 0.006839
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  0.2719185 0.9194684
## sample estimates:
##       cor
## 0.7316438
```

- The instructor is referring to a multiple regression.
- The contradiction exists because the model now consists of multiple predictor values, which if correlated may deflate the r^2 value

Q1e

```
new.dat = data.frame(attend = 0, gpa = 2.0)
badgrade <- predict(examscoresattend,new.dat)
```

The student who does not go to class and has a gpa of 2.0 would receive a 49

Q2

Loading data

```
load("C:/Users/Branly Mclanbry/Downloads/lab2AA.RData")
```

renaming and cleaning data

```
clean_dat <- lab2AA %>%
 mutate(
   p_agree = q1agree,
   p_fair = q1fair,
   p_eff = q1eff,
   education = q4,
   employment = q5,
   happiness = q7,
   job_choice = q8,
   job_satis = q9,
   ethnicity = qa,
   aa_support = (p_agree + p_fair + p_eff))%>%
  na.omit()
```

General linear model with all variables

```
every.mod <- lm(aa_support ~ education + employment + happiness + job_choice + job_satis, dat =
clean_dat)
summary(every.mod)
```

```
##
## Call:
## lm(formula = aa_support ~ education + employment + happiness +
##     job_choice + job_satis, data = clean_dat)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -12.2728  -2.6192   0.0128   2.6491  12.5421
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   4.9150     0.4605  10.674  < 2e-16 ***
## education     0.2213     0.1896   1.167 0.244005
## employment    0.5061     0.2035   2.488 0.013349 *
## happiness     0.1991     0.1987   1.002 0.317049
## job_choice   -0.1227     0.2071  -0.592 0.554076
## job_satis     0.7391     0.2101   3.518 0.000494 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.041 on 334 degrees of freedom
## Multiple R-squared:  0.3187, Adjusted R-squared:  0.3085
## F-statistic: 31.25 on 5 and 334 DF,  p-value: < 2.2e-16
```

```
lm.beta(every.mod)
```

```
##   education  employment   happiness  job_choice   job_satis
##  0.09871666  0.21827856  0.07550335 -0.05187809  0.29905318
```

filtering across ethnicity lines

```
white <- clean_dat %>%
  filter(ethnicity == "White") %>%
  na.omit()

minority <- clean_dat %>%
  filter(ethnicity != "White")
```

Running series of linear models

```
white.1 <- lm(aa_support ~ education + employment, dat = white)
white.2 <- lm(aa_support ~ education + employment + happiness + job_choice + job_satis, dat = wh
ite)
minority.1 <- lm(aa_support ~ education + employment, dat = minority)
minority.2 <- lm(aa_support ~ education + employment + happiness + job_choice + job_satis, dat =
minority)
```

Let's take a look at all the models and some standardized units *b**

```
summary(white.1)
```

```
##
## Call:
## lm(formula = aa_support ~ education + employment, data = white)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -8.2340 -2.7881 -0.6037  2.0100 11.8866
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   6.2893     0.5106  12.319  < 2e-16 ***
## education     1.0700     0.3324   3.219  0.00153 **
## employment   -0.2459     0.3671  -0.670  0.50383
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.867 on 173 degrees of freedom
## Multiple R-squared:  0.1417, Adjusted R-squared:  0.1318
## F-statistic: 14.29 on 2 and 173 DF,  p-value: 1.81e-06
```

```
lm.beta(white.1)
```

```
##   education  employment
##  0.45580267 -0.09484471
```

```r
summary(white.2)
```

```
##
## Call:
## lm(formula = aa_support ~ education + employment + happiness +
##     job_choice + job_satis, data = white)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -8.9124 -2.5246 -0.6429  1.9482 12.2180
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  5.688558   0.539302  10.548  < 2e-16 ***
## education    0.947837   0.344958   2.748  0.00665 **
## employment  -0.191080   0.357908  -0.534  0.59412
## happiness   -0.007591   0.315762  -0.024  0.98085
## job_choice  -0.730417   0.290372  -2.515  0.01282 *
## job_satis    1.074669   0.322146   3.336  0.00104 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.696 on 170 degrees of freedom
## Multiple R-squared:  0.2295, Adjusted R-squared:  0.2068
## F-statistic: 10.13 on 5 and 170 DF,  p-value: 1.669e-08
```

```r
lm.beta(white.2)
```

```
##    education   employment    happiness   job_choice    job_satis
##  0.403758044 -0.073700034 -0.002896568 -0.303625714  0.442818796
```

```r
summary(minority.1)
```

```
##
## Call:
## lm(formula = aa_support ~ education + employment, data = minority)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -11.6510  -2.7331   0.4535   3.1570  10.7669
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   5.3107     1.0151   5.232 5.16e-07 ***
## education     0.2647     0.2486   1.065    0.289
## employment    1.0697     0.2479   4.314 2.79e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.455 on 161 degrees of freedom
## Multiple R-squared:  0.2222, Adjusted R-squared:  0.2126
## F-statistic:    23 on 2 and 161 DF,  p-value: 1.638e-09
```

```
lm.beta(minority.1)
```

```
##  education employment
##  0.0987673  0.4001477
```

```
summary(minority.2)
```

```
##
## Call:
## lm(formula = aa_support ~ education + employment + happiness +
##     job_choice + job_satis, data = minority)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -13.2071  -2.6187   0.6848   2.9531   9.5060
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  4.43767    1.01223   4.384 2.12e-05 ***
## education    0.04644    0.24532   0.189   0.8501
## employment   0.63099    0.26690   2.364   0.0193 *
## happiness    0.26387    0.26218   1.006   0.3157
## job_choice   0.25861    0.29922   0.864   0.3887
## job_satis    0.49471    0.28797   1.718   0.0878 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.284 on 158 degrees of freedom
## Multiple R-squared:  0.2942, Adjusted R-squared:  0.2719
## F-statistic: 13.17 on 5 and 158 DF,  p-value: 1.003e-10
```

```
lm.beta(minority.2)
```

```
##  education employment  happiness job_choice  job_satis
## 0.01732864 0.23604759 0.09719706 0.09817709 0.19297729
```

The writes up suggest that for white participants, affirmitave action is supported multiple variables $R^2 = 0.14$, $F(2,173) = 14.29$, $p <.05$. Although, not all variables contributed to the prediction. Greater perceived benefit of education ($b^* = .45$, $p < .05$) related to more support for affirmative action. Greater perceived benefit of employment did not relate to affirmative action ($b^* = -.10$, $p = .50$)

For minority participants, affirmitave action is supported multiple variables $R^2 = 0.22$, $F(2,161) = 23$, $p <.05$. Although, not all variables contributed to the prediction. Greater perceived benefit of employment ($b^* = .40$, $p < .05$) is related to more support for affirmative action. Greater perceived benefit of education did not relate to affirmative action ($b^* = .10$, $p = .29$)

Lastly, comparison of models against each other.

```
anova(minority.1,minority.2)
anova(white.1,white.2)
```

I like to use `modelCompare`

```
modelCompare(minority.1,minority.2)
```

```
## SSE (Compact) =  3195.92
## SSE (Augmented) =  2900.129
## Delta R-Squared =  0.07198628
## Partial Eta-Squared (PRE) =  0.09255275
## F(3,158) = 5.371601, p = 0.001509836
```

```
modelCompare(white.1,white.2)
```

```
## SSE (Compact) =  2587.155
## SSE (Augmented) =  2322.668
## Delta R-Squared =  0.08773977
## Partial Eta-Squared (PRE) =  0.1022308
## F(3,170) = 6.452751, p = 0.0003660598
```

Looking at the hierarchical multiple regression, we find that the R^2 change = 0.09, $p < .05$ for white participants. For minorities, the R^2 change = 0.07,$p < .05$

Semi-partial correlations

Here is the formula that is used.

```
values <-summary(white.2)
r2 <- values$r.squared[1]
dfr<-values$df[2]
dfr
values <-summary(white.2)
r2 <- values$r.squared[1]
dfr<-values$df[2]
t1 <- values$coefficients[2,3]
t2 <- values$coefficients[3,3]
t3 <- values$coefficients[4,3]
t4 <- values$coefficients[5,3]
t5 <- values$coefficients[6,3]
sr1<-((t1^2)/dfr)*(1-r2)
sr2<-((t2^2)/dfr)*(1-r2)
sr3<-((t3^2)/dfr)*(1-r2)
sr4<-((t4^2)/dfr)*(1-r2)
sr5<-((t5^2)/dfr)*(1-r2)
```

Here is the `modelEffectSizes`.

```
modelEffectSizes(white.2)
```

```
## lm(formula = aa_support ~ education + employment + happiness +
##     job_choice + job_satis, data = white)
##
## Coefficients
##                   SSR df pEta-sqr dR-sqr
## (Intercept) 1520.1221  1   0.3956     NA
## education    103.1508  1   0.0425 0.0342
## employment     3.8943  1   0.0017 0.0013
## happiness      0.0079  1   0.0000 0.0000
## job_choice    86.4512  1   0.0359 0.0287
## job_satis    152.0485  1   0.0614 0.0504
##
## Sum of squared errors (SSE): 2322.7
## Sum of squared total  (SST): 3014.4
```

```
modelEffectSizes(minority.2)
```

```
## lm(formula = aa_support ~ education + employment + happiness +
##     job_choice + job_satis, data = minority)
##
## Coefficients
##                  SSR df pEta-sqr dR-sqr
## (Intercept) 352.7864  1   0.1085     NA
## education     0.6577  1   0.0002 0.0002
## employment  102.5918  1   0.0342 0.0250
## happiness    18.5925  1   0.0064 0.0045
## job_choice   13.7110  1   0.0047 0.0033
## job_satis    54.1720  1   0.0183 0.0132
##
## Sum of squared errors (SSE): 2900.1
## Sum of squared total  (SST): 4109.0
```

```
varDescribe(white, Detail = 3)
```

```
##            vars   n mean   sd median trimmed  mad min max range skew
## q1agree       1 176 2.72 1.62      2    2.55 1.48   1   7     6 0.74
## q1fair        2 176 2.68 1.56      2    2.47 1.48   1   7     6 1.02
## q1eff         3 176 2.87 1.42      3    2.78 1.48   1   6     5 0.46
## q4            4 176 2.37 1.77      1    2.09 0.00   1   7     6 1.03
## q5            5 176 2.27 1.60      2    2.01 1.48   1   7     6 1.07
## q7            6 176 2.33 1.58      2    2.09 1.48   1   7     6 1.00
## q8            7 176 2.33 1.73      2    2.01 1.48   1   7     6 1.25
## q9            8 176 2.31 1.71      1    2.02 0.00   1   7     6 1.15
## qa*           9 176 1.00 0.00      1    1.00 0.00   1   1     0  NaN
## p_agree      10 176 2.72 1.62      2    2.55 1.48   1   7     6 0.74
## p_fair       11 176 2.68 1.56      2    2.47 1.48   1   7     6 1.02
## p_eff        12 176 2.87 1.42      3    2.78 1.48   1   6     5 0.46
## education    13 176 2.37 1.77      1    2.09 0.00   1   7     6 1.03
## employment   14 176 2.27 1.60      2    2.01 1.48   1   7     6 1.07
## happiness    15 176 2.33 1.58      2    2.09 1.48   1   7     6 1.00
## job_choice   16 176 2.33 1.73      2    2.01 1.48   1   7     6 1.25
## job_satis    17 176 2.31 1.71      1    2.02 0.00   1   7     6 1.15
## ethnicity*   18 176 1.00 0.00      1    1.00 0.00   1   1     0  NaN
## aa_support   19 176 8.27 4.15      8    7.89 4.45   3  19    16 0.69
##            kurtosis   se
## q1agree       -0.35 0.12
## q1fair         0.46 0.12
## q1eff         -0.68 0.11
## q4            -0.30 0.13
## q5             0.04 0.12
## q7             0.03 0.12
## q8             0.59 0.13
## q9             0.30 0.13
## qa*             NaN 0.00
## p_agree       -0.35 0.12
## p_fair         0.46 0.12
## p_eff         -0.68 0.11
## education     -0.30 0.13
## employment     0.04 0.12
## happiness      0.03 0.12
## job_choice     0.59 0.13
## job_satis      0.30 0.13
## ethnicity*      NaN 0.00
## aa_support    -0.16 0.31
```

```
varDescribe(minority, Detail = 3)
```

```
##            vars   n  mean   sd median trimmed  mad min max range  skew
## q1agree       1 164  3.98 1.96    4.0    3.97 2.97   1   7     6 -0.12
## q1fair        2 164  3.66 1.81    4.0    3.61 1.48   1   7     6  0.15
## q1eff         3 164  3.86 1.64    4.0    3.91 1.48   1   7     6 -0.21
## q4            4 164  4.73 1.87    5.0    4.86 2.22   1   7     6 -0.44
## q5            5 164  4.61 1.88    5.0    4.73 1.48   1   7     6 -0.41
## q7            6 164  3.68 1.85    4.0    3.64 1.48   1   7     6 -0.01
## q8            7 164  4.27 1.91    4.5    4.33 2.22   1   7     6 -0.26
## q9            8 164  3.74 1.96    4.0    3.68 2.97   1   7     6  0.02
## qa*           9 164  3.43 0.88    3.0    3.39 1.48   2   6     4  0.79
## p_agree      10 164  3.98 1.96    4.0    3.97 2.97   1   7     6 -0.12
## p_fair       11 164  3.66 1.81    4.0    3.61 1.48   1   7     6  0.15
## p_eff        12 164  3.86 1.64    4.0    3.91 1.48   1   7     6 -0.21
## education    13 164  4.73 1.87    5.0    4.86 2.22   1   7     6 -0.44
## employment   14 164  4.61 1.88    5.0    4.73 1.48   1   7     6 -0.41
## happiness    15 164  3.68 1.85    4.0    3.64 1.48   1   7     6 -0.01
## job_choice   16 164  4.27 1.91    4.5    4.33 2.22   1   7     6 -0.26
## job_satis    17 164  3.74 1.96    4.0    3.68 2.97   1   7     6  0.02
## ethnicity*   18 164  3.43 0.88    3.0    3.39 1.48   2   6     4  0.79
## aa_support   19 164 11.49 5.02   12.0   11.55 5.93   3  21    18 -0.13
##            kurtosis   se
## q1agree       -1.26 0.15
## q1fair        -1.01 0.14
## q1eff         -0.90 0.13
## q4            -0.97 0.15
## q5            -0.92 0.15
## q7            -1.01 0.14
## q8            -1.10 0.15
## q9            -1.18 0.15
## qa*            1.23 0.07
## p_agree       -1.26 0.15
## p_fair        -1.01 0.14
## p_eff         -0.90 0.13
## education     -0.97 0.15
## employment    -0.92 0.15
## happiness     -1.01 0.14
## job_choice    -1.10 0.15
## job_satis     -1.18 0.15
## ethnicity*     1.23 0.07
## aa_support    -1.05 0.39
```

Table 1

Model predicting support for affirmative action attitudes from white participants

Predictor	Range	*M*(*SD*)	*b**	*sr*^{2}
Education	1-7	2.37(1.77)	.40	.03
Employement	1-7	2.27(1.60)	.07	.00
Happiness	1-7	2.33(1.58)	.00	.00

Predictor	Range	*M*(*SD*)	*b**	*sr*
R^2			.14	
Job Choice	1-7	2.33(1.73)	.30	.03
Job Satisfaction	1-7	2.31(1.71)	.44	.01
R^2 Change			.09	
R^2 Model			.23	

Note.* $p<.05$. $n = 170$

Table 2

Model predicting support for affirmative action attitudes from minority participants

Predictor	Range	*M*(*SD*)	*b**	sr^2
Education	1-7	4.73(1.87)	.02	.00
Employement	1-7	4.61(1.88)	.24	.03
Happiness	1-7	3.68(1.85)	.10	.00
R^2			.22	
Job Choice	1-7	4.27(1.91)	.10	.00
Job Satisfaction	1-7	3.74(1.96)	.20	.01
R^2 Change			.07	
R^2 Model			.29	

Note.* $p<.05$. $n = 170$

In minority populations attitudes predicting affirmative action from a concrete belief system accounted for 22% of the variance in attitudes. However, there was an increase (R^2 *change* = .07) when entering beliefs from an abstract perspective.

This is compared to white populations whose support of affirmative action from a concrete belief system only acounted for 14% of the variance. While their attitudes did increase (R^2 *change* = .09), the model only accounted for 23% of the total variance.