

# Psychology 405: Psychometric Theory

## More on Correlations

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# Outline

## Applied Problems

### Partial Correlation

## Multiple Correlation Unit Weighted correlations

## Other correlations

## Categorical variables

categorical data

## Consider the following correlation matrix

Variable	V	Q	A	nach	Anx	gpa	Pre	MA
V	1.00	0.72	0.54	0.00	0.00	0.38	0.32	0.25
Q	0.72	1.00	0.48	0.00	0.00	0.34	0.28	0.22
A	0.54	0.48	1.00	0.48	-0.42	0.50	0.42	0.34
nach	0.00	0.00	0.48	1.00	-0.56	0.34	0.28	0.22
Anx	0.00	0.00	-0.42	-0.56	1.00	-0.29	-0.24	-0.20
gpa	0.38	0.34	0.50	0.34	-0.29	1.00	0.30	0.24
Pre	0.32	0.28	0.42	0.28	-0.24	0.30	1.00	0.20
MA	0.25	0.22	0.34	0.22	-0.20	0.24	0.20	1.00
Mean	600	650				3.0		
SD	80	100				.5		

We will use this matrix for the following problems.

Taken from the help page for `sim.structure` and called  
`gre.gpa$model`

## Predicting scores: Question 1

1. If a person has a GRE verbal score of 680, then what would you expect his/her GRE quantitative score to be?
  2. Mean GRE V = 600 SD = 80 r = .72
  3. Mean GRE Q = 650 SD = 100
  4. Observe GRE V = 680
  5. Predicted GRE Q = ?

## Predicting scores: Answer 1

1. If a person has a GRE verbal score of 680, then what would you expect his/her GRE quantitative score to be?
2. Mean GRE V = 600 SD = 80 r = .72
3. Mean GRE Q = 650 SD = 100
4. Observe GRE V = 680
5.  $z \text{ GRE V} = (680 - 600)/80 = 1.0$
6. predicted  $z \text{ GRE Q} = r_{xy} z_x = .72 * (1) = .72$
7. predicted GRE Q =  $.72 * 100 + 650 = 722$

## Predicting scores: Question 2

1. If a person has a GRE Quant score of 722, then what would you expect his/her GRE Verbal score to be?
2. Mean GRE V = 600 SD = 80 r = .72
3. Mean GRE Q = 650 SD = 100
4. Observe GRE Q = 722
5. Predicted GRE V = ?

## Predicting scores: Answer 2

1. If a person has a GRE Quant score of 722, then what would you expect his/her GRE Verbal score to be?
2. Mean GRE V = 600 SD = 80 r = .72
3. Mean GRE Q = 650 SD = 100
4. Observed GRE Q = 722
5. Predicted GRE V = ?
6.  $z_{GRE_Q} = (722 - 650)/100 = .72$
7. predicted  $z_{GRE_V} = r_{xy}z_x = .72 * (.72) = .52$
8. predicted GRE Q =  $.52 * 80 + 600 = 642$
9. Note that although 680 predicts 722, 722 predicts 642.

## Predicting Scores: Question 3

1. For a person with an anxiety score of 16, what is the expected GPA?
2. Anxiety Mean = 12 sd = 4 r = -.39
3. GPA Mean = 3.0 sd = .5

## Predicting Scores: Answer 3

1. For a person with an anxiety score of 16, what is the expected GPA?
2. Anxiety Mean = 12 sd = 4 r = -.39
3. GPA Mean = 3.0 sd = .5
4.  $z_{\text{anx}} = (16 - 12)/4 = 1.0$
5. predicted z gpa =  $r_{xy}z_x = -.39 * (1) = -.39$
6. predicted gpa =  $-.39 * .5 + 3 = 2.805$

## Partial Correlations: Question

- Assuming the classical model of partial correlations, what is the correlation between GRE Quantitative and GPA with GRE Verbal held constant?
- $r_{GREQ, GPA} = .34$
- $r_{GREQ, V} = .72$   $r_{GREV, GPA} = .38$
- We want to find the covariance of Q and GPA without V.
- All correlations are  $= \frac{C_{xy}}{\sqrt{V_x V_y}}$ . So we just need to find the Covariances and Variances.

## Partial Correlations: Answer

1. Assuming the classical model of partial correlations, what is the correlation between GRE Quantitative and GPA with GRE Verbal held constant?
2.  $r_{GREQ,GPA} = .34$
3.  $r_{GREQ,V} = .72$   $r_{GREV,GPA} = .38$
4. All correlations are  $= \frac{C_{xy}}{\sqrt{V_x V_y}}$ . So we just need to find the Covariances and Variances.
5. partial  $r_{xy.z} = \frac{r_{xy} - r_{xz} * r_{yz}}{\sqrt{(1 - r_{xz}^2) * (1 - r_{yz}^2)}}$
6.  $r_{qgpa.v} = \frac{(.34 - .72 * .38)}{\sqrt{(.482 * .856)}} = .103$  partial
7. part  $r = \frac{r_{xy} - r_{xz} * r_{yz}}{\sqrt{1 - r_{xz}^2}} = .096$  part

## Multiple Correlation: Question 1

- What is the multiple correlation of GRE V and GRE Q with rated quality of the MA?
  - $r_{GREV,MA} = .32$      $r_{GREQ,MA} = .29$      $r_{GREV,Q} = .72$
  - $\beta_{y,x} = \frac{r_{xy} - r_{xz} * r_{yz}}{1 - r_{xz}^2}$
  - $R^2 = \sum \beta_j r_{x_j y}$

## Multiple Correlation: Answer 1

- What is the multiple correlation of GRE V and GRE Q with rated quality of the MA?
  - $r_{GRE\ V,\ MA} = .32$   $r_{GRE\ Q,\ MA} = .29$   $r_{GRE\ V,Q} = .72$
  - $\beta_{y,x} = \frac{r_{xy} - r_{xz} * r_{yz}}{1 - r_{xz}^2}$
  - $\beta_{GREV,MA} = (.32 - .72 * .29) / (1 - .72^2) = .231$
  - $\beta_{GREQ,MA} = (.29 - .72 * .32) / (1 - .72^2) = .124$
  - $R^2 = \beta_{y,x} * r_{xy} + \beta_{y,z} * r_{yz} \dots$
  - $R^2 = \beta_{GRE\ Q,\ MA} * r_{GRE\ Q,\ MA} + \beta_{GRE\ V,\ MA} * r_{GRE\ V,\ MA} =$
  - $R^2 = .124 * .29 + .231 * .32 = .108$
  - $R = .329$

## Unit Weighted Multiple R

- What is the unit weighted correlation of GREV and GREQ with MA?

Variable	GREV	GREQ	MA
GREV	1.00	0.72	0.32
GREQ	0.72	1.00	0.29
MA	0.32	0.29	1.00

- All correlations are  $= \frac{C_{xy}}{\sqrt{V_x V_y}}$ . So we just need to find the Covariances and Variances.

## Unit Weighted Multiple R

1. Weight the two predictors equally

Variable	GREV	GREQ	MA
GREV	1.00	0.72	0.32
GREQ	0.72	1.00	0.29
MA	0.32	0.29	1.00

2. All correlations are  $= \frac{C_{xy}}{\sqrt{V_x V_y}}$ . So we just need to find the Covariances and Variances.

3.  $C_{v+q, MA} = .32 + .29 = .61$

4.  $V_{v+q} = 1.00 + .72 + .72 + 1.00 = 3.44$

5.  $r_{v+q, MA} = \frac{.61}{\sqrt{3.44 * 1}} = .329$

## Correlating two composites – unit weights

Table: Ability and Performance

Hypothetical relationships

Variable	GREV	GREQ	GREA	GPA	Pre	MA
GREV	1.00	0.72	0.54	0.38	0.32	0.27
GREQ	0.72	1.00	0.48	0.34	0.29	0.24
GREA	0.54	0.48	1.00	0.55	0.47	0.39
GPA	0.38	0.34	0.55	1.00	0.42	0.35
Pre	0.32	0.29	0.47	0.42	1.00	0.30
MA	0.27	0.24	0.39	0.35	0.30	1.00

- What is the unit weighted correlation between the ability measures and the performance measures?
- All correlations are  $= \frac{C_{xy}}{\sqrt{V_x V_y}}$ . So we just need to find the Covariances and Variances.

## Correlating two composites – unit weights

## Table: Ability and Performance

## Hypothetical relationships

Variable	GREV	GREQ	GREA	GPA	Pre	MA
GREV	1.00	0.72	0.54	0.38	0.32	0.27
GREQ	0.72	1.00	0.48	0.34	0.29	0.24
GREA	0.54	0.48	1.00	0.55	0.47	0.39
GPA	0.38	0.34	0.55	1.00	0.42	0.35
Pre	0.32	0.29	0.47	0.42	1.00	0.30
MA	0.27	0.24	0.39	0.35	0.30	1.00

set

- $V_{ability} = 1.0 + .72 + .54 + .72 + 1.0 + .48 + .54 + .48 + 1 = 3 * 1 + 2 * (.72 + .54 + .48) = 6.48$
  - $V_{performance} = 3 * 1 + 2 * (.42 + .35 + .30) = 5.14$
  - $C_{ability, performance} = .38 + .34 + .55 + .32 + .29 + .47 + .27 + .24 + .39 = 3.25$
  - $R_{ability, performance} = \frac{3.25}{\sqrt{6.48 * 5.14}} = .563$

**R code**

```
R <- structure(list(GREV = c(1, 0.72, 0.54, 0.38, 0.32, 0.27),  
GREQ = c(0.72, 1, 0.48, 0.34, 0.29, 0.24),  
GREA = c(0.54, 0.48, 1, 0.55, 0.47, 0.39),  
GPA = c(0.38, 0.34, 0.55, 1, 0.42, 0.35),  
Pre = c(0.32, 0.29, 0.47, 0.42, 1, 0.3),  
MA = c(0.27, 0.24, 0.39, 0.35, 0.3,  
1)), row.names = c("GREV", "GREQ", "GREA", "GPA", "Pre", "MA"  
, class = "data.frame")  
Rx <- R[1:3,1:3]  
Ry <- R[4:6,4:6]  
Rxy <- R[1:3,4:6]  
sum(Rx); sum(Ry); sum(Rxy)  
sum(Rxy)/sqrt(sum(Rx) * sum(Ry))
```

```
R  
      GREV GREQ GREA GPA  Pre   MA  
GREV 1.00 0.72 0.54 0.38 0.32 0.27  
GREQ 0.72 1.00 0.48 0.34 0.29 0.24  
GREA 0.54 0.48 1.00 0.55 0.47 0.39  
GPA  0.38 0.34 0.55 1.00 0.42 0.35  
Pre  0.32 0.29 0.47 0.42 1.00 0.30  
MA   0.27 0.24 0.39 0.35 0.30 1.00  
sum(Rx)  
[1] 6.48  
> sum(Ry)  
[1] 5.14  
> sum(Rxy)  
[1] 3.25  
sum(Rxy)/sqrt(sum(Rx) * sum(Ry)) = 0.56
```

## Do all of these problems using R

(see the `sim.structural` example to create `gre.gpa`)

R code

```
#First, create a sem like model with a factor model of x and ys with
#correlation Phi
fx <- matrix(c( .9,.8,.6,rep(0,4),.6,.8,-.7),ncol=2)
fy <- matrix(c(.6,.5,.4),ncol=1)
rownames(fx) <- c("V","Q","A","nach","Anx")
rownames(fy)<- c("gpa","Pre","MA")
Phi <-matrix( c(1,0,.7,.0,1,.7,.7,.7,1),ncol=3)
#now create this structure
gre.gpa <- sim.structural(fx,Phi,fy)

#Now do problem MR 1
mod.mr <- lmCor(MA ~ V + Q, data=gre.gpa$model)
```

Call: `lmCor(y = MA ~ V + Q, data = gre.gpa$model)`

Multiple Regression from matrix input

DV = MA  
slope VIF Vy.x  
V 0.19 2.08 0.05  
Q 0.09 2.08 0.02

Multiple Regression  
R R2 Ruw R2uw  
MA 0.26 0.07 0.26 0.07

## Now do the unit weight problem

R code

```
print(lmCor(MA ~ V + Q, data=gre.gpa$model), digits=4)
```

```
print(lmCor(MA ~ V + Q, data=gre.gpa$model), digits=4)
Call: lmCor(y = MA ~ V + Q, data = gre.gpa$model)
```

Multiple Regression from matrix input

```
DV = MA
slope    VIF   Vy.x
V 0.1884 2.0764 0.0475
Q 0.0884 2.0764 0.0198
```

```
Multiple Regression
      R      R2     Ruw    R2uw
MA 0.2594 0.0673 0.2566 0.0659
```

## correlating two composites

R code

```
mod.comp <- lmCor(V + Q + A ~ gpa+Pre+MA, data=gre.gpa$model)
```

```
mod.comp
Call: lmCor(y = V + Q + A ~ gpa + Pre + MA, data = gre.gpa$model)
```

Multiple Regression from matrix input

...

Various estimates of between set correlations  
Squared Canonical Correlations  
[1] 4.5e-01 3.9e-17 2.2e-19

Average squared canonical correlation = 0.15  
Cohen's Set Correlation R2 = 0.39  
Unweighted correlation between the two sets = 0.57

## Instability of beta weights

An example from Niels Waller

R code

	Y	X1	X2	X3	C
Y	1.000	0.561	0.568	0.520	0.35
X1	0.561	1.000	0.720	0.526	0.40
X2	0.568	0.720	1.000	0.554	-0.25
X3	0.520	0.526	0.554	1.000	0.30
C	0.350	0.400	-0.250	0.300	1.00

```
lmCor(Y ~ X1 + X2 + X3, data=niels)
```

```
lmCor(Y ~ X1 + X2 + X3, data=niels)
Call: lmCor(y = Y ~ X1 + X2 + X3, data = niels)
```

Multiple Regression from matrix input  
 DV = Y  
 slope VIF Vy.x  
 X1 0.25 2.18 0.14  
 X2 0.25 2.28 0.14  
 X3 0.25 1.52 0.13

Multiple Regression  
 R R2 Ruw R2uw  
 Y 0.64 0.41 0.64 0.41

```
lmCor(Y ~ X1 + X2 + X3+C, data=niels)
Call: lmCor(y = Y ~ X1 + X2 + X3 + C, data = niels)

Multiple Regression from matrix input
DV = Y
slope VIF Vy.x
X1 -1.99 12.47 -1.12
X2 2.87 16.34 1.63
X3 -0.64 3.14 -0.33
C 2.06 8.66 0.72
```

Multiple Regression  
 R R2 Ruw R2uw  
 Y 0.95 0.9 0.69 0.47

## Cohen's Set correlation versus unit weighted correlations

1. What is the relationship between two sets of variables? Three alternative answers.
2. Set correlation: 1 - the ratio of determinants (Cohen, 1982)
  - $R = 1 - \frac{||\mathbf{R}_{xy}||}{||\mathbf{R}_x|| ||\mathbf{R}_y||}$
3. Canonical Correlation (Hotelling, 1936)
  - $R_c = R_x^{-1} R_{xy} R_y^{-1} R'_{xy}$
4. Unit weighted correlation
  - $R_{uw} = \frac{\mathbf{1}\mathbf{R}_{yx}\mathbf{1}'}{(\mathbf{1}\mathbf{R}_{yy}\mathbf{1}')^{.5}(\mathbf{1}\mathbf{R}_{xx}\mathbf{1}')^{.5}}$
5. All three are found using the lmCor function

## lmCor to find multiple correlations from correlation matrices

```
mod1 <- lmCor(4:6, 1:3, data=R)
summary(mod1)
```

```
GREV GREQ GREA  GPA  Pre   MA
GREV 1.00 0.72 0.54 0.38 0.32 0.27
GREQ 0.72 1.00 0.48 0.34 0.29 0.24
GREA 0.54 0.48 1.00 0.55 0.47 0.39
GPA  0.38 0.34 0.55 1.00 0.42 0.35
Pre   0.32 0.29 0.47 0.42 1.00 0.30
MA    0.27 0.24 0.39 0.35 0.30 1.00
Multiple Regression from matrix input
setCor(y = 4:6, x = 1:3, data = R)
```

```
Multiple Regression from matrix input
```

```
Beta weights
```

```
      GPA  Pre   MA
GREV 0.087 0.064 0.064
GREQ 0.047 0.045 0.030
GREA 0.481 0.414 0.341
```

```
Multiple R
```

```
      GPA  Pre   MA
0.56 0.48 0.40
```

```
Multiple R2
```

```
      GPA  Pre   MA
0.31 0.23 0.16
```

```
Cohen's set correlation R2
[1] 0.41
```

```
Unweighted multiple R
      GPA  Pre   MA
0.50 0.42 0.35
Unweighted multiple R2
      GPA  Pre   MA
0.25 0.18 0.13
```

```
Various estimates of between set correlations
Squared Canonical Correlations
[1] 4.1e-01 6.0e-05 1.6e-06
```

```
Average squared canonical correlation = 0.14
Cohen's Set Correlation R2 = 0.41
Unweighted correlation between the two sets = 0
```

## Just use Verbal and Quant

R

```
mod2 <- lmCor(4:6, 1:2, R)
```

```
GREV GREQ GREA  GPA  Pre   MA
GREV 1.00 0.72 0.54 0.38 0.32 0.27
GREQ 0.72 1.00 0.48 0.34 0.29 0.24
GREA 0.54 0.48 1.00 0.55 0.47 0.39
GPA  0.38 0.34 0.55 1.00 0.42 0.35
Pre   0.32 0.29 0.47 0.42 1.00 0.30
MA    0.27 0.24 0.39 0.35 0.30 1.00
```

```
summary(mod2)
```

Multiple Regression from matrix input  
`lmCor(y = 4:6, x = 1:2, data = R)`

Multiple Regression from matrix input

Beta weights

	GPA	Pre	MA
GREV	0.28	0.23	0.202
GREQ	0.14	0.12	0.095

Multiple R

	GPA	Pre	MA
	0.39	0.33	0.28

Multiple R2

	GPA	Pre	MA
	0.154	0.110	0.077

Unweighted multiple R

GPA	Pre	MA
0.39	0.33	0.27

Unweighted multiple R2

GPA	Pre	MA
0.15	0.11	0.08

Various estimates of between set correlations

Squared Canonical Correlations

[1]	2.0e-01	4.2e-05
-----	---------	---------

Average squared canonical correlation = 0.1

Cohen's Set Correlation R2 = 0.2

Unweighted correlation between the two sets = 0

# Comorbidity

1. Symptoms are said to be comorbid if one has both symptoms.
    - This is really just one cell in a  $2 \times 2$  table
    - We need base rates as well
  2. Consider Anxiety and Depression
    - 50 % of anxiety patients are also depressed
    - 67% of depressed patients are also anxious
    - base rates are 20% for anxiety, 15% for depression

```
comorbidity(.2,.15,.1,c("Anxiety","Depression"))
```

```
Call: comorbidity(d1 = 0.2, d2 = 0.15, com = 0.1, labels = c("Anxiety",  
    "Depression"))  
Comorbidity table
```

### Comorbidity table

	Anxiety	-Anxiety
Depression	0.1	0.05
-Depression	0.1	0.75

implies phi = 0.49 with Yule = 0.87 and tetrachoric correlation of 0.75  
and normal thresholds of 1.04 0.84

Can also treat this as an Area Under the Curve – signal detection problem

## R code

```
com <- comorbidity(.2,.15,.1,c("Anxiety","Depression")) #find the comorbidity  
AUC(com$twobytwo) #convert to a Signal Detection Approach
```

```
AUC(com$twobytwo) #convert to a Signal Detection Approach  
Decision Theory and Area under the Curve
```

The original data implied the following 2 x 2 table

	Predicted.Pos	Predicted.Neg
True.Pos	0.1	0.05
True.Neg	0.1	0.75

### Conditional probabilities of

conditional probabilities of  
 Predicted.Pos Predicted.Neg

True.Pos	0.67	0.33
True.Neg	0.12	0.88

Accuracy = 0.85 Sensitivity = 0.67 Specificity = 0.88  
with Area Under the Curve = 0.87

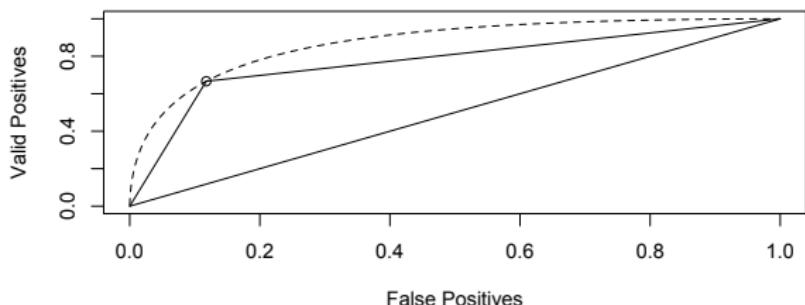
d\_prime = 1.62 Criterion = 1.19 Beta = 0.13

Observed Phi correlation = 0.49

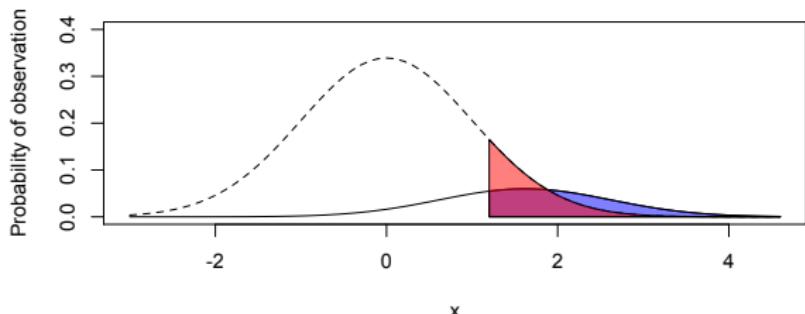
Inferred latent (tetrachoric) correlation = 0.75

## Show the Signal Detection graphic

## Valid Positives as function of False Positives



## Decision Theory



## Three ways to compare categorical means

## R code

```
dim(spi)
t.test(wellness ~ sex, data=spi)
t.test(education ~ sex, data=spi)
```

```
t.t.test(wellness ~ sex, data=spi)
```

### Welch Two Sample t-test

```
data: wellness by sex
t = -6.021, df = 2872.4, p-value = 1.954e-09
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-0.14075230 -0.07159818
sample estimates:
mean in group 1 mean in group 2
1.479228      1.585404
```

```
> t.test(education ~ sex, data=spi)
```

### Welch Two Sample t-test

```
data: education by sex
t = 4.5873, df = 2908.4, p-value = 4.68e-06
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 0.2040981 0.5088266
sample estimates:
mean in group 1 mean in group 2
        4.314540         3.958078
```

## Try regression

## R code

```
lm (wellness ~ sex, data=spi)  
lm (education ~ sex, data=spi)
```

```
lm (wellness ~ sex, data=spi)
```

```
Call:  
lm(formula = wellness ~ sex, data = spi)
```

#### Coefficients:

(Intercept) sex  
1.3731 0.1062

```
> lm (education ~ sex, data=spi)
```

```
Call:  
lm(formula = education ~ sex, data = spi)
```

#### Coefficients:

(Intercept) sex  
4.6710 -0.3565

# Regression with significance tests

## R code

```
summary(lm (wellness ~ sex, data=spi))
```

```
summary(lm (wellness ~ sex, data=spi))
```

Call:

```
lm(formula = wellness ~ sex, data = spi)
```

### Residuals:

Min 1Q Median 3Q Max  
-0.5854 -0.4792 0.4146 0.4146 0.5208

#### Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	1.37305	0.02926	46.925	< 2e-16 ***
sex	0.10618	0.01759	6.036	1.76e-09 ***
---				

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4957 on 3278 degrees of freedom  
(720 observations deleted due to missingness)

Multiple R-squared: 0.01099 Adjusted R-squared: 0.01069

F-statistic: 36.43 on 1 and 3278 DF. p-value: 1.756e-09

## raw units

## R code

```
spi.complete <- complete.cases(spi[c("wellness", "sex")])
lmCor(wellness ~ sex, data=spi[spi.complete,], std=FALSE)
Call: lmCor(v = wellness ~ sex, data = spi[spi.complete, ], std = FALSE)
```

```
spi.complete <- complete.cases(spi[c("wellness", "sex")])  
Call: lmCor(y = wellness ~ sex, data = spi[spi.complete, ], std = FALSE)
```

## Multiple Regression from raw data

DV	wellness	slope	se	t	p	lower.ci	upper.ci	VIF	Vy	x
(Intercept)	1.37	0.03	46.93	0.0e+00	1.32	1.43	1	0.00		
sex	0.11	0.02	6.04	1.8e-09	0.07	0.14	1	0.01		

Residual Standard Error = 0.5 with 3278 degrees of freedom

## Multiple Regression

	R	R2	Ruw	R2uw	Shrunken R2	SE of R2	overall F	df1	df2	P
wellness	0.1	0.01	0.07	0.01	0.01	0	36.43	1	3278	1.76e-09

### **Do the ImCor operation with default values – standardized units**

## R code

```
lmCor(wellness ~ sex, data=spi[spi$complete,])
```

```
setCor(wellness ~ sex, data=spi[spi.complete,])  
Call: setCor(v = wellness ~ sex, data = spi[spi.complete, 1])
```

Multiple Regression from raw data

DV = wellness

	slope	se	t	p	lower.ci	upper.ci	VIF
(Intercept)	0.0	0.02	0.00	1.0e+00	-0.03	0.03	1
sex	0.1	0.02	6.04	1.8e-09	0.07	0.14	1

Residual Standard Error = 0.99 with 3278 degrees of freedom

## Multiple Regression

	R	R2	Ruw	R2uw	Shrunken	R2	SE of R2	overall F	df1	df2	P
wellness	0.1	0.01	0.1	0.01		0.01	0	36.43	1	3278	1 76e-09

Or, just show the correlations

## R code

```
lowerCor(spi[cs(sex,wellness,education)])  
corr.test(spi[cs(sex,wellness,education)])
```

```
lowerCor(spi[cs(sex,wellness,education)])
      sex    wllns edctn
sex      1.00
wellness  0.10  1.00
education -0.08  0.00  1.00
```

```
corr.test(spi[cs(sex,wellness,education)])
Call:corr.test(x = spi[cs(sex, wellness, education)])
Correlation matrix
```

```

correlation matrix
          sex   wellness   education
sex      1.00        0.1       -0.08
wellness 0.10        1.0       0.00
education -0.08       0.0       1.00

```

Sample Size	sex	wellness	education
sex	3946	3280	3304
wellness	3280	3311	3000
education	3304	3000	3000

Probability values (Entries above the diagonal are adjusted for multiple tests.)

	sex	wellness	education
sex	0	0.00	0.00
wellness	0	0.00	0.92
education	0	0.82	0.00

To see confidence intervals of the correlations, print with the short=FALSE option.

## Correlations with dichotomous variable

## R code

```
corCi(spi[cs(education, sex, wellness)])  
corCi(spi[cs(education, sex, wellness)], poly=TRUE)
```

```

Call:corCi(x = spi[cs(education, sex, wellness)])
Coefficients and bootstrapped confidence intervals
      edctn sex    wllns
education  1.00
sex        -0.08  1.00
wellness   0.00  0.10  1.00

scale correlations and bootstrapped confidence intervals
      lower.emp lower.norm estimate upper.norm upper.emp P
edctn-sex     -0.11      -0.08     -0.05     -0.05  0.00
edctn-wllns   -0.03      -0.03      0.00      0.04  0.03 0.91
sex-wllns     0.07      0.07      0.10      0.14  0.14 0.00

```

```
Call: corCI(x = sp1[cs(education, sex, wellness)], poly = TRUE)
```

```
Coefficients and bootstrapped confidence intervals
      edctn sex    wlns
education  1.00
sex        -0.11  1.00
wellness   -0.02  0.17  1.00
```

	scale correlations and bootstrapped confidence intervals					
	lower.emp	lower.norm	estimate	upper.norm	upper.emp	p
edctn-sex	-0.15	-0.15	-0.11	-0.07	-0.07	0.00
edctn-wlns	-0.07	-0.07	-0.02	0.03	0.02	0.48
sex-wlns	0.11	0.11	0.17	0.22	0.23	0.00

Cohen, J. (1982). Set correlation as a general multivariate data-analytic method. *Multivariate Behavioral Research*, 17(3).

Hotelling, H. (1936). Relations between two sets of variates. *Biometrika*, 28(3/4):321–377.