

Self-Assessment

Weeks 8: Multiple Regression with Qualitative Predictors; Multiple Comparisons

1. Suppose we wish to assess the impact of five treatments while blocking for study participant race (Black, Hispanic, White) on an outcome Y. How would these five treatments and three race categories be coded as dummy variables? Present actual data to illustrate the coding. Note: The term “blocking” used above represents analysis of variance language and indicates a variable for which one wishes to control statistically by including it in the model because the researcher believes it accounts for (predicts) variability in the outcome (DV). For example, when studying the effects of different fertilizers on tomato production, it is important to block other factors that can affect tomato production such as soil conditions and irrigation levels. Thus, blocking a variable simply means including it in the model so error variance can be reduced and thereby produce more powerful (i.e., lower Type 2 errors) statistical tests of the treatment.

Each case for a given treatment would be coded as 1, and if a case does not occur for that treatment, it would be coded as 0. The same procedure would be used to model race with dummy variables.

Y	Treat. 1	Treat. 2	Treat. 3	Treat. 4	Treat. 5	Treatment Received	Black	Hisp	White	Race
Score	1	0	0	0	0	1	1	0	0	B
Score	0	1	0	0	0	2	1	0	0	B
Score	0	0	1	0	0	3	0	1	0	H
Score	0	0	0	1	0	4	0	1	0	H
Score	0	0	0	0	1	5	0	0	1	W
Score	0	0	0	0	1	5	0	0	1	W

2. Both the Bonferroni and Scheffé adjustments are designed to hold the familywise Type 1 error rate to a specific level. Can we be assured that both function to do this? One way to test this is to calculate the inflation to the Type 1 error rate using the adjusted Bonferroni and Scheffé per-comparison alpha (Type 1 error rate per test or per comparison).

The Week 6 Self-assessment Activity Question 4 asked that you calculate both Bonferroni and Scheffé confidence intervals for a study containing $n = 76$ observations with four drug treatments and a familywise error rate of .05.

DV = Heart rate = beats per minute

IV = Blood Pressure Medication = four drugs prescriptions (Losartan, Ziac, Lisinopril [12.5mg], and Lisinopril [40mg])

Critical t-values were as follows

Bonferroni adjusted critical t ratio
= ± 2.7129

Scheffé adjusted critical t ratio
= ± 2.8627

As a review, the appendix below shows how these values were obtained.

Both of these critical t-ratios have corresponding specific pairwise comparison alpha levels. The alpha values have been adjusted using either the Bonferroni or Scheffé procedure.

To determine the corresponding specific alpha level for each, we can use Excel to find the two-tailed significance level and this will be the alpha level for each pairwise comparison.

Bonferroni adjusted pairwise alpha level

$$=T.DIST.2T(2.7129,72) = .008338$$

Scheffé adjusted pairwise alpha level

$$=T.DIST.2T(2.8627,72) = 0.005497$$

So these numbers tell us that if we wished to compare a p-value for each comparison against an alpha level, the Bonferroni adjusted alpha level would be .008338 and the Scheffé adjusted alpha level would be .005497.

(a) If one performed six pairwise comparisons using the Bonferroni adjusted pairwise comparison alpha of .008338, what would be the calculated familywise error rate across these six comparisons?

Recall that the familywise error rate represents the probability of at least one false positive across a collection of tests. If there are six tests to be performed, then the familywise error rate could be as high as

$$\text{FW alpha} = 1 - (1 - \text{alpha})^c$$

Where FW alpha is the familywise alpha; alpha is the unadjusted, per comparison alpha; and c is the number tests performed. Since the Bonferroni adjusted alpha is .008338, the FW alpha would be

$$\text{FW alpha} = 1 - (1 - \text{alpha})^c$$

$$\text{FW alpha} = 1 - (1 - .008338)^6$$

$$\text{FW alpha} = 1 - (.991662)^6$$

$$\text{FW alpha} = 1 - .9510033$$

$$\text{FW alpha} = .04899$$

Thus, the familywise Type 1 error rate for these six comparisons would be .04899 or just under the targeted value of .05.

(b) If one performed six pairwise comparisons using the Bonferroni adjusted pairwise comparison alpha of .005497, what would be the calculated familywise error rate across these six comparisons?

The Scheffé adjusted FW alpha would be

$$\text{FW alpha} = 1 - (1 - \text{alpha})^c$$

$$\text{FW alpha} = 1 - (1 - .005497)^6$$

$$\text{FW alpha} = 1 - (.967467)^6$$

$$\text{FW alpha} = 1 - .967467$$

$$\text{FW alpha} = .03253$$

The Scheffé familywise Type 1 error rate is .03253, further under the targeted .05 level than the Bonferroni familywise rate and this is consistent with what we know about these two procedures – for only a few comparisons the Scheffé procedure produces a more conservative overall test (i.e. less likely to reject Ho).

3. Ian Walker collected data on bicycle overtaking (vehicles passing bicycles) in the UK. His data are available from this link:

<http://drianwalker.com/overtaking/>

For this self-assessment activity we will focus on the following variables:

Dependent Variable

Passing_distance = distance in meters that vehicles gave bicycles while passing

Predictor Variables

Distance_from_kerb = distance of bicycle from curb. Distances, in meters, were 0.25, 0.50, 0.75, 1.00, and 1.25.

Helmet = whether rider used a helmet (1 = yes, 0 = no)

Car = whether vehicle that passed was a car or some other vehicle type (e.g., bus, lorry, etc.; 1 = car, 0 = other)

Time = time of day overtaking recorded grouped into three categories, morning, midday, and afternoon

Two of the above variables contain more than two categories, so dummy variables were constructed as follows:

Distance_from_kerb dummy variables:

Curb_0.25 (1 = yes, 0 = no)

Curb_0.50 (1 = yes, 0 = no)

Curb_0.75 (1 = yes, 0 = no)

Curb_1.00 (1 = yes, 0 = no)

Curb_1.25 (1 = yes, 0 = no)

Time dummy variables:

Morning (1 = yes, 0 = no; this represents times of 7am to 10:59am)

Midday (1 = yes, 0 = no; from 11am to 2pm)

Afternoon (1 = yes, 0 = no; between 2:01pm and 6pm)

Below is an SPSS regression analysis of passing_distance regressed on the four predictors outlined above.

Descriptive Statistics

	Mean	Std. Deviation	N
Passing distance	1.31391	.383454	2355
Car	.7253	.44648	2355
helmet	.49	.500	2355
Curb_0.50	.2314	.42183	2355
Curb_0.75	.1439	.35111	2355
Curb_1.00	.1992	.39945	2355
Curb_1.25	.1410	.34807	2355
Midday	.2917	.45465	2355
Afternoon	.3125	.46362	2355

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	Change Statistics			
						F Change	df1	df2	Sig. F Change
1	.285(a)	.081	.078	.368225	.081	25.844	8	2346	.000

a Predictors: (Constant), Afternoon, Curb_0.50, Car, helmet, Curb_1.25, Curb_0.75, Midday, Curb_1.00

ANOVA(c)

Model		Sum of Squares	df	Mean Square	F	Sig.	R Square Change
1	Subset Tests						
	Car	2.368	1	2.368	17.465	.000(a)	.007
	helmet	1.806	1	1.806	13.322	.000(a)	.005
	Curb_0.50, Curb_0.75, Curb_1.00, Curb_1.25	14.874	4	3.719	27.426	.000(a)	.043
	Midday, Afternoon	.022	2	.011	.081	.922(a)	.000
	Regression	28.033	8	3.504	25.844	.000(b)	
	Residual	318.093	2346	.136			
	Total	346.126	2354				

a Tested against the full model.

b Predictors in the Full Model: (Constant), Afternoon, Curb_0.50, Car, helmet, Curb_1.25, Curb_0.75, Midday, Curb_1.00.

c Dependent Variable: Passing distance

Coefficients(a)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	1.406	.028		49.808	.000	1.350	1.461
	Car	.072	.017	.083	4.179	.000	.038	.105
	helmet	-.057	.016	-.074	-3.650	.000	-.087	-.026
	Curb_0.50	-.092	.023	-.101	-4.028	.000	-.137	-.047
	Curb_0.75	-.173	.028	-.158	-6.163	.000	-.228	-.118
	Curb_1.00	-.184	.026	-.191	-7.083	.000	-.235	-.133
	Curb_1.25	-.267	.027	-.242	-9.804	.000	-.320	-.214
	Midday	.008	.021	.009	.386	.700	-.032	.048
	Afternoon	.007	.022	.008	.298	.765	-.037	.050

a Dependent Variable: Passing distance

(a) Note that all predictor variables included in this regression are dummy variables with 0, 1 coding. The "Descriptive Statistics" table shows the following means:

Variable	Mean
Car	.7253
helmet	.4900
Curb_0.50	.2314
Curb_0.75	.1439
Curb_1.00	.1992
Curb_1.25	.1410
Midday	.2917
Afternoon	.3125

(a1) What does the mean value of .7253 for Car tell us? What is the interpretation of this value?

Since this variable is scored 0 and 1, the value .7253 is a proportion and tells us that .7253 or 72.53% of vehicles that overtook the bicycle were cars.

(a2) For helmet, the mean is .4900, what does this tell us?

Same logic as above, .49 or 49% of the observations the bicycle rider wore a helmet.

(a3) For Curb_0.75 the mean value is .1439, what does this tell us?

Same logic as above, .1439 or 14.39% of the observations the bicycle rider was about 0.75 meters from the curb.

(a4) For midday the mean value is .2917 – what interpretation may we use for this?

Same logic as above, .2917 or 29.17% of the observations occurred midday.

(b) The squared semi-partial correlations (ΔR^2) for each of the predictors are

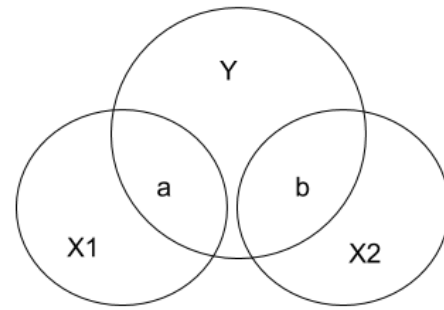
Car Type	= 0.007
Helmet Use	= 0.005
Curb Distance	= 0.043
Time of Data	= 0.000

When added together, these produce a summed R^2 value of $0.007 + 0.005 + 0.043 + 0.000 = 0.055$. However, SPSS reports that the total model R^2 is .081. Why is there a discrepancy between the summed R^2 and the model R^2 reported by SPSS?

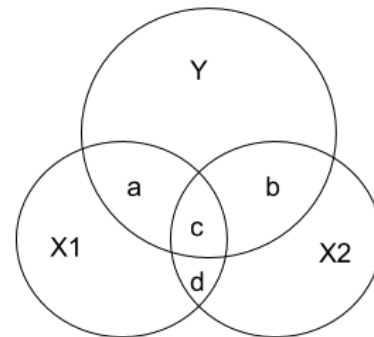
Squared semi-partial correlations tell us the shared variance between X1 and Y controlling for X2. These values will be additive only if X1 and X2 are uncorrelated or orthogonal. If predictor variables are not orthogonal, then summing squared semi-partial correlations will not add to model R^2 because X1 and X2 share variance with Y. Only when X1 and X2 do not share variance with Y will the sum of squared semi-partial correlations = model R^2 .

This is illustrated in the Venn diagrams below.

Example 1:
 Areas a and b are unique portions of Y that are explained by X1 and X2 separately, so $a + b = \text{model } R^2$



Example 2:
 Areas a and b are unique portions of Y that are explained by X1 and X2 separately, but X1 and X2 also share common variance with Y in area c, so $a + b + c = \text{model } R^2$. X1 and X2 are correlated and share common variance of c and d.



(c) The ANOVA table shows us F ratios and p-values for each predictor variable. For Helmet use, $F = 13.322$ and $p = .000$, so there are differences in passing distances between riders wearing helmets and riders not wearing helmets. Suppose for a moment that the ANOVA table was not presented so we don't have access to this F ratio or ΔR^2 values. Would we be able to determine whether the null for helmet use could be rejected with any other information provided in the regression output? If yes, what information could we use?

Yes, since this variable has only two categories, or one dummy variable, the t-ratio provided by the regression coefficient table provides the same test as the F ratio in the ANOVA table. For helmet use, $t = -3.65$ with a $p = .000$, so H_0 is rejected. When a variable is represented by one vector (or one variable) in the regression (i.e., the variable as 1 model degree of freedom), the F and t ratios can be found from each other as

$$F = t^2$$

And

$$t = \sqrt{F}$$

For example, $t = -3.65$ squared is 13.3225 which is the same value as the F ratio reported above.

Additionally, one could use the confidence interval for helmet use to test H_0 . Since 0.00 is not within the interval (-0.087 to -0.026), H_0 would be rejected.

(d) As noted above in (c), the ANOVA table shows us F ratios and p-values for each predictor variable. For Curb (Kerb in the UK) Distance, $F = 27.426$ with $p = .000$. Suppose for a moment that the ANOVA table was not presented so we don't have access to this F ratio or ΔR^2 values. Would we be able to determine whether the global test of the null for Curb Distance could be rejected with any other information provided in the regression output? If yes, what information could we use?

In this case the global test of mean differences based upon Curb Distance could not be tested. To test whether this variable contributes to prediction of Passing Distance, we must know some component that would allow us to calculate a global F test such as the ΔR^2 value for including Curb Distance, or the sums of squares or mean square for Curb Distance. Without this information it is not possible to test the global contribution of Curb Distance.

We do have, however, individual pairwise comparisons of Curb Distances presented in the regression table, but these provide only partial information about Curb Distance effect.

(e) Provide literal interpretations for each of the unstandardized regression coefficients listed below.

- Intercept, $B_0 = 1.406$: **Predicted passing distance (1.406 meters) for non-cars, no helmet, curb distance of .25, and morning.**
- Car, $B_1 = .072$: **Cars provide .072 meters more distance when passing than non-cars controlling for helmet use, curb distance, and time of day**
- Helmet, $B_2 = -.057$: **Helmet wearers have less passing distance, -.057 meters, than non-helmet wearers controlling for vehicle type, curb distance, and time of day**
- Curb_1.00, $B_5 = -.184$: **Riders who are 1 meter from the curb has -.184 meters passing distance controlling for helmet use, car type, and time of day**
- Afternoon, $B_8 = .007$: **Afternoon riders experience more passing distance, .007 meters, compared with morning riders controlling for car type, helmet use, and curb distance**

(f) What is the predicted mean passing distance for someone with the following variable values:

Scenario 1:
 Passing Car
 Not wearing a helmet
 Curb distance of .25
 Midday riding

Factor	Coefficient	Dummy Code
intercept	1.406	
car	0.072	1
helmet	-0.057	0
curb .5	-0.092	0
curb .75	-0.173	0
curb 1	-0.184	0
curb 1.25	-0.267	0
midday	0.008	1
afternoon	0.007	0
predicted passing =		1.486

Scenario 2:
 Passing Truck
 Wearing a helmet
 Curb distance of 1.25
 Morning Riding

Factor	Coefficient	Dummy Code
Intercept	1.406	
car	0.072	0
helmet	-0.057	1
curb .5	-0.092	0
curb .75	-0.173	0
curb 1	-0.184	0
curb 1.25	-0.267	1
midday	0.008	0
afternoon	0.007	0
predicted passing =		1.082

(g) Which factors (predictors) are not statistically associated with passing distance?

Only time of day is unrelated to passing distance with global $F = 0.081$ and $p = .922$.

(h) What is the interpretation for the 95% confidence interval for b_4 (Curb 0.75 dummy)?

One may be 95% confident that the true mean difference in passing distance between curb distance of 0.25 meters and curb distance of 0.75 meters lies between $-.228$ and $-.118$.

(i) Suppose one wished to perform all pairwise comparisons among curb distances and also among time of day. Using the Bonferroni correction, what would be the adjusted Bonferroni alpha (Type 1 error rate) per comparison if the familywise error rate is to be .05?

First, determine the number of pairwise comparisons for each variable. With 5 curb distances, there are $5(5-1)/2 = 10$ possible pairwise comparisons. With three times of day, there are $3(3-1)/2 = 3$ pairwise comparisons.

Next, determine how the family of tests will be defined. Some may opt to group all $10 + 3$ comparisons into one family of 13 tests. I believe the better approach is to treat the two variables independently and calculate Bonferroni corrections separately for the two variables.

For curb distance comparisons, there are 10 possible tests so the Bonferroni alpha would be $.05 / 10 = .005$.

For time of day, there are 3 possible tests so the Bonferroni alpha would be $.05 / 3 = .0167$.

(j) Which of the four independent variables appears to be the strongest predictor of passing distances?

There is not always agreement among statisticians how to make this assessment, but one approach is to examine the unique variance explained (or predicted) by each predictor. This is measured by ΔR^2 values.

According to these measures, curb distance has the largest ΔR^2 value at .043 so it appears to be the best predictor of passing distance. One problem with using ΔR^2 values to assess variable importance is that it is greatly affected by the correlations among predictors (lack of orthogonality among predictors). The more predictors are correlated, the weaker will be ΔR^2 values and the more difficult to assess unique contributions of predictors.

4. Below is a data file containing the following variables for cars taken between 1970 and 1982:

- mpg: miles per gallon
- engine: engine displacement in cubic inches
- horse: horsepower
- weight: vehicle weight in pounds
- accel: time to accelerate from 0 to 60 mph in seconds
- year: model year (70 = 1970, to 82 = 1982)
- origin: country of origin (1=American, 2=Europe, 3=Japan)
- cylinder: number of cylinders

SPSS Data: http://www.bwgriffin.com/gsu/courses/edur8132/selfassessments/Week04/cars_missing_deleted.sav

(Note: There are underscore marks between words in the SPSS data file name.)

Other Data Format: If you prefer a data file format other than SPSS, let me know.

For this problem we wish to know whether MPG differs among car origins and number of cylinders:

$$\text{Predicted MPG} = b_0 + \text{origin of car with appropriate dummy variables} + \text{number of cylinders}$$

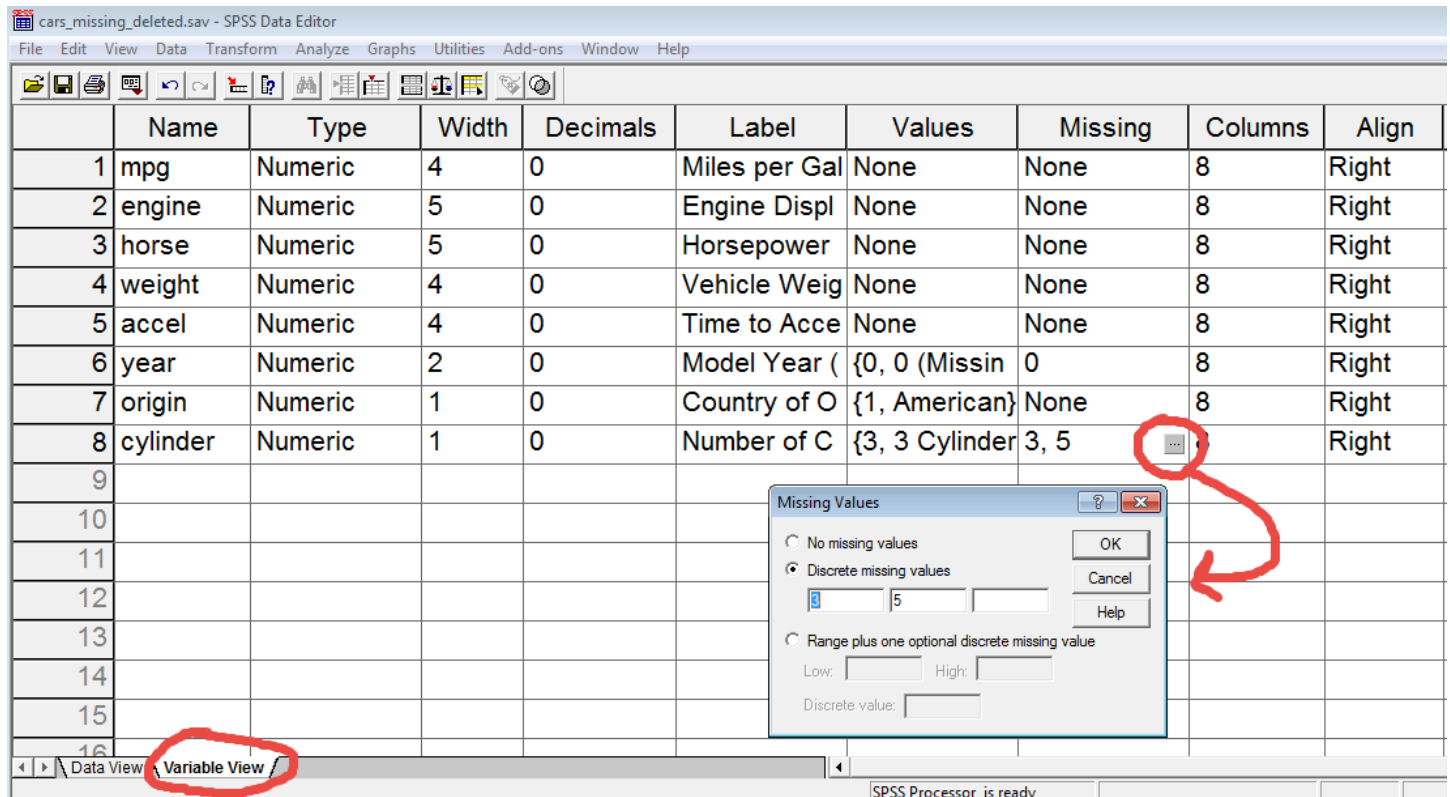
Origin of car is categorical. Number of cylinders may appear to be ratio, but since observed categories of this variable are limited, it is best to treat this variable as categorical. Note the following number of cylinders reported:

Number of Cylinders

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	3 Cylinders	4	1.0	1.0	1.0
	4 Cylinders	199	50.9	50.9	51.9
	5 Cylinders	3	.8	.8	52.7
	6 Cylinders	83	21.2	21.2	73.9
	8 Cylinders	102	26.1	26.1	100.0
	Total	391	100.0	100.0	

As the frequency display above shows, the number of cylinders include 3, 4, 5, 6, and 8. However, only 4 cars had 3 cylinders and only 3 cars had 5 cylinders. Given the small sample sizes for these categories, it is best to remove these cases from the regression analysis. There are several ways to accomplish this. Three approaches are (a) manually delete these cases after sorting all cases on number of cylinders, (b) telling SPSS to treat these 7 cases as missing values so they will not be included in any analysis (use Recode into Same Variable and set 3 Cylinders and 5 Cylinders as system missing), or (c) defining 3 and 5 Cylinders as missing values in the variable missing values (see Figure 1 below for how this is accomplished in SPSS). Other possibilities also exist.

Figure 1: Defining Cylinders 3 and 5 as missing in the “Variable View” tab

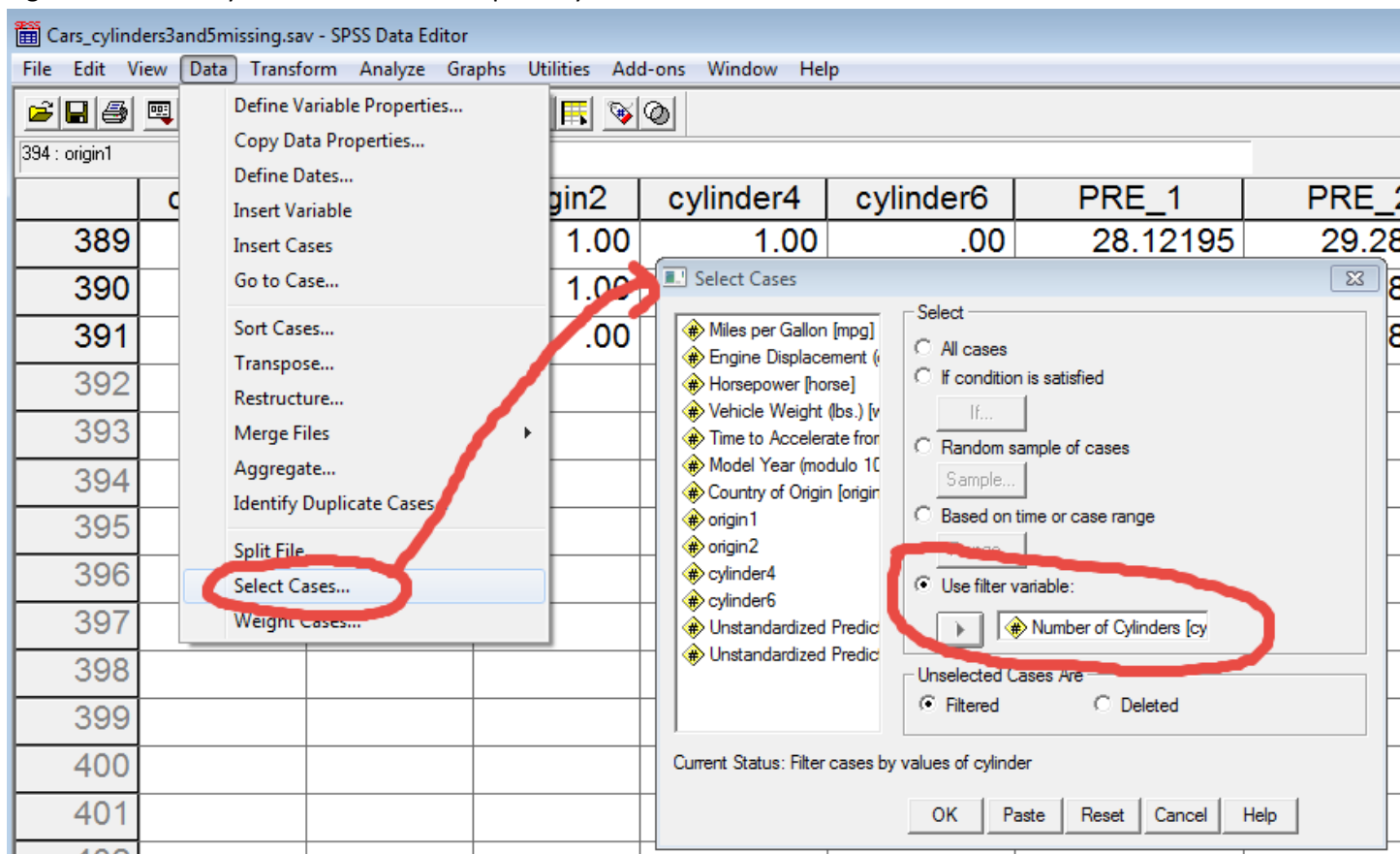


After defining Cylinders 3 and 5 as missing as illustrated in the Figure 1 above, I re-ran the Frequency command for Cylinders and obtained the following results. Note that Cylinders 3 and 5 are now identified as missing and SPSS will automatically discard these cases when performing various statistical tests IF the variable Cylinders is used in the analysis. If you use dummy variables created from Cylinders, then you need to tell SPSS to select only those cases that are complete for Cylinders. Use the Select Cases command as illustrated in Figure 2 below and identify the variable Cylinders as the selection filter variable. This tells SPSS to only use cases with complete Cylinder information – missing cases are ignored in all analyses.

Number of Cylinders

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	4 Cylinders	199	50.9	51.8	51.8
	6 Cylinders	83	21.2	21.6	73.4
	8 Cylinders	102	26.1	26.6	100.0
	Total	384	98.2	100.0	
Missing	3 Cylinders	4	1.0		
	5 Cylinders	3	.8		
	Total	7	1.8		
Total		391	100.0		

Figure 2: Select only those cases with complete Cylinders data



Present an APA styled regression analysis with DV = MPG, IV = origin, and IV = Cylinders (4, 6, and 8 only). Set alpha = .01. You will have to create the dummy variables for origins and Cylinders. Also present Scheffé confidence intervals comparisons among origins and among cylinders.

Results

Table 1: Descriptive Statistics for MPG, Origin, and Number of Cylinders

Variable	MPG	Origin 2	Origin 3	Cylinder 6	Cylinder 8
MPG	---				
Origin 2 (Europe)	.239*	---			
Origin 3 (Japan)	.473*	-.222*	---		
Cylinder 6	-.236*	-.170*	-.163*	---	
Cylinder 8	-.652*	-.271*	-.296*	-.316*	---
Mean	23.48	.1693	.1953	.2161	.2656
SD	7.812	.375	.396	.412	.442

Note: Origin 2 and 3 are dummy variables (1, 0) and Cylinder 6 and 8 are dummy variables (1, 0); n = 384.

*p<.01

Table 2: Regression of MPG on Origins and Cylinders

Variable	b	se	ΔR^2	99%CI	F	t
Origin			.028		16.31*	
2 = Europe	.166	.740		-1.75, 2.08		0.22
3 = Japan	3.683	.706		1.85, 5.51		5.21*
Number of Cylinders			.322		185.59*	
6	-8.256	.673		-10.00, -6.51		-12.26*
8	-12.934	.679		-14.69, -11.17		-19.03*
Intercept	27.955	.512		26.62, 29.28		54.54*

Note: $R^2 = .67$, adj. $R^2 = .67$, $F_{4,379} = 193.21^*$, $MSE = 20.293$, $n = 384$. ΔR^2 represents the squared semi-partial correlation or the increment in R^2 due to adding the respective variable.

* $p < .01$.

Table 3: Comparisons of MPG among Vehicle Origins

Contrast	Estimated Mean Difference	Standard Error of Difference	99% Scheffé Corrected CI of Mean Difference
Europe vs USA	.166	.74	-2.09, 2.42
Japan vs USA	3.68*	.71	1.53, 5.84
Japan vs Europe	3.51*	.76	1.19, 5.85

* $p < .01$, where p-values are adjusted using the Scheffé method.

Table 4: Comparisons of MPG among Number of Cylinders

Contrast	Estimated Mean Difference	Standard Error of Difference	99% Scheffé Corrected CI of Mean Difference
6 vs 4	-8.25*	.67	-10.31, -6.20
8 vs 4	-12.93*	.68	-15.01, -10.86
8 vs 6	-4.68*	.67	-6.72, -2.63

* $p < .01$, where p-values are adjusted using the Scheffé method.

Results show that there are statistical differences in MPG by both vehicles' origin and number of cylinders. For origins, cars from Japan appear to have about a 3.5 to 3.6 MPG advantage over cars from Europe and the USA once number of cylinders are taken into account, and there seems to be little to no difference in MPG between cars from Europe and the USA. For number of cylinders, cars with 4 cylinders appear to obtain 8.3 to 12.9 MPGs more than cars with 6 and 8 cylinders once vehicle origin is controlled, and these differences are significant at the .01 level. Additionally, cars with 6 cylinders appear to have a 4.6 MPG advantage over cars with 8 cylinders, and this difference is also statistically significant at the .01 level.

STATA Results

```
. xi: reg mpg i.origin i.cylinder, level(99)
i.origin      _Iorigin_1-3      (naturally coded; _Iorigin_1 omitted)
i.cylinder    _Icylinder_4-8    (naturally coded; _Icylinder_4 omitted)
```

Source	SS	df	MS	Number of obs	=	384
-----				F(4, 379)	=	193.21
Model	15683.6251	4	3920.90627	Prob > F	=	0.0000
Residual	7691.35491	379	20.2938124	R-squared	=	0.6710
-----				Adj R-squared	=	0.6675
Total	23374.98	383	61.0312793	Root MSE	=	4.5049

mpg	Coef.	Std. Err.	t	P> t	[99% Conf. Interval]	

_Iorigin_2	.1660589	.740277	0.22	0.823	-1.750417	2.082535
_Iorigin_3	3.68331	.7063696	5.21	0.000	1.854616	5.512005
_Icylinder_6	-8.256662	.6734514	-12.26	0.000	-10.00014	-6.513188
_Icylinder_8	-12.93432	.679511	-19.03	0.000	-14.69348	-11.17516
_cons	27.95589	.512617	54.54	0.000	26.62879	29.28298

```
. test _Iorigin_2 _Iorigin_3
( 1) _Iorigin_2 = 0
( 2) _Iorigin_3 = 0
```

```
F( 2, 379) = 16.31
Prob > F = 0.0000
```

```
. di 16.21 * (1-.671)/379*2
.02814296
```

Note, the above calculation uses this formula to calculate ΔR^2 values from F ratios and df.
 $\Delta R^2_{origin} = F_{origin} * (1-R^2_{full model}) / (df_{error full model}) * (df_{change})$

```
. test _Icylinder_6 _Icylinder_8
( 1) _Icylinder_6 = 0
( 2) _Icylinder_8 = 0
```

```
F( 2, 379) = 185.59
Prob > F = 0.0000
```

```
. di 185.59 * (1-.671)/379*2
.32221166
```

Note, the above calculation uses this formula to calculate ΔR^2 values from F ratios and df.
 $\Delta R^2_{origin} = F_{origin} * (1-R^2_{full model}) / (df_{error full model}) * (df_{change})$

. margins cylinder, mcompare(scheffe) pwcompare level(99)

Pairwise comparisons of predictive margins

Model VCE : OLS

Expression : Linear prediction, predict()

```

-----
          |      Number of
          |      Comparisons
-----+-----
cylinder |              3
-----

```

```

-----
          |      Delta-method      Scheffe
          |      Contrast  Std. Err.  [99% Conf. Interval]
-----+-----
cylinder |
  6 vs 4 | -8.256662   .6734514   -10.31297   -6.200355
  8 vs 4 | -12.93432   .679511    -15.00913  -10.85951
  8 vs 6 | -4.677659   .6700444    -6.723563  -2.631755
-----

```

. margins origin, mcompare(scheffe) pwcompare level(99)

Pairwise comparisons of predictive margins

Model VCE : OLS

Expression : Linear prediction, predict()

```

-----
          |      Number of
          |      Comparisons
-----+-----
origin   |              3
-----

```

```

-----
          |      Delta-method      Scheffe
          |      Contrast  Std. Err.  [99% Conf. Interval]
-----+-----
origin   |
  2 vs 1 | .1660589    .740277    -2.094293   2.42641
  3 vs 1 | 3.68331     .7063696   1.526491    5.840129
  3 vs 2 | 3.517251    .7635124   1.185953    5.848549
-----

```

Descriptive Statistics

	Mean	Std. Deviation	N
Miles per Gallon	23.48	7.812	384
origin2	.1693	.37548	384
origin3	.1953	.39696	384
cylinder6	.2161	.41215	384
cylinder8	.2656	.44224	384

Correlations

		Miles per Gallon	origin2	origin3	cylinder6	cylinder8
Miles per Gallon	Pearson Correlation	1	.239(**)	.473(**)	-.236(**)	-.652(**)
	Sig. (2-tailed)		.000	.000	.000	.000
	N	384	384	384	384	384
origin2	Pearson Correlation	.239(**)	1	-.222(**)	-.170(**)	-.271(**)
	Sig. (2-tailed)	.000		.000	.001	.000
	N	384	384	384	384	384
origin3	Pearson Correlation	.473(**)	-.222(**)	1	-.163(**)	-.296(**)
	Sig. (2-tailed)	.000	.000		.001	.000
	N	384	384	384	384	384
cylinder6	Pearson Correlation	-.236(**)	-.170(**)	-.163(**)	1	-.316(**)
	Sig. (2-tailed)	.000	.001	.001		.000
	N	384	384	384	384	384
cylinder8	Pearson Correlation	-.652(**)	-.271(**)	-.296(**)	-.316(**)	1
	Sig. (2-tailed)	.000	.000	.000	.000	
	N	384	384	384	384	384

** Correlation is significant at the 0.01 level (2-tailed).

Appendix

Question 2

Review: Determining Bonferroni and Scheffé critical t values for confidence interval construction.

Study consisted of $n = 72$ observations on heart rate across four medications.

DV = Heart rate = beats per minute

IV = Blood Pressure Medication = four drugs prescriptions (Losartan, Ziac, Lisinopril [12.5mg], and Lisinopril [40mg])

Wish to maintain a familywise error rate of .05.

Bonferroni adjusted critical t ratio:

- (a) Adjusted alpha per comparison is $.05/6 = .083333$ (divide by 6, the number of possible pairwise comparisons among four drug treatments)
- (b) Study degrees of freedom is $n - k - 1$ where k is the number of dummy variables (number of groups minus 1), so $76 - 3 - 1 = 72$
- (c) Then use Excel critical t function to find the critical t-value:

=T.INV.2T(adjusted alpha, df)

=T.INV.2T(.008333, 72)

= ± 2.7129

Scheffé adjusted critical t ratio:

(a) Since the Scheffé adjusted critical t is based upon an F ratio, we must determine the critical F by first finding the model degrees of freedom

$$df1 = J - 1 = 4 - 1 = 3$$

$$df2 = n - k - 1 = 76 - 3 - 1 = 72$$

where J is the number of groups, and k is the number of dummy variables in the regression equation.

(b) Next find the critical F ratio for a familywise error rate of .05. This can be found using Excel

$$=F.INV.RT(\text{alpha level}, df1, df2)$$

$$=F.INV.RT(0.05,3,72)$$

$$= 2.7318$$

(c) Next convert this critical F ratio to a Scheffé adjusted F ratio

$$\text{Scheffé } F = (J - 1) (\text{original critical } F)$$

$$\text{Scheffé } F = (3) (2.7318)$$

$$\text{Scheffé } F = 8.1954$$

(d) Next convert this Scheffé F ratio to a critical Scheffé t value by taking the square root of the Scheffé F:

$$\text{Scheffé } t = \sqrt{\text{Scheffé } F}$$

$$\text{Scheffé } t = \sqrt{8.1954}$$

$$\text{Scheffé } t = \pm 2.8627$$

Now we have the critical t-value used to test the six possible pairwise comparisons among four drug treatments with an overall familywise error rate of .05 or less.