Chapter 17 - Log-Linear Analysis

17.1 Possible models for data on race, gender, and sexual intercourse.

It is easiest to specify the variables that would need to be included. Because there are clear differences in the numbers of whites and blacks, in the choices on Intercourse (No's are much more common), those two main effects must be included. We also see that their appears to be a significant interaction of Race and Intercourse, so that must be included. It would seem that there is an interaction of Gender and Intercourse, so we need both that interaction and the main effect of Gender (because this will be a hierarchical model). It is hard to tell whether there is likely to be a Race by Gender interaction, so we should at least consider including that.

17.3 Optimal model from HILOGLINEAR:

It is important to remember that you will obtain different results depending on how you code the data, but the expected frequencies and the chi-square values that result will not be affected.

Backward Elimination Statistics

Step Summary

Step[a]			Effects	Chi-Square[c]	df	Sig.	Number of Iterations
0	Generating Class[b]		Race*Gender*Intercourse	.000	0	.	
	Deleted Effect	1	Race*Gender*Intercourse	.065	1	.798	2
1	Generating Class[b]		Race*Gender, Race*Intercourse, Gender*Intercourse	.065	1	.798	
	Deleted Effect	1	Race*Gender	1.686	1	.194	2
		2	Race*Intercourse	30.359	1	.000	2
		3	Gender*Intercourse	8.475	1	.004	2
2	Generating Class[b]		Race*Intercourse, Gender*Intercourse	1.752	2	.417	
	Deleted Effect	1	Race*Intercourse	28.977	1	.000	2
		2	Gender*Intercourse	7.093	1	.008	2
3	Generating Class[b]		Race*Intercourse, Gender*Intercourse	1.752	2	.417	

a. At each step, the effect with the largest significance level for the Likelihood Ratio Change is deleted, provided the significance level is larger than .050.

b. Statistics are displayed for the best model at each step after step 0.

c. For 'Deleted Effect', this is the change in the Chi-Square after the effect is deleted from the model.

Step 0 tells us that if we delete the three way interaction the fit will not deteriorate significantly, so we move to a model with RI, RG, and GI. Step 1 shows that we can delete RG without a significant decrease, so we go to step 2 with RI, GI. There we see that if we delete either interaction we will have a significant decrement, so our final model is RI,RG or, if you prefer, R, G, I, RI, RG.

17.5 It is difficult to tell about interactions in such a large table, but I would expect there to be a motor vehicle × injury interaction (you are more likely to be injured if you are hit with a car), an age × motor vehicle interaction (we think of kids being more likely to ride out in front of a car), and we hope for a helmet × injury interaction (because we want to think that helmets will protect us from injury). There may be at least one higher order interaction, but it is hard to tell from looking at the data.

17.7 Output from SPSS HILOGLINEAR.

Step Summary

Step[a]			Effects	Chi-Square[c]	df	Sig.	Number of Iterations
0	Generating Class[b]		Age*Motorveh*Helmet*Injury	.000	0	.	
	Deleted Effect	1	Age*Motorveh*Helmet*Injury	.000	1	.994	2
1	Generating Class[b]		Age*Motorveh*Helmet, Age*Motorveh*Injury, Age*Helmet*Injury, Motorveh*Helmet*Injury	.000	1	.994	
	Deleted Effect	1	Age*Motorveh*Helmet	.181	1	.670	2
		2	Age*Motorveh*Injury	.768	1	.381	2
		3	Age*Helmet*Injury	4.737	1	.030	2
		4	Motorveh*Helmet*Injury	.074	1	.785	2
2	Generating Class[b]		Age*Motorveh*Helmet, Age*Motorveh*Injury, Age*Helmet*Injury	.074	2	.964	
	Deleted Effect	1	Age*Motorveh*Helmet	.226	1	.634	2
		2	Age*Motorveh*Injury	.723	1	.395	2
		3	Age*Helmet*Injury	4.688	1	.030	2
3	Generating Class[b]		Age*Motorveh*Injury, Age*Helmet*Injury, Motorveh*Helmet	.301	3	.960	
	Deleted Effect	1	Age*Motorveh*Injury	.870	1	.351	2
		2	Age*Helmet*Injury	4.576	1	.032	2
		3	Motorveh*Helmet	.002	1	.966	2
4	Generating Class[b]		Age*Motorveh*Injury, Age*Helmet*Injury	.303	4	.990	
	Deleted Effect	1	Age*Motorveh*Injury	.847	1	.358	2
		2	Age*Helmet*Injury	4.573	1	.032	2
5	Generating Class[b]		Age*Helmet*Injury, Age*Motorveh, Motorveh*Injury	1.149	5	.950	
	Deleted Effect	1	Age*Helmet*Injury	4.576	1	.032	2
		2	Age*Motorveh	25.514	1	.000	2
		3	Motorveh*Injury	25.604	1	.000	2
6	Generating Class[b]		Age*Helmet*Injury, Age*Motorveh, Motorveh*Injury	1.149	5	.950	

a. At each step, the effect with the largest significance level for the Likelihood Ratio Change is deleted, provided the significance level is larger than .050.

17.9 As I predicted, to produce adequate expected values we need to take into account the fact that there is an Age by Motor Vehicle interaction, but, contrary to prediction, children are less likely to be injured by a motor vehicle (OR = 0.44). There clearly is a relationship between Injury and Motor Vehicles, with an OR = 2.96. It is difficult to interpret the three way interaction because the 0 for young children being injured while wearing a helmet is 0 and no odds or odds ratios can be calculated.

17.11 For adults the odds of an injury|helmet is 4/60 = 0.067. The odds of injury|no helmet = 72/595 = .12. Thus the odds ratio is 0.067/0.12 = 0.56, meaning that an adult is about half as likely to be injured when wearing a helmet. You cannot do this for children because it is impossible to calculate odds when one of the frequencies is 0.

17.13 Odds ratios of High vs. normal testosterone groups

Odds ratio for delinquency (high/normal) by SES:
Low SES = .4429/.1721 = 2.57
High SES = .0429/.0476 = .90

For subjects in the low SES group the odds of being delinquent are 2.57 time higher for high testosterone men than for normal testosterone men. For the high SES group this ratio is only .90. The effect of high testosterone levels is substantially different in the two SES groups. Some of this might be due to the fact that men involved in adult delinquency are much less likely to appear in the high SES group.

17.15 We could not include multiple behaviors in the same design because the observations would not be independent. Each person would contribute data on each behavior.

17.17 Data on death penalty and race

```
* * * * * * * *  H I E R A R C H I C A L   L O G   L I N E A R  * * * * * * * *

Backward Elimination (p = .050) for DESIGN 1 with generating class
  DefRace*VictimRa*DeathPen
 Likelihood ratio chi square =      .00000    DF = 0  P =  .

- - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - -
If Deleted Simple Effect is                DF   L.R. Chisq Change    Prob  Iter
 DefRace*VictimRa*DeathPen                  1                .701   .4024     4

Step 1
  The best model has generating class
      DefRace*VictimRa
      DefRace*DeathPen
      VictimRa*DeathPen

  Likelihood ratio chi square =      .70121    DF = 1  P =  .402
- - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - -
If Deleted Simple Effect is                DF   L.R. Chisq Change    Prob  Iter
 DefRace*VictimRa                           1             130.757   .0000     2
 DefRace*DeathPen                           1               1.181   .2772     2
 VictimRa*DeathPen                          1               7.209   .0073     2

Step 2
  The best model has generating class
      DefRace*VictimRa
      VictimRa*DeathPen
```

```
  Likelihood ratio chi square =     1.88191    DF = 2  P =  .390
- - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - -
If Deleted Simple Effect is                 DF   L.R. Chisq Change    Prob  Iter
 DefRace*VictimRa                            1             129.798   .0000     2
 VictimRa*DeathPen                           1               6.250   .0124     2

Step 3

  The best model has generating class
      DefRace*VictimRa
      VictimRa*DeathPen
  Likelihood ratio chi square =     1.88191    DF = 2  P =  .390
```

Notice that the DefendantRace * Penalty interaction has been dropped from the model, indicating that the penalty is independent of the defendant's race if we hold constant the victim's race.

17.19 The answers depend on the software packages the student uses.