Binary Logistic Regression with SPSS[©]

Logistic regression is used to predict a categorical (usually dichotomous) variable from a set of predictor variables. With a categorical dependent variable, discriminant function analysis is usually employed if all of the predictors are continuous and nicely distributed; logit analysis is usually employed if all of the predictors are categorical; and logistic regression is often chosen if the predictor variables are a mix of continuous and categorical variables and/or if they are not nicely distributed (logistic regression makes no assumptions about the distributions of the predictor variables). Logistic regression has been especially popular with medical research in which the dependent variable is whether or not a patient has a disease.

For a logistic regression, the predicted dependent variable is a function of the probability that a particular subject will be in one of the categories (for example, the probability that Suzie Cue has the disease, given her set of scores on the predictor variables).

Description of the Research Used to Generate Our Data

As an example of the use of logistic regression in psychological research, consider the research done by Wuensch and Poteat and published in the *Journal of Social Behavior and Personality*, 1998, *13*, 139-150. College students (*N* = 315) were asked to pretend that they were serving on a university research committee hearing a complaint against animal research being conducted by a member of the university faculty. The complaint included a description of the research in simple but emotional language. Cats were being subjected to stereotaxic surgery in which a cannula was implanted into their brains. Chemicals were then introduced into the cats' brains via the cannula and the cats given various psychological tests. Following completion of testing, the cats' brains were subjected to histological analysis. The complaint asked that the researcher's authorization to conduct this research be withdrawn and the cats turned over to the animal rights group that was filing the complaint. It was suggested that the research could just as well be done with computer simulations.

In defense of his research, the researcher provided an explanation of how steps had been taken to assure that no animal felt much pain at any time, an explanation that computer simulation was not an adequate substitute for animal research, and an explanation of what the benefits of the research were. Each participant read one of five different scenarios which described the goals and benefits of the research. They were:

- COSMETIC -- testing the toxicity of chemicals to be used in new lines of hair care products.
- THEORY -- evaluating two competing theories about the function of a particular nucleus in the brain.
- MEAT -- testing a synthetic growth hormone said to have the potential of increasing meat production.
- VETERINARY -- attempting to find a cure for a brain disease that is killing both domestic cats and endangered species of wild cats.
- MEDICAL -- evaluating a potential cure for a debilitating disease that afflicts many young adult humans.

After reading the case materials, each participant was asked to decide whether or not to withdraw Dr. Wissen's authorization to conduct the research and, among other things, to fill out D. R. Forysth's Ethics Position Questionnaire (*Journal of Personality and Social Psychology*, 1980, *39*, 175-184), which consists of 20 Likert-type items, each with a 9-point response scale from "completely

disagree" to "completely agree." Persons who score high on the relativism dimension of this instrument reject the notion of universal moral principles, preferring personal and situational analysis of behavior. Persons who score high on the idealism dimension believe that ethical behavior will always lead only to good consequences, never to bad consequences, and never to a mixture of good and bad consequences.

Having committed the common error of projecting myself onto others, I once assumed that all persons make ethical decisions by weighing good consequences against bad consequences -- but for the idealist the presence of any bad consequences may make a behavior unethical, regardless of good consequences. Research by Hal Herzog and his students at Western Carolina has shown that animal rights activists tend to be high in idealism and low in relativism (see me for references if interested). Are idealism and relativism (and gender and purpose of the research) related to attitudes towards animal research in college students? Let's run the logistic regression and see.

Using a Single Dichotomous Predictor, Gender of Subject

Let us first consider a simple (bivariate) logistic regression, using subjects' **decisions** as the dichotomous criterion variable and their **gender** as a dichotomous predictor variable. I have coded gender with 0 = Female, 1 = Male, and decision with 0 = "Stop the Research" and 1 = "Continue the Research".

Our regression model will be predicting the logit, that is, the natural log of the odds of having made one or the other decision. That is,

$$\ln(ODDS) = \ln\left(\frac{\hat{Y}}{1-\hat{Y}}\right) = a + bX$$

, where $\hat{Y}$ is **the predicted probability of the event which is coded with 1 (continue the research)** rather than with 0 (stop the research), $1 - \hat{Y}$ is the predicted probability of the other decision, and X is our predictor variable, gender. Some statistical programs (such as SAS) predict the event which is coded with the smaller of the two numeric codes. By the way, if you have ever wondered what is "natural" about the natural log, you can find an answer of sorts at http://www.math.toronto.edu/mathnet/answers/answers_13.html.

Our model will be constructed by **an iterative maximum likelihood procedure**. The program will start with arbitrary values of the regression coefficients and will construct an initial model for predicting the observed data. It will then evaluate errors in such prediction and change the regression coefficients so as make the likelihood of the observed data greater under the new model. This procedure is repeated until the model converges -- that is, until the differences between the newest model and the previous model are trivial.

Open the data file at http://core.ecu.edu/psyc/wuenschk/SPSS/Logistic.sav. Click **Analyze, Regression, Binary Logistic**. Scoot the decision variable into the Dependent box and the gender variable into the Covariates box. The dialog box should now look like this:
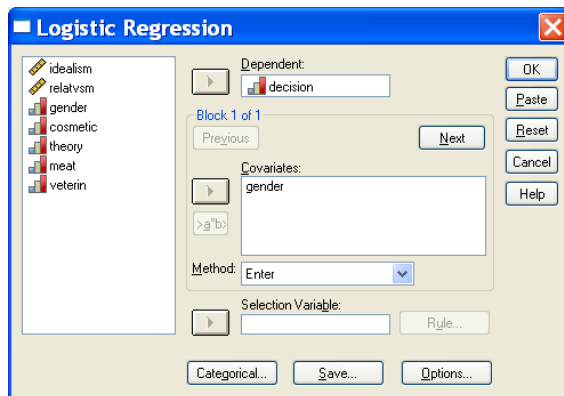
Open the data file at http://core.ecu.edu/psyc/wuenschk/SPSS/Logistic.sav. Click **Analyze, Regression, Binary Logistic**. Scoot the decision variable into the Dependent box and the gender variable into the Covariates box. The dialog box should now look like this:

Click **OK**.

Look at the statistical output. We see that there are 315 cases used in the analysis.

Case Processing Summary

Unweighted Cases [a]		N	Percent
Selected Cases	Included in Analysis	315	100.0
	Missing Cases	0	.0
	Total	315	100.0
Unselected Cases		0	.0
Total		315	100.0

a. If weight is in effect, see classification table for the total number of cases.

The **Block 0** output is for a model that includes only the intercept (which SPSS calls the constant). Given the base rates of the two decision options (187/315 = 59% decided to stop the research, 41% decided to allow it to continue), and no other information, the best strategy is to predict, for every case, that the subject will decide to stop the research. Using that strategy, you would be correct 59% of the time.

Classification Table[a,b]

			Predicted		
			decision		Percentage
	Observed		stop	continue	Correct
Step 0	decision	stop	187	0	100.0
		continue	128	0	.0
	Overall Percentage				59.4

a. Constant is included in the model.

b. The cut value is .500

Under **Variables in the Equation** you see that the intercept-only model is **ln(odds) = -.379**. If we exponentiate both sides of this expression we find that our predicted odds [Exp(B)] = .684. That is, the predicted odds of deciding to continue the research is .684. Since 128 of our subjects decided to continue the research and 187 decided to stop the research, our **observed odds are 128/187 = .684**.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-.379	.115	10.919	1	.001	.684

Now look at the **Block 1** output. Here SPSS has added the gender variable as a predictor. **Omnibus Tests of Model Coefficients** gives us a Chi-Square of 25.653 on 1 *df*, significant beyond .001. This is a test of the null hypothesis that adding the gender variable to the model has not significantly increased our ability to predict the decisions made by our subjects.

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	25.653	1	.000
	Block	25.653	1	.000
	Model	25.653	1	.000

Under **Model Summary** we see that the **-2 Log Likelihood** statistic is 399.913. This statistic **measures how poorly the model predicts the decisions** -- the smaller the statistic the better the model. Although SPSS does not give us this statistic for the model that had only the intercept, I know it to be 425.666. Adding the gender variable reduced the -2 Log Likelihood statistic by 425.666 - 399.913 = 25.653, the χ^2 statistic we just discussed in the previous paragraph. The **Cox & Snell R^2** can be interpreted like R^2 in a multiple regression, but cannot reach a maximum value of 1. The **Nagelkerke R^2** can reach a maximum of 1.

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	399.913[a]	.078	.106

a. Estimation terminated at iteration number 3 because parameter estimates changed by less than .001.

The **Variables in the Equation** output shows us that the regression equation is $\ln(ODDS) = -.847 + 1.217 Gender$.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	gender	1.217	.245	24.757	1	.000	3.376
	Constant	-.847	.154	30.152	1	.000	.429

a. Variable(s) entered on step 1: gender.

We can now use this model to **predict the odds** that a subject of a given gender will decide to continue the research. The odds prediction equation is $ODDS = e^{a+bX}$. If our subject is a woman (gender = 0), then the $ODDS = e^{-.847+1.217(0)} = e^{-.847} = 0.429$. That is, a woman is only .429 as likely to decide to continue the research as she is to decide to stop the research. If our subject is a man (gender = 1), then the $ODDS = e^{-.847+1.217(1)} = e^{.37} = 1.448$. That is, a man is 1.448 times more likely to decide to continue the research than to decide to stop the research.

We can easily **convert odds to probabilities**. For our women, $\hat{Y} = \dfrac{ODDS}{1+ODDS} = \dfrac{0.429}{1.429} = 0.30$. That is, our model predicts that 30% of women will decide to continue the research. For our men, $\hat{Y} = \dfrac{ODDS}{1+ODDS} = \dfrac{1.448}{2.448} = 0.59$. That is, our model predicts that 59% of men will decide to continue the research

The **Variables in the Equation** output also gives us the **Exp(B)**. This is better known as **the odds ratio** predicted by the model. This odds ratio can be computed by **raising the base of the natural log to the bth power, where b is the slope from our logistic regression equation**. For

our model, $\boxed{e^{1.217} = 3.376}$. That tells us that the model predicts that the odds of deciding to continue the research are 3.376 times higher for men than they are for women. For the men, the odds are 1.448, and for the women they are 0.429. The odds ratio is $\boxed{1.448 \ / \ 0.429 = 3.376}$.

The results of our logistic regression can be used to **classify subjects** with respect to what decision we think they will make. As noted earlier, our model leads to the prediction that the probability of deciding to continue the research is 30% for women and 59% for men. Before we can use this information to classify subjects, we need to have a decision rule. Our **decision rule** will take the following form: If the probability of the event is greater than or equal to some threshold, we shall predict that the event will take place. By default, SPSS sets this threshold to .5. While that seems reasonable, in many cases we may want to set it higher or lower than .5. More on this later. Using the default threshold, SPSS will classify a subject into the "Continue the Research" category if the estimated probability is .5 or more, which it is for every male subject. SPSS will classify a subject into the "Stop the Research" category if the estimated probability is less than .5, which it is for every female subject.

The **Classification Table** shows us that this rule allows us to correctly classify 68 / 128 = 53% of the subjects where the predicted event (deciding to continue the research) was observed. This is known as the **sensitivity** of prediction, the P(correct | event did occur), that is, the percentage of occurrences correctly predicted. We also see that this rule allows us to correctly classify 140 / 187 = 75% of the subjects where the predicted event was not observed. This is known as the **specificity** of prediction, the P(correct | event did not occur), that is, the percentage of nonoccurrences correctly predicted. Overall our predictions were correct 208 out of 315 times, for an **overall success rate** of 66%. Recall that it was only 59% for the model with intercept only.

Classification Table [a]

			Predicted		
			decision		Percentage Correct
Observed			stop	continue	
Step 1	decision	stop	140	47	74.9
		continue	60	68	53.1
	Overall Percentage				66.0

a. The cut value is .500

We could focus on error rates in classification. A **false positive** would be predicting that the event would occur when, in fact, it did not. Our decision rule predicted a decision to continue the research 115 times. That prediction was wrong 47 times, for a false positive rate of 47 / 115 = 41%. A **false negative** would be predicting that the event would not occur when, in fact, it did occur. Our decision rule predicted a decision not to continue the research 200 times. That prediction was wrong 60 times, for a false negative rate of 60 / 200 = 30%.

It has probably occurred to you that you could have used a simple **Pearson Chi-Square Contingency Table Analysis** to answer the question of whether or not there is a significant relationship between gender and decision about the animal research. Let us take a quick look at such an analysis. In SPSS click **Analyze, Descriptive Statistics, Crosstabs**. Scoot gender into the rows box and decision into the columns box. The dialog box should look like this:
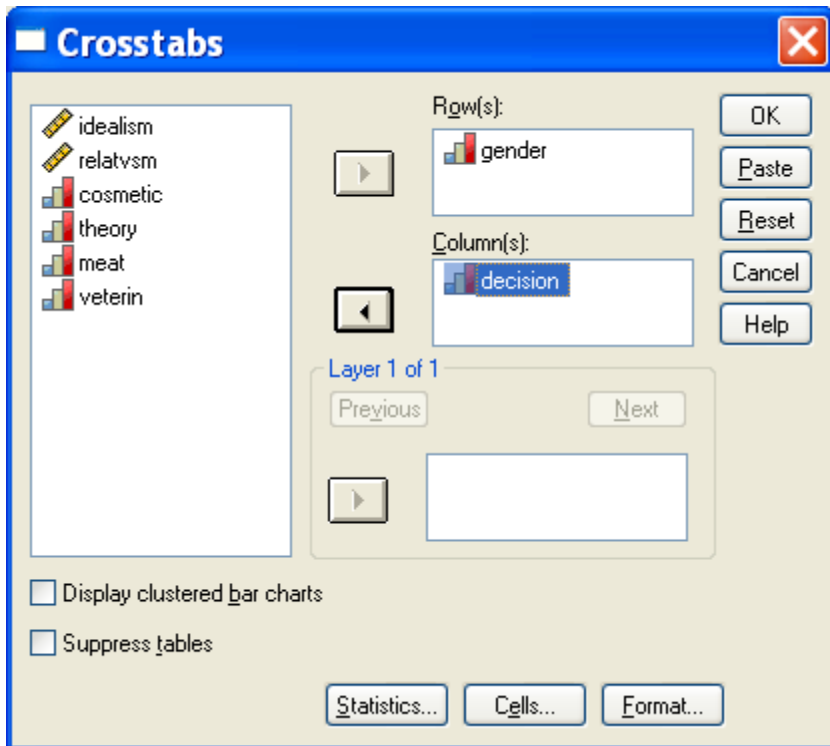
Now click the **Statistics** box. Check **Chi-Square** and then click **Continue**.

Now click the **Cells** box. Check **Observed Counts** and **Row Percentages** and then click Continue.
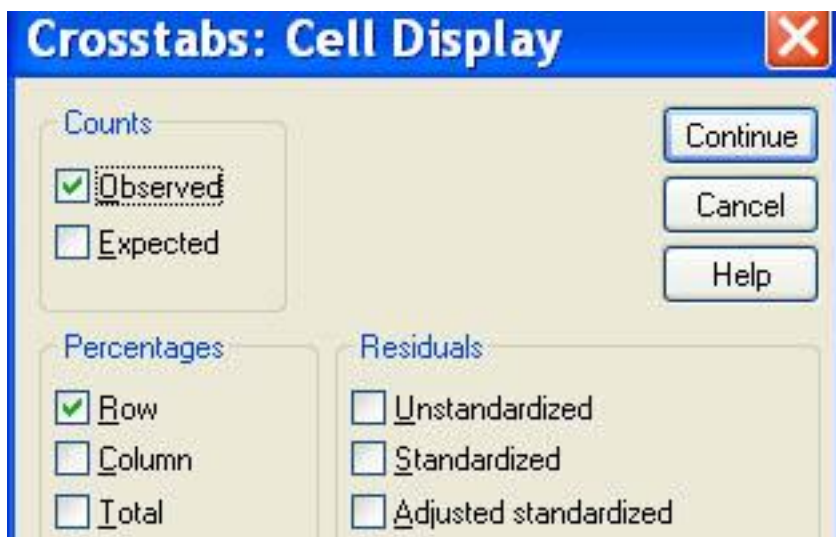
Back on the initial page, click **OK**.

In the **Crosstabulation output** you will see that 59% of the men and 30% of the women decided to continue the research, just as predicted by our logistic regression.

gender * decision Crosstabulation

			decision	decision	
			stop	continue	Total
gender	Female	Count	140	60	200
		% within gender	70.0%	30.0%	100.0%
	Male	Count	47	68	115
		% within gender	40.9%	59.1%	100.0%
Total		Count	187	128	315
		% within gender	59.4%	40.6%	100.0%

You will also notice that the **Likelihood Ratio Chi-Square** is 25.653 on 1 *df*, the same test of significance we got from our logistic regression, and the Pearson Chi-Square is almost the same (25.685). If you are thinking, "Hey, this logistic regression is nearly equivalent to a simple Pearson Chi-Square," you are correct, in this simple case. Remember, however, that we can add additional predictor variables, and those additional predictors can be either categorical or continuous -- you can't do that with a simple Pearson Chi-Square.

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	25.685[b]	1	.000
Likelihood Ratio	25.653	1	.000
N of Valid Cases	315		

a. Computed only for a 2x2 table

b. 0 cells (.0%) have expected count less than 5. The minimum expected count is 46.73.

Multiple Predictors, Both Categorical and Continuous

Now let us conduct an analysis that will better tap the strengths of logistic regression. Click **Analyze, Regression, Binary Logistic**. Scoot the decision variable in the **Dependent** box and gender, idealism, and relatvsm into the **Covariates** box.
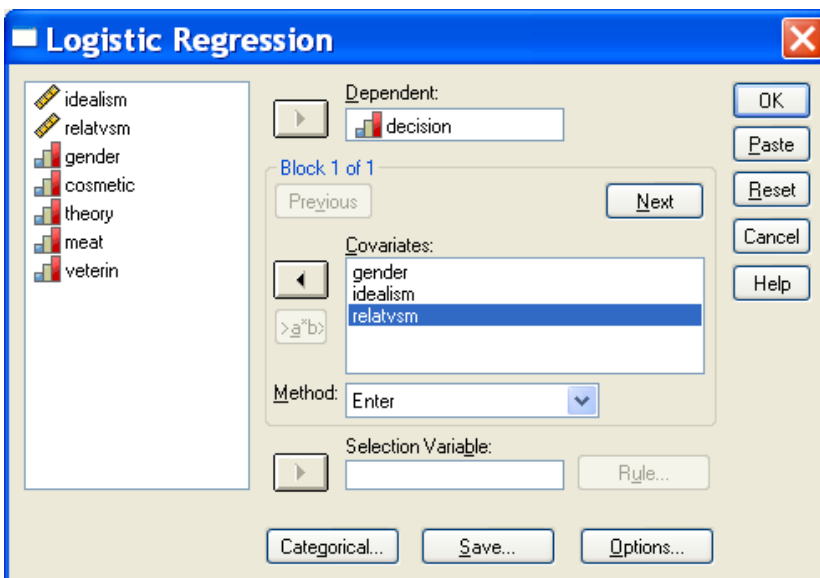
Click **Options** and check "Hosmer-Lemeshow goodness of fit" and "CI for exp(B) 95%."
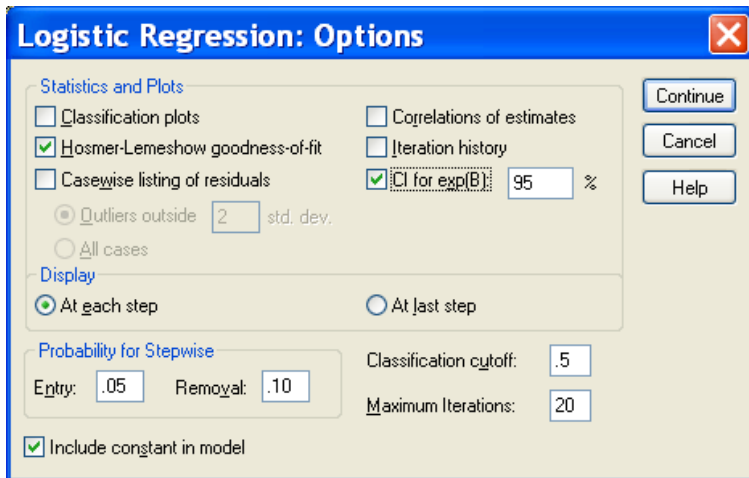
Continue, OK. Look at the output.

In the **Block 1** output, notice that the -2 Log Likelihood statistic has dropped to 346.503, indicating that our expanded model is doing a better job at predicting decisions than was our one-predictor model. The R^2 statistics have also increased.

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	346.503[a]	.222	.300

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

We can test the significance of the difference between any two models, as long as one model is nested within the other. Our one-predictor model had a **–2 Log Likelihood** statistic of 399.913. Adding the ethical ideology variables (idealism and relatvsm) produced a **decrease of 53.41**. This difference is a χ^2 **on 2 *df*** (one *df* for each predictor variable).

To **determine the *p* value** associated with this χ^2, just click **Transform, Compute**. Enter the letter p in the **Target Variable** box. In the **Numeric Expression** box, type **1-CDF.CHISQ(53.41,2)**. The dialog box should look like this:
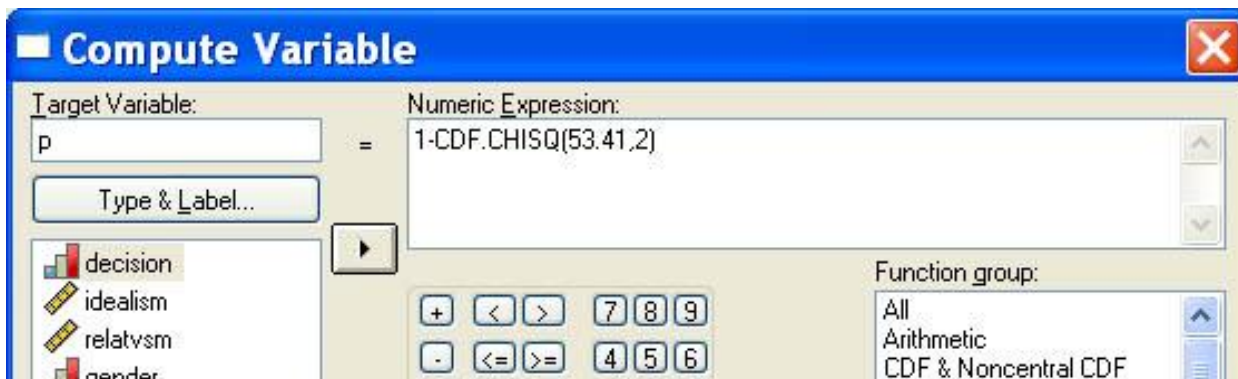
Click **OK** and then go to the **SPSS Data Editor, Data View**. You will find a new column, p, with the value of .00 in every cell. If you go to the **Variable View** and set the number of **decimal points** to 5 for the p variable you will see that the value of p is.00000. **We conclude that adding the ethical ideology variables significantly improved the model, χ^2(2, *N* = 315) = 53.41, *p* < .001.**

Note that our overall success rate in classification has improved from 66% to 71%.

Classification Table[a]

			Predicted		
			decision		Percentage
	Observed		stop	continue	Correct
Step 1	decision	stop	151	36	80.7
		continue	55	73	57.0
	Overall Percentage				71.1

a. The cut value is .500

The **Hosmer-Lemeshow** tests the null hypothesis that predictions made by the model fit perfectly with observed group memberships. Cases are arranged in order by their predicted probability on the criterion variable. These ordered cases are then divided into ten (usually) groups of equal or near equal size ordered with respect to the predicted probability of the target event. For each of these groups we then obtain the predicted group memberships and the actual group memberships This results in a 2 x 10 contingency table, as shown below. A chi-square statistic is computed comparing the observed frequencies with those expected under the linear model. A nonsignificant chi-square indicates that the data fit the model well.

This procedure suffers from several problems, one of which is that it relies on a test of significance. With large sample sizes, the test may be significant, even when the fit is good. With small sample sizes it may not be significant, even with poor fit. Even Hosmer and Lemeshow have acknowledged problems with this test.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	8.810	8	.359

Contingency Table for Hosmer and Lemeshow Test

		decision = stop		decision = continue		
		Observed	Expected	Observed	Expected	Total
Step 1	1	29	29.331	3	2.669	32
	2	30	27.673	2	4.327	32
	3	28	25.669	4	6.331	32
	4	20	23.265	12	8.735	32
	5	22	20.693	10	11.307	32
	6	15	18.058	17	13.942	32
	7	15	15.830	17	16.170	32
	8	10	12.920	22	19.080	32
	9	12	9.319	20	22.681	32
	10	6	4.241	21	22.759	27

Box-Tidwell Test. Although logistic regression is often thought of as having no assumptions, we do assume that the relationships between the continuous predictors and the logit (log odds) is linear. This assumption can be tested by including in the model interactions between the continuous predictors and their logs. If such an interaction is significant, then the assumption has been violated. I should caution you that sample size is a factor here too, so you should not be very concerned with a just significant interaction when sample sizes are large.

Below I show how to create the natural log of a predictor. If the predictor has values of 0 or less, first add to each score a constant such that no value will be zero or less. Also shown below is how to enter the interaction terms. In the pane on the left, select both of the predictors to be included in the interaction and then click the >a*b> button.
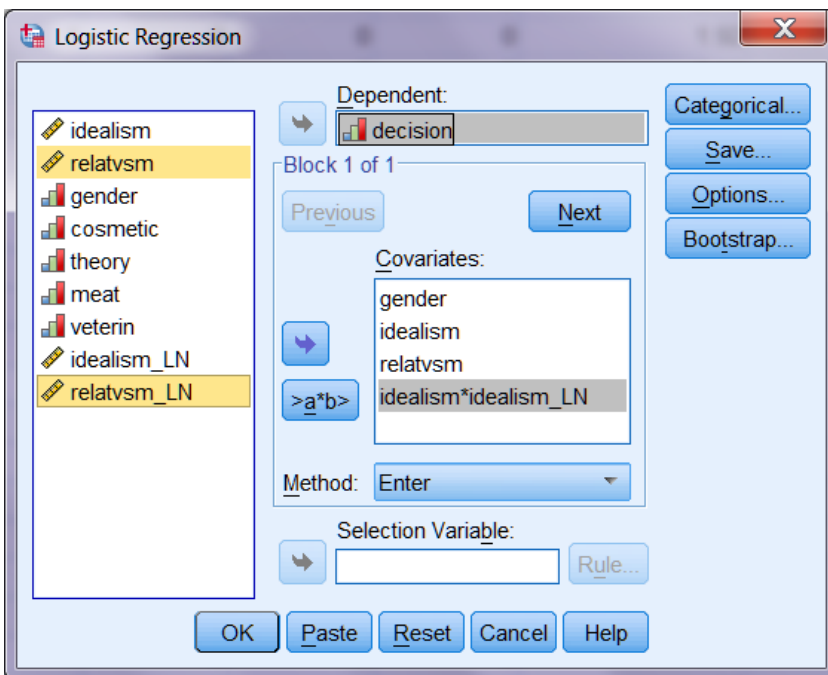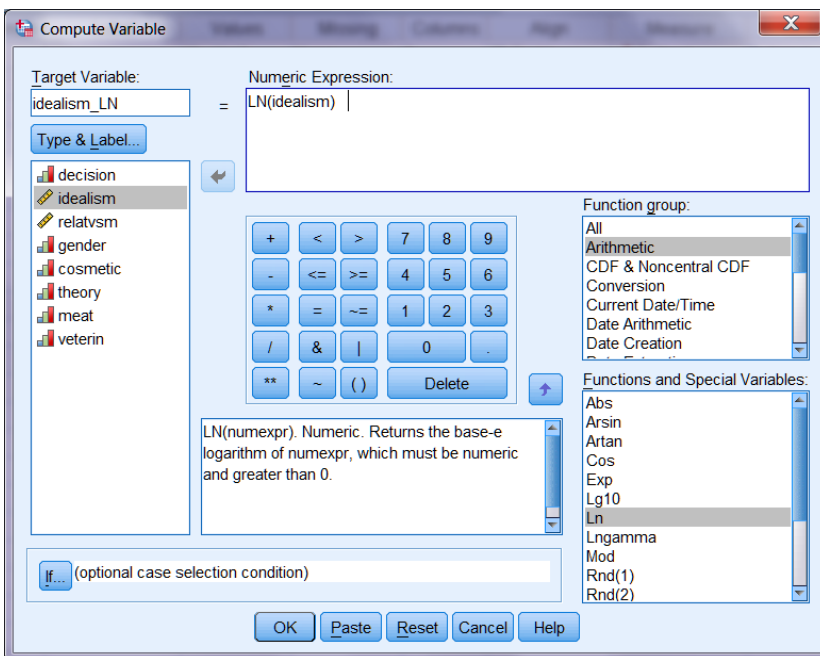
Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	gender	1.147	.269	18.129	1	.000	3.148
	idealism	1.130	1.921	.346	1	.556	3.097
	relatvsm	1.656	2.637	.394	1	.530	5.240
	idealism by idealism_LN	-.652	.690	.893	1	.345	.521
	relatvsm by relatvsm_LN	-.479	.949	.254	1	.614	.620
	Constant	-5.015	5.877	.728	1	.393	.007

a. Variable(s) entered on step 1: gender, idealism, relatvsm, idealism * idealism_LN , relatvsm * relatvsm_LN .

Bravo, neither of the interaction terms is significant. If one were significant, I would try adding to the model powers of the predictor (that is, going polynomial). For an example, see my document Independent Samples T Tests versus Binary Logistic Regression.

Using a *K* > 2 Categorical Predictor

We can use a categorical predictor that has more than two levels. For our data, the stated purpose of the research is such a predictor. While SPSS can dummy code such a predictor for you, I prefer to set up my own dummy variables. To see how to get SPSS to create the dummy variables, go here. You will need **K-1 dummy variables** to represent K groups. Since we have five levels of purpose of the research, we shall need 4 dummy variables. Each of the subjects will have a score of either 0 or 1 on each of the dummy variables. For each dummy variable a score of 0 will indicate that the subject does not belong to the group represented by that dummy variable and a score of 1 will indicate that the subject does belong to the group represented by that dummy variable. One of the groups will not be represented by a dummy variable. If it is reasonable to consider one of your groups as a **reference group to which each other group should be compared**, make that group the one which is not represented by a dummy variable.

I decided that I wanted to compare each of the cosmetic, theory, meat, and veterinary groups with the medical group, so I set up a dummy variable for each of the groups except the medical group. Take a look at our data in the **data editor**. Notice that the first subject has a score of 1 for the cosmetic dummy variable and 0 for the other three dummy variables. That subject was told that the purpose of the research was to test the safety of a new ingredient in hair care products. Now scoot to the bottom of the data file. The last subject has a score of 0 for each of the four dummy variables. That subject was told that the purpose of the research was to evaluate a treatment for a debilitating disease that afflicts humans of college age.

Click **Analyze, Regression, Binary Logistic** and add to the list of covariates the four dummy variables. You should now have the decision variable in the **Dependent** box and all of the other variables (but not the p value column) in the **Covariates** box. Click **OK**.

The Block 0 "Variables not in the Equation" show how much the -2LL would drop if a single predictor were added to the model (which already has the intercept)

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	gender	25.685	1	.000
		idealism	47.679	1	.000
		relatvsm	7.239	1	.007
		cosmetic	.003	1	.955
		theory	2.933	1	.087
		meat	.556	1	.456
		veterin	.013	1	.909
	Overall Statistics		77.665	7	.000

Look at the output, **Block 1**. Under **Omnibus Tests of Model Coefficients** we see that our latest model is significantly better than a model with only the intercept.

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	87.506	7	.000
	Block	87.506	7	.000
	Model	87.506	7	.000

Under **Model Summary** we see that our R^2 statistics have increased again and the **-2 Log Likelihood** statistic has dropped from 346.503 to 338.060. Is this drop statistically significant? The χ^2, is the difference between the two -2 log likelihood values, 8.443, on 4 *df* (one *df* for each dummy variable). Using **1-CDF.CHISQ(8.443,4)**, we obtain an upper-tailed *p* of .0766, short of the usual standard of statistical significance. I shall, however, retain these dummy variables, since I have an a priori interest in the comparison made by each dummy variable.

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	338.060[a]	.243	.327

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

In the **Classification Table**, we see a small increase in our overall success rate, from 71% to 72%.

Classification Table[a]

			Predicted		
			decision		Percentage
	Observed		stop	continue	Correct
Step 1	decision	stop	152	35	81.3
		continue	54	74	57.8
	Overall Percentage				71.7

a. The cut value is .500

I would like you to compute the values for Sensitivity, Specificity, False Positive Rate, and False Negative Rate for this model, using the default .5 cutoff.

Sensitivity	percentage of occurrences correctly predicted
Specificity	percentage of nonoccurrences correctly predicted
False Positive Rate	percentage of predicted occurrences which are incorrect
False Negative Rate	percentage of predicted nonoccurrences which are incorrect

Remember that the predicted event was a decision to continue the research.

Under **Variables in the Equation** we are given regression coefficients and odds ratios.

Variables in the Equation

		B	Wald	df	Sig.	Exp(B)	95.0% C.I.f or EXP(B) Lower	Upper
Step 1ᵃ	gender	1.255	20.586	1	.000	3.508	2.040	6.033
	idealism	-.701	37.891	1	.000	.496	.397	.620
	relatvsm	.326	6.634	1	.010	1.386	1.081	1.777
	cosmetic	-.709	2.850	1	.091	.492	.216	1.121
	theory	-1.160	7.346	1	.007	.314	.136	.725
	meat	-.866	4.164	1	.041	.421	.183	.966
	veterin	-.542	1.751	1	.186	.581	.260	1.298
	Constant	2.279	4.867	1	.027	9.766		

a. Variable(s) entered on step 1: gender, idealism, relatvsm, cosmetic, theory, meat, veterin.

We are also given a statistic I have ignored so far, the **Wald Chi-Square** statistic, which tests the unique contribution of each predictor, in the context of the other predictors -- that is, holding constant the other predictors -- that is, eliminating any overlap between predictors. Notice that each predictor meets the conventional .05 standard for statistical significance, except for the dummy variable for cosmetic research and for veterinary research. I should note that the Wald χ^2 has been criticized for being too **conservative**, that is, lacking adequate power. An alternative would be to test the significance of each predictor by eliminating it from the full model and testing the significance of the increase in the -2 log likelihood statistic for the reduced model. That would, of course, require that you construct $p+1$ models, where p is the number of predictor variables.

Let us now interpret the odds ratios.

- The .496 odds ratio for idealism indicates that the odds of approval are more than cut in half for each one point increase in respondent's idealism score. Inverting this odds ratio for easier interpretation, for each one point increase on the idealism scale there was a doubling of the odds that the respondent would not approve the research.

- Relativism's effect is smaller, and in the opposite direction, with a one point increase on the nine-point relativism scale being associated with the odds of approving the research increasing by a multiplicative factor of 1.39.

- The odds ratios of the scenario dummy variables compare each scenario except medical to the medical scenario. For the theory dummy variable, the .314 odds ratio means that the odds of approval of theory-testing research are only .314 times those of medical research.

- Inverted odds ratios for the dummy variables coding the effect of the scenario variable indicated that the odds of approval for the medical scenario were 2.38 times higher than for the meat scenario and 3.22 times higher than for the theory scenario.

Let us now revisit the issue of the **decision rule** used to determine into which group to classify a subject given that subject's estimated probability of group membership. While the most obvious decision rule would be to classify the subject into the target group if $p > .5$ and into the other group if $p < .5$, you may well want to choose a different decision rule given the relative seriousness of making one sort of error (for example, declaring a patient to have breast cancer when she does not) or the other sort of error (declaring the patient not to have breast cancer when she does).

Repeat our analysis with classification done with a different decision rule. Click **Analyze, Regression, Binary Logistic, Options**. In the resulting dialog window, change the **Classification Cutoff** from .5 to .4. The window should look like this:
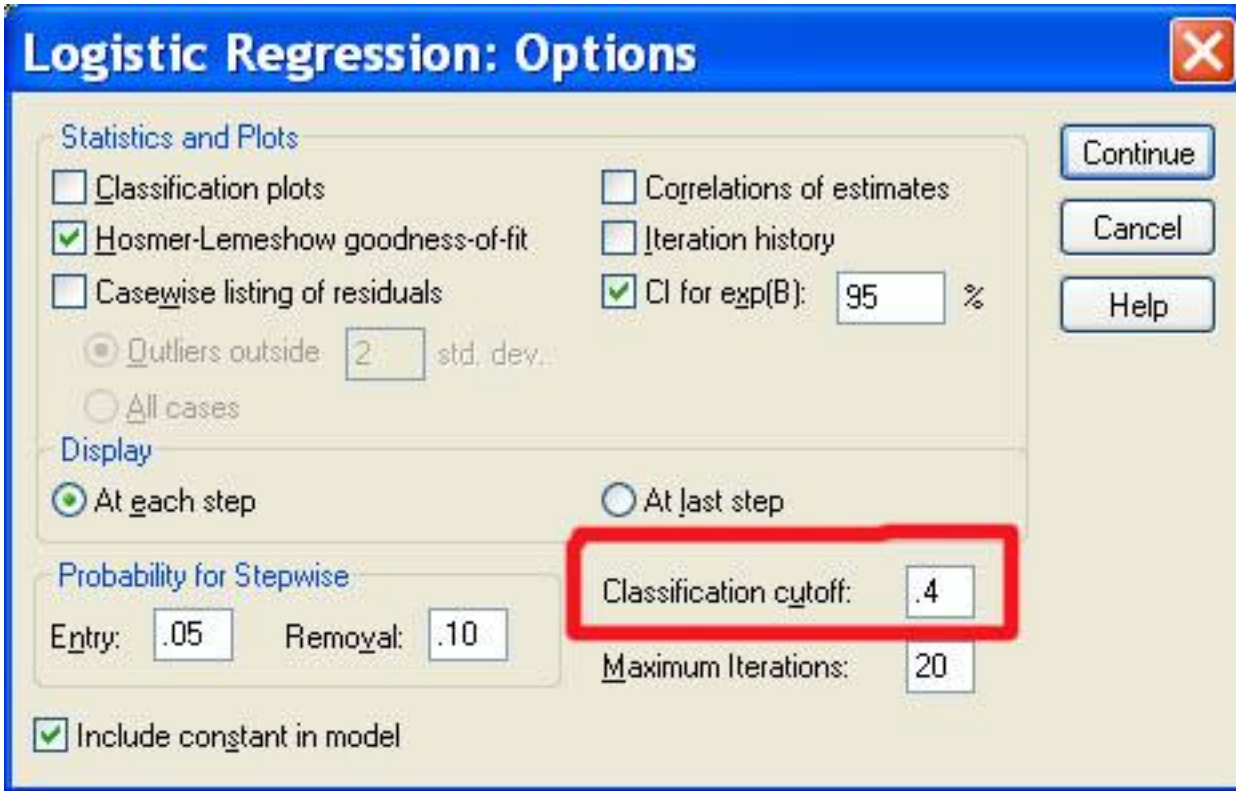
Click Continue, OK.

Now SPSS will classify a subject into the "Continue the Research" group if the estimated probability of membership in that group is .4 or higher, and into the "Stop the Research" group otherwise. Take a look at the classification output and see how the change in cutoff has changed the classification results. Fill in the table below to compare the two models with respect to classification statistics.

Value When Cutoff =	.5	.4
Sensitivity		
Specificity		
False Positive Rate		
False Negative Rate		
Overall % Correct		

SAS makes it much easier to see the effects of the decision rule on sensitivity etc. Using the ctable option, one gets output like this:

```
-----------------------------------------------------------------------------------

                              The LOGISTIC Procedure

                              Classification Table

                  Correct        Incorrect                    Percentages
         Prob            Non-            Non-          Sensi-  Speci-  False  False
         Level  Event   Event   Event   Event  Correct tivity ficity   POS    NEG

         0.160   123     56      131      5      56.8   96.1   29.9   51.6    8.2
         0.180   122     65      122      6      59.4   95.3   34.8   50.0    8.5
         0.200   120     72      115      8      61.0   93.8   38.5   48.9   10.0
         0.220   116     84      103     12      63.5   90.6   44.9   47.0   12.5
```

```
0.240    113    93    94    15    65.4    88.3    49.7    45.4    13.9
0.260    110   100    87    18    66.7    85.9    53.5    44.2    15.3
0.280    108   106    81    20    67.9    84.4    56.7    42.9    15.9
0.300    105   108    79    23    67.6    82.0    57.8    42.9    17.6
0.320    103   115    72    25    69.2    80.5    61.5    41.1    17.9
0.340    100   118    69    28    69.2    78.1    63.1    40.8    19.2
0.360     97   120    67    31    68.9    75.8    64.2    40.9    20.5
0.380     96   124    63    32    69.8    75.0    66.3    39.6    20.5
0.400     94   130    57    34    71.1    73.4    69.5    37.7    20.7
0.420     88   134    53    40    70.5    68.8    71.7    37.6    23.0
0.440     86   140    47    42    71.7    67.2    74.9    35.3    23.1
0.460     79   141    46    49    69.8    61.7    75.4    36.8    25.8
0.480     75   144    43    53    69.5    58.6    77.0    36.4    26.9
0.500     71   147    40    57    69.2    55.5    78.6    36.0    27.9
0.520     69   152    35    59    70.2    53.9    81.3    33.7    28.0
0.540     67   157    30    61    71.1    52.3    84.0    30.9    28.0
0.560     65   159    28    63    71.1    50.8    85.0    30.1    28.4
0.580     61   159    28    67    69.8    47.7    85.0    31.5    29.6
0.600     56   162    25    72    69.2    43.8    86.6    30.9    30.8
0.620     50   165    22    78    68.3    39.1    88.2    30.6    32.1
0.640     48   166    21    80    67.9    37.5    88.8    30.4    32.5
0.660     43   170    17    85    67.6    33.6    90.9    28.3    33.3
0.680     40   170    17    88    66.7    31.3    90.9    29.8    34.1
0.700     36   173    14    92    66.3    28.1    92.5    28.0    34.7
0.720     30   177    10    98    65.7    23.4    94.7    25.0    35.6
0.740     28   178     9   100    65.4    21.9    95.2    24.3    36.0
0.760     23   180     7   105    64.4    18.0    96.3    23.3    36.8
0.780     22   180     7   106    64.1    17.2    96.3    24.1    37.1
0.800     18   181     6   110    63.2    14.1    96.8    25.0    37.8
0.820     17   182     5   111    63.2    13.3    97.3    22.7    37.9
0.840     13   184     3   115    62.5    10.2    98.4    18.8    38.5
0.860     12   185     2   116    62.5     9.4    98.9    14.3    38.5
0.880      8   185     2   120    61.3     6.3    98.9    20.0    39.3
0.900      7   185     2   121    61.0     5.5    98.9    22.2    39.5
0.920      5   187     0   123    61.0     3.9   100.0     0.0    39.7
0.940      1   187     0   127    59.7     0.8   100.0     0.0    40.4
0.960      1   187     0   127    59.7     0.8   100.0     0.0    40.4
0.980      0   187     0   128    59.4     0.0   100.0     .      40.6
```

     The classification results given by SAS are a little less impressive because SAS uses a jackknifed classification procedure. Classification results are biased when the coefficients used to classify a subject were developed, in part, with data provided by that same subject. SPSS' classification results do not remove such bias. With jackknifed classification, SAS eliminates the subject currently being classified when computing the coefficients used to classify that subject. Of course, this procedure is computationally more intense than that used by SPSS. If you would like to learn more about conducting logistic regression with SAS, see my document at http://core.ecu.edu/psyc/wuenschk/MV/MultReg/Logistic-SAS.pdf.

Beyond An Introduction to Logistic Regression

     I have left out of this handout much about logistic regression. We could consider logistic regression with a criterion variable with more than two levels, with that variable being either qualitative or ordinal. We could consider testing of interaction terms. We could consider sequential and stepwise construction of logistic models. We could talk about detecting outliers among the cases, dealing with multicollinearity and nonlinear relationships between predictors and the logit, and so on. If you wish to learn more about logistic regression, I recommend, as a starting point, Chapter 10 in *Using Multivariate Statistics*, 5th edition, by Tabachnick and Fidell (Pearson, 2007).

Presenting the Results

     Let me close with an example of how to present the results of a logistic regression. In the example below you will see that I have included both the multivariate analysis (logistic regression)

and univariate analysis. I assume that you all already know how to conduct the univariate analyses I present below.

Table 1

Effect of Scenario on Percentage of Participants Voting to Allow the Research to Continue and Participants' Mean Justification Score

Scenario	Percentage Support
Theory	31
Meat	37
Cosmetic	40
Veterinary	41
Medical	54

As shown in Table 1, only the medical research received support from a majority of the respondents. Overall a majority of respondents (59%) voted to stop the research. Logistic regression analysis was employed to predict the probability that a participant would approve continuation of the research. The predictor variables were participant's gender, idealism, relativism, and four dummy variables coding the scenario. A test of the full model versus a model with intercept only was statistically significant, $\chi^2(7, N = 315) = 87.51$, $p < .001$. The model was able correctly to classify 73% of those who approved the research and 70% of those who did not, for an overall success rate of 71%.

Table 2 shows the logistic regression coefficient, Wald test, and odds ratio for each of the predictors. Employing a .05 criterion of statistical significance, gender, idealism, relativism, and two of the scenario dummy variables had significant partial effects. The odds ratio for gender indicates that when holding all other variables constant, a man is 3.5 times more likely to approve the research than is a woman. Inverting the odds ratio for idealism reveals that for each one point increase on the nine-point idealism scale there is a doubling of the odds that the participant will not approve the research. Although significant, the effect of relativism was much smaller than that of idealism, with a one point increase on the nine-point idealism scale being associated with the odds of approving the research increasing by a multiplicative factor of 1.39. The scenario variable was dummy coded using the medical scenario as the reference group. Only the theory and the meat scenarios were approved significantly less than the medical scenario. Inverted odds ratios for these dummy variables indicate that the odds of approval for the medical scenario were 2.38 times higher than for the meat scenario and 3.22 times higher than for the theory scenario.

Univariate analysis indicated that men were significantly more likely to approve the research (59%) than were women (30%), $\chi^2(1, N = 315) = 25.68$, $p < .001$, that those who approved the research were significantly less idealistic ($M = 5.87$, $SD = 1.23$) than those who didn't ($M = 6.92$, $SD = 1.22$), $t(313) = 7.47$, $p < .001$, that those who approved the research were significantly more relativistic ($M = 6.26$, $SD = 0.99$) than those who didn't ($M = 5.91$, $SD = 1.19$), $t(313) = 2.71$, $p = .007$, and that the omnibus effect of scenario fell short of significance, $\chi^2(4, N = 315) = 7.44$, $p = .11$.
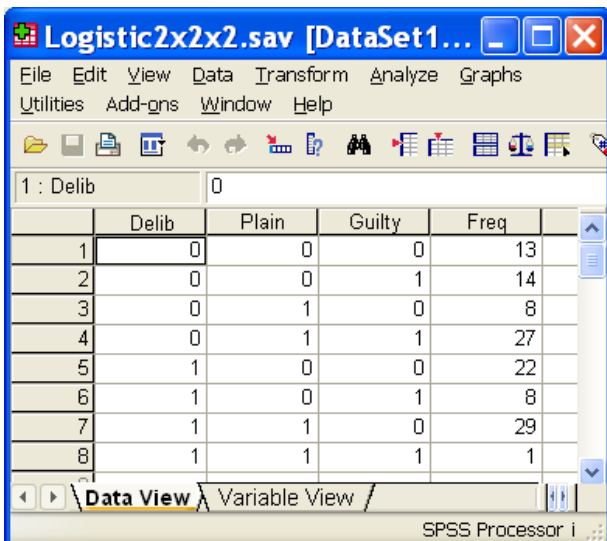
Table 2

Logistic Regression Predicting Decision From Gender, Ideology, and Scenario

Predictor	*B*	Wald χ^2	*p*	Odds Ratio
Gender	1.25	20.59	< .001	3.51
Idealism	-0.70	37.89	< .001	0.50
Relativism	0.33	6.63	.01	1.39
Scenario				
Cosmetic	-0.71	2.85	.091	0.49
Theory	-1.16	7.35	.007	0.31
Meat	-0.87	4.16	.041	0.42
Veterinary	-0.54	1.75	.186	0.58

Interaction Terms

Interaction terms can be included in a logistic model. When the variables in an interaction are continuous they probably should be centered. Consider the following research: Mock jurors are presented with a criminal case in which there is some doubt about the guilt of the defendant. For half of the jurors the defendant is physically attractive, for the other half she is "plain." Half of the jurors are asked to recommend a verdict without having deliberated, the other half are asked about their recommendation only after a short deliberation with others. The deliberating mock jurors were primed with instructions predisposing them to change their opinion if convinced by the arguments of others. We could use a logit analysis here, but elect to use a logistic regression instead. The article in which these results were published is: Patry, M. W. (2008). Attractive but guilty: Deliberation and the physical attractiveness bias. *Psychological Reports*, *102*, 727-733.
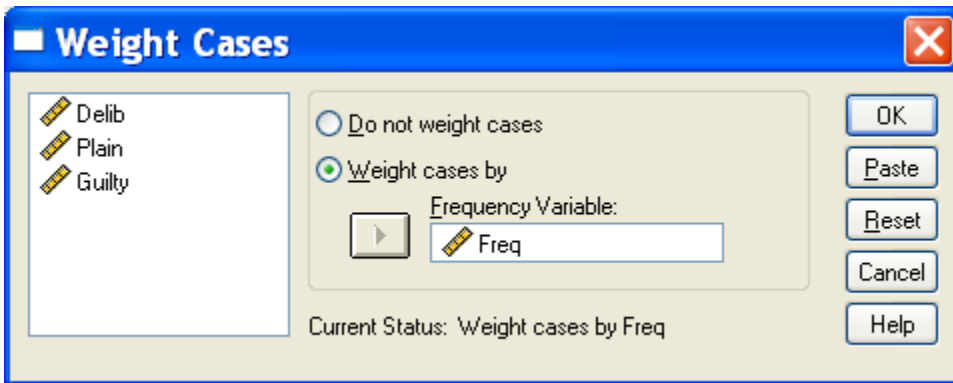
The data are in Logistic2x2x2.sav at my SPSS Data Page. Download the data and bring them into SPSS. Each row in the data file represents one cell in the three-way contingency table. Freq is the number of scores in the cell.
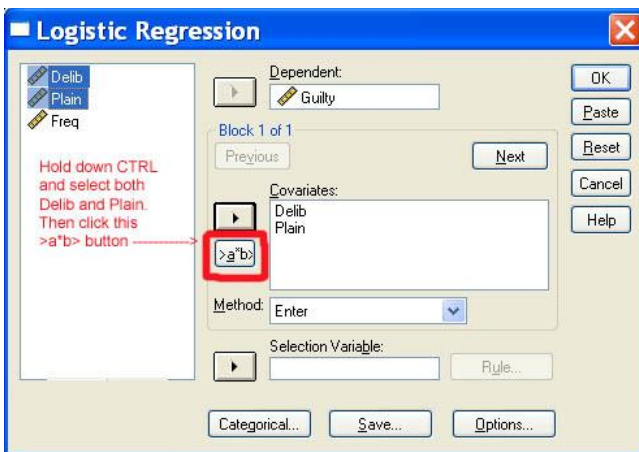

Tell SPSS to weight cases by Freq. Data, Weight Cases:

Analyze, Regression, Binary Logistic. Slide Guilty into the Dependent box and Delib and Plain into the Covariates box. Highlight both Delib and Plain in the pane on the left and then click the >a*b> box.

This creates the interaction term. It could also be created by simply creating a new variable, Interaction = Delib∗Plain.
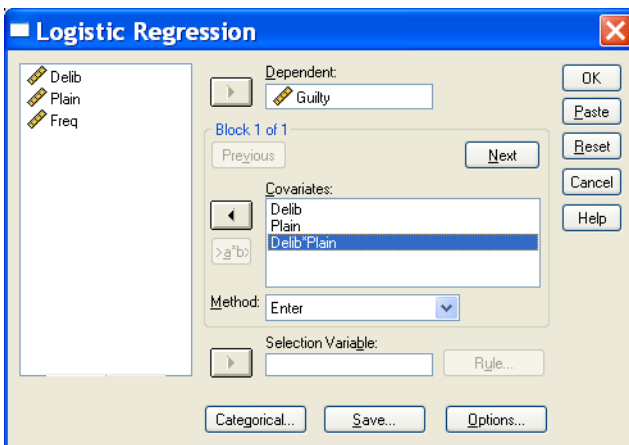
Under Options, ask for the Hosmer-Lemeshow test and confidence intervals on the odds ratios.
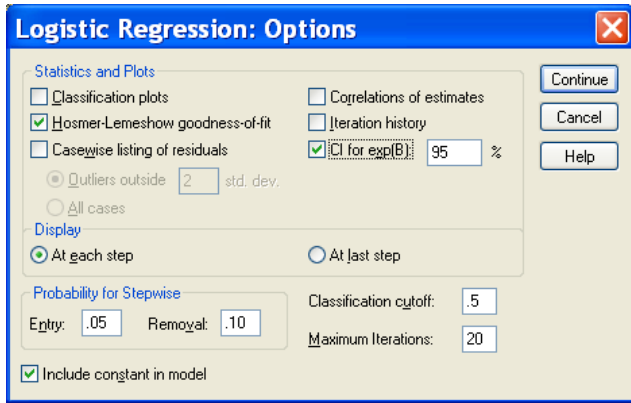
You will find that the odds ratios are .338 for Delib, 3.134 for Plain, and 0.030 for the interaction.

Variables in the Equation

		Wald	df	Sig.	Exp(B)	95.0% C.I.f or EXP(B) Lower	Upper
Step 1[a]	Delib	3.697	1	.054	.338	.112	1.021
	Plain	4.204	1	.040	3.134	1.052	9.339
	Delib by Plain	8.075	1	.004	.030	.003	.338
	Constant	.037	1	.847	1.077		

a. Variable(s) entered on step 1: Delib, Plain, Delib * Plain .

Those who deliberated were less likely to suggest a guilty verdict (15%) than those who did not deliberate (66%), but this (partial) effect fell just short of statistical significance in the logistic regression (but a 2 x 2 chi-square would show it to be significant).

Plain defendants were significantly more likely (43%) than physically attractive defendants (39%) to be found guilty. This effect would fall well short of statistical significance with a 2 x 2 chi-square.

We should not pay much attention to the main effects, given that the interaction is powerful.

The interaction odds ratio can be simply computed, by hand, from the cell frequencies.

- For those who did deliberate, the odds of a guilty verdict are 1/29 when the defendant was plain and 8/22 when she was attractive, yielding a conditional odds ratio of 0.09483.

Plain * Guilty Crosstabulation[a]

			Guilty No	Yes	Total
Plain	Attrractive	Count	22	8	30
		% within Plain	73.3%	26.7%	100.0%
	Plain	Count	29	1	30
		% within Plain	96.7%	3.3%	100.0%
Total		Count	51	9	60
		% within Plain	85.0%	15.0%	100.0%

a. Delib = Yes

- For those who did not deliberate, the odds of a guilty verdict are 27/8 when the defendant was plain and 14/13 when she was attractive, yielding a conditional odds ratio of 3.1339.

Plain * Guilty Crosstabulation[a]

|			Guilty		Total
			No	Yes	
Plain	Attractive	Count	13	14	27
		% within Plain	48.1%	51.9%	100.0%
	Plain	Count	8	27	35
		% within Plain	22.9%	77.1%	100.0%
Total		Count	21	41	62
		% within Plain	33.9%	66.1%	100.0%

a. Delib = No

- The interaction odds ratio is simply the ratio of these conditional odds ratios – that is, .09483/3.1339 = 0.030.

Follow-up analysis shows that among those who did not deliberate the plain defendant was found guilty significantly more often than the attractive defendant, $\chi^2(1, N = 62) = 4.353$, $p = .037$, but among those who did deliberate the attractive defendant was found guilty significantly more often than the plain defendant, $\chi^2(1, N = 60) = 6.405$, $p = .011$.

Interaction Between a Dichotomous Predictor and a Continuous Predictor

Suppose that I had some reason to suspect that the effect of idealism differed between men and women. I can create the interaction term just as shown above.
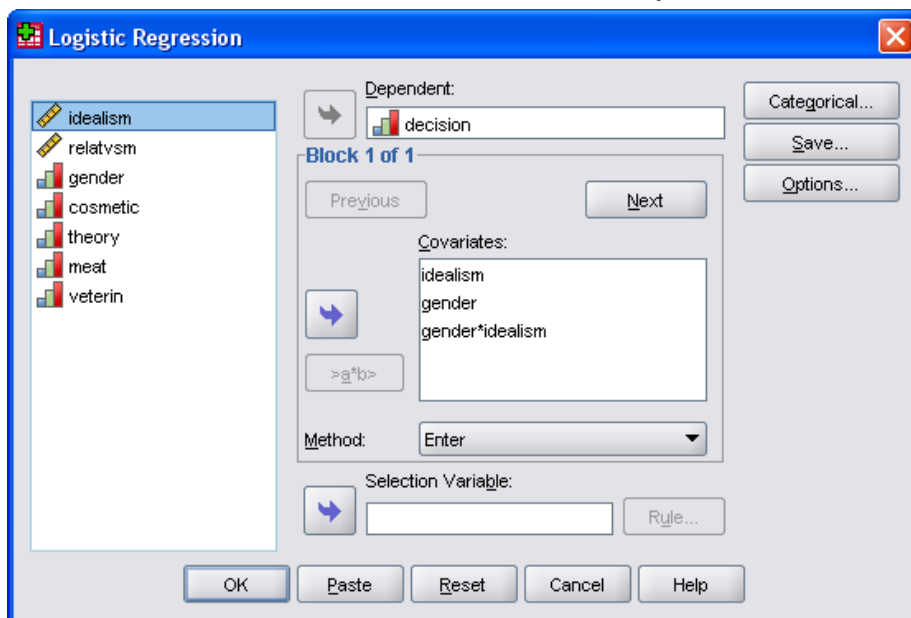
Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	idealism	-.773	.145	28.572	1	.000	.461
	gender	-.530	1.441	.135	1	.713	.589
	gender by idealism	.268	.223	1.439	1	.230	1.307
	Constant	4.107	.921	19.903	1	.000	60.747

a. Variable(s) entered on step 1: idealism, gender, gender * idealism .

As you can see, the interaction falls short of significance.

Partially Standardized B Weights and Odds Ratios

The value of a predictor's B (and the associated odds ratio) is highly dependent on the unit of measure. Suppose I am predicting whether or not an archer hits the target. One predictor is distance to the target. Another is how much training the archer has had. Suppose I measure distance in inches and training in years. I would not expect much of an increase in the logit when decreasing distance by an inch, but I would expect a considerable increase when increasing training by a year. Suppose I measured distance in miles and training in seconds. Now I would expect a large B for distance and a small B for training. For purposes of making comparisons between the predictors, it may be helpful to standardize the B weights.

Suppose that a third predictor is the archer's score on a survey of political conservatism and that a photo of Karl Marx appears on the target. The unit of measure here is not intrinsically meaningful – how much is a one point change in score on this survey. Here too it may be helpful to standardize the predictors. Menard (*The American Statistician*, 2004, *58*, 218-223) discussed several ways to standardize B weights. I favor simply standardizing the predictor, which can be simply accomplished by converting the predictor scores to *z* scores or by multiplying the unstandardized B weight by the predictor's standard deviation. While one could also standardize the dichotomous outcome variable (group membership), I prefer to leave that unstandardized.

In research here at ECU, Cathy Hall gathered data that is useful in predicting who will be retained in our engineering program. Among the predictor variables are high school GPA, score on the quantitative section of the SAT, and one of the Big Five personality measures, openness to experience. Here are the results of a binary logistic regression predicting retention from high school GPA, quantitative SAT, and openness (you can find more detail here).

Predictor	Unstandardized		Standardized	
	B	Odds Ratio	B	Odds Ratio
HS-GPA	1.296	3.656	0.510	1.665
SAT-Q	0.006	1.006	0.440	1.553
Openness	0.100	1.105	0.435	1.545

The novice might look at the unstandardized statistics and conclude that SAT-Q and openness to experience are of little utility, but the standardized coefficients show that not to be true. The three predictors differ little in their unique contributions to predicting retention in the engineering program.

Practice Your Newly Learned Skills

Now that you know how to do a logistic regression, you should practice those skills. I have presented below three exercises designed to give you a little practice.

Exercise 1: What is Beautiful is Good, and Vice Versa

Castellow, Wuensch, and Moore (1990, *Journal of Social Behavior and Personality, 5,* 547-562) found that physically attractive litigants are favored by jurors hearing a civil case involving

alleged sexual harassment (we manipulated physical attractiveness by controlling the photos of the litigants seen by the mock jurors). Guilty verdicts were more likely when the male defendant was physically unattractive and when the female plaintiff was physically attractive. We also found that jurors rated the physically attractive litigants as more socially desirable than the physically unattractive litigants -- that is, more warm, sincere, intelligent, kind, and so on. Perhaps the jurors treated the physically attractive litigants better because they assumed that physically attractive people are more socially desirable (kinder, more sincere, etc.).

Our next research project (Egbert, Moore, Wuensch, & Castellow, 1992, *Journal of Social Behavior and Personality, 7,* 569-579) involved our manipulating (via character witness testimony) the litigants' social desirability but providing mock jurors with no information on physical attractiveness. The jurors treated litigants described as socially desirable more favorably than they treated those described as socially undesirable. However, these jurors also rated the socially desirable litigants as more physically attractive than the socially undesirable litigants, despite having never seen them! Might our jurors be treating the socially desirable litigants more favorably because they assume that socially desirable people are more physically attractive than are socially undesirable people?

We next conducted research in which we manipulated both the physical attractiveness and the social desirability of the litigants (Moore, Wuensch, Hedges, & Castellow, 1994*, Journal of Social Behavior and Personality*, *9*, 715-730). Data from selected variables from this research project are in the SPSS data file found at http://core.ecu.edu/psyc/wuenschk/SPSS/Jury94.sav. Please download that file now.

You should use SPSS to predict verdict from all of the other variables. The variables in the file are as follows:

- VERDICT -- whether the mock juror recommended a not guilty (0) or a guilty (1) verdict -- that is, finding in favor of the defendant (0) or the plaintiff (1)
- ATTRACT -- whether the photos of the defendant were physically unattractive (0) or physically attractive (1)
- GENDER -- whether the mock juror was female (0) or male (1)
- SOCIABLE -- the mock juror's rating of the sociability of the defendant, on a 9-point scale, with higher representing greater sociability
- WARMTH -- ratings of the defendant's warmth, 9-point scale
- KIND -- ratings of defendant's kindness
- SENSITIV -- ratings of defendant's sensitivity
- INTELLIG -- ratings of defendant's intelligence

You should also conduct bivariate analysis (Pearson Chi-Square and independent samples t-tests) to test the significance of the association between each predictor and the criterion variable (verdict). You will find that some of the predictors have significant zero-order associations with the criterion but are not significant in the full model logistic regression. Why is that?

You should find that the sociability predictor has an odds ratio that indicates that the odds of a guilty verdict increase as the rated sociability of the defendant increases -- but one would expect that greater sociability would be associated with a reduced probability of being found guilty, and the univariate analysis indicates exactly that (mean sociability was significantly higher with those who were found not guilty). How is it possible for our multivariate (partial) effect to be opposite in direction to that indicated by our univariate analysis? You may wish to consult the following documents to help understand this:

Redundancy and Suppression

Simpson's Paradox

Exercise 2: Predicting Whether or Not Sexual Harassment Will Be Reported

Download the SPSS data file found at http://core.ecu.edu/psyc/wuenschk/SPSS/Harass-Howell.sav. This file was obtained from David Howell's site, http://www.uvm.edu/~dhowell/StatPages/Methods/DataMethods5/Harass.dat. I have added value labels to a couple of the variables. You should use SPSS to conduct a logistic regression predicting the variable "reported" from all of the other variables. Here is a brief description for each variable:

- REPORTED -- whether (1) or not (0) an incident of sexual harassment was reported
- AGE -- age of the victim
- MARSTAT -- marital status of the victim -- 1 = married, 2 = single
- FEMinist ideology -- the higher the score, the more feminist the victim
- OFFENSUV -- offensiveness of the harassment -- higher = more offensive

I suggest that you obtain, in addition to the multivariate analysis, some bivariate statistics, including independent samples t-tests, a Pearson chi-square contingency table analysis, and simple Pearson correlation coefficients for all pairs of variables.

Exercise 3: Predicting Who Will Drop-Out of School

Download the SPSS data file found at http://core.ecu.edu/psyc/wuenschk/SPSS/Dropout.sav. I simulated these data based on the results of research by David Howell and H. R. Huessy (*Pediatrics*, *76*, 185-190). You should use SPSS to predict the variable "dropout" from all of the other variables. Here is a brief description for each variable:

- DROPOUT -- whether the student dropped out of high school before graduating -- 0 = No, 1 = Yes.
- ADDSC -- a measure of the extent to which each child had exhibited behaviors associated with attention deficit disorder. These data were collected while the children were in the 2nd, 4th, and 5th grades combined into one variable in the present data set.
- REPEAT -- did the child ever repeat a grade -- 0 = No, 1 = Yes.
- SOCPROB -- was the child considered to have had more than the usual number of social problems in the 9th grade -- 0 = No, 1 = Yes.

I suggest that you obtain, in addition to the multivariate analysis, some bivariate statistics, including independent samples t-tests, a Pearson chi-square contingency table analysis, and simple Pearson correlation coefficients for all pairs of variables. Imagine that you were actually going to use the results of your analysis to decide which children to select as "at risk" for dropping out before graduation. Your intention is, after identifying those children, to intervene in a way designed to make it less likely that they will drop out. What cutoff would you employ in your decision rule?

Having SPSS Create the Dummy Variables for You

Dependent Variable Encoding

Original Value	Internal Value
stop	0
continue	1

The predicted event is that the subject will vote to continue the research. The scenario variable is categorical, with five levels. SPSS allows you to select as the reference group either the

group with the lowest numeric code or that with the highest numeric code. I selected the highest (last) code, the medical scenario.
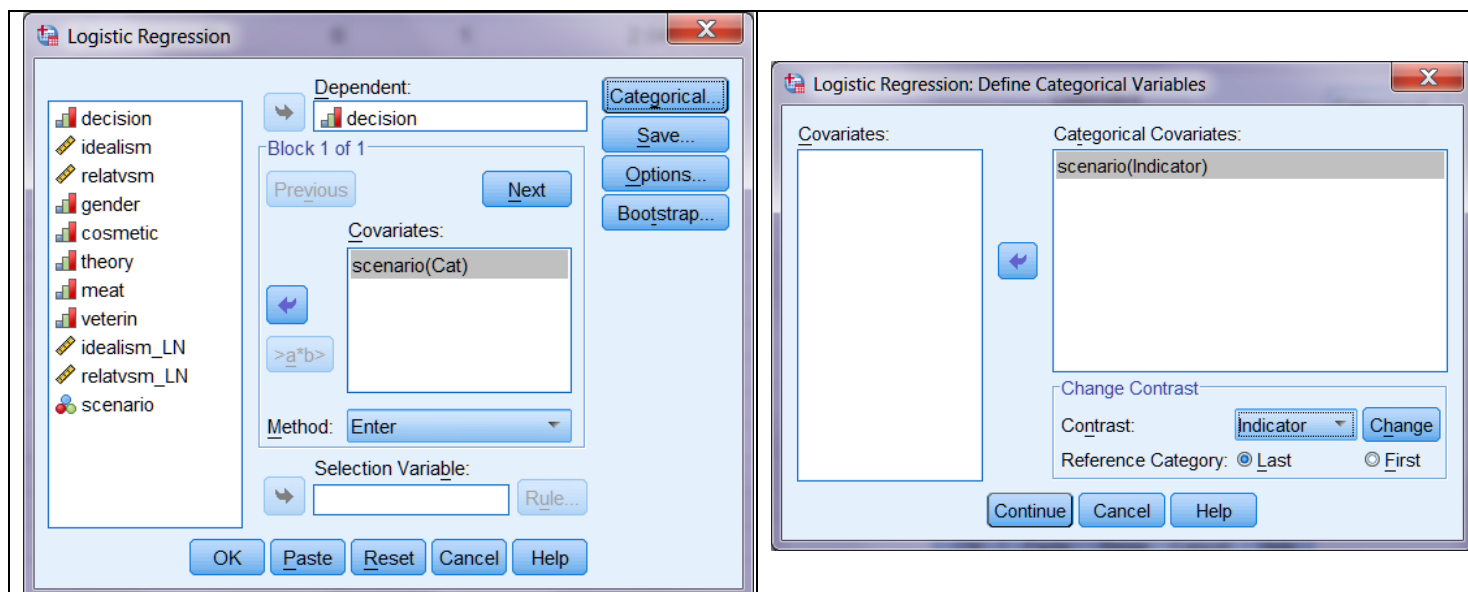
SPSS shows you the coding of the k-1 = 4 dummy variables it has created

Categorical Variables Codings

		Frequency	Parameter coding			
			(1)	(2)	(3)	(4)
scenario	1.00	62	1.000	.000	.000	.000
	2.00	64	.000	1.000	.000	.000
	3.00	63	.000	.000	1.000	.000
	4.00	63	.000	.000	.000	1.000
	5.00	63	.000	.000	.000	.000

Block 0: Beginning Block

Classification Table[a,b]

Observed			Predicted		
			decision		Percentage Correct
			stop	continue	
Step 0	decision	stop	187	0	100.0
		continue	128	0	.0
	Overall Percentage				59.4

a. Constant is included in the model.

b. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-.379	.115	10.919	1	.001	.684

Block 1: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	7.417	4	.115
	Block	7.417	4	.115
	Model	7.417	4	.115

Addition of the four scenario dummy variables has lowered the -2 Log Likelihood by 7.417.

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	418.149[a]	.023	.031

a. Estimation terminated at iteration number 3 because parameter estimates changed by less than .001.

Classification Table[a]

Observed			Predicted		
			decision		Percentage
			stop	continue	Correct
Step 1	decision	stop	158	29	84.5
		continue	94	34	26.6
	Overall Percentage				61.0

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	scenario			7.291	4	.121	
	scenario(1)	-.551	.362	2.320	1	.128	.576
	scenario(2)	-.948	.370	6.571	1	.010	.388
	scenario(3)	-.712	.364	3.835	1	.050	.490
	scenario(4)	-.512	.360	2.025	1	.155	.599
	Constant	.159	.253	.396	1	.529	1.172

a. Variable(s) entered on step 1: scenario.

The Wald chi-square is more conservative than the drop in the -2 Log Likelihood chi-square (7.291 rather than 7.417). SPSS gives a Wald chi-square for each of the four dummy variables. The second and third contrasts are significant. Inverting the odds ratio for ease of interpretation, the odds of voting to continue the research were 2.58 times higher when the scenario was medical than when the scenario was neuroscience research and 2.04 times higher when medical than when agricultural (feed the poor). Distressingly, approval of the research was not significantly different between the cosmetic scenario and the medical scenario. Our students are reluctant to condone animal research intended to feed the poor or to investigate brain function, but they condone animal research that is used to gain approval of new cosmetic products.
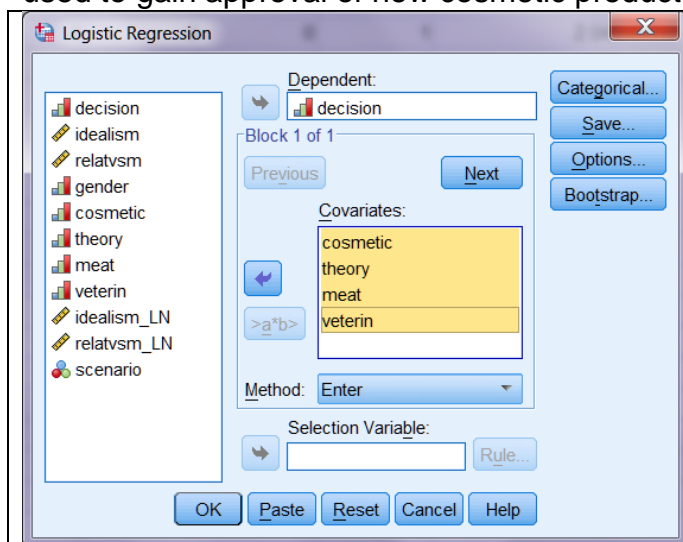
Here is some of the output from the analysis where I created the dummy variables myself.

		Chi-square	df	Sig.
Step 1	Step	7.417	4	.115

As earlier, adding the dummy variables lowered the -2 Log Likelihood by 7.417, an effect short of significance.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	cosmetic	-.551	.362	2.320	1	.128	.576
	theory	-.948	.370	6.571	1	.010	.388
	meat	-.712	.364	3.835	1	.050	.490
	veterin	-.512	.360	2.025	1	.155	.599
	Constant	.159	.253	.396	1	.529	1.172

a. Variable(s) entered on step 1: cosmetic, theory, meat, veterin.

Notice that we obtain a Wald chi-square for each of the four dummy variables. We do not get a Wald chi-square for the omnibus effect of scenario, nor do we need one, since the reduction in the -2 Log Likelihood chi-square tests the omnibus effect of scenario.

Types of Contrasts Available in SPSS Binary Logistic Regression

- Indicator. Contrasts indicate the presence or absence of category membership. The reference category is represented in the contrast matrix as a row of zeros.
- Simple. Each category of the predictor variable (except the reference category) is compared to the reference category.
- Difference. Each category of the predictor variable except the first category is compared to the average effect of previous categories. Also known as reverse Helmert contrasts.
- Helmert. Each category of the predictor variable except the last category is compared to the average effect of subsequent categories.
- Repeated. Each category of the predictor variable except the first category is compared to the category that precedes it.
- Polynomial. Orthogonal polynomial contrasts. Categories are assumed to be equally spaced. Polynomial contrasts are available for numeric variables only.
- Deviation. Each category of the predictor variable except the reference category is compared to the overall effect.
- If you select Deviation, Simple, or Indicator, select either First or Last as the reference category.
- Note that the method is not actually changed until you click Change.

Here is an example. Sudden heart failure patients are the subjects here. They were asked whether or not anxiety had been a problem for them recently (this is the predicted event). Our predictor variables were sex and group, where group was (1) No ICD, (2) ICD but no history of shock from it, and (3) ICD with history of shock from it.

We first tested a model with Group, Sex, and Group x Sex predictors.

```
LOGISTIC REGRESSION VARIABLES AnxietyNow
 /METHOD=ENTER Sex Group Group*Sex
 /CONTRAST (Sex)=Helmert
 /CONTRAST (Group)=Helmert
 /CRITERIA=PIN(.05) POUT(.10) ITERATE(20) CUT(.5).
```

The output showed that the Group X Sex interaction fell just short of statistical significance.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
	Group * Sex			5.258	2	.072			
	Group(1) by Sex(1)	2.202	1.305	2.847	1	.092	9.045	.701	116.743
	Group(2) by Sex(1)	-1.078	.711	2.300	1	.129	.340	.085	1.370
	Constant	.363	.296	1.507	1	.220	1.438		

Accordingly, we dropped the interaction from the model. Here is the output for the main effects model.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	Group			8.065	2	.018			
	Group(1)	1.315	.569	5.352	1	.021	3.727	1.223	11.359
	Group(2)	.591	.354	2.784	1	.095	1.805	.902	3.614
	Sex(1)	.585	.338	2.995	1	.084	1.795	.925	3.482
	Constant	.655	.281	5.429	1	.020	1.925		

The effect of sex fell just short of significance, but group had a significant effect. Recall that we used Helmert contrasts for the effect of group.

Categorical Variables Codings

		Frequency	Parameter coding	
			(1)	(2)
Group	No ICD	32	.667	.000
	ICD No Shock	80	-.333	.500
	ICD Shock	63	-.333	-.500
Sex	Male	97	1.000	
	Female	78	.000	

The first contrast compares those who did not have an ICD (Group 1) with those who did (Groups 2 and 3). That contrast was significant. Those who had an ICD were 3.7 times more likely to identify anxiety as a problem than were those who did not have an ICD. The second contrast compared those who had an ICD but no history of shock with those who had an ICD with a history of shock. This contrast fell short of statistical significance.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	Group			8.065	2	.018			
	Group(1)	1.315	.569	5.352	1	.021	3.727	1.223	11.359
	Group(2)	.591	.354	2.784	1	.095	1.805	.902	3.614
	Sex(1)	.585	.338	2.995	1	.084	1.795	.925	3.482
	Constant	.655	.281	5.429	1	.020	1.925		

LINKS

- [Fair Use of This Document](#)
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- [Why Not Let SPSS Do The Dummy Coding of Categorical Predictors?](#)
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