

Sections 5.3, 5.4, 5.5

Timothy Hanson

Department of Statistics, University of South Carolina

Stat 770: Categorical Data Analysis

Alcohol consumption and malformation example continued:

Let's use $X = 1$ as the reference level. Then the model is

$$\text{logit } \pi(X) = \beta_0 + \beta_1 I\{X = 2\} + \beta_2 I\{X = 3\} + \beta_3 I\{X = 4\} + \beta_4 I\{X = 5\}.$$

We may be interested in the how the odds of malformation changes when dropping from 3-4 drinks per week ($X = 4$) to less than one drink per week ($X = 2$), given by $e^{\beta_3 - \beta_1}$.

A *contrast* is a linear combination

$\mathbf{c}'\boldsymbol{\beta} = c_1\beta_1 + c_2\beta_2 + \cdots + c_{p-1}\beta_{p-1}$. We are specifically interested in $H_0 : \beta_3 = \beta_1$, or equivalently, $H_0 : \beta_3 - \beta_1 = 0$, as well as estimating $e^{\beta_3 - \beta_1}$.

```
proc logistic; class cons / param=ref ref=first; model present/total = cons;  
  contrast "beta3-beta1" cons -1 0 1 0;  
  contrast "exp(beta3-beta1)" cons -1 0 1 0 / estimate=exp;  
  contrast "beta3-beta1" cons -1 0 1 0 / estimate;
```

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-5.8736	0.1445	1651.3399	<.0001
cons	2	-0.0682	0.2174	0.0984	0.7538
cons	3	0.8136	0.4713	2.9795	0.0843
cons	4	1.0374	1.0143	1.0460	0.3064
cons	5	2.2632	1.0235	4.8900	0.0270

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
cons 2 vs 1	0.934	0.610	1.430
cons 3 vs 1	2.256	0.896	5.683
cons 4 vs 1	2.822	0.386	20.602
cons 5 vs 1	9.614	1.293	71.460

Let θ_{ij} be the odds ratio for malformation when going from level $X = i$ to $X = j$. We automatically get $\hat{\theta}_{21} = e^{-0.068} = 0.934$, $\hat{\theta}_{31} = e^{0.814} = 2.26$, etc. Since $\theta_{42} = \theta_{41}/\theta_{21}$ we can estimate $\hat{\theta}_{42} = 2.822/0.934 = 3.02$, or else directly from the dummy variable coefficients, $e^{1.037 - (-0.068)} = 3.02$.

Contrast statement

The CONTRAST command allows us to further test $H_0 : \beta_3 = \beta_1$ and to get a 95% CI for the odds ratio $\theta_{42} = e^{\beta_3 - \beta_1}$.

Contrast Test Results			
Contrast	DF	Chi-Square	Pr > ChiSq
beta3-beta1	1	1.1817	0.2770
exp(beta3-beta1)	1	1.1817	0.2770
beta3-beta1	1	1.1817	0.2770

Contrast Rows Estimation and Testing Results

Contrast	Type	Standard		Alpha Confidence Limits			Wald		
		Row Estimate	Error	Lower	Upper	Chi-Square	Pr > ChiSq		
exp(beta3-beta1)	EXP	1	3.0209	3.0723	0.05	0.4116	22.1728	1.1817	0.277
beta3-beta1	PARM	1	1.1056	1.0170	0.05	-0.8878	3.0989	1.1817	0.277

We are allowed linear contrasts or the exponential of linear contrasts. To get, for example, the *relative risk* of malformation,

$$h(\beta) = \frac{P(Y = 1|X = 4)}{P(Y = 1|X = 2)} = \frac{e^{\beta_0 + \beta_3} / [1 + e^{\beta_0 + \beta_3}]}{e^{\beta_0 + \beta_1} / [1 + e^{\beta_0 + \beta_1}]},$$

takes more work.

5.3.4–5.3.6 $l \times 2$ tables

Let $X = 1, 2, \dots, l$ be an ordinal predictor. If the log odds increases linearly with category $X = i$ we have

$$\text{logit } \pi(i) = \alpha + \beta i.$$

If the probability increases linearly we have

$$\pi(i) = \alpha + \beta i.$$

If we replace $X = 1, 2, \dots, l$ by scores $u_1 \leq u_2 \leq \dots \leq u_l$ we get

$$\text{logit } \pi(i) = \alpha + \beta u_i,$$

and

$$\pi(i) = \alpha + \beta u_i.$$

Cochran-Armitage trend test

In any of these models testing $H_0 : \beta = 0$ is a test of $X \perp Y$ versus a particular monotone alternative. The last of the four is called the Cochran-Armitage trend test (p. 178). These can all be fit in GENMOD.

```
proc genmod; model present/total = cons / dist=bin link=logit;  
proc genmod; model present/total = cons / dist=bin link=identity;  
proc genmod; model present/total = score / dist=bin link=logit;  
proc genmod; model present/total = score / dist=bin link=identity;
```

For alcohol consumption/malformation data, the p -values are respectively 0.17, 0.28, 0.01, 0.13. The first two use $X = 1, 2, 3, 4, 5$ and the last two use $X = 0.0, 0.5, 1.5, 4.0, 7.0$. The Pearson $X^2 = 2.05$ with $p = 0.56$ for the logit model with scores and $X^2 = 5.68$ with $p = 0.13$ for using 1, 2, 3, 4, 5. The model using scores fits better and from this model we reject $H_0 : \beta = 0$ with $p = 0.01$.

Does this analysis make you uneasy for any reason?

5.3.7 Better living through models

Consider an $I \times 2$ table where X is categorical and Y is binary. When the probability of $Y = 2$ is the same for each level of $X = i$, $\pi(i) = P(Y = 2|X = i) = \pi$, we have $X \perp Y$. In terms of log-odds this is

$$\text{logit } \pi(i) = \alpha.$$

- If X is nominal, allowing a separate probability for each level of X gives

$$\text{logit } \pi(i) = \alpha + \beta_i,$$

for $i = 1, \dots, I$; the saturated model.

- When X is ordinal, we can use the above alternative model, or instead use scores $u_1 \leq u_2 \leq \dots \leq u_I$ in place of X and fit the model

$$\text{logit } \pi(i) = \alpha + \beta u_i.$$

Power can increase or decrease...

In the first case a test of $H_0 : \beta_1 = \dots = \beta_I = 0$ is a test of $H_0 : X \perp Y$ versus the most general possible alternative. The test statistic (score, Wald, or LRT) has a χ^2_{I-1} distribution under H_0 . In the second case a test of $H_0 : \beta = 0$ tests $X \perp Y$ versus a focused, *linear* alternative. The test statistic has a χ^2_1 distribution under H_0 .

- If X is ordinal and the logistic regression model treating X as continuous fits okay, you can increase your power to reject $H_0 : X \perp Y$ by looking in one particular direction (linear log-odds of scores).
- If the model *does not* fit then you can *lose* power by looking in only one place to the exclusion of other alternatives.
- For nominal X we pretty much can only test the saturated model to the intercept model.

5.4 Multiple predictors

Now we have $p - 1$ predictors $\mathbf{x}_i = (1, x_{i1}, \dots, x_{i,p-1})$ and fit

$$Y_i \sim \text{bin} \left(n_i, \frac{\exp(\beta_0 + \beta_1 x_{i1} + \dots + \beta_{p-1} x_{i,p-1})}{1 + \exp(\beta_0 + \beta_1 x_{i1} + \dots + \beta_{p-1} x_{i,p-1})} \right).$$

- Many of these predictors may be sets of dummy variables associated with categorical predictors.
- e^{β_j} is now termed the *adjusted* odds ratio. This is how the odds of the event occurring changes when x_j increases by one unit *keeping the remaining predictors constant*.
- This interpretation may not make sense if two predictors are highly related. Examples?

$$H_0 : \text{logit } \pi(\mathbf{x}) = \beta_0$$

An overall test of $H_0 : \text{logit } \pi(\mathbf{x}) = \beta_0$ versus $H_1 : \text{logit } \pi(\mathbf{x}) = \mathbf{x}'\beta$ is generated in PROC LOGISTIC three different ways: LRT, score, and Wald versions. This checks whether some subset of variables in the model is important.

Recall the crab data covariates:

- C = color (1,2,3,4=light medium, medium, dark medium, dark).
- S = spine condition (1,2,3=both good, one worn or broken, both worn or broken).
- W = carapace width (cm).
- Wt = weight (kg).

We'll take $C = 4$ and $S = 3$ as baseline categories.

Full additive model

There are two categorical predictors, C and S , and two continuous predictors W and Wt . Let $Y = 1$ if a randomly drawn crab has one or more satellites and $\mathbf{x} = (C, S, W, Wt)$ be her covariates. An *additive* model including all four covariates would look like

$$\begin{aligned} \text{logit } \pi(\mathbf{x}) = & \beta_0 + \beta_1 I\{C = 1\} + \beta_2 I\{C = 2\} + \beta_3 I\{C = 3\} \\ & + \beta_4 I\{S = 1\} + \beta_5 I\{S = 2\} + \beta_6 W + \beta_7 Wt \end{aligned}$$

This model is fit via

```
proc logistic data=crabs1 descending;
  class color spine / param=ref;
  model y = color spine width weight / lackfit;
```

The H-L GOF statistic yields $p = 0.88$ so there's no evidence of gross lack of fit. The parameter estimates are:

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-9.2734	3.8378	5.8386	0.0157
color	1	1.6087	0.9355	2.9567	0.0855
color	2	1.5058	0.5667	7.0607	0.0079
color	3	1.1198	0.5933	3.5624	0.0591
spine	1	-0.4003	0.5027	0.6340	0.4259
spine	2	-0.4963	0.6292	0.6222	0.4302
width	1	0.2631	0.1953	1.8152	0.1779
weight	1	0.8258	0.7038	1.3765	0.2407

Color seems to be important. Plugging in $\hat{\beta}$ for β ,

$$\text{logit } \hat{\pi}(\mathbf{x}) = -9.27 + 1.61I\{C = 1\} + 1.51I\{C = 2\} + 1.11I\{C = 3\} \\ -0.40I\{S = 1\} - 0.50I\{S = 2\} + 0.26W + 0.83Wt$$

Overall checks that one or more predictors are important:

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	40.5565	7	<.0001
Score	36.3068	7	<.0001
Wald	29.4763	7	0.0001

Type III tests for dropping effects

Type III tests are (1) $H_0 : \beta_1 = \beta_2 = \beta_3 = 0$, color not needed to explain whether a female has satellite(s), (2) $H_0 : \beta_4 = \beta_5 = 0$, spine not needed, (3) $H_0 : \beta_6 = 0$, width not needed, and (4) $H_0 : \beta_7 = 0$, weight not needed:

Type 3 Analysis of Effects

Effect	DF	Wald	
		Chi-Square	Pr > ChiSq
color	3	7.1610	0.0669
spine	2	1.0105	0.6034
width	1	1.8152	0.1779
weight	1	1.3765	0.2407

The largest p -value is 0.6 for dropping spine condition from the model. When refitting the model without spine condition, we still strongly reject $H_0 : \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = 0$, and the H-L shows no evidence of lack of fit. We have:

Type 3 Analysis of Effects

Effect	DF	Wald	
		Chi-Square	Pr > ChiSq
color	3	6.3143	0.0973
width	1	2.3355	0.1265
weight	1	1.2263	0.2681

Drop weight too

We do not reject that we can drop weight from the model, and so we do:

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	38.3015	4	<.0001
Score	34.3384	4	<.0001
Wald	27.6788	4	<.0001

Type 3 Analysis of Effects

Effect	DF	Wald Chi-Square	Pr > ChiSq
color	3	6.6246	0.0849
width	1	19.6573	<.0001

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-12.7151	2.7618	21.1965	<.0001
color	1	1.3299	0.8525	2.4335	0.1188
color	2	1.4023	0.5484	6.5380	0.0106
color	3	1.1061	0.5921	3.4901	0.0617
width	1	0.4680	0.1055	19.6573	<.0001

Model with color and width

The new model is

$$\text{logit } \pi(\mathbf{x}) = \beta_0 + \beta_1 I\{C = 1\} + \beta_2 I\{C = 2\} + \beta_3 I\{C = 3\} + \beta_4 W.$$

We *do not* reject that color can be dropped from the model $H_0 : \beta_1 = \beta_2 = \beta_3$, but we do reject that the dummy for $C = 2$ can be dropped, $H_0 : \beta_2 = 0$. Maybe unnecessary levels in color are clouding its importance. Let's see what happens when we try to combine levels of C .

```
proc logistic data=crabs1 descending;
  class color spine / param=ref;
  model y = color width / lackfit;
  contrast '1 vs 2' color 1 -1 0;
  contrast '1 vs 3' color 1 0 -1;
  contrast '1 vs 4' color 1 0 0;
  contrast '2 vs 3' color 0 1 -1;
  contrast '2 vs 4' color 0 1 0;
  contrast '3 vs 4' color 0 0 1;
```

p -values for combining levels:

Contrast Test Results

Contrast	DF	Wald	
		Chi-Square	Pr > ChiSq
1 vs 2	1	0.0096	0.9220
1 vs 3	1	0.0829	0.7733
1 vs 4	1	2.4335	0.1188
2 vs 3	1	0.5031	0.4781
2 vs 4	1	6.5380	0.0106
3 vs 4	1	3.4901	0.0617

We reject that we can combine levels $C = 2$ and $C = 4$, and almost reject combining $C = 3$ and $C = 4$. Let's combine $C = 1, 2, 3$ into one category $D = 1$ "not dark" and $C = 4$ is $D = 2$, "dark." See also Figure 5.7 (p. 188).

```
proc logistic data=crabs1 descending;  
  class dark / param=ref ref=first;  
  model y = dark width / lackfit;
```

We include `dark=1; if color=4 then dark=2;` in the DATA step.

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	37.8006	2	<.0001

Type 3 Analysis of Effects

Effect	DF	Wald	
		Chi-Square	Pr > ChiSq
dark	1	6.1162	0.0134
width	1	21.0841	<.0001

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard	Wald	
			Error	Chi-Square	Pr > ChiSq
Intercept	1	-11.6790	2.6925	18.8143	<.0001
dark	2	-1.3005	0.5259	6.1162	0.0134
width	1	0.4782	0.1041	21.0841	<.0001

Odds Ratio Estimates

Effect		Point	95% Wald	
		Estimate	Confidence Limits	
dark	2 vs 1	0.272	0.097	0.764
width		1.613	1.315	1.979

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
5.5744	8	0.6948

- The odds of having satellite(s) significantly decreases by a little less than a third, 0.27, for dark crabs regardless of width.
- The odds of having satellite(s) significantly increases by a factor of 1.6 for every *cm* increase in carapice width regardless of color.
- Lighter, wider crabs tend to have satellite(s) more often.
- The H-L GOF test shows no gross LOF.
- We didn't check for interactions. If an interaction between color and width existed, then the odds ratio of satellite(s) for dark versus not dark crabs would change with how wide she is.

Interactions and quadratic effects

An additive model is easily interpreted because an odds ratio from changing values of one predictor does not change with levels of another predictor. However, often this is incorrect and we may introduce additional terms into the model such as interactions.

An interaction between two predictors allows the odds ratio for increasing one predictor to change with levels of another. For example, in the last model fit the odds of having satellite(s) decreases by 0.27 for dark crabs vs. not dark *regardless of carapace width*.

A two-way interaction is defined by multiplying the variables together; if one or both variables are categorical then all possible pairings of dummy variables are considered.

Two categorical predictors

Example: Say we have two categorical predictors, $X = 1, 2, 3$ and $Z = 1, 2, 3, 4$. An additive model is

$$\begin{aligned}\text{logit } \pi(X, Z) &= \beta_0 + \beta_1 I\{X = 1\} + \beta_2 I\{X = 2\} \\ &\quad + \beta_3 I\{Z = 1\} + \beta_4 I\{Z = 2\} + \beta_5 I\{Z = 3\}.\end{aligned}$$

The model that includes an interaction between X and Z adds $(3 - 1)(4 - 1) = 6$ additional dummy variables accounting for all possible ways, i.e. all levels of Z , the log odds can change between from $X = i$ to $X = j$. The new model is rather cumbersome:

$$\begin{aligned}\text{logit } \pi(X, Z) &= \beta_0 + \beta_1 I\{X = 1\} + \beta_2 I\{X = 2\} \\ &\quad + \beta_3 I\{Z = 1\} + \beta_4 I\{Z = 2\} + \beta_5 I\{Z = 3\} \\ &\quad + \beta_6 I\{X = 1\} I\{Z = 1\} + \beta_7 I\{X = 1\} I\{Z = 2\} \\ &\quad + \beta_8 I\{X = 1\} I\{Z = 3\} + \beta_9 I\{X = 2\} I\{Z = 1\} \\ &\quad + \beta_{10} I\{X = 2\} I\{Z = 2\} + \beta_{11} I\{X = 2\} I\{Z = 3\}.\end{aligned}$$

SAS's CLASS statement for categorical predictors

In PROC GENMOD and PROC LOGISTIC, categorical variables are defined through the CLASS statement and all dummy variables are created and handled internally.

The Type III table provides a test that the interaction can be dropped; the table of regression coefficients tell you whether individual dummies can be dropped.

Let's consider the crab data again, but consider an interaction between categorical D and continuous W :

```
proc logistic data=crabs1 descending;  
  class dark / param=ref ref=first;  
  model y = dark width dark*width / lackfit;
```

Type 3 Analysis of Effects

Effect	DF	Wald Chi-Square	Pr > ChiSq
dark	1	0.9039	0.3417
width	1	20.7562	<.0001
width*dark	1	1.2686	0.2600

We accept that the interaction is not needed.

Consider the interaction model anyway, for illustration

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-12.8116	2.9577	18.7629	<.0001
dark	2	6.9578	7.3182	0.9039	0.3417
width	1	0.5222	0.1146	20.7562	<.0001
width*dark	2	-0.3217	0.2857	1.2686	0.2600

The model is:

$$\text{logit } \pi(D, W) = -12.81 + 6.96I\{D = 2\} + 0.52W - 0.32I\{D = 2\}W.$$

The odds ratio for the probability of satellite(s) going from $D = 2$ to $D = 1$ is estimated

$$\begin{aligned} \frac{P(Y = 1|D = 2, W)/P(Y = 0|D = 2, W)}{P(Y = 1|D = 1, W)/P(Y = 0|D = 1, W)} &= \frac{e^{-12.81+6.96+0.52W-0.32W}}{e^{-12.81+0.52W}} \\ &= e^{6.96-0.32W}. \end{aligned}$$

How about the odds ratio going from W to $W + 1$?

For a categorical predictor X with I levels, adding $I - 1$ dummy variables allows for a different event probability at each level of X .

For a continuous predictor Z , the model assumes that the log-odds of the event increases *linearly* with Z . This may or may not be a reasonable assumption, but can be checked by adding nonlinear terms, the simplest being Z^2 .

Consider a simple model with continuous Z :

$$\text{logit } \pi(Z) = \beta_0 + \beta_1 Z.$$

LOF from this model can manifest itself in rejecting a GOF test (Pearson, deviance, or H-L) or a residual plot that shows curvature (Chapter 6).

Adding a quadratic term

$$\text{logit } \pi(Z) = \beta_0 + \beta_1 Z + \beta_2 Z^2,$$

may improve fit and allows testing the adequacy of the simpler model via $H_0 : \beta_2 = 0$. Higher order powers can be added, but the model can become unstable with, say, higher than cubic powers. A better approach might be to fit a *generalized additive model* (GAM):

$$\text{logit } \pi(Z) = f(Z),$$

where $f(\cdot)$ is estimated from the data, often using splines. Coming up in Chapter 7.

Adding a simple quadratic term can be done, e.g.,
`proc logistic; model y/n = z z*z;`

5.5 Fitting logistic regression models

The data are (\mathbf{x}_i, Y_i) for $i = 1, \dots, N$.

The model is

$$Y_i \sim \text{bin} \left(n_i, \frac{e^{\beta' \mathbf{x}_i}}{1 + e^{\beta' \mathbf{x}_i}} \right).$$

The pmf of Y_i in terms of β is

$$p(y_i; \beta) = \binom{n_i}{y_i} \left[\frac{e^{\beta' \mathbf{x}_i}}{1 + e^{\beta' \mathbf{x}_i}} \right]^{y_i} \left[1 - \frac{e^{\beta' \mathbf{x}_i}}{1 + e^{\beta' \mathbf{x}_i}} \right]^{n_i - y_i}.$$

The likelihood is the product of all N of these and the log-likelihood simplifies to

$$L(\beta) = \sum_{j=1}^p \beta_j \sum_{i=1}^N y_i x_{ij} - \sum_{i=1}^N \log \left[1 + \exp \left(\sum_{j=1}^p \beta_j x_{ij} \right) \right] + \text{constant}.$$

Likelihood equations

The likelihood (or score) equations are obtained by taking partial derivatives of $L(\boldsymbol{\beta})$ with respect to elements of $\boldsymbol{\beta}$ and setting equal to zero. Newton-Raphson is used to get $\hat{\boldsymbol{\beta}}$, see 5.5.4 if interested.

The inverse of the covariance of $\hat{\boldsymbol{\beta}}$ has ij^{th} element

$$-\frac{\partial^2 L(\boldsymbol{\beta})}{\partial \beta_i \partial \beta_j} = \sum_{s=1}^N x_{si} x_{sj} n_s \pi_s (1 - \pi_s),$$

where $\pi_s = \frac{e^{\boldsymbol{\beta}' \mathbf{x}_s}}{1 + e^{\boldsymbol{\beta}' \mathbf{x}_s}}$. The *estimated* covariance matrix $\widehat{\text{cov}}(\hat{\boldsymbol{\beta}})$ is obtained by replacing $\boldsymbol{\beta}$ with $\hat{\boldsymbol{\beta}}$. This can be rewritten

$$\widehat{\text{cov}}(\hat{\boldsymbol{\beta}}) = \{\mathbf{X}' \text{diag}[n_i \hat{\pi}_i (1 - \hat{\pi}_i)] \mathbf{X}\}^{-1}.$$