




Chapter 14 Weighted Least Squares

14.1 Introduction

- Previous chapters discussed logistic regression models using maximum likelihood estimation
- Functions modeled were logits, or cumulative logits
- What about modeling other functions of categorical data? Might be interested in mean scores, proportions, or more complicated functions of responses
- Weighted least squares provides methodology for wide range of functions. This chapter focuses on mean scores and proportions, as well as estimates from complex sample survey designs


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- CATMOD is a general procedure used for modeling categorical data:
 - 1) For response function = **generalized logits**, CATMOD performs **logistic regression** using **maximum likelihood estimation**
 - 2) For response function = **means, etc.**, CATMOD performs **weighted least squares** analysis

Statistical Methodology for Weighted Least Squares

Group	Response				Total
	1	2	...	r	
1	n_{11}	n_{12}	...	n_{1r}	n_{1+}
2	n_{21}	n_{22}	...	n_{2r}	n_{2+}
.
.
.
s	n_{s1}	n_{s2}	...	n_{sr}	n_{s+}

Proportion of subjects in i^{th} group who have j^{th} response is

$$p_{ij} = n_{ij} / n_{i+}$$



Suppose $\mathbf{n}'_i = (n_{i1}, n_{i2}, \dots, n_{ir})$ represents vector of responses for i^{th} subpopulation, and $\mathbf{n}' = (\mathbf{n}'_1, \mathbf{n}'_2, \dots, \mathbf{n}'_s)$, then \mathbf{n} follows product multinomial distribution:

$$\Pr\{\mathbf{n}\} = \prod_{i=1}^s n_{i+}! \prod_{j=1}^r \pi_{ij}^{n_{ij}} / n_{ij}!,$$

where π_{ij} is probability that a randomly selected subject from i^{th} group has j^{th} response profile. The π_{ij} satisfy the natural restrictions

$$\sum_{j=1}^r \pi_{ij} = 1 \text{ for } i = 1, 2, \dots, s.$$


Suppose $\mathbf{p}_i = \mathbf{n}_i / n_{i+}$ is $r \times 1$ vector of observed proportions for i th group, and $\mathbf{p}' = (\mathbf{p}'_1, \mathbf{p}'_2, \dots, \mathbf{p}'_s)$ is $(sr \times 1)$ compound vector of proportions. Then a consistent estimator of covariance matrix for proportions in i th row is:

$$\mathbf{V}(\mathbf{p}_i) = \frac{1}{n_{i+}} \begin{bmatrix} p_{i1}(1-p_{i1}) & -p_{i1}p_{i2} & \dots & -p_{i1}p_{ir} \\ -p_{i2}p_{i1} & p_{i2}(1-p_{i2}) & \dots & -p_{i2}p_{ir} \\ \vdots & \vdots & \ddots & \vdots \\ -p_{ir}p_{i1} & -p_{ir}p_{i2} & \dots & p_{ir}(1-p_{ir}) \end{bmatrix}$$

and covariance matrix for vector \mathbf{p} is:

$$\mathbf{V}_p = \begin{bmatrix} \mathbf{V}_1 & \mathbf{0} & \dots & \mathbf{0} \\ \mathbf{0} & \mathbf{V}_2 & \dots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \dots & \mathbf{V}_s \end{bmatrix}$$


where \mathbf{V}_i is covariance matrix for \mathbf{p}_i .



Suppose $F_1(\mathbf{p}), F_2(\mathbf{p}), \dots, F_u(\mathbf{p})$ is a set of u functions of \mathbf{p} . Each is required to have continuous partial derivatives through order two, and \mathbf{F} must have nonsingular covariance matrix:

$$\mathbf{V}_F(\boldsymbol{\pi}) = [\mathbf{H}(\boldsymbol{\pi})][\mathbf{V}(\boldsymbol{\pi})][\mathbf{H}(\boldsymbol{\pi})]',$$

where $\mathbf{H}(\boldsymbol{\pi}) = \left[\frac{\partial \mathbf{F}}{\partial \mathbf{z}} \right]_{\mathbf{z}=\boldsymbol{\pi}}$ is the first derivative matrix of $\mathbf{F}(\mathbf{z})$.



F is consistent estimator of $F(\pi)$, so linear model can be used to investigate variability among elements of $F(\pi)$:

$$E_A\{F(p)\} = F(\pi) = X\beta,$$

where X is known model matrix with rank $t \leq u$, β is $t \times 1$ vector of unknown parameters.

Goodness of fit of model is assessed with

$$Q(X, F) = (WF)' [WV_F W']^{-1} WF,$$

where W is any fullrank $[(u - t) \times u]$ matrix orthogonal to X . $Q(X, F)$ is approximately distributed chi-square with $(u - t)$ degrees of freedom when sample sizes large enough so that elements of F have approximate multivariate normal distribution. (Wald statistics).



The following statistic

$$Q_W = (F - Xb)'V_F^{-1}(F - Xb)$$


is identical to $Q(X, F)$ and obtained by using weighted least squares to produce estimate for β .

$$b = (X'V_F^{-1}X)^{-1}X'V_F^{-1}F$$

which is minimum modified chi-square estimator.

Consistent estimator for covariance matrix of b is

$$V(b) = (X'V_F^{-1}X)^{-1}.$$




Linear hypotheses of form $\mathbf{C}\boldsymbol{\beta} = \mathbf{0}$, where \mathbf{C} is known $c \times t$ matrix of constants of rank c , can be tested with Wald statistic

$$Q_C = (\mathbf{C}\mathbf{b})' \left[\mathbf{C}(\mathbf{X}'\mathbf{V}_F^{-1}\mathbf{X})^{-1}\mathbf{C}' \right]^{-1} (\mathbf{C}\mathbf{b})$$

Q_C is distributed chi-square with c degrees of freedom.

Predicted values for $\mathbf{F}(\boldsymbol{\pi})$ can be calculated from

$$\hat{\mathbf{F}} = \mathbf{X}\mathbf{b} = \mathbf{X}(\mathbf{X}'\mathbf{V}_F^{-1}\mathbf{X})^{-1}\mathbf{X}'\mathbf{V}_F^{-1}\mathbf{F}$$



and consistent estimators for variances of \hat{F} can be obtained from diagonal elements of


$$V_{\hat{F}} = X(X'V_F^{-1}X)^{-1}X'.$$

While $F(p)$ can take on wide range of forms, a few functions are commonly used. You can fit a strictly linear model

$$F(p) = Ap,$$

where A is matrix for known constants. Covariance matrix of F is written

$$V_F = AV_pA'.$$




Another common model is loglinear:

$$\mathbf{F}(\mathbf{p}) = \mathbf{A} \log \mathbf{p},$$

where \log transforms vector to corresponding vector of natural logarithms and \mathbf{A} is orthogonal to $\mathbf{1}$ (vector of 1's). In this case,

$$\mathbf{V}_F = \mathbf{A} \mathbf{D}_p^{-1} \mathbf{A}'$$

Where \mathbf{D}_p is diagonal matrix with elements of \mathbf{p} on diagonal.



Many other useful functions can be generated as a sequence of linear, logarithmic, and exponential operations on vector \mathbf{p} .

- linear transformations: $\mathbf{F}_1(\mathbf{p}) = \mathbf{A}_1 \mathbf{p} = \boldsymbol{\alpha}_1$
- logarithmic: $\mathbf{F}_2(\mathbf{p}) = \log(\mathbf{p}) = \boldsymbol{\alpha}_2$
- exponential: $\mathbf{F}_3(\mathbf{p}) = \exp(\mathbf{p}) = \boldsymbol{\alpha}_3$

Corresponding \mathbf{H}_k matrix operators needed to produce covariance matrix for \mathbf{F} are

- $\mathbf{H}_1 = \mathbf{A}_1$
- $\mathbf{H}_2 = \mathbf{D}_p^{-1}$
- $\mathbf{H}_3 = \mathbf{D}_{\alpha 3}$


\mathbf{V}_F is estimated by $\mathbf{V}_F = [\mathbf{H}(\mathbf{p})] \mathbf{V}_p [\mathbf{H}(\mathbf{p})]'$ where $\mathbf{H}(\mathbf{p})$ is a product of first derivative matrices $\mathbf{H}_k(\mathbf{p})$ where k indicates i th operation in accordance with chain rule.

14.2 Weighted Least Squares Methodology

- The following example is used to motivate this discussion:

Epidemiologists investigating air pollution effects conducted a study of childhood respiratory disease. Investigators interested in determining whether sex or residence affected the distribution of colds.

		Periods with colds			
Sex	Res	0	1	2	Total
Female	Rural	45	64	71	180
Female	Urban	80	104	116	300
Male	Rural	84	124	82	290
Male	Urban	106	117	87	310

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- Chapter 9 would suggest using proportional odds model, but response measure of interest is mean number of periods with colds
 - Due to small, discrete number of response values, assumptions of standard linear model are unlikely to be met
 - With only assumption of sufficient sample size (≈ 30 per group), weighted least squares provides useful strategy for analyzing data



To compute the mean periods of colds for females
in a rural residence:

$$\begin{aligned}\text{mean colds} &= 0 \times p_{11} + 1 \times p_{12} + 2 \times p_{13} \\ &= 0 \times (0.25) + 1 \times (0.36) + 2 \times (0.39) \\ &= 1.14\end{aligned}$$




In matrix formulation, this is written

$$A\mathbf{p}_1 = \begin{bmatrix} 0 & 1 & 2 \end{bmatrix} \mathbf{p}_1 = \begin{bmatrix} 0 & 1 & 2 \end{bmatrix} \begin{bmatrix} 0.25 \\ 0.36 \\ 0.39 \end{bmatrix} = 1.14$$

The response functions for all of the colds data are


$$\mathbf{F}(\mathbf{p}) = A\mathbf{p} = \begin{bmatrix} 1.14 \\ 1.12 \\ 0.99 \\ 0.94 \end{bmatrix}$$



Now fit a statistical model that determines the effect of sex and residence on the mean functions.

$$\begin{bmatrix} \mathbf{F}(\mathbf{p}_1) \\ \mathbf{F}(\mathbf{p}_2) \\ \mathbf{F}(\mathbf{p}_3) \\ \mathbf{F}(\mathbf{p}_4) \end{bmatrix} = \begin{bmatrix} \alpha + \beta_1 + \beta_2 + \beta_3 \\ \alpha + \beta_1 - \beta_2 - \beta_3 \\ \alpha - \beta_1 + \beta_2 - \beta_3 \\ \alpha - \beta_1 - \beta_2 + \beta_3 \end{bmatrix}$$
$$= \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & -1 & -1 \\ 1 & -1 & 1 & -1 \\ 1 & -1 & -1 & 1 \end{bmatrix} \begin{bmatrix} \alpha \\ \beta_1 \\ \beta_2 \\ \beta_3 \end{bmatrix}$$

- α is the intercept
- β_1 is the differential effect for gender
- β_2 is the differential effect for residence
- β_3 represents their interaction

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- The intercept is the mean number of colds averaged equally over all the groups.
 - The differential effects represent deviations from the mean, so this model is known as a *deviation from the mean* model.
 - The CATMOD procedure uses *fullrank* parameterization. If an effect such as gender or residence has r levels, then it is represented by $r - 1$ parameters.

14.3 Using PROC CATMOD for Weighted Least Squares Analysis

The following statements create SAS data set COLDS.

```
data colds;
    input sex $ residence $ periods count @@;
    datalines;
female rural 0 45 female rural 1 64 female rural 2 71
female urban 0 80 female urban 1 104 female urban 2 116
male rural 0 84 male rural 1 124 male rural 2 82
male urban 0 106 male urban 1 117 male urban 2 87
;
run;
```



The following set of SAS statements requests that a weighted least squares analysis be performed for the mean response, using the saturated model.

```
proc catmod;  
  weight count;  
  response means;  
  model periods = sex residence sex*residence  
                  /freq prob design;  
run;
```

- one mean function computed per group
- WLS is the default estimation method for functions other than logits (maximum likelihood for logits)
- WEIGHT statement required for frequency from data

Output 14.1 Population and Response Profiles

POPULATION PROFILES			
Sample	SEX	RESIDNCE	Sample Size
1	female	rural	180
2	female	urban	300
3	male	rural	290
4	male	urban	310

RESPONSE PROFILES

Response	PERIODS
1	0
2	1
3	2

Output 14.2 Table Frequencies and Proportions

RESPONSE FREQUENCIES

Sample	Response Number		
	1	2	3
1	45	64	71
2	80	104	116
3	84	124	82
4	106	117	87

RESPONSE PROBABILITIES

Sample	Response Number		
	1	2	3
1	0.25	0.35556	0.39444
2	0.26667	0.34667	0.38667
3	0.28966	0.42759	0.28276
4	0.34194	0.37742	0.28065

Output 14.3 Observed Response Functions and Model Matrix

Sample	Response Function	DESIGN MATRIX			
		1	2	3	4
1	1.14444	1	1	1	1
2	1.12000	1	1	-1	-1
3	0.99310	1	-1	1	-1
4	0.93871	1	-1	-1	1

Output 14.4 ANOVA Table

ANALYSIS-OF-VARIANCE TABLE

Source	DF	Chi-Square	Prob

INTERCEPT	1	1841.13	<.0001
SEX	1	11.57	0.0007
RESIDNCE	1	0.65	0.4202
SEX*RESIDNCE	1	0.09	0.7594
RESIDUAL	0	.	.

The main effects model is specified.

```
proc catmod;  
  weight count;  
  response means ;  
  model periods = sex residence ;  
run;
```

ANALYSIS-OF-VARIANCE TABLE

Source	DF	Chi-Square	Prob

INTERCEPT	1	1882.77	<.0001
SEX	1	12.08	0.0005
RESIDNCE	1	0.76	0.3839
RESIDUAL	1	0.09	0.7594

The following code requests the single main effect model.

```
proc catmod;  
  population sex residence;  
  weight count;  
  response means;  
  model periods = sex;  
run;
```

ANALYSIS-OF-VARIANCE TABLE

Source	DF	Chi-Square	Prob

INTERCEPT	1	1899.55	<.0001
SEX	1	11.53	0.0007
RESIDUAL	2	0.85	0.6531

14.4 Obstetrical Pain Data: Advanced Modeling of Means

Table 14.4 Number of Hours with Little or No Pain for Women Who Recently Delivered a Baby

Center	Initial Pain		Hours With Little or No Pain									Total
	Status	Treatment	0	1	2	3	4	5	6	7	8	
1	lot	placebo	6	1	2	2	2	3	7	3	0	26
1	lot	a	6	3	1	2	4	4	7	1	0	28
1	lot	b	3	1	0	4	2	3	11	4	0	28
1	lot	ba	0	0	0	1	1	7	9	6	2	26
1	some	placebo	1	0	3	0	2	2	4	4	2	18
1	some	a	2	1	0	2	1	2	4	5	1	18
1	some	b	0	0	0	1	0	3	7	6	2	19
1	some	ba	0	0	0	0	1	3	5	4	6	19
2	lot	placebo	7	2	3	2	3	2	3	2	2	26
2	lot	a	3	1	0	0	3	2	9	7	1	26
2	lot	b	0	0	0	1	1	5	8	7	4	26
2	lot	ba	0	1	0	0	1	2	8	9	5	26
2	some	placebo	2	0	2	1	3	1	2	5	4	20
2	some	a	0	0	0	1	1	1	8	1	7	19
2	some	b	0	2	0	1	0	1	4	6	6	20
2	some	ba	0	0	0	1	3	0	4	7	5	20

Table 14.4 Continued

Initial Pain			Hours With Little or No Pain									Total
Center	Status	Treatment	0	1	2	3	4	5	6	7	8	
3	lot	placebo	6	0	2	2	2	6	1	2	1	22
3	lot	a	4	2	1	5	1	1	3	2	3	22
3	lot	b	5	0	2	3	1	0	2	6	7	26
3	lot	ba	3	2	1	0	0	2	5	9	4	26
3	some	placebo	5	0	0	1	3	1	4	4	5	23
3	some	a	1	0	0	1	3	5	3	3	6	22
3	some	b	3	0	1	1	0	0	3	7	11	26
3	some	ba	0	0	0	1	1	4	2	4	13	25
4	lot	placebo	4	0	1	3	2	1	1	2	2	16
4	lot	a	0	1	3	1	1	6	1	3	6	22
4	lot	b	0	0	0	0	2	7	2	2	9	22
4	lot	ba	1	0	3	0	1	2	3	4	8	22
4	some	placebo	1	0	1	1	4	1	1	0	10	19
4	some	a	0	0	0	1	0	2	2	1	13	19
4	some	b	0	0	0	1	1	1	1	2	11	20
4	some	ba	1	0	0	0	0	2	2	2	14	21

```

proc catmod;
  weight count;
  response 0 .125 .25 .375 .5 .625 .75 .875 1;
  model no_hours = center initial treat
               treat*initial;
run;

```

Output 14.5 Preliminary ANOVA Table

Source	DF	Chi-Square	Prob

INTERCEPT	1	5271.98	<.0001
CENTER	3	29.02	<.0001
INITIAL	1	62.65	<.0001
TREAT	3	92.15	<.0001
INITIAL*TREAT	3	12.63	0.0055
RESIDUAL	21	26.90	0.1743

```
model no_hours = center initial treat(initial);
```

Outputs 14.6 and 14.7 Nested Value ANOVA Table and Parameter Estimates

ANALYSIS-OF-VARIANCE TABLE					
Source		DF	Chi-Square	Prob	

INTERCEPT		1	5271.98	<.0001	
CENTER		3	29.02	<.0001	
INITIAL		1	62.65	<.0001	
TREAT(INITIAL)		6	102.70	<.0001	
RESIDUAL		21	26.90	0.1743	
ANALYSIS OF WEIGHTED-LEAST-SQUARES ESTIMATES					
Effect	Parameter	Estimate	Standard Error	Chi-Square	Prob

INTERCEPT		0.6991	0.00963	5271.98	<.0001
CENTER	1	-0.0484	0.0145	11.24	0.0008
	2	0.0187	0.0145	1.66	0.1982
	3	-0.0415	0.0176	5.56	0.0184
INITIAL	lot	-0.0753	0.00951	62.65	<.0001
TREAT(INITIAL)	placebo lot	-0.1739	0.0283	37.81	<.0001
	treat_a lot	-0.0644	0.0255	6.39	0.0115
	treat_b lot	0.0952	0.0206	21.45	<.0001
	placebo some	-0.1159	0.0284	16.68	<.0001
	treat_a some	0.00740	0.0217	0.12	0.7331
	treat b some	0.0347	0.0206	2.84	0.0921

Table 14.5 Parameter Interpretations

CATMOD Parameter	Model Parameter	Interpretation
1	α	intercept
2	β_1	differential effect for center 1
3	β_2	differential effect for center 2
4	β_3	differential effect for center 3
5	β_4	differential effect for a lot of initial pain
6	β_5	differential effect for placebo for a lot of pain
7	β_6	differential effect for treatment a for a lot of pain
8	β_7	differential effect for treatment b for a lot of pain
9	β_8	differential effect for placebo for some pain
10	β_9	differential effect for treatment a for some pain
11	β_{10}	differential effect for treatment b for some pain

Table 14.6 Hypothesis Tests

Hypothesis	Initial Pain	Contrast	Coefficients					
			β_5	β_6	β_7	β_8	β_9	β_{10}
treatment a vs. placebo	a lot	$-\beta_5 + \beta_6$	-1	1	0	0	0	0
treatment b vs. placebo	a lot	$-\beta_5 + \beta_7$	-1	0	1	0	0	0
treatment ba vs. placebo	a lot	$-2\beta_5 - \beta_6 - \beta_7$	-2	-1	-1	0	0	0
treatment ba vs. a	a lot	$-\beta_5 - 2\beta_6 - \beta_7$	-1	-2	-1	0	0	0
treatment ba vs. b	a lot	$-\beta_5 - \beta_6 - 2\beta_7$	-1	-1	-2	0	0	0
treatment a vs. placebo	some	$-\beta_8 + \beta_9$	0	0	0	-1	1	0
treatment b vs. placebo	some	$-\beta_8 + \beta_{10}$	0	0	0	-1	0	1
treatment ba vs. placebo	some	$-2\beta_8 - \beta_9 - \beta_{10}$	0	0	0	-2	-1	-1
treatment ba vs. a	some	$-\beta_8 - 2\beta_9 - \beta_{10}$	0	0	0	-1	-2	-1
treatment ba vs. b	some	$-\beta_8 - \beta_9 - 2\beta_{10}$	0	0	0	-1	-1	-2

```

contrast 'lot: a-placebo' treat(initial) -1  1  0  0  0  0 ;
contrast 'lot: b-placebo' treat(initial) -1  0  1  0  0  0 ;
contrast 'lot: ba-placebo' treat(initial) -2 -1 -1  0  0  0 ;
contrast 'lot: ba-a'      treat(initial) -1 -2 -1  0  0  0 ;
contrast 'lot: ba-b'      treat(initial) -1 -1 -2  0  0  0 ;
contrast 'some:a-placebo' treat(initial)  0  0  0 -1  1  0 ;
contrast 'some:b-placebo' treat(initial)  0  0  0 -1  0  1 ;
contrast 'some:ba-placebo' treat(initial)  0  0  0 -2 -1 -1 ;
contrast 'some:ba-a'      treat(initial)  0  0  0 -1 -2 -1 ;
contrast 'some:ba-b'      treat(initial)  0  0  0 -1 -1 -2 ;

```


Output 14.8 Contrast Results

Analysis of Contrasts			
Contrast	DF	Chi-Square	Pr > ChiSq
lot: a-placebo	1	5.59	0.0180
lot: b-placebo	1	42.81	<.0001
lot: ba-placebo	1	61.48	<.0001
lot: ba-a	1	32.06	<.0001
lot: ba-b	1	2.59	0.1076
some:a-placebo	1	8.19	0.0042
some:b-placebo	1	12.83	0.0003
some:ba-placebo	1	21.45	<.0001
some:ba-a	1	4.37	0.0365
some:ba-b	1	1.67	0.1964

Table 14.7 Hypothesis Tests

Hypothesis	Coefficients					
	β_5	β_6	β_7	β_8	β_9	β_{10}
treatment a vs. placebo, some vs. a lot	-1	1	0	1	-1	0
treatment b vs. placebo, some vs. a lot	-1	0	1	1	0	-1
treatment ba vs. placebo, some vs. a lot	-2	-1	-1	2	1	1
treatment ba vs. a, some vs. a lot	-1	-2	-1	1	2	1
treatment ba vs. b, some vs. a lot	-1	-1	-2	1	1	2
average treatment a effect	-1	1	0	-1	1	0
average treatment b effect	-1	0	1	-1	0	1
average treatment ba effect	-2	-1	-1	-2	-1	-1
average ba vs. a	-1	-2	-1	-1	-2	-1
average ba vs. b	-1	-1	-2	-1	-1	-2

The next block of CONTRAST statements performs these tests. The last two CONTRAST statements request the 3 df TREAT*INITIAL interaction and the 3 df TREAT effect, respectively. The output is displayed in Output 14.9.

```

contrast 'interact:a-placebo'      treat(initial) -1  1  0  1 -1  0 ;
contrast 'interact:b-placebo'      treat(initial) -1  0  1  1  0 -1 ;
contrast 'interact:ba-placebo'     treat(initial) -2 -1 -1  2  1  1 ;
contrast 'interact:ba-a'           treat(initial)  -1 -2 -1  1  2  1 ;
contrast 'interact:ba-b'           treat(initial)  -1 -1 -2  1  1  2 ;
contrast 'average:a-placebo'       treat(initial) -1  1  0 -1  1  0 ;
contrast 'average:b-placebo'       treat(initial) -1  0  1 -1  0  1 ;
contrast 'average:ba-placebo'      treat(initial) -2 -1 -1 -2 -1 -1 ;
contrast 'average:ba-a'            treat(initial) -1 -2 -1 -1 -2 -1 ;
contrast 'average:ba-b'            treat(initial) -1 -1 -2 -1 -1 -2 ;
contrast 'interaction'             treat(initial) -1  1  0  1 -1  0 ,
                                   treat(initial) -1  0  1  1  0 -1 ,
                                   treat(initial) -2 -1 -1  2  1  1 ;
contrast 'treatment effect'        treat(initial) -1  1  0 -1  1  0 ,
                                   treat(initial) -1  0  1 -1  0  1 ,
                                   treat(initial) -2 -1 -1 -2 -1 -1 ;

```

Output 14.9 Contrast Results

Analysis of Contrasts


Contrast	DF	Chi-Square	Pr > ChiSq
interact:a-placebo	1	0.05	0.8266
interact:b-placebo	1	4.05	0.0441
interact:ba-placebo	1	4.89	0.0271
interact:ba-a	1	8.61	0.0033
interact:ba-b	1	0.04	0.8344
average:a-placebo	1	13.51	0.0002
average:b-placebo	1	50.93	<.0001
average:ba-placebo	1	77.60	<.0001
average:ba-a	1	31.42	<.0001
average:ba-b	1	4.22	0.0399
interaction	3	12.63	0.0055
treatment effect	3	92.15	<.0001

14.7 Repeated Measurements Analysis

- Many studies have research designs that involve multiple measurements of a response over time.
- This section describes methods for analyzing repeated measurements data with weighted least squares

The following data are from Grizzle, Starmer, Koch (1969)

	F = Favorable, U = Unfavorable								
Drug A response	F	F	F	F	U	U	U	U	
Drug B response	F	F	U	U	F	F	U	U	
Drug C response	F	U	F	U	F	U	F	U	Total
Number of subjects	6	16	2	4	2	4	6	6	46



The hypothesis that the marginal distribution of the response variable is the same for all of the repeated measurement factor is called *marginal homogeneity*.

For one population, when you are analyzing marginal probabilities, the test of marginal homogeneity is the test of the main effect of the repeated measurement factor.



WLS Methods for Repeated Measurements

- single subpopulation
- $r = 2^3 = 8$ response profiles
- three correlated marginal proportions of interest are $Pr\{\text{favorable for Drug A}\}$, $Pr\{\text{favorable for Drug B}\}$, and $Pr\{\text{favorable for Drug C}\}$
- Analyzing these functions answers the question of whether there is a difference between the three drugs (conditions).

WLS Methods for Repeated Measurements

If p represents the proportion vector corresponding to the row of counts, then you can compute the desired marginal proportions with a linear transformation

$$F(p) = Ap = \begin{bmatrix} F_1(p) \\ F_2(p) \\ F_3(p) \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} P_{FFF} \\ P_{FFU} \\ P_{FUF} \\ P_{FUU} \\ P_{UFF} \\ P_{UFU} \\ P_{UUF} \\ P_{UUU} \end{bmatrix}$$

The hypothesis of marginal homogeneity can now be addressed by fitting models of the form $F(\pi) = X\beta$, where X is a known model matrix and β is a vector of unknown parameters.



Using PROC CATMOD for Repeated Measurements Analysis

- Specify the repeated measures as a crossed effect on the left-hand side of the MODEL statement.
- The rightmost variable on the left hand side of the MODEL statement varies fastest and the leftmost variable varies slowest.
- The keyword `_RESPONSE_` specifies that the variation among the dependent variables is to be modeled.



Using PROC CATMOD for Repeated Measurements Analysis

- The REPEATED statement specifies a name for each repeated measurement factor and can also be used to specify the type (numeric or character), number of levels, and the identification of each level.
- The ONeway option prints one-way marginal frequency distributions for each response variable in the MODEL statement.

14.7.2 One Population, Dichotomous Response

The following statements create SAS data set DRUG.

```
data drug;  
    input druga $ drugb $ drugc $ count;  
    datalines;  
F   F   F   6  
F   F   U  16  
F   U   F   2  
F   U   U   4  
U   F   F   2  
U   F   U   4  
U   U   F   6  
U   U   U   6  
;
```



These statements request a repeated measurements analysis.

```
proc catmod;  
    weight count;  
    response marginals;  
    model druga*drugb*drugc=_response_ / oneway cov;  
    repeated drug 3 / _response_=drug;  
run;
```

One-Way Frequencies

Variable	Value	Frequency

druga	F	28
	U	18
drugb	F	28
	U	18
drugc	F	16
	U	30

Sample	Sample Size

1	46

Response Profiles

Response	druga	drugb	drugc

1	F	F	F
2	F	F	U
3	F	U	F
4	F	U	U
5	U	F	F
6	U	F	U
7	U	U	F
8	U	U	U


Sample	Function Number	Response Function	Design Matrix		
			1	2	3
1	1	0.60870	1	1	0
	2	0.60870	1	0	1
	3	0.34783	1	-1	-1

Analysis of Variance

Source	DF	Chi-Square	Pr > ChiSq
Intercept	1	146.84	<.0001
drug	2	6.58	0.0372
Residual	0	.	.


Analysis of Weighted Least Squares Estimates

Effect	Parameter	Estimate	Standard Error	Chi- Square	Pr > ChiSq
Intercept	1	0.5217	0.0431	146.84	<.0001
drug	2	0.0870	0.0507	2.95	0.0861
	3	0.0870	0.0507	2.95	0.0861

- 
- Section 14.7.3 (Pages 471-478) provides an example of WLS analysis of repeated measures when there are more than two response levels and the repeated measurement factor is not time.

14.7.4 One Population Regression Analysis of Logits

- In longitudinal study of health effects of air pollution (Ware, Lipsitz, and Speizer 1988) children were examined annually at ages 9, 10, 11, 12

- 
- At each examination, response measured was presence of wheezing. Interested in following questions:
 - Does prevalence of wheezing change with age?
 - Is there a quantifiable trend in age-specific prevalence rates?
 - The following data are from 1019 children included in study. In this single population example, crossclassification of dichotomous outcome at 4 time points defines

$$r = 2^4 = 16 \text{ response profiles}$$

Table 14.8 Breath Test Results at Four Ages

Wheeze				No. of Children
Age 9	Age 10	Age 11	Age 12	
Present	Present	Present	Present	94
Present	Present	Present	Absent	30
Present	Present	Absent	Present	15
Present	Present	Absent	Absent	28
Present	Absent	Present	Present	14
Present	Absent	Present	Absent	9
Present	Absent	Absent	Present	12
Present	Absent	Absent	Absent	63
Absent	Present	Present	Present	19
Absent	Present	Present	Absent	15
Absent	Present	Absent	Present	10
Absent	Present	Absent	Absent	44
Absent	Absent	Present	Present	17
Absent	Absent	Present	Absent	42
Absent	Absent	Absent	Present	35
Absent	Absent	Absent	Absent	572

```

proc catmod order=data;
  weight count;
  response marginals;
  model wheeze9*wheeze10*wheeze11*wheeze12=_response_
        / oneway;
  repeated age;
run;

```

Output 14.10 One-Way Frequency Distributions

One-Way Frequencies		
Variable	Value	Frequency

wheeze9	Present	265
	Absent	754
wheeze10	Present	255
	Absent	764
wheeze11	Present	240
	Absent	779
wheeze12	Present	216
	Absent	803

Output 14.11 Response Functions and Model Matrix

Sample	Function Number	Response Function	Design Matrix			
			1	2	3	4
1	1	0.26006	1	1	0	0
	2	0.25025	1	0	1	0
	3	0.23553	1	0	0	1
	4	0.21197	1	-1	-1	-1

Output 14.12 Analysis-of-Variance Table

Analysis of Variance			
Source	DF	Chi-Square	Pr > ChiSq
Intercept	1	523.63	<.0001
age	3	12.85	0.0050
Residual	0	.	.

Could have manually specified the Linear Model:

```
proc catmod order=data;
  weight count;
  response marginals;
  model wheeze9*wheeze10*wheeze11*wheeze12= (1 9,
                                              1 10,
                                              1 11,
                                              1 12)
                                              (1=Intercept',
                                              2='Linear Age')
                                              / noprofile design;
run;
```

Output 14.13 Response Functions and Model Matrix

Sample	Function Number	Response Function	Design Matrix	
			1	2

1	1	0.26006	1	9
	2	0.25025	1	10
	3	0.23553	1	11
	4	0.21197	1	12

Output 14.14 ANOVA Table

Analysis of Variance			
Source	DF	Chi-Square	Pr > ChiSq

Intercept	1	66.70	<.0001
Linear Age	1	12.31	0.0005
Residual	2	0.54	0.7620

Output 14.15 Parameter Estimates

Analysis of Weighted Least Squares Estimates					
Effect	Parameter	Estimate	Standard Error	Chi-Square	Pr > ChiSq

Model	1	0.4083	0.0500	66.70	<.0001
	2	-0.0161	0.00460	12.31	0.0005

Specify a logit transformation of the probabilities:

```
proc catmod order=data;
    weight count;
    response logits;
    model wheeze9*wheeze10*wheeze11*wheeze12= (1 9,
                                                1 10,
                                                1 11,
                                                1 12)
                                                (1=Intercept',
                                                2='Linear Age')
                                                / noprofile design;
run;
```

Output 14.16 Response Functions and Model Matrix

Sample	Function Number	Response Function	Design Matrix	
			1	2

1	1	-1.04566	1	9
	2	-1.09730	1	10
	3	-1.17737	1	11
	4	-1.31308	1	12

Output 14.17 ANOVA Table


Analysis of Variance			
Source	DF	Chi-Square	Pr > ChiSq

Intercept	1	0.76	0.3824
Linear Age	1	11.77	0.0006
Residual	2	0.67	0.7167

Output 14.18 Parameter Estimates

Analysis of Weighted Least Squares Estimates					
Effect	Parameter	Estimate	Standard Error	Chi-Square	Pr > ChiSq


Model	1	-0.2367	0.2710	0.76	0.3824
	2	-0.0879	0.0256	11.77	0.0006



Example: Study to compare test treatment and placebo for management of a respiratory disorder (Reference: Koch, Carr, Amara, Stokes, and Uryniak [1990])

1. Two centers
2. Four visits
3. Ordered global response with 5 categories (terrible, poor, fair, good, excellent as scores 0,1,2,3,4)
4. Age, gender, baseline are covariables

Partial Listing of Data from a Multicenter, Multivisit Clinical Trial to Compare Two Treatments for Patients with a Respiratory Disorder (Reference: Koch *et al* [1990])



Center	Patient	Drug	Sex	Age	Base	Visit 1	Visit 2	Visit 3	Visit 4
1	53	A	F	32	1	2	2	4	2
	18	A	F	47	2	2	3	4	4
	54	A	M	11	4	4	4	4	2
	12	A	M	14	2	3	3	3	2
	51	A	M	15	0	2	3	3	3
	20	A	M	20	3	3	2	3	1
	16	A	M	22	1	2	2	2	3
	50	A	M	22	2	1	3	4	4
	03	A	M	23	3	3	4	4	3
	32	A	M	23	2	3	4	4	4
	56	A	M	25	2	3	3	2	3
	35	A	M	26	1	2	2	3	2
	26	A	M	26	2	2	2	2	2
	21	A	M	26	2	4	1	4	2
	08	A	M	28	1	2	2	1	2
	30	A	M	28	0	0	1	2	1
	33	A	M	30	3	3	4	4	2
	11	A	M	30	3	4	4	4	3



WLS FOR CATEGORICAL DATA: EXAMPLE USING CHAPTER 13 DATA WITH BINARY RESPONSE MEASURED AT FOUR VISITS


```
/* Model with Interactions */  
PROC CATMOD;  
  RESPONSE LOGITS;  
  POPULATION CENTER DRUG;  
  MODEL VIS1_BIN*VIS2_BIN*VIS3_BIN*VIS4_BIN =  
        CENTER|DRUG CENTER|_RESPONSE_  
        DRUG|_RESPONSE_  
        / NODESIGN NOPARM NOPROFILE;  
  REPEATED TIME;  
RUN;
```

CATMOD PROCEDURE

Response	vis1_*vis2_*vis3_*vis4_b	Response Levels	15
Weight Variable	None	Populations	4
Data Set	CH13T	Total Frequency	111
Frequency Missing	0	Observations	111

Analysis of Variance

Source	DF	Chi-Square	Pr > ChiSq
Intercept	1	3.34	0.0678
center	1	8.37	0.0038
drug	1	10.92	0.0010
center*drug	1	1.18	0.2770
time	3	3.86	0.2769
center*time	3	3.82	0.2821
drug*time	3	2.74	0.4338
Residual	3	0.59	0.8994



```
/* MAIN EFFECTS MODEL */  
PROC CATMOD;  
    RESPONSE LOGITS;  
    POPULATION CENTER DRUG;  
    MODEL VIS1_BIN*VIS2_BIN*VIS3_BIN*VIS4_BIN =CENTER  
          DRUG _RESPONSE_ / NODESIGN NOPROFILE;  
    REPEATED TIME;  
RUN;
```

The CATMOD Procedure

Response	vis1_*vis2_*vis3_*vis4_b	Response Levels	15
Weight Variable	None	Populations	4
Data Set	CH13T	Total Frequency	111
Frequency Missing	0	Observations	111

Analysis of Variance

Source	DF	Chi-Square	Pr > ChiSq
Intercept	1	1.68	0.1947
center	1	7.62	0.0058
drug	1	10.61	0.0011
time	3	2.76	0.4303
Residual	10	13.04	0.2212

Analysis of Weighted Least Squares Estimates

Effect	Parameter	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Intercept	1	-0.2041	0.1574	1.68	0.1947
center	2	0.4401	0.1594	7.62	0.0058
drug	3	0.5217	0.1602	10.61	0.0011
time	4	-0.1159	0.1261	0.85	0.3579
	5	0.0856	0.1147	0.56	0.4554
	6	-0.0754	0.1129	0.45	0.5038



RESPIRATORY DISORDER DATA

Model with Default Coding for Mean Score Response
with All Interactions

```
PROC CATMOD;  
  RESPONSE MEAN;  
  MODEL VISIT1*VISIT2*VISIT3*VISIT4 = DRUG|CENTER|_RESPONSE_/COV;  
  REPEATED TIME;  
RUN;
```

The CATMOD Procedure
Data Summary


Response	visit*visit*visit*visit4	Response Levels	67
Weight Variable	None	Populations	4
Data Set	CH13T2	Total Frequency	111
Frequency Missing	0	Observations	111

Response Functions and Covariance Matrix

Sample	Function Number	Response Function	Covariance Matrix			
			1	2	3	4
1	1	2.24138	0.06101	0.04875	0.05031	0.04371
	2	2.00000	0.04875	0.05945	0.04400	0.03686
	3	2.24138	0.05031	0.04400	0.06815	0.05560
	4	2.03448	0.04371	0.03686	0.05560	0.05584
2	1	2.82143	0.03330	0.01713	0.01667	0.01827
	2	2.28571	0.01713	0.0583	0.05266	0.05649
	3	2.21429	0.01667	0.05266	0.07744	0.07425
	4	2.46429	0.01827	0.05649	0.07425	0.09052
3	1	2.51852	0.03394	0.01793	0.01590	0.00996
	2	2.85185	0.01793	0.03485	0.01956	0.02185
	3	2.81481	0.01590	0.01956	0.04948	0.02251
	4	2.48148	0.00996	0.02185	0.02251	0.03942
4	1	3.33333	0.02469	0.01829	0.01555	0.02012
	2	3.40741	0.01829	0.03363	0.02845	0.02764
	3	3.29630	0.01555	0.02845	0.03516	0.02733
	4	3.25926	0.02012	0.02764	0.02733	0.05375

ANOVA Table

Analysis of Variance			
Source	DF	Chi-Square	Pr > ChiSq
Intercept	1	767.19	<.0001
drug	1	13.76	0.0002
center	1	6.53	0.0106
drug*center	1	0.80	0.3724
time	3	2.40	0.4929
drug*time	3	12.60	0.0056
center*time	3	8.13	0.0433
drug*center*time	3	0.58	0.9010
Residual	0	.	.




Many studies have response variables with ordinal data for which only rankings are meaningful.

1. Ordered categorical response variables
 - a. Arbitrary scores may not be meaningful
 - b. Models such as the proportional odds model may have unsatisfactory goodness of fit
2. Response variables with continuous scales can have skewed distributions and/or outliers to an extent that contradicts a metric scale and thereby differences and/or other functions of observed values may not be meaningful. In these situations, analyses involving rank measures of association are potentially of interest.


Combined use of FREQ and CATMOD for analysis of Mann-Whitney estimators from a study with eight strata for the comparison of two treatments for an ordered categorical response variable (Reference: Stokes *et al* [2000]).

Diagnostic			Patient Status				
Class	Investigator	Treatment	Poor	Fair	Moderate	Good	Excellent
I	A	Placebo	7	0	1	1	1
I	A	Active	3	2	2	1	0
I	B	Placebo	5	4	2	3	3
I	B	Active	1	6	1	5	3
II	A	Placebo	1	1	0	1	1
II	A	Active	1	0	1	2	2
II	B	Placebo	3	1	1	5	0
II	B	Active	0	1	1	1	6
III	A	Placebo	5	0	0	8	1
III	A	Active	2	0	3	3	2
III	B	Placebo	2	5	1	4	2
III	B	Active	2	4	1	10	3
IV	A	Placebo	5	0	3	3	0
IV	A	Active	8	1	3	4	0
IV	B	Placebo	3	4	3	4	2
IV	B	Active	1	5	2	3	1



FREQ is used to obtain Somer's D and corresponding standard error for each of the eight strata according to (Diagnostic Class \times Investigators).

$U = \frac{(\text{Somer's } D \ C|R)+1}{2}$ and $S = \frac{SE(D)}{2}$ are used to obtain the Mann-Whitney estimators and their standard errors. The respective estimates for the eight strata are independent.



Diagnostic Class	Researcher	Somer's D	ASE	U_i	S_i
I	A	0.2000	0.3515	0.6000	0.1758
I	B	0.2002	0.1915	0.6001	0.0958
II	A	0.2083	0.3622	0.6042	0.1811
II	B	0.6778	0.1834	0.8389	0.0917
III	A	0.0260	0.2271	0.5130	0.1136
III	B	0.1893	0.1923	0.5947	0.0962
IV	A	0.0000	0.2007	0.5000	0.1004
IV	B	-0.0156	0.2116	0.4922	0.1058

The variation among the Mann-Whitney estimators is analyzed by weighted least squares methods through CATMOD.

The input for this analysis and the specification of a model that addresses the effects of diagnosis and investigator on the association between treatment and response are as follows:

```
data MannWhitney;
  input b1-b8 _type_ $ _name_ $8.;
  datalines;
    .6000   .6011   .6042   .8389   .5130   .5947   .5000   .4922   parms
    .03091  .0000   .0000   .0000   .0000   .0000   .0000   .0000   cov  b1
    .0000   .00918 .0000   .0000   .0000   .0000   .0000   .0000   cov  b2
    .0000   .0000   .3280   .0000   .0000   .0000   .0000   .0000   cov  b3
    .0000   .0000   .0000   .0084   .0000   .0000   .0000   .0000   cov  b4
    .0000   .0000   .0000   .0000   .0129   .0000   .0000   .0000   cov  b5
    .0000   .0000   .0000   .0000   .0000   .0093   .0000   .0000   cov  b6
    .0000   .0000   .0000   .0000   .0000   .0000   .0101   .0000   cov  b7
    .0000   .0000   .0000   .0000   .0000   .0000   .0000   .0112   cov  b8
  ;
```




```
proc catmod data=MannWhitney;
  response read b1-b8;
  factors diagnosis $ 4 , invest $ 2 /
    _response_ = diagnosis invest
  profile = (I    A,
             I    B,
             II   A,
             II   B,
             III  A,
             III  B,
             IV   A,
             IV   B);
  model _f_ = _response_ / cov;
run;
```



The resulting test statistics from this analysis are as follows:

Analysis of Variance			
Source	DF	Chi-Square	Pr > ChiSq
Intercept	1	193.69	<.0001
diagnosis	3	6.98	0.0725
invest	1	0.14	0.7122
Residual	3	0.33	0.9540


Since there is essentially no variation among the Mann-Whitney estimators across the eight strata, a model which specifies a homogenous value is applied.



```
model _f_ = ( 1 ,  
              1 ,  
              1 ,  
              1 ,  
              1 ,  
              1 ,  
              1 ,  
              1 ) ;
```

The results for this model for homogenous association between treatment and response are as follows:

Analysis of Variance					
	Source	DF	Chi-Square	Pr > ChiSq	
	Model Mean	0	.	.	
	Residual	7	9.41	0.2247	
Analysis of Weighted Least Squares Estimates					
Effect	Parameter	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Model	1	0.6027	0.0396	231.30	<.0001



The resulting Mann-Whitney estimator of 0.60 is interpretable as the probability of better response for a randomly selected patient with active treatment than placebo. Note that the test statistic for this association is about

$$Z = \{(0.6027 - 0.5) / 0.0396\} = 2.59$$

And has two-sided p-value 0.0095.

Van Elteren test from PROC FREQ:

$$Q = 3.89, p = 0.0486$$