Supplement to Session 4

S4.1 Analysis of grouped ordinal data using SAS

```
* Set up formats for GCS at entry and outcome *;

proc format;
  value gcsfmt 1 = 'GCS 3-5'
               2 = 'GCS 6-8';
  value gosfmt 1 = 'Good'
               2 = 'Mod Dis'
               3 = 'Severe Dis'
               4 = 'Vegetative'
               5 = 'Dead';
run;

* Read in grouped data from severe head injury study (example 1) *;

data head1;
format gcsentry gcsfmt. gos gosfmt.;
input gcsentry gos frequency;
cards;
1  1   73
1  2   55
1  3   79
1  4   37
1  5  358
2  1  219
2  2  118
2  3   66
2  4   10
2  5   92
;
run;

* Fit proportional odds model for more favourable outcome with *
* GCS at entry                                                  *;

proc logistic data=head1;
  weight frequency;
  class gcsentry (ref='GCS 3-5') / param=ref order=internal;
  model gos (order=internal) = gcsentry;
run;
```

WEIGHT statement is only used when the data are entered in summarised form, rather than with a row for each individual.

The LOGISTIC Procedure

Model Information

Data Set	WORK.HEAD1
Response Variable	gos
Number of Response Levels	5
Weight Variable	frequency
Model	cumulative logit
Optimization Technique	Fisher's scoring

Number of Observations Read	10
Number of Observations Used	10
Sum of Weights Read	1107
Sum of Weights Used	1107

Response Profile

Ordered Value	gos	Total Frequency	Total Weight
1	Good	2	292.00000
2	Mod Dis	2	173.00000
3	Severe Dis	2	145.00000
4	Vegetative	2	47.00000
5	Dead	2	450.00000

Probabilities modeled are cumulated over the lower Ordered Values.

Class Level Information

Class	Value	Design Variables
gcsentry	GCS 3-5	0
	GCS 6-8	1

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Score Test for the Proportional Odds Assumption

Chi-Square	DF	Pr > ChiSq
11.8845	3	0.0078

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	3125.079	2860.319
SC	3126.289	2861.832
-2 Log L	3117.079	2850.319

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	266.7602	1	<.0001
Score	250.7737	1	<.0001
Wald	246.1540	1	<.0001

Type 3 Analysis of Effects

Effect	DF	Wald Chi-Square	Pr > ChiSq
gcsentry	1	246.1540	<.0001

Analysis of Maximum Likelihood Estimates

Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	Good	1	-2.1223	0.1044	413.6292	<.0001
Intercept	Mod Dis	1	-1.2698	0.0907	196.0272	<.0001
Intercept	Severe Dis	1	-0.6006	0.0830	52.3620	<.0001
Intercept	Vegetative	1	-0.3861	0.0816	22.3715	<.0001
gcsentry	GCS 6-8	1	1.8984	0.1210	246.1540	<.0001

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
gcsentry GCS 6-8 vs GCS 3-5	6.676	5.266	8.462

Association of Predicted Probabilities and Observed Responses

Percent Concordant	25.0	Somers' D	0.000
Percent Discordant	25.0	Gamma	0.000
Percent Tied	50.0	Tau-a	0.000
Pairs	40	c	0.500

Response variable

Always check the Response Profile has the correct ordering

Response Profile

Ordered Value	gos	Total Frequency	Total Weight
1	Good	2	292.00000
2	Mod Dis	2	173.00000
3	Severe Dis	2	145.00000
4	Vegetative	2	47.00000
5	Dead	2	450.00000

If ORDER = INTERNAL had not been used in the MODEL or PROC LOGISTIC statement then the response by default is ordered by its formatted labels and so would be incorrect, e.g.

Response Profile

Ordered Value	gos	Total Frequency	Total Weight
1	Dead	2	450.00000
2	Good	2	292.00000
3	Mod Dis	2	173.00000
4	Severe Dis	2	145.00000
5	Vegetative	2	47.00000

and all the results would be incorrect!

From output:

(1) Estimation of difference

To compare subject S_i to subject S_h

S_i: baseline GCS 6-8 i.e. $\underline{z}_i = 1$
S_h: baseline GCS 3-5 i.e. $\underline{z}_h = 0$

$$\log\left[\frac{Q_k(1)\{1-Q_k(0)\}}{Q_k(0)\{1-Q_k(1)\}}\right] = (\alpha_k + \beta\times 1) - (\alpha_k + \beta \times 0)$$

$$\hat{\theta} = \hat{\beta} = 1.90$$

Analysis of Maximum Likelihood Estimates

Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept Good	$\hat{\alpha}_1$	1	**-2.1223**	0.1044	413.6292	<.0001
Intercept Mod Dis	$\hat{\alpha}_2$	1	**-1.2698**	0.0907	196.0272	<.0001
Intercept Severe Dis	$\hat{\alpha}_3$	1	**-0.6006**	0.0830	52.3620	<.0001
Intercept Vegetative	$\hat{\alpha}_4$	1	**-0.3861**	0.0816	22.3715	<.0001
gcsentry GCS 6-8	$\hat{\beta}$	1	**1.8984**	0.1210	246.1540	<.0001

Odds ratio (baseline GCS 6-8 : baseline GCS 3-5) of
Good GOS : Moderate, ... , Dead GOS $= \hat{\psi} = e^{1.90}$
= 6.676

| |
| |
| |

Odds ratio (baseline GCS 6-8 : baseline GCS 3-5) of
Good, ... , Vegetative GOS : Dead GOS $= \hat{\psi} = e^{1.90}$
= 6.676

$$\hat{\psi} > 1$$

Advantage of having baseline GCS of 6-8 rather than 3-5 is 6.676

The higher the baseline GCS the greater the odds of a better GOS

Confidence interval

95% C.I. for $\hat{\psi}$: $\exp\left[\hat{\theta} \pm 1.96\,\text{s.e.}\left(\hat{\theta}\right)\right]$

$= \exp\,[1.8984 \pm 1.96\ (0.1210)]$

$= \exp\,[1.661,\ 2.136]$

$= (5.266,\ 8.462)$

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
gcsentry GCS 6-8 vs GCS 3-5	**6.676**	**5.266**	**8.462**

(2) Fitted values

$\hat{\alpha}_1$ = **– 2.1223** baseline GCS 3-5: $\eta(0) = \hat{\beta} \times 0$ = 0

$\hat{\alpha}_2$ = **– 1.2698**

$\hat{\alpha}_3$ = **– 0.6006** baseline GCS 6-8: $\eta(1) = \hat{\beta} \times 1$ = 1.8984

$\hat{\alpha}_4$ = **–0.3861**

$$\frac{Q_k(\underline{z}_i)}{1 - Q_k(\underline{z}_i)} = e^{(\alpha_k + \eta(\underline{z}_i))}$$

$$Q_k(\underline{z}_i) = \left(1 + e^{-(\alpha_k + \eta(\underline{z}_i))}\right)^{-1}$$

$Q_1(0)$ = P(C_1 or better; 0)

= P(Good; GCS 3-5)

= $\left(1 + e^{-\hat{\alpha}_1}\right)^{-1}$

= $\left(1 + e^{+2.1223}\right)^{-1} = 0.107$

$Q_2(0)$ = P(C_2 or better; 0)

= P(Good or Moderate; GCS 3-5)

= $\left(1 + e^{-\hat{\alpha}_2}\right)^{-1}$

= $\left(1 + e^{+1.2698}\right)^{-1} = 0.219$

$Q_3(0)$ = P(C_3 or better; 0)

= P(Good to Severe; GCS 3-5)

= 0.354

$Q_4(0)$ = P(C_4 or better; 0)

= P(Good to Vegetative; GCS 3-5)

= 0.405

$Q_5(0)$ = P(C_5 or better; 0)

= 1

$Q_1(1)$ = P(C_1 or better; 1)

= P(Good; GCS 6-8)

$$= \left(1 + e^{-\left(\hat{\alpha}_1 + \hat{\beta}\right)}\right)^{-1}$$

$$= \left(1 + e^{-\left(-2.1223 + 1.8984\right)}\right)^{-1} = 0.444$$

$Q_2(1)$ = 0.652

$Q_3(1)$ = 0.785

$Q_4(1)$ = 0.819

$Q_5(1)$ = P(C_5 or better; 1) = 1

(3) Hypothesis testing

To test H_0: $\theta = 0$

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	3125.079	2860.319
SC	3126.289	2861.832
-2 Log L	**3117.079**	**2850.319**

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	**266.7602**	1	<.0001
Score	**250.7737**	1	<.0001
Wald	**246.1540**	1	<.0001

Type 3 Analysis of Effects

Effect	DF	Wald Chi-Square	Pr > ChiSq
gcsentry	1	**246.1540**	<.0001

a) **Likelihood ratio test**

$$\begin{aligned} D(0) - D(\hat{\theta}) &= -2\ell(0) - -2\ell(\hat{\theta}) \\ &= 3117.079 - 2850.319 \\ &= 266.760 \quad (\text{cf. } \chi_1^2) \end{aligned}$$

b) Score test

$$\frac{Z^2}{V} = 250.774 \quad (\text{c.f. } \chi_1^2)$$

c) Wald's chi-square

$$\left(\frac{\text{parameter estimate}}{\text{se(estimate)}}\right)^2 = 246.145$$

Significant difference between GCS 6-8 to GCS 3-5

Alternative SAS commands

PROC LOGISTIC

```
  class gcsentry / param=ref ref=first order=internal;
  model gos (order=internal) = gcsentry;
```

or

```
  class gcsentry / param=glm order=internal descending;
  model gos (order=internal) = gcsentry;
```

PROC GENMOD

```
proc genmod data=head1 rorder=internal;
  freq frequency;
  class gcsentry (order=internal);
  model gos = gcsentry / d=multinomial link=clogit expected type1;
run;
```

parameterisation in PROC GENMOD compares:

GCS 3-5 relative to 6-8
not
GCS 6-8 relative to 3-5 *as required*

$\Rightarrow$ change in sign of parameter estimates

S4.2 Analysis of ungrouped ordinal data using SAS

Data from head injury study (example 2) in head2 dataset. See supplement to session 2 for details of these data.

```
* Set up formats for GCS motor score, treatment and outcome *;

proc format;
  value motfmt 1 = 'None/Ext'
               2 = 'Flexion'
               3 = 'Localises';
  value trtfmt 0 = 'Control'
               1 = 'Treated';
  value gosfmt 1 = 'Good'
               2 = 'Moderate'
               3 = 'Severe'
               4 = 'Veg/Dead';
run;

* Fit proportional odds model for more favourable outcome with *;
* age, GCS motor score and treatment                            *;

proc logistic data=head2;
  class gcsmotor (ref='None/Ext')
        treat (ref='Control') / param=ref order=internal;
  model gos4 (order=internal)= age gcsmotor treat;
  format gos4 gosfmt. gcsmotor motfmt. treat trtfmt.;
run;
```

The LOGISTIC Procedure

Model Information

Data Set	WORK.HEAD2
Response Variable	gos4
Number of Response Levels	4
Model	cumulative logit
Optimization Technique	Fisher's scoring

Number of Observations Read	341
Number of Observations Used	341

Response Profile

Ordered Value	gos4	Total Frequency
1	Good	113
2	Moderate	57
3	Severe	60
4	Veg/Dead	111

Probabilities modeled are cumulated over the lower Ordered Values.

Class Level Information

Class	Value	Design Variables	
gcsmotor	None/Ext	0	0
	Flexion	1	0
	Localises	0	1
treat	Control	0	
	Treated	1	

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Score Test for the Proportional Odds Assumption

Chi-Square	DF	Pr > ChiSq
5.4898	8	0.7042

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	917.209	857.191
SC	928.705	884.014
-2 Log L	911.209	843.191

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	68.0181	4	<.0001
Score	60.9636	4	<.0001
Wald	59.0992	4	<.0001

Type 3 Analysis of Effects

Effect	DF	Wald Chi-Square	Pr > ChiSq
age	1	13.0823	0.0003
gcsmotor	2	45.1389	<.0001
treat	1	8.5885	0.0034

Analysis of Maximum Likelihood Estimates

Parameter			DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	Good		1	-0.8217	0.2924	7.8956	0.0050
Intercept	Moderate		1	0.00116	0.2878	0.0000	0.9968
Intercept	Severe		1	0.8461	0.2914	8.4323	0.0037
age		$\hat{\beta}_1$	1	**-0.0247**	0.00682	13.0823	0.0003
gcsmotor	Flexion	$\hat{\beta}_2$	1	**0.5058**	0.2324	4.7387	0.0295
gcsmotor	Localises	$\hat{\beta}_3$	1	**1.9026**	0.2832	45.1285	<.0001
treat	Treated	$\hat{\beta}_4$	1	**0.6019**	0.2054	8.5885	0.0034

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
age	0.976	0.963	0.989
gcsmotor Flexion vs None/Ext	1.658	1.052	2.615
gcsmotor Localises vs None/Ext	6.703	3.848	11.677
treat Treated vs Control	1.826	1.221	2.731

Association of Predicted Probabilities and Observed Responses

Percent Concordant	67.9	Somers' D	0.365
Percent Discordant	31.5	Gamma	0.367
Percent Tied	0.6	Tau-a	0.265
Pairs	42171	c	0.682

Interpretation with multiple covariates

Model: $$\log\left[\frac{Q_k(\underline{z}_i)}{1-Q_k(\underline{z}_i)}\right]=\alpha_k+\eta(\underline{z}_i)$$

where $\eta(\underline{z}_i) = \beta_1 z_{i1} + \beta_2 z_{i2} + \beta_3 z_{i3} + \beta_4 z_{i4}$

z_{i1} = age

$$z_{i2}=\begin{cases}1: \text{ if gcsmotor} = 2 \text{ (Flexion)}\\ 0: \text{ if gcsmotor} = 1 \text{ (None/Ext) or } 3 \text{ (Localises)}\end{cases}$$

$$z_{i3}=\begin{cases}1: \text{ if gcsmotor} = 3 \text{ (Localises)}\\ 0: \text{ if gcsmotor} = 1 \text{ (None/Ext) or } 2 \text{ (Flexion)}\end{cases}$$

$$z_{i4}=\begin{cases}1: \text{ if treat} = 1 \text{ (Treated)}\\ 0: \text{ if treat} = 0 \text{ (Control)}\end{cases}$$

To compare subject S_i to subject S_h

S_i: age = 20, gcsmotor = Flexion, treat = Control
$\underline{z}_i$ = (20, 1, 0, 0)

S_h: age = 50, gcsmotor = None/extension, treat = Treated
$\underline{z}_h$ = (50, 0, 0, 1)

$$\log\left[\frac{Q_k(\underline{z}_i)}{1-Q_k(\underline{z}_i)}\right] = \alpha_k + \beta_1 20 + \beta_2 1 + \beta_3 0 + \beta_4 0$$

$$\log\left[\frac{Q_k(\underline{z}_h)}{1-Q_k(\underline{z}_h)}\right] = \alpha_k + \beta_1 50 + \beta_2 0 + \beta_3 0 + \beta_4 1$$

$$\begin{aligned}\hat{\theta} &= \log\left[\frac{Q_k(\underline{z}_i)}{1-Q_k(\underline{z}_i)}\right] - \log\left[\frac{Q_k(\underline{z}_h)}{1-Q_k(\underline{z}_h)}\right] \\ &= \hat{\beta}_1(20-50) + \hat{\beta}_2 - \hat{\beta}_4 \\ &= -0.0247(-30) + 0.5058 - 0.6019 \\ &= 0.6449\end{aligned}$$

$$\hat{\Psi} = e^{\hat{\theta}} = 1.91$$

Odds of being in category k or better are higher for younger patients with a GCS motor score of flexion at baseline receiving control treatment relative to older patients receiving experimental treatment but having a baseline GCS motor score of none/extension.

S4.3 Analysis of grouped ordinal data using R

```
# Read grouped data from severe head injury study (example 1) into a data frame

head1 <- data.frame(GCSENTRY=c(1,1,1,1,1,2,2,2,2,2),
                    GOS=c(1,2,3,4,5,1,2,3,4,5),
                    FREQUENCY=c(73,55,79,37,358,219,118,66,10,92))


# Convert ordinal outcome variable from numeric variable to factor variable
# with 5 (Dead) as the first level and 1 (Good) as the last level so that
# lrm function will model cumulative probabilities of more favourable outcome

head1$GOS <- factor(head1$GOS, levels=c('5','4','3','2','1'),
labels=c('Dead','Vegetative','Severe Dis','Mod Dis','Good'))


# Convert categorical predictor from numeric variable to factor variable

head1$GCSENTRY <- factor(head1$GCSENTRY, levels=c('1','2'),
labels=c('GCS 3-5','GCS 6-8'))


# Load rms package

library(rms)


# Fit proportional odds model for more favourable outcome with GCS at entry

pom.fit1 <- lrm(GOS ~ GCSENTRY, data=head1, weight=FREQUENCY)
print(pom.fit1)
cat('Deviance (-2 Log L)', "\n", pom.fit1$deviance, "\n", "\n", "\n")
anova(pom.fit1)
summary(pom.fit1, GCSENTRY='GCS 3-5')
```

The **weight=** option is used because the data are in summarised form rather than with a row for each individual.

Proportional Odds Model

```
Logistic Regression Model

lrm(formula = GOS ~ GCSENTRY, data = head1, weights = FREQUENCY)

Frequencies of Responses

      Dead Vegetative Severe Dis    Mod Dis       Good
         2          2          2          2          2

Sum of Weights by Response Category

  0   1   2   3   4
450  47 145 173 292
```

		Model Likelihood Ratio Test		Discrimination Indexes		Rank Discrim. Indexes	
Obs	10	LR chi2	**266.76**	R2	0.228	C	0.681
Sum of weights	1107	d.f.	1	g	1.055	Dxy	0.361
max |deriv|	1e-07	Pr(> chi2)	<0.0001	gr	2.871	gamma	0.658
				gp	0.240	tau-a	0.261
				Brier	0.196		

		Coef	S.E.	Wald Z	Pr(>|Z|)
y>=Vegetative	$\hat{\alpha}_4$	**-0.3861**	0.0816	-4.73	<0.0001
y>=Severe Dis	$\hat{\alpha}_3$	**-0.6006**	0.0831	-7.23	<0.0001
y>=Mod Dis	$\hat{\alpha}_2$	**-1.2698**	0.0915	-13.88	<0.0001
y>=Good	$\hat{\alpha}_1$	**-2.1223**	0.1051	-20.19	<0.0001
GCSENTRY=GCS 6-8	$\hat{\beta}$	**1.8985**	0.1214	15.64	<0.0001

Deviance (-2 Log L)
3117.079 2850.319

Wald Statistics Response: GOS

Factor	Chi-Square	d.f.	P
GCSENTRY	**244.63**	1	<.0001
TOTAL	**244.63**	1	<.0001

Effects Response : GOS

Factor	Low	High	Diff.	Effect	S.E.	Lower 0.95	Upper 0.95
GCSENTRY - GCS 6-8:GCS 3-5	1	2	NA	1.90	0.12	1.66	2.14
Odds Ratio	1	2	NA	**6.68**	NA	**5.26**	**8.47**

Note: When the response/outcome variable has more than two categories the lrm function assigns ordered values to the categories, starting at zero. It then models the cumulative probabilities of higher ordered values. So in this example to model the cumulative probabilities of more favourable outcomes the five levels of GOS have been ordered with ‘Dead’ as the first and ‘Good’ as the last level. This ordering is the opposite of that required by PROC LOGISTIC and PROC GENMOD in SAS.

The intercept labelled ‘y>=Vegetative’ is modelling the log odds of response being ‘Vegetative’ or higher on order scale, i.e. ‘Vegetative’ or further to the right in the Frequencies of Response table. Similarly the intercepts labelled ‘y>=Severe Dis’ and ‘y>=Mod Dis’ are modelling the log odds of response being ‘Severe Dis’ or better, and ‘Mod Dis or better respectively. Finally the intercept labelled ‘y>=Good’ is actually an estimate of the log odds of response being ‘Good’ only as there are no response categories to the right in the Frequencies of Response table, i.e. no better response categories than this.

Although there are small differences between R and SAS in the estimated standard errors of the parameter estimates these are all too small to be of any consequence. These differences are due to the estimated covariance matrix for the parameter estimates being computed by the lrm function in R using the observed information matrix while in SAS the method employed by PROC LOGISTIC for maximum likelihood estimation uses the expected information matrix to compute the estimated covariance matrix for the parameter estimates.

S4.4 Analysis of ungrouped ordinal data using R

Data from head injury study (example 2) in head2 data frame. See supplement to session 2 for details of these data.

```
# Load saved workspace which contains data frame with ungrouped data from
# head injury study (example 2)

load('head2.RData')


# Convert ordinal outcome variable from numeric variable to factor variable
# with 4 (Veg/Dead) as the first level and 1 (Good) as the last level so that
# lrm function will model cumulative probabilities of more favourable outcome

head2$GOS4 <- factor(head2$GOS4, levels=c('4','3','2','1'),
labels=c('Veg/Dead','Severe','Moderate','Good'))


# Convert categorical predictors from numeric variables to factor variables

head2$GCSMOTOR <- factor(head2$GCSMOTOR, levels=c('1','2','3'),
labels=c('None/Ext','Flexion','Localises'))
head2$TREAT <- factor(head2$TREAT, levels=c('0','1'),
labels=c('Control','Treated'))


# Load rms package

library(rms)


# Fit proportional odds model for more favourable outcome with age,
# GCS motor score and treatment

pom.fit2 <- lrm(GOS4 ~ AGE + GCSMOTOR + TREAT, data=head2)
print(pom.fit2)
cat('Deviance (-2 Log L)', "\n", pom.fit2$deviance, "\n", "\n", "\n")
anova(pom.fit2)
summary(pom.fit2, AGE=c(34,34,35), GCSMOTOR='None/Ext', TREAT='Control')
```

Proportional Odds Model

```
Logistic Regression Model

lrm(formula = GOS4 ~ AGE + GCSMOTOR + TREAT, data = head2)

Frequencies of Responses

Veg/Dead   Severe Moderate     Good
     111       60       57      113

                      Model Likelihood     Discrimination     Rank Discrim.
                         Ratio Test            Indexes            Indexes

Obs             341    LR chi2      68.02    R2        0.194    C       0.682
max |deriv| 7e-10    d.f.             4    g         0.987    Dxy     0.365
                     Pr(> chi2) <0.0001    gr        2.683    gamma   0.367
                                           gp        0.216    tau-a   0.265
                                           Brier     0.213
```

<table>
<tr><th></th><th></th><th>Coef</th><th>S.E.</th><th>Wald Z</th><th>Pr(>|Z|)</th></tr>
<tr><td>y>=Severe</td><td></td><td>0.8462</td><td>0.2918</td><td>2.90</td><td>0.0037</td></tr>
<tr><td>y>=Moderate</td><td></td><td>0.0012</td><td>0.2873</td><td>0.00</td><td>0.9967</td></tr>
<tr><td>y>=Good</td><td></td><td>-0.8217</td><td>0.2919</td><td>-2.82</td><td>0.0049</td></tr>
<tr><td>AGE</td><td>$\hat{\beta}_1$</td><td>-0.0247</td><td>0.0069</td><td>-3.56</td><td>0.0004</td></tr>
<tr><td>GCSMOTOR=Flexion</td><td>$\hat{\beta}_2$</td><td>0.5058</td><td>0.2338</td><td>2.16</td><td>0.0305</td></tr>
<tr><td>GCSMOTOR=Localises</td><td>$\hat{\beta}_3$</td><td>1.9026</td><td>0.2803</td><td>6.79</td><td><0.0001</td></tr>
<tr><td>TREAT=Treated</td><td>$\hat{\beta}_4$</td><td>0.6019</td><td>0.2056</td><td>2.93</td><td>0.0034</td></tr>
</table>

```
Deviance (-2 Log L)
 911.2093 843.1912
```

Wald Statistics   Response: GOS4

Factor	Chi-Square	d.f.	P
AGE	12.69	1	0.0004
GCSMOTOR	46.07	2	<.0001
TREAT	8.57	1	0.0034
TOTAL	59.65	4	<.0001

Effects   Response : GOS4

Factor	Low	High	Diff.	Effect	S.E.	Lower 0.95	Upper 0.95
AGE	34	35	1	-0.02	0.01	-0.04	-0.01
Odds Ratio	34	35	1	0.98	NA	0.96	0.99
GCSMOTOR - Flexion:None/Ext	1	2	NA	0.51	0.23	0.05	0.96
Odds Ratio	1	2	NA	1.66	NA	1.05	2.62
GCSMOTOR - Localises:None/Ext	1	3	NA	1.90	0.28	1.35	2.45
Odds Ratio	1	3	NA	6.70	NA	3.87	11.61
TREAT - Treated:Control	1	2	NA	0.60	0.21	0.20	1.00
Odds Ratio	1	2	NA	1.83	NA	1.22	2.73

Note: When the response/outcome variable has more than two categories the lrm function assigns ordered values to the categories, starting at zero. It then models the cumulative probabilities of higher ordered values. So in this example to model the cumulative probabilities of more favourable outcomes the four levels of GOS have been ordered with ‘Veg/Dead’ as the first and ‘Good’ as the last level. This ordering is the opposite of that required by PROC LOGISTIC and PROC GENMOD in SAS.