

Discrete Choice for GAUSSTM

Version 1.0

Aptech Systems, Inc.

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Chapter 1

Installation

1.1 UNIX

If you are unfamiliar with UNIX, see your system administrator or system documentation for information on the system commands referred to below. The device names given are probably correct for your system.

1.1.1 Download

1. Copy the `.tar.gz` file to `/tmp`.
2. Unzip the file.

```
gunzip appxxx.tar.gz
```

3. `cd` to the **GAUSS** or **GAUSS Engine** installation directory. We are assuming `/usr/local/gauss` in this case.

```
cd /usr/local/gauss
```

4. Untar the file.

```
tar xvf /tmp/appxxx.tar
```

1.1.2 Floppy

1. Make a temporary directory.

```
mkdir /tmp/workdir
```

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2. `cd` to the temporary directory.

```
cd /tmp/workdir
```

3. Use `tar` to extract the files.

```
tar xvf device_name
```

If this software came on diskettes, repeat the `tar` command for each diskette.

4. Read the README file.

```
more README
```

5. Run the `install.sh` script in the work directory.

```
./install.sh
```

The directory the files are install to should be the same as the install directory of **GAUSS** or the **GAUSS Engine**.

6. Remove the temporary directory (optional).

The following device names are suggestions. See your system administrator. If you are using Solaris 2.x, see Section 1.1.3.

Operating System	3.5-inch diskette	1/4-inch tape	DAT tape
Solaris 1.x SPARC	<code>/dev/rfd0</code>	<code>/dev/rst8</code>	
Solaris 2.x SPARC	<code>/dev/rfd0a</code> (vol. mgt. off)	<code>/dev/rst12</code>	<code>/dev/rmt/11</code>
Solaris 2.x SPARC	<code>/vol/dev/aliases/floppy0</code>	<code>/dev/rst12</code>	<code>/dev/rmt/11</code>
Solaris 2.x x86	<code>/dev/rfd0c</code> (vol. mgt. off)		<code>/dev/rmt/11</code>
Solaris 2.x x86	<code>/vol/dev/aliases/floppy0</code>		<code>/dev/rmt/11</code>
HP-UX	<code>/dev/rfloppy/c20Ad1s0</code>		<code>/dev/rmt/0m</code>
IBM AIX	<code>/dev/rfd0</code>	<code>/dev/rmt.0</code>	
SGI IRIX	<code>/dev/rdisk/fds0d2.3.5hi</code>		

1.1.3 Solaris 2.x Volume Management

If Solaris 2.x volume management is running, insert the floppy disk and type

```
volcheck
```

to signal the system to mount the floppy.

The floppy device names for Solaris 2.x change when the volume manager is turned off and on. To turn off volume management, become the superuser and type

```
/etc/init.d/volmgt off
```

To turn on volume management, become the superuser and type

```
/etc/init.d/volmgt on
```

1. INSTALLATION

1.2 Windows/NT/2000

1.2.1 Download

Unzip the .zip file into the **GAUSS** or **GAUSS Engine** installation directory.

1.2.2 Floppy

1. Place the diskette in a floppy drive.
2. Call up a DOS window
3. In the DOS window log onto the root directory of the diskette drive. For example:

```
A:<enter>
cd\

```

4. Type: **ginstall** *source_drive* *target_path*

source_drive Drive containing files to install
with colon included

For example: **A:**

target_path Main drive and subdirectory to install
to without a final \

For example: **C:\GAUSS**

A directory structure will be created if it does not already exist and the files will be copied over.

<i>target_path</i> \ src	source code files
<i>target_path</i> \ lib	library files
<i>target_path</i> \ examples	example files

1.3 Differences Between the UNIX and Windows/NT/2000 Versions

- If the functions can be controlled during execution by entering keystrokes from the keyboard, it may be necessary to press *Enter* after the keystroke in the UNIX version.

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- On the Intel math coprocessors used by the Windows/NT/2000 machines, intermediate calculations have 80-bit precision, while on the current UNIX machines, all calculations are in 64-bit precision. For this reason, **GAUSS** programs executed under UNIX may produce slightly different results, due to differences in roundoff, from those executed under Windows/NT/2000.

Chapter 2

Introduction

DISCRETE CHOICE estimation uses the **sqpsolvent** procedure, a sequential quadratic programming method that solves general nonlinear programming problems. Data are passed in a *dcDesc* structure instance. The optimization process is controlled with a *dcControl* structure instance. Output arguments are in a *dcOut* structure instance and an array of *ds* structure instances.

2.1 Getting Started

GAUSS 5.0.30+ is required to use the **DISCRETE CHOICE** procedures.

2. INTRODUCTION

Chapter 3

Discrete Choice

3.1 Poisson Model

Given independent variables x_i for an observation with count y_i , the Poisson density function is

$$P(y_i|x_i) = \frac{\exp(-\mu_i)\mu_i^{y_i}}{y_i!}$$

where

$$\mu_i = E(y_i|x_i) = \exp(x_i\beta)$$

is the number of events expected to occur per unit time (or space).

The Poisson regression model log likelihood function is:

$$\ln L = \sum_{i=1}^n [-\mu_i + y_i\beta'x_i - \ln(y_i!)]$$

The Poisson distribution function is

$$F(c) = P(y_i \leq c) = \sum_{j=0}^c P(y_i = j|x_i)$$

3.1.1 Poisson Overdispersion

The **psnprt** function shows three tests for overdispersion when a Poisson model is estimated.

Following Cameron and Trivedi's (1998, p62) notation, let $\omega_i = V[y_i|\mathbf{x}_i]$ be the conditional variance of y_i . Two possible variance functions are the NB1 and NB2 functions:

$$\begin{aligned} NB1 & : \omega_i = (1 + \alpha)\mu_i \\ NB2 & : \omega_i = \mu_i + \alpha\mu_i^2 \end{aligned}$$

Tests of $H_0 : \alpha = 0$ in both cases are conducted using auxillary regressions. Overdispersion of the NB1 form is indicated by a significant t statistic for $\hat{\alpha}$ in the regression $\frac{(y_i - \hat{\mu}_i)^2 - y_i}{\hat{\mu}_i} = \alpha + u_i$. Overdispersion of the NB2 form is indicated by a significant t statistic for $\hat{\alpha}$ in the regression $\frac{(y_i - \hat{\mu}_i)^2 - y_i}{\hat{\mu}_i} = \alpha\hat{\mu}_i + u_i$. In both cases u_i is an i.i.d. disturbance term. **psnprt** reports the t statistics for both cases and their probability values, against a two sided alternative hypothesis.

A Lagrange Multiplier test for overdispersion is presented by Greene (2000, pp 885-886). The Poisson model is a restriction on the Negative Binomial model. The LM statistic has a $\chi^2(1)$ distribution under the null hypothesis that the mean equals the variance.

$$LM = \frac{(e'e - N\bar{y})^2}{2\hat{\mu}'\hat{\mu}}$$

where e is an $N \times 1$ vector of residuals and $\hat{\mu}$ the $N \times 1$ vector of fitted values. **psnprt** reports this statistic and its probability value.

3.2 Negative Binomial Model

The Poisson model assumes that the conditional variance always equal the conditional mean. Consistent but inefficient Poisson model estimates and downward biased standard errors result if this assumption is not true (Gourieroux et al, 1984, Cameron and Trivedi, 1986, p. 31).

The negative binomial regression model lets the conditional variance exceed the conditional mean. Let the conditional mean, μ_i be:

$$\mu_i = \exp(x_i\beta + \varepsilon_i)$$

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where ε is random and uncorrelated with x . Rewrite (3.1) in terms of the Poisson mean to get

$$\mu_i = \exp(x_i\beta) \exp(\varepsilon_i) = \mu_i \exp(\varepsilon_i) = \mu_i \delta_i$$

Assume that δ_i has a gamma distribution with parameter v_i (this sets $E(\delta_i) = 1$, identifying the model, and $Var(\delta_i) = 1/v_i$) and integrate $P(y_i|x_i; \delta_i)$ over the unknown δ_i to get the negative binomial density function:

$$P(y_i|x_i) = \frac{\Gamma(y_i + v_i)}{y_i! \Gamma(v_i)} \left(\frac{v_i}{v_i + \mu_i}\right)^{v_i} \left(\frac{\mu_i}{v_i + \mu_i}\right)^{y_i}$$

with distribution function

$$F(c) = P(y_i \leq c) = \sum_{j=0}^c P(y_i = j|x_i)$$

The conditional variance is

$$Var(y_i|x_i) = \mu_i \left(1 + \frac{\mu_i}{v_i}\right) = \exp(x_i\beta) \left(1 + \frac{x_i\beta}{v_i}\right)$$

which is greater than the conditional variance of the Poisson distribution.

3.3 Truncation and Censoring

This discussion of truncated and censored models closely follows Hayashi (2000) and Long (1997). It assumes that $\{y_t, \mathbf{x}_t\}$ is i.i.d.

y_t is truncated if observations above or below given levels are not in the sample. A double truncation rule is that y_t is observable if it is greater than c_l or less than c_u . The density function is

$$\begin{aligned} f(y|(y > c_l) \text{ and } (y < c_u)) &= \frac{f(y)}{P((y > c_l) \text{ and } (y < c_u))} \\ &= \frac{f(y)}{F(c_l)(1 - F(c_u))} \end{aligned}$$

where F is the cumulative distribution function of y . The corresponding log conditional likelihood function is

$$\begin{aligned} L(y_t|x_t; \theta, c_l, c_u) &= \log(f(y_t|x_t; \theta, c_l, c_u)) - \log(F(c_l|x_t; \theta, c_l, c_u)) \\ &\quad - \log(1 - F(c_u|x_t; \theta, c_l, c_u)) \end{aligned}$$

where θ represents all parameters of the distribution.

A censored model is defined by

$$y_t^* = x_t\beta + \varepsilon_t, \quad t = 1, 2, \dots, n$$

with observed y_t values:

$$y_t = \begin{cases} y_t^* & \text{if } y_t^* > c_l \text{ and } y_t^* < c_u \\ c_l & \text{if } y_t^* < c_l \\ c_u & \text{if } y_t^* > c_u \end{cases}$$

where c_l and c_u are known. All observations are in the sample, though the observable values, y_t , for which $y_t^* > c_l$ and $y_t^* < c_u$ are set equal to c_l and c_u respectively.

The density of y_t is

$$[f(y_t|x_t, \theta, c_u, c_l)]^{1-(D_u+D_l)} \times [F(c_l)]^{D_l} \times [1 - F(c_u)]^{D_u}$$

where

$$\begin{aligned} D_l &= \begin{cases} 0 & \text{if } y_t > c_l \text{ (i.e. } y_t^* > c_l) \\ 1 & \text{if } y_t = c_l \text{ (i.e. } y_t^* \leq c_l) \end{cases} \\ D_u &= \begin{cases} 0 & \text{if } y_t < c_u \text{ (i.e. } y_t^* \leq c_u) \\ 1 & \text{if } y_t = c_u \text{ (i.e. } y_t^* > c_u) \end{cases} \end{aligned}$$

with the corresponding conditional log likelihood

$$\begin{aligned} \log f(y_t|x_t; \theta, c_u, c_l) &= (1 - (D_u + D_l)) \log f(y_t|xxx) \\ &\quad + D_l \log F(c_l) + D_u \log[1 - F(c_u)] \end{aligned}$$

3.4 Zero-Inflated Models

A zero-inflated (sometimes called zero-altered) model allows for the possibility that count outcomes equal to zero are generated by two regimes, a regime where the outcome is always zero and either a Poisson or Negative Binomial model with zero as one of the outcomes.

Suppose $z_i = 0$ when regime 1 generates outcome i (equalling zero) and $z_i = 1$ when regime two generates outcome i (possibly equalling zero).

$P[z_i = 1]$ is determined by a logit or probit model and $P[y_i = j|z_i = 1]$ is given by a Poisson probability density function.

Greene (2000, p890) summarizes these ideas, citing works by Mullahey (1986), Heilbron (1989), Lambert (1992), Johnson and Kotz (1970), and Greene (1994):

$$\begin{aligned} P[y_i = 0] &= P[y_i = 0|\text{regime1}]P[\text{regime1}] + P[y_i = 0|\text{regime2}]P[\text{regime2}] \\ &= P[\text{regime1}] + P[y_i = 0|\text{regime2}]P[\text{regime2}] \\ P[y_i = j] &= P[y_i = j|\text{regime2}]P[\text{regime2}] \quad j = 1, 2, \dots \end{aligned}$$

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3.4.1 Testing Zero-Inflated Regime Assumptions

Vuong (1989) proposes a method that can be used to test whether two regimes likely generate the data. The statistic compares the probabilities of counts occurring under two regimes. Following Greene's (2000, p891) notation, let $f_i(y_i|\mathbf{x}_i)$ be the predicted probability that y_i is observed assuming the data are sampled from distribution j , $j = 1, 2$. Compare these values with

$$m_i = \log \left(\frac{f_1(y_i|\mathbf{x}_i)}{f_2(y_i|\mathbf{x}_i)} \right)$$

Vuong's statistic is:

$$\nu = \frac{\sqrt{N}[\frac{1}{N} \sum_{i=1}^N m_i]}{\sqrt{\frac{1}{N} \sum_{i=1}^N (m_i - \bar{m})^2}}$$

which converges in distribution to a standard normal distribution. Large values of ν suggest that model 1 more likely generates the data while small values of ν suggest that model 2 more likely generates the data.

3.5 Multinomial Logit Model

The **MultinomialLogit** procedure estimates a multinomial logit model.

For the probability of observing $y_i = m$ we have

$$Pr(y_i = m|x_i) = \frac{\exp(x_i\beta_m)}{\sum_{j=1}^J \exp(x_i\beta_j)}$$

By default the set of coefficients for the first category, β_1 , is set to a zero vector as a "reference" category. This can be modified by the user to any of the categories.

Estimates are found by minimizing

$$-\ln L = - \sum_{i=1}^N Pr(y_i = m|x_i)$$

3.6 Adjacent Categories Multinomial Logit

The adjacent categories model is a special case of multinomial logit (Long, 1997, p 146). It specifies that the log odds of one category versus the next higher category is linear in the cutpoints and explanatory variables, i.e.

$$\ln \left[\frac{P(y_i = j + 1 | \mathbf{x}_i)}{P(y_i = j | \mathbf{x}_i)} \right] = x_i \beta_j$$

This implies

$$\begin{aligned} \beta_1^{mnl} &= \beta_1^{acl} \\ \beta_2^{mnl} &= \beta_2^{acl} + \beta_1^{acl} \\ \beta_3^{mnl} &= \beta_3^{acl} + \beta_2^{acl} + \beta_1^{acl} \\ &\vdots \end{aligned}$$

AdjacentCategories first estimates the standard multinomial logit model, transforms the β_m^{mnl} parameters to the β_m^{acl} parameters and computes the covariance matrix of the parameters by the delta method.

3.7 Stereotype Multinomial Logit

For the stereotype model, regression vectors across categories are constrained to a linear function of each other. For $Pr(y_i = m | x_i)$ we have

$$Pr(y_i = m | x_i) = \frac{\exp(x_i \phi_m \beta_m)}{\sum_{j=1}^J \exp(x_i \phi_j \beta_j)}$$

where ϕ_m is a distance coefficient. This model requires two reference categories, one with the distance set to zero, and another which is set to one. By default $\phi_0 = 0$ and $\phi_M = 1$, The remaining distances are constrained to be between zero and one.

3.8 Ordered Logit/Probit

Suppose $y_i^* = x_i \beta + \epsilon$ is an unobserved latent variable where x_i is $1 \times K$, β is $K \times 1$, and ϵ is i.i.d. logistic with zero mean and variance $\frac{\pi^2}{3}$. There are J ordinal categories. The model is identified by excluding the constant term. (See Long, 1997, page 124 for discussion of alternate parameterizations).

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The observed y for an individual depends on the intensity of y^* relative to cutpoint parameters τ_i $i = 1, \dots, J - 1$, defined by

$$P(y_i = j | \mathbf{x}_i) = P(\tau_{j-1} \leq y_i^* < \tau_j | \mathbf{x}_i) = F(\tau_j - x_i \beta | \mathbf{x}_i) - F(\tau_{j-1} - x_i \beta | \mathbf{x}_i)$$

where $\tau_0 = -\infty$, $0 < \tau_1 < \dots < \tau_{J-1}$ and $F(j | \mathbf{x}_i) = P(y_i \leq j | \mathbf{x}_i) = \sum_{k=1}^j P(y_i = k | \mathbf{x}_i)$. F is a logit cumulative distribution function.

The cumulative log odds in the ordered logit model is linear in the cutpoints and explanatory variables, i.e.

$$\ln \left[\frac{P(y_i \leq j | \mathbf{x}_i)}{P(y_i > j | \mathbf{x}_i)} \right] = \tau_j - x_i \beta$$

The ordered log likelihood is:

$$\ln L(\beta, \tau) = \sum_{j=1}^J \sum_{y_i=j} \ln [F(\tau_j - x_i \beta | \mathbf{x}_i) - F(\tau_{j-1} - x_i \beta | \mathbf{x}_i)]$$

For the ordered logit model, F is the cdf of the logistic distribution and for the ordered probit model, F is the Normal cdf.

3.9 Conditional Logit

In the conditional logit model variables that measure the attributes of the categories are added to the model.

$$Pr(y_i = m | x_i, z_{ij}) = \frac{\exp(x_i \beta_m + z_{im} \gamma)}{\sum_{j=1}^J \exp(x_i \beta_j + z_{ij} \gamma)}$$

3.9.1 Example

We have 152 respondents reporting preferences for mode of transportation between Sydney and Melbourne by train, bus, and car (Hensher and Greene, 1995; air travel excluded for the purposes of this example). Several attributes of these categories were recorded, TTME - terminal waiting time (zero for car), INVT - in-vehicle time, INVC - in-vehicle cost, and GC - a generalized cost measure. The command file for this estimation is

```
library dc;
#include dc.sdf
```

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```
struct dcDesc d1;
d1 = dcDescCreate;

d1.yname = "Mode";
d1.catvarname = "choiceno";
d1.catnames = "train$|bus$|car";
d1.atnames = "ttme$|invc$|invt$|GC";

d1.noconstant = 1;

struct dcout dcout1;

dcout1 = dcConditionalLogit("powersxie",d1,dccontrolCreate);
call dcpert(dcout1);
```

The results are

CONDITIONAL LOGIT RESULTS 2003-08-17 14:50:27

Number of Observations: 152
Degrees of Freedom: 148

1 - train
2 - bus
3 - car

DISTRIBUTION AMONG OUTCOME CATEGORIES for Mode

Dependent Variable	Proportion
train	0.4145
bus	0.1974
car	0.3882

ATTRIBUTES

ttme

Attribute Variable	Mean	Std Dev	Minimum	Maximum
--------------------	------	---------	---------	---------

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train	0.0000	0.0000	0.0000	0.0000
bus	6.4934	17.1293	-46.0000	43.0000
car	-34.6250	13.8744	-99.0000	-1.0000

invc

Attribute Variable	Mean	Std Dev	Minimum	Maximum
train	0.0000	0.0000	0.0000	0.0000
bus	-15.4737	20.5984	-61.0000	25.0000
car	-28.5263	23.8895	-87.0000	26.0000

invt

Attribute Variable	Mean	Std Dev	Minimum	Maximum
train	0.0000	0.0000	0.0000	0.0000
bus	24.6842	94.7064	-317.0000	552.0000
car	-30.5461	131.0412	-327.0000	522.0000

GC

Attribute Variable	Mean	Std Dev	Minimum	Maximum
train	0.0000	0.0000	0.0000	0.0000
bus	-12.0461	27.4335	-86.0000	105.0000
car	-32.4079	32.9388	-120.0000	78.0000

Discrete Choice

ATTRIBUTE COEFFICIENTS

Variable	Coefficient	Std Err	t-stat	Prob
ttme	-0.0022	0.0071	-0.3138	0.7537
invc	-0.4351	0.1328	-3.2770	0.0010
invt	-0.0772	0.0194	-3.9912	0.0001
GC	0.4312	0.1332	3.2371	0.0012

MARGINAL EFFECTS OF ATTRIBUTE VARIABLES

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partial probability with respect to mean attribute

train

train

Variable	Coefficient	Std Err	t-stat	Prob
ttme	-0.0003	0.0009	-0.3129	0.7544
invc	-0.0564	0.0159	-3.5477	0.0004
invt	-0.0100	0.0023	-4.4402	0.0000
GC	0.0559	0.0161	3.4728	0.0005

bus

Variable	Coefficient	Std Err	t-stat	Prob
ttme	0.0001	0.0003	0.3222	0.7473
invc	0.0184	0.0053	3.5069	0.0005
invt	0.0033	0.0008	4.2558	0.0000
GC	-0.0183	0.0053	-3.4586	0.0005

car

Variable	Coefficient	Std Err	t-stat	Prob
ttme	0.0002	0.0006	0.3085	0.7577
invc	0.0379	0.0111	3.4094	0.0007
invt	0.0067	0.0016	4.2251	0.0000
GC	-0.0376	0.0113	-3.3322	0.0009

bus

train

Variable	Coefficient	Std Err	t-stat	Prob
----------	-------------	---------	--------	------

3. DISCRETE CHOICE

ttme	0.0001	0.0003	0.3222	0.7473
invc	0.0184	0.0053	3.5069	0.0005
invt	0.0033	0.0008	4.2558	0.0000
GC	-0.0183	0.0053	-3.4586	0.0005

bus

Variable	Coefficient	Std Err	t-stat	Prob
ttme	-0.0002	0.0007	-0.3188	0.7499
invc	-0.0423	0.0123	-3.4475	0.0006
invt	-0.0075	0.0017	-4.3723	0.0000
GC	0.0419	0.0122	3.4304	0.0006

car

Variable	Coefficient	Std Err	t-stat	Prob
ttme	0.0001	0.0004	0.3161	0.7520
invc	0.0238	0.0074	3.2256	0.0013
invt	0.0042	0.0010	4.0875	0.0000
GC	-0.0236	0.0073	-3.2303	0.0012

car

train

Variable	Coefficient	Std Err	t-stat	Prob
ttme	0.0002	0.0006	0.3085	0.7577
invc	0.0379	0.0111	3.4094	0.0007
invt	0.0067	0.0016	4.2251	0.0000
GC	-0.0376	0.0113	-3.3322	0.0009

bus

3. DISCRETE CHOICE

Variable	Coefficient	Std Err	t-stat	Prob
ttme	0.0001	0.0004	0.3161	0.7520
invc	0.0238	0.0074	3.2256	0.0013
invtt	0.0042	0.0010	4.0875	0.0000
GC	-0.0236	0.0073	-3.2303	0.0012

car

Variable	Coefficient	Std Err	t-stat	Prob
ttme	-0.0003	0.0010	-0.3114	0.7555
invc	-0.0618	0.0181	-3.4109	0.0006
invtt	-0.0110	0.0025	-4.3221	0.0000
GC	0.0612	0.0182	3.3648	0.0008

*****SUMMARY STATISTICS*****

MEASURES OF FIT:

-2 Ln(Lu):	192.6971
-2 Ln(Lr): All coeffs equal zero	333.9781
-2 Ln(Lr): J-1 intercepts	320.0034
LR Chi-Square (coeffs equal zero):	141.2811
d.f.	4.0000
p-value =	0.0000
LR Chi-Square (J-1 intercepts):	127.3064
d.f.	2.0000
p-value =	0.0000
Count R2, Percent Correctly Predicted:	0.8092
Adjusted Percent Correctly Predicted:	-0.6988
Madalla's pseudo R-square:	0.5672
McFadden's pseudo R-square:	0.3978
Ben-Akiva and Lerman's Adjusted R-square:	0.3978
Cragg and Uhler's pseudo R-square:	0.1818
Akaike Information Criterion:	1.3204
Bayesian Information Criterion1:	0.0796
Hannan-Quinn Information Criterion:	1.3527

OBSERVED and PREDICTED OUTCOMES

Observed	Predicted			Total
	Y01	Y02	Y03	

3. DISCRETE CHOICE

Y01	47	0	16	63
Y02	0	23	7	30
Y03	3	3	53	59
Total	50	26	76	152

3.10 Nested Logit

NestedLogit is a generalization of the conditional logit model in which categories are grouped into subcategories. Define the probability of an observation being in the m -th category given being in the j -th subcategory:

$$P_{m|j} = \frac{\exp(z_{m|j}\beta_1)}{\sum_k^J \exp(z_{k|j}\beta_1)}$$

Now let

$$P_j = \frac{\exp(z_j\beta_2 + \tau_j I_j)}{\sum_k^J \exp(z_k\beta_2 + \tau_k I_k)}$$

where

$$I_j = \ln \left(\sum_{k=1}^{K_j} \exp(z_{m|j}\beta_1) \right)$$

$\rho_j = 1 - \tau_j$ can be interpreted as an approximate subcategory correlation (Maddala, 1983).

Then the joint probability of category and subcategory is

$$P_{m,j} = P_{m|j}P_j$$

and maximum likelihood estimates are produced by minimizing

$$-\ln L = - \sum_{i=1}^N P_{m,j}$$

This model can be generalized to any number of levels of subcategories (Maddala, 1983; Greene, 2000).

3.10.1 Example

This example is presented in Greene, 2000, page 868, and the data are from Greene and Hensher, 1997. The dataset contains 210 observations on choices between air, train, bus, and car modes of transportation. Attributes of the first level categories are TTME – terminal time, and GC – a generalized cost of transportation. These categories are grouped into two subcategories, Air and Ground, and an attribute of these categories is AIRHINC – traveling by air times household income.

The command file for this problem is

```

library dc;
#include dc.sdf

struct dcDesc d1;
d1 = dcDescCreate;

d1.level = reshape(d1.level,2,1);

d1.yname = "Mode";
d1.catnames = "Air"|"Train"|"Bus"|"Car";
d1.refcatName = "Car";

d1.level[1].atNames = "TTME"|"GC";
d1.level[1].nests = { 1, 2, 2, 2 };

d1.level[2].catnames = "Fly"|"Ground";
d1.level[2].atNames = "airhinc";

struct dcout dcout1;
struct ds d0;

dcout1 = dcNestedLogit("hensher",d1,dccontrolCreate);
call dcprt(dcout1);

```

The results are

```

NESTED LOGIT RESULTS
2003-08-17 16:27:06

```

```

Number of Observations: 210
Degrees of Freedom: 202

```

```

1 - Air
2 - Train

```


3. DISCRETE CHOICE

- 3 - Bus
- 4 - Car

DISTRIBUTION AMONG OUTCOME CATEGORIES for Mode

Dependent Variable	Proportion
Air	0.2762
Train	0.3000
Bus	0.1429
Car	0.2810

CONSTANTS

Variable Comparison	Coefficient	Std Err	t-stat	Prob
Air 1/4	6.0423	1.3313	4.5386	0.0000
Train 2/4	5.0646	0.6760	7.4919	0.0000
Bus 3/4	4.0963	0.6289	6.5138	0.0000

ATTRIBUTE COEFFICIENTS

level 1

Variable	Coefficient	Std Err	t-stat	Prob
TTME	-0.1126	0.0118	-9.5232	0.0000
GC	-0.0316	0.0074	-4.2490	0.0000

level 2

Variable	Coefficient	Std Err	t-stat	Prob
airhinc	0.0153	0.0111	1.3785	0.1681

3. DISCRETE CHOICE

1 - correlations

Variable	Coefficient	Std Err	t-stat	Prob
Fly	0.5860	0.1131	5.1833	0.0000
Ground	0.3890	0.1579	2.4633	0.0138

MARGINAL EFFECTS OF ATTRIBUTE VARIABLES
partial probability with respect to mean attributes

Air

Air

Variable	Coefficient	Std Err	t-stat	Prob
TTME	-0.0130	0.0031	-4.1503	0.0000
GC	-0.0036	0.0010	-3.6320	0.0003

Train

Variable	Coefficient	Std Err	t-stat	Prob
TTME	0.0055	0.0016	3.4465	0.0006
GC	0.0015	0.0006	2.7311	0.0063

Bus

Variable	Coefficient	Std Err	t-stat	Prob
TTME	-0.0017	0.0007	-2.5782	0.0099
GC	-0.0005	0.0002	-2.1611	0.0307

3. DISCRETE CHOICE

Car

Variable	Coefficient	Std Err	t-stat	Prob
TTME	0.0058	0.0015	3.8266	0.0001
GC	0.0016	0.0008	2.0445	0.0409

Train

Air

Variable	Coefficient	Std Err	t-stat	Prob
TTME	0.0036	0.0018	2.0331	0.0420
GC	0.0010	0.0003	3.2721	0.0011

Train

Variable	Coefficient	Std Err	t-stat	Prob
TTME	-0.0216	0.0034	-6.4167	0.0000
GC	-0.0061	0.0017	-3.4736	0.0005

Bus

Variable	Coefficient	Std Err	t-stat	Prob
TTME	0.0022	0.0007	3.2351	0.0012
GC	0.0006	0.0002	2.4789	0.0132

Car

Variable	Coefficient	Std Err	t-stat	Prob
TTME	0.0139	0.0032	4.3983	0.0000
GC	0.0039	0.0012	3.1612	0.0016

3. DISCRETE CHOICE

Bus

Air

Variable	Coefficient	Std Err	t-stat	Prob
TTME	0.0011	0.0013	0.8568	0.3916
GC	0.0003	0.0005	0.6127	0.5400

Train

Variable	Coefficient	Std Err	t-stat	Prob
TTME	0.0041	0.0019	2.2059	0.0274
GC	0.0011	0.0005	2.1280	0.0333

Bus

Variable	Coefficient	Std Err	t-stat	Prob
TTME	-0.0033	0.0009	-3.4924	0.0005
GC	-0.0009	0.0004	-2.5794	0.0099

Car

Variable	Coefficient	Std Err	t-stat	Prob
TTME	0.0043	0.0019	2.2819	0.0225
GC	0.0012	0.0009	1.3605	0.1737

Car

Air

3. DISCRETE CHOICE

Variable	Coefficient	Std Err	t-stat	Prob
TTME	0.0038	4.5025	0.0009	0.9993
GC	0.0011	0.0006	1.7829	0.0746

Train

Variable	Coefficient	Std Err	t-stat	Prob
TTME	0.0139	5.7323	0.0024	0.9981
GC	0.0039	0.0015	2.5925	0.0095

Bus

Variable	Coefficient	Std Err	t-stat	Prob
TTME	0.0023	1.1325	0.0020	0.9984
GC	0.0006	0.0003	2.1380	0.0325

Car

Variable	Coefficient	Std Err	t-stat	Prob
TTME	-0.0220	9.2929	-0.0024	0.9981
GC	-0.0062	0.0016	-3.7781	0.0002

Fly

Fly

Variable	Coefficient	Std Err	t-stat	Prob
airhinc	0.0030	0.0006	4.8805	0.0000

3. DISCRETE CHOICE

Ground

Variable	Coefficient	Std Err	t-stat	Prob
airhinc	-0.0013	0.0009	-1.3862	0.1657

Ground

Fly

Variable	Coefficient	Std Err	t-stat	Prob
airhinc	-0.0030	4.0953	-0.0007	0.9994

Ground

Variable	Coefficient	Std Err	t-stat	Prob
airhinc	0.0013	4.8130	0.0003	0.9998

*****SUMMARY STATISTICS*****

MEASURES OF FIT:

-2 Ln(Lu):	387.3123
-2 Ln(Lr): All coeffs equal zero	582.2436
-2 Ln(Lr): J-1 intercepts	567.5175
LR Chi-Square (coeffs equal zero):	194.9313
d.f.	8.0000
p-value =	0.0000
LR Chi-Square (J-1 intercepts):	180.2052
d.f.	5.0000
p-value =	0.0000
Count R2, Percent Correctly Predicted:	0.7048
Adjusted Percent Correctly Predicted:	-0.4238
Madalla's pseudo R-square:	0.5760
McFadden's pseudo R-square:	0.3175
Ben-Akiva and Lerman's Adjusted R-square:	0.3175

3. DISCRETE CHOICE

Cragg and Uhler's pseudo R-square:	0.0976
Akaike Information Criterion:	1.9205
Bayesian Information Criterion1:	0.1275
Hannan-Quinn Information Criterion:	1.9721

OBSERVED and PREDICTED OUTCOMES

Observed	Predicted				Total
	Y01	Y02	Y03	Y04	
Y01	37	3	2	16	58
Y02	2	49	1	11	63
Y03	0	3	23	4	30
Y04	5	14	1	39	59
Total	44	69	27	70	210

3.11 Summary Statistics

Several goodness-of-fit measures are printed by **mnlprt**. Suppose the dependent variable is y ; there are N observations and $K + 1$ explanatory variables (including a constant term); the fitted values are $\hat{\mu}_i$; $L(r)$ is the restricted likelihood of the model with only an intercept and no other explanatory variables and $L(u)$ is the unrestricted likelihood, the model estimated with an intercept and all explanatory variables.

These include

1. The likelihood ratio statistic is:

$$LR = -2 \ln \left[\frac{L(r)}{L(u)} \right]$$

Under the null hypothesis that the $K - 1$ explanatory variables have no information about the dependent variable, LR is distributed $\chi^2(K - 1)$.

2. McFadden's (1973) pseudo R-square is:

$$R_{McF}^2 = 1 - 2 \ln \left[\frac{L(u)}{L(r)} \right]$$

3. Ben-Akiva and Lerman (1985) revise McFadden's measure to compensate for the effect of additional variables on a regression's explanatory power. Their measure, analogous to adjusted R^2 , is

$$\bar{R}_{McF}^2 = 1 - \frac{\ln L(u) - K}{\ln L(r)}$$

3. DISCRETE CHOICE

4. Greene (2000, p882) presents an R^2 measure based on standardized residuals.

$$R_p^2 = 1 - \frac{\sum_{i=1}^N \left[\frac{y_i - \hat{\mu}_i}{\sqrt{\hat{\mu}_i}} \right]^2}{\sum_{i=1}^N \left[\frac{y_i - \bar{y}}{\sqrt{\bar{y}}} \right]^2}$$

5. As noted in Greene (2000, p 883), Cameron and Windmeijer (1993) present an R^2 measure based on the deviances of individual observations,

$$d_i = 2[y_i \ln(\frac{y_i}{\mu_i}) - (y_i - \hat{\mu}_i)]:$$

$$R_d^2 = 1 - \frac{\sum_{i=1}^N [y_i \log(\frac{y_i}{\mu_i}) - (y_i - \hat{\mu}_i)]}{\sum_{i=1}^N [y_i \log(\frac{y_i}{\mu_i})]}$$

6. Cragg and Uhler (1970) propose a normed likelihood ratio, based on Maddala's (1983) showing that the maximum of R_{ML}^2 is $1 - L(r)^{2/N}$

$$R_{C\&U}^2 = \frac{R_{ML}^2}{\max R_{ML}^2} = \frac{1 - [L(r)/L(u)]^{2/N}}{1 - L(r)^{2/N}}$$

7. The count R^2 is the proportion of correct predictions, i.e.

$$R_{Count}^2 = \frac{1}{N} \sum_j n_{jj}$$

where n_{jj} is the number of correct predictions for outcome j .

8. The adjusted count R^2 uses the highest marginal frequency to adjust for the "spurious" successes that result by predicting that an outcome will fall in the category with the greatest percentage of observed successes. It is the proportion of successful categorizations occurring above what would occur by simply choosing the category with the greatest prior chance of success.

$$R_{AdjCount}^2 = \frac{\sum_j n_{jj} - \max_r(n_{r+})}{N - \max_r(n_{r+})}$$

where $\max(n_{r+})$ is the maximum of the contingency table row marginals, the "number of cases in the outcome with the most observations" (Long, 1997, p 108).

9. The average Akaike information criterion (AIC) is

$$AIC = \frac{-2[\ln L(u) - K]}{N}$$

10. The average Bayesian (Schwarz) information criterion (BIC) is

$$BIC = \frac{-2 \ln L(u) + K \ln(N)}{N}$$

11. The average Hannan-Quinn criterion is

$$HQIC = \frac{-2[\ln L(u) - K \ln(\ln(N))]}{N}$$

Chapter 4

Estimation and Optimization

A general constrained maximum likelihood estimation problem is:

$$\max_{\theta} L = \sum_{i=1}^N \log P(Y_i|x_i; \theta)$$

where N is the number of observations, $P(Y_i|x_i; \theta)$ is the probability of Y_i given x_i , and θ , a vector of parameters subject to linear constraints, nonlinear constraints, and bounds constraints.

The linear constraints are:

$$\begin{aligned} A\theta &= B \\ C\theta &\geq D \end{aligned}$$

The nonlinear constraints are:

$$\begin{aligned} G(\theta) &= 0 \\ H(\theta) &\geq 0 \end{aligned}$$

The bounds constraints are:

$$\theta_l \leq \theta \leq \theta_u$$

$G(\theta)$ and $H(\theta)$ are functions provided by the user and must be differentiable at least once with respect to θ .

4. ESTIMATION AND OPTIMIZATION

Under **sqpSolvemt**, parameters are updated in a series of iterations beginning with starting values provided by the user. Let θ_t be the current parameter values. Successive values are

$$\theta_{t+1} = \theta_t + \rho\delta$$

where δ is a $K \times 1$ *direction* vector, and ρ a scalar *step length*.

sqpSolvemt finds values for the parameters in θ such that L is maximized (the actual procedure is to minimize $-L$.)

Numerous user controllable variables affect the **sqpSolvemt** optimization. These are put into a *dcControl* structure instance. Suppose this instance has the name *dc1*, i.e.

```
struct dcControl cont;
cont = dcControlCreate;
```

The following are the members of the **dcControl** structure relevant to the management of the optimization:

- cont.A* $M \times K$ matrix, linear equality constraint coefficients: `cont.A * p = cont.B` where *p* is a vector of the parameters.
- cont.B* $M \times 1$ vector, linear equality constraint constants: `cont.A * p = cont.B` where *p* is a vector of the parameters.
- cont.C* $M \times K$ matrix, linear inequality constraint coefficients: `cont.C * p <= cont.D` where *p* is a vector of the parameters.
- cont.D* $M \times 1$ vector, linear inequality constraint constants: `cont.C * p >= cont.D` where *p* is a vector of the parameters.
- cont.eqProc* scalar, pointer to a procedure that computes the nonlinear equality constraints. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed equality constraints. For more details see Remarks below. Default = `{.}`, i.e., no equality procedure.
- cont.IneqProc* scalar, pointer to a procedure that computes the nonlinear inequality constraints. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed inequality constraints. For more details see Remarks below. Default = `{.}`, i.e., no inequality procedure.
- cont.Bounds* 1×2 or $K \times 2$ matrix, bounds on parameters. If 1×2 all parameters have same bounds. Default = `{ -1e256 1e256 }`.

4. ESTIMATION AND OPTIMIZATION

cont.GradProc scalar, pointer to a procedure that computes the gradient of the function with respect to the parameters. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed inequality constraints. For more details see Remarks below. Default = `{.}`, i.e., no gradient procedure has been provided.

cont.HessProc scalar, pointer to a procedure that computes the Hessian, i.e., the matrix of second order partial derivatives of the function with respect to the parameters. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed inequality constraints. For more details see Remarks below. Default = `.`, i.e., no Hessian procedure has been provided.

cont.MaxIters scalar, maximum number of iterations. Default = $1e + 5$.

cont.MaxTries scalar, maximum number of attempts in random search. Default = 100.

cont.DirTol scalar, convergence tolerance for gradient of estimated coefficients. Default = $1e - 5$. When this criterion has been satisfied `sqpSolve` exits the iterations.

cont.FeasibleTest scalar, if nonzero, parameters are tested for feasibility before computing function in line search. If function is defined outside inequality boundaries, then this test can be turned off. Default = 1;

cont.randRadius scalar, If zero, no random search is attempted. If nonzero, it is the radius of the random search. Default = .001.

cont.trustRadius scalar, radius of the trust region. If scalar missing, trust region not applied. The trust sets a maximum amount of the direction at each iteration. Default = .001.

cont.output scalar, if nonzero, optimization results are printed. Default = 0.

cont.PrintIters scalar, if nonzero, prints iteration information. Default = 0.

4.0.1 Constraints

The *dc1.A*, *dc1.B*, *dc1.C*, *dc1.D*, *dc1.EqProc*, *dc1.IneqProc*, and *dc1.Bounds* matrix structure members control constraints in the **DISCRETE CHOICE** procedures. Each row in one of these matrices is associated with a single constraint.

For computational convenience, nonlinear equality constraints and nonlinear inequality constraints are divided into five types: linear equality, linear inequality, nonlinear equality, nonlinear inequality, and bounds constraints.

4.0.2 Linear Equality Constraints

Linear constraints are of the form:

$$A\theta = B$$

where A is an $m_1 \times k$ matrix of known constants, B an $m_1 \times 1$ vector of known constants, and θ the vector of parameters.

To specify linear equality constraints, assign the A and B matrices to the `dc1.A` and `dc1.B` structure members. To constrain the first of four parameters to equal the third,

```
dc1.A = { 1 0 -1 0 };
dc1.B = { 0 };
```

4.0.3 Linear Inequality Constraints

Linear constraints are of the form:

$$C\theta \geq D$$

where C is an $m_2 \times k$ matrix of known constants, D an $m_2 \times 1$ vector of known constants, and θ the vector of parameters.

To specify linear inequality constraints, assign the C and D matrices to the structure members `dc1.C` and `dc1.D`. To constrain the first of four parameters to be greater than the third, and the second plus the fourth to be greater than 10:

```
dc1.C = { 1 0 -1 0,
          0 1  0 1 };
dc1.D = {  0,
          10 };
```

4.0.4 Nonlinear Equality

Nonlinear equality constraints are of the form:

$$G(\theta) = 0$$

where θ is the vector of parameters and $G(\theta)$ is an arbitrary, user-supplied function.

To specify nonlinear equality constraints, assign the pointer to the user-supplied constraint function to the `dc1.EqProc` member. To constrain the norm of the parameters to equal 1:

```
proc eqp(b);
    retp(b'b - 1);
endp;
dc1.EqProc = &eqp;
```

4. ESTIMATION AND OPTIMIZATION

4.0.5 Nonlinear Inequality

Nonlinear inequality constraints are of the form:

$$H(\theta) \geq 0$$

where θ is the vector of parameters, and $H(\theta)$ is an arbitrary, user-supplied function.

To specify nonlinear inequality constraints, assign the pointer to the user-supplied constraint function to the structure member *dc1.IneqProc*. To constrain a covariance matrix to be positive definite, the lower left nonredundant portion of which is stored in elements $r : r + s$ of the parameter vector:

```
proc ineqp(b);
    local v;
    v = xpnd(b[r:r+s]); /* r and s defined elsewhere */
    retp(minc(eigh(v)) - 1e-5);
endp;
dc1.IneqProc = &ineqp;
```

This constrains the minimum eigenvalue of the covariance matrix to be greater than a small number (1e-5), guaranteeing that the covariance matrix is positive definite.

4.0.6 Bounds

Bounds are a type of linear inequality constraint. For computational convenience they are specified separately from the other inequality constraints.

To specify bounds constraints, enter the lower and upper bounds respectively in the first and second columns of a matrix that has the same number of rows as the parameter vector. Assign this matrix to the structure member *dc1.Bounds*. Only the first row is necessary if the bounds are the same for all of the parameters. To bound four parameters:

```
dc1.Bounds = { -10 10,
               -10 0,
                1 10,
                0 1 };
```

To bound all the parameters between -50 and +50:

```
dc1.Bounds = { -50 50 };
```

4.0.7 Imposing Constraints in DISCRETE CHOICE models

To impose constraints in **DISCRETE CHOICE** models, you will need to know the order of parameters in the parameter vector. The simplest way to do this is to first run the model unconstrained and inspect the parameter vector upon output. For example run your command file adding a call to **pvGetParNames**:

```

library dc;
#include dc.sdf

struct dcDesc d1;
d1 = dcDescCreate;

d1.yname = "occatt";
d1.xnames = "exper" $| "educ" $| "white";
d1.catnames = "Menial" $| "BC" $| "Craft" $| "WC" $| "Pro";

struct dcControl c0;
c0 = dcControlCreate;

struct dcout dcout1;
dcout1 = mnl("gssocc",d1,c0);

print (ftostrC(seqa(1,1,pvLength(dcout1.par)),"%1.01f")
      $~ pvGetParNames(dcout1.par));

      1      b0[1,2]
      2      b0[1,3]
      3      b0[1,4]
      4      b0[1,5]
      5      b[1,2]
      6      b[1,3]
      7      b[1,4]
      8      b[1,5]
      9      b[2,2]
     10      b[2,3]
     11      b[2,4]
     12      b[2,5]
     13      b[3,2]
     14      b[3,3]
     15      b[3,4]
     16      b[3,5]

```

Now suppose you want to constrain columns two and three of b to be equal to each other (the first column is the reference column fixed to zeros), the last two columns to

4. ESTIMATION AND OPTIMIZATION

be equal to each other (a type of adjacent categories model), i.e., $b[1,3] = b[1,2]$, $b[2,3] = b[2,2]$, etc., and $b[1,5] = b[1,4]$, $b[2,5] = b[2,4]$, etc., and as well, $b[1,4] \neq b[1,2]$, $b[2,4] \neq b[2,2]$, etc.

To accomplish this we set up the following constraint matrices:

```
/*          1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16  */
c0.A = { 0  0  0  0  1 -1  0  0  0  0  0  0  0  0  0  0,
         0  0  0  0  0  0  0  0  1 -1  0  0  0  0  0  0,
         0  0  0  0  0  0  0  0  0  0  0  0  1 -1  0  0,
         0  0  0  0  0  0  1 -1  0  0  0  0  0  0  0  0,
         0  0  0  0  0  0  0  0  0  0  1 -1  0  0  0  0,
         0  0  0  0  0  0  0  0  0  0  0  0  0  0  1 -1 };

c0.B = { 0,
        0,
        0,
        0,
        0,
        0 };
```

Now suppose we wish to constrain the second column to be equal to the square of the third column, i.e., $b[1,2] = b[1,3]^2$, $b[2,2] = b[2,3]^2$, etc. For nonlinear constraints we must provide a procedure for computing the constraint. Our command file now looks like this:

```
library dc;
#include dc.sdf

struct dcDesc d1;
d1 = dcDescCreate;

d1.yname = "occatt";
d1.xnames = "exper" $| "educ" $| "white";
d1.catnames = "Menial" $| "BC" $| "Craft" $| "WC" $| "Pro";

struct dcControl c0;
c0 = dcControlCreate;

proc eqp(struct PV par, struct DS d);
  local p,r;
  p = pvGetParVector(par);
```

```

    r = zeros(3,1);
    r[1] = p[5] - p[6]^2;
    r[2] = p[9] - p[10]^2;
    r[3] = p[13] - p[14]^2;

    retp(r);
endp;

c0.eqProc = &eqp;

struct dcout dcout1;
dcout1 = mnl("gssocc",d1,c0);

```

Equality constraints aren't required to be feasible. Inequality constraints however must be feasible. If you are imposing inequality constraints, start values computed by the procedures may not be feasible and the optimization will fail. In that case you will have to supply feasible start values.

4.1 Direction

Define the likelihood function's gradient and Hessian:

$$\begin{aligned}\Psi(\theta) &= \frac{\partial L}{\partial \theta} \\ \Sigma(\theta) &= \frac{\partial^2 L}{\partial \theta \partial \theta'}\end{aligned}$$

and the Jacobians

$$\begin{aligned}\dot{G}(\theta) &= \frac{\partial G(\theta)}{\partial \theta} \\ \dot{H}(\theta) &= \frac{\partial H(\theta)}{\partial \theta}\end{aligned}$$

For the purposes of this exposition and without loss of generality, assume that the linear constraints and bounds have been incorporated into G and H .

In practice, linear constraints are specified separately from the G and H because their Jacobians are known and easy to compute. The bounds are more easily handled separately from the linear inequality constraints.

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The direction, δ , solves the quadratic program

$$\begin{aligned} & \text{minimize } \frac{1}{2} \delta' \Sigma(\theta_t) \delta + \Psi(\theta_t) \delta \\ & \text{subject to } \dot{G}(\theta_t) \delta + G(\theta_t) = 0 \\ & \quad \dot{H}(\theta_t) \delta + H(\theta_t) \geq 0 \end{aligned}$$

This solution requires that Σ be positive semi-definite.

4.2 Line Search

Define the merit function

$$m(\theta) = L + \max_j |\kappa_j| |g_j(\theta)| - \max_\ell |\lambda_\ell| \sum_\ell \min(0, h_\ell(\theta))$$

where g_j is the j -th row of G , h_ℓ is the ℓ -th row of H , κ is the vector of Lagrangean coefficients of the equality constraints, and λ the Lagrangean coefficients of the inequality constraints.

The line search finds a value of ρ that minimizes or decreases $m(\theta_t + \rho\delta)$.

4.2.1 Line Search Methods

Given a direction vector d , the updated estimate of the parameters is computed

$$\theta_{t+1} = \theta_t + \rho\delta$$

where ρ is a constant, usually called the *step length*, that increases the descent of the function given the direction. The value of the function to be minimized as a function of ρ is

$$m(\theta_t + \rho\delta)$$

Given θ and d , this is a function of a single variable ρ . The STEPBT polynomial line fitting/line search method attempts to find a value for ρ that decreases m .

STEPBT is an implementation of a similarly named algorithm described in Dennis and Schnabel (1983). It first attempts to fit a quadratic function to $m(\theta_t + \rho\delta)$, computing a ρ that minimizes the quadratic. If that fails it attempts to fit a cubic function. The cubic function is more costly to compute.

If *dc1.RandRadius* is greater than zero, a random search is tried if STEPBT fails. The random search uses the radius specified by *dc1.RandRadius*.

4.3 Managing Optimization

The critical elements in optimization are scaling, the starting point, and the condition of the model. When the data are scaled, the starting point is reasonably close to the solution, and the data and model go together well, the iterations converge quickly and without difficulty.

When the optimization is not proceeding well, it is sometimes useful to examine the function, the gradient Ψ , the direction δ , the Hessian Σ , the parameters θ_t , or the step length ρ , during the iterations.

Unless user-supplied functions are provided, **sqpSolve**mt calculates the gradient and Hessian numerically, using **gradmt** and **hessmt**. They have the same input arguments as **sqpSolve**mt, a *PV* instance containing the parameters and a *DS* instance containing the data.

Pointers to explicit gradient and Hessian functions are assigned to *dc1.gradproc* and *dc1.hessproc* respectively, i.e.

```
dc1.gradproc = &mygradproc;
dc1.hessproc = &myhessproc;
```

4.3.1 Scaling

For best performance, the diagonal elements of the Hessian matrix should be roughly equal. If some diagonal elements contain numbers that are very large and/or very small with respect to the others, **sqpSolve**mt has difficulty converging. It's not always obvious how to scale the diagonal elements of the Hessian. One rule-of-thumb is that the data be of roughly of the same magnitude.

4.3.2 Condition

The specification of the model may be measured by the condition of the Hessian, the ratio of the Hessian's largest to smallest eigenvalues.

The optimization solution is found by searching for parameter values for which the gradient is zero. It is difficult to determine a parameter's optimal value when the gradient of the function with respect to a parameter is nearly flat. When this occurs, elements of the Hessian associated with the parameter are very small and the inverse of the Hessian contains very large numbers. The search direction gets buried in the large numbers. In this case it is necessary to respecify the model to exclude the parameter.

4. ESTIMATION AND OPTIMIZATION

Poor condition can be caused by bad scaling. It can also be caused by a poor specification of the model or by bad data. A poorly specified model and bad data are two sides of the same coin.

If the problem is highly nonlinear, it is important that data be available to describe the features of the curve described by each of the parameters. For example, one of the parameters of the Weibull function describes the shape of the curve as it approaches the upper asymptote. This parameter is poorly estimated if data are not available on for that portion of the curve.

4.3.3 Starting Point

When the model is not particularly well-defined, the starting point can be critical. Try different starting points when the optimization doesn't seem to be working. A closed form solution may exist for a simpler problem with the same parameters. For example, ordinary least squares estimates may be used for nonlinear least squares problems or nonlinear regressions like probit or logit. There are no general methods for computing starting values. It may also be necessary to attempt the estimation from a variety of starting points.

4. ESTIMATION AND OPTIMIZATION

Chapter 5

References

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5. REFERENCES

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Chapter 6

Procedure Reference

■ Purpose

Estimates the Adjacent Categories Multinomial Logit model.

■ Library

dc

■ Format

{ *out* } = **dcAdjacentCategories**(*data*, *desc*, *cont*)

■ Input

data string or $N \times K$ matrix, if string, the name of a GAUSS data set or if matrix, matrix of data

desc1 an instance of a *dcDesc* structure

desc.yname name of dependent variable

desc.yvar scalar, index of dependent variable. If *data* is name of **GAUSS** dataset, either *desc.yname* or *desc.yvar* may be specified. If *data* is matrix of data *desc.yvar* must be specified.

desc.ytype scalar, 0 if *desc.yvar* character variable, otherwise 1 if numeric. Default = 1.

desc.xnames $K \times 1$ string vector, names of the independent variable(s).

desc.xvars $K \times 1$ vector, indices of the independent variable(s). If *data* is name of **GAUSS** dataset, either *desc.xnames* or *desc.xvars* may be specified. If *data* is matrix of data *desc.xvars* must be specified.

desc.catnames $L \times 1$ string vector, names of categories

desc.refcat reference category. If *desc.refcatName* is specified *desc.refcat* is optional. Default = 1.

desc.refcatName string, reference category name. If *desc.refcat* has been specified *desc.refcatName* is optional. Default = *desc.catnames*[1].

desc.noconstant scalar, 1 if no constants in model. Default = 0.

desc.marginType scalar, 1 - average partial probability with respect to independent variables, 0 - partial probability with respect to mean x. Default = 0.

desc.wgtname string, name of weight variable. If *desc.wgtvar* is specified, the specification of *desc.wgtname* is optional. Default = ;

desc.wgtvar scalar, index of weight variable. If *desc.wgtname* is specified, the specification of *desc.wgtvar* is optional. Default = 0;

cont an instance of a *dcControl* structure.

cont.startValues instance of **PV** structure containing starting values, if not provided, **Adjacent Categories** computes start values.

b0 $1 \times L$ matrix, constants in regression

b $2 \times K \times L$ matrix, regression coefficients (if any). Coefficients associated with reference category are fixed to zeros.

For example:

```

struct dcControl cont;
cont = dcControlCreate;

b0 = { 0  1  1 };

b = { 0  .1  .1
      0  .1  .1 };

mask = { 0  1  1,
         0  1  1,
         0  1  1 };

cont.startValues =
    pvPackmi(cont.startValues,b0,"b0",mask[1,.,1],1);
cont.startValues =
    pvPackmi(cont.startValues,b,"b",mask,2);

```

cont.A $M \times K$ matrix, linear equality constraint coefficients: $\text{cont.A} * p = \text{cont.B}$ where p is a vector of the parameters. For more details see section4.0.7.

cont.B $M \times 1$ vector, linear equality constraint constants: $\text{cont.A} * p = \text{cont.B}$ where p is a vector of the parameters. For more details see section4.0.7.

cont.C $M \times K$ matrix, linear inequality constraint coefficients: $\text{cont.C} * p \geq \text{cont.D}$ where p is a vector of the parameters. For more details see section4.0.7.

cont.D $M \times 1$ vector, linear inequality constraint constants: $\text{cont.C} * p \geq \text{cont.D}$ where p is a vector of the parameters. For more details see section4.0.7.

cont.eqProc scalar, pointer to a procedure that computes the nonlinear equality constraints. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed equality constraints. For more details see Remarks below. Default = $\{.\}$, i.e., no equality procedure. For more details see section4.0.7.

- cont.IneqProc* scalar, pointer to a procedure that computes the nonlinear inequality constraints. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed inequality constraints. For more details see Remarks below. Default = {`.`}, i.e., no inequality procedure. For more details see section 4.0.7.
- cont.Bounds* 1×2 or $K \times 2$ matrix, bounds on parameters. If 1×2 all parameters have same bounds. Default = {`-1e256 1e256`}. For more details see section 4.0.7.
- cont.GradProc* scalar, pointer to a procedure that computes the gradient of the function with respect to the parameters. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed inequality constraints. For more details see section 4.0.7. Default = {`.`}, i.e., no gradient procedure has been provided.
- cont.HessProc* scalar, pointer to a procedure that computes the Hessian, i.e., the matrix of second order partial derivatives of the function with respect to the parameters. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed inequality constraints. For more details see section 4.0.7. Default = `.`, i.e., no Hessian procedure has been provided.
- cont.MaxIters* scalar, maximum number of iterations. Default = `1e + 5`.
- cont.MaxTries* scalar, maximum number of attempts in random search. Default = `100`.
- cont.DirTol* scalar, convergence tolerance for gradient of estimated coefficients. Default = `1e - 5`. When this criterion has been satisfied sqpSolve exits the iterations.
- cont.FeasibleTest* scalar, if nonzero, parameters are tested for feasibility before computing function in line search. If function is defined outside inequality boundaries, then this test can be turned off. Default = `1`;
- cont.randRadius* scalar, If zero, no random search is attempted. If nonzero, it is the radius of the random search. Default = `.001`.
- cont.trustRadius* scalar, radius of the trust region. If scalar missing, trust region not applied. The trust sets a maximum amount of the direction at each iteration. Default = `.001`.
- cont.output* scalar, if nonzero, optimization results are printed. Default = `0`.
- cont.PrintIters* scalar, if nonzero, prints iteration information. Default = `0`.

■ Output

out An instance of a *dcOut* structure.

out.par instance of PV structure containing estimates

b0 $1 \times L$ matrix, constants in regression

b $2 \times L \times K$ matrix, regression coefficients (if any). Coefficients associated with reference category are fixed to zeros.

To retrieve, e.g., regression coefficients:

```
b = pvUnpack(out.par, "b");
```

or

```
b = pvUnpack(out.par, 2);
```

The coefficients may also be retrieved as a single parameter vector:

```
b = pvGetParVector(out.par);
```

The location of the coefficients in *out.par* can be described by

```
b = pvgetParNames(out.par);
```

if model doesn't contain a parameter, *pvUnpack* returns a scalar missing value with error code = 99.

out.vc $NPARM \times NPARM$ variance-covariance matrix of coefficient estimates

out.ydist $L \times 1$ vector, percentages of dependent variable by category

out.xdata $K \times 4$ matrix, the means, standard deviations, minimums, and maximums of independent variables

out.margineffects $L \times 1 \times K$ array, marginal effects of independent variables by category of dependent variable

out.marginvc $L \times K \times K$ array, covariance matrices of marginal effects of independent variables by category of dependent variable

out.fittedvals $N \times 1$ matrix of predicted (fitted) counts

out.resids $N \times 1$ matrix of residuals

out.gf 12×1 matrix of goodness-of-fit measures

- 1 Log-Likelihood, full model
- 2 Log-Likelihood, restricted model (all slope coefficients equal zero)
- 3 Chi-square statistic
- 4 Agresti's G-Squared statistic
- 5 Likelihood Ratio statistics (from the full and restricted models above)
- 6 Probability values for the likelihood ratio statistics

- 7 McFadden's Pseudo R-Squared
- 8 McKelvey and Zovcina's Pseudo R-Squared
- 9 Cragg and Uhler's normed likelihood ratios
- 10 Count R-Squared
- 11 Adjusted Count R-Squared
- 12 Akaike information criterion (AIC)
- 13 Bayesian information criterion (BIC)

■ Example

```
library dc;
#include dc.sdf

struct dcDesc d1;
d1 = dcDescCreate;

d1.yname = "occatt";
d1.xnames = "exper" $| "educ" $| "white";
d1.catnames = "Menial" $| "BC" $| "Craft" $| "WC" $| "Pro";

struct dcout dcout1;

dcout1 = dcAdjacentCategories("gssocc",d1,dccontrolCreate);

call dcprt(dcout1);
```

■ Remarks

The adjacent category model is a special case of the multinomial logit model where the coefficients of succeeding categories are constrained to be greater than their preceding counterparts.

■ Source

dcaclogit.src

■ Purpose

Estimates a logit regression model

■ Library

dc

■ Format

{ *out* } = **dcBinaryLogit**(*data*, *desc*, *cont*)

■ Input

data string or $N \times K$ matrix, if string, the name of a GAUSS data set or if matrix, matrix of data

desc1 an instance of a *dcDesc* structure

desc.yname name of dependent variable

desc.yvar scalar, index of dependent variable. If *data* is name of **GAUSS** dataset, either *desc.yname* or *desc.yvar* may be specified. If *data* is matrix of data *desc.yvar* must be specified.

desc.ytype scalar, 0 if *desc.yvar* character variable, otherwise 1 if numeric. Default = 1.

desc.xnames $K \times 1$ string vector, names of the independent variable(s).

desc.xvars $K \times 1$ vector, indices of the independent variable(s). If *data* is name of **GAUSS** dataset, either *desc.xnames* or *desc.xvars* may be specified. If *data* is matrix of data *desc.xvars* must be specified.

desc.catnames $L \times 1$ string vector, names of categories

desc.refcat reference category. If *desc.refcatName* is specified *desc.refcat* is optional. Default = 1.

desc.refcatName string, reference category name. If *desc.refcat* has been specified *desc.refcatName* is optional. Default = *desc.catnames*[1].

desc.wgtname string, name of weight variable. If *desc.wgtvar* is specified, the specification of *desc.wgtname* is optional. Default = ;

desc.wgtvar scalar, index of weight variable. If *desc.wgtname* is specified, the specification of *desc.wgtvar* is optional. Default = 0;

desc.noconstant scalar, 1 if no constants in model. Default = 0.

desc.marginType scalar, 1 - average partial probability with respect to independent variables, 0 - partial probability with respect to mean x. Default = 0.

cont an instance of a *dcControl* structure.

cont.startValues instance of **PV** structure containing starting values, if not provided, **dcBinaryLogit** computes start values.

b0 1 constant in regression

b 2 regression coefficients (if any)

For example:

```

struct dcControl cont;
cont = dcControlCreate;

b0 = 1;
b = { .1, .2 };
cont.startValues = pvPacki(cont.startValues,b0,"b0",1);
cont.startValues = pvPacki(cont.startValues,b,"b",2);

```

cont.A $M \times K$ matrix, linear equality constraint coefficients: $\text{cont.A} * \mathbf{p} = \text{cont.B}$ where \mathbf{p} is a vector of the parameters. For more details see section4.0.7.

cont.B $M \times 1$ vector, linear equality constraint constants: $\text{cont.A} * \mathbf{p} = \text{cont.B}$ where \mathbf{p} is a vector of the parameters. For more details see section4.0.7.

cont.C $M \times K$ matrix, linear inequality constraint coefficients: $\text{cont.C} * \mathbf{p} \geq \text{cont.D}$ where \mathbf{p} is a vector of the parameters. For more details see section4.0.7.

cont.D $M \times 1$ vector, linear inequality constraint constants: $\text{cont.C} * \mathbf{p} \geq \text{cont.D}$ where \mathbf{p} is a vector of the parameters. For more details see section4.0.7.

cont.eqProc scalar, pointer to a procedure that computes the nonlinear equality constraints. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed equality constraints. For more details see Remarks below. Default = $\{.\}$, i.e., no equality procedure. For more details see section4.0.7.

cont.IneqProc scalar, pointer to a procedure that computes the nonlinear inequality constraints. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed inequality constraints. For more details see Remarks below. Default = $\{.\}$, i.e., no inequality procedure. For more details see section4.0.7.

cont.Bounds 1×2 or $K \times 2$ matrix, bounds on parameters. If 1×2 all parameters have same bounds. Default = $\{-1e256 \ 1e256\}$. For more details see section4.0.7.

cont.GradProc scalar, pointer to a procedure that computes the gradient of the function with respect to the parameters. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed inequality constraints. For more details see section 4.0.7. Default = {.}, i.e., no gradient procedure has been provided.

cont.HessProc scalar, pointer to a procedure that computes the Hessian, i.e., the matrix of second order partial derivatives of the function with respect to the parameters. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed inequality constraints. For more details see section 4.0.7. Default = ., i.e., no Hessian procedure has been provided.

cont.MaxIters scalar, maximum number of iterations. Default = $1e + 5$.

cont.MaxTries scalar, maximum number of attempts in random search. Default = 100.

cont.DirTol scalar, convergence tolerance for gradient of estimated coefficients. Default = $1e - 5$. When this criterion has been satisfied `sqpSolve` exits the iterations.

cont.FeasibleTest scalar, if nonzero, parameters are tested for feasibility before computing function in line search. If function is defined outside inequality boundaries, then this test can be turned off. Default = 1;

cont.randRadius scalar, If zero, no random search is attempted. If nonzero, it is the radius of the random search. Default = .001.

cont.trustRadius scalar, radius of the trust region. If scalar missing, trust region not applied. The trust sets a maximum amount of the direction at each iteration. Default = .001.

cont.output scalar, if nonzero, optimization results are printed. Default = 0.

cont.PrintIters scalar, if nonzero, prints iteration information. Default = 0.

■ Output

out An instance of a *dcOut* structure.

out.par instance of PV structure containing estimates

b0 1 constant in regression

b 2 regression coefficients (if any)

To retrieve, e.g., regression coefficients:

```
b = pvUnpack(out.par,"b");
```

or

```
b = pvUnpack(out.par,2);
```

The coefficients may also be retrieved as a single parameter vector:

```
b = pvGetParVector(out.par);
```

The location of the coefficients in `out.par` can be described by

```
b = pvgetParNames(out.par);
```

if model doesn't contain a parameter, `pvUnpack` returns a scalar missing value with error code = 99.

out.vc $NPARM \times NPARM$ variance-covariance matrix of coefficient estimates

out.ydist $L \times 1$ vector, percentages of dependent variable by category

out.xdata $K \times 4$ matrix, the means, standard deviations, minimums, and maximums of independent variables

out.margineffects $L \times 1 \times K$ array, marginal effects of independent variables by category of dependent variable

out.marginvc $L \times K \times K$ array, covariance matrices of marginal effects of independent variables by category of dependent variable

out.fittedvals $N \times 1$ matrix of predicted (fitted) counts

out.resids $N \times 1$ matrix of residuals

out.gf 12×1 matrix of goodness-of-fit measures

- 1 Log-Likelihood, full model
- 2 Log-Likelihood, restricted model (all slope coefficients equal zero)
- 3 Chi-square statistic
- 4 Agresti's G-Squared statistic
- 5 Likelihood Ratio statistics (from the full and restricted models above)
- 6 Probability values for the likelihood ratio statistics
- 7 McFadden's Pseudo R-Squared
- 8 McKelvey and Zovcina's Pseudo R-Squared
- 9 Cragg and Uhler's normed likelihood ratios
- 10 Count R-Squared
- 11 Adjusted Count R-Squared
- 12 Akaike information criterion (AIC)
- 13 Bayesian information criterion (BIC)

■ Example

6. PROCEDURE REFERENCE

dcBinaryLogit

```
library dc;
#include dc.sdf

struct dcDesc d1;
d1 = dcDescCreate;

d1.yname = "A";
d1.xnames = "GPA" $| "TUCE" $| "PSI";

struct dcout dcout1;

dcout1 = dcBinaryLogit("aldnel",d1,dccontrolCreate);

call dcprt(dcout1);
```

■ Source

dcbin.src

■ Purpose

Estimates a probit regression model.

■ Library

dc

■ Format

{ *out* } = **dcBinaryProbit**(*data*, *desc*, *cont*)

■ Input

data string or $N \times K$ matrix, if string, the name of a GAUSS data set or if matrix, matrix of data

desc1 an instance of a *dcDesc* structure

desc.yname name of dependent variable

desc.yvar scalar, index of dependent variable. If *data* is name of **GAUSS** dataset, either *desc.yname* or *desc.yvar* may be specified. If *data* is matrix of data *desc.yvar* must be specified.

desc.ytype scalar, 0 if *desc.yvar* character variable, otherwise 1 if numeric. Default = 1.

desc.xnames $K \times 1$ string vector, names of the independent variable(s).

desc.xvars $K \times 1$ vector, indices of the independent variable(s). If *data* is name of **GAUSS** dataset, either *desc.xnames* or *desc.xvars* may be specified. If *data* is matrix of data *desc.xvars* must be specified.

desc.catnames $L \times 1$ string vector, names of categories

desc.refcat reference category. If *desc.refcatName* is specified *desc.refcat* is optional. Default = 1.

desc.refcatName string, reference category name. If *desc.refcat* has been specified *desc.refcatName* is optional. Default = *desc.catnames*[1].

desc.wgtname string, name of weight variable. If *desc.wgtvar* is specified, the specification of *desc.wgtname* is optional. Default = ;

desc.wgtvar scalar, index of weight variable. If *desc.wgtname* is specified, the specification of *desc.wgtvar* is optional. Default = 0;

desc.noconstant scalar, 1 if no constants in model. Default = 0.

desc.marginType scalar, 1 - average partial probability with respect to independent variables, 0 - partial probability with respect to mean x. Default = 0.

cont an instance of a *dcControl* structure.

cont.startValues instance of **PV** structure containing starting values, if not provided, **dcBinaryProbit** computes start values.

b0 1 constant in regression

b 2 regression coefficients (if any)

For example:

```

struct dcControl cont;
cont = dcControlCreate;

b0 = 1;
b = { .1, .2 };
cont.startValues = pvPacki(cont.startValues,b0,"b0",1);
cont.startValues = pvPacki(cont.startValues,b,"b",2);

```

cont.A $M \times K$ matrix, linear equality constraint coefficients: *cont.A* * *p* = *cont.B* where *p* is a vector of the parameters. For more details see section4.0.7.

cont.B $M \times 1$ vector, linear equality constraint constants: *cont.A* * *p* = *cont.B* where *p* is a vector of the parameters. For more details see section4.0.7.

cont.C $M \times K$ matrix, linear inequality constraint coefficients: *cont.C* * *p* >= *cont.D* where *p* is a vector of the parameters. For more details see section4.0.7.

cont.D $M \times 1$ vector, linear inequality constraint constants: *cont.C* * *p* >= *cont.D* where *p* is a vector of the parameters. For more details see section4.0.7.

cont.eqProc scalar, pointer to a procedure that computes the nonlinear equality constraints. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed equality constraints. For more details see Remarks below. Default = {*.*}, i.e., no equality procedure. For more details see section4.0.7.

cont.IneqProc scalar, pointer to a procedure that computes the nonlinear inequality constraints. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed inequality constraints. For more details see Remarks below. Default = {*.*}, i.e., no inequality procedure. For more details see section4.0.7.

cont.Bounds 1×2 or $K \times 2$ matrix, bounds on parameters. If 1×2 all parameters have same bounds. Default = { -1e256 1e256 }. For more details see section4.0.7.

cont.GradProc scalar, pointer to a procedure that computes the gradient of the function with respect to the parameters. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed inequality constraints. For more details see section 4.0.7. Default = `{.}`, i.e., no gradient procedure has been provided.

cont.HessProc scalar, pointer to a procedure that computes the Hessian, i.e., the matrix of second order partial derivatives of the function with respect to the parameters. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed inequality constraints. For more details see section 4.0.7. Default = `.`, i.e., no Hessian procedure has been provided.

cont.MaxIters scalar, maximum number of iterations. Default = $1e + 5$.

cont.MaxTries scalar, maximum number of attempts in random search. Default = 100.

cont.DirTol scalar, convergence tolerance for gradient of estimated coefficients. Default = $1e - 5$. When this criterion has been satisfied `sqpSolve` exits the iterations.

cont.FeasibleTest scalar, if nonzero, parameters are tested for feasibility before computing function in line search. If function is defined outside inequality boundaries, then this test can be turned off. Default = 1;

cont.randRadius scalar, If zero, no random search is attempted. If nonzero, it is the radius of the random search. Default = .001.

cont.trustRadius scalar, radius of the trust region. If scalar missing, trust region not applied. The trust sets a maximum amount of the direction at each iteration. Default = .001.

cont.output scalar, if nonzero, optimization results are printed. Default = 0.

cont.PrintIters scalar, if nonzero, prints iteration information. Default = 0.

■ Output

out An instance of a *dcOut* structure.

out.par instance of PV structure containing estimates

b0 1 constant in regression

b 2 regression coefficients (if any)

To retrieve, e.g., regression coefficients:

```
b = pvUnpack(out.par,"b");
```

or

```
b = pvUnpack(out.par,2);
```

The coefficients may also be retrieved as a single parameter vector:

```
b = pvGetParVector(out.par);
```

The location of the coefficients in `out.par` can be described by

```
b = pvgetParNames(out.par);
```

if model doesn't contain a parameter, `pvUnpack` returns a scalar missing value with error code = 99.

out.vc $NPARM \times NPARM$ variance-covariance matrix of coefficient estimates

out.ydist $L \times 1$ vector, percentages of dependent variable by category

out.xdata $K \times 4$ matrix, the means, standard deviations, minimums, and maximums of independent variables

out.margineffects $L \times 1 \times K$ array, marginal effects of independent variables by category of dependent variable

out.marginvc $L \times K \times K$ array, covariance matrices of marginal effects of independent variables by category of dependent variable

out.fittedvals $N \times 1$ matrix of predicted (fitted) counts

out.resids $N \times 1$ matrix of residuals

out.gf 12×1 matrix of goodness-of-fit measures

- 1 Log-Likelihood, full model
- 2 Log-Likelihood, restricted model (all slope coefficients equal zero)
- 3 Chi-square statistic
- 4 Agresti's G-Squared statistic
- 5 Likelihood Ratio statistics (from the full and restricted models above)
- 6 Probability values for the likelihood ratio statistics
- 7 McFadden's Pseudo R-Squared
- 8 McKelvey and Zovcina's Pseudo R-Squared
- 9 Cragg and Uhler's normed likelihood ratios
- 10 Count R-Squared
- 11 Adjusted Count R-Squared
- 12 Akaike information criterion (AIC)
- 13 Bayesian information criterion (BIC)

■ Example

dcBinaryProbit

6. PROCEDURE REFERENCE

```
library dc;
#include dc.sdf

struct dcDesc d1;
d1 = dcDescCreate;

d1.yname = "A";
d1.xnames = "GPA" $| "TUCE" $| "PSI";

struct dcout dcout1;

dcout1 = dcBinaryProbit("aldnel",d1,dccontrolCreate);

call dcprt(dcout1);
```

■ Source

dcbin.src

■ Purpose

Estimates the Conditional Logit model.

■ Library

dc

■ Format

$\{ out \} = \text{dcConditionalLogit}(data, desc, cont)$

■ Input

data string or $N \times K$ matrix, if string, the name of a GAUSS data set or if matrix, matrix of data

desc1 an instance of a *dcDesc* structure

desc.dataType scalar, if 1, the dataset contains a single row for each observation and attribute variables are stored in separate columns in that row. If 0, category data are stored by row within observation and attribute data are stored in single columns

desc.yname name of dependent variable

desc.yvar scalar, index of dependent variable. If data is name of **GAUSS** dataset, either *desc.yname* or *desc.yvar* may be specified. If data is matrix of data *desc.yvar* must be specified.

desc.ytype scalar, 0 if *desc.yvar* character variable, otherwise 1 if numeric. Default = 1.

desc.xnames $K \times 1$ string vector, names of the independent variable(s).

desc.xvars $K \times 1$ vector, indices of the independent variable(s). If data is name of **GAUSS** dataset, either *desc.xnames* or *desc.xvars* may be specified. If data is matrix of data *desc.xvars* must be specified.

desc.catnames $L \times 1$ string vector, names of categories

desc.refcat reference category. If *desc.refcatName* is specified *desc.refcat* is optional. Default = 1.

desc.refcatName string, reference category name. If *desc.refcat* has been specified *desc.refcatName* is optional. Default = *desc.catnames[1]*.

desc.atNames $P \times 1$ string vector, names of the attribute variable(s).

desc.atVars $P \times 1$ numeric vector, indices of the attribute variable(s).

desc.atCatNames $P \times L$ string array, names of the categories of attribute variable(s). Required if *desc.datatype* = 1 and *desc.atCatVars* not specified.

desc.atCatVars $P \times L$ numeric vector, indices of the categories of attribute variable(s). Required if *desc.datatype* = 1 and *desc.atCatNames* not specified.

desc.wgtname string, name of weight variable. If *desc.wgtvar* is specified, the specification of *desc.wgtname* is optional. Default = ;

desc.wgtvar scalar, index of weight variable. If *desc.wgtname* is specified, the specification of *desc.wgtvar* is optional. Default = 0;

desc.noconstant scalar, 1 if no constants in model. Default = 0.

desc.marginType scalar, 1 - average partial probability with respect to independent variables, 0 - partial probability with respect to mean x. Default = 0.

cont an instance of a *dcControl* structure.

cont.startValues instance of **PV** structure containing starting values, if not provided, **Adjacent Categories** computes start values.

b0 $1 \times L$ vector, constants in regression

b $2 \times K \times L$ Matrix, regression coefficients of independent variables if any. Coefficients associated with reference category are fixed to zeros.

gm $3 \times M \times 1$ vector, coefficients of attribute variables.

For example:

```

struct dcControl cont;
cont = dcControlCreate;

b0 = { 0  1  1 };

b = { 0  .1  .1
      0  .1  .1 };

mask = { 0  1  1,
         0  1  1,
         0  1  1 };

gm = { .1, .1 };

cont.startValues =
  pvPackmi(cont.startValues,b0,"b0",mask[1,],1);
cont.startValues =
  pvPackmi(cont.startValues,b,"b",mask,2);
cont.startValues =
  pvPackmi(cont.startValues,gm,"gm",mask,3);

```


- cont.A* $M \times K$ matrix, linear equality constraint coefficients: `cont.A * p = cont.B` where `p` is a vector of the parameters. For more details see section4.0.7.
- cont.B* $M \times 1$ vector, linear equality constraint constants: `cont.A * p = cont.B` where `p` is a vector of the parameters. For more details see section4.0.7.
- cont.C* $M \times K$ matrix, linear inequality constraint coefficients: `cont.C * p >= cont.D` where `p` is a vector of the parameters. For more details see section4.0.7.
- cont.D* $M \times 1$ vector, linear inequality constraint constants: `cont.C * p >= cont.D` where `p` is a vector of the parameters. For more details see section4.0.7.
- cont.eqProc* scalar, pointer to a procedure that computes the nonlinear equality constraints. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed equality constraints. For more details see Remarks below. Default = `{.}`, i.e., no equality procedure. For more details see section4.0.7.
- cont.IneqProc* scalar, pointer to a procedure that computes the nonlinear inequality constraints. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed inequality constraints. For more details see Remarks below. Default = `{.}`, i.e., no inequality procedure. For more details see section4.0.7.
- cont.Bounds* 1×2 or $K \times 2$ matrix, bounds on parameters. If 1×2 all parameters have same bounds. Default = `{ -1e256 1e256 }`. For more details see section4.0.7.
- cont.GradProc* scalar, pointer to a procedure that computes the gradient of the function with respect to the parameters. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed inequality constraints. For more details see section4.0.7. Default = `{.}`, i.e., no gradient procedure has been provided.
- cont.HessProc* scalar, pointer to a procedure that computes the Hessian, i.e., the matrix of second order partial derivatives of the function with respect to the parameters. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed inequality constraints. For more details see section4.0.7. Default = `.`, i.e., no Hessian procedure has been provided.
- cont.MaxIters* scalar, maximum number of iterations. Default = `1e + 5`.
- cont.MaxTries* scalar, maximum number of attempts in random search. Default = `100`.

cont.DirTol scalar, convergence tolerance for gradient of estimated coefficients. Default = $1e - 5$. When this criterion has been satisfied sqpSolvevt exits the iterations.

cont.FeasibleTest scalar, if nonzero, parameters are tested for feasibility before computing function in line search. If function is defined outside inequality boundaries, then this test can be turned off. Default = 1;

cont.randRadius scalar, If zero, no random search is attempted. If nonzero, it is the radius of the random search. Default = .001.

cont.trustRadius scalar, radius of the trust region. If scalar missing, trust region not applied. The trust sets a maximum amount of the direction at each iteration. Default = .001.

cont.output scalar, if nonzero, optimization results are printed. Default = 0.

cont.PrintIters scalar, if nonzero, prints iteration information. Default = 0.

■ Output

out An instance of a *dcOut* structure.

out.par instance of PV structure containing estimates

b0 $1 \times L$ matrix, constants in regression

b $2 \times L \times K$ matrix, regression coefficients (if any). Coefficients associated with reference category are fixed to zeros.

gm $3 \times M \times 1$ vector, coefficients of attribute variables.

To retrieve, e.g., regression coefficients:

```
b = pvUnpack(out.par, "b");
```

or

```
b = pvUnpack(out.par, 2);
```

The coefficients may also be retrieved as a single parameter vector:

```
b = pvGetParVector(out.par);
```

The location of the coefficients in *out.par* can be described by

```
b = pvgetParNames(out.par);
```

if model doesn't contain a parameter, *pvUnpack* returns a scalar missing value with error code = 99.

out.vc $NPARM \times NPARM$ variance-covariance matrix of coefficient estimates

- out.ydist* $L \times 1$ vector, percentages of dependent variable by category
- out.xdata* $K \times 4$ matrix, the means, standard deviations, minimums, and maximums of independent variables
- out.margineffects* $L \times 1 \times K$ array, marginal effects of independent variables by category of dependent variable
- out.marginvc* $L \times K \times K$ array, covariance matrices of marginal effects of independent variables by category of dependent variable
- out.atmargineffects* $L \times L \times 1 \times R$ array, marginal effects by category of attribute variables by category of dependent variable
- out.atmarginvc* $L \times L \times R \times R$ array, covariance matrices of marginal effects by category of attribute variables by category of dependent variable
- out.fittedvals* $N \times 1$ matrix of predicted (fitted) counts
- out.resids* $N \times 1$ matrix of residuals
- out.gf* 12×1 matrix of goodness-of-fit measures
- 1 Log-Likelihood, full model
 - 2 Log-Likelihood, restricted model (all slope coefficients equal zero)
 - 3 Chi-square statistic
 - 4 Agresti's G-Squared statistic
 - 5 Likelihood Ratio statistics (from the full and restricted models above)
 - 6 Probability values for the likelihood ratio statistics
 - 7 McFadden's Pseudo R-Squared
 - 8 McKelvey and Zovcina's Pseudo R-Squared
 - 9 Cragg and Uhler's normed likelihood ratios
 - 10 Count R-Squared
 - 11 Adjusted Count R-Squared
 - 12 Akaike information criterion (AIC)
 - 13 Bayesian information criterion (BIC)

■ Example

```
new;
library dc;
#include dc.sdf

struct dcDesc d1;
d1 = dcDescCreate;

d1.yname = "Mode";
d1.catvarname = "choiceno";
```

dcConditionalLogit

6. PROCEDURE REFERENCE

```
d1.catnames = "train$"|"bus$"|"car";  
d1.atnames = "ttme$"|"invc$"|"invt$"|"GC";  
  
d1.noconstant = 1;  
  
struct dcout dcout1;  
dcout1 = dcConditionalLogit("powersxie",d1,dccontrolCreate);  
call dcprt(dcout1);
```

■ Purpose

Estimates the Multinomial Logit model.

■ Library

dc

■ Format

{ *out* } = **dcMultinomialLogit**(*data*, *desc*, *cont*)

■ Input

data string or $N \times K$ matrix, if string, the name of a GAUSS data set or if matrix, matrix of data

desc1 an instance of a *dcDesc* structure

desc.yname name of dependent variable

desc.yvar scalar, index of dependent variable. If *data* is name of **GAUSS** dataset, either *desc.yname* or *desc.yvar* may be specified. If *data* is matrix of data *desc.yvar* must be specified.

desc.ytype scalar, 0 if *desc.yvar* character variable, otherwise 1 if numeric. Default = 1.

desc.xnames $K \times 1$ string vector, names of the independent variable(s).

desc.xvars $K \times 1$ vector, indices of the independent variable(s). If *data* is name of **GAUSS** dataset, either *desc.xnames* or *desc.xvars* may be specified. If *data* is matrix of data *desc.xvars* must be specified.

desc.catnames $L \times 1$ string vector, names of categories

desc.refcat reference category. If *desc.refcatName* is specified *desc.refcat* is optional. Default = 1.

desc.refcatName string, reference category name. If *desc.refcat* has been specified *desc.refcatName* is optional. Default = *desc.catnames*[1].

desc.wgtname string, name of weight variable. If *desc.wgtvar* is specified, the specification of *desc.wgtname* is optional. Default = ;

desc.wgtvar scalar, index of weight variable. If *desc.wgtname* is specified, the specification of *desc.wgtvar* is optional. Default = 0;

desc.noconstant scalar, 1 if no constants in model. Default = 0.

desc.marginType scalar, 1 - average partial probability with respect to independent variables, 0 - partial probability with respect to mean x. Default = 0.

cont an instance of a *dcControl* structure.

cont.startValues instance of **PV** structure containing starting values, if not provided, **Adjacent Categories** computes start values.

b0 $1 \times L$ matrix, constants in regression

b $2 \times K \times L$ matrix, regression coefficients (if any). Coefficients associated with reference category are fixed to zeros.

For example:

```

struct dcControl cont;
cont = dcControlCreate;

b0 = { 0  1  1 };

b = { 0  .1  .1
      0  .1  .1 };

mask = { 0  1  1,
         0  1  1,
         0  1  1 };

cont.startValues =
    pvPackmi(cont.startValues,b0,"b0",mask[1,],1);
cont.startValues =
    pvPackmi(cont.startValues,b,"b",mask,2);

```

cont.A $M \times K$ matrix, linear equality constraint coefficients: $\text{cont.A} * \mathbf{p} = \text{cont.B}$ where \mathbf{p} is a vector of the parameters. For more details see section4.0.7.

cont.B $M \times 1$ vector, linear equality constraint constants: $\text{cont.A} * \mathbf{p} = \text{cont.B}$ where \mathbf{p} is a vector of the parameters. For more details see section4.0.7.

cont.C $M \times K$ matrix, linear inequality constraint coefficients: $\text{cont.C} * \mathbf{p} \geq \text{cont.D}$ where \mathbf{p} is a vector of the parameters. For more details see section4.0.7.

cont.D $M \times 1$ vector, linear inequality constraint constants: $\text{cont.C} * \mathbf{p} \geq \text{cont.D}$ where \mathbf{p} is a vector of the parameters. For more details see section4.0.7.

cont.eqProc scalar, pointer to a procedure that computes the nonlinear equality constraints. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed equality constraints. For more details see Remarks below. Default = $\{.\}$, i.e., no equality procedure. For more details see section4.0.7.

- cont.IneqProc* scalar, pointer to a procedure that computes the nonlinear inequality constraints. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed inequality constraints. For more details see Remarks below. Default = {`.`}, i.e., no inequality procedure. For more details see section 4.0.7.
- cont.Bounds* 1×2 or $K \times 2$ matrix, bounds on parameters. If 1×2 all parameters have same bounds. Default = {`-1e256 1e256`}. For more details see section 4.0.7.
- cont.GradProc* scalar, pointer to a procedure that computes the gradient of the function with respect to the parameters. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed inequality constraints. For more details see section 4.0.7. Default = {`.`}, i.e., no gradient procedure has been provided.
- cont.HessProc* scalar, pointer to a procedure that computes the Hessian, i.e., the matrix of second order partial derivatives of the function with respect to the parameters. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed inequality constraints. For more details see section 4.0.7. Default = `.`, i.e., no Hessian procedure has been provided.
- cont.MaxIters* scalar, maximum number of iterations. Default = `1e + 5`.
- cont.MaxTries* scalar, maximum number of attempts in random search. Default = `100`.
- cont.DirTol* scalar, convergence tolerance for gradient of estimated coefficients. Default = `1e - 5`. When this criterion has been satisfied `sqpSolve` exits the iterations.
- cont.FeasibleTest* scalar, if nonzero, parameters are tested for feasibility before computing function in line search. If function is defined outside inequality boundaries, then this test can be turned off. Default = `1`;
- cont.randRadius* scalar, If zero, no random search is attempted. If nonzero, it is the radius of the random search. Default = `.001`.
- cont.trustRadius* scalar, radius of the trust region. If scalar missing, trust region not applied. The trust sets a maximum amount of the direction at each iteration. Default = `.001`.
- cont.output* scalar, if nonzero, optimization results are printed. Default = `0`.
- cont.PrintIters* scalar, if nonzero, prints iteration information. Default = `0`.

■ Output

out An instance of a *dcOut* structure.

out.par instance of PV structure containing estimates

b0 $1 \times L$ matrix, constants in regression

b $2 \times L \times K$ matrix, regression coefficients (if any). Coefficients associated with reference category are fixed to zeros.

To retrieve, e.g., regression coefficients:

```
b = pvUnpack(out.par, "b");
```

or

```
b = pvUnpack(out.par, 2);
```

The coefficients may also be retrieved as a single parameter vector:

```
b = pvGetParVector(out.par);
```

The location of the coefficients in *out.par* can be described by

```
b = pvgetParNames(out.par);
```

if model doesn't contain a parameter, *pvUnpack* returns a scalar missing value with error code = 99.

out.vc $NPARM \times NPARM$ variance-covariance matrix of coefficient estimates

out.ydist $L \times 1$ vector, percentages of dependent variable by category

out.xdata $K \times 4$ matrix, the means, standard deviations, minimums, and maximums of independent variables

out.margineffects $L \times 1 \times K$ array, marginal effects of independent variables by category of dependent variable

out.marginvc $L \times K \times K$ array, covariance matrices of marginal effects of independent variables by category of dependent variable

out.fittedvals $N \times 1$ matrix of predicted (fitted) counts

out.resids $N \times 1$ matrix of residuals

out.gf 12×1 matrix of goodness-of-fit measures

1 Log-Likelihood, full model

2 Log-Likelihood, restricted model (all slope coefficients equal zero)

3 Chi-square statistic

4 Agresti's G-Squared statistic

5 Likelihood Ratio statistics (from the full and restricted models above)

6 Probability values for the likelihood ratio statistics

- 7 McFadden's Pseudo R-Squared
- 8 McKelvey and Zovcina's Pseudo R-Squared
- 9 Cragg and Uhler's normed likelihood ratios
- 10 Count R-Squared
- 11 Adjusted Count R-Squared
- 12 Akaike information criterion (AIC)
- 13 Bayesian information criterion (BIC)

■ Example

```
library dc;
#include dc.sdf

struct dcDesc d1;
d1 = dcDescCreate;

d1.yname = "occatt";
d1.xnames = "exper" $| "educ" $| "white";
d1.catnames = "Menial" $| "BC" $| "Craft" $| "WC" $| "Pro";

struct dcout dcout1;

dcout1 = dcMultinomialLogit("gssocc",d1,dccontrolCreate);

call dcprt(dcout1);
```

■ Source

dcmnlogit.src

■ Purpose

Estimates a negative binomial regression model

■ Library

dc

■ Format

{ *out* } = **dcNegativeBinomial**(*data*, *desc*, *cont*)

■ Input

data string or $N \times K$ matrix, if string, the name of a GAUSS data set or if matrix, matrix of data

desc1 an instance of a *dcDesc* structure

desc.yname name of dependent variable

desc.yvar scalar, index of dependent variable. If data is name of **GAUSS** dataset, either *desc.yname* or *desc.yvar* may be specified. If data is matrix of data *desc.yvar* must be specified.

desc.xnames $K \times 1$ string vector, names of the independent variable(s).

desc.xvars $K \times 1$ vector, indices of the independent variable(s). If data is name of **GAUSS** dataset, either *desc.xnames* or *desc.xvars* may be specified. If data is matrix of data *desc.xvars* must be specified.

desc.znames $L \times 1$ string vector, names of the exogenous variable(s), if any, for zero-inflated model

desc.zvars $K \times 1$ vector, indices of the exogenous variable(s), if any, for zero-inflated model. If data is name of **GAUSS** dataset, either *desc.znames* or *desc.zvars* may be specified. If data is matrix of data *desc.zvars* must be specified.

desc.timeName string, name of variable for inclusion as a fixed exogenous log-variable. if *desc.timeVar* is is specified, *desc.timeName* is optional.

desc.timeVar string, index of variable for inclusion as a fixed exogenous log-variable. if *desc.timeName* is is specified, *desc.timeVar* is optional.

desc.wgtname string, name of weight variable. If *desc.wgtvar* is specified, the specification of *desc.wgtname* is optional. Default = ;

desc.wgtvar scalar, index of weight variable. If *desc.wgtname* is specified, the specification of *desc.wgtvar* is optional. Default = 0;

desc.limited scalar, 0 - no censoring or truncation, 1 - truncated model,
2 - censored model

desc.lh scalar, value of left side truncation or censoring

if the data are truncated on the left, all values must be greater than or equal to *desc.lh* (i.e. specify *desc.lh* = 1 if there are no zeros in the dependent variable).

if the data are censored on the left, all values must be greater than or equal to *desc.lh*

desc.rh scalar value of right side truncation or censoring

if the data are truncated on the right, all values must be less than or equal to *desc.rh*

if the data are censored on the left, all values must be less than or equal to *desc.rh*

desc.zeroInflated scalar, if nonzero a zero-inflated model is estimated.

Mixture probability can be a function of exogenous variables as specified in *desc.zvars*.

desc.marginType scalar, 1 - average partial probability with respect to independent variables, 0 - partial probability with respect to mean x. Default = 0.

cont an instance of a *dcControl* structure.

cont.startValues instance of **PV** structure containing starting values, if not provided, **dcNegativeBinomial** computes start values.

b0 1 constant in regression

b 2 regression coefficients (if any)

alpha 3 dispersion parameter

p0 4 constant in zero-inflated model

p 5 coefficients in zero-inflated model (if any)

For example:

```

struct dcControl cont;
cont = dcControlCreate;
b0 = .5;
b = { .1, .1, .1 };
a = .01;
cont.startValues = pvPacki(cont.startValues,b0,"b0",1);
cont.startValues = pvPacki(cont.startValues,b,"b",2);
cont.startValues = pvPacki(cont.startValues,a,"alpha",3);

```

cont.A $M \times K$ matrix, linear equality constraint coefficients: *cont.A* * *p* = *cont.B* where *p* is a vector of the parameters. For more details see section4.0.7.

- cont.B* $M \times 1$ vector, linear equality constraint constants: `cont.A * p = cont.B` where `p` is a vector of the parameters. For more details see section4.0.7.
- cont.C* $M \times K$ matrix, linear inequality constraint coefficients: `cont.C * p >= cont.D` where `p` is a vector of the parameters. For more details see section4.0.7.
- cont.D* $M \times 1$ vector, linear inequality constraint constants: `cont.C * p >= cont.D` where `p` is a vector of the parameters. For more details see section4.0.7.
- cont.eqProc* scalar, pointer to a procedure that computes the nonlinear equality constraints. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed equality constraints. For more details see Remarks below. Default = `{.}`, i.e., no equality procedure. For more details see section4.0.7.
- cont.IneqProc* scalar, pointer to a procedure that computes the nonlinear inequality constraints. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed inequality constraints. For more details see Remarks below. Default = `{.}`, i.e., no inequality procedure. For more details see section4.0.7.
- cont.Bounds* 1×2 or $K \times 2$ matrix, bounds on parameters. If 1×2 all parameters have same bounds. Default = `{ -1e256 1e256 }`. For more details see section4.0.7.
- cont.GradProc* scalar, pointer to a procedure that computes the gradient of the function with respect to the parameters. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed inequality constraints. For more details see section4.0.7. Default = `{.}`, i.e., no gradient procedure has been provided.
- cont.HessProc* scalar, pointer to a procedure that computes the Hessian, i.e., the matrix of second order partial derivatives of the function with respect to the parameters. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed inequality constraints. For more details see section4.0.7. Default = `.`, i.e., no Hessian procedure has been provided.
- cont.MaxIters* scalar, maximum number of iterations. Default = `1e + 5`.
- cont.MaxTries* scalar, maximum number of attempts in random search. Default = `100`.
- cont.DirTol* scalar, convergence tolerance for gradient of estimated coefficients. Default = `1e - 5`. When this criterion has been satisfied `sqpSolve` exits the iterations.

cont.FeasibleTest scalar, if nonzero, parameters are tested for feasibility before computing function in line search. If function is defined outside inequality boundaries, then this test can be turned off. Default = 1;

cont.randRadius scalar, If zero, no random search is attempted. If nonzero, it is the radius of the random search. Default = .001.

cont.trustRadius scalar, radius of the trust region. If scalar missing, trust region not applied. The trust sets a maximum amount of the direction at each iteration. Default = .001.

cont.output scalar, if nonzero, optimization results are printed. Default = 0.

cont.PrintIters scalar, if nonzero, prints iteration information. Default = 0.

■ Output

out An instance of a *dcOut* structure.

out.par instance of PV structure containing estimates

b0 1 constant in regression

b 2 regression coefficients (if any)

alpha 3 dispersion parameter

p0 4 constant in zero-inflated model

p 5 coefficients in zero-inflated model (if any)

To retrieve, e.g., regression coefficients:

```
b = pvUnpack(out.par,"b");
```

or

```
b = pvUnpack(out.par,2);
```

The coefficients may also be retrieved as a single parameter vector:

```
b = pvGetParVector(out.par);
```

The location of the coefficients in *out.par* can be described by

```
b = pvgetParNames(out.par);
```

if model doesn't contain a parameter, *pvUnpack* returns a scalar missing value with error code = 99.

out.vc $NPARM \times NPARM$ variance-covariance matrix of coefficient estimates

out.ydist $L \times 1$ vector, percentages of dependent variable by category

out.xdata $K \times 4$ matrix, the means, standard deviations, minimums, and maximums of independent variables

out.margineffects $L \times 1 \times K$ array, marginal effects of independent variables by category of dependent variable

out.marginvc $L \times K \times K$ array, covariance matrices of marginal effects of independent variables by category of dependent variable

out.fittedvals $N \times 1$ matrix of predicted (fitted) counts

out.resids $N \times 1$ matrix of residuals

out.gf 12×1 matrix of goodness-of-fit measures

- 1 Log-Likelihood, full model
- 2 Log-Likelihood, restricted model (all slope coefficients equal zero)
- 3 Chi-square statistic
- 4 Agresti's G-Squared statistic
- 5 Likelihood Ratio statistics (from the full and restricted models above)
- 6 Probability values for the likelihood ratio statistics
- 7 McFadden's Pseudo R-Squared
- 8 McKelvey and Zovcina's Pseudo R-Squared
- 9 Cragg and Uhler's normed likelihood ratios
- 10 Count R-Squared
- 11 Adjusted Count R-Squared
- 12 Akaike information criterion (AIC)
- 13 Bayesian information criterion (BIC)

■ Example

```
library dc;
#include dc.sdf

struct dcDesc d1;
d1 = dcDescCreate;

d1.yname = "ACC";
d1.xnames = "TB" $| "TC" $| "TD" $| "TE" $| "T6569" $|
           "T7074" $| "T7579" $| "07579";
d1.timeName = "months";

struct dcOut dcOut1;

dcout1 = dcNegativeBinomial("greenedata",d1,dccontrolCreate);

call dcprt(dcout1);
```

■ Source

dcbin.src

■ Purpose

Estimates the Conditional Logit model.

■ Library

dc

■ Format

$\{ out \} = \text{dcNestedLogit}(data, desc, cont)$

■ Input

data string or $N \times K$ matrix, if string, the name of a GAUSS data set or if matrix, matrix of data

desc1 an instance of a *dcDesc* structure

desc.datatype scalar, if 1, the dataset contains a single row for each observation and attribute variables are stored in separate columns in that row. If 0, category data are stored by row within observation and attribute data are stored in single columns

desc.yname name of dependent variable

desc.yvar scalar, index of dependent variable. If data is name of **GAUSS** dataset, either *desc.yname* or *desc.yvar* may be specified. If data is matrix of data *desc.yvar* must be specified.

desc.ytype scalar, 0 if *desc.yvar* character variable, otherwise 1 if numeric. Default = 1.

desc.xnames $K \times 1$ string vector, names of the independent variable(s).

desc.xvars $K \times 1$ vector, indices of the independent variable(s). If data is name of **GAUSS** dataset, either *desc.xnames* or *desc.xvars* may be specified. If data is matrix of data *desc.xvars* must be specified.

desc.catnames $L \times 1$ string vector, names of categories

desc.refcat reference category. If *desc.refcatName* is specified *desc.refcat* is optional. Default = 1.

desc.refcatName string, reference category name. If *desc.refcat* has been specified *desc.refcatName* is optional. Default = *desc.catnames[1]*.

desc.level $M \times 1$ vector of instances of a *dcLevel* structure, one for each level of the model

desc.level[m] .catnames] $L_m \times 1$ string array, names of categories

desc.level[m] .atNames] if *desc.datatype* = 0, $P_m \times 1$ string vector, names of the attribute variable(s). If *desc.level[m].atVars* is specified the specification of *desc.level[m].atNames* is optional.

desc.level[m .atVars] if *desc.datatype* = 0, $P_m \times 1$ numeric vector, indices of the attribute variable(s). If *desc.level[m].atNames* is specified the specification of *desc.level[m].atVars* is optional.

desc.level[m .nests] $L_m \times 1$ vector, category number in the next higher level of each category at this level. The highest category doesn't contain one.

desc.level[m .atCatnames] $R_m \times L_m$ string array, L_m names of categories in GAUSS dataset of R_m attribute variables in level m . Required only if *desc.dataType* = 1. If *desc.level[m].atCatvars* is specified the specification of *desc.level[m].atCatnames* is optional.

desc.level[m .atCatvars] $R_m \times L_m$ matrix, L_m indices of categories in data matrix or GAUSS dataset of R_m attribute variables in level m . Required only if *desc.dataType* = 1. If *desc.level[m].atCatnames* is specified the specification of *desc.level[m].atCatvars* is optional.

desc.wgtname string, name of weight variable. If *desc.wgtvar* is specified, the specification of *desc.wgtname* is optional. Default = ;

desc.wgtvar scalar, index of weight variable. If *desc.wgtname* is specified, the specification of *desc.wgtvar* is optional. Default = 0;

desc.noconstant scalar, 1 if no constants in model. Default = 0.

desc.marginType scalar, 1 - average partial probability with respect to independent variables, 0 - partial probability with respect to mean x. Default = 0.

cont an instance of a *dcControl* structure.

cont.startValues instance of **PV** structure containing starting values, if not provided, **Adjacent Categories** computes start values.

b0 $1 \times L$ vector, constants in regression

b $2 \times K \times L$ Matrix, regression coefficients of independent variables if any. Coefficients associated with reference category are fixed to zeros.

g1 $3 \times R_1 \times 1$ vector, coefficients of attribute variables for first level

g2 $4 \times R_2 \times 1$ vector, coefficients of attribute variables for second level

...

gM $2+M \times R_M \times 1$ vector, coefficients of attribute variables for M-th level

t2 $3+M \times L_2 \times 1$ vector, proportionality coefficients for second level (first level doesn't have these coefficients)

t3 $4+M \times L_3 \times 1$ vector, proportionality coefficients for third level (first level doesn't have these coefficients)

...

tM $2M+1$ $L_M \times 1$ vector, proportionality coefficients for M-th level
(first level doesn't have these coefficients)

For example:

```

struct dcControl cont;
cont = dcControlCreate;

b0 = { 0 1 1 }; /* three categories at first level */

b = { 0 .1 .1 /* two independent variables */
      0 .1 .1 };

mask = { 0 1 1,
         0 1 1,
         0 1 1 };

g1 = { .1, .1 }; /* two attribute variables at first level
g2 = { .1 }; /* one attribute variable at second level */
t2 = { .1, .1 }; /* two categories at second level */

cont.startValues =
    pvPackmi(cont.startValues,b0,"b0",mask[1,.,],1);
cont.startValues =
    pvPackmi(cont.startValues,b,"b",mask,2);
cont.startValues =
    pvPackmi(cont.startValues,g1,"g1",3);
cont.startValues =
    pvPacki(cont.startValues,g2,"g2",4);
cont.startValues =
    pvPacki(cont.startValues,t2,"t2",5);

```

cont.A $M \times K$ matrix, linear equality constraint coefficients: *cont.A* * *p* = *cont.B* where *p* is a vector of the parameters. For more details see section4.0.7.

cont.B $M \times 1$ vector, linear equality constraint constants: *cont.A* * *p* = *cont.B* where *p* is a vector of the parameters. For more details see section4.0.7.

cont.C $M \times K$ matrix, linear inequality constraint coefficients: *cont.C* * *p* >= *cont.D* where *p* is a vector of the parameters. For more details see section4.0.7.

cont.D $M \times 1$ vector, linear inequality constraint constants: *cont.C* * *p* >= *cont.D* where *p* is a vector of the parameters. For more details see section4.0.7.

cont.eqProc scalar, pointer to a procedure that computes the nonlinear equality constraints. When such a procedure has been provided, it

has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed equality constraints. For more details see Remarks below. Default = $\{.\}$, i.e., no equality procedure. For more details see section4.0.7.

cont.IneqProc scalar, pointer to a procedure that computes the nonlinear inequality constraints. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed inequality constraints. For more details see Remarks below. Default = $\{.\}$, i.e., no inequality procedure. For more details see section4.0.7.

cont.Bounds 1×2 or $K \times 2$ matrix, bounds on parameters. If 1×2 all parameters have same bounds. Default = $\{-1e256 \ 1e256\}$. For more details see section4.0.7.

cont.GradProc scalar, pointer to a procedure that computes the gradient of the function with respect to the parameters. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed inequality constraints. For more details see section4.0.7. Default = $\{.\}$, i.e., no gradient procedure has been provided.

cont.HessProc scalar, pointer to a procedure that computes the Hessian, i.e., the matrix of second order partial derivatives of the function with respect to the parameters. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed inequality constraints. For more details see section4.0.7. Default = $.$, i.e., no Hessian procedure has been provided.

cont.MaxIters scalar, maximum number of iterations. Default = $1e + 5$.

cont.MaxTries scalar, maximum number of attempts in random search. Default = 100.

cont.DirTol scalar, convergence tolerance for gradient of estimated coefficients. Default = $1e - 5$. When this criterion has been satisfied sqpSolvevt exits the iterations.

cont.FeasibleTest scalar, if nonzero, parameters are tested for feasibility before computing function in line search. If function is defined outside inequality boundaries, then this test can be turned off. Default = 1;

cont.randRadius scalar, If zero, no random search is attempted. If nonzero, it is the radius of the random search. Default = .001.

cont.trustRadius scalar, radius of the trust region. If scalar missing, trust region not applied. The trust sets a maximum amount of the direction at each iteration. Default = .001.

cont.output scalar, if nonzero, optimization results are printed. Default = 0.

cont.PrintIters scalar, if nonzero, prints iteration information. Default = 0.

■ Output

out An instance of a *dcOut* structure.

out.par instance of PV structure containing estimates

b0 $1 \times L$ vector, constants in regression

b $2 \times K \times L$ Matrix, regression coefficients of independent variables if any. Coefficients associated with reference category are fixed to zeros.

g1 $3 \times R_1 \times 1$ vector, coefficients of attribute variables for first level

g2 $4 \times R_2 \times 1$ vector, coefficients of attribute variables for second level

...

gM $2+M \times R_M \times 1$ vector, coefficients of attribute variables for M-th level

t2 $3+M \times L_2 \times 1$ vector, proportionality coefficients for second level (first level doesn't have these coefficients)

t3 $4+M \times L_3 \times 1$ vector, proportionality coefficients for third level (first level doesn't have these coefficients)

...

tM $2M+1 \times L_M \times 1$ vector, proportionality coefficients for M-th level (first level doesn't have these coefficients)

To retrieve, e.g., regression coefficients:

```
b = pvUnpack(out.par,"b");
```

or

```
b = pvUnpack(out.par,2);
```

The coefficients may also be retrieved as a single parameter vector:

```
b = pvGetParVector(out.par);
```

The location of the coefficients in *out.par* can be described by

```
b = pvgetParNames(out.par);
```

if model doesn't contain a parameter, *pvUnpack* returns a scalar missing value with error code = 99.

out.vc $NPARM \times NPARM$ variance-covariance matrix of coefficient estimates

out.ydist $L \times 1$ vector, percentages of dependent variable by category
out.xdata $K \times 4$ matrix, the means, standard deviations, minimums, and maximums of independent variables
out.margineffects $L \times 1 \times K$ array, marginal effects of independent variables by category of dependent variable
out.marginvc $L \times K \times K$ array, covariance matrices of marginal effects of independent variables by category of dependent variable
out.atmargineffects $M \times 1$ DS structure containing M $L_m \times L_m \times 1 \times R_m$ arrays, marginal effects by category of attribute variables by categories at the m -th level
out.atmarginvc $M \times 1$ DS structure containing M $L_m \times L_m \times R_m \times R_m$ arrays, covariance matrices of marginal effects by category of attribute variables by categories at the m -th level
out.fittedvals $N \times 1$ matrix of predicted (fitted) counts
out.resids $N \times 1$ matrix of residuals
out.gf 12×1 matrix of goodness-of-fit measures

- 1 Log-Likelihood, full model
- 2 Log-Likelihood, restricted model (all slope coefficients equal zero)
- 3 Chi-square statistic
- 4 Agresti's G-Squared statistic
- 5 Likelihood Ratio statistics (from the full and restricted models above)
- 6 Probability values for the likelihood ratio statistics
- 7 McFadden's Pseudo R-Squared
- 8 McKelvey and Zovcina's Pseudo R-Squared
- 9 Cragg and Uhler's normed likelihood ratios
- 10 Count R-Squared
- 11 Adjusted Count R-Squared
- 12 Akaike information criterion (AIC)
- 13 Bayesian information criterion (BIC)

■ Example

```

library dc;
#include dc.sdf

struct dcDesc d1;
d1 = dcDescCreate;

d1.level = reshape(d1.level,2,1);

```

```
d1.yname = "Mode";
d1.catnames = "Air"|"Train"|"Bus"|"Car";
d1.refcatName = "Car";

d1.level[1].atNames = "TTME"|"GC";
d1.level[1].nests = { 1, 2, 2, 2 };

d1.level[2].catnames = "Fly"|"Ground";
d1.level[2].atNames = "airhinc";

struct dcout dcout1;

dcout1 = dcNestedLogit("hensher",d1,dccontrolCreate);
call dcpert(dcout1);
```

■ Source

dcnlogit.src

■ Purpose

Estimates an ordered logit regression model

■ Library

dc

■ Format

{ *out* } = **dcOrderedLogit**(*data*, *desc*, *cont*)

■ Input

data string or $N \times K$ matrix, if string, the name of a GAUSS data set or if matrix, matrix of data

desc1 an instance of a *dcDesc* structure

desc.yname name of dependent variable

desc.yvar scalar, index of dependent variable. If *data* is name of **GAUSS** dataset, either *desc.yname* or *desc.yvar* may be specified. If *data* is matrix of data *desc.yvar* must be specified.

desc.ytype scalar, 0 if *desc.yvar* character variable, otherwise 1 if numeric. Default = 1.

desc.xnames $K \times 1$ string vector, names of the independent variable(s).

desc.xvars $K \times 1$ vector, indices of the independent variable(s). If *data* is name of **GAUSS** dataset, either *desc.xnames* or *desc.xvars* may be specified. If *data* is matrix of data *desc.xvars* must be specified.

desc.wgtname string, name of weight variable. If *desc.wgtvar* is specified, the specification of *desc.wgtname* is optional. Default = ;

desc.wgtvar scalar, index of weight variable. If *desc.wgtname* is specified, the specification of *desc.wgtvar* is optional. Default = 0;

desc.catnames $L \times 1$ string vector, names of categories

desc.marginType scalar, 1 - average partial probability with respect to independent variables, 0 - partial probability with respect to mean x. Default = 0.

cont an instance of a *dcControl* structure.

cont.startValues instance of **PV** structure containing starting values, if not provided, **dcOrderedLogit** computes start values.

tau 1 thresholds

b 2 regression coefficients (if any)

For example:

```

struct dcControl cont;
cont = dcControlCreate;

tau = { -5, -2 };
b = { .1, .1, .1 };
cont.startValues = pvPacki(cont.startValues,tau,"tau",1);
cont.startValues = pvPacki(cont.startValues,b,"b",2);

```

cont.A $M \times K$ matrix, linear equality constraint coefficients: $\text{cont.A} * \mathbf{p} = \text{cont.B}$ where \mathbf{p} is a vector of the parameters. For more details see section4.0.7.

cont.B $M \times 1$ vector, linear equality constraint constants: $\text{cont.A} * \mathbf{p} = \text{cont.B}$ where \mathbf{p} is a vector of the parameters. For more details see section4.0.7.

cont.C $M \times K$ matrix, linear inequality constraint coefficients: $\text{cont.C} * \mathbf{p} \geq \text{cont.D}$ where \mathbf{p} is a vector of the parameters. For more details see section4.0.7.

cont.D $M \times 1$ vector, linear inequality constraint constants: $\text{cont.C} * \mathbf{p} \geq \text{cont.D}$ where \mathbf{p} is a vector of the parameters. For more details see section4.0.7.

cont.eqProc scalar, pointer to a procedure that computes the nonlinear equality constraints. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed equality constraints. For more details see Remarks below. Default = { \cdot }, i.e., no equality procedure. For more details see section4.0.7.

cont.IneqProc scalar, pointer to a procedure that computes the nonlinear inequality constraints. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed inequality constraints. For more details see Remarks below. Default = { \cdot }, i.e., no inequality procedure. For more details see section4.0.7.

cont.Bounds 1×2 or $K \times 2$ matrix, bounds on parameters. If 1×2 all parameters have same bounds. Default = { -1e256 1e256 }. For more details see section4.0.7.

cont.GradProc scalar, pointer to a procedure that computes the gradient of the function with respect to the parameters. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed inequality constraints. For more details see section4.0.7. Default = { \cdot }, i.e., no gradient procedure has been provided.

cont.HessProc scalar, pointer to a procedure that computes the Hessian, i.e., the matrix of second order partial derivatives of the function with respect to the parameters. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed inequality constraints. For more details see section 4.0.7. Default = ., i.e., no Hessian procedure has been provided.

cont.MaxIters scalar, maximum number of iterations. Default = $1e + 5$.

cont.MaxTries scalar, maximum number of attempts in random search. Default = 100.

cont.DirTol scalar, convergence tolerance for gradient of estimated coefficients. Default = $1e - 5$. When this criterion has been satisfied sqpSolve exits the iterations.

cont.FeasibleTest scalar, if nonzero, parameters are tested for feasibility before computing function in line search. If function is defined outside inequality boundaries, then this test can be turned off. Default = 1;

cont.randRadius scalar, If zero, no random search is attempted. If nonzero, it is the radius of the random search. Default = .001.

cont.trustRadius scalar, radius of the trust region. If scalar missing, trust region not applied. The trust sets a maximum amount of the direction at each iteration. Default = .001.

cont.output scalar, if nonzero, optimization results are printed. Default = 0.

cont.PrintIters scalar, if nonzero, prints iteration information. Default = 0.

■ Output

out An instance of a *dcOut* structure.

out.par instance of PV structure containing estimates

tau 1 thresholds

b 2 regression coefficients (if any)

To retrieve, e.g., regression coefficients:

```
b = pvUnpack(out.par, "b");
```

or

```
b = pvUnpack(out.par, 2);
```

The coefficients may also be retrieved as a single parameter vector:


```
b = pvGetParVector(out.par);
```

The location of the coefficients in `out.par` can be described by

```
b = pvgetParNames(out.par);
```

if model doesn't contain a parameter, `pvUnpack` returns a scalar missing value with error code = 99.

out.vc $NPARM \times NPARM$ variance-covariance matrix of coefficient estimates

out.ydist $L \times 1$ vector, percentages of dependent variable by category

out.xdata $K \times 4$ matrix, the means, standard deviations, minimums, and maximums of independent variables

out.margineffects $L \times 1 \times K$ array, marginal effects of independent variables by category of dependent variable

out.marginvc $L \times K \times K$ array, covariance matrices of marginal effects of independent variables by category of dependent variable

out.fittedvals $N \times 1$ matrix of predicted (fitted) counts

out.resids $N \times 1$ matrix of residuals

out.gf 12×1 matrix of goodness-of-fit measures

- 1 Log-Likelihood, full model
- 2 Log-Likelihood, restricted model (all slope coefficients equal zero)
- 3 Chi-square statistic
- 4 Agresti's G-Squared statistic
- 5 Likelihood Ratio statistics (from the full and restricted models above)
- 6 Probability values for the likelihood ratio statistics
- 7 McFadden's Pseudo R-Squared
- 8 McKelvey and Zovcina's Pseudo R-Squared
- 9 Cragg and Uhler's normed likelihood ratios
- 10 Count R-Squared
- 11 Adjusted Count R-Squared
- 12 Akaike information criterion (AIC)
- 13 Bayesian information criterion (BIC)

■ Example

```
library dc;
#include dc.sdf

struct dcDesc d1;
```

dcOrderedLogit

```
d1 = dcDescCreate;

d1.yname = "ABC";
d1.xnames = "GPA" $| "TUCE" $| "PSI";

struct dcout dcout1;

dcout1 = dcOrderedLogit("aldnel",d1,dccontrolCreate);

call dcprt(dcout1);
```

■ Source

dcord.src

■ Purpose

Estimates an ordered probit regression model.

■ Library

dc

■ Format

{ *out* } = **dcOrderedProbit**(*data*, *desc*, *cont*)

■ Input

data string or $N \times K$ matrix, if string, the name of a GAUSS data set or if matrix, matrix of data

desc1 an instance of a *dcDesc* structure

desc.yname name of dependent variable

desc.yvar scalar, index of dependent variable. If *data* is name of **GAUSS** dataset, either *desc.yname* or *desc.yvar* may be specified. If *data* is matrix of data *desc.yvar* must be specified.

desc.ytype scalar, 0 if *desc.yvar* character variable, otherwise 1 if numeric. Default = 1.

desc.xnames $K \times 1$ string vector, names of the independent variable(s).

desc.xvars $K \times 1$ vector, indices of the independent variable(s). If *data* is name of **GAUSS** dataset, either *desc.xnames* or *desc.xvars* may be specified. If *data* is matrix of data *desc.xvars* must be specified.

desc.catnames $L \times 1$ string vector, names of categories

desc.wgtname string, name of weight variable. If *desc.wgtvar* is specified, the specification of *desc.wgtname* is optional. Default = ;

desc.wgtvar scalar, index of weight variable. If *desc.wgtname* is specified, the specification of *desc.wgtvar* is optional. Default = 0;

desc.marginType scalar, 1 - average partial probability with respect to independent variables, 0 - partial probability with respect to mean x. Default = 0.

cont an instance of a *dcControl* structure.

cont.startValues instance of **PV** structure containing starting values, if not provided, **dcOrderedProbit** computes start values.

tau 1 thresholds

b 2 regression coefficients (if any)

For example:

```

struct dcControl cont;
cont = dcControlCreate;

tau = { -5, -2 };
b = { .1, .1, .1 };
cont.startValues = pvPacki(cont.startValues,tau,"tau",1);
cont.startValues = pvPacki(cont.startValues,b,"b",2);

```

cont.A $M \times K$ matrix, linear equality constraint coefficients: $\text{cont.A} * \mathbf{p} = \text{cont.B}$ where \mathbf{p} is a vector of the parameters. For more details see section4.0.7.

cont.B $M \times 1$ vector, linear equality constraint constants: $\text{cont.A} * \mathbf{p} = \text{cont.B}$ where \mathbf{p} is a vector of the parameters. For more details see section4.0.7.

cont.C $M \times K$ matrix, linear inequality constraint coefficients: $\text{cont.C} * \mathbf{p} \geq \text{cont.D}$ where \mathbf{p} is a vector of the parameters. For more details see section4.0.7.

cont.D $M \times 1$ vector, linear inequality constraint constants: $\text{cont.C} * \mathbf{p} \geq \text{cont.D}$ where \mathbf{p} is a vector of the parameters. For more details see section4.0.7.

cont.eqProc scalar, pointer to a procedure that computes the nonlinear equality constraints. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed equality constraints. For more details see Remarks below. Default = { \cdot }, i.e., no equality procedure. For more details see section4.0.7.

cont.IneqProc scalar, pointer to a procedure that computes the nonlinear inequality constraints. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed inequality constraints. For more details see Remarks below. Default = { \cdot }, i.e., no inequality procedure. For more details see section4.0.7.

cont.Bounds 1×2 or $K \times 2$ matrix, bounds on parameters. If 1×2 all parameters have same bounds. Default = { -1e256 1e256 }. For more details see section4.0.7.

cont.GradProc scalar, pointer to a procedure that computes the gradient of the function with respect to the parameters. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed inequality constraints. For more details see section4.0.7. Default = { \cdot }, i.e., no gradient procedure has been provided.

cont.HessProc scalar, pointer to a procedure that computes the Hessian, i.e., the matrix of second order partial derivatives of the function with respect to the parameters. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed inequality constraints. For more details see section 4.0.7. Default = ., i.e., no Hessian procedure has been provided.

cont.MaxIters scalar, maximum number of iterations. Default = $1e + 5$.

cont.MaxTries scalar, maximum number of attempts in random search. Default = 100.

cont.DirTol scalar, convergence tolerance for gradient of estimated coefficients. Default = $1e - 5$. When this criterion has been satisfied sqpSolvevt exits the iterations.

cont.FeasibleTest scalar, if nonzero, parameters are tested for feasibility before computing function in line search. If function is defined outside inequality boundaries, then this test can be turned off. Default = 1;

cont.randRadius scalar, If zero, no random search is attempted. If nonzero, it is the radius of the random search. Default = .001.

cont.trustRadius scalar, radius of the trust region. If scalar missing, trust region not applied. The trust sets a maximum amount of the direction at each iteration. Default = .001.

cont.output scalar, if nonzero, optimization results are printed. Default = 0.

cont.PrintIters scalar, if nonzero, prints iteration information. Default = 0.

■ Output

out An instance of a *dcOut* structure.

out.par instance of PV structure containing estimates

tau 1 thresholds

b 2 regression coefficients (if any)

To retrieve, e.g., regression coefficients:

```
b = pvUnpack(out.par, "b");
```

or

```
b = pvUnpack(out.par, 2);
```

The coefficients may also be retrieved as a single parameter vector:

```
b = pvGetParVector(out.par);
```

The location of the coefficients in `out.par` can be described by

```
b = pvgetParNames(out.par);
```

if model doesn't contain a parameter, `pvUnpack` returns a scalar missing value with error code = 99.

out.vc $NPARM \times NPARM$ variance-covariance matrix of coefficient estimates

out.ydist $L \times 1$ vector, percentages of dependent variable by category

out.xdata $K \times 4$ matrix, the means, standard deviations, minimums, and maximums of independent variables

out.margineffects $L \times 1 \times K$ array, marginal effects of independent variables by category of dependent variable

out.marginvc $L \times K \times K$ array, covariance matrices of marginal effects of independent variables by category of dependent variable

out.fittedvals $N \times 1$ matrix of predicted (fitted) counts

out.resids $N \times 1$ matrix of residuals

out.gf 12×1 matrix of goodness-of-fit measures

- 1 Log-Likelihood, full model
- 2 Log-Likelihood, restricted model (all slope coefficients equal zero)
- 3 Chi-square statistic
- 4 Agresti's G-Squared statistic
- 5 Likelihood Ratio statistics (from the full and restricted models above)
- 6 Probability values for the likelihood ratio statistics
- 7 McFadden's Pseudo R-Squared
- 8 McKelvey and Zovcina's Pseudo R-Squared
- 9 Cragg and Uhler's normed likelihood ratios
- 10 Count R-Squared
- 11 Adjusted Count R-Squared
- 12 Akaike information criterion (AIC)
- 13 Bayesian information criterion (BIC)

■ Example

```
library dc;
#include dc.sdf

struct dcDesc d1;
```

6. PROCEDURE REFERENCE

dcOrderedProbit

```
d1 = dcDescCreate;

d1.yname = "A";
d1.xnames = "GPA" $| "TUCE" $| "PSI";

struct dcout dcout1;

dcout1 = dcOrderedProbit("aldnel",d1,dccontrolCreate);

call dcprt(dcout1);
```

■ Source

dcord.src

■ Purpose

Estimates a Poisson regression model

■ Library

dc

■ Format

{ *out* } = **dcPoisson**(*data*, *desc*, *cont*)

■ Input

- data* string or $N \times K$ matrix, if string, the name of a GAUSS data set or if matrix, matrix of data
- desc1* an instance of a *dcDesc* structure
- desc.yname* name of dependent variable
- desc.yvar* scalar, index of dependent variable. If data is name of **GAUSS** dataset, either *desc.yname* or *desc.yvar* may be specified. If data is matrix of data *desc.yvar* must be specified.
- desc.xnames* $K \times 1$ string vector, names of the independent variable(s).
- desc.xvars* $K \times 1$ vector, indices of the independent variable(s). If data is name of **GAUSS** dataset, either *desc.xnames* or *desc.xvars* may be specified. If data is matrix of data *desc.xvars* must be specified.
- desc.znames* $L \times 1$ string vector, names of the exogenous variable(s), if any, for zero-inflated model
- desc.zvars* $K \times 1$ vector, indices of the exogenous variable(s), if any, for zero-inflated model. If data is name of **GAUSS** dataset, either *desc.znames* or *desc.zvars* may be specified. If data is matrix of data *desc.zvars* must be specified.
- desc.timeName* string, name of variable for inclusion as a fixed exogenous log-variable. if *desc.timeVar* is is specified, *desc.timeName* is optional.
- desc.timeVar* string, index of variable for inclusion as a fixed exogenous log-variable. if *desc.timeName* is is specified, *desc.timeVar* is optional.
- desc.wgtname* string, name of weight variable. If *desc.wgtvar* is specified, the specification of *desc.wgtname* is optional. Default = ;
- desc.wgtvar* scalar, index of weight variable. If *desc.wgtname* is specified, the specification of *desc.wgtvar* is optional. Default = 0;

desc.limited scalar, 0 - no censoring or truncation, 1 - truncated model, 2 - censored model

desc.lh scalar, value of left side truncation or censoring

if the data are truncated on the left, all values must be greater than or equal to *desc.lh* (i.e. specify *desc.lh* = 1 if there are no zeros in the dependent variable).

if the data are censored on the left, all values must be greater than or equal to *desc.lh*

desc.rh scalar value of right side truncation or censoring

if the data are truncated on the right, all values must be less than or equal to *desc.rh*

if the data are censored on the left, all values must be less than or equal to *desc.rh*

desc.zeroInflated scalar, if nonzero a zero-inflated model is estimated.

Mixture probability can be a function of exogenous variables as specified in *desc.zvars*.

desc.marginType scalar, 1 - average partial probability with respect to independent variables, 0 - partial probability with respect to mean x. Default = 0.

cont an instance of a *dcControl* structure.

cont.startValues instance of **PV** structure containing starting values, if not provided, **dcPoisson** computes start values.

b0 1 constant in regression

b 2 regression coefficients (if any)

p0 3 constant in zero-inflated model

p 4 coefficients in zero-inflated model (if any)

For example:

```

struct dcControl cont;
cont = dcControlCreate;
b0 = { .5 };
b = { .1, .1, .1 };
cont.startValues = pvPacki(cont.startValues,b0,"b0",1);
cont.startValues = pvPacki(cont.startValues,b,"b",2);

```

cont.A $M \times K$ matrix, linear equality constraint coefficients: *cont.A* * *p* = *cont.B* where *p* is a vector of the parameters. For more details see section4.0.7.

cont.B $M \times 1$ vector, linear equality constraint constants: *cont.A* * *p* = *cont.B* where *p* is a vector of the parameters. For more details see section4.0.7.

- cont.C* $M \times K$ matrix, linear inequality constraint coefficients: `cont.C * p >= cont.D` where `p` is a vector of the parameters. For more details see section4.0.7.
- cont.D* $M \times 1$ vector, linear inequality constraint constants: `cont.C * p >= cont.D` where `p` is a vector of the parameters. For more details see section4.0.7.
- cont.eqProc* scalar, pointer to a procedure that computes the nonlinear equality constraints. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed equality constraints. For more details see Remarks below. Default = `{.}`, i.e., no equality procedure. For more details see section4.0.7.
- cont.IneqProc* scalar, pointer to a procedure that computes the nonlinear inequality constraints. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed inequality constraints. For more details see Remarks below. Default = `{.}`, i.e., no inequality procedure. For more details see section4.0.7.
- cont.Bounds* 1×2 or $K \times 2$ matrix, bounds on parameters. If 1×2 all parameters have same bounds. Default = `{ -1e256 1e256 }`. For more details see section4.0.7.
- cont.GradProc* scalar, pointer to a procedure that computes the gradient of the function with respect to the parameters. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed inequality constraints. For more details see section4.0.7. Default = `{.}`, i.e., no gradient procedure has been provided.
- cont.HessProc* scalar, pointer to a procedure that computes the Hessian, i.e., the matrix of second order partial derivatives of the function with respect to the parameters. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed inequality constraints. For more details see section4.0.7. Default = `.`, i.e., no Hessian procedure has been provided.
- cont.MaxIters* scalar, maximum number of iterations. Default = `1e + 5`.
- cont.MaxTries* scalar, maximum number of attempts in random search. Default = `100`.
- cont.DirTol* scalar, convergence tolerance for gradient of estimated coefficients. Default = `1e - 5`. When this criterion has been satisfied `sqpSolve` exits the iterations.
- cont.FeasibleTest* scalar, if nonzero, parameters are tested for feasibility before computing function in line search. If function is defined

outside inequality boundaries, then this test can be turned off.
Default = 1;

cont.randRadius scalar, If zero, no random search is attempted. If nonzero, it is the radius of the random search. Default = .001.

cont.trustRadius scalar, radius of the trust region. If scalar missing, trust region not applied. The trust sets a maximum amount of the direction at each iteration. Default = .001.

cont.output scalar, if nonzero, optimization results are printed. Default = 0.

cont.PrintIters scalar, if nonzero, prints iteration information. Default = 0.

■ Output

out An instance of a *dcOut* structure.

out.par instance of PV structure containing estimates

b0 1 constant in regression

b 2 regression coefficients (if any)

p0 3 constant in zero-inflated model

p 4 coefficients in zero-inflated model (if any)

To retrieve, e.g., regression coefficients:

```
b = pvUnpack(out.par, "b");
```

or

```
b = pvUnpack(out.par, 2);
```

The coefficients may also be retrieved as a single parameter vector:

```
b = pvGetParVector(out.par);
```

The location of the coefficients in *out.par* can be described by

```
b = pvgetParNames(out.par);
```

if model doesn't contain a parameter, *pvUnpack* returns a scalar missing value with error code = 99.

out.vc $NPARM \times NPARM$ variance-covariance matrix of coefficient estimates

out.ydist $L \times 1$ vector, percentages of dependent variable by category

out.xdata $K \times 4$ matrix, the means, standard deviations, minimums, and maximums of independent variables

out.margineffects $L \times 1 \times K$ array, marginal effects of independent variables by category of dependent variable

out.marginvc $L \times K \times K$ array, covariance matrices of marginal effects of independent variables by category of dependent variable

out.fittedvals $N \times 1$ matrix of predicted (fitted) counts

out.resids $N \times 1$ matrix of residuals

out.gf 12×1 matrix of goodness-of-fit measures

- 1 Log-Likelihood, full model
- 2 Log-Likelihood, restricted model (all slope coefficients equal zero)
- 3 Chi-square statistic
- 4 Agresti's G-Squared statistic
- 5 Likelihood Ratio statistics (from the full and restricted models above)
- 6 Probability values for the likelihood ratio statistics
- 7 McFadden's Pseudo R-Squared
- 8 McKelvey and Zovcina's Pseudo R-Squared
- 9 Cragg and Uhler's normed likelihood ratios
- 10 Count R-Squared
- 11 Adjusted Count R-Squared
- 12 Akaike information criterion (AIC)
- 13 Bayesian information criterion (BIC)

■ Example

```
library dc;
  #include dc.sdf

  struct dcDesc d1;
  d1 = dcDescCreate;

  d1.yname = "ACC";
  d1.xnames = "TB" $| "TC" $| "TD" $| "TE" $| "T6569" $|
             "T7074" $| "T7579" $| "07579";
  d1.timeName = "months";

  struct dcOut dcOut1;

  dcout1 = dcPoisson("greenedata",d1,dccontrolCreate);

  call psnprt(dcout1);
```

■ Source

dcpsn.src

■ Purpose

Prints output from **Discrete Choice** procedures

■ Library

dc

■ Format

{ *out* } = **dcprt**(*out*)

■ Input

out an instance of a *dcOut* structure

■ Output

out an instance of a *dcOut* structure

■ Remarks

The input argument is returned unchanged

■ Source

dc.src

■ Purpose

Estimates the Stereotype Multinomial Logit model.

■ Library

dc

■ Format

$\{ out \} = \mathbf{dcStereo}(data, desc, cont)$

■ Input

data string or $N \times K$ matrix, if string, the name of a GAUSS data set or if matrix, matrix of data

desc1 an instance of a *dcDesc* structure

desc.yname name of dependent variable

desc.yvar scalar, index of dependent variable. If data is name of **GAUSS** dataset, either *desc.yname* or *desc.yvar* may be specified. If data is matrix of data *desc.yvar* must be specified.

desc.ytype scalar, 0 if *desc.yvar* character variable, otherwise 1 if numeric. Default = 1.

desc.xnames $K \times 1$ string vector, names of the independent variable(s).

desc.xvars $K \times 1$ vector, indices of the independent variable(s). If data is name of **GAUSS** dataset, either *desc.xnames* or *desc.xvars* may be specified. If data is matrix of data *desc.xvars* must be specified.

desc.catnames $L \times 1$ string vector, names of categories

desc.refcat reference category. If *desc.refcatName* is specified *desc.refcat* is optional. Default = 1.

desc.refcatName string, reference category name. If *desc.refcat* has been specified *desc.refcatName* is optional. Default = *desc.catnames[1]*.

desc.wgtname string, name of weight variable. If *desc.wgtvar* is specified, the specification of *desc.wgtname* is optional. Default = ;

desc.wgtvar scalar, index of weight variable. If *desc.wgtname* is specified, the specification of *desc.wgtvar* is optional. Default = 0;

desc.noconstant scalar, 1 if no constants in model. Default = 0.

desc.marginType scalar, 1 - average partial probability with respect to independent variables, 0 - partial probability with respect to mean x. Default = 0.

cont an instance of a *dcControl* structure.

cont.startValues instance of **PV** structure containing starting values, if not provided, **stereo** computes start values.

b0 $1 \times L$ vector, constants in regression

b $2 \times K \times 1$ vector, regression coefficients

distance $3(L - 1) \times 1$ vector, distance coefficients

For example:

```

struct dcControl cont;
cont = dcControlCreate;

b0 = 1;
b = { .1, .2 };
d = .01;
cont.startValues = pvPacki(cont.startValues,b0,"b0",1);
cont.startValues = pvPacki(cont.startValues,b,"b",2);
cont.startValues = pvPacki(cont.startValues,d,"distance",2);

```

cont.A $M \times K$ matrix, linear equality constraint coefficients: *cont.A* * *p* = *cont.B* where *p* is a vector of the parameters. For more details see section4.0.7.

cont.B $M \times 1$ vector, linear equality constraint constants: *cont.A* * *p* = *cont.B* where *p* is a vector of the parameters. For more details see section4.0.7.

cont.C $M \times K$ matrix, linear inequality constraint coefficients: *cont.C* * *p* >= *cont.D* where *p* is a vector of the parameters. For more details see section4.0.7.

cont.D $M \times 1$ vector, linear inequality constraint constants: *cont.C* * *p* >= *cont.D* where *p* is a vector of the parameters. For more details see section4.0.7.

cont.eqProc scalar, pointer to a procedure that computes the nonlinear equality constraints. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed equality constraints. For more details see Remarks below. Default = { }, i.e., no equality procedure. For more details see section4.0.7.

cont.IneqProc scalar, pointer to a procedure that computes the nonlinear inequality constraints. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed inequality constraints. For more details see Remarks below. Default = { }, i.e., no inequality procedure. For more details see section4.0.7.

- cont.Bounds* 1×2 or $K \times 2$ matrix, bounds on parameters. If 1×2 all parameters have same bounds. Default = { -1e256 1e256 }. For more details see section4.0.7.
- cont.GradProc* scalar, pointer to a procedure that computes the gradient of the function with respect to the parameters. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed inequality constraints. For more details see section4.0.7. Default = {.,}, i.e., no gradient procedure has been provided.
- cont.HessProc* scalar, pointer to a procedure that computes the Hessian, i.e., the matrix of second order partial derivatives of the function with respect to the parameters. When such a procedure has been provided, it has two input arguments, a **PV** parameter structure and a **DS** data structure, and one output argument, a vector of computed inequality constraints. For more details see section4.0.7. Default = ., i.e., no Hessian procedure has been provided.
- cont.MaxIters* scalar, maximum number of iterations. Default = $1e + 5$.
- cont.MaxTries* scalar, maximum number of attempts in random search. Default = 100.
- cont.DirTol* scalar, convergence tolerance for gradient of estimated coefficients. Default = $1e - 5$. When this criterion has been satisfied sqpSolve exits the iterations.
- cont.FeasibleTest* scalar, if nonzero, parameters are tested for feasibility before computing function in line search. If function is defined outside inequality boundaries, then this test can be turned off. Default = 1;
- cont.randRadius* scalar, If zero, no random search is attempted. If nonzero, it is the radius of the random search. Default = .001.
- cont.trustRadius* scalar, radius of the trust region. If scalar missing, trust region not applied. The trust sets a maximum amount of the direction at each iteration. Default = .001.
- cont.output* scalar, if nonzero, optimization results are printed. Default = 0.
- cont.PrintIters* scalar, if nonzero, prints iteration information. Default = 0.

■ Output

- out* An instance of a *dcOut* structure.
- out.par* instance of PV structure containing estimates

b0 1 constant in regression
b 2 regression coefficients
distance 3 distance coefficients

To retrieve, e.g., regression coefficients:

```
b = pvUnpack(out.par,"b");
```

or

```
b = pvUnpack(out.par,2);
```

The coefficients may also be retrieved as a single parameter vector:

```
b = pvGetParVector(out.par);
```

The location of the coefficients in `out.par` can be described by

```
b = pvgetParNames(out.par);
```

if model doesn't contain a parameter, `pvUnpack` returns a scalar missing value with error code = 99.

out.vc $NPARM \times NPARM$ variance-covariance matrix of coefficient estimates

out.ydist $L \times 1$ vector, percentages of dependent variable by category

out.xdata $K \times 4$ matrix, the means, standard deviations, minimums, and maximums of independent variables

out.margineffects $L \times 1 \times K$ array, marginal effects of independent variables by category of dependent variable

out.marginvc $L \times K \times K$ array, covariance matrices of marginal effects of independent variables by category of dependent variable

out.fittedvals $N \times 1$ matrix of predicted (fitted) counts

out.resids $N \times 1$ matrix of residuals

out.gf 12×1 matrix of goodness-of-fit measures

- 1 Log-Likelihood, full model
- 2 Log-Likelihood, restricted model (all slope coefficients equal zero)
- 3 Chi-square statistic
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- 8 McKelvey and Zovcina's Pseudo R-Squared
- 9 Cragg and Uhler's normed likelihood ratios
- 10 Count R-Squared

- 11 Adjusted Count R-Squared
- 12 Akaike information criterion (AIC)
- 13 Bayesian information criterion (BIC)

■ Example

```
library dc;
#include dc.sdf

struct dcDesc d1;
d1 = dcDescCreate;

d1.yvar = 1;
let d1.xvars = { 2,3,4 };

struct dcout dcout1;

dcout1 = dcStereo("aldnel",d1,dcControlCreate);
call dcprt(dcout1);
```

■ Remarks

The stereotype model is a special case of the multinomial logit model where the coefficients of succeeding categories are a linear function of a single vector of coefficients.

■ Source

dcstereo.src

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