## nag_regsn_mult_linear_newyvar (g02dgc)

## 1. Purpose

nag_regsn_mult_linear_newyvar (g02dgc) calculates the estimates of the parameters of a general linear regression model for a new dependent variable after a call to nag_regsn_mult_linear (g02dac).

## 2. Specification

```
#include <nag.h>
#include <nagg02.h>
void nag_regsn_mult_linear_newyvar(Integer n, double wt[], double *rss,
    Integer ip, Integer rank, double cov[], double q[], Integer tdq,
    Boolean svd, double p[], double y[], double b[], double se[],
    double res[], double com_ar[], NagError *fail)
```


## 3. Description

nag_regsn_mult_linear_newyvar uses the results given by nag_regsn_mult_linear (g02dac) to fit the same set of independent variables to a new dependent variable.
nag_regsn_mult_linear (g02dac) computes a $Q R$ decomposition of the matrix of $p$ independent variables and also, if the model is not of full rank, a singular value decomposition (SVD). These results can be used to compute estimates of the parameters for a general linear model with a new dependent variable. The $Q R$ decomposition leads to the formation of an upper triangular $p$ by $p$ matrix $R$ and an $n$ by $n$ orthogonal matrix $Q$. In addition the vector $c=Q^{T} y$ (or $Q^{T} W^{1 / 2} y$ ) is computed. For a new dependent variable, $y_{\text {new }}$, nag_regsn_mult_linear_newyvar computes a new value of $c=Q^{T} y_{\text {new }}$ or $Q^{T} W^{1 / 2} y_{\text {new }}$.

If $R$ is of full rank, then the least-squares parameter estimates, $\hat{\beta}$, are the solution to: $R \hat{\beta}=c_{1}$, where $c_{1}$ is the first $p$ elements of $c$.

If $R$ is not of full rank, then nag_regsn_mult_linear (g02dac) will have computed the SVD of $R$,

$$
R=Q_{*}\left(\begin{array}{cc}
D & 0 \\
0 & 0
\end{array}\right) P^{T}
$$

where $D$ is a $k$ by $k$ diagonal matrix with non-zero diagonal elements, $k$ being the rank of $R$, and $Q_{*}$ and $P$ are $p$ by $p$ orthogonal matrices. This gives the solution

$$
\hat{\beta}=P_{1} D^{-1} Q_{*_{1}}^{T} c_{1}
$$

$P_{1}$ being the first $k$ columns of $P$, i.e., $P=\left(P_{1} P_{0}\right)$ and $Q_{*_{1}}$ being the first $k$ columns of $Q_{*}$. Details of the SVD are made available by nag_regsn_mult_linear (g02dac) in the form of the matrix $P^{*}$ :

$$
P^{*}=\binom{D^{-1} P_{1}^{T}}{P_{0}^{T}}
$$

The matrix $Q_{*}$ is made available through the com_ar parameter of nag_regsn_mult_linear (g02dac).
In addition to parameter estimates, the new residuals are computed and the variance-covariance matrix of the parameter estimates are found by scaling the variance-covariance matrix for the original regression.

## 4. Parameters

n
Input: the number of observations, $n$. Constraint: $\mathbf{n} \geq 2$.
$\mathrm{wt}[\mathrm{n}]$
Input: if weighted estimates are required then wt must contain the weights to be used in the weighted regression. Otherwise wt need not be defined and may be set to the null pointer NULL, i.e., (double *) 0.
If $\mathbf{w t}[i]=0.0$, then the $i$ th observation is not included in the model, in which case the effective number of observations is the number of observations with non-zero weights. The values of res and $\mathbf{h}$ will be set to zero for observations with zero weights.
If $\mathbf{w t}=\mathbf{N U L L}$, then the effective number of observations is $n$.
Constraint: $\mathbf{w t}=\mathbf{N U L L}$ or $\mathbf{w t}[i] \geq 0.0$, for $i=0,1, \ldots, n-1$.
rss
Input: the residual sum of squares for the original dependent variable.
Output: the residual sum of squares for the new dependent variable.
ip
Input: the number $p$ of independent variables in the model (including the mean if fitted).
Constraint: $1 \leq \mathbf{i p} \leq \mathbf{n}$.

## rank

Input: the rank of the independent variables, as given by nag_regsn_mult_linear (g02dac).
Constraint: rank $>0$ and if $\mathbf{s v d}=$ FALSE, $\mathbf{r a n k}=\mathbf{i p}$ otherwise $\mathbf{r a n k} \leq \mathbf{i p}$.

## $\operatorname{cov}[\mathrm{ip} *(\mathrm{ip}+1) / 2]$

Input: the covariance matrix of the parameter estimates as given by nag_regsn_mult_linear (g02dac).
Output: the upper triangular part of the variance-covariance matrix of the ip parameter estimates given in b. They are stored packed by column, i.e., the covariance between the parameter estimate given in $\mathbf{b}[i]$ and the parameter estimate given in $\mathbf{b}[j], j \geq i$, is stored in $\operatorname{cov}[j(j+1) / 2+i]$ for $i=0,1, \ldots, \mathbf{i p}-1$ and $j=i, i+1, \ldots, \mathbf{i p}-1$.
$\mathrm{q}[\mathrm{n}][\mathrm{tdq}]$
Input: the results of the $Q R$ decomposition as returned by nag_regsn_mult_linear (g02dac).
Output: the first column of $\mathbf{q}$ contains the new values of $c$, the remainder of $\mathbf{q}$ will be unchanged.
tdq
Input: the second dimension of the array $\mathbf{q}$ as declared in the function from which nag_regsn_mult_linear_newyvar is called.
Constraint: $\mathbf{t d q} \geq \mathbf{i p}+1$.
svd
Input: indicates if a singular value decomposition was used by nag_regsn_mult_linear (g02dac).
If svd $=$ TRUE, a singular value decomposition was used by nag_regsn_mult_linear (g02dac).
If svd = FALSE, a singular value decomposition was not used by nag_regsn_mult_linear (g02dac).

## $\mathrm{p}[2 * \mathbf{i p}+\mathbf{i p} * \mathbf{i p}]$

Input: details of the $Q R$ decomposition and SVD, if used, as returned in array $\mathbf{p}$ by nag_regsn_mult_linear (g02dac).
If $\mathbf{s v d}=\mathbf{F A L S E}$, only the first ip elements of $\mathbf{p}$ are used, these will contain the zeta values for the $Q R$ decomposition (see nag_real_qr (f01qcc) for details).
If $\mathbf{s v d}=\mathbf{T R U E}$, the first ip elements of $\mathbf{p}$ will contain the zeta values for the $Q R$ decomposition (see nag_real_qr (f01qcc) for details) and the next ip elements of $\mathbf{p}$ contain singular values. The following ip by ip elements contain the matrix $P^{*}$ stored by rows.
$\mathrm{y}[\mathbf{n}]$
Input: the new dependent variable $y_{\text {new }}$.
b[ip]
Output: $\mathbf{b}[i], i=0,1, \ldots, \mathbf{i p}-1$ contain the least-squares estimates of the parameters of the regression model, $\hat{\beta}$.
se[ip]
Output: $\mathbf{s e}[i], i=0,1, \ldots, \mathbf{i p}-1$ contain the standard errors of the $\mathbf{i p}$ parameter estimates given in $\mathbf{b}$.
$\operatorname{res}[\mathbf{n}]$
Output: the residuals for the new regression model.
com_ar $[5 *(i p-1)+i p * i p]$
Input: if svd $=$ TRUE, com_ar must be unaltered from the previous call to nag_regsn_mult_linear (g02dac).
fail
The NAG error parameter, see the Essential Introduction to the NAG C Library.
5. Error Indications and Warnings

## NE_INT_ARG_LT

On entry, ip must not be less than 1: $\mathbf{i p}=\langle$ value $\rangle$.
NE_INT_ARG_LE
On entry, rank must not be less than or equal to 0 : $\mathbf{r a n k}=\langle$ value $\rangle$.

## NE_2_INT_ARG_LT

On entry, $\mathbf{t d q}=\langle$ value $\rangle$ while $\mathbf{i p}+1=\langle$ value $\rangle$. These parameters must satisfy $\mathbf{t d q} \geq \mathbf{i p}+1$.
On entry, $\mathbf{n}=\langle$ value $\rangle$ while $\mathbf{i p}=\langle$ value $\rangle$. These parameters must satisfy $\mathbf{n} \geq \mathbf{i p}$.

## NE_REAL_ARG_LE

On entry, rss must not be less than or equal to $0.0:$ rss $=\langle$ value $\rangle$.

## NE_REAL_ARG_LT

On entry, wt $[\langle$ value $\rangle]$ must not be less than 0.0 : $\mathbf{w t}[\langle$ value $\rangle]=\langle$ value $\rangle$.

## NE_SVD_RANK_NE_IP

On entry, the Boolean variable, svd, is FALSE and rank must be equal to ip: rank $=\langle$ value $\rangle$, ip $=\langle$ value $\rangle$.

## NE_SVD_RANK_GT_IP

On entry, the Boolean variable, svd, is TRUE and rank must not be greater than ip: rank $=\langle$ value $\rangle, \mathbf{i p}=\langle$ value $\rangle$.
6. Further Comments

The values of the leverages, $h_{i}$, are unaltered by a change in the dependent variable so a call to nag_regsn_std_resid_influence (g02fac) can be made using the value of $\mathbf{h}$ from nag_regsn_mult_linear (g02dac).
6.1. Accuracy

The same accuracy as nag_regsn_mult_linear (g02dac) is obtained.

### 6.2. References

Golub G H and Van Loan C F (1983) Matrix Computations Johns Hopkins University Press, Baltimore.
Hammarling S (1985) The Singular Value Decomposition in Multivariate Statistics ACM Signum Newsletter 20 (3) 2-25.
Searle S R (1971) Linear Models Wiley.

## 7. See Also

```
nag_real_qr (f01qcc)
nag_regsn_mult_linear (g02dac)
nag_regsn_std_resid_influence (g02fac)
```


## 8. Example

A data set consisting of 12 observations with four independent variables and two dependent variables is read in. A model with all four independent variables is fitted to the first dependent variable by nag_regsn_mult_linear (g02dac) and the results printed. The model is then fitted to the second dependent variable by nag_regsn_mult_linear_newyvar and those results printed.
8.1. Program Text

```
/* nag_regsn_mult_linear_newyvar(g02dgc) Example Program
    *
    * Copyright 1990 Numerical Algorithms Group.
    *
    * Mark 2 revised, 1992.
    */
#include <nag.h>
#include <stdio.h>
#include <nag_stdlib.h>
#include <nagg02.h>
#define NMAX 12
#define MMAX 5
#define TDQ MMAX+1
#define TDXM MMAX
main()
{
    double rss, tol;
    Integer i, ip, rank, j, m, n;
    double df;
    Boolean svd;
    Nag_IncludeMean mean;
    char weight, meanc;
    double b[MMAX], cov[MMAX*(MMAX+1)/2], h[NMAX], newy [NMAX],
    p[MMAX*(MMAX+2)], q[NMAX] [MMAX+1], res[NMAX], se[MMAX],
    com_ar [5*(MMAX-1)+MMAX*MMAX], wt [NMAX], xm [NMAX] [MMAX], y [NMAX];
    Integer sx[MMAX];
    double *wtptr;
    Vprintf("g02dgc Example Program Results\n");
    /* Skip heading in data file */
    Vscanf("%*[^\n]");
    Vscanf("%ld %ld %c %c", &n, &m, &weight, &meanc);
    if (meanc=='m')
        mean = Nag_MeanInclude;
    else
        mean = Nag_MeanZero;
    if (n<=NMAX && m<MMAX)
        {
            if (weight=='w')
                wtptr = wt;
                    for (i=0; i<n; i++)
                            {
                        for (j=0; j<m; j++)
                        Vscanf("%lf", &xm[i][j]);
                                Vscanf("%lf%lf%lf", &y[i], &wt[i], &newy[i]);
                                }
                }
            else
                {
                    wtptr = (double *)0;
                    for (i=0; i<n; i++)
                                {
                                for (j=0; j<m; j++)
                        Vscanf("%lf",&xm[i][j]);
                                Vscanf("%lf%lf", &y[i], &newy[i]);
                                }
                }
            for (j=0; j<m; j++)
```

```
                    Vscanf("%ld", &sx[j]);
                Vscanf("%ld", &ip);
            /* Set tolerance */
            tol = 0.00001e0;
            /* Fit initial model using g02dac */
            g02dac(mean, n, (double *)xm, (Integer)TDXM, m, sx, ip,
                        y, wtptr, &rss, &df, b, se, cov, res, h, (double *)q,
                        (Integer)(TDQ), &svd, &rank, p, tol, com_ar, NAGERR_DEFAULT);
            Vprintf("Results from g02dac\n\n");
            if (svd)
                    Vprintf("Model not of full rank\n\n");
            Vprintf("Residual sum of squares = %12.4e\n", rss);
            Vprintf("Degrees of freedom = %3.1f\n\n", df);
            Vprintf("Variable Parameter estimate Standard error\n\n");
            for (j=0; j<ip; j++)
                    Vprintf("%61d%20.4e%20.4e\n", j+1, b[j], se[j]);
            Vprintf("\n");
            g02dgc(n, wtptr, &rss, ip, rank, cov, (double *)q, (Integer)(TDQ), svd, p,
                    newy, b, se, res, com_ar, NAGERR_DEFAULT);
            Vprintf("\n");
            Vprintf("Results for second y-variable using g02dgc\n\n");
            Vprintf("Residual sum of squares = %12.4e\n", rss);
            Vprintf("Degrees of freedom = %3.1f\n\n", df);
            Vprintf("Variable Parameter estimate Standard error\n\n");
            for (j=0; j<ip; j++)
                Vprintf("%6ld%20.4e%20.4e\n", j+1, b[j], se[j]);
            Vprintf("\n");
        }
        else
            {
                Vfprintf(stderr, "One or both of m and n are out of range:\
m = %-3ld while n = %-3ld\n", m, n);
            exit(EXIT_FAILURE);
        }
    exit(EXIT_SUCCESS);
}
```


### 8.2. Program Data

| g02dgc | Example Program Data |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 12 | 4 | u | m |  |  |
| 1.0 | 0.0 | 0.0 | 0.0 | 33.63 | 63.0 |
| 0.0 | 0.0 | 0.0 | 1.0 | 39.62 | 69.0 |
| 0.0 | 1.0 | 0.0 | 0.0 | 38.18 | 68.0 |
| 0.0 | 0.0 | 1.0 | 0.0 | 41.46 | 71.0 |
| 0.0 | 0.0 | 0.0 | 1.0 | 38.02 | 68.0 |
| 0.0 | 1.0 | 0.0 | 0.0 | 35.83 | 65.0 |
| 0.0 | 0.0 | 0.0 | 1.0 | 35.99 | 65.0 |
| 1.0 | 0.0 | 0.0 | 0.0 | 36.58 | 66.0 |
| 0.0 | 0.0 | 1.0 | 0.0 | 42.92 | 72.0 |
| 1.0 | 0.0 | 0.0 | 0.0 | 37.80 | 67.0 |
| 0.0 | 0.0 | 1.0 | 0.0 | 40.43 | 70.0 |
| 0.0 | 1.0 | 0.0 | 0.0 | 37.89 | 67.0 |
| 1 | 1 | 1 | 1 | 5 |  |

### 8.3. Program Results

| g02dgc Example Program Results Results from g02dac |  |  |
| :---: | :---: | :---: |
| Model not of full rank |  |  |
| ```Residual sum of squares = 2.2227e+01 Degrees of freedom = 8.0``` |  |  |
| Variable | Parameter estimate | Standard error |
| 1 | $3.0557 \mathrm{e}+01$ | $3.8494 \mathrm{e}-01$ |
| 2 | $5.4467 e+00$ | $8.3896 e^{-01}$ |
| 3 | $6.7433 \mathrm{e}+00$ | $8.3896 e^{-01}$ |
| 4 | $1.1047 \mathrm{e}+01$ | $8.3896 \mathrm{e}-01$ |
| 5 | $7.3200 \mathrm{e}+00$ | $8.3896 \mathrm{e}-01$ |
| Results for second y-variable using g02dgc |  |  |
| Residual sum of squares $=2.4000 \mathrm{e}+01$Degrees of freedom $=8.0$ |  |  |
| Variable | Parameter estimate | Standard error |
| 1 | $5.4067 \mathrm{e}+01$ | $4.0000 \mathrm{e}-01$ |
| 2 | $1.1267 e+01$ | $8.7178 \mathrm{e}-01$ |
| 3 | $1.2600 \mathrm{e}+01$ | $8.7178 \mathrm{e}-01$ |
| 4 | $1.6933 \mathrm{e}+01$ | $8.7178 \mathrm{e}-01$ |
| 5 | $1.3267 e+01$ | $8.7178 \mathrm{e}-01$ |

