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Hunting the missing score functions

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1 Outline

1. Introduction
2. The `ml` command
3. Linear-form Restriction
4. The Problem
5. Robust Variance Covariance Matrix: A very brief review
6. The Solution
7. Conclusions

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- In particular: we will focus on models where the log-likelihood function does not meet the linear-form restrictions, which can be fitted using the `d`-family of evaluators.
- The minimum requirement to implement a model using the `ml` command is to write its log-likelihood function (i.e., `d0` evaluator).
- Faster methods can be implemented depending on what we provide the `ml` command with:
  - `d0` evaluator = **Log-likelihood**
  - `d1` evaluator = Log-likelihood + Gradient
  - `d2` evaluator = Log-likelihood + Gradient + Hessian

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```
. list in 1/3, sep(1)
```

	y	x1	x2
1.	-1.09811	-.3591099	.3387246
2.	-1.742268	.1902105	-1.498368
3.	1.273768	-1.602709	1.034604

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```
. list in 1/6 , sep(3)

     +-----------------------------------------------------+
     | id   altern~e          x1           x2     choice |
     |-----------------------------------------------------|
  1. |  1          1   -1.666827    -1.969941          0 |
  2. |  1          2    .5580259    -.2189879          0 |
  3. |  1          3    1.054737     1.894969          1 |
     |-----------------------------------------------------|
  4. |  2          1   -1.913301    -.1506114          0 |
  5. |  2          2   -.1818884    -.2132395          1 |
  6. |  2          3     1.19467    -.6775483          0 |
     +-----------------------------------------------------+
```

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- In other words, if the model uses data in `long` format, it probably does not meet the restriction.

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```
. qui clogit choice x1 x2 , gr(id) nolog
. matrix b_clogit = e(b)
. MyClogit choice x1 x2 , gr(id) nolog
MyClogit                                        Number of obs     =        300
                                                Wald chi2(2)      =      38.72
Log likelihood =  -53.10466                     Prob > chi2       =     0.0000

------------------------------------------------------------------------------
      choice |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          x1 |   .5233348   .1771384     2.95   0.003     .1761499    .8705197
          x2 |   1.922775   .3146272     6.11   0.000     1.306117    2.539433
------------------------------------------------------------------------------

. matrix b_MyClogit = e(b)
. di mreldif(b_MyClogit, b_clogit)
2.308e-08
```

  - We also check that the estimates from our program are numerically equivalent to Stata's `clogit` command.

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- **Hence, we are in ⚠ trouble ⚠ !**

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5 Robust Variance Covariance Matrix: A very brief review

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$$G(\boldsymbol{\beta}) = \sum_{n=1}^{N} \boldsymbol{S}(\boldsymbol{\beta}; y_n, \boldsymbol{x}_n) = \mathbf{0} \quad \text{where} \quad \underbrace{\boldsymbol{S}(\boldsymbol{\beta}; y_n, \boldsymbol{x}_n)}_{\text{Score functions}} = \partial \ln L_n / \partial \boldsymbol{\beta}$$

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- $\boldsymbol{u}_n = \boldsymbol{S}(\widehat{\boldsymbol{\beta}}; y_n, \boldsymbol{x}_n)$ are row vectors that contains the score functions evaluated at $\widehat{\boldsymbol{\beta}}$.
- Hence, $\boldsymbol{u}_n$ is the only object that is missing in order to compute $\widehat{V}(\widehat{\boldsymbol{\beta}})$.

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- ⚠**SPOILER ALERT**⚠:
  - Our solution will consist in:
    1. (Numerically) approximate the vector $\boldsymbol{u}_n$.
    2. Compute $\widehat{V}(\widehat{\boldsymbol{\beta}})$ using it.

6 The Solution [2]: Collecting everything we need

- First, we provide Mata with everything we need to compute the log-likelihood contribution of each individual.

```
. // We create relevant matrices on Stata to push them to Mata afterwards.
. matrix b = e(b)                // Maximum Likelihood estimates
. matrix W = e(V)                // Non-robust variance-covariance matrix
. // We initialize Mata
. mata:
------------------------------------------------- mata (type end to exit) ----------------
: // Invoking Stata matrices
: betas = st_matrix("b")          // Calls from Stata the matrix "b"
: W     = st_matrix("W")          // Calls from Stata the matrix "W"
:
: // Invoking Stata Variables
: st_view(X = ., ., "x1 x2")      // View of all regressors x1 and x2
: st_view(Y = ., ., "choice")     // View of response variable "choice"
: XY = (Y,X)                      // Generates XY matrix for future usage.
:
: // Extracting information about the id of individuals.
: st_view(panvar = ., ., "id")    // View of individuals id
: paninfo = panelsetup(panvar, 1) // Sets up panel processing
: N = panelstats(paninfo)[1]      // Number of Individuals
: end
------------------------------------------------------------------------------------------
```

6 The Solution [3]: Writing our log-likelihood function

- Second, we will create a void function, `LL_d()`, that resembles our log-likelihood function.

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- We will invoke it later when using Mata's deriv() function.

```
. mata:
------------------------------------------------- mata (type end to exit) -----------------------
: // Creating the function we will invoke using Mata´s deriv().
: void LL_d(real rowvector b ,   // 1ST ARGUMENT: Maximum likelihood estimates
>           real matrix    XY ,  // 2ND ARGUMENT: Convariates + dependent variable
>           real scalar lnf)     // Output:       Log-likelihood contribution
> {
>   Y = XY[.,1]                 // Extract variable Y
>   X = XY[., (2::cols(XY))]    // Extract the regressors (x1 and x2)
>   U = rowsum(b:*X)            // Observed Utility
>   P = exp(U):/colsum(exp(U )) // Multinomial Probability
>   lnf = colsum(Y:*ln(P))      // Individual contribution to the log-likelihood
> }
: end
--------------------------------------------------------------------------------------------------
```

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> }
: end
------------------------------------------------------------------------------------------------
```

- As you can see, this resembles exactly our log-likelihood.

$$\ln L = \sum_{n=1}^{N} \sum_{i=1}^{J} y_{in} \ln\left(P_{in}\right) = \sum_{n=1}^{N} \sum_{i=1}^{J} y_{in} \ln\left(\frac{\exp\left(\beta' x_{in}\right)}{\sum_{j=1}^{J} \exp\left(\beta' x_{in}\right)}\right)$$

6 The Solution [4]: Score function of the first individual

- Third, to begin with, we will illustrate how to compute the score function of the first individual using `deriv()`:

```
. mata:
------------------------------------------------- mata (type end to exit) ---------------------
: D =deriv_init()                   // Init deriv() object and call it "D"
: deriv_init_evaluator(D, &LL_d()) // We provide the object D with function LL_d()
: deriv_init_evaluatortype(D,"d")  // Set that deriv() must returns a scalar
: deriv_init_params(D, betas)      // Provide D with beta estimates (deriv at)
: xy_n = panelsubmatrix(XY, 1, paninfo) // Extract first individual´s X and Y
: xy_n
                 1              2              3
    +----------------------------------------------+
  1 |            0   -1.666826963   -1.969941497  |
  2 |            0    .5580258965    -.218987897  |
  3 |            1    1.054736972    1.894969106  |
    +----------------------------------------------+

: deriv_init_argument(D, 1, xy_n)  // provide D with X and Y of the first individual
: score_fn= deriv(D, 1)            // <--- Perform the numerical derivation!
: score_fn                         // Display it
                 1              2
    +-----------------------------+
  1 |  .006871893   .0281603095  |
    +-----------------------------+

: end
-----------------------------------------------------------------------------------------------
```

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6 The Solution [5]: Score functions of the entire sample

- Now that we know how to perform the derivative of a function we can apply it to the whole sample (e.g., to all the individuals in the sample):

```
. mata:
------------------------------------------------- mata (type end to exit) -------------------
: D = deriv_init()                    // Init deriv() object
: deriv_init_evaluator(D, &LL_d()) // Object D is prodived with the pointer LL_d()
: deriv_init_evaluatortype(D,"d")  // Set that deriv() must returns a scalar
: score_fn = J(0, cols(betas),.)   // Vector length 0xcols(betas)
: for(n=1; n <= N; ++n) {          // Looping over n individuals
>          xy_n = panelsubmatrix(XY, n, paninfo)  // Extract submatrix of individual n
>          deriv_init_params(D, betas)            // provide D with beta estimates
>          deriv_init_argument(D, 1, xy_n)        // provide D with attributes values
>          score_fn = score_fn \  deriv(D, 1)     // Collect score functions from each individual
>
> }
: score_fn[1..4,]  // display the score functions of the first 4 individuals
                 1              2
    +-------------------------------+
  1 |     .006871893    .0281603095 |
  2 |   -.1607972318    .1576732297 |
  3 |   -.0730075944    .1282049291 |
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: // Finally, we save the score functions  as S just for a handy matrix multiplication afterwards.
: S = score_fn
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---------------------------------------------------------------------------------------------
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- All we have to do now is just perform the matrix multiplication described below to find the robust variance-covariance matrix.

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- $\boldsymbol{u}_n = \boldsymbol{S}(\widehat{\boldsymbol{\beta}}; y_n, \boldsymbol{x}_n)$ are row vectors that contains the score functions evaluated at $\widehat{\boldsymbol{\beta}}$ (Object `S`).
- Accordingly, it is as simple as:

```
. mata:
------------------------------------------------- mata (type end to exit) ---------------------------
: meat =  (N/(N-1)) * S´ * S                    // Some people call this part the "meat".
: V_robust_approx= W * meat * W                 // Approximated robust variance-covariance matrix.
: st_matrix("V_robust_approx", V_robust_approx) // Save robust matrix into a Stata Matrix.
: end
-----------------------------------------------------------------------------------------------------
```

6 The Solution [7]: Checking our approximation

- Using V_robust_approx we can check how far are our numerically approximated robust covariance matrices compared with Stata's clogit.

```
. clogit choice x* ,gr(id) robust nolog
Conditional (fixed-effects) logistic regression
                                                Number of obs     =        300
                                                Wald chi2(2)      =      42.15
                                                Prob > chi2       =     0.0000
Log pseudolikelihood =  -53.10466               Pseudo R2         =     0.5166
                                     (Std. Err. adjusted for clustering on id)
------------------------------------------------------------------------------
             |               Robust
      choice |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          x1 |   .5233348   .1587735     3.30   0.001     .2121444    .8345252
          x2 |   1.922775   .3334521     5.77   0.000      1.26922    2.576329
------------------------------------------------------------------------------

. mat V_robust_clogit = e(V)
. mat li V_robust_approx
symmetric V_robust_approx[2,2]
           c1         c2
r1  .02520903
r2  .00291664  .11119032
. mat li V_robust_clogit
symmetric V_robust_clogit[2,2]
               choice:     choice:
                   x1          x2
choice:x1   .02520903
choice:x2   .00291664   .11119031
. display mreldif(V_robust_approx, V_robust_clogit)
7.734e-09
```


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7 Outline

1. Introduction
2. The ml command
3. Linear-form Restriction
4. The Problem
5. Robust Variance Covariance Matrix: A very brief review
6. The Solution
7. Conclusions

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- We have seen a workaround for those ***rare*** cases when the `ml` command fails to produce robust standard errors.

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- All the source code of this talk is available at this GitHub repository.

7 Conclusions

- We have seen a workaround for those ***rare*** cases when the `ml` command fails to produce robust standard errors.
- The illustrated solution is not meant to replace the algebraic computation of the score functions, but a complement and a way to check our results.
- All the source code of this talk is available at this GitHub repository.
- **Questions? :)**

8 Outline

1. Introduction
2. The `ml` command
3. Linear-form Restriction
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5. Robust Variance Covariance Matrix: A very brief review
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9 Bibliography

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10 Outline

9. MyClogit

10. MyLikelihood_LL.mata

10 MyClogit.ado

```
program MyClogit
    version 12
    if replay() {
    if ("`e(cmd)´" != "MyClogit") error 301
    Replay `0´
    }
    else Estimate `0´
end

program Estimate, eclass sortpreserve
    syntax varlist(fv) [if] [in] , GRoup(varname) ///
        [TECHnique(passthru) noLOg ROBUST ]
    local mlopts  `technique´
    if ("`technique´" == "technique(bhhh)") {
    di in red "technique(bhhh) is not allowed."
    exit 498
    }
    gettoken lhs rhs : varlist
    marksample touse
    markout `touse´ `group´
    global MY_panel = "`group´"
    ml model d0 MyLikelihood_LL()      ///
        (MyClogit: `lhs´ = `rhs´, nocons)  ///
        if `touse´, missing  first   `log´ ///
        title("MyClogit") `robust´ maximize
        // Show model
        ereturn local cmd MyClogit
        Replay , level(`level´)
        ereturn local  cmdline `"`0´"´
end

 program Replay
    syntax [, Level(cilevel) ]
    ml display , level(`level´)
 end

// include mata functions from MyLikelihood_LL.mata
findfile "MyLikelihood_LL.mata"
do "`r(fn)´"
```

11 Outline

9 MyClogit

10 MyLikelihood_LL.mata

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11 MyLikelihood_LL.mata

```
mata:
    void MyLikelihood_LL(transmorphic scalar M, real scalar todo,
    real rowvector b, real scalar lnf,
    real rowvector g, real matrix H)
{
  // variables declaration
  real matrix panvar
  real matrix paninfo
  real scalar npanels
  real scalar n
  real matrix Y
  real matrix X
  real matrix x_n
  real matrix y_n
  Y = moptimize_util_depvar(M, 1)               // Response Variable
  X = moptimize_init_eq_indepvars(M,1)          // Attributes
  id_beta_eq=moptimize_util_eq_indices(M,1)     // id parameters
  betas= b[|id_beta_eq|]                        // parameters
  st_view(panvar = ., ., st_global("MY_panel"))
  paninfo = panelsetup(panvar, 1)
  npanels = panelstats(paninfo)[1]
  lnfj = J(npanels, 1, 0)                       // object to store loglikelihood
  for(n=1; n <= npanels; ++n) {
        x_n = panelsubmatrix(X, n, paninfo)
        y_n = panelsubmatrix(Y, n, paninfo)
        U_n =exp(rowsum(betas :* x_n))        // Linear utility
        p_i = colsum(U_n:* y_n) / colsum(U_n) // Probability of each alternative
        lnfj[n] = ln(p_i)                     // Add contribution to the likelihood
}
  lnf = moptimize_util_sum(M, lnfj)
}
end
```