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# Trabajo Práctico N° 4:
# Modelos para Variables Categóricas Ordenadas.

## Ejercicio 1: Predicción de Calificaciones de Clientes.

*Considerar el ejercicio del Problem Set anterior con el mismo título que éste. Repetir el análisis utilizando un modelo ordenado.*

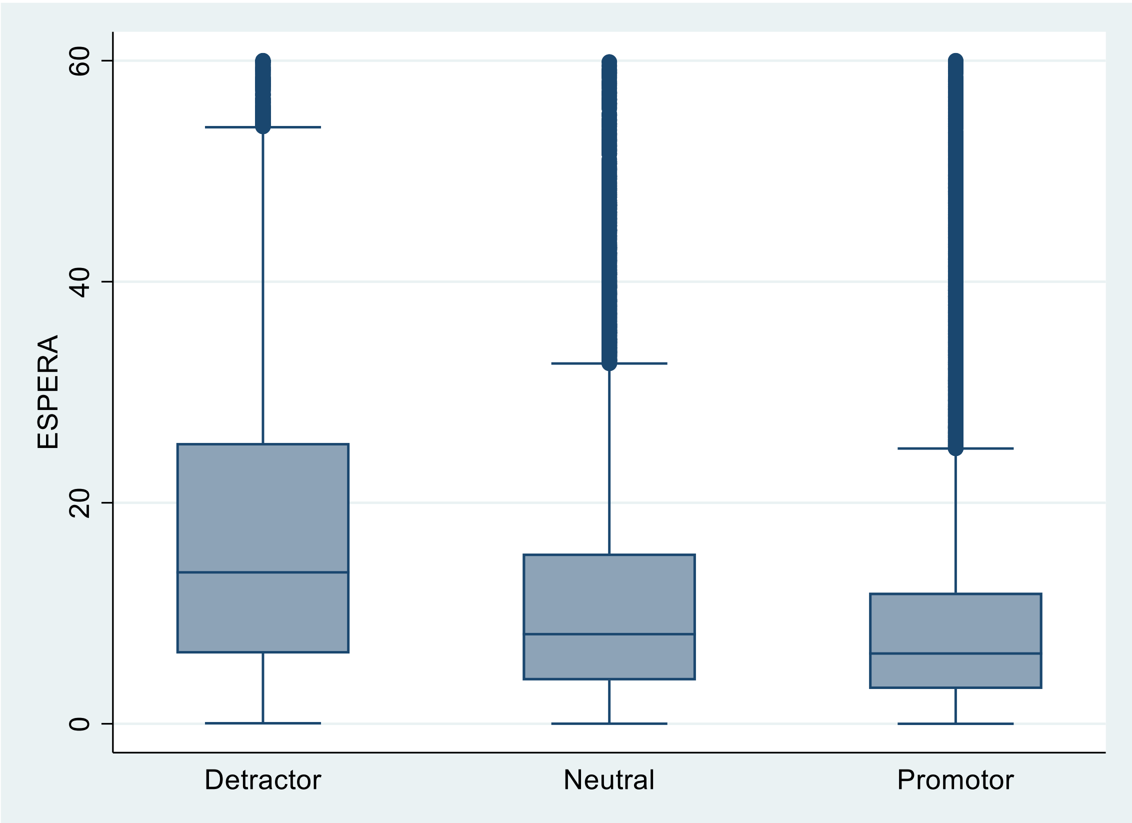
**(a)** *Abrir y describir la base.*

```
    Variable |        Obs        Mean    Std. dev.       Min        Max
-------------+---------------------------------------------------------
         nps |     42,019    8.369975    2.263878          1         10
marital_st~e |          0
 gender_code |          0
        edad |     42,020    52.16497    12.56996         19        101
 branch_desc |          0
-------------+---------------------------------------------------------
    segmento |          0
 operaciones |     42,020    1.728439    1.476585          1         31
         mes |     42,020    6.736292    3.241668          1         12
nps_anterior |          0
        hora |     42,020     11.7812    1.743031          7         18
-------------+---------------------------------------------------------
         dia |     42,020    14.91792    8.634796          1         31
  dia_semana |          0
      espera |     42,020    10.89938    10.70589          0         60
     cliente |     42,020    21372.36    12335.51          1      42760
```

**(b)** *Generar una variable que clasifique a los clientes en función de si son promotores, detractores o neutrales.*

| clasificacion | Freq. | Percent | Cum. |
|---|---|---|---|
| Detractor | 6,265 | 14.91 | 14.91 |
| Neutral | 9,579 | 22.80 | 37.71 |
| Promotor | 26,175 | 62.29 | 100.00 |
| Total | 42,019 | 100.00 | |

**(c)** *Analizar cómo cambia la variable de espera en función de la clasificación de los clientes.*




**(d)** *Tomar una muestra del 10% de los datos. Estimar un logit multinomial ordenado para predecir cómo cambian las clasificaciones en función de la espera, condicionando en explicativas que se considere relevantes.*

## Logit multinomial ordenado (betas):

Ordered logistic regression — Number of obs = 4,202; LR chi2(7) = 394.03; Prob > chi2 = 0.0000; Log likelihood = -3659.6981; Pseudo R2 = 0.0511

| clasificacion | Coefficient | Std. err. | z | P>\|z\| | [95% conf. | interval] |
|---|---|---|---|---|---|---|
| _Igender_co_2 | -.0667762 | .0687925 | -0.97 | 0.332 | -.201607 | .0680546 |
| edad | .0163998 | .0026606 | 6.16 | 0.000 | .0111852 | .0216144 |
| _Isegmento_2 | .7313334 | .8363563 | 0.87 | 0.382 | -.9078948 | 2.370562 |
| _Isegmento_3 | .2147268 | .1144579 | 1.88 | 0.061 | -.0096065 | .4390601 |
| _Isegmento_4 | -.478007 | .1271562 | -3.76 | 0.000 | -.7272286 | -.2287855 |
| _Isegmento_5 | -.3697909 | .1299945 | -2.84 | 0.004 | -.6245754 | -.1150063 |
| espera | -.0359647 | .0030773 | -11.69 | 0.000 | -.041996 | -.0299333 |
| /cut1 | -1.429497 | .178061 | | | -1.77849 | -1.080504 |
| /cut2 | -.1286401 | .1758049 | | | -.4732113 | .2159311 |

## Logit multinomial ordenado (odds ratios):

Ordered logistic regression — Number of obs = 4,202; LR chi2(7) = 394.03; Prob > chi2 = 0.0000; Log likelihood = -3659.6981; Pseudo R2 = 0.0511

| clasificacion | Odds ratio | Std. err. | z | P>\|z\| | [95% conf. | interval] |
|---|---|---|---|---|---|---|
| _Igender_co_2 | .9354045 | .0643488 | -0.97 | 0.332 | .8174161 | 1.070424 |
| edad | 1.016535 | .0027045 | 6.16 | 0.000 | 1.011248 | 1.02185 |
| _Isegmento_2 | 2.077849 | 1.737822 | 0.87 | 0.382 | .4033725 | 10.7034 |
| _Isegmento_3 | 1.239523 | .1418732 | 1.88 | 0.061 | .9904395 | 1.551249 |
| _Isegmento_4 | .6200178 | .0788391 | -3.76 | 0.000 | .4832464 | .7954992 |
| _Isegmento_5 | .6908788 | .0898104 | -2.84 | 0.004 | .5354887 | .8913605 |
| espera | .9646744 | .0029686 | -11.69 | 0.000 | .9588736 | .9705103 |
| /cut1 | -1.429497 | .178061 | | | -1.77849 | -1.080504 |
| /cut2 | -.1286401 | .1758049 | | | -.4732113 | .2159311 |

Note: Estimates are transformed only in the first equation to odds ratios.

**(e)** *Calcular los efectos marginales.*

## Efectos marginales en Logit multinomial ordenado (clasificación 1):

Marginal effects after ologit
y = Pr(clasificacion==1) (predict, pr outcome(1))
= .13947074

| variable | dy/dx | Std. err. | z | P>\|z\| | [ 95% | C.I. ] | X |
|---|---|---|---|---|---|---|---|
| _Igend~2* | .0079445 | .00812 | 0.98 | 0.328 | -.007962 | .023851 | .682532 |
| edad | -.0019683 | .00032 | -6.13 | 0.000 | -.002597 | -.001339 | 51.9412 |
| _Isegm~2* | -.0671776 | .05629 | -1.19 | 0.233 | -.177512 | .043157 | .001666 |
| _Isegm~3* | -.0261068 | .0141 | -1.85 | 0.064 | -.053748 | .001534 | .580438 |
| _Isegm~4* | .063994 | .01889 | 3.39 | 0.001 | .02698 | .101008 | .179914 |
| _Isegm~5* | .0486811 | .01869 | 2.60 | 0.009 | .012049 | .085313 | .149929 |
| espera | .0043164 | .00038 | 11.41 | 0.000 | .003575 | .005058 | 11.1349 |

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Efectos marginales en Logit multinomial ordenado (clasificación 2):

```
Marginal effects after ologit
      y  = Pr(clasificacion==2) (predict, pr outcome(2))
         =  .23365369
------------------------------------------------------------------------------
variable |      dy/dx    Std. err.     z    P>|z|  [    95% C.I.   ]      X
---------+--------------------------------------------------------------------
_Igend~2*|   .0076247      .00788    0.97   0.333  -.007815  .023064   .682532
    edad |  -.0018677      .00031   -6.00   0.000  -.002478 -.001258   51.9412
_Isegm~2*|  -.0833501      .08871   -0.94   0.347   -.25722   .09052   .001666
_Isegm~3*|  -.0242958      .01287   -1.89   0.059  -.049518  .000926   .580438
_Isegm~4*|   .0511031      .01252    4.08   0.000   .026558  .075648   .179914
_Isegm~5*|   .0401242      .01326    3.03   0.002   .014131  .066118   .149929
  espera |   .0040958      .00038   10.66   0.000   .003342  .004849   11.1349
------------------------------------------------------------------------------
(*) dy/dx is for discrete change of dummy variable from 0 to 1
```

Efectos marginales en Logit multinomial ordenado (clasificación 3):

```
Marginal effects after ologit
      y  = Pr(clasificacion==3) (predict, pr outcome(3))
         =  .62687557
------------------------------------------------------------------------------
variable |      dy/dx    Std. err.     z    P>|z|  [    95% C.I.   ]      X
---------+--------------------------------------------------------------------
_Igend~2*|  -.0155692      .01599   -0.97   0.330  -.046903  .015764   .682532
    edad |    .003836      .00062    6.17   0.000   .002618  .005054   51.9412
_Isegm~2*|   .1505277      .14494    1.04   0.299  -.133553  .434608   .001666
_Isegm~3*|   .0504026      .02693    1.87   0.061  -.002378  .103183   .580438
_Isegm~4*|  -.1150971       .0312   -3.69   0.000  -.176246 -.053948   .179914
_Isegm~5*|  -.0888053      .03183   -2.79   0.005  -.151197 -.026414   .149929
  espera |  -.0084122      .00072  -11.67   0.000  -.009825 -.006999   11.1349
------------------------------------------------------------------------------
(*) dy/dx is for discrete change of dummy variable from 0 to 1
```

**(f)** *Repetir el análisis con un Probit multinomial ordenado y comparar.*

Probit multinomial ordenado:

```
Ordered probit regression                               Number of obs =  4,202
                                                        LR chi2(7)    = 450.86
                                                        Prob > chi2   = 0.0000
Log likelihood = -3631.2859                             Pseudo R2     = 0.0585

------------------------------------------------------------------------------
clasificacion | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
--------------+---------------------------------------------------------------
_Igender_co_2 |   .0079382    .040891     0.19   0.846    -.0722067    .0880831
         edad |   .0088488   .0015378     5.75   0.000     .0058348    .0118628
 _Isegmento_2 |   .3043314   .5146773     0.59   0.554    -.7044176     1.31308
 _Isegmento_3 |   .1132939   .0664574     1.70   0.088    -.0169602    .2435479
 _Isegmento_4 |  -.3667121   .0740819    -4.95   0.000    -.5119099   -.2215144
 _Isegmento_5 |  -.3928859   .0764502    -5.14   0.000    -.5427255   -.2430463
       espera |  -.0202896   .0018409   -11.02   0.000    -.0238977   -.0166814
--------------+---------------------------------------------------------------
        /cut1 |  -.9159207   .1025571                     -1.116929   -.7149126
        /cut2 |  -.1473535   .1017522                     -.3467842    .0520771
------------------------------------------------------------------------------
```

<u>Efectos marginales en Progit multinomial ordenado (clasificación 1):</u>

```
Marginal effects after oprobit
      y  = Pr(clasificacion==1) (predict, pr outcome(1))
         =  .13680723
------------------------------------------------------------------------------
variable |      dy/dx    Std. err.     z    P>|z|  [    95% C.I.   ]      X
---------+--------------------------------------------------------------------
_Igend~2*|   -.001742      .00899   -0.19   0.846  -.019358  .015873   .680866
    edad |  -.0019388      .00034   -5.73   0.000  -.002602 -.001276   52.1171
_Isegm~2*|   -.055947      .07726   -0.72   0.469  -.207383  .095489   .001428
_Isegm~3*|  -.0250324      .01481   -1.69   0.091  -.054056  .003991   .567111
_Isegm~4*|   .0905003      .02035    4.45   0.000   .050614  .130386   .186578
_Isegm~5*|    .099153      .02183    4.54   0.000    .05637  .141936   .147787
  espera |   .0044455      .00041   10.79   0.000   .003638  .005253   11.1349
------------------------------------------------------------------------------
(*) dy/dx is for discrete change of dummy variable from 0 to 1
```

<u>Efectos marginales en Probit multinomial ordenado (clasificación 2):</u>

```
Marginal effects after oprobit
      y  = Pr(clasificacion==2) (predict, pr outcome(2))
         =  .23532568
------------------------------------------------------------------------------
variable |      dy/dx    Std. err.     z    P>|z|  [    95% C.I.   ]      X
---------+--------------------------------------------------------------------
_Igend~2*|  -.0012622      .00649   -0.19   0.846  -.013992  .011467   .680866
    edad |  -.0014084      .00025   -5.61   0.000  -.001901 -.000916   52.1171
_Isegm~2*|  -.0520378      .09116   -0.57   0.568  -.230701  .126626   .001428
_Isegm~3*|  -.0179079      .01044   -1.71   0.086  -.038376   .00256   .567111
_Isegm~4*|   .0518055       .0091    5.69   0.000   .033965  .069646   .186578
_Isegm~5*|    .053895      .00872    6.18   0.000   .036803  .070987   .147787
  espera |   .0032294      .00032   10.13   0.000   .002605  .003854   11.1349
------------------------------------------------------------------------------
(*) dy/dx is for discrete change of dummy variable from 0 to 1
```

<u>Efectos marginales en Probit multinomial ordenado (clasificación 3):</u>

```
Marginal effects after oprobit
      y  = Pr(clasificacion==3) (predict, pr outcome(3))
         =   .6278671
------------------------------------------------------------------------------
variable |      dy/dx    Std. err.     z    P>|z|  [    95% C.I.   ]      X
---------+--------------------------------------------------------------------
_Igend~2*|   .0030042      .01548    0.19   0.846   -.02734  .033349   .680866
    edad |   .0033472      .00058    5.75   0.000   .002207  .004487   52.1171
_Isegm~2*|   .1079848      .16839    0.64   0.521   -.22206   .43803   .001428
_Isegm~3*|   .0429403      .02522    1.70   0.089  -.006492  .092373   .567111
_Isegm~4*|  -.1423059      .02913   -4.88   0.000  -.199406 -.085205   .186578
_Isegm~5*|  -.1530479      .03018   -5.07   0.000  -.212194 -.093902   .147787
  espera |   -.007675       .0007  -11.01   0.000  -.009042 -.006308   11.1349
------------------------------------------------------------------------------
(*) dy/dx is for discrete change of dummy variable from 0 to 1
```

**(g)** *Realizar un test de la significatividad de las variables.*

Stata.

# <u>Ejercicio 2:</u> Modelo Secuencial.

**(a)** *Considerar la base de datos "nlsw88.dta". En la misma, hay datos de un grupo de mujeres de entre 30 y 40 años para estudiar los patrones de la fuerza laboral. Estimar un logit secuencial con la decisión de educación utilizando el comando seqlogit y mostrar que se pueden obtener los mismos resultados estimando varios modelos logit por separado.*

<u>Logit secuencial:</u>

```
                                                        Number of obs =  2,244
                                                        LR chi2(9)    = 108.50
Log likelihood = -2882.1386                             Prob > chi2   = 0.0000

------------------------------------------------------------------------------
    educ_cat | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
_2_3_4v1     |
        race |
      Black  |  -.9151569   .1282466    -7.14   0.000    -1.166516   -.6637983
      Other  |  -.4910998   .5511525    -0.89   0.373    -1.571339    .5891394
             |
       south |
      South  |  -.4175069   .1259601    -3.31   0.001    -.6643841   -.1706298
       _cons |   2.250353   .0952967    23.61   0.000     2.063574    2.437131
-------------+----------------------------------------------------------------
_3_4v2       |
        race |
      Black  |   -.173837   .1131414    -1.54   0.124    -.3955902    .0479161
      Other  |   1.745005   .6241267     2.80   0.005     .5217389    2.968271
             |
       south |
      South  |  -.1495226   .0968386    -1.54   0.123    -.3393228    .0402777
       _cons |   .1079773   .0617595     1.75   0.080    -.0130691    .2290237
-------------+----------------------------------------------------------------
_4v3         |
        race |
      Black  |  -.3065161   .1648533    -1.86   0.063    -.6296227    .0165905
      Other  |  -.3798123   .4723054    -0.80   0.421    -1.305514    .5458893
             |
       south |
      South  |   .4052292    .138966     2.92   0.004     .1328609    .6775975
       _cons |   .0396236   .0855118     0.46   0.643    -.1279765    .2072237
------------------------------------------------------------------------------
```

Logit (High School):

```
Logistic regression                                     Number of obs =  2,244
                                                        LR chi2(3)    =  78.50
                                                        Prob > chi2   = 0.0000
Log likelihood = -904.78566                             Pseudo R2     = 0.0416

------------------------------------------------------------------------------
          hs | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
        race |
      Black  |  -.9151569   .1282466    -7.14   0.000    -1.166516   -.6637983
      Other  |  -.4910998   .5511525    -0.89   0.373    -1.571339    .5891394
             |
       south |
      South  |  -.4175069   .1259601    -3.31   0.001    -.6643841   -.1706298
       _cons |   2.250353   .0952967    23.61   0.000     2.063574    2.437131
------------------------------------------------------------------------------
```

Logit (Junior College):

```
Logistic regression                                     Number of obs =  1,910
                                                        LR chi2(3)    =  18.95
                                                        Prob > chi2   = 0.0003
Log likelihood = -1314.2871                             Pseudo R2     = 0.0072

------------------------------------------------------------------------------
          sc | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
        race |
      Black  |   -.173837   .1131414    -1.54   0.124    -.3955902    .0479161
      Other  |   1.745005   .6241267     2.80   0.005     .5217389    2.968271
             |
       south |
      South  |  -.1495226   .0968386    -1.54   0.123    -.3393228    .0402777
       _cons |   .1079773   .0617595     1.75   0.080    -.0130691    .2290237
------------------------------------------------------------------------------
```

Logit (College):

```
Logistic regression                                     Number of obs =    967
                                                        LR chi2(3)    =  11.05
                                                        Prob > chi2   = 0.0114
Log likelihood = -663.06592                             Pseudo R2     = 0.0083

------------------------------------------------------------------------------
           c | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
        race |
      Black  |  -.3065161   .1648533    -1.86   0.063    -.6296227    .0165905
      Other  |  -.3798123   .4723054    -0.80   0.421    -1.305514    .5458893
             |
       south |
      South  |   .4052292    .138966     2.92   0.004     .1328609    .6775974
       _cons |   .0396236   .0855118     0.46   0.643    -.1279765    .2072236
------------------------------------------------------------------------------
```

**(b)** *Considerar la base de datos "gss.dta". La misma posee datos de la encuesta GSS (General Social Survey). Esta encuesta realiza investigaciones científicas básicas sobre la estructura y el desarrollo de la sociedad estadounidense con un programa de recopilación de datos diseñado tanto para monitorear el cambio social dentro de Estados Unidos como para comparar a Estados Unidos con otras naciones. Iniciado en 1972, el*

*GSS contiene un núcleo estándar de preguntas demográficas, de comportamiento y de actitud, además de temas de especial interés. Muchas de las preguntas centrales se han mantenido sin cambios desde 1972 para facilitar los estudios de tendencias temporales, así como la replicación de hallazgos anteriores. En este ejercicio, se utilizan datos de educación similares a los del inciso anterior. Estimar un logit secuencial, interpretar los resultados y mostrar el efecto de la educación del padre en las decisiones de educación en cada transición.*

Logit secuencial:

```
                                                       Number of obs =   9,842
                                                       LR chi2(18)   = 2461.15
Log likelihood = -9530.0004                            Prob > chi2   =  0.0000

--------------------------------------------------------------------------------------
              degree | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
---------------------+----------------------------------------------------------------
_1_2_3v0             |
               south |  -.7967635   .0736484   -10.82   0.000    -.9411116   -.6524153
                 coh |   .7483053   .3414704     2.19   0.028     .0790356    1.417575
                     |
         c.coh#c.coh |  -.0482221   .0400122    -1.21   0.228    -.1266445    .0302003
                     |
              paeduc |   .1124402   .0778119     1.45   0.148    -.0400684    .2649488
                     |
      c.paeduc#c.coh |   .0469452   .0369009     1.27   0.203    -.0253792    .1192696
                     |
c.paeduc#c.coh#c.coh |  -.0050879   .0041484    -1.23   0.220    -.0132187    .0030428
                     |
               _cons |  -1.782385   .6862366    -2.60   0.009    -3.127385   -.4373864
---------------------+----------------------------------------------------------------
_2_3v1               |
               south |   .0469273   .0521384     0.90   0.368     -.055262    .1491166
                 coh |   .3228634   .4189998     0.77   0.441     -.498361    1.144088
                     |
         c.coh#c.coh |  -.0371565   .0445171    -0.83   0.404    -.1244084    .0500954
                     |
              paeduc |   .1222627   .0808644     1.51   0.131    -.0362286     .280754
                     |
      c.paeduc#c.coh |   .0188174   .0344105     0.55   0.584    -.0486259    .0862607
                     |
c.paeduc#c.coh#c.coh |   -.000731   .0035726    -0.20   0.838    -.0077331    .0062712
                     |
               _cons |  -3.497795    .956858    -3.66   0.000    -5.373202   -1.622388
---------------------+----------------------------------------------------------------
_3v2                 |
               south |   .0710731   .0976914     0.73   0.467    -.1203984    .2625446
                 coh |   .9594559   .8457289     1.13   0.257    -.6981422    2.617054
                     |
         c.coh#c.coh |  -.1700969   .0872356    -1.95   0.051    -.3410755    .0008818
                     |
              paeduc |   .3357249   .1775429     1.89   0.059    -.0122528    .6837027
                     |
      c.paeduc#c.coh |  -.1217749   .0719208    -1.69   0.090     -.262737    .0191873
                     |
c.paeduc#c.coh#c.coh |   .0155494   .0071984     2.16   0.031     .0014408    .0296579
                     |
               _cons |  -.6964155   2.011413    -0.35   0.729    -4.638713    3.245882
--------------------------------------------------------------------------------------
```