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Trabajo Práctico N° 3:
Modelos para Variables Categóricas No Ordenadas.

Ejercicio 1: Alternativas de Pesca.

La variable dependiente y toma el valor 1, 2, 3 o 4, dependiendo de cuál de los cuatro modos alternativos de pesca, respectivamente, playa, muelle, barco privado y barco chárter, se elija. En la base de datos, estos son beach, pier, private o charter. Los datos provienen de Herriges, J. A. y Kling, C. L. (1999): "Nonlinear Income Effects in Random Utility Models", Review of Economics and Statistics, 81, 62-72.

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

Fishing mode	N(income)	mean(income)	sd(income)
beach	134	4.051617	2.50542
pier	178	3.387172	2.340324
private	418	4.654107	2.777898
charter	452	3.880899	2.050029

Fishing mode	mean(pbeach)	mean(ppier)	mean(pprivate)	mean(pcharter)
beach	35.69949	35.69949	97.80914	125.0032
pier	30.57133	30.57133	82.42908	109.7634
private	137.5271	137.5271	41.60681	70.58408
charter	120.6483	120.6483	44.56376	75.09694

Fishing mode	mean(qbeach)	mean(qpier)	mean(qprivate)	mean(qcharter)
beach	.2791948	.2190015	.1593985	.5176089
pier	.2614444	.2025348	.1501489	.4980798
private	.2082868	.1297646	.1775412	.6539167
charter	.2519077	.1595341	.1771628	.6914998

(b) *Estimar un modelo logit multinomial.*

Logit multinomial (betas):

```
Multinomial logistic regression                         Number of obs =  1,182
                                                        LR chi2(3)    =  41.14
                                                        Prob > chi2   = 0.0000
Log likelihood = -1477.1506                             Pseudo R2     = 0.0137

------------------------------------------------------------------------------
        mode | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
beach        |  (base outcome)
-------------+----------------------------------------------------------------
pier         |
      income |  -.1434029   .0532884    -2.69   0.007    -.2478463   -.0389595
       _cons |   .8141503    .228632     3.56   0.000     .3660399    1.262261
-------------+----------------------------------------------------------------
private      |
      income |   .0919064   .0406637     2.26   0.024     .0122069    .1716058
       _cons |   .7389208   .1967309     3.76   0.000     .3533352    1.124506
-------------+----------------------------------------------------------------
charter      |
      income |  -.0316399   .0418463    -0.76   0.450    -.1136571    .0503774
       _cons |   1.341291   .1945167     6.90   0.000     .9600457    1.722537
------------------------------------------------------------------------------
```

Logit multinomial (relative-risk ratios):

```
Multinomial logistic regression                         Number of obs =  1,182
                                                        LR chi2(3)    =  41.14
                                                        Prob > chi2   = 0.0000
Log likelihood = -1477.1506                             Pseudo R2     = 0.0137

------------------------------------------------------------------------------
        mode |        RRR   Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
beach        |  (base outcome)
-------------+----------------------------------------------------------------
pier         |
      income |   .8664049   .0461693    -2.69   0.007     .7804799    .9617896
       _cons |   2.257257    .516081     3.56   0.000     1.442013      3.5334
-------------+----------------------------------------------------------------
private      |
      income |   1.096262   .0445781     2.26   0.024     1.012282     1.18721
       _cons |   2.093675   .4118906     3.76   0.000     1.423808    3.078697
-------------+----------------------------------------------------------------
charter      |
      income |   .9688554    .040543    -0.76   0.450     .8925639    1.051668
       _cons |   3.823979   .7438278     6.90   0.000     2.611816    5.598715
------------------------------------------------------------------------------
Note: _cons estimates baseline relative risk for each outcome.
```

(c) *Estimar un modelo logit condicional.*

Logit condicional:

```
Alternative-specific conditional logit         Number of obs      =      4,728
Case ID variable: id                           Number of cases    =       1182

Alternatives variable: fishmode                Alts per case: min =          4
                                                              avg =        4.0
                                                              max =          4

                                                  Wald chi2(5)    =     252.98
Log likelihood = -1215.1376                       Prob > chi2     =     0.0000

------------------------------------------------------------------------------
           d | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
fishmode     |
           p |  -.0251166   .0017317   -14.50   0.000    -.0285106   -.0217225
           q |    .357782   .1097733     3.26   0.001     .1426302    .5729337
-------------+----------------------------------------------------------------
beach        |  (base alternative)
-------------+----------------------------------------------------------------
charter      |
      income |  -.0332917   .0503409    -0.66   0.508     -.131958    .0653745
       _cons |   1.694366   .2240506     7.56   0.000     1.255235    2.133497
-------------+----------------------------------------------------------------
pier         |
      income |  -.1275771   .0506395    -2.52   0.012    -.2268288   -.0283255
       _cons |   .7779593   .2204939     3.53   0.000     .3457992    1.210119
-------------+----------------------------------------------------------------
private      |
      income |   .0894398   .0500671     1.79   0.074    -.0086898    .1875694
       _cons |   .5272788   .2227927     2.37   0.018     .0906132    .9639444
------------------------------------------------------------------------------
```

<u>Ejercicio 2:</u> Predicción de Calificaciones de Clientes.

Net Promoter Score®, o NPS®, mide la experiencia del cliente y predice el crecimiento del negocio. Es utilizada por empresas que brindan servicios al consumidor final (bancos, telefónicas, etc). EL NPS se calcula usando la respuesta a una pregunta usando una escala de 0 a 10: ¿Qué tan probable es que recomiende a un amigo o colega? Los encuestados se agrupan de la siguiente manera:

- *Los promotores (puntuación 9-10) son entusiastas leales que seguirán comprando y recomendarán a otros, lo que impulsará el crecimiento.*
- *Los neutrales (puntuación 7-8) son clientes satisfechos pero poco entusiastas que son vulnerables a las ofertas de la competencia.*
- *Los detractores (puntuación 1-6) son clientes insatisfechos que pueden dañar su marca e impedir el crecimiento a través del boca a boca negativo.*

Al restar el porcentaje de detractores del porcentaje de promotores, se obtiene el puntaje neto del promotor, que puede oscilar entre un mínimo de -100 (si todos los clientes son detractores) y un máximo de 100 (si todos los clientes son promotores). Estas encuestas se utilizan para generar estrategias de originacion (nuevos clientes) y de reducción de churn (fuga de clientes). La base con la que se va a hacer la primera parte de la práctica consiste en la encuesta de NPS que se le hace a los clientes de un Banco luego de efectuar una transacción en caja. En base a esto, utilizando la base "NPS.dta", responder las siguientes preguntas.

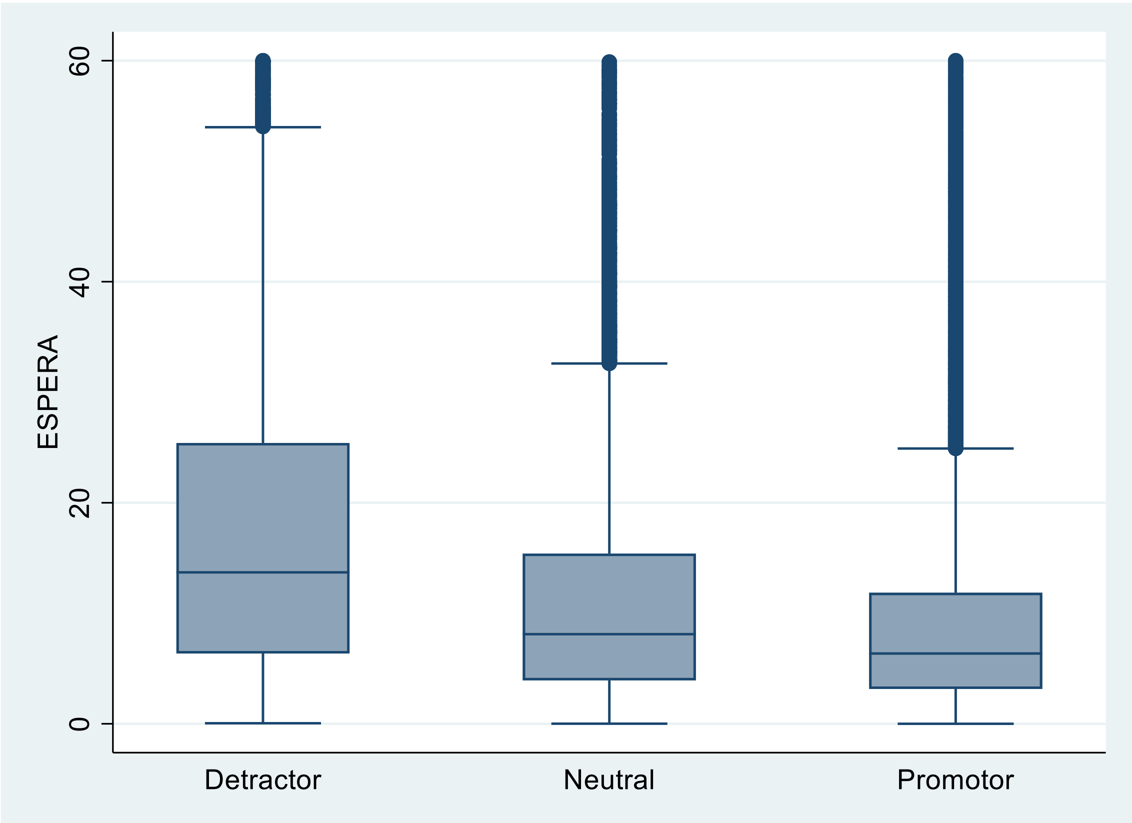
(a) *Abrir y describir la base.*

```
    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.*

```
clasificaci |
         on |      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 para predecir cómo cambian las clasificaciones en función de la espera, condicionando en explicativas que se considere relevantes.*

Logit (betas):

```
Multinomial logistic regression                         Number of obs =  4,202
                                                        LR chi2(14)   = 418.26
                                                        Prob > chi2   = 0.0000
Log likelihood = -3647.5859                             Pseudo R2     = 0.0542

------------------------------------------------------------------------------
clasificacion | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
--------------+----------------------------------------------------------------
Detractor     |  (base outcome)
--------------+----------------------------------------------------------------
Neutral       |
_Igender_co_2 |  -.0022797   .1117659    -0.02   0.984    -.2213368    .2167774
         edad |   .0106823   .0042832     2.49   0.013     .0022873    .0190772
  _Isegmento_2 |   12.80348   730.9035     0.02   0.986    -1419.741    1445.348
  _Isegmento_3 |   .0192837   .1868698     0.10   0.918    -.3469745    .3855418
  _Isegmento_4 |  -.7049277   .1983862    -3.55   0.000    -1.093758   -.3160979
  _Isegmento_5 |  -.5423917   .2023154    -2.68   0.007    -.9389226   -.1458607
       espera |  -.0234117   .0044156    -5.30   0.000     -.032066   -.0147573
        _cons |   .4567806   .2819115     1.62   0.105    -.0957557    1.009317
--------------+----------------------------------------------------------------
Promotor      |
_Igender_co_2 |  -.0740685   .0991182    -0.75   0.455    -.2683366    .1201995
         edad |   .0222569   .0038062     5.85   0.000     .0147969    .0297169
  _Isegmento_2 |   13.38895    730.903     0.02   0.985    -1419.155    1445.933
  _Isegmento_3 |    .254493   .1689136     1.51   0.132    -.0765715    .5855575
  _Isegmento_4 |  -.6899248   .1774649    -3.89   0.000     -1.03775     -.3421
  _Isegmento_5 |  -.7035198   .1827513    -3.85   0.000    -1.061706   -.3453338
       espera |  -.0479308   .0040826   -11.74   0.000    -.0559326    -.039929
        _cons |   1.070479   .2520943     4.25   0.000     .5763835    1.564575
------------------------------------------------------------------------------
```

Logit multinomial (relative-risk ratios):

```
Multinomial logistic regression                         Number of obs =  4,202
                                                        LR chi2(14)   = 418.26
                                                        Prob > chi2   = 0.0000
Log likelihood = -3647.5859                             Pseudo R2     = 0.0542

------------------------------------------------------------------------------
clasificacion |        RRR   Std. err.      z    P>|z|     [95% conf. interval]
--------------+----------------------------------------------------------------
Detractor     |  (base outcome)
--------------+----------------------------------------------------------------
Neutral       |
_Igender_co_2 |   .9977229   .1115114    -0.02   0.984     .8014467    1.242068
         edad |    1.01074   .0043292     2.49   0.013      1.00229     1.01926
  _Isegmento_2 |   363481.5   2.66e+08     0.02   0.986            0           .
  _Isegmento_3 |   1.019471   .1905084     0.10   0.918     .7068233    1.470411
  _Isegmento_4 |   .4941443   .0980314    -3.55   0.000     .3349555    .7289881
  _Isegmento_5 |   .5813562   .1176173    -2.68   0.007     .3910489    .8642781
       espera |   .9768603   .0043134    -5.30   0.000     .9684427     .985351
        _cons |   1.578982   .4451333     1.62   0.105     .9086859    2.743726
--------------+----------------------------------------------------------------
Promotor      |
_Igender_co_2 |   .9286081   .0920419    -0.75   0.455     .7646504    1.127722
         edad |   1.022506   .0038919     5.85   0.000     1.014907    1.030163
  _Isegmento_2 |   652751.9   4.77e+08     0.02   0.985            0           .
  _Isegmento_3 |   1.289808    .217866     1.51   0.132     .9262867    1.795992
  _Isegmento_4 |   .5016138   .0890188    -3.89   0.000      .354251    .7102772
  _Isegmento_5 |   .4948405   .0904327    -3.85   0.000     .3458654     .707984
       espera |   .9531997   .0038915   -11.74   0.000     .9456029    .9608576
        _cons |   2.916777   .7353029     4.25   0.000     1.779591    4.780643
------------------------------------------------------------------------------
Note: _cons estimates baseline relative risk for each outcome.
```

(e) *Calcular los efectos marginales.*

Efectos marginales en Logit multinomial (detractor):

```
Marginal effects after mlogit
      y  = Pr(clasificacion==Detractor) (predict, pr outcome(1))
         =  .13172136
------------------------------------------------------------------------------
variable |      dy/dx    Std. err.     z    P>|z|  [    95% C.I.   ]      X
---------+--------------------------------------------------------------------
_Igend~2*|   .0062526      .01127    0.56   0.579  -.015827  .028332   .678486
    edad |  -.0021919       .0012   -1.83   0.067  -.004541  .000157   52.2109
_Isegm~2*|  -.1331684      .00569  -23.41   0.000  -.144317  -.12202   .000952
_Isegm~3*|  -.0220274      .02219   -0.99   0.321  -.065524  .021469   .567587
_Isegm~4*|   .0931274      .05089    1.83   0.067  -.006608  .192863   .183246
_Isegm~5*|   .0890482      .04974    1.79   0.073  -.008432  .186529   .148263
  espera |   .0047328      .00246    1.92   0.055  -.000097  .009562   11.1349
------------------------------------------------------------------------------
(*) dy/dx is for discrete change of dummy variable from 0 to 1
```

Efectos marginales en Logit multinomial (neutral):

```
Marginal effects after mlogit
      y  = Pr(clasificacion==Neutral) (predict, pr outcome(2))
         =  .23194672
------------------------------------------------------------------------------
variable |      dy/dx    Std. err.     z    P>|z|  [    95% C.I.   ]      X
---------+--------------------------------------------------------------------
_Igend~2*|     .01049      .01435    0.73   0.465  -.017644  .038624   .678486
    edad |   -.001382      .00072   -1.91   0.056  -.002801  .000037   52.2109
_Isegm~2*|  -.0628502       .1635   -0.38   0.701  -.383304  .257604   .000952
_Isegm~3*|   -.034214      .02341   -1.46   0.144   -.08009  .011662   .567587
_Isegm~4*|    -.02724      .02669   -1.02   0.307  -.079548  .025068   .183246
_Isegm~5*|   .0021924      .02992    0.07   0.942  -.056453  .060838   .148263
  espera |   .0029036      .00123    2.37   0.018   .000501  .005306   11.1349
------------------------------------------------------------------------------
(*) dy/dx is for discrete change of dummy variable from 0 to 1
```

Efectos marginales en Logit multinomial (promotor):

```
Marginal effects after mlogit
      y  = Pr(clasificacion==Promotor) (predict, pr outcome(3))
         =  .63633192
------------------------------------------------------------------------------
variable |      dy/dx    Std. err.     z    P>|z|  [    95% C.I.   ]      X
---------+--------------------------------------------------------------------
_Igend~2*|  -.0167426      .01648   -1.02   0.310  -.049037  .015551   .678486
    edad |   .0035739       .0009    3.99   0.000   .001817  .005331   52.2109
_Isegm~2*|   .1960187      .16356    1.20   0.231  -.124551  .516589   .000952
_Isegm~3*|   .0562415      .02657    2.12   0.034   .004172  .108311   .567587
_Isegm~4*|  -.0658873      .04487   -1.47   0.142  -.153828  .022054   .183246
_Isegm~5*|  -.0912406      .04211   -2.17   0.030  -.173769 -.008712   .148263
  espera |  -.0076364       .0016   -4.77   0.000  -.010776 -.004497   11.1349
------------------------------------------------------------------------------
(*) dy/dx is for discrete change of dummy variable from 0 to 1
```

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

Probit multinomial:

```
Multinomial probit regression                          Number of obs =  4,202
                                                       Wald chi2(14) = 416.83
Log likelihood = -3635.6144                            Prob > chi2   = 0.0000

-----------------------------------------------------------------------------
clasificacion | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
--------------+--------------------------------------------------------------
Detractor     |  (base outcome)
--------------+--------------------------------------------------------------
Neutral       |
_Igender_co_2 |  -.0536078   .0798336    -0.67   0.502    -.2100787    .1028631
         edad |   .0092218    .003062     3.01   0.003     .0032205    .0152231
 _Isegmento_2 |   -.352632   .5757431    -0.61   0.540    -1.481068    .7758037
 _Isegmento_3 |   .0867023   .1308623     0.66   0.508    -.1697831    .3431876
 _Isegmento_4 |  -.7015738   .1429056    -4.91   0.000    -.9816635    -.421484
 _Isegmento_5 |  -.3109711   .1472973    -2.11   0.035    -.5996685   -.0222737
       espera |  -.0138713   .0033331    -4.16   0.000     -.020404   -.0073386
        _cons |   .2119086   .2034099     1.04   0.298    -.1867675    .6105848
--------------+--------------------------------------------------------------
Promotor      |
_Igender_co_2 |   -.097611   .0738029    -1.32   0.186     -.242262    .0470399
         edad |    .012833    .002822     4.55   0.000      .007302     .018364
 _Isegmento_2 |  -1.411541   .6475008    -2.18   0.029    -2.680619   -.1424626
 _Isegmento_3 |   .2629534   .1220016     2.16   0.031     .0238348    .5020721
 _Isegmento_4 |  -.6144694   .1313595    -4.68   0.000    -.8719294   -.3570095
 _Isegmento_5 |  -.4984651   .1378136    -3.62   0.000    -.7685749   -.2283554
       espera |  -.0350071   .0031476   -11.12   0.000    -.0411763   -.0288379
        _cons |   1.035228   .1878494     5.51   0.000     .6670502    1.403406
-----------------------------------------------------------------------------
```

Efectos marginales en Probit multinomial (detractor):

```
Marginal effects after mprobit
      y  = Pr(clasificacion==Detractor) (predict, pr outcome(1))
         =  .13404784
------------------------------------------------------------------------------
variable |      dy/dx    Std. err.     z    P>|z|  [    95% C.I.   ]      X
---------+--------------------------------------------------------------------
_Igend~2*|   .0136968      .01125    1.22   0.223  -.008346   .03574   .677297
    edad |  -.0019418      .00044   -4.41   0.000  -.002806 -.001078   52.1844
_Isegm~2*|   .2216672      .14863    1.49   0.136   -.06965  .512984   .002618
_Isegm~3*|  -.0345801      .01966   -1.76   0.079   -.07312   .00396   .578058
_Isegm~4*|   .1251906      .02726    4.59   0.000   .071753  .178628   .183484
_Isegm~5*|   .0823211      .02707    3.04   0.002    .02926  .135382   .140171
  espera |   .0046788      .00048    9.74   0.000   .003737  .005621   11.1349
------------------------------------------------------------------------------
(*) dy/dx is for discrete change of dummy variable from 0 to 1
```

Efectos marginales en Probit multinomial (neutral):

```
Marginal effects after mprobit
      y  = Pr(clasificacion==Neutral) (predict, pr outcome(2))
         =  .23112599
------------------------------------------------------------------------------
variable |      dy/dx    Std. err.     z    P>|z|  [    95% C.I.   ]      X
---------+--------------------------------------------------------------------
_Igend~2*|   .0048601      .01424    0.34   0.733  -.023054  .032774   .677297
    edad |    -.00013      .00055   -0.24   0.812    -.0012   .00094   52.1844
_Isegm~2*|   .1369606      .15124    0.91   0.365  -.159457  .433378   .002618
_Isegm~3*|  -.0261368       .0229   -1.14   0.254  -.071021  .018747   .578058
_Isegm~4*|  -.0571084      .02392   -2.39   0.017  -.103993 -.010224   .183484
_Isegm~5*|   .0120419      .02754    0.44   0.662  -.041943  .066027   .140171
  espera |   .0029577      .00066    4.52   0.000   .001674  .004242   11.1349
------------------------------------------------------------------------------
(*) dy/dx is for discrete change of dummy variable from 0 to 1
```

Efectos marginales en Probit multinomial (promotor):

```
Marginal effects after mprobit
      y  = Pr(clasificacion==Promotor) (predict, pr outcome(3))
         =  .63482617
------------------------------------------------------------------------------
variable |      dy/dx    Std. err.     z    P>|z|  [    95% C.I.   ]      X
---------+--------------------------------------------------------------------
_Igend~2*|  -.0185569      .01634   -1.14   0.256   -.05058  .013466   .677297
    edad |   .0020718      .00063    3.31   0.001   .000845  .003298   52.1844
_Isegm~2*|  -.3586278      .15141   -2.37   0.018  -.655388 -.061868   .002618
_Isegm~3*|   .0607169       .0265    2.29   0.022   .008771  .112663   .578058
_Isegm~4*|  -.0680822       .0313   -2.18   0.030   -.12943 -.006734   .183484
_Isegm~5*|  -.0943629      .03271   -2.88   0.004  -.158476  -.03025   .140171
  espera |  -.0076366      .00076  -10.01   0.000  -.009132 -.006141   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.

Ejercicio 3.

Utilizando la EPH del cuarto trimestre de 2016, estimar un modelo multinomial que permita predecir la condición de actividad de una persona, entre inactivo, ocupado o desocupado.

Stata.