

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.

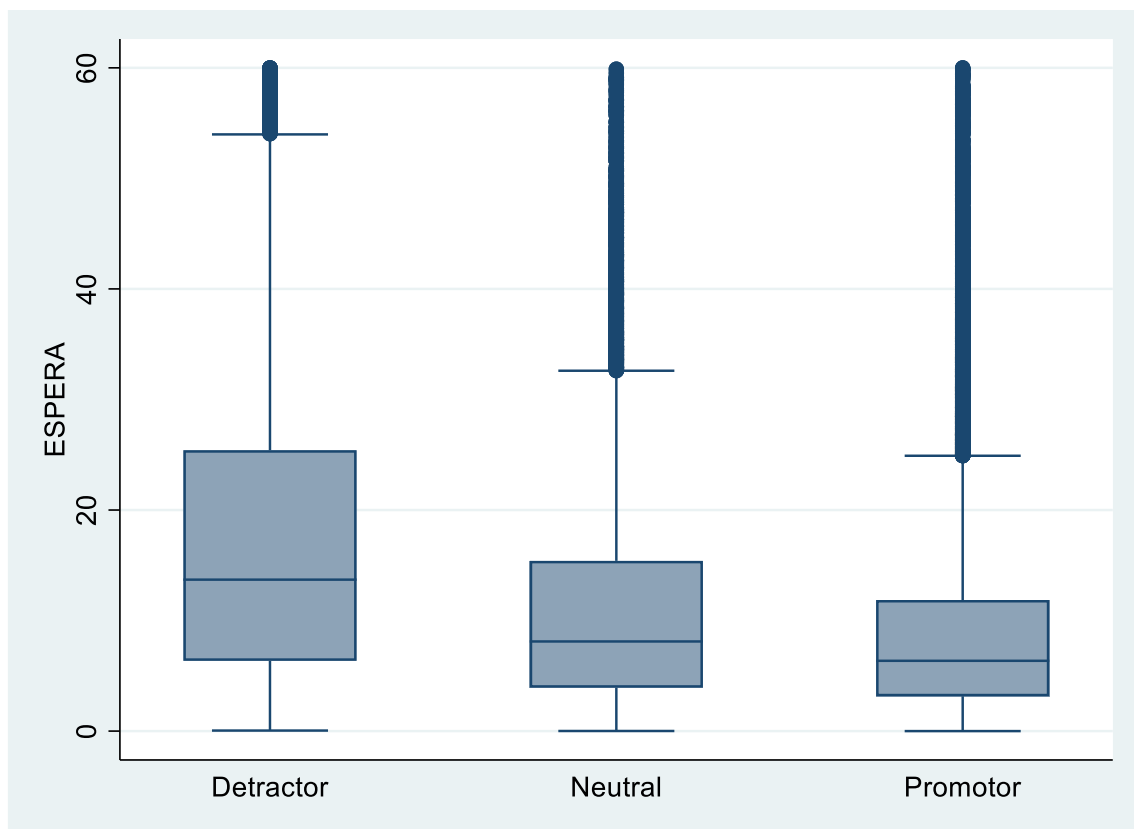
(a) *Abrir y describir la base.*

Variable	Obs	Mean	Std. dev.	Min	Max
nps	42,019	8.369975	2.263878	1	10
marital_status	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 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
Log likelihood = -3659.6981

Number of obs = 4,202
LR chi2(7) = 394.03
Prob > chi2 = 0.0000
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
Log likelihood = -3659.6981

Number of obs = 4,202
LR chi2(7) = 394.03
Prob > chi2 = 0.0000
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

Pseudo R2 = 0.0585

Log likelihood = -3631.2859

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

Efectos marginales en Progit multinomial ordenado (clasificación 1):

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

Efectos marginales en Probit multinomial ordenado (clasificación 2):

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

Efectos marginales en Probit multinomial ordenado (clasificación 3):

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.

(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.

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

educ_cat	Coefficient	Std. err.	z	P> z	[95% conf. interval]	
<hr/>						
_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
<hr/>						
_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
<hr/>						
_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 secuencial:

					Number of obs = 9,842		
					LR chi2(18) = 2461.15		
Log likelihood = -9530.0004					Prob > chi2 = 0.0000		
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degree		Coefficient	Std. err.	z	P> z	[95% conf. interval]	
<hr/>							
_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
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_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
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_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