

intreg hypothetical example

Here is a hypothetical example using `intreg`. `y` is a continuous var that ranges from about -70 to 88. It is normally distributed. `ycat` is a collapsed, ordinal version of `y`. `y1` and `y2` are the upper and lower bounds of the `y` intervals.

```
. use "http://www.nd.edu/~rwilliam/xsoc73994/statafiles/intreg.dta", clear
(Hypothetical data for intreg example)
```

```
. des
```

```
Contains data from D:\Soc73994\Statafiles\intreg.dta
  obs:          1,000              Hypothetical data for intreg
                                      example
vars:           7                  6 Nov 2006 07:57
size:          32,000 (99.9% of memory free)
```

```
-----
variable name  storage  display  value  variable label
              type    format   label
-----
y              float    %9.0g
              ycat    Y collapsed into 5 intervals
ycat           float    %10.0g
y1             float    %9.0g    Lower bound of Y interval
y2            float    %9.0g    Upper bound of Y interval
x1            float    %9.0g
x2            float    %9.0g
x3            float    %9.0g
-----
```

```
Sorted by:
```

```
. sum y
```

```
-----+-----
Variable |      Obs      Mean   Std. Dev.   Min       Max
-----+-----
y        |    1000    14.01144   25.05774  -70.36776   88.0509
```

```
. tab1 ycat
```

```
-> tabulation of ycat
```

```
Y collapsed |
into 5 |
intervals |      Freq.      Percent      Cum.
-----+-----
LE 0 |      287      28.70      28.70
0 to 15 |      224      22.40      51.10
15 to 30 |      203      20.30      71.40
30 to 45 |      183      18.30      89.70
45 or more |      103      10.30     100.00
-----+-----
Total |    1,000     100.00
```

```
. * intreg with collapsed Y
. intreg y1 y2 x1 x2 x3
```

Fitting constant-only model:

```
Iteration 0: log likelihood = -1688.3436
Iteration 1: log likelihood = -1574.6026
Iteration 2: log likelihood = -1565.5637
Iteration 3: log likelihood = -1565.5603
Iteration 4: log likelihood = -1565.5603
```

Fitting full model:

```
Iteration 0: log likelihood = -1508.2373
Iteration 1: log likelihood = -1379.0543
Iteration 2: log likelihood = -1372.4038
Iteration 3: log likelihood = -1372.3949
Iteration 4: log likelihood = -1372.3949
```

```
Interval regression                                Number of obs =      1000
                                                    LR chi2(3)      =      386.33
Log likelihood = -1372.3949                       Prob > chi2     =      0.0000
```

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
x1	1.221547	.2544077	4.80	0.000	.7229169	1.720177
x2	.8989353	.0799428	11.24	0.000	.7422503	1.05562
x3	.9384835	.2191945	4.28	0.000	.5088702	1.368097
_cons	.0771196	1.451354	0.05	0.958	-2.767483	2.921722
/lnsigma	3.003777	.0320312	93.78	0.000	2.940997	3.066557
sigma	20.16155	.6457982			18.93472	21.46787

```
Observation summary:      287 left-censored observations
                          0 uncensored observations
                          103 right-censored observations
                          610 interval observations
```

```
. * OLS regression with original Y
. reg y x1 x2 x3
```

Source	SS	df	MS	Number of obs =	1000
Model	227500.386	3	75833.4619	F(3, 996) =	188.94
Residual	399761.928	996	401.367397	Prob > F =	0.0000
Total	627262.313	999	627.890204	R-squared =	0.3627
				Adj R-squared =	0.3608
				Root MSE =	20.034

	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
x1	1.120216	.2308738	4.85	0.000	.6671616	1.573271
x2	.9312722	.0706904	13.17	0.000	.792553	1.069991
x3	.8474134	.1983744	4.27	0.000	.4581337	1.236693
_cons	.196622	1.245274	0.16	0.875	-2.247039	2.640284

```
. * oprobit with collapsed Y
. oprobit ycat x1 x2 x3
```

```
Iteration 0: log likelihood = -1561.9813
Iteration 1: log likelihood = -1370.1889
Iteration 2: log likelihood = -1368.7383
Iteration 3: log likelihood = -1368.7378
```

```
Ordered probit regression                Number of obs   =       1000
                                         LR chi2(3)      =       386.49
                                         Prob > chi2     =       0.0000
Log likelihood = -1368.7378             Pseudo R2      =       0.1237
```

ycat	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
x1	.0604916	.0126526	4.78	0.000	.035693	.0852902
x2	.0445961	.004006	11.13	0.000	.0367445	.0524476
x3	.0466968	.0108907	4.29	0.000	.0253514	.0680421
/cut1	.0091044	.0732018			-.1343684	.1525773
/cut2	.7462179	.0751763			.5988751	.8935608
/cut3	1.415098	.0809962			1.256348	1.573848
/cut4	2.285878	.0952678			2.099156	2.472599

Several things to note about the above:

- The nice thing about `intreg`, as opposed to other ordinal methods, is that you interpret its parameters the same way you do the parameters from an OLS regression. The sigma that `intreg` reports is equivalent to the root mean square error (i.e. the standard error of the residuals) from an OLS regression
- In this particular example, `intreg` does remarkably well. Its coefficients, standard errors, etc. are very similar to those produced by OLS regression on the un-collapsed y variable.
- Also, `intreg` produces almost the exact same log-likelihood as does `oprobit`, and also the same z values. (NOTE: You should compare the log-likelihoods rather than the model chi-squares when comparing `intreg` and `oprobit`.) But, the coefficients from `intreg` are much easier to interpret.
 - As the Stata manual points out, if `oprobit` fit much better, you might want to modify the `intreg` model (e.g. take logs of the interval points) or use `oprobit` or `ologit` or some other ordinal method instead.
- I caution, however, that the example is “rigged” in `intreg`’s favor, in that the assumptions it makes about normality are true in the constructed data set. You can’t always count on it working this well. As the Stata manual notes, `intreg` assumes normality.