

0.1 `ls.net`: Network Least Squares Regression for Continuous Proximity Matrix Dependent Variables

Use network least squares regression analysis to estimate the best linear predictor when the dependent variable is a continuously-valued proximity matrix (a.k.a. sociomatrices, adjacency matrices, or matrix representations of directed graphs).

Syntax

```
> z.out <- zelig(y ~ x1 + x2, model = "ls.net", data = mydata)
> x.out <- setx(z.out)
> s.out <- sim(z.out, x = x.out)
```

Examples

1. Basic Example with First Differences

Load sample data and format it for social networkx analysis:

```
> data(sna.ex)
```

Estimate model:

```
> z.out <- zelig(Var1 ~ Var2 + Var3 + Var4, model = "ls.net", data = sna.ex)
```

Summarize regression results:

```
> summary(z.out)
```

Set explanatory variables to their default (mean/mode) values, with high (80th percentile) and low (20th percentile) for the second explanatory variable (Var3).

```
> x.high <- setx(z.out, Var3 = quantile(sna.ex$Var3, 0.8))
```

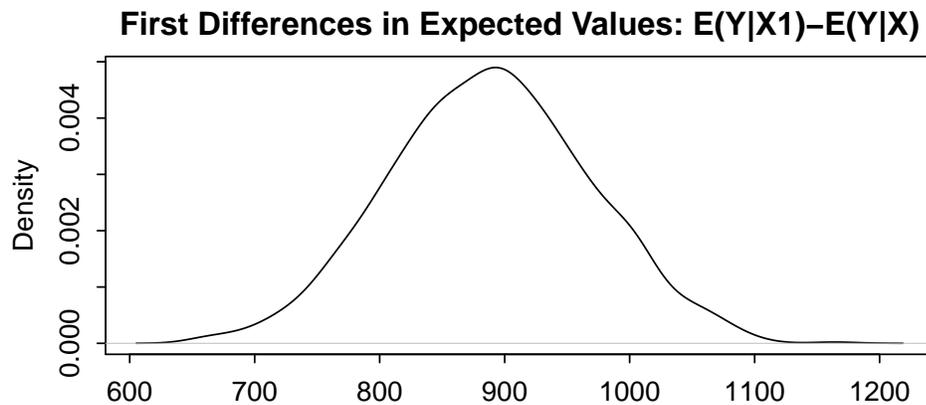
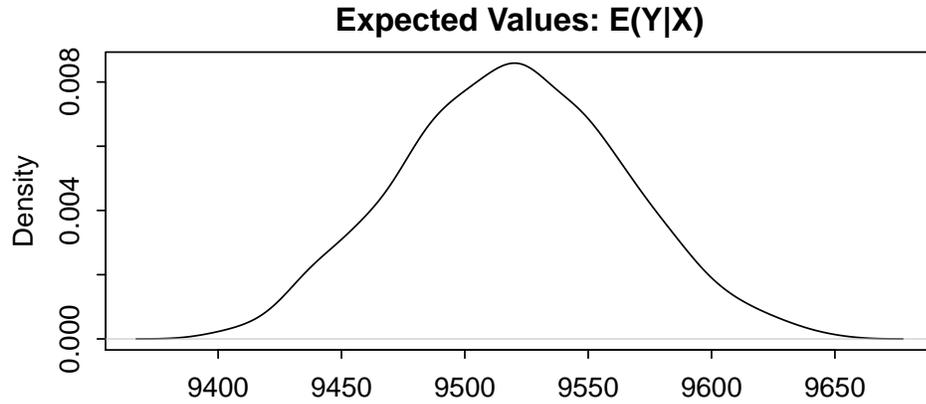
```
> x.low <- setx(z.out, Var3 = quantile(sna.ex$Var3, 0.2))
```

Generate first differences for the effect of high versus low values of Var3 on the outcome variable.

```
> try(s.out <- sim(z.out, x = x.high, x1 = x.low))
```

```
> try(summary(s.out))
```

```
> plot(s.out)
```



Model

The `ls.net` model performs a least squares regression of the sociomatrix \mathbf{Y} , a $m \times m$ matrix representing network ties, on a set of sociomatrices \mathbf{X} . This network regression model is a directly analogue to standard least squares regression element-wise on the appropriately vectorized matrices. Sociomatrices are vectorized by creating Y , an $m^2 \times 1$ vector to represent the sociomatrix. The vectorization which produces the Y vector from the \mathbf{Y} matrix is performed by simple row-concatenation of \mathbf{Y} . For example if \mathbf{Y} is a 15×15 matrix, the $\mathbf{Y}_{1,1}$ element is the first element of Y , and the \mathbf{Y}_{21} element is the second element of Y and so on. Once the input matrices are vectorized, standard least squares regression is performed. As such:

- The *stochastic component* is described by a density with mean μ_i and the common variance σ^2

$$Y_i \sim f(y_i | \mu_i, \sigma^2).$$

- The *systematic component* models the conditional mean as

$$\mu_i = x_i\beta$$

where x_i is the vector of covariates, and β is the vector of coefficients.

The least squares estimator is the best linear predictor of a dependent variable given x_i , and minimizes the sum of squared errors $\sum_{i=1}^n (Y_i - x_i\beta)^2$.

Quantities of Interest

The quantities of interest for the network least squares regression are the same as those for the standard least squares regression.

- The expected value (`qi$ev`) is the mean of simulations from the stochastic component,

$$E(Y) = x_i\beta,$$

given a draw of β from its sampling distribution.

- The first difference (`qi$fd`) is:

$$FD = E(Y|x_1) - E(Y|x)$$

Output Values

The output of each `Zelig` command contains useful information which you may view. For example, you run `z.out <- zelig(y ~ x, model="ls.net", data)`, then you may examine the available information in `z.out` by using `names(z.out)`, see the coefficients by using `z.out$coefficients`, and a default summary of information through `summary(z.out)`. Other elements available through the `$` operator are listed below.

- From the `zelig()` output stored in `z.out`, you may extract:
 - `coefficients`: parameter estimates for the explanatory variables.
 - `fitted.values`: the vector of fitted values for the explanatory variables.
 - `residuals`: the working residuals in the final iteration of the IWLS fit.
 - `df.residual`: the residual degrees of freedom.
 - `zelig.data`: the input data frame if `save.data = TRUE`
- From `summary(z.out)`, you may extract:
 - `mod.coefficients`: the parameter estimates with their associated standard errors, p -values, and t statistics.

$$\hat{\beta} = \left(\sum_{i=1}^n x_i'x_i \right)^{-1} \sum x_i y_i$$

- `sigma`: the square root of the estimate variance of the random error ε :

$$\hat{\sigma} = \frac{\sum(Y_i - x_i\hat{\beta})^2}{n - k}$$

- `r.squared`: the fraction of the variance explained by the model.

$$R^2 = 1 - \frac{\sum(Y_i - x_i\hat{\beta})^2}{\sum(y_i - \bar{y})^2}$$

- `adj.r.squared`: the above R^2 statistic, penalizing for an increased number of explanatory variables.
- `cov.unscaled`: a $k \times k$ matrix of unscaled covariances.

- From the `sim()` output stored in `s.out`, you may extract:

- `qi$ev`: the simulated expected values for the specified values of `x`.
- `qi$fd`: the simulated first differences (or differences in expected values) for the specified values of `x` and `x1`.

How to Cite

To cite the *ls.net* Zelig model:

Skyler J. Cranmer. 2007. "ls.net: Social Network Least Squares Regression for Continuous Dependent Variables" in Kosuke Imai, Gary King, and Olivia Lau, "Zelig: Everyone's Statistical Software," <http://gking.harvard.edu/zelig>

To cite Zelig as a whole, please reference these two sources:

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Imai, Kosuke, Gary King, and Olivia Lau. (2008). "Toward A Common Framework for Statistical Analysis and Development." *Journal of Computational and Graphical Statistics*, Vol. 17, No. 4 (December), pp. 892-913.

See also

The network least squares regression is part of the `sna` package by Carter T. Butts (Butts and Carley 2001). In addition, advanced users may wish to refer to `help(netlm)`.

Bibliography

Butts, C. and Carley, K. (2001), "Multivariate Methods for Interstructural Analysis," Tech. rep., CASOS working paper, Carnegie Mellon University.