

Calculating R^2 for MLM With Gutten Tree Data

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Figure 1: Norway Spruce and Larch Forest in Austrian Alps

<https://ec.europa.eu/jrc/en/research-topic/forestry/qr-tree-project/norway-spruce>

Data Source

The data used in this example are derived from the R package *Functions and Datasets for “Forest Analytics with R”*.

According to the documentation, the source of these data are: “von Guttenberg’s Norway spruce (*Picea abies* [L.] Karst) tree measurement data.”



Figure 2: Old Tjikko, a 9,550 Year Old Norway Spruce in Sweden

The documentation goes on to further note that:

“The data are measures from 107 trees. The trees were selected as being of average size from healthy and well stocked stands in the Alps.”

```
.      use gutten.dta, clear
```

Variables

site Growth *quality* class of the tree’s habitat. 5 levels.

location Distinguishes tree *location*. 7 levels.

tree An identifier for the tree within location.

age.base The tree age taken at ground level.

It might be best to use a centered age variable, centered at the grand mean of tree age:

```
. egen ageMEAN = mean(age_base)

. generate ageCENTERED = age_base - ageMEAN
```

height Tree height, m.

dbh.cm Tree diameter, cm.

volume Tree volume.

age.bh Tree age taken at 1.3 m.

tree.ID A factor uniquely identifying the tree.

Calculating R^2

Roberts et al. (2015) explain that there are multiple competing perspectives, and formulas, for calculating an estimate of R^2 for multilevel models.

Here we adopt an approach advanced by Cox (link below).

Outline

1. Estimate MLM: `mixed y x1 x2 x3 || id:`
2. Generate predicted values: `predict yhat`
3. Estimate correlation of observed and predicted: `corr y yhat`
4. Then square this correlation: $R^2 = r^2$

Estimate MLM

```
. mixed height age_base site i.location || tree_ID:
Performing EM optimization:
Performing gradient-based optimization:
Iteration 0:   log likelihood = -3050.2621
Iteration 1:   log likelihood = -3050.2621
Computing standard errors:
Mixed-effects ML regression              Number of obs   =       1,200
Group variable: tree_ID                  Number of groups =        107
Obs per group:
      min =          5
      avg =       11.2
      max =         15
Wald chi2(8)          =    8663.47
Prob > chi2           =      0.0000
Log likelihood = -3050.2621
```

height	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age_base	.2143496	.0023831	89.95	0.000	.2096789	.2190203
site	-3.866312	.1608021	-24.04	0.000	-4.181478	-3.551145
location						
2	-.5436647	1.247694	-0.44	0.663	-2.989099	1.90177
3	.5090705	.6487789	0.78	0.433	-.7625129	1.780654
4	.0954239	.7056685	0.14	0.892	-1.287661	1.478509
5	-.0590126	.5182994	-0.11	0.909	-1.074861	.9568356
6	.2078246	.6884815	0.30	0.763	-1.141574	1.557224

7	-1.210496	.7524348	-1.61	0.108	-2.685241	.2642491
_cons	12.27241	.5513051	22.26	0.000	11.19187	13.35294

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]	
tree_ID: Identity				
var(_cons)	2.106718	.3939037	1.460337	3.039204
var(Residual)	8.397623	.359	7.722667	9.131569

LR test vs. linear model: chibar2(01) = 127.84 Prob >= chibar2 = 0.0000

Predict \hat{y}

```
. predict yhat if e(sample) // calculate predicted values
(option xb assumed)
```

Estimate Correlation of y and \hat{y}

We then obtain the correlation of y and \hat{y} , the observed and predicted values.

```
. corr height yhat
(obs=1,200)
```

	height	yhat
height	1.0000	
yhat	0.9364	1.0000

So our estimate for R^2 is .93636423 squared, or .87677798.

References

- Cox, N. J. (n.d.). *Stata FAQ: Do-it-yourself R-squared*. Retrieved May 7, 2020, from <https://www.stata.com/support/faqs/statistics/r-squared/>
- Roberts, J. K., Monaco, J. P., Stovall, H., & Foster, V. (2015). Explained Variance in Multilevel Models. In *Handbook of Advanced Multilevel Analysis*. <https://doi.org/10.4324/9780203848852.ch12>