

Estimating Equations in R: **geex**

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M-estimation theory provides a framework for asymptotic properties of estimators that are solutions to estimating equations. Regression methods such as Generalized Linear Models (GLM) and Generalized Estimating Equations (GEE) fit in this framework. Countless R packages implement specific applications of estimating equations. A common reason to use M-estimation is to compute the empirical sandwich variance estimator - an asymptotically Normal and “robust” covariance. Many packages compute this variance estimator automatically, and packages such as **sandwich** take the output of other modeling methods to compute this variance estimate.

geex aims to be provide a more general framework that any modelling method can use to compute point and variance estimates for parameters that are solutions to estimating equations. The basic idea:

- Analyst provides three things: (1) data, (2) instructions on how to split the data into independent units and (3) a function that takes unit-level data and returns a function in terms of parameters.
- **geex** computes point estimates and variance estimates for the parameters.

Basic Setup

I mostly follow the notation of Stefanski and Boos. I tried to keep notation in the code similar to mathematical notation.

Suppose we have m independent or nearly independent units of observations.

$$\sum_{i=1}^m \psi(O_i, \theta) = 0$$

Where ψ is vector of length p corresponding to the number of parameters in θ .

For notational ease, let $\psi(O_i, \theta) = \psi_i$ Let:

$$A_i = -\frac{\partial \psi(O_i, \theta)}{\partial \theta}$$

$$A = \sum_{i=1}^m A_i$$

$$B_i = \psi_i \psi_i^T$$

$$B = \sum_{i=1}^m B_i$$

$$\Sigma = A^{-1} B \{A^{-1}\}^T$$

Stefanski & Boos example 1

Example 1 illustrates calculation of sample mean and variance using estimating equations. I generate a data set with 100 observations drawn from a Normal(5, 2) distribution. Table translates the estimating equations into the R function needed for **geex**:

Table 1: Translating math to code

$$\psi(Y_i, \theta) = \begin{pmatrix} Y_i - \theta_1 \\ (Y_i - \theta_1)^2 - \theta_2 \end{pmatrix}$$

```
SB1_eefun <- function(data){
  function(theta){
    with(data,
      c(Y - theta[1],
        (Y - theta[1])^2 - theta[2] )
    )
  }
}
```

With the **eeFUN** function prepared, it is passed to **estimate_equations** along with the data, a character string naming the variable that identifies groups within the dataset, and starting values for the root finder.

```
estimates <- estimate_equations(eeFUN = SB1_eefun,
  data = dt,
  units = 'id',
  roots = c(1,1))
```

Table 2: " Comparing estimates from closed form versus geex "

	$\hat{\theta}$	$\hat{\Sigma}$
Closed form	(4.7367 4.5474)	$\begin{pmatrix} 0.0455 & -0.0429 \\ -0.0429 & 0.3929 \end{pmatrix}$
geex	(4.7367 4.5474)	$\begin{pmatrix} 0.0455 & -0.0429 \\ -0.0429 & 0.3929 \end{pmatrix}$
Decimal of difference	(Inf 16)	$\begin{pmatrix} 13 & 14 \\ 14 & 12 \end{pmatrix}$

Stefanski & Boos example 2

Example 2 illustrates calculation of a ratio estimator. I generate a data set with 100 observations where $Y \sim N(5, 2)$ and $X \sim N(2, 0.2)$. Table translates the estimating equations into the R function needed for **geex**:

Table 3: Translating math to code

$$\psi(Y_i, \theta) = \begin{pmatrix} Y_i - \theta_1 \\ X_i - \theta_2 \\ \theta_1 - \theta_3 \theta_2 \end{pmatrix}$$

```
SB2_eefun <- function(data){
  function(theta){
    with(data,
      c(Y - theta[1],
        X - theta[2],
        theta[1] - (theta[3] * theta[2]) )
    )
  }
}
```

```
estimates <- estimate_equations(eeFUN = SB2_eefun,
                                data = dt, units = 'id',
                                roots = c(1, 1, 1))
```

Table 4: " test "				$\hat{\Sigma}$		
	$\hat{\theta}$					
Closed form	(5.2481	1.9874	2.6407)	$\begin{pmatrix} 0.0435 & 0.0003 & 0.0215 \\ 0.0003 & 0.0004 & -0.0004 \\ 0.0215 & -0.0004 & 0.0114 \end{pmatrix}$		
geex	(5.2481	1.9874	2.6407)	$\begin{pmatrix} 0.0431 & 0.0003 & 0.0213 \\ 0.0003 & 0.0004 & -0.0004 \\ 0.0213 & -0.0004 & 0.0113 \end{pmatrix}$		
Decimal of difference	(Inf	Inf	Inf)	$\begin{pmatrix} 4 & 6 & 4 \\ 6 & 6 & 6 \\ 4 & 6 & 4 \end{pmatrix}$		

Stefanski & Boos example 3

Example 3 illustrates calculation of a ratio estimator. I generate a data set with 100 observations where $Y \sim N(5, 4)$. Table 5 translates the estimating equations into the R function needed for **geex**:

Table 5: Translating math to code	
$\psi(Y_i, \theta) = \begin{pmatrix} Y_i - \theta_1 \\ X_i - \theta_2 \\ \sqrt{\theta_2} - \theta_3 \\ \log(\theta_2) - \theta_4 \end{pmatrix}$	<pre>SB3_eefun <- function(data){ function(theta){ with(data, c(Y - theta[1], (Y - theta[1])^2 - theta[2], sqrt(theta[2]) - theta[3], log(theta[2]) - theta[4])) } }</pre>

```
estimates <- estimate_equations(eeFUN= SB3_eefun,
                                data = dt, units = 'id',
                                roots = c(1, 1, 1, 1))
```

Table 6: " Example 3 "

	$\hat{\theta}$	$\hat{\Sigma}$
Closed form	(5.0117 16.5029 4.0624 2.8035)	$\begin{pmatrix} 0.1650 & 0.1116 & 0.0137 & 0.0068 \\ 0.1116 & 5.3752 & 0.6616 & 0.3257 \\ 0.0137 & 0.6616 & 0.0814 & 0.0401 \\ 0.0068 & 0.3257 & 0.0401 & 0.0197 \end{pmatrix}$
geex	(5.0117 16.5029 4.0624 2.8035)	$\begin{pmatrix} 0.1650 & 0.1116 & 0.0137 & 0.0068 \\ 0.1116 & 5.3752 & 0.6616 & 0.3257 \\ 0.0137 & 0.6616 & 0.0814 & 0.0401 \\ 0.0068 & 0.3257 & 0.0401 & 0.0197 \end{pmatrix}$
Decimal of difference	(<i>Inf</i> <i>Inf</i> <i>Inf</i> 16)	$\begin{pmatrix} 13 & 12 & 13 & 13 \\ 12 & 10 & 12 & 12 \\ 13 & 12 & 12 & 13 \\ 13 & 12 & 13 & 13 \end{pmatrix}$