

# Estimability

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Consider an  $n$  dimensional random vector  $y$  for which  $\mathbb{E}(y) = \mu = X\beta$  and  $\text{Cov}(y) = V$ . Here  $X$  is an  $n \times p$  with  $n > p$  matrix which does not necessarily have full rank. A least squares estimate for  $\beta$  is

$$\hat{\beta} = (X^T V^{-1} X)^- X^T V^{-1} y$$

where  $A^-$  is a generalized inverse of  $A$ . We are interested in contrasts of the form  $c = \lambda^T \beta$ . An estimate of such a contrast is  $\hat{c} = \lambda^T \hat{\beta}$ . Generalized inverses are not unique and therefore  $\hat{\beta}$  is not uniquely estimated, and hence the contrasts are not uniquely estimated. On the other hand the fitted values  $\hat{y} = X\hat{\beta}$  are uniquely identified.

However, for some  $\lambda$ s we always get the same estimated contrast. Such contrasts are said to be estimable. These contrasts can be described as follows: We can only learn about  $\beta$  through  $X\beta$  so the only thing we can say something about is linear combinations  $\rho^T X\beta$ . Hence we can only say something about  $\lambda^T \beta$  if there exists  $\rho$  such that  $\lambda^T \beta = \rho^T X\beta$ , i.e., if  $\lambda = X^T \rho$ , that is, if  $\lambda$  is in the column space  $C(X^T)$  of  $X^T$ . That is, if  $\lambda$  is perpendicular to all vectors in the null space  $N(X)$  of  $X$ . To check this, we find a basis  $B$  for  $N(X) \subset R^p$  which can be done using SVD:

Example:

```
> ff <- factor(rep(1:3, each=2))
> X <- cbind(rep(1,6),model.matrix(~0+ff)); X

      ff1 ff2 ff3
1 1      1    0    0
2 1      1    0    0
3 1      0    1    0
4 1      0    1    0
5 1      0    0    1
6 1      0    0    1

> y <- 1:6

> S <- svd(X)
> lapply(S, zapsmall)

$d
[1] 2.828427 1.414214 1.414214 0.000000

$u
      [,1]      [,2]      [,3]      [,4]
[1,] -0.4082483  0.5534366  0.1644422 -0.7071068
[2,] -0.4082483  0.5534366  0.1644422  0.7071068
[3,] -0.4082483 -0.1343072 -0.5615113  0.0000000
[4,] -0.4082483 -0.1343072 -0.5615113  0.0000000
[5,] -0.4082483 -0.4191294  0.3970691  0.0000000
[6,] -0.4082483 -0.4191294  0.3970691  0.0000000

$v
      [,1]      [,2]      [,3] [,4]
[1,] -0.8660254  0.0000000  0.0000000  0.5
[2,] -0.2886751  0.7826776  0.2325563 -0.5
[3,] -0.2886751 -0.1899391 -0.7940968 -0.5
[4,] -0.2886751 -0.5927385  0.5615405 -0.5
```

The basis of  $N(X)$  is

```
> B <- S$v[, S$d/max(S$d) < 1e-10, drop=F]
> (B <- as.numeric(B/max(B)))
```

```
[1] 1 -1 -1 -1
```

Hence valid vectors  $\lambda$  must satisfy that  $\lambda_1 - \lambda_2 - \lambda_3 - \lambda_4 = 0$ .

```
> lam <- c(1, 1, 0, 0)
> sum( lam*B ) # Orthogonal
```

```
[1] 2.220446e-16
```

```
> (b.hat <- as.numeric(MASS::ginv(t(X)%*%X) %*% t(X) %*% y))
```

```
[1] 2.625 -1.125 0.875 2.875
```

```
> sum( lam * b.hat )
```

```
[1] 1.5
```

Take another basis for the mean space:

```
> X2 <- X
> X2[,3]<-0
> (b.hat2 <- as.numeric(MASS::ginv(t(X2)%*%X2) %*% t(X2) %*% y))
```

```
[1] 3.5 -2.0 0.0 2.0
```

```
> sum( lam * b.hat2 )
```

```
[1] 1.5
```

On the other other hand, the following does not produce a unique estimate:

```
> lam2 <- c(1, 0, 0, 0)
> sum( lam2 * b.hat )
```

```
[1] 2.625
```

```
> sum( lam2 * b.hat2 )
```

```
[1] 3.5
```