

# STAT 135

# 15. Multiple linear regression and inference

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# Inference for matrix formulation of linear regression

# Matrix notation

$$Y = X\beta + \epsilon$$

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ \vdots \\ y_n \end{bmatrix}_{(n \times 1)} = \begin{bmatrix} 1 & x_{1,1} & x_{1,2} & \dots & x_{1,p-1} \\ 1 & x_{2,1} & x_{2,2} & \dots & x_{2,p-1} \\ 1 & x_{3,1} & x_{3,2} & \dots & x_{3,p-1} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & x_{n,1} & x_{n,2} & \dots & x_{n,p-1} \end{bmatrix}_{(n \times p)} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_{p-1} \end{bmatrix}_{(p \times 1)} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \epsilon_3 \\ \vdots \\ \epsilon_n \end{bmatrix}_{(n \times 1)}$$

The LS prediction is

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

# Example

$$sale\_price_i = \beta_0 + \beta_1 area_i + \beta_2 quality_i + \beta_3 year_i + \beta_4 beds_i + \epsilon_i$$

$$Y = X\beta + \epsilon$$

Sale price	(Int)	living_area	quality	year	beds
177000	1	1913	6	1928	3
130000	1	1709	6	2004	3
88000	1	858	4	1971	3
140000	1	1164	7	1969	3
125000	1	960	5	1958	3
165000	1	1376	6	1920	3
265900	1	1484	8	2006	2
127000	1	864	5	1972	3
155000	1	1200	7	2004	2
98000	1	1436	4	1910	3

$$= \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_{p-1} \end{bmatrix}_{(p \times 1)} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \epsilon_3 \\ \vdots \\ \epsilon_n \end{bmatrix}_{(n \times 1)}$$

$(n \times 1)$ 
 $(n \times p)$ 
 $(p \times 1)$ 
 $(n \times 1)$

The LS prediction is

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



# Example

The LS prediction is

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

$$Y = \begin{bmatrix} 177000 \\ 130000 \\ 88000 \\ 140000 \\ 125000 \\ 165000 \\ 265900 \\ 127000 \\ 155000 \\ 98000 \end{bmatrix} \quad (n \times 1)$$

$$X = \begin{bmatrix} 1 & 1913 & 6 & 1928 & 3 \\ 1 & 1709 & 6 & 2004 & 3 \\ 1 & 858 & 4 & 1971 & 3 \\ 1 & 1164 & 7 & 1969 & 3 \\ 1 & 960 & 5 & 1958 & 3 \\ 1 & 1376 & 6 & 1920 & 3 \\ 1 & 1484 & 8 & 2006 & 2 \\ 1 & 864 & 5 & 1972 & 3 \\ 1 & 1200 & 7 & 2004 & 2 \\ 1 & 1436 & 4 & 1910 & 3 \end{bmatrix} \quad (n \times p)$$

$$X^T = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1913 & 1709 & 858 & 1164 & 960 & 1376 & 1484 & 864 & 1200 & 1436 \\ 6 & 6 & 4 & 7 & 5 & 6 & 8 & 5 & 7 & 4 \\ 1928 & 2004 & 1971 & 1969 & 1958 & 1920 & 2006 & 1972 & 2004 & 1910 \\ 3 & 3 & 3 & 3 & 3 & 3 & 2 & 3 & 2 & 3 \end{bmatrix} \quad (p \times n)$$

$$X^T X = \begin{array}{cc} & \begin{array}{ccccc} \text{int} & \text{living\_area} & \text{quality\_score} & \text{year\_built} & \text{bedrooms} \end{array} \\ \begin{array}{c} \text{int} \\ \text{living\_area} \\ \text{quality\_score} \\ \text{year\_built} \\ \text{bedrooms} \end{array} & \begin{bmatrix} 10 & 12964 & 58 & 19642 & 28 \\ 12964 & 17937134 & 76704 & 25446006 & 36208 \\ 58 & 76704 & 352 & 114145 & 159 \\ 19642 & 25446006 & 114145 & 38592102 & 54916 \\ 28 & 36208 & 159 & 54916 & 80 \end{bmatrix} \end{array}$$

# Example

The LS prediction is

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

$$Y = \begin{bmatrix} 177000 \\ 130000 \\ 88000 \\ 140000 \\ 125000 \\ 165000 \\ 265900 \\ 127000 \\ 155000 \\ 98000 \end{bmatrix} \quad (n \times 1)$$

$$X = \begin{bmatrix} 1 & 1913 & 6 & 1928 & 3 \\ 1 & 1709 & 6 & 2004 & 3 \\ 1 & 858 & 4 & 1971 & 3 \\ 1 & 1164 & 7 & 1969 & 3 \\ 1 & 960 & 5 & 1958 & 3 \\ 1 & 1376 & 6 & 1920 & 3 \\ 1 & 1484 & 8 & 2006 & 2 \\ 1 & 864 & 5 & 1972 & 3 \\ 1 & 1200 & 7 & 2004 & 2 \\ 1 & 1436 & 4 & 1910 & 3 \end{bmatrix} \quad (n \times p)$$

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$$(X^T X)^{-1} = \begin{array}{cc} & \begin{array}{c} \text{int} \quad \text{living\_area} \quad \text{quality\_score} \quad \text{year\_built} \quad \text{bedrooms} \end{array} \\ \begin{array}{c} \text{int} \\ \text{living\_area} \\ \text{quality\_score} \\ \text{year\_built} \\ \text{bedrooms} \end{array} & \begin{bmatrix} 722.3664 & -0.0109 & 2.2965 & -0.3457 & -15.1243 \\ -0.0109 & 0.0000 & -0.0002 & 0.0000 & -0.0001 \\ 2.2965 & -0.0002 & 0.1667 & -0.0019 & 0.2462 \\ -0.3457 & 0.0000 & -0.0019 & 0.0002 & 0.0051 \\ -15.1243 & -0.0001 & 0.2462 & 0.0051 & 1.3988 \end{bmatrix} \end{array} \quad (p \times p)$$



# Example

The LS prediction is

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

$$Y = \begin{bmatrix} 177000 \\ 130000 \\ 88000 \\ 140000 \\ 125000 \\ 165000 \\ 265900 \\ 127000 \\ 155000 \\ 98000 \end{bmatrix} \quad (n \times 1)$$

$$X^T = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1913 & 1709 & 858 & 1164 & 960 & 1376 & 1484 & 864 & 1200 & 1436 \\ 6 & 6 & 4 & 7 & 5 & 6 & 8 & 5 & 7 & 4 \\ 1928 & 2004 & 1971 & 1969 & 1958 & 1920 & 2006 & 1972 & 2004 & 1910 \\ 3 & 3 & 3 & 3 & 3 & 3 & 2 & 3 & 2 & 3 \end{bmatrix}$$

$$(X^T X)^{-1} = \begin{array}{cc} & \begin{array}{ccccc} \text{int} & \text{living\_area} & \text{quality\_score} & \text{year\_built} & \text{bedrooms} \end{array} \\ \begin{array}{c} \text{int} \\ \text{living\_area} \\ \text{quality\_score} \\ \text{year\_built} \\ \text{bedrooms} \end{array} & \begin{bmatrix} 722.3664 & -0.0109 & 2.2965 & -0.3457 & -15.1243 \\ -0.0109 & 0.0000 & -0.0002 & 0.0000 & -0.0001 \\ 2.2965 & -0.0002 & 0.1667 & -0.0019 & 0.2462 \\ -0.3457 & 0.0000 & -0.0019 & 0.0002 & 0.0051 \\ -15.1243 & -0.0001 & 0.2462 & 0.0051 & 1.3988 \end{bmatrix} \end{array}$$

$$\hat{\beta} = (X^T X)^{-1} X^T Y = \begin{array}{cc} & \begin{array}{c} \text{int} \\ \text{living\_area} \\ \text{quality\_score} \\ \text{year\_built} \\ \text{bedrooms} \end{array} \\ \begin{array}{c} (p \times 1) \end{array} & \begin{bmatrix} 731418.02374 \\ 18.97778 \\ 26094.62901 \\ -330.71265 \\ -39533.52530 \end{bmatrix} \end{array}$$

$\hat{\beta}$  is unbiased



# $\hat{\beta}$ is unbiased

Assume that the errors,  $\epsilon_i$ , are IID with  $E(\epsilon_i) = 0$  and  $Var(\epsilon_i) = \sigma^2$

This means that  $Cov(\epsilon) = \sigma^2 I_{n \times n}$  and  $E(\epsilon) = 0$

The LS estimator is:

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

The LS estimate,  $\hat{\beta}$  is unbiased:

$$E[\hat{\beta}] = \beta$$

Proof:

$$\begin{aligned} E(\hat{\beta}) &= E\left((X^T X)^{-1} X^T Y\right) \\ &= (X^T X)^{-1} X^T E(Y) \\ &= (X^T X)^{-1} X^T E(X\beta + \epsilon) \\ &= (X^T X)^{-1} X^T X\beta \\ &= \beta \end{aligned}$$

$$\text{Cov}(\hat{\beta})$$

# $\hat{\beta}$ variance-covariance matrix

Assume that the errors,  $\epsilon_i$ , are IID with  $E(\epsilon_i) = 0$ ,  $Var(\epsilon_i) = \sigma^2$

This means that  $Cov(\epsilon) = \sigma^2 I_{n \times n}$  and  $E(\epsilon) = 0$

Note if  $A$  is a constant matrix and  $Y$  is a random vector, then:

$$Cov(AY) = ACov(Y)A^T$$
$$Cov(A + Y) = Cov(Y)$$

The LS estimator is:

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

The LS estimate,  $\hat{\beta}$  is has variance-covariance matrix:

$$Cov(\hat{\beta}) = \sigma^2 (X^T X)^{-1}$$

$(p \times p)$

Proof:

$$\begin{aligned} Cov(\hat{\beta}) &= Cov\left((X^T X)^{-1} X^T Y\right) \\ &= (X^T X)^{-1} X^T Cov(Y) X (X^T X)^{-1} \\ &= (X^T X)^{-1} X^T Cov(X\beta + \epsilon) X (X^T X)^{-1} \\ &= (X^T X)^{-1} X^T Cov(\epsilon) X (X^T X)^{-1} \\ &= (X^T X)^{-1} X^T \sigma^2 I_{n \times n} X (X^T X)^{-1} \\ &= \sigma^2 (X^T X)^{-1} \end{aligned}$$

The distribution of  $\hat{\beta}$



# The theoretical distribution of the $\hat{\beta}$ vector

Assume that the errors,  $\epsilon_i \stackrel{IID}{\sim} N(0, \sigma^2)$  i.e.,  $\epsilon \stackrel{IID}{\sim} N(0, \sigma^2 I_{n \times n})$

The LS estimator is:

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

And we have shown that:

$$E[\hat{\beta}] = \beta \quad \text{Cov}(\hat{\beta}) = \sigma^2 (X^T X)^{-1}$$

Because the components of  $\hat{\beta}$  are linear combinations of independent normal RVs, they are themselves normal, and so

The LS estimate,  $\hat{\beta}$  is has distribution:

$$\hat{\beta} \sim N \left( \beta, \underset{\vdots}{\sigma^2 (X^T X)^{-1}} \right)$$

This means that each element

$$\hat{\beta}_j \sim N(\beta_j, \sigma^2 c_{jj})$$

(Where  $C = (X^T X)^{-1}$ )

But this assumes we know  $\hat{\sigma}^2$

# Distribution of $\hat{\beta}_j$ when estimating variance

Assume that the errors,  $\epsilon_i \stackrel{IID}{\sim} N(0, \sigma^2)$  i.e.,  $\epsilon \stackrel{IID}{\sim} N(0, \sigma^2 I_{n \times n})$

We have that  $\hat{\beta}_j \sim N(\beta_j, \sigma^2 c_{jj})$ , where  $C = (X^T X)^{-1}$  ( $c_{jj}$  is the  $j$ th diagonal entry)

If we estimate  $\sigma^2$  with some  $\hat{\sigma}^2$ , then we can estimate the variance of  $\hat{\beta}_j$  as:

$$\hat{\sigma}_{\hat{\beta}_j}^2 = \hat{\sigma}^2 c_{jj}$$

Then, we have

$$\frac{\hat{\beta}_j - \beta_j}{\hat{\sigma}_{\hat{\beta}_j}} \sim t_{n-p}$$

But what should  $\hat{\sigma}^2$  be?

# Estimating $\sigma^2$

Assume that the errors,  $\epsilon_i \stackrel{IID}{\sim} N(0, \sigma^2)$  i.e.,  $\epsilon \stackrel{IID}{\sim} N(0, \sigma^2 I_{n \times n})$

The variance-covariance matrix is:  $Cov(\hat{\beta}) = \sigma^2 (X^T X)^{-1}$

Similarly to the 1-dim case, we can estimate  $\sigma^2$  using the RSS

Let  $r = Y - X\hat{\beta}$  be the vector of residuals

Then, an unbiased estimator for  $\sigma^2$  is:

$$\hat{\sigma}^2 = \frac{RSS}{n - p} = \frac{\|r\|_2^2}{n - p} = \frac{\sum_i r_i^2}{n - p}$$

The proof of unbiasedness requires some understanding of matrix properties such as the *trace*. If you're curious, check out Section 14.4.3 of Rice.

# Example

$$Y = \begin{bmatrix} 177000 \\ 130000 \\ 88000 \\ 140000 \\ 125000 \\ 165000 \\ 265900 \\ 127000 \\ 155000 \\ 98000 \end{bmatrix} \quad (n \times 1)$$

$$X = \begin{bmatrix} 1 & 1913 & 6 & 1928 & 3 \\ 1 & 1709 & 6 & 2004 & 3 \\ 1 & 858 & 4 & 1971 & 3 \\ 1 & 1164 & 7 & 1969 & 3 \\ 1 & 960 & 5 & 1958 & 3 \\ 1 & 1376 & 6 & 1920 & 3 \\ 1 & 1484 & 8 & 2006 & 2 \\ 1 & 864 & 5 & 1972 & 3 \\ 1 & 1200 & 7 & 2004 & 2 \\ 1 & 1436 & 4 & 1910 & 3 \end{bmatrix} \quad (n \times p)$$

$$\hat{\beta} = \begin{matrix} \text{int} & 731418.02374 \\ \text{living\_area} & 18.97778 \\ \text{quality\_score} & 26094.62901 \\ \text{year\_built} & -330.71265 \\ \text{bedrooms} & -39533.52530 \end{matrix} \quad (p \times 1)$$

$$\hat{Y} = X\hat{\beta} = \begin{bmatrix} 1 & 1913 & 6 & 1928 & 3 \\ 1 & 1709 & 6 & 2004 & 3 \\ 1 & 858 & 4 & 1971 & 3 \\ 1 & 1164 & 7 & 1969 & 3 \\ 1 & 960 & 5 & 1958 & 3 \\ 1 & 1376 & 6 & 1920 & 3 \\ 1 & 1484 & 8 & 2006 & 2 \\ 1 & 864 & 5 & 1972 & 3 \\ 1 & 1200 & 7 & 2004 & 2 \\ 1 & 1436 & 4 & 1910 & 3 \end{bmatrix} \begin{bmatrix} 731418.02374 \\ 18.97778 \\ 26094.62901 \\ -330.71265 \\ -39533.52530 \end{bmatrix} = \begin{bmatrix} 168075.72 \\ 139070.09 \\ 81644.26 \\ 166396.77 \\ 113973.89 \\ 160530.35 \\ 225861.45 \\ 107522.04 \\ 195038.55 \\ 112786.89 \end{bmatrix}$$

The residual vector is:

$$r = Y - \hat{Y} = \begin{bmatrix} 177000 \\ 130000 \\ 88000 \\ 140000 \\ 125000 \\ 165000 \\ 265900 \\ 127000 \\ 155000 \\ 98000 \end{bmatrix} - \begin{bmatrix} 168075.72 \\ 139070.09 \\ 81644.26 \\ 166396.77 \\ 113973.89 \\ 160530.35 \\ 225861.45 \\ 107522.04 \\ 195038.55 \\ 112786.89 \end{bmatrix} = \begin{bmatrix} 8924.283 \\ -9070.088 \\ 6355.741 \\ -26396.771 \\ 11026.114 \\ 4469.649 \\ 40038.554 \\ 19477.958 \\ -40038.554 \\ -14786.886 \end{bmatrix} \quad (n \times 1)$$



# Example

$$r = Y - \hat{Y} = \begin{bmatrix} 177000 \\ 130000 \\ 88000 \\ 140000 \\ 125000 \\ 165000 \\ 265900 \\ 127000 \\ 155000 \\ 98000 \end{bmatrix} - \begin{bmatrix} 168075.72 \\ 139070.09 \\ 81644.26 \\ 166396.77 \\ 113973.89 \\ 160530.35 \\ 225861.45 \\ 107522.04 \\ 195038.55 \\ 112786.89 \end{bmatrix} = \begin{bmatrix} 8924.283 \\ -9070.088 \\ 6355.741 \\ -26396.771 \\ 11026.114 \\ 4469.649 \\ 40038.554 \\ 19477.958 \\ -40038.554 \\ -14786.886 \end{bmatrix}$$

$(n \times 1)$

We can estimate  $\sigma^2$  using:

$$\hat{\sigma}^2 = \frac{\|r\|_2^2}{n-p} = \frac{\sum_i r_i^2}{n-p} = \frac{8924.3^2 + 9070.1^2 + \dots + 14786.9^2}{10-5} = 968,972,338$$

Which we can plug into:

$$\hat{\sigma}_{\hat{\beta}_j}^2 = \hat{\sigma}^2 c_{jj} \dots \rightarrow C = (X^T X)^{-1} = \begin{matrix} & \text{int} & \text{living\_area} & \text{quality\_score} & \text{year\_built} & \text{bedrooms} \\ \begin{matrix} \text{int} \\ \text{living\_area} \\ \text{quality\_score} \\ \text{year\_built} \\ \text{bedrooms} \end{matrix} & \begin{bmatrix} 722.3664 & -0.0109 & 2.2965 & -0.3457 & -15.1243 \\ -0.0109 & 0.0000 & -0.0002 & 0.0000 & -0.0001 \\ 2.2965 & -0.0002 & 0.1667 & -0.0019 & 0.2462 \\ -0.3457 & 0.0000 & -0.0019 & 0.0002 & 0.0051 \\ -15.1243 & -0.0001 & 0.2462 & 0.0051 & 1.3988 \end{bmatrix} \end{matrix}$$

$(p \times p)$

So the SD estimate for  $\hat{\beta}_{quality}$  is:

$$\hat{\sigma}_{\hat{\beta}_{quality}}^2 = \hat{\sigma}^2 c_{quality,quality} = 968,972,338 \times 0.1667 = 161,527,689$$

$$\Rightarrow \hat{\sigma}_{\hat{\beta}_{quality}} = 12,709$$

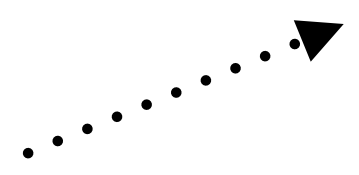
# Hypothesis testing and confidence intervals for $\hat{\beta}$

# Hypothesis testing for $\beta_j$

Assume that the errors,  $\epsilon_i \stackrel{IID}{\sim} N(0, \sigma^2)$  i.e.,  $\epsilon \stackrel{IID}{\sim} N(0, \sigma^2 I_{n \times n})$

$$H_0 : \beta_j = 0 \text{ against } H_1 : \beta_j \neq 0$$

**Test statistic:**  $t = \frac{\hat{\beta}_j}{\hat{\sigma}_{\hat{\beta}_j}}$  **P-value:**  $P(|T| \geq |t|)$



Where  $T \sim t_{n-p}$   
(p is the number of parameters in the model)

These standardized coefficients are comparable to one another

Where

$$\hat{\sigma}_{\hat{\beta}_j}^2 = \hat{\sigma}^2 c_{jj} \quad \text{And} \quad \hat{\sigma}^2 = \frac{RSS}{n-p} = \frac{\|r\|_2^2}{n-p} = \frac{\|Y - X\hat{\beta}\|_2^2}{n-p}$$

# Confidence interval for $\beta_j$

Assume that the errors,  $\epsilon_i \stackrel{IID}{\sim} N(0, \sigma^2)$  i.e.,  $\epsilon \stackrel{IID}{\sim} N(0, \sigma^2 I_{n \times n})$

A  $(1 - \alpha) \%$  **confidence interval** is:

$$[\hat{\beta}_j - t_{n-p, \alpha/2} \hat{\sigma}_{\hat{\beta}_j}, \hat{\beta}_j + t_{n-p, \alpha/2} \hat{\sigma}_{\hat{\beta}_j}]$$

Where

$$\hat{\sigma}_{\hat{\beta}_j}^2 = \hat{\sigma}^2 c_{jj} \quad \text{And} \quad \hat{\sigma}^2 = \frac{RSS}{n-p} = \frac{\|r\|_2^2}{n-p} = \frac{\|Y - X\hat{\beta}\|_2^2}{n-p}$$



# Example

$$\hat{\beta}_{(p \times 1)} = \begin{matrix} \text{int} & 731418.02374 \\ \text{living\_area} & 18.97778 \\ \text{quality\_score} & 26094.62901 \\ \text{year\_built} & -330.71265 \\ \text{bedrooms} & -39533.52530 \end{matrix}$$

$$C = (X^T X)^{-1} = \begin{matrix} & \text{int} & \text{living\_area} & \text{quality\_score} & \text{year\_built} & \text{bedrooms} \\ \begin{matrix} 722.3664 & -0.0109 & 2.2965 & -0.3457 & -15.1243 \\ -0.0109 & 0.0000 & -0.0002 & 0.0000 & -0.0001 \\ 2.2965 & -0.0002 & 0.1667 & -0.0019 & 0.2462 \\ -0.3457 & 0.0000 & -0.0019 & 0.0002 & 0.0051 \\ -15.1243 & -0.0001 & 0.2462 & 0.0051 & 1.3988 \end{matrix} \end{matrix}$$

$$\hat{\sigma}^2 = \frac{\|r\|_2^2}{n - p} = 968,972,338$$

$\hat{\beta}_j$	$(\hat{\sigma}_{\hat{\beta}_j}^2 = \hat{\sigma}^2 c_{jj})$	$(t_{\hat{\beta}_j} = \hat{\beta}_j / \hat{\sigma}_{\hat{\beta}_j})$	$P( T  \geq  t )$
$\hat{\beta}_{int} = 731,418.02$	$\hat{\sigma}_{\hat{\beta}_{int}} = 836,632.00$	$t_{\hat{\beta}_{int}} = 0.874$	$p_{\hat{\beta}_{int}} = 0.4220$
$\hat{\beta}_{area} = 18.98$	$\hat{\sigma}_{\hat{\beta}_{area}} = 35.12$	$t_{\hat{\beta}_{area}} = 0.540$	$p_{\hat{\beta}_{area}} = 0.6122$
$\hat{\beta}_{quality} = 26,094.63$	$\hat{\sigma}_{\hat{\beta}_{quality}} = 12,708.79$	$t_{\hat{\beta}_{quality}} = 2.053$	$p_{\hat{\beta}_{quality}} = 0.0952$
$\hat{\beta}_{year} = -330.71$	$\hat{\sigma}_{\hat{\beta}_{year}} = 406.57$	$t_{\hat{\beta}_{year}} = -0.813$	$p_{\hat{\beta}_{year}} = 0.4530$
$\hat{\beta}_{beds} = -39,533.53$	$\hat{\sigma}_{\hat{\beta}_{beds}} = 36,816.08$	$t_{\hat{\beta}_{beds}} = -1.074$	$p_{\hat{\beta}_{beds}} = 0.3320$

# Example

```
> ls_fit <- lm(sale_price ~ ., ames_train)
> summary(ls_fit)
```

Call:

```
lm(formula = sale_price ~ ., data = ames_train)
```

Residuals:

1	2	3	4	5	6	7	8	9	10
8924	-9070	6356	-26397	11026	4470	40039	19478	-40039	-14787

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	731418.02	836632.00	0.874	0.4220
total_living_area	18.98	35.12	0.540	0.6122
quality_score	26094.63	12708.79	2.053	0.0952 .
year_built	-330.71	406.57	-0.813	0.4530
bedrooms	-39533.53	36816.08	-1.074	0.3320

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Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 31130 on 5 degrees of freedom

Multiple R-squared: 0.785, Adjusted R-squared: 0.6129

F-statistic: 4.563 on 4 and 5 DF, p-value: 0.06353

# Example

lm\_inference\_multi.R