

Stat 312: Lecture 21

Linear Regression II.

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Concepts

1. *Maximum likelihood estimation.* Given a linear model

$$Y_j = \beta_0 + \beta_1 x_j + \epsilon_j$$

with $\epsilon_j \sim N(0, \sigma^2)$, we will estimate β_0, β_1 using the maximum likelihood estimation. Note that

$$Y_j \sim N(\beta_0 + \beta_1 x_j, \sigma^2).$$

The density function for Y_j are

$$f(y_j) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left[-\frac{(y_j - \beta_0 - \beta_1 x_j)^2}{2\sigma^2}\right].$$

The loglikelihood is

$$L(\beta_0, \beta_1) = \text{const} - \frac{1}{2\sigma^2} \sum_{j=1}^n (y_j - \beta_0 - \beta_1 x_j)^2.$$

We maximize the loglikelihood which is equivalent to minimizing the sum of the residuals

$$\frac{1}{2\sigma^2} \sum_{j=1}^n (y_j - \beta_0 - \beta_1 x_j)^2.$$

Hence MLE is LSE in linear regression.

2. The least squares estimation for β_1 are given by

$$\hat{\beta}_1 = \frac{S_{xy}}{S_{xx}}$$

where $S_{xy} = n(\bar{x}\bar{y} - \bar{x}\bar{y})$. It can be shown that

$$\hat{\beta}_1 = \frac{S_{xy}}{S_{xx}} = \sum_{j=1}^n c_j Y_j,$$

where

$$c_j = (x_j - \bar{x})/S_{xx}.$$

So LSE is a linear estimation. From $\sum_{j=1}^n c_j = 0$, $\sum_{j=1}^n c_j x_j = 1$ and $\sum_{j=1}^n c_j^2 = S_{xx}^{-1}$ we can show that

$$\mathbb{E}\hat{\beta}_1 = \beta_1$$

showing unbiasedness. Further, $\text{Var}\hat{\beta}_1 = \sigma^2/S_{xx}$. Since $\hat{\beta}_1$ is a linear combination of normals, $\hat{\beta}_1 \sim N(\beta_1, \sigma^2/S_{xx})$.

3. We are interested in hypothesis testing

$$H_0 : \beta_1 = 0 \text{ vs. } H_1 : \beta_1 \neq 0.$$

Inference on the slope parameter β_1 is based on test statistic

$$T = \frac{\hat{\beta}_1 - \beta_1}{S_{\hat{\beta}_1}} \sim t_{n-2},$$

where $S_{\hat{\beta}_1} = \hat{\sigma}/\sqrt{S_{xx}}$ and $\hat{\sigma} = \text{SSE}/(n-2)$.

It can be shown that $\text{SSE} = S_{yy} - S_{xy}^2/S_{xx}$, we

get $S_{\hat{\beta}_1} = \frac{1}{\sqrt{n-2}} \sqrt{\frac{S_{yy}}{S_{xx}} - \left(\frac{S_{xy}}{S_{xx}}\right)^2}$. Then we reject

H_0 if $|t| > t_{\alpha/2, n-2}$ at $100(1-\alpha)\%$ significance.

We don't usually compute the test statistic by hand. Use R-package.

Example. We continue Lecture 19 example.

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>summary(lm(y~x))
```

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Call: lm(formula = y ~ x)
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Residuals:

Min	1Q	Median	3Q	Max
-10.908	-6.312	1.758	4.354	10.836

Coefficients:

Estimate	Std. Error	t value	Pr(> t)
(Intercept)	29.48	13.23	2.22 0.06
x	0.55	0.17	3.12 0.01 *

(Intercept) 29.48 13.23 2.22 0.06

x 0.55 0.17 3.12 0.01 *

Signif. codes: 0 '***' 0.001 '**' 0.01 '*'

Residual standard error: 7.647 on 8 degrees of freedom
Multiple R-Squared: 0.5519,
Adjusted R-squared: 0.4959 F-statistic: 9.854
1 and 8 DF, p-value: 0.01383