Lecture 03

Simple Linear Models: Leverage, Hypothesis Tests, Goodness of Fit

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Notes

- Problem Set #1 Online: Due Next Wednesday, 2015-09-16
- R code online
- Course Pace

Goals for today

1. simulation of leverage
2. hypothesis tests for simple linear regression
3. goodness of fit, R^2
4. Galton's heights data

Leverage Simulation

Hypothesis Tests

Z-Test

Take the simple linear regression model:

$$y_i = x_i\beta + \epsilon_i, \quad i = 1, \ldots n.$$

With independent, identically distributed normal error terms:

$$\epsilon_i \sim \mathcal{N}(0, \sigma^2)$$

Last time we calculated the MLE estimator,

$$\widehat{\beta}_{MLE} = \frac{\sum_i y_i x_i}{\sum_i x_i^2}$$

And showed that it has a normally distribution with the following mean and variance:

$$\widehat{\beta} \sim \mathcal{N}(\beta, \frac{\sigma^2}{\sum_i x_i^2})$$

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Under the null hypothesis, we have

$$z | H_0 \sim \mathcal{N}(0, 1)$$

When we know σ^2 that is all we need to do, however outside of simulations we (very) rarely known the true variance of the noise. Otherwise, we first need to estimate it.

T-Test

The residuals from a given prediction of β are given by:

$$\begin{aligned} r_i &= y_i - \widehat{y}_i \\ &= y_i - x_i\widehat{\beta} \end{aligned}$$

These represent an estimate of the error terms ϵ_i.

If r_i is the sampled and estimated version of ϵ_i, it would seem reasonable to have:

$$\begin{aligned}\frac{1}{n}\sum_{i=1}^{n} r_i^2 &\approx \mathbb{E}\epsilon^2 \\ &= \sigma^2\end{aligned}$$

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I will delay a formal derivation of this until the multivariate case; conceptually seems reasonable that the estimate will be slightly smaller due to the estimation of r_i by the same data.

So, we instead use a corrected form to estimate the error variance, an estimator that we will call s^2:

$$
\begin{aligned}
s^2 &= \frac{1}{n-1} \cdot \sum_i r_i^2 \\
&= \frac{1}{n-1} \cdot \sum_i (y_i - \widehat{y}_i)^2 \\
&= \frac{1}{n-1} \cdot \sum_i (y_i - x_i\beta)^2
\end{aligned}
$$

The ratio of our estimator to the true variance has a χ^2 distribution with $n-1$ degrees of freedom.

$$\frac{s^2}{\sigma^2} \sim \chi^2_{n-1}$$

The standard error is then given by:

$$\begin{aligned}
\text{S.E.}(\widehat{\beta}) &= \sqrt{\frac{s^2}{\sum_i x_i^2}} \\
&= \sqrt{\frac{(y - x_i\widehat{\beta})^2}{(n-1)\cdot\sum_i x_i^2}}
\end{aligned}$$

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And under the null hypothesis, we have

$$t | H_0 \sim t_{n-1}$$

On a related note, we can similarly calculate a confidence interval for β using the standard error. A $100(1-\alpha)\%$. confidence interval is given by:

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For a reasonably large sample size n, we can approximate this by a normal distribution:

$$\widehat{\beta} \pm z_{1-\alpha/2} \cdot \text{S.E.}(\widehat{\beta})$$

F-Test

As an alternative to the T-test, consider squaring the test statistic

$$
\begin{aligned}
T^2 &= \left(\frac{\widehat{\beta} - b}{\text{S.E.}(\widehat{\beta})}\right)^2 \\
&= \frac{\left(\frac{\widehat{\beta} - b}{\sigma^2 / \sum_i x_i^2}\right)^2}{s^2/\sigma^2} \\
&= \frac{U}{V}
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And therefore $T^2 \sim F_{1,n-1}$.

Intercept Model

When we have the model $y = \alpha + x\beta + \epsilon$, the form of s^2 changes slightly:

$$s^2 = \frac{1}{n-2} \cdot \sum_i (y_i - \widehat{y}_i)^2$$

as well as the standard errors:

$$\text{S.E.}(\alpha) = \sqrt{s^2 \cdot \left(\frac{1}{n} + \frac{\bar{x}}{\sum_i (x_i - \bar{x})^2} \right)}$$

$$\text{S.E.}(\beta) = \sqrt{\frac{s^2}{\sum_i (x_i - \bar{x})^2}}$$

Goodness of Fit

R^2

A common measurement of how well a linear model explains the data is the R^2. For the non-intercept version, it can be written as:

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The more typically seen version compares the estimated residuals with the centered values of y.

$$R^2 = 1 - \frac{\sum_i (y_i - \widehat{y}_i)^2}{\sum_i (y_i - \bar{y})^2}$$

With a bit of algebraic manipulation, we see that this is equal to the squared sample correlation of x and y:

$$
\begin{aligned}
R^2 &= \left(\frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_i (x_i - \bar{x})^2 \cdot \sum_i (y_i - \bar{y})^2}} \right)^2 \\
&= cor(x, y)^2
\end{aligned}
$$

Applications