Chapter One of *Regression Analysis*: Overview[1]

STA302 Fall 2017

[1] See last slide for copyright information.

Simple regression model

$$y_i = \beta_0 + \beta_1 x_i + \epsilon_i,$$

where

$x_1, \ldots, x_n$ are observed, known constants.

$\epsilon_1, \ldots, \epsilon_n$ are random variables satisfying the *Gauss-Markov conditions.*

$E(\epsilon_i) = 0$
$Var(\epsilon_i) = \sigma^2$
$Cov(\epsilon_i, \epsilon_j) = 0$ for $i \neq j$.

β_0, β_1 and σ^2 are unknown constants with $\sigma^2 > 0$.

Least Squares

Background that's not in the text

- The random variable y has a distribution that depends on the parameter θ.
- How can we estimate θ from data $y_1, \ldots, y_n$?
- The expected value $E(y)$ is a function of θ.
- Write it $E_\theta(y)$.
- Estimate θ by the value that gets the observed data values as close as possible to their expected values.
- Minimize

$$\mathcal{S} = \sum_{i=1}^{n} (y_i - E_\theta(y_i))^2$$

  over all θ.
- The value of θ that minimizes $\mathcal{S}$ is the *least squares estimate*.

Simplest example of least squares

Again, not in the text

- $y_1, \ldots, y_n$ all have $E(y_i) = \mu$.
- The least squares estimate of μ is the value that makes the observed y_i values as close as possible to what you would expect.
- Minimize $\mathcal{S} = \sum_{i=1}^{n} (y_i - \mu)^2$

$$
\begin{aligned}
\frac{d\mathcal{S}}{d\mu} &= \frac{d}{d\mu} \sum_{i=1}^{n} (y_i - \mu)^2 \\
&= \sum_{i=1}^{n} \frac{d}{d\mu} (y_i - \mu)^2 \\
&= 2 \sum_{i=1}^{n} (y_i - \mu) \, (-1) \\
&\stackrel{set}{=} 0
\end{aligned}
$$

Continuing the calculation: $-2\sum_{i=1}^{n}(y_i - \mu) = 0$

$$
\begin{aligned}
&\Rightarrow \quad \sum_{i=1}^{n}(y_i - \mu) = 0 \\
&\Rightarrow \quad \sum_{i=1}^{n} y_i - \sum_{i=1}^{n} \mu = 0 \\
&\Rightarrow \quad \sum_{i=1}^{n} y_i - n\mu = 0 \\
&\Rightarrow \quad \sum_{i=1}^{n} y_i = n\mu \\
&\Rightarrow \quad \mu = \frac{1}{n}\sum_{i=1}^{n} y_i = \overline{y}
\end{aligned}
$$

So the least-squares estimate of μ is $\overline{y}$.

Least squares regression

Minimize $\mathcal{S} = \sum_{i=1}^{n} (y_i - E_\theta(y_i))^2$

- Model equation is $y_i = \beta_0 + \beta_1 x_i + \epsilon_i$
- $E(y_i) = \beta_0 + \beta_1 x_i$
- Minimize $\mathcal{S} = \sum_{i=1}^{n} (y_i - \beta_0 - \beta_1 x_i)^2$ over $\theta = (\beta_0, \beta_1)$.
- Take partial derivatives, set to zero, solve two equations in two unknowns.
- Least squares estimate of β_0 is b_0. Least squares estimate of β_1 is b_1.

Vocabulary and concepts

A preview of almost the entire course

$y_i = \beta_0 + \beta_1 x_i + \epsilon_i$

- Linear regresson means linear in the β parameters.
- Polynomial regression $y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \epsilon_i$, etc.
- Centered model $y_i = (\beta_0 + \beta_1 \overline{x}) + \beta_1 (x_i - \overline{x}) + \epsilon_i$
- Predicted value $\widehat{y}_i = b_0 + b_1 x_i$
- Residual $e_i = y_i - \widehat{y}_i$
- Plotting residuals (p.5) to diagnose problems with the model.
- Gauss-Markov conditions.
- Measure of model fit R^2
- Mean and variance of b_0 and b_1.
- Confidence intervals and tests.
- Predicting future observations.

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