Linear regression

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1

Consider the following optimization problem:

$$(\beta_0^*, \beta_1^*) = \operatorname*{argmin}_{(\beta_0, \beta_1) \in \mathbb{R}^2} E_{\text{out}}(\beta_0, \beta_1) := \mathbb{E}_{x, y}[(y - (\beta_0 + \beta_1 x))^2]$$

where $x, y \in \mathbb{R}$.

Show that the solution is given by

$$\beta_1^* = \frac{\operatorname{Cov}(x, y)}{\operatorname{Var}(x)},$$

$$\beta_0^* = \mathbb{E}[y] - \beta_1 \mathbb{E}[x].$$

Consider a dataset $\mathscr{D} = \{(x_i, y_i)\}_{i=1}^n$ with $x_i, y_i \in \mathbb{R}$, and the following optimization problem:

$$(\hat{eta}_0,\hat{eta}_1) = \operatorname*{argmin}_{(eta_0,eta_1) \in \mathbb{R}^2} E_{\mathrm{in}}(eta_0,eta_1),$$

where

$$E_{\rm in}(\beta_0, \beta_1) = \frac{1}{n} \sum_{i=1}^n (y_i - (\beta_0 + \beta_1 x_i))^2.$$

Prove that the minimizing values $\hat{\beta}_1$ and $\hat{\beta}_0$ are given by

$$\hat{\beta}_{1} = \frac{\frac{1}{n} \sum_{i=1}^{n} (x_{i} - \bar{x})(y_{i} - \bar{y})}{\frac{1}{n} \sum_{i=1}^{n} (x_{i} - \bar{x})^{2}}$$
$$\hat{\beta}_{0} = \bar{y} - \hat{\beta}_{1} \bar{x},$$

where $\bar{y} = \frac{1}{n} \sum_{i=1}^{n} y_i$ and $\bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i$.

3

We now assume the data has been generated by the following model

$$y_i = f(x_i) + \varepsilon_i$$

where x_i is fixed (non-random), ε_i are i.i.d. with $E[\varepsilon_i] = 0$, $Var(\varepsilon_i) = \sigma^2$.

Show that the variance of $\hat{\beta}_1$ is given by $\text{Var}(\hat{\beta}_1) = \frac{\sigma^2}{\sum_i (x_i - \bar{x})^2}$. You can use the following equalities

$$\begin{split} \sum_{i} (x_i - \bar{x})(y_i - \bar{y}) &= \sum_{i} (x_i - \bar{x})y_i - \sum_{i} (x_i - \bar{x})\bar{y} \\ &= \sum_{i} (x_i - \bar{x})y_i \\ &= \sum_{i} (x_i - \bar{x})(\beta_0 + \beta_1 x_i + \varepsilon_i) \end{split}$$

Show that the variance of $\hat{\beta}_0$ is given by

$$Var(\hat{\beta}_0) = \frac{\sigma^2}{n} + \frac{\bar{x}^2 \sigma^2}{\sum_{i=1}^{n} (x_i - \bar{x})^2}$$

Under the same set of assumptions as the previous exercise, show that the estimates $\hat{\beta_0}$ and $\hat{\beta_1}$ are unbiased, i.e. $\text{Bias}(\hat{\beta_0}) = 0$ and $\text{Bias}(\hat{\beta_1}) = 0$.