MATH 205: Statistical methods

Lecture 35: Linear regression

Announcements

- Final exam:

12/15/2022, Thursday
3:30PM - 5:30PM
Gore Hall Room 304

- Plan for the rest of the semester
  - Linear regression
  - Review of materials + Practice exam
- **There will be no lab next week**
- Course evaluations will be available 12/01 through 12/08

Linear regression: Using correlation to predict

Procedure 2.1 (Predicting a Value Using Correlation) Assume we have N data items which are 2-vectors $(x_1, y_1), \ldots, (x_N, y_N)$, where $N > 1$. These could be obtained, for example, by extracting components from larger vectors. Assume we have an x value x_0 for which we want to give the best prediction of a y value, based on this data. The following procedure will produce a prediction:

- Transform the data set into standard coordinates, to get

$$\hat{x}_i = \frac{1}{\mathsf{std}(x)}(x_i - \mathsf{mean}(\{x\}))$$
$$\hat{y}_i = \frac{1}{\mathsf{std}(y)}(y_i - \mathsf{mean}(\{y\}))$$
$$\hat{x}_0 = \frac{1}{\mathsf{std}(x)}(x_0 - \mathsf{mean}(\{x\})).$$

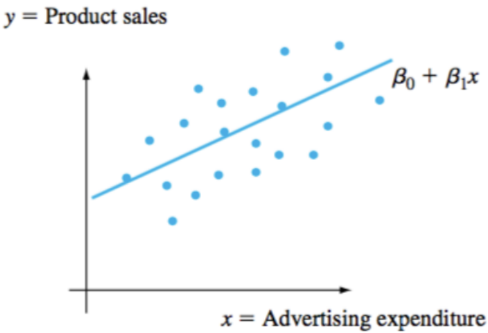
- Compute the correlation

$$r = \mathsf{corr}(\{(x, y)\}) = \mathsf{mean}(\{\hat{x}\hat{y}\}).$$

- Predict $\hat{y}_0 = r\hat{x}_0$.
- Transform this prediction into the original coordinate system, to get

$$y_0 = \mathsf{std}(y) r\hat{x}_0 + \mathsf{mean}(\{y\})$$

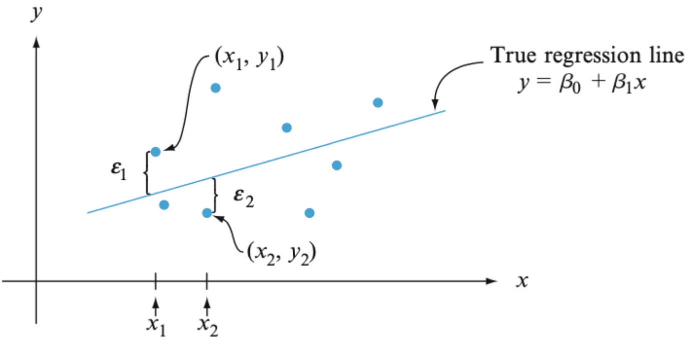
Linear regression



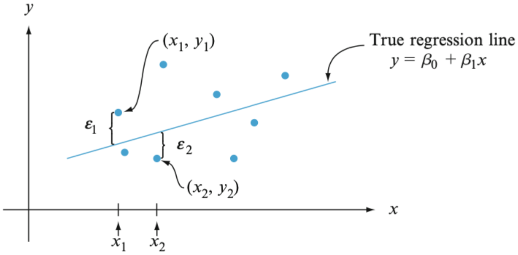
Mathematical model:

$$y_i = \beta_0 + \beta_1 x_i + \epsilon_i, \quad \epsilon_i \sim \mathcal{N}(0, \sigma^2)$$

Linear regression



Why do we do regression?



- Regression to Make Predictions
  $\rightarrow$ You already knew how to do this!

- Regression to Spot Trends $\rightarrow$ Are you sure that $\beta_1 > 0$?

Linear regression: settings

Assumption

1. *$x_1, x_2, \ldots, x_n$ are fixed design points (non-random)*
2. *Linear model:*
$$Y_i = \beta_0 + \beta_1 x_i + \epsilon_i$$
where $\epsilon_1, \epsilon_2, \ldots, \epsilon_n$ are random sample from $\mathcal{N}(0, \sigma^2)$
3. *Let assume (for now), that σ is known*

We want to make inferences about the trend, so β_1 is important

Estimate β_1

The true value of β_1 will be estimated by

$$\hat{\beta}_1 = \frac{\sum (x_i - \bar{x})(Y_i - \bar{Y})}{\sum (x_i - \bar{x})^2}$$

We first note that

$$\sum (x_i - \bar{x})\bar{Y} = \bar{Y} \cdot \sum x_i - \bar{x} = 0$$

We can write $\hat{\beta}_1$ as

$$\hat{\beta}_1 = \frac{\sum (x_i - \bar{x})Y_i}{\sum (x_i - \bar{x})^2}$$

thus $\hat{\beta}_1$ is a linear combination of independent normal random variables

Problem

We have

$$\hat{\beta}_1 = \frac{\sum (x_i - \bar{x})(Y_i - \bar{Y})}{\sum (x_i - \bar{x})^2} = \frac{\sum (x_i - \bar{x}) Y_i}{\sum (x_i - \bar{x})^2}$$

where

$$Y_i = \beta_0 + \beta_1 x_i + \epsilon_i, \quad \epsilon_i \sim \mathcal{N}(0, \sigma^2)$$

thus $\hat{\beta}_1$ is a linear combination of independent normal random variables Y_i.
Tasks:

- What are $E[Y_i]$ and $Var(Y_i)$ in terms of x_i, β_0 and β_1?
- What are $E[\bar{Y}]$ in terms of $\bar{x}$, β_0 and β_1?
- What are $E[\hat{\beta}_1]$ and $Var[\hat{\beta}_1]$ in terms of β_0, β_1 and x_i's.