Introduction to Multiple Linear Regression

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*This material is part of the **statsTeachR** project*

Today's lecture

Multiple Linear Regression: basic concepts

- Motivation
- Assumptions
- Interpretation of βs
- More on confounding (omitted variable bias)
- Matrix notation for MLR

Relevant reading: Faraway Chapter 2, *ISL* Chapter 3.2-3.3

Motivation

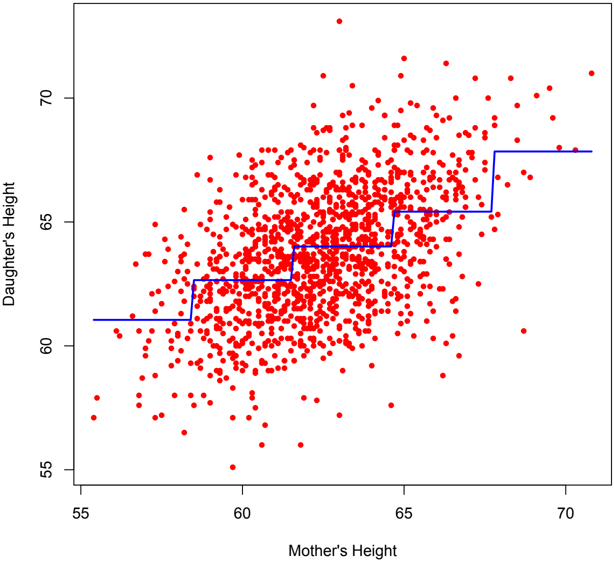
Most applications involve more that one covariate – if more than one thing can influence an outcome, you need multiple linear regression.

- Improved description of $y|\mathbf{x}$
- More accurate estimates and predictions
- Allow testing of multiple effects
- Includes multiple predictor types

Why not bin all predictors?

- Divide x_i into k_i bins
- Stratify data based on inclusion in bins across x's
- Find mean of the y_i in each category
- Possibly a reasonable non-parametric model

Why not bin all predictors?



Why not bin all predictors?

- More predictors = more bins
- If each x has 5 bins, you have 5^p overall categories
- May not have enough data to estimate distribution in each category
- Curse of dimensionality is a problem in a lot of non-parametric statistics

For more, see this interactive Shiny app.

Multiple linear regression model

- Observe data $(y_i, x_{i1}, \ldots, x_{ip})$ for subjects $1, \ldots, n$. Want to estimate $\beta_0, \beta_1, \ldots, \beta_p$ in the model

$$y_i = \beta_0 + \beta_1 x_{i1} + \ldots + \beta_1 x_{ip} + \epsilon_i; \; \epsilon_i \overset{iid}{\sim} (0, \sigma^2)$$

- Assumptions (residuals have mean zero, constant variance, are independent) are as in SLR
- Impose linearity which (as in the SLR) is a big assumption
- Our primary interest will be $E(y|\mathbf{x})$
- Eventually estimate model parameters using least squares

Predictor types

- Continuous
- Categorical
- Ordinal

Interpretation of coefficients

$$\beta_0 = E(y|x_1 = 0, \ldots, x = 0)$$

- Centering some of the x's may make this more interpretable

Interpretation of β_1

Interpretation of β_1

$\beta_1 =$ the expected change in y for a one unit increase in x_1, holding all other x's constant.

Example with two predictors

Suppose we want to regress weight on age and sex.

- Model is $y_i = \beta_0 + \beta_1 x_{i,age} + \beta_2 x_{i,sex} + \epsilon_i$
- Age is continuous starting with age 0; sex is binary, coded so that $x_{i,sex} = 0$ for men and $x_{i,sex} = 1$ for women

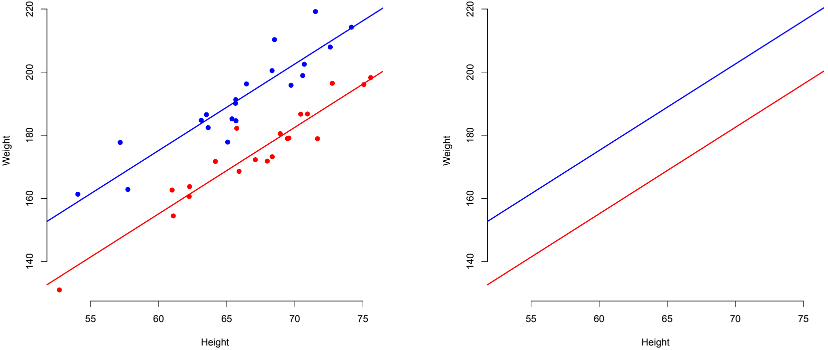
Example with two predictors

Model: $y_i = \beta_0 + \beta_1 x_{i,age} + \beta_2 x_{i,sex} + \epsilon_i$

$\beta_1 =$

$\beta_2 =$

Example with two predictors



Omitted variable bias

What happens if the true regression model is

$$y_i = \beta_0 + \beta_1 x_{i,1} + \beta_2 x_{i,2} + \epsilon_i$$

but we ignore x_2 and fit the simple linear regression

$$y_i = \beta_0^* + \beta_1^* x_{i,1} + \epsilon_i^*$$

Does $\beta_1^* = \beta_1$?

Omitted variable bias

When should you be concerned?

If both of the following conditions are met, then $\beta_1^* = \beta_1$:

- The omitted variable is unrelated to the outcome
- The omitted variable is uncorrelated with the retained variable

Note: A Simpson's paradox can be explained by omitted variable bias.

Matrix notation

- Observe data $(y_i, x_{i1}, \ldots, x_{ip})$ for subjects $1, \ldots, n$. Want to estimate $\beta_0, \beta_1, \ldots, \beta_p$ in the model

$$y_i = \beta_0 + \beta_1 x_{i1} + \ldots + \beta_1 x_{ip} + \epsilon_i; \; \epsilon_i \overset{iid}{\sim} (0, \sigma^2)$$

- Notation is cumbersome. To fix this, let
  - $\mathbf{x}_i = [1, x_{i1}, \ldots, x_{ip}]$
  - $\boldsymbol{\beta}^T = [\beta_0, \beta_1, \ldots, \boldsymbol{\beta}_p]$
  - Then $y_i = \mathbf{x}_i \boldsymbol{\beta} + \epsilon_i$

Multiple linear regression

- Let

$$\mathbf{y} = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix}, \quad \mathbf{X} = \begin{bmatrix} 1 & x_{11} & \dots & x_{1p} \\ \vdots & \vdots & x_{ij} & \vdots \\ 1 & x_{n1} & \dots & x_{np} \end{bmatrix}, \quad \boldsymbol{\beta} = \begin{bmatrix} \beta_0 \\ \vdots \\ \beta_p \end{bmatrix}, \quad \boldsymbol{\epsilon} = \begin{bmatrix} \epsilon_1 \\ \vdots \\ \epsilon_n \end{bmatrix}$$

- Then we can write the model in a more compact form:

$$\mathbf{y}_{n\times 1} = \mathbf{X}_{n\times(p+1)}\boldsymbol{\beta}_{(p+1)\times 1} + \boldsymbol{\epsilon}_{n\times 1}$$

- $\mathbf{X}$ is called the *design matrix*

Matrix notation

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$$

- ϵ is a random vector rather than a random variable
- $E(\boldsymbol{\epsilon}) = 0$ and $Cov(\boldsymbol{\epsilon}) = \sigma^2 I$
- Note that *Cov* means the "variance-covariance matrix"

Mean, variance and covariance of a random vector

- Let $\mathbf{y}^T = [y_1, \ldots, y_n]$ be an n-component random vector. Then its mean and variance are defined as

$$\begin{aligned} E(\mathbf{y})^T &= [E(y_1), \ldots, E(y_n)] \\ Var(\mathbf{y}) &= E\left[(\mathbf{y} - E\mathbf{y})(\mathbf{y} - E\mathbf{y})^T\right] = E(\mathbf{y}\mathbf{y}^T) - (E\mathbf{y})(E\mathbf{y})^T \end{aligned}$$

- Let $\mathbf{y}$ and $\mathbf{z}$ be an n-component and an m-component random vector respectively. Then their covariance is an $n \times m$ matrix defined by

$$Cov(\mathbf{y}, \mathbf{z}) = E\left[(\mathbf{y} - E\mathbf{y})(\mathbf{z} - \mathbf{z})^T\right]$$

Coming up next...

Today we covered

- Motivation
- Assumptions
- Interpretation of βs
- More on confounding (omitted variable bias)
- Matrix notation for MLR

Next time...

- estimation (more least squares)
- more detailed model diagnostics
- inference