ROS Edits

- pg 52, second paragraph: The second paragraph says the distribution of women's heights has a mean of 63.7, but the R code directly under this codes for a mean of 64.5
- pg 71, section 6.1: the vector x is created with 10 values, 1:10. However, this same vector x is used on page 72 in an lm summary table. This R output shows x to have 20 values (n=20), rather than 10.
- pg 75: the R output displays n=16, but the text referencing this output has n=15 listed instead.
- pg 92: "From the model above, our point predict a 70-inch-tall person to have an income of...." appears to either be missing a word or contain a typo, and 'income' should be 'weight'
- pg 93, Figure 7.3: Histogram has no y-axis
- pg 216, Figure 13.1 caption: "When the standard error is small..." should be "When the standard error is big..."
- pg 258, Fig 15.9, Histogram has no y-axis
- pg 260, Fig 15.11, Histogram has a y-axis but no label
- This isn't so much an errata as it is a stylistic point, but the large numbers with spaces rather than commas looks funky (e.g pg 129, pg 140). I don't know if it's because Latex's math environment deleted it for some reason or if you purposefully use a space rather than a comma to 'improve readability', but it looks awkward. Scientific notation would alleviate the need for a comma, however.
- It would be nice to have the difference between δ and Δ defined somewhere in the book. It aids in the interpretation of equations.
- Because the material in Chapter 11 is so intense, having a table to aid in condensing the information would be extremely helpful. I've included one below that I made for Lizzie's course (1). Perhaps other readers might find it useful, as well?

Name	Data Type	Data Distribution	Link Function	Inverse Link Function	Notes
Linear	Continuous (-inf, inf)	Normal	$g(u) \equiv u$	u	Good for data where response trends linearly
Logistic (Logit)	Binary (0,1)	Bernoulli	$g(u) = log\left(\frac{u}{1-u}\right)$	$\frac{e^u}{(1+e^U)}$	(vs. Probit) Coefficients can be interpreted in terms of odds ratios
Probit	Binary (0,1)	Normal Cumulative	$g(u) = \phi^{-1}(u)$	$\phi(u)$	(vs. Logit) Can account for non-constant error variances
Robit	Binary (0,1)	Student-t	$g(u) = log\left(\frac{u}{1-u}\right)$	$\frac{e^u}{(1+e^U)}$	(vs. Logit/Probit) For use with binary data when outliers are present
Multinomial	Categorical [0,N]	Bernoulli	N-1 logit functions	N-1 inverse logit functions	Extension of Logit to categorical response variables
Logistic Binomial	Count (0,1,2…N)	Binomial/ Bernoulli	$g(u) = log\left(\frac{u}{1-u}\right)$	$\frac{e^u}{(1+e^U)}$	Bernoulli $\subset$ Binomial, count data for expected number of successes in N independent Bernoulli trials
Poisson	Count (0,1,2,3…)	Poisson	$g(u) = \ln(u)$	e^u	Suited to normally distributed count data

Figure 1: Summary table of generalized linear models.