Chapter 12: Linear regression II

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Stat 205: Elementary Statistics for the Biological and Life Sciences

12.4 The regression model

• We assume the underlying model with Greek letters (as usual)

$$y = \beta_0 + \beta_1 x + \epsilon$$

- For each subject *i* we see x_i and $y_i = \beta_0 + \beta_1 x_i + \epsilon_i$.
- β_0 is the population intercept.
- β_1 is the population slope.
- ϵ_i is the *i*th error, we assume these are $N(0, \sigma_e)$.
- We don't know any of β_0 , β_1 , or σ_e .

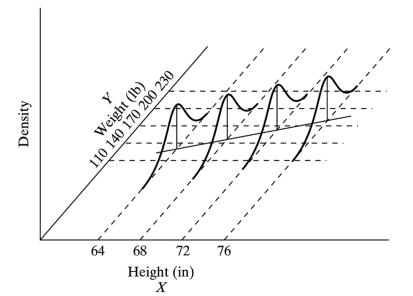
Visualizing the model

- $\mu_{y|x} = \beta_0 + \beta_1 x$ is mean response for <u>everyone</u> with covariate x.
- σ_e is constant variance. Variance doesn't change with x.
- Example 12.4.4, pretend we know that the mean weight $\mu_{y|x}$ given height x is

$$\mu_{y|x} = -145 + 4.25x$$
 and $\sigma_e = 20$.

Height (in) X	Mean weight (lb) $\mu_{Y X}$	Standard deviation of weights (lb) $\sigma_{Y X}$
64	127	20
68	144	20
72	161	20
76	178	20

Weight vs. height



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Estimating β_0 , β_1 , and σ_ϵ

- b_0 estimates β_0 .
- b_1 estimates β_1 .
- s_e estimates σ_e .
- Example 12.4.5. For the snake data, $b_0 = -301$ estimates β_0 , $b_1 = 7.19$ estimates β_1 , and $s_e = 12.5$ estimates σ_e .
- We estimate the the mean weight \hat{y} of snakes with length x as

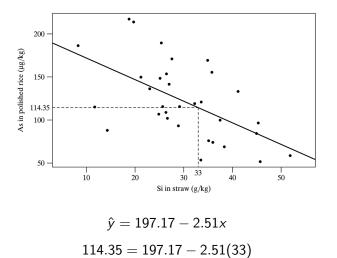
$$\hat{y} = -301 + 7.19x$$

Example 12.4.6 Arsenic in rice

- If we believe the data follow a line, we can estimate the mean for any x we want.
- $b_0 = 197.17$ estimates β_0 , $b_1 = 2.51$ estimates β_1 , and $s_e = 37.30$ estimates σ_e .
- For straw silicon concentration of x = 33 g/kg we estimate a mean arsenic level of

 $\hat{y} = 197.17 - 2.51(33) = 114.35 \,\mu {
m gm/kg}$ with $s_e = 37.30 \,\mu {
m gm/kg}$.

Arsenic in rice at X = 33 g/kg



12.5 Inference for β_1

- Often people want a 95% confidence interval for β_1 and want to test H_0 : $\beta_1 = 0$.
- If we reject H₀: β₁ = 0, then y is significantly linearly assocatied with x. Same as testing H₀: ρ = 0.
- A 95% confidence interval for β₁ gives us a range for how the mean changes when x is increased by one unit.
- Everything comes from

$$rac{b_1 - eta_0}{SE_{b_1}} \sim t_{n-2}, \ \ SE_{b_1} = rac{s_e}{s_x \sqrt{n-1}}.$$

- R automatically gives a P-value for testing H_0 : $\beta_1 = 0$.
- Need to ask R for 95% confidence interval for β_1 .

R code

```
> cons=c(112.6.102.1.90.2.81.5.105.6.93.0.106.6.108.3.73.3.84.8.67.3.55.3.
       80.7,90.0,75.5,77.1,38.5,81.3,57.1,62.3,51.5,48.3,42.7,57.9)
> fit=lm(cons~amph)
> summarv(fit)
Coefficients:
         Estimate Std. Error t value Pr(>|t|)
(Intercept) 99.331
                     3.680 26.99 < 2e-16 ***
amph
         -9.007 1.140 -7.90 7.27e-08 ***
_ _ _
Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 1
> confint(fit)
             2.5 %
                     97.5 %
(Intercept) 91.69979 106.962710
amph
         -11.37202 -6.642979
```

P-value for testing H_0 : $\beta_1 = 0$ vs. H_A : $\beta_1 \neq 0$ is 0.0000000727, we reject at the 5% level. We are 95% confidence that true mean consumption is reduced by 6.6 to 11.4 g/kg for every mg/kg increase in amphetamine dose.

Multiple regression

- Often there are more than one predictors we are interested in, say we have two x₁ and x₂.
- The model is easily extended to

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \epsilon$$

- Example: Dwayne Portrait Studio is doing a sales analysis based on data from n = 21 cities.
 - y = sales (thousands of dollars) for a city
 - x_1 = number of people 16 years or younger (thousands)
 - $x_2 = per capita disposable income (thousands of dollars)$

The data

<i>x</i> ₁	<i>x</i> ₂	у	<i>x</i> ₁	<i>x</i> ₂	у
68.5	16.7	174.4	45.2	16.8	164.4
91.3	18.2	244.2	47.8	16.3	154.6
46.9	17.3	181.6	66.1	18.2	207.5
49.5	15.9	152.8	52.0	17.2	163.2
48.9	16.6	145.4	38.4	16.0	137.2
87.9	18.3	241.9	72.8	17.1	191.1
88.4	17.4	232.0	42.9	15.8	145.3
52.5	17.8	161.1	85.7	18.4	209.7
41.3	16.5	146.4	51.7	16.3	144.0
89.6	18.1	232.6	82.7	19.1	224.1
52.3	16.0	166.5			

R code for multiple regression

```
> under16=c(68.5,45.2,91.3,47.8,46.9,66.1,49.5,52.0,48.9,38.4,87.9,72.8,88.4,42.9,52.5,
+
           85.7,41.3,51.7,89.6,82.7,52.3)
>
> income=c(16.7,16.8,18.2,16.3,17.3,18.2,15.9,17.2,16.6,16.0,18.3,17.1,17.4,15.8,17.8,
          18.4,16.5,16.3,18.1,19.1,16.0)
+
>
> sales=c(174.4,164.4,244.2,154.6,181.6,207.5,152.8,163.2,145.4,137.2,241.9,191.1,232.0,
         145.3,161.1,209.7,146.4,144.0,232.6,224.1,166.5)
> fit=lm(sales~under16+income)
> summarv(fit)
Call:
lm(formula = sales ~ under16 + income)
Residuals:
    Min
              10 Median
                               30
                                       Max
-18 4239 -6 2161 0 7449 9 4356 20 2151
Coefficients:
           Estimate Std. Error t value Pr(>|t|)
(Intercept) -68.8571 60.0170 -1.147 0.2663
under16
         1.4546 0.2118 6.868 2e-06 ***
       9.3655
                       4.0640 2.305 0.0333 *
income
---
Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 1
Residual standard error: 11.01 on 18 degrees of freedom
Multiple R-squared: 0.9167, Adjusted R-squared: 0.9075
```

F-statistic: 99.1 on 2 and 18 DF, p-value: 1.921e-10

Interpretation...

• The fitted regression *surface* is

```
sales = -68.857 + 1.455 (under 16) + 9.366 income.
```

- For every unit increase (1000 people) in those under 16, average sales go up 1.455 thousand, \$1,455.
- For every unit increase (\$1000) in disposable income, average sales go up 9.366 thousand, \$9,366.
- 91.67% of the variability in sales is explained by those under 16 and disposable income.
- σ_e is estimated to be 11.01.

Regression homework

- 12.2.5, 12.2.7, 12.3.1, 12.3.3, 12.3.5, 12.3.7, 12.3.8. Use R for all problems; i.e. don't do anything by hand.
- 12.4.3, 12.4.6, 12.4.8, 12.4.9, 12.5.1, 12.5.3, 12.5.5, 12.5.9(a). Use R for all problems; don't do anything by hand.