R05 - Multiple Regression

STAT 587 (Engineering)
Iowa State University

October 30, 2020

Multiple regression

Recall the simple linear regression model is

$$Y_i \stackrel{ind}{\sim} N(\mu_i, \sigma^2), \quad \mu_i = \beta_0 + \beta_1 X_i$$

The multiple regression model has mean

$$\mu_i = \beta_0 + \beta_1 X_{i,1} + \cdots + \beta_p X_{i,p}$$

where for observation i

- Y_i is the response and
- $X_{i,p}$ is the p^{th} explanatory variable.

Explanatory variables

There is a lot of flexibility in the mean

$$\mu_i = \beta_0 + \beta_1 X_{i,1} + \cdots + \beta_p X_{i,p}$$

as there are many possibilities for the explanatory variables $X_{i,1}, \ldots, X_{i,p}$:

- Functions ($f(X)$)
- Dummy variables for categorical variables ($X_1 = \mathrm{I}()$)
- Higher order terms (X^2)
- Additional explanatory variables (X_1, X_2)
- Interactions ($X_1 X_2$)
  - Continuous-continuous
  - Continuous-categorical
  - Categorical-categorical

Parameter interpretation

Model:

$$Y_i \stackrel{ind}{\sim} N(\beta_0 + \beta_1 X_{i,1} + \cdots + \beta_p X_{i,p}, \sigma^2)$$

The interpretation is

- β_0 is the expected value of the response Y_i when all explanatory variables are zero.
- β_p, $p \neq 0$ is the expected increase in the response for a one-unit increase in the p^{th} explanatory variable when all other explanatory variables are held constant.
- R^2 is the proportion of the variability in the response explained by the model

Parameter estimation and inferece

Let

$$y = X\beta + \epsilon$$

where

- $y = (y_1, \ldots, y_n)^\top$
- X is $n \times p$ with ith row $X_i = (1, X_{i,1}, \ldots, X_{i,p})$
- $\beta = (\beta_0, \beta_1, \ldots, \beta_p)^\top$
- $\epsilon = (\epsilon_1, \ldots, \epsilon_n)^\top$

Then we have

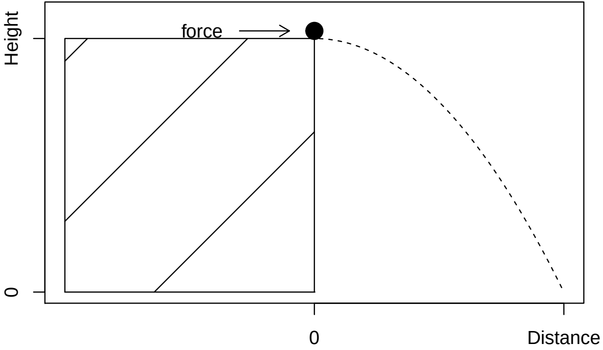
$$\begin{aligned} \hat{\beta} &= (X^\top X)^{-1} X^\top y \\ Var(\hat{\beta}) &= \sigma^2 (X^\top X)^{-1} \\ r &= y - X\hat{\beta} \\ \hat{\sigma}^2 &= \frac{1}{n-(p+1)} r^\top r \end{aligned}$$

Confidence/credible intervals and (two-sided) p-values are constructed using

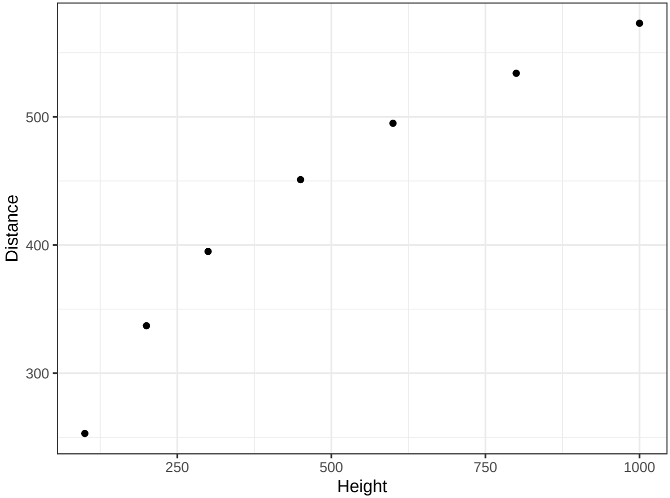
$$\hat{\beta}_j \pm t_{n-(p+1),1-a/2} SE(\hat{\beta}_j) \quad \text{and} \quad \text{pvalue} = 2P\left(T_{n-(p+1)} > \left|\frac{\hat{\beta}_j - b_j}{SE(\hat{\beta}_j)}\right|\right)$$

where $T_{n-(p+1)} \sim t_{n-(p+1)}$ and $SE(\hat{\beta}_j)$ is the jth diagonal element of $\hat{\sigma}^2 (X^\top X)^{-1}$.

Galileo experiment



Galileo data (Sleuth3::case1001)



Higher order terms (X^2)

Let

- Y_i be the distance for the i^{th} run of the experiment and
- H_i be the height for the i^{th} run of the experiment.

Simple linear regression assumes

$$Y_i \stackrel{ind}{\sim} N(\beta_0 + \beta_1 H_i \qquad\qquad\qquad\qquad, \sigma^2)$$

The quadratic multiple regression assumes

$$Y_i \stackrel{ind}{\sim} N(\beta_0 + \beta_1 H_i + \beta_2 H_i^2 \qquad\qquad, \sigma^2)$$

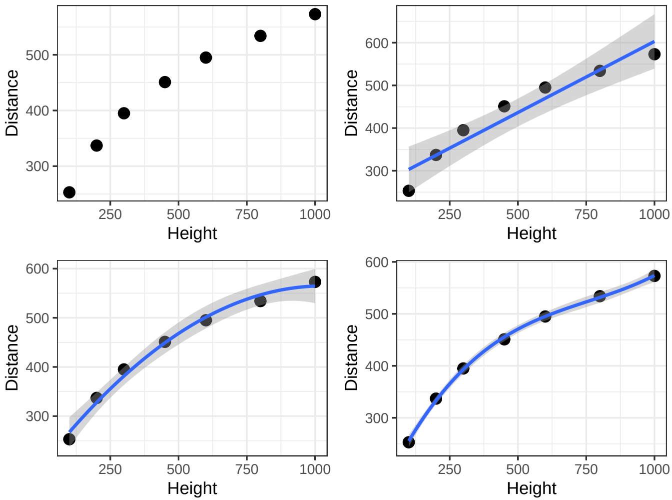
The cubic multiple regression assumes

$$Y_i \stackrel{ind}{\sim} N(\beta_0 + \beta_1 H_i + \beta_2 H_i^2 + \beta_3 H_i^3, \sigma^2)$$

R code and output

```
# Construct the variables by hand
m1 = lm(Distance ~ Height,                              case1001)
m2 = lm(Distance ~ Height + I(Height^2),                case1001)
m3 = lm(Distance ~ Height + I(Height^2) + I(Height^3), case1001)

coefficients(m1)

(Intercept)      Height
 269.712458    0.333337

coefficients(m2)

  (Intercept)        Height   I(Height^2)
 1.999128e+02  7.083225e-01 -3.436937e-04

coefficients(m3)

  (Intercept)        Height   I(Height^2)   I(Height^3)
 1.557755e+02  1.115298e+00 -1.244943e-03  5.477104e-07
```

Galileo experiment (Sleuth3::case1001)



Longnose Dace Abundance

From `http://udel.edu/~mcdonald/statmultreg.html`:

> *I extracted some data from the Maryland Biological Stream Survey. ... The [response] variable is the number of Longnose Dace ... per 75-meter section of [a] stream. The [explanatory] variables are ... the maximum depth (in cm) of the 75-meter segment of stream; nitrate concentration (mg/liter) ....*

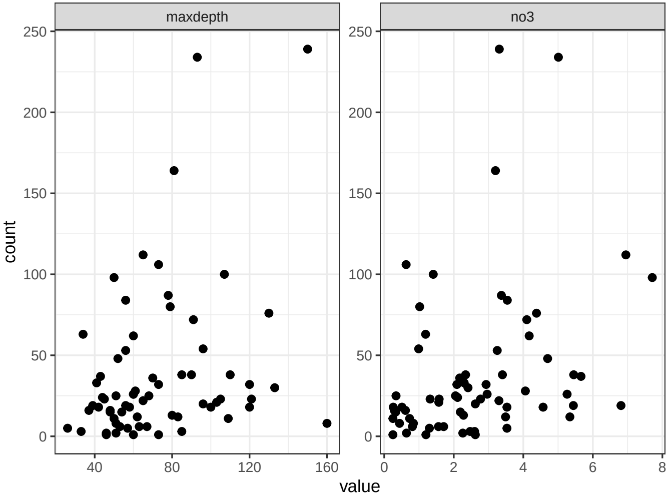
Consider the model

$$Y_i \stackrel{ind}{\sim} N(\beta_0 + \beta_1 X_{i,1} + \beta_2 X_{i,2}, \sigma^2)$$

where

- Y_i: count of Longnose Dace in stream i
- $X_{i,1}$: maximum depth (in cm) of stream i
- $X_{i,2}$: nitrate concentration (mg/liter) of stream i

Exploratory



R code and output

```
m <- lm(count ~ maxdepth + no3, longnosedace)
summary(m)

Call:
lm(formula = count ~ maxdepth + no3, data = longnosedace)

Residuals:
    Min      1Q  Median      3Q     Max
-55.060 -27.704  -8.679  11.794 165.310

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -17.5550    15.9586  -1.100  0.27544
maxdepth      0.4811     0.1811   2.656  0.00997 **
no3           8.2847     2.9566   2.802  0.00671 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 43.39 on 64 degrees of freedom
Multiple R-squared:  0.1936,Adjusted R-squared:  0.1684
F-statistic: 7.682 on 2 and 64 DF,  p-value: 0.001022
```

Interpretation

- Intercept (β_0): The expected count of Longnose Dace when maximum depth and nitrate concentration are both zero is -18.
- Coefficient for maxdepth (β_1): Holding nitrate concentration constant, each cm increase in maximum depth is associated with an additional 0.48 Longnose Dace counted on average.
- Coefficient for no3 (β_2): Holding maximum depth constant, each mg/liter increase in nitrate concentration is associated with an addition 8.3 Longnose Dace counted on average.
- Coefficient of determination (R^2): The model explains 19% of the variability in the count of Longnose Dace.

Interactions

Why an interaction?

> *Two explanatory variables are said to interact if the effect that one of them has on the mean response depends on the value of the other.*

For example,

- Longnose dace count: The effect of nitrate (no3) on longnose dace count depends on the maxdepth. (Continuous-continuous)
- Energy expenditure: The effect of mass depends on the species type. (Continuous-categorical)
- Crop yield: the effect of tillage method depends on the fertilizer brand (Categorical-categorical)

Continuous-continuous interaction

For observation i, let

- Y_i be the response
- $X_{i,1}$ be the first explanatory variable and
- $X_{i,2}$ be the second explanatory variable.

The mean containing only main effects is

$$\mu_i = \beta_0 + \beta_1 X_{i,1} + \beta_2 X_{i,2}.$$

The mean with the interaction is

$$\mu_i = \beta_0 + \beta_1 X_{i,1} + \beta_2 X_{i,2} + \beta_3 X_{i,1} X_{i,2}.$$

Intepretation - main effects only

Let $X_{i,1} = x_1$ and $X_{i,2} = x_2$, then we can rewrite the line (μ) as

$$\mu = (\beta_0 + \beta_2 x_2) + \beta_1 x_1$$

which indicates that the intercept of the line for x_1 depends on the value of x_2.

Similarly,

$$\mu = (\beta_0 + \beta_1 x_1) + \beta_2 x_2$$

which indicates that the intercept of the line for x_2
depends on the value of x_1.

Intepretation - with an interaction

Let $X_{i,1} = x_1$ and $X_{i,2} = x_2$, then we can rewrite the mean (μ) as

$$\mu = (\beta_0 + \beta_2 x_2) + (\beta_1 + \beta_3 x_2) x_1$$

which indicates that both the intercept and slope for x_1 depend on the value of x_2.

Similarly,

$$\mu = (\beta_0 + \beta_1 x_1) + (\beta_2 + \beta_3 x_1) x_2$$

which indicates that both the intercept and slope for x_2
depend on the value of x_1.

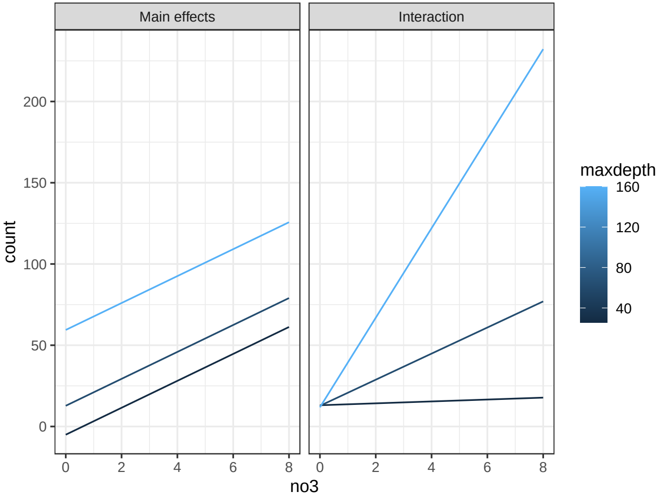
R code and output - main effects only

```
Call:
lm(formula = count ~ no3 + maxdepth, data = longnosedace)

Residuals:
    Min      1Q  Median      3Q     Max 
-55.060 -27.704  -8.679  11.794 165.310 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)   
(Intercept) -17.5550    15.9586  -1.100  0.27544   
no3           8.2847     2.9566   2.802  0.00671 **
maxdepth      0.4811     0.1811   2.656  0.00997 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 43.39 on 64 degrees of freedom
Multiple R-squared:  0.1936,Adjusted R-squared:  0.1684 
F-statistic: 7.682 on 2 and 64 DF,  p-value: 0.001022
```

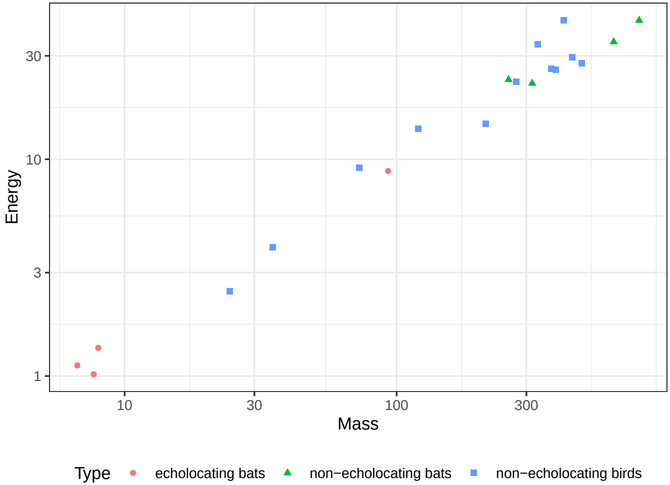
R code and output - with an interaction

```
Call:
lm(formula = count ~ no3 * maxdepth, data = longnosedace)

Residuals:
    Min      1Q  Median      3Q     Max 
-65.111 -21.399  -9.562   5.953 151.071 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)  
(Intercept)  13.321043  23.455710   0.568   0.5721  
no3          -4.646272   7.856932  -0.591   0.5564  
maxdepth     -0.009338   0.329180  -0.028   0.9775  
no3:maxdepth  0.201219   0.113576   1.772   0.0813 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 42.68 on 63 degrees of freedom
Multiple R-squared:  0.2319,Adjusted R-squared:  0.1953 
F-statistic: 6.339 on 3 and 63 DF,  p-value: 0.0007966
```

Visualizing the model



In-flight energy expenditure (Sleuth3::case1002)



Continuous-categorical interaction

Let category A be the reference level. For observation i, let

- Y_i be the response
- $X_{i,1}$ be the continuous explanatory variable,
- B_i be a dummy variable for category B, and
- C_i be a dummy variable for category C.

The mean containing only main effects is

$$\mu_i = \beta_0 + \beta_1 X_{i,1} + \beta_2 B_i + \beta_3 C_i.$$

The mean with the interaction is

$$\mu_i = \beta_0 + \beta_1 X_{i,1} + \beta_2 B_i + \beta_3 C_i + \beta_4 X_{i,1} B_i + \beta_5 X_{i,1} C_i.$$

Interpretation for the main effect model

The mean containing only main effects is

$$\mu_i = \beta_0 + \beta_1 X_{i,1} + \beta_2 B_i + \beta_3 C_i.$$

For each category, the line is

Category	Line (μ)		
A	β_0	$+$	$\beta_1 X$
B	$(\beta_0 + \beta_2)$	$+$	$\beta_1 X$
C	$(\beta_0 + \beta_3)$	$+$	$\beta_1 X$

Each category has a different intercept, but a common slope.

Interpretation for the model with an interaction

The model with an interaction is

$$\mu_i = \beta_0 + \beta_1 X_{i,1} + \beta_2 B_i + \beta_3 C_i + \beta_4 X_{i,1} B_i + \beta_5 X_{i,1} C_i$$

For each category, the line is

Category	Line (μ)		
A	β_0	$+\ \beta_1$	X
B	$(\beta_0 + \beta_2)$	$+(\beta_1 + \beta_4)$	X
C	$(\beta_0 + \beta_3)$	$+(\beta_1 + \beta_5)$	X

Each category has its own intercept and its own slope.

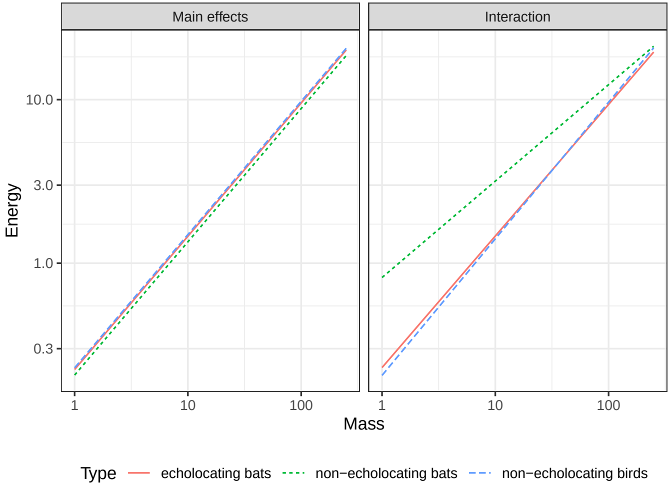
R code and output - main effects only

```
summary(mM <- lm(log(Energy) ~ log(Mass) + Type, case1002))

Call:
lm(formula = log(Energy) ~ log(Mass) + Type, data = case1002)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.23224 -0.12199 -0.03637  0.12574  0.34457 

Coefficients:
                           Estimate Std. Error t value Pr(>|t|)    
(Intercept)                -1.49770    0.14987  -9.993 2.77e-08 ***
log(Mass)                   0.81496    0.04454  18.297 3.76e-12 ***
Typenon-echolocating bats  -0.07866    0.20268  -0.388    0.703    
Typenon-echolocating birds  0.02360    0.15760   0.150    0.883    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.186 on 16 degrees of freedom
Multiple R-squared:  0.9815,Adjusted R-squared:  0.9781 
F-statistic: 283.6 on 3 and 16 DF,  p-value: 4.464e-14
```

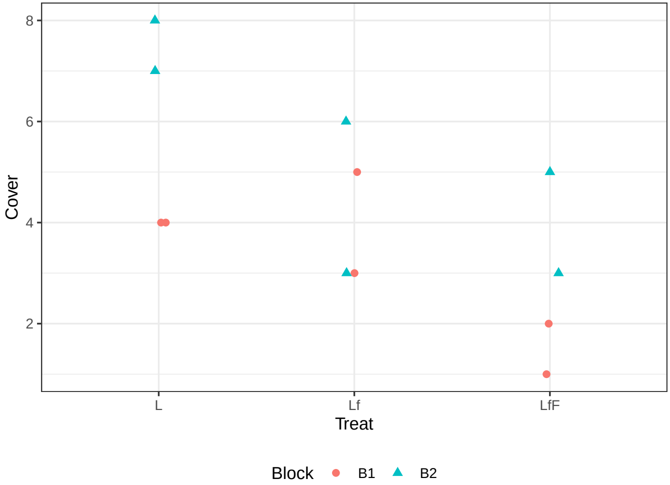
R code and output - with an interaction

```
summary(mI <- lm(log(Energy) ~ log(Mass) * Type, case1002))

Call:
lm(formula = log(Energy) ~ log(Mass) * Type, data = case1002)

Residuals:
     Min       1Q   Median       3Q      Max
-0.25152 -0.12643 -0.00954  0.08124  0.32840

Coefficients:
                                     Estimate Std. Error t value Pr(>|t|)
(Intercept)                          -1.47052    0.24767  -5.937 3.63e-05 ***
log(Mass)                             0.80466    0.08668   9.283 2.33e-07 ***
Typenon-echolocating bats             1.26807    1.28542   0.987    0.341
Typenon-echolocating birds           -0.11032    0.38474  -0.287    0.779
log(Mass):Typenon-echolocating bats  -0.21487    0.22362  -0.961    0.353
log(Mass):Typenon-echolocating birds  0.03071    0.10283   0.299    0.770
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1899 on 14 degrees of freedom
Multiple R-squared:  0.9832,Adjusted R-squared:  0.9771
F-statistic: 163.4 on 5 and 14 DF,  p-value: 6.696e-12
```

Visualizing the models



Seaweed regeneration (Sleuth3::case1301 subset)



Categorical-categorical

Let category A and type 0 be the reference level. For observation i, let

- Y_i be the response,
- 1_i be a dummy variable for type 1,
- B_i be a dummy variable for category B, and
- C_i be a dummy variable for category C.

The mean containing only main effects is

$$\mu_i = \beta_0 + \beta_1 1_i + \beta_2 B_i + \beta_3 C_i.$$

The mean with an interaction is

$$\mu_i = \beta_0 + \beta_1 1_i + \beta_2 B_i + \beta_3 C_i + \beta_4 1_i B_i + \beta_5 1_i C_i.$$

Interpretation for the main effects model

The mean containing only main effects is

$$\mu_i = \beta_0 + \beta_1 1_i + \beta_2 B_i + \beta_3 C_i.$$

The means in the main effect model are

	Category		
Type	A	B	C
0	β_0	$\beta_0 + \beta_2$	$\beta_0 + \beta_3$
1	$\beta_0 + \beta_1$	$\beta_0 + \beta_1 + \beta_2$	$\beta_0 + \beta_1 + \beta_3$

Interpretation for the model with an interaction

The mean with an interaction is

$$\mu_i = \beta_0 + \beta_1 1_i + \beta_2 B_i + \beta_3 C_i + \beta_4 1_i B_i + \beta_5 1_i C_i.$$

The means are

	Category		
Type	A	B	C
0	β_0	$\beta_0 \quad + \beta_2$	$\beta_0 \quad + \beta_3$
1	$\beta_0 + \beta_1$	$\beta_0 + \beta_1 + \beta_2 + \beta_4$	$\beta_0 + \beta_1 + \beta_3 + \beta_5$

This is equivalent to a cell-means model where each combination has its own mean.

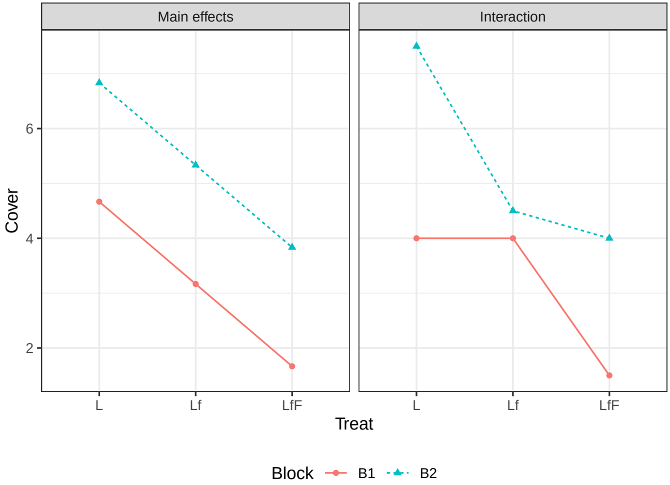
R code and output - main effects only

```
Call:
lm(formula = Cover ~ Block + Treat, data = case1301_subset)

Residuals:
    Min      1Q  Median      3Q     Max
-2.3333 -0.6667  0.0000  0.7917  1.8333

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   4.6667     0.7683   6.074 0.000298 ***
BlockB2       2.1667     0.7683   2.820 0.022491 *
TreatLf      -1.5000     0.9410  -1.594 0.149578
TreatLfF     -3.0000     0.9410  -3.188 0.012838 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.331 on 8 degrees of freedom
Multiple R-squared:  0.6937,Adjusted R-squared:  0.5788
F-statistic: 6.039 on 3 and 8 DF,  p-value: 0.01881
```

R code and output - with an interaction

```
Call:
lm(formula = Cover ~ Block * Treat, data = case1301_subset)

Residuals:
   Min     1Q Median     3Q    Max
-1.500 -0.625  0.000  0.625  1.500

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)      4.000e+00  8.898e-01   4.496  0.00412 **
BlockB2          3.500e+00  1.258e+00   2.782  0.03193 *
TreatLf         -2.719e-16  1.258e+00   0.000  1.00000
TreatLfF        -2.500e+00  1.258e+00  -1.987  0.09413 .
BlockB2:TreatLf  -3.000e+00  1.780e+00  -1.686  0.14280
BlockB2:TreatLfF -1.000e+00  1.780e+00  -0.562  0.59450
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.258 on 6 degrees of freedom
Multiple R-squared:  0.7946,Adjusted R-squared:  0.6234
F-statistic: 4.642 on 5 and 6 DF,  p-value: 0.04429
```

Visualizing the models



When to include interaction terms

From The Statistical Sleuth (3rd ed) page 250:

- when a question of interest pertains to an interaction
- when good reason exists to suspect an interaction or
- when interactions are proposed as a more general model for the purpose of examining the goodness of fit of a model without interaction.

Multiple regression explanatory variables

The possibilities for explanatory variables are

- Higher order terms (X^2)
- Additional explanatory variables (X_1 and X_2)
- Dummy variables for categorical variables ($X_1 = \mathrm{I}()$)
- Interactions ($X_1 X_2$)
  - Continuous-continuous
  - Continuous-categorical
  - Categorical-categorical

We can also combine these explanatory variables, e.g.

- including higher order terms for continuous variables along with dummy variables for categorical variables and
- including higher order interactions ($X_1 X_2 X_3$).