

R05 - Multiple Regression

STAT 587 (Engineering)
Iowa State University

March 30, 2021

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 $X_{i,1}, \dots, X_{i,p}$:

- Functions ($f(X)$)
- Dummy variables for categorical variables ($X_1 = I()$)
- 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.
- $\beta_p, p \neq 0$ 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 inference

Let

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

where

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

Then we have

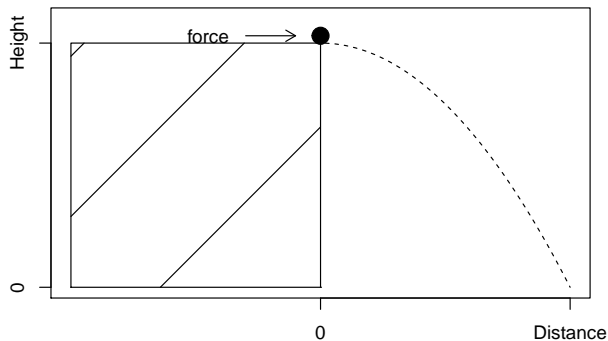
$$\begin{aligned}\hat{\beta} &= (X^\top X)^{-1} X^\top y \\ \text{Var}(\hat{\beta}) &= \sigma^2 (X^\top X)^{-1} \\ r &= y - X\hat{\beta} \\ \hat{\sigma}^2 &= \frac{1}{n-(p+1)} r^\top r\end{aligned}$$

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

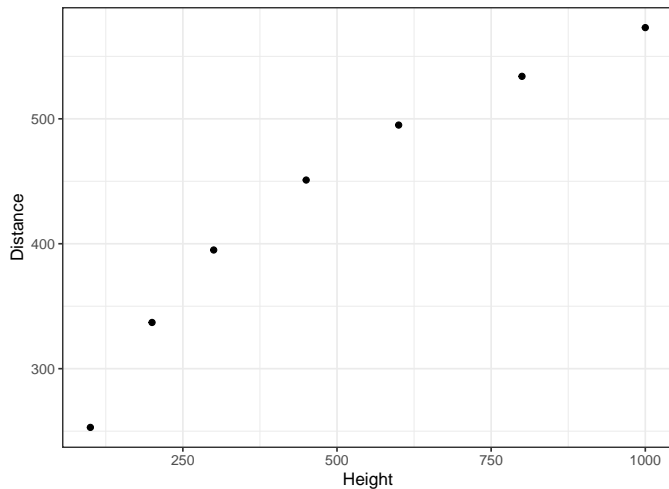
$$\hat{\beta}_j \pm t_{n-(p+1), 1-\alpha/2} SE(\hat{\beta}_j) \quad \text{and} \quad \text{pvalue} = 2P\left(T_{n-(p+1)} > \left| \frac{\hat{\beta}_j - b_j}{SE(\hat{\beta}_j)} \right| \right)$$

where $T_{n-(p+1)} \sim t_{n-(p+1)}$ and $SE(\hat{\beta}_j)$ is the j th 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

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

The quadratic multiple regression assumes

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

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
```

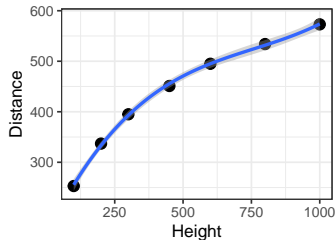
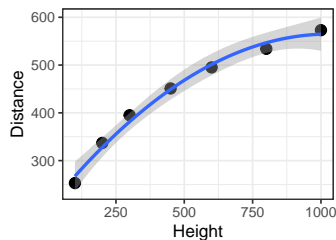
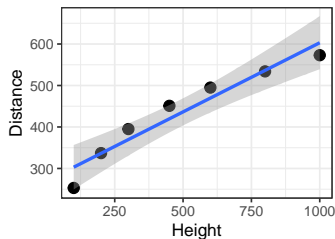
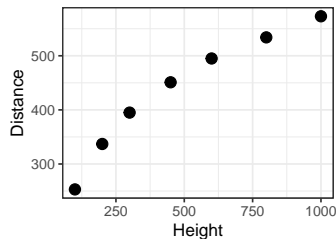
```
coefficients(m2)
```

```
(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)

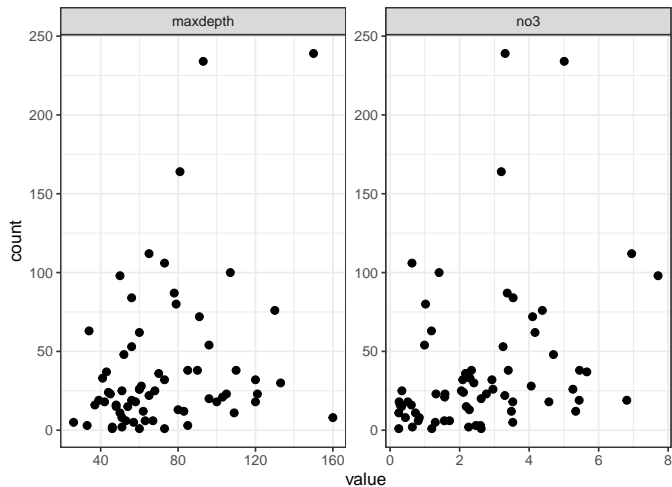
Consider the model

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

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

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

Interpretation - 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

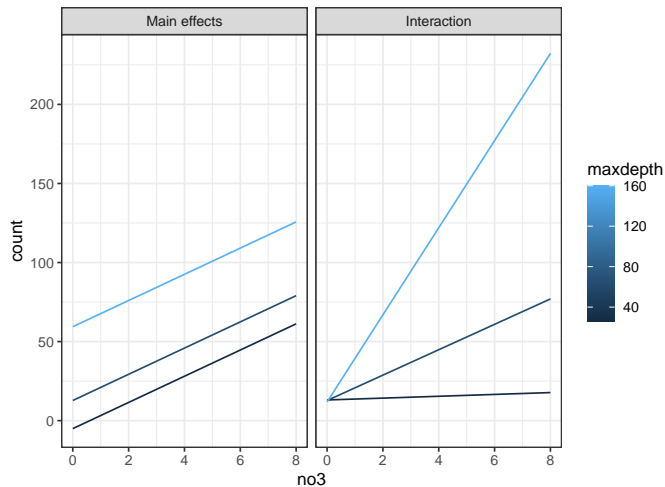
```
Call:
lm(formula = count ~ no3 * maxdepth, data = longnosedace)

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

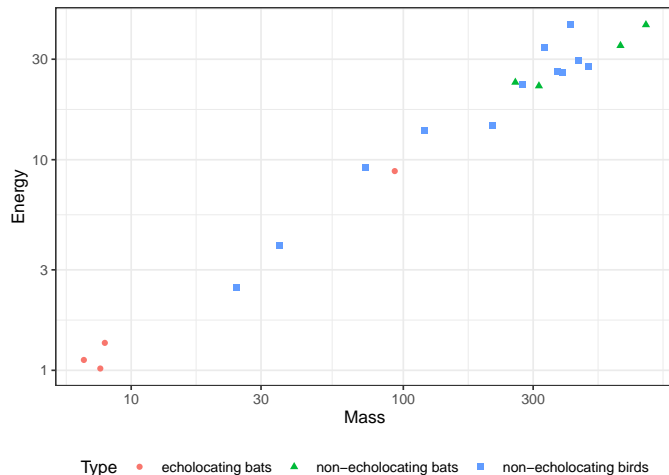
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  13.321043   23.455710   0.568  0.5721
no3          -4.646272    7.856932  -0.591  0.5564
maxdepth     -0.009338    0.329180  -0.028  0.9775
no3:maxdepth  0.201219    0.113576   1.772  0.0813 .
---
Signif. codes:  0 '***' 0.001 '**' 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	***
Type non-echolocating bats	-0.07866	0.20268	-0.388	0.703	
Type non-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

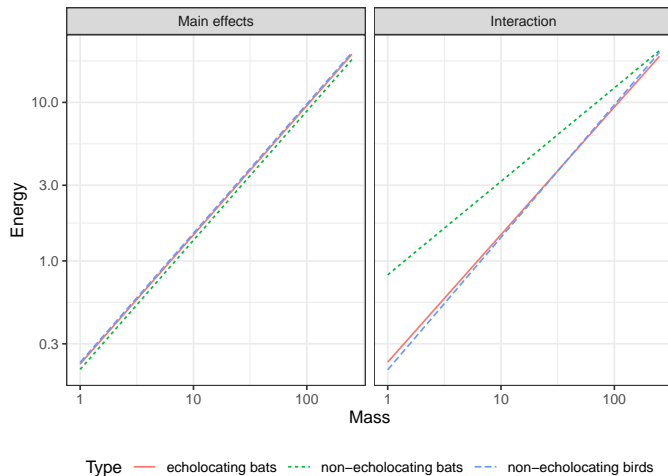
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1899 on 14 degrees of freedom

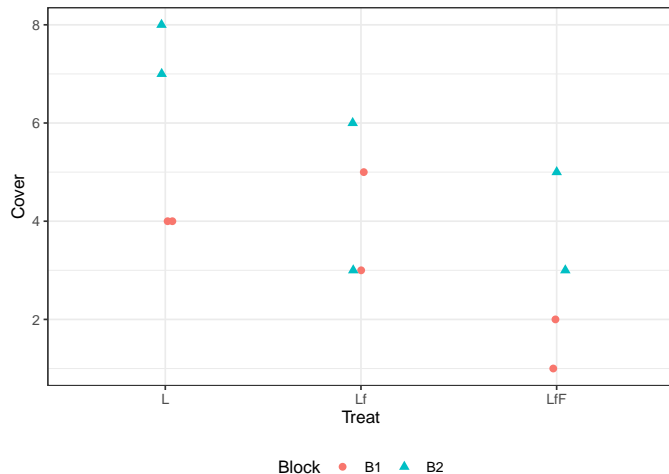
Multiple R-squared: 0.9832, Adjusted R-squared: 0.9771

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

Type	Category		
	<i>A</i>	<i>B</i>	<i>C</i>
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

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

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

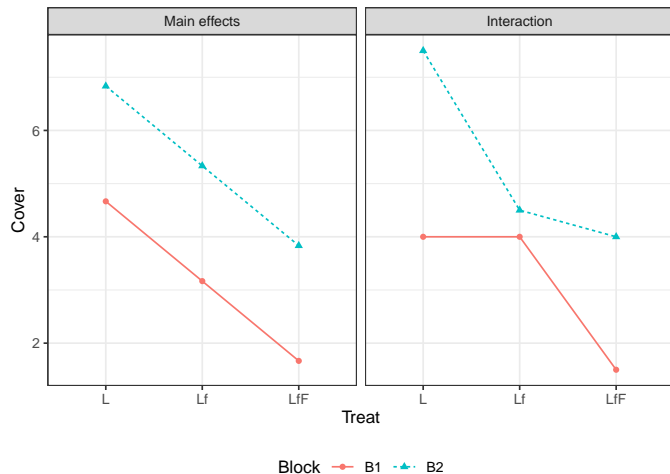
```
Call:
lm(formula = Cover ~ Block * Treat, data = case1301_subset)

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 ($X_1 = I()$)
- Interactions (X_1X_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 ($X_1X_2X_3$).