

R05 - Multiple Regression

STAT 401 (Engineering) - Iowa State University

March 25, 2018

Multiple regression

Recall the simple linear regression model is

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

The **multiple regression model** is

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

where

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

We may also write

$$Y_i \stackrel{ind}{\sim} N(\mu_i, \sigma^2) \quad \text{or} \quad Y_i = \mu_i + e_i, e_i \stackrel{iid}{\sim} N(0, \sigma^2)$$

where

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

Explanatory variables

There is a lot of flexibility in the mean

$$\mu_i = E[Y_i | X_{i,1}, \dots, X_{i,p}] = \beta_0 + \beta_1 X_{i,1} + \dots + \beta_p X_{i,p}$$

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

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

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

Let

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

where

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

Then we have

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

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

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

where $SE(\hat{\beta}_j)$ is the j th diagonal element of $\hat{\sigma}^2 (X^\top X)^{-1}$.

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

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

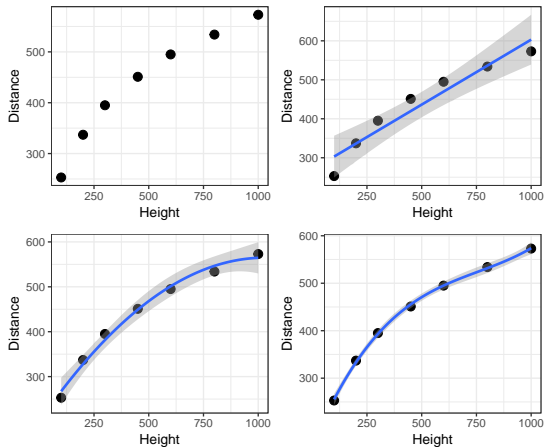
The quadratic multiple regression assumes

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

The cubic multiple regression assumes

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

Case1001



R code and output

```
# Construct the variables by hand
case1001$Height2 = case1001$Height^2
case1001$Height3 = case1001$Height^3

m1 = lm(Distance~Height,          case1001)
m2 = lm(Distance~Height+Height2,  case1001)
m3 = lm(Distance~Height+Height2+Height3, case1001)

coefficients(m1)

(Intercept)      Height
269.712458      0.333337

coefficients(m2)

(Intercept)      Height      Height2
1.999128e+02  7.083225e-01 -3.436937e-04

coefficients(m3)

(Intercept)      Height      Height2      Height3
1.557755e+02  1.115298e+00 -1.244943e-03  5.477104e-07
```


R code and output

```
# Let R construct the variables for you
m = lm(Distance~poly(Hight, 3, raw=TRUE), case1001)
summary(m)
```

Call:
lm(formula = Distance ~ poly(Hight, 3, raw = TRUE), data = case1001)

Residuals:

1	2	3	4	5	6	7
-2.40359	3.58091	1.89175	-4.46885	-0.08044	2.32159	-0.84138

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	1.558e+02	8.326e+00	18.710	0.000333 ***
poly(Hight, 3, raw = TRUE)1	1.115e+00	6.567e-02	16.983	0.000445 ***
poly(Hight, 3, raw = TRUE)2	-1.245e-03	1.384e-04	-8.994	0.002902 **
poly(Hight, 3, raw = TRUE)3	5.477e-07	8.327e-08	6.577	0.007150 **

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

Residual standard error: 4.011 on 3 degrees of freedom
Multiple R-squared: 0.9994, Adjusted R-squared: 0.9987
F-statistic: 1595 on 3 and 3 DF, p-value: 2.662e-05

Longnose Dace Abundance

From <http://udel.edu/~mcdonald/statmultreg.html>:

*I extracted some data from the Maryland Biological Stream Survey. ... The dependent variable is the number of Longnose Dace (*Rhinichthys cataractae*) per 75-meter section of [a] stream. The independent variables are the area (in acres) drained by the stream; the dissolved oxygen (in mg/liter); the maximum depth (in cm) of the 75-meter segment of stream; nitrate concentration (mg/liter); sulfate concentration (mg/liter); and the water temperature on the sampling date (in degrees C).*

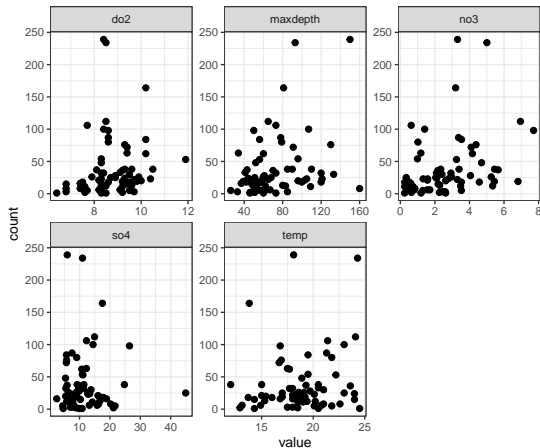
Consider the model

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

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~no3+maxdepth, longnosedace)
summary(m)
```

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 **

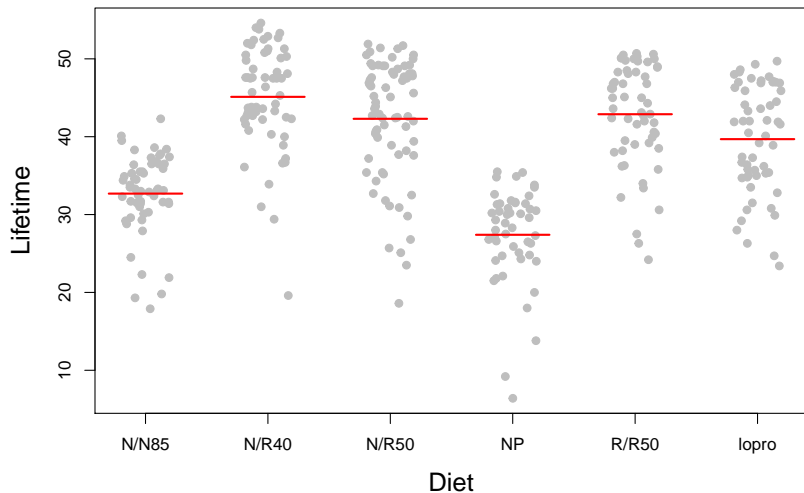
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

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

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.

Using a categorical variable as an explanatory variable.



Regression with a categorical variable

- Choose one of the levels as the **reference** level, e.g. N/N85
- Construct dummy variables using indicator functions, i.e.

$$I(A) = \begin{cases} 1 & A \text{ is TRUE} \\ 0 & A \text{ is FALSE} \end{cases}$$

for the other levels, e.g.

$$X_{i,1} = I(\text{diet for observation } i \text{ is N/R40})$$

$$X_{i,2} = I(\text{diet for observation } i \text{ is N/R50})$$

$$X_{i,3} = I(\text{diet for observation } i \text{ is NP})$$

$$X_{i,4} = I(\text{diet for observation } i \text{ is R/R50})$$

$$X_{i,5} = I(\text{diet for observation } i \text{ is loopro})$$

- Estimate the parameters of a multiple regression model using these dummy variables.

R code and output

```
# by default, R uses the alphabetically first group as the reference level
case0501$Diet = relevel(case0501$Diet, ref='N/N85')
```

```
m = lm(Lifetime~Diet, case0501)
summary(m)
```

Call:

```
lm(formula = Lifetime ~ Diet, data = case0501)
```

Residuals:

Min	1Q	Median	3Q	Max
-25.5167	-3.3857	0.8143	5.1833	10.0143

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	32.6912	0.8846	36.958	< 2e-16 ***
DietN/R40	12.4254	1.2352	10.059	< 2e-16 ***
DietN/R50	9.6060	1.1877	8.088	1.06e-14 ***
DietNP	-5.2892	1.3010	-4.065	5.95e-05 ***
DietR/R50	10.1945	1.2565	8.113	8.88e-15 ***
Dietlopro	6.9945	1.2565	5.567	5.25e-08 ***

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

Residual standard error: 6.678 on 343 degrees of freedom

Multiple R-squared: 0.4543, Adjusted R-squared: 0.4463

F-statistic: 57.1 on 5 and 343 DF, p-value: < 2.2e-16

Interpretation

- $\beta_0 = E[Y_i | \text{reference level}]$, i.e. expected response for the reference level

Note: the only way $X_{i,1} = \dots = X_{i,p} = 0$ is if all indicators are zero, i.e. at the reference level.

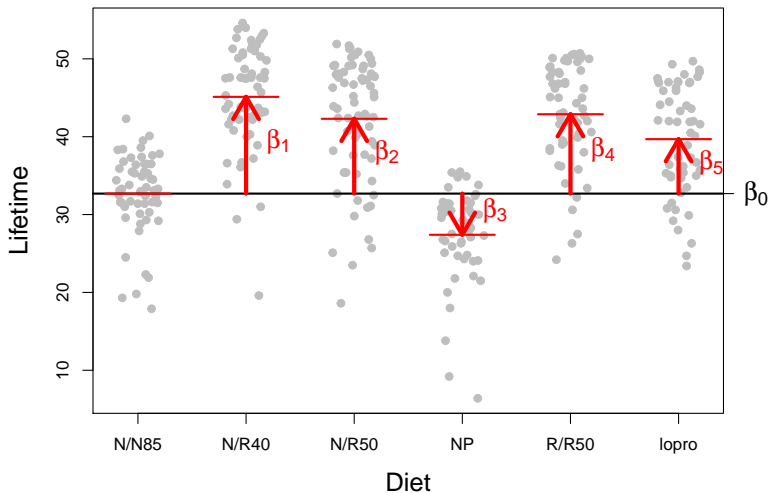
- $\beta_p, p > 0$: expected change in the response moving from the reference level to the level associated with the p^{th} dummy variable

Note: the only way for $X_{i,p}$ to increase by one and all other indicators to stay constant is if initially $X_{i,1} = \dots = X_{i,p} = 0$ and now $X_{i,p} = 1$

For example,

- The expected lifetime for mice on the N/N85 diet is 32.7 weeks.
- The expected increase in lifetime for mice on the N/R40 diet compared to the N/N85 diet is 12.4 weeks.
- The model explains 45% of the variability in mice lifetimes.

Using a categorical variable as an explanatory variable.



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: The effect of nitrate (no3) on longnose dace count depends on the maxdepth. (Continuous-continuous)
- Case1002: The effect of mass on energy depends on the species type. (Continuous-categorical)
- 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 .

Interpretation - 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 .

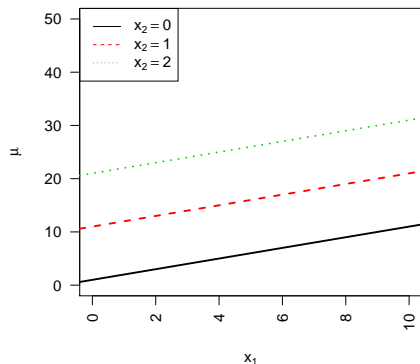
Similarly,

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

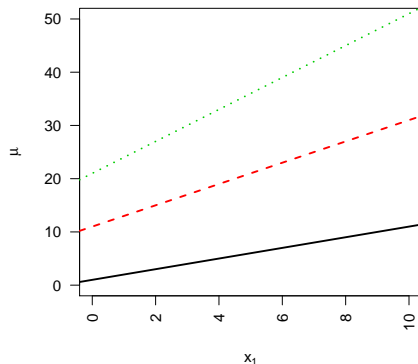
which indicates that both the intercept and slope for x_2 depend on the value of x_1 .

Visualizing the models

Main effects only



with an interaction



R code and output - main effects only

```
mM = lm(count ~ no3+maxdepth, longnosedace)
summary(mM)
```

```
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

```
mI = lm(count ~ no3*maxdepth, longnosedace)
summary(mI)
```

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:

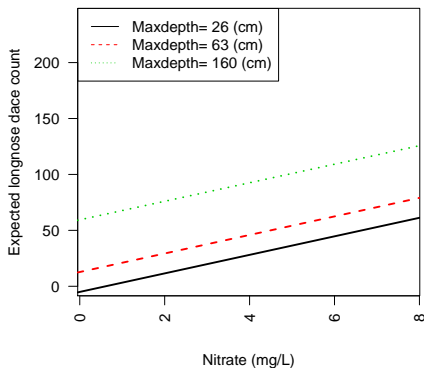
	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	13.321043	23.455710	0.568	0.5721
no3	-4.646272	7.856932	-0.591	0.5564
maxdepth	-0.009338	0.329180	-0.028	0.9775
no3:maxdepth	0.201219	0.113576	1.772	0.0813

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

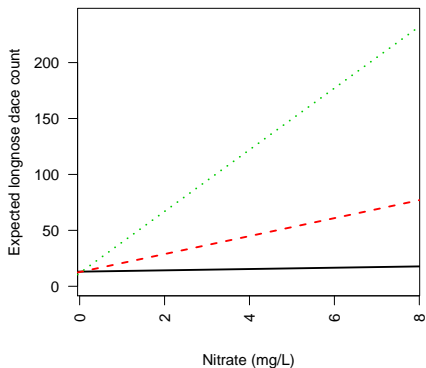
Residual standard error: 42.68 on 63 degrees of freedom
Multiple R-squared: 0.2319, Adjusted R-squared: 0.1953
F-statistic: 6.339 on 3 and 63 DF, p-value: 0.0007966

Visualizing the model

Main effects only



with an interaction



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

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

Think about this model as a different line for each level of the categorical explanatory variable.

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

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

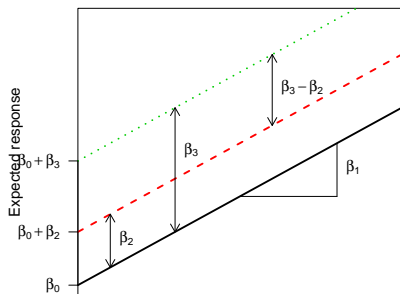
For each category, the line is

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.

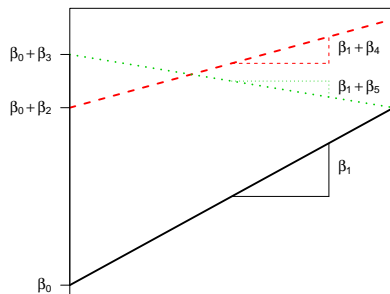
Visualizing the models

Main effects only



Continuous explanatory variable

with an interaction



Continuous explanatory variable

R code and output - main effects only

```
case1002$Type = relevel(case1002$Type, ref='non-echolocating bats') # match SAS
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)	-1.57636	0.28724	-5.488	4.96e-05 ***
log(Mass)	0.81496	0.04454	18.297	3.76e-12 ***
Typeecholocating bats	0.07866	0.20268	0.388	0.703
Type non-echolocating birds	0.10226	0.11418	0.896	0.384

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)	-0.2024	1.2613	-0.161	0.8748
log(Mass)	0.5898	0.2061	2.861	0.0126 *
Typeecholocating bats	-1.2681	1.2854	-0.987	0.3406
Typenon-echolocating birds	-1.3784	1.2952	-1.064	0.3053
log(Mass):Typeecholocating bats	0.2149	0.2236	0.961	0.3529
log(Mass):Typenon-echolocating birds	0.2456	0.2134	1.151	0.2691

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

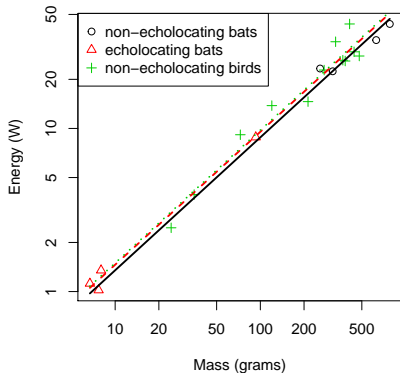
Residual standard error: 0.1899 on 14 degrees of freedom

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

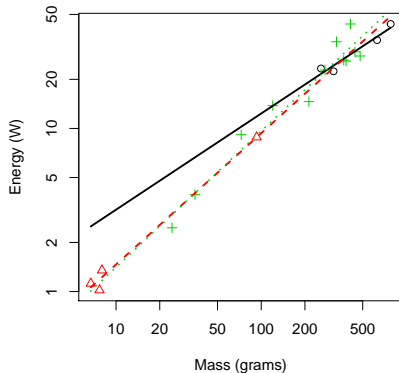
F-statistic: 163.4 on 5 and 14 DF, p-value: 6.696e-12

Visualizing the models

Main effects only



with an interaction



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

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

- β_0 is the expected response for category A and type 0
- β_1 is the change in response for moving from type 0 to type 1
- β_2 is the change in response for moving from category A to category B
- β_3 is the change in response for moving from category A to category C

The means are then

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

Interpretation for the model with an interaction

The mean with an interaction is

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

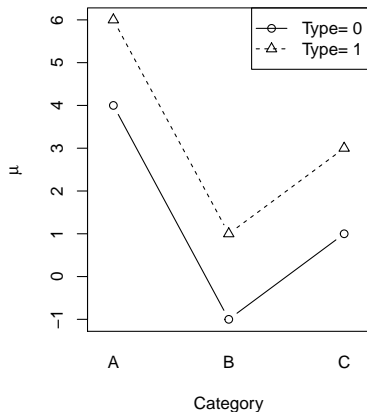
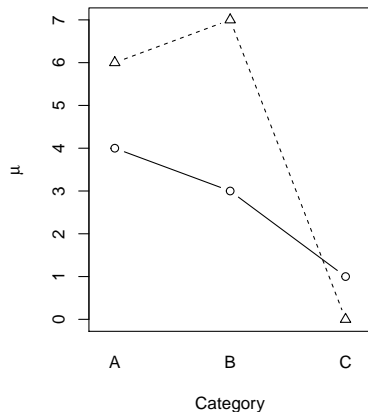
- β_0 is the expected response for category A and type 0
- β_1 is the change in response for moving from type 0 to type 1 for category A
- β_2 is the change in response for moving from category A to category B for type 0
- β_3 is the change in response for moving from category A to category C for type 0
- β_4 is the difference in change in response for moving from category A to category B for type 1 compared to type 0
- β_5 is the difference in change in response for moving from category A to category C for type 1 compared to type 0

The means are then

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.

Visualizing the models

Main effect only**with interaction**

R code and output - main effects only

```
# Set the reference levels
case1301$Block = relevel(case1301$Block, ref='B1')
case1301$Treat = relevel(case1301$Treat, ref='L' )
summary(mM <- lm(Cover~Block*Treat, case1301, subset=Block %in% c("B1","B2") & Treat %in% c("L","Lf","LfF")))
```

Call:

```
lm(formula = Cover ~ Block + Treat, data = case1301, subset = Block %in%
    c("B1", "B2") & Treat %in% c("L", "Lf", "LfF"))
```

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

```
summary(mI <- lm(Cover~Block*Treat, case1301, subset=Block %in% c("B1","B2") & Treat %in% c("L","Lf","LfF")))
```

Call:

```
lm(formula = Cover ~ Block * Treat, data = case1301, subset = Block %in%  
  c("B1", "B2") & Treat %in% c("L", "Lf", "LfF"))
```

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

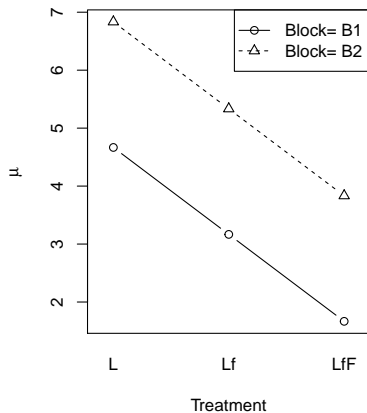
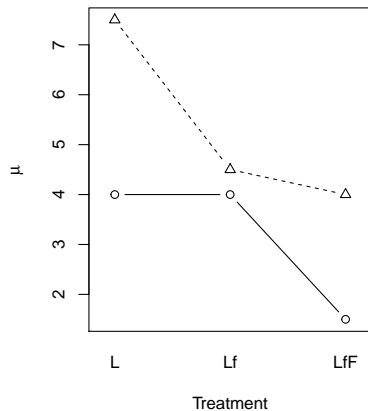
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

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

Main effect only**with interaction**

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 ($X_1X_2X_3$).