

Winter Workshop: **Basic and Intermediate Statistics with R**

Chai Jun Ho, PhD



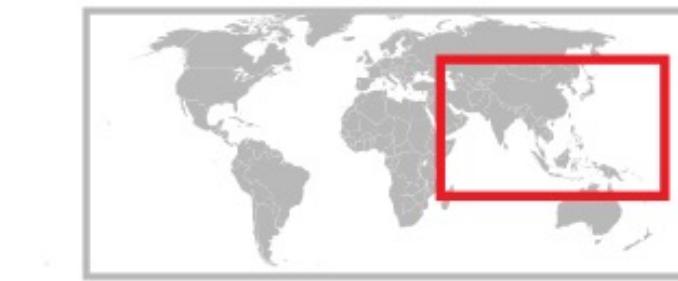
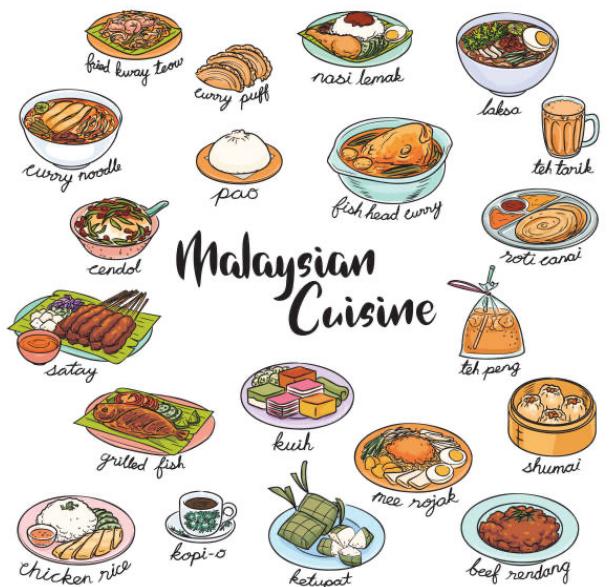
Download R and RStudio

R:

<https://cran.r-project.org/bin/windows/base/>

RStudio

<https://posit.co/products/open-source/rstudio/>



Schedule

Day 1	Day 2	Day 3
Introduction to Statistics	Linear Model I	Linear Model II
Introduction to R	Data Visualization	Mixed-Effect Model

Introduction to Statistics



Is there a relationship
between **teaching style** and
students' **learning**?

Introduction to Statistics



Is there a relationship
between **teaching style** and
students' **learning**?



Collect **data**...

Introduction to Statistics



Is there a relationship
between **teaching style** and
students' **learning**?



Collect **data**...



Conduct **statistical test**

Introduction to Statistics



Is there a relationship
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Visualizing **results**

Introduction to Statistics



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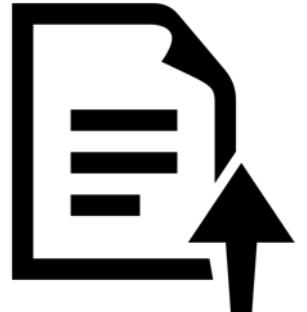
Collect **data**...



Conduct **statistical test**



Visualizing **results**



Publish **findings**

Introduction to Statistics



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Collect **data**...



Conduct **statistical test**

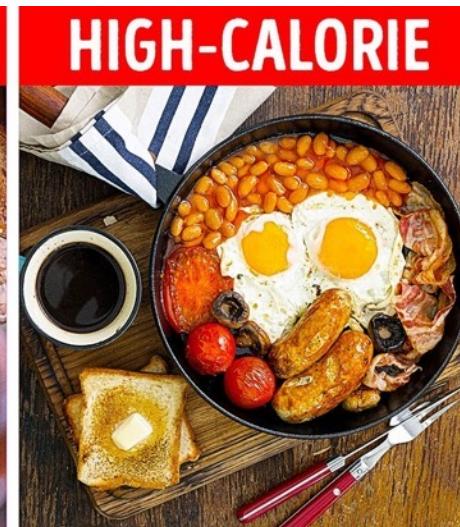
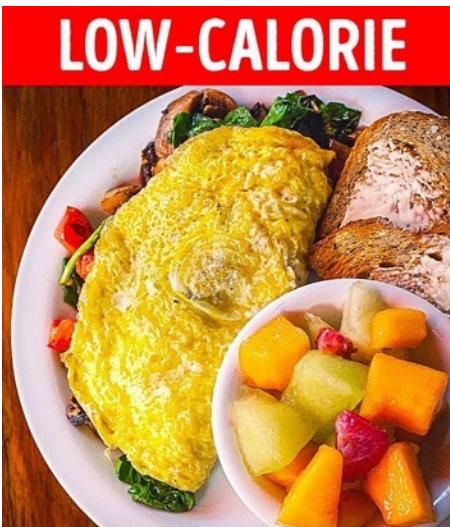


Visualizing **results**



Publish **findings**

high calorie vs low calorie



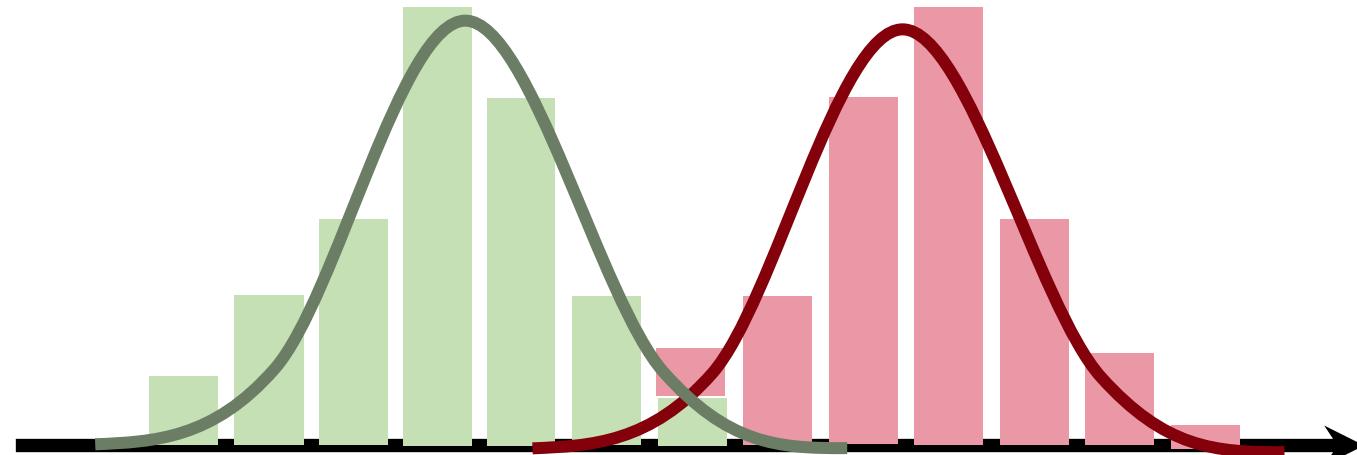
high calorie vs **low calorie**



high calorie

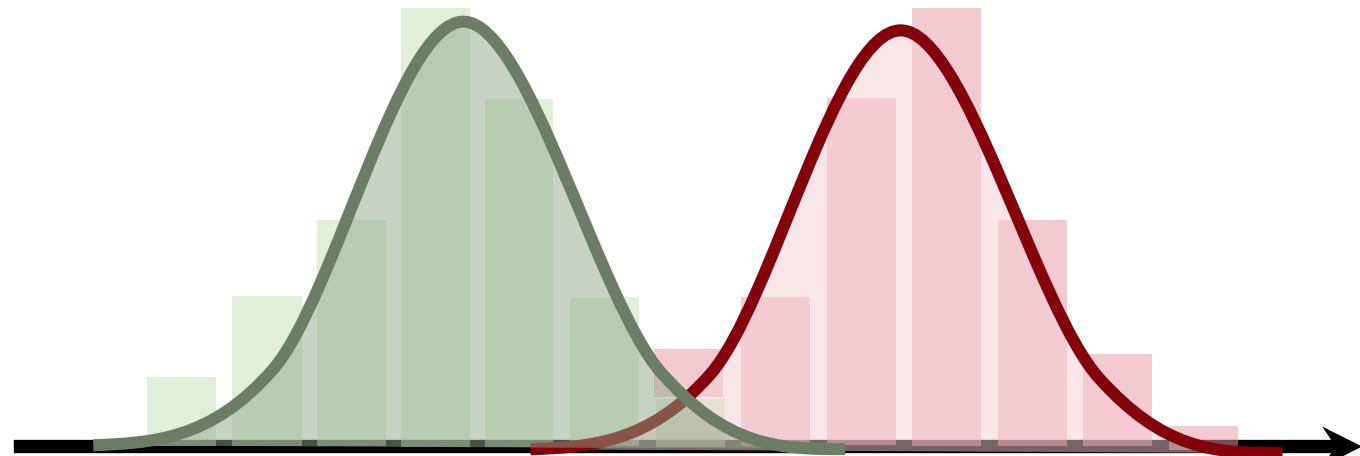
vs

low calorie



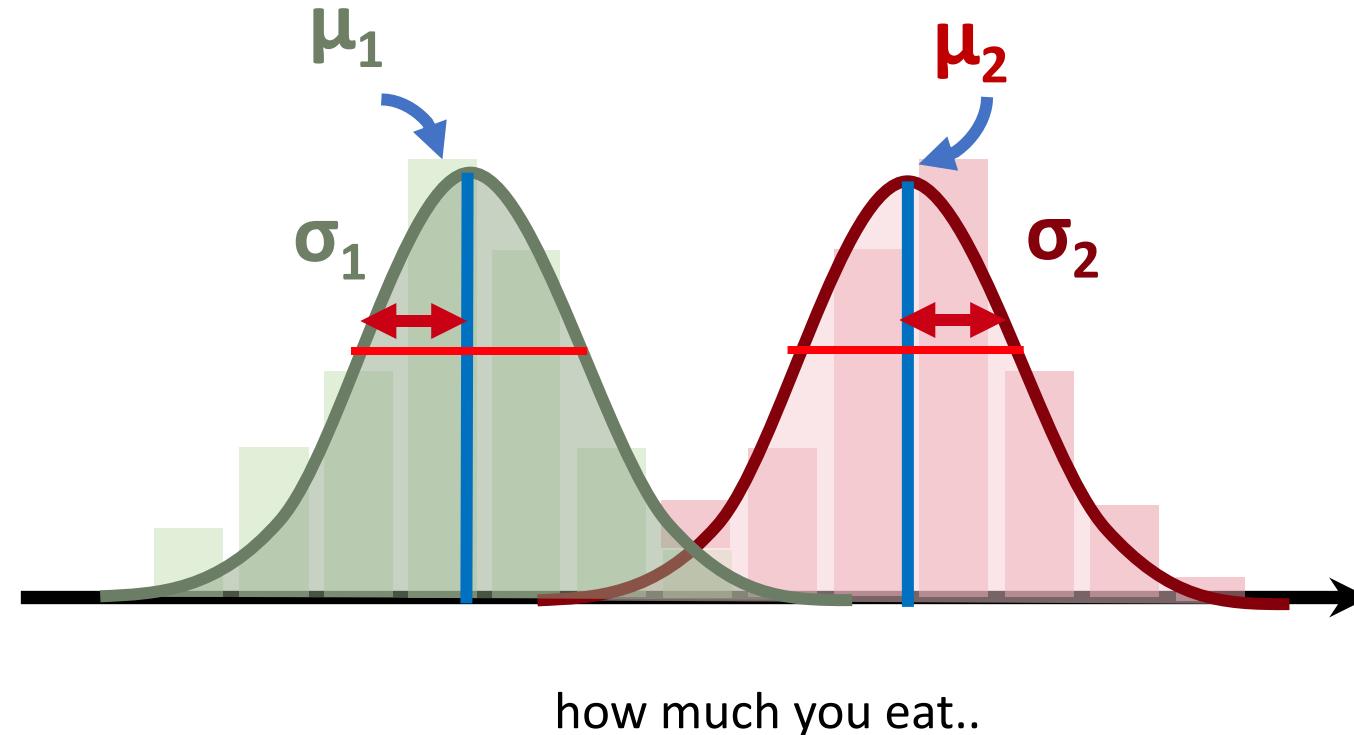
how much you eat..

high calorie vs **low calorie**



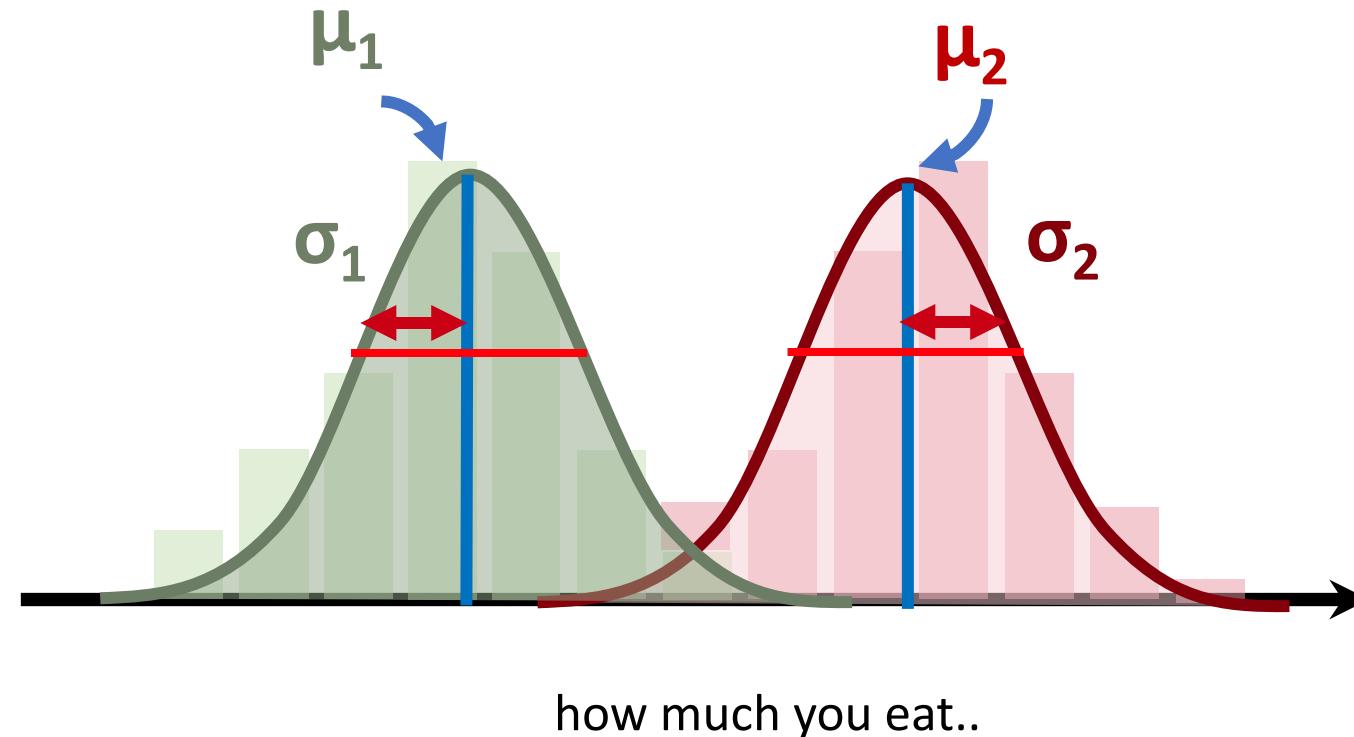
how much you eat..

- mean μ
- standard deviation σ



Null Hypothesis, H_0 : $\mu_1 = \mu_2$

Alternative Hypothesis, H_a : $\neg H_0$



H_a : consumed different amount of food

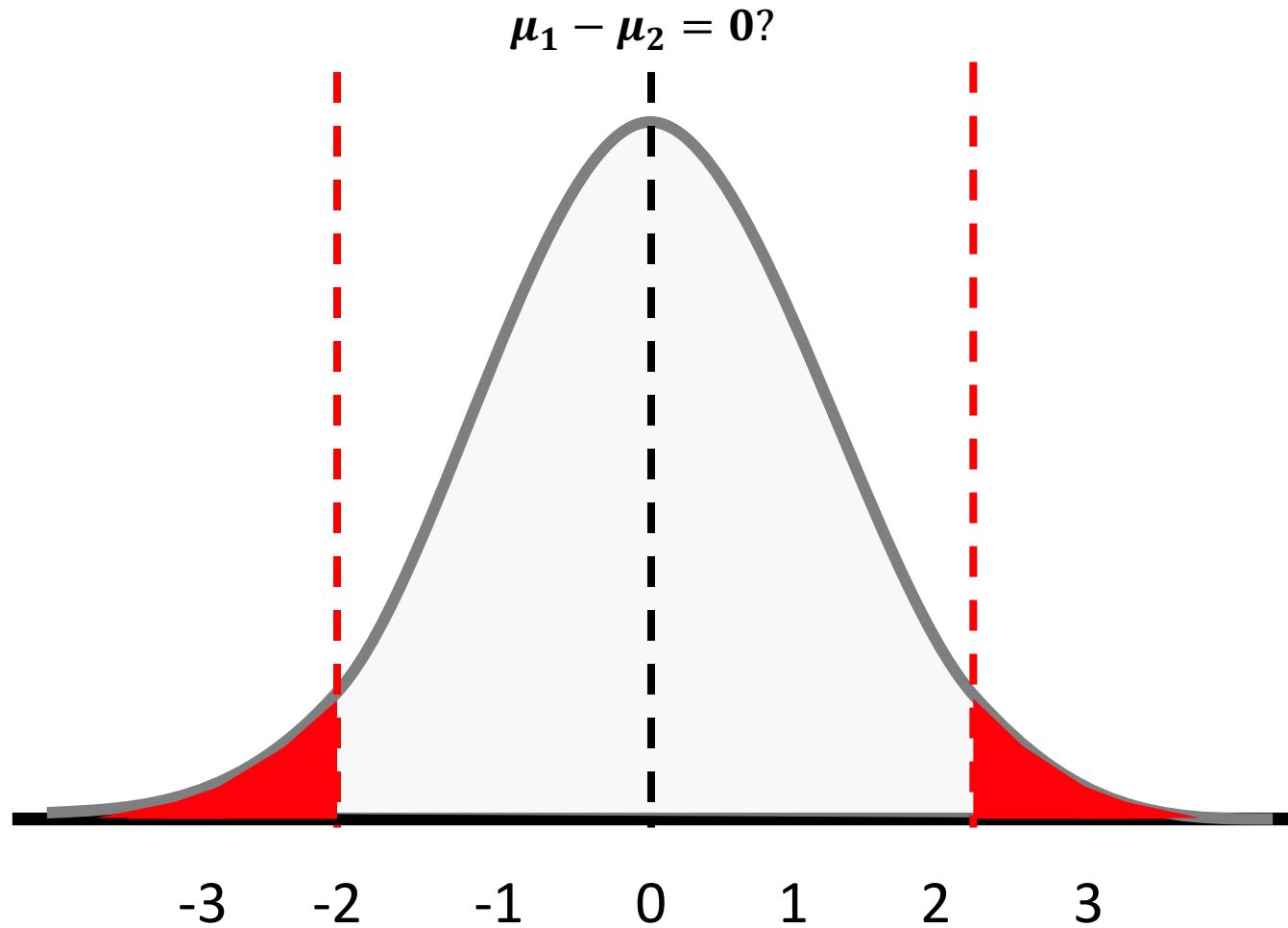
H_a : low calorie > high calorie

H_0 : consumed similar amount of food

H_0 : high calorie = low calorie



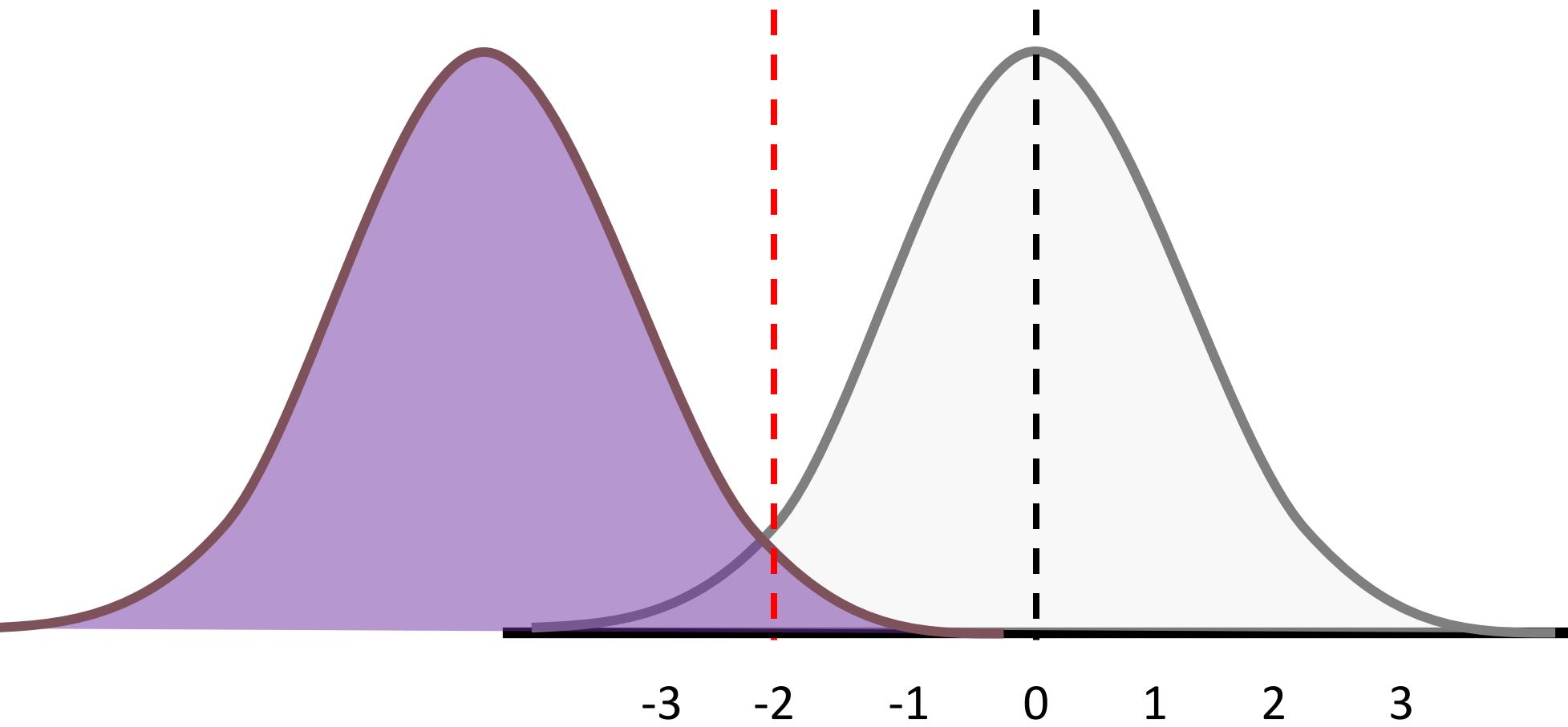
null hypothesis



null hypothesis

$$\mu_1 - \mu_2$$

$$\mu_1 - \mu_2 = 0?$$

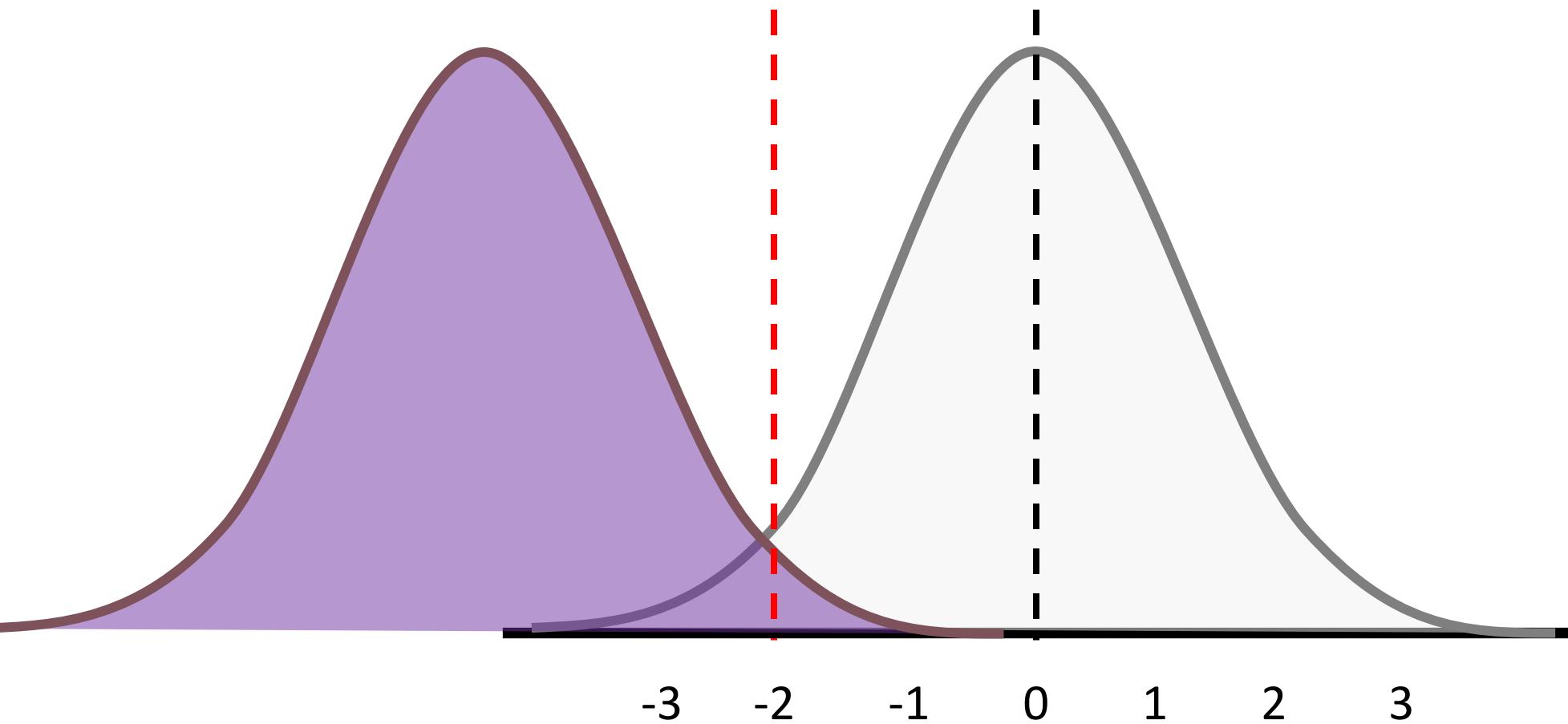


theoretical
differences

$$\mu_1 - \mu_2$$

null hypothesis

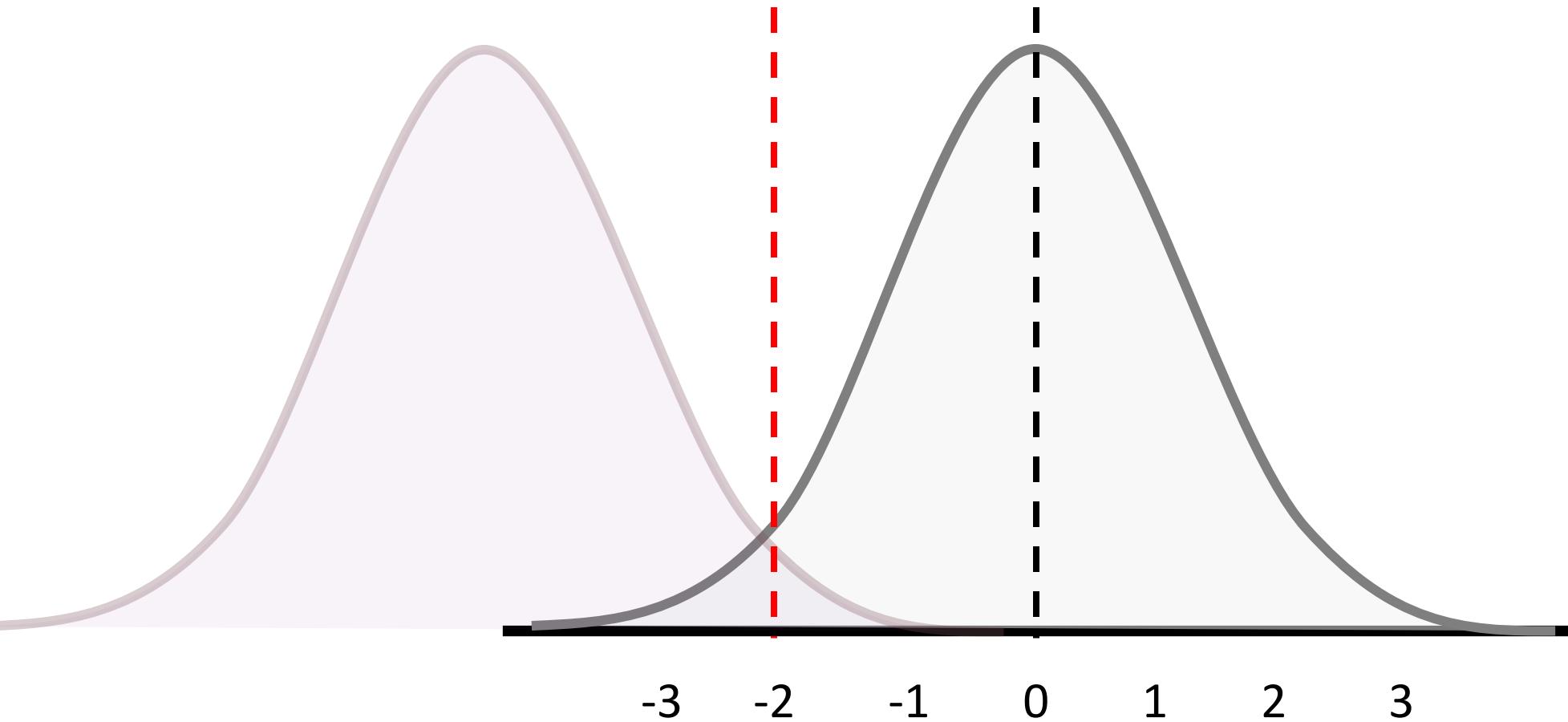
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theoretical
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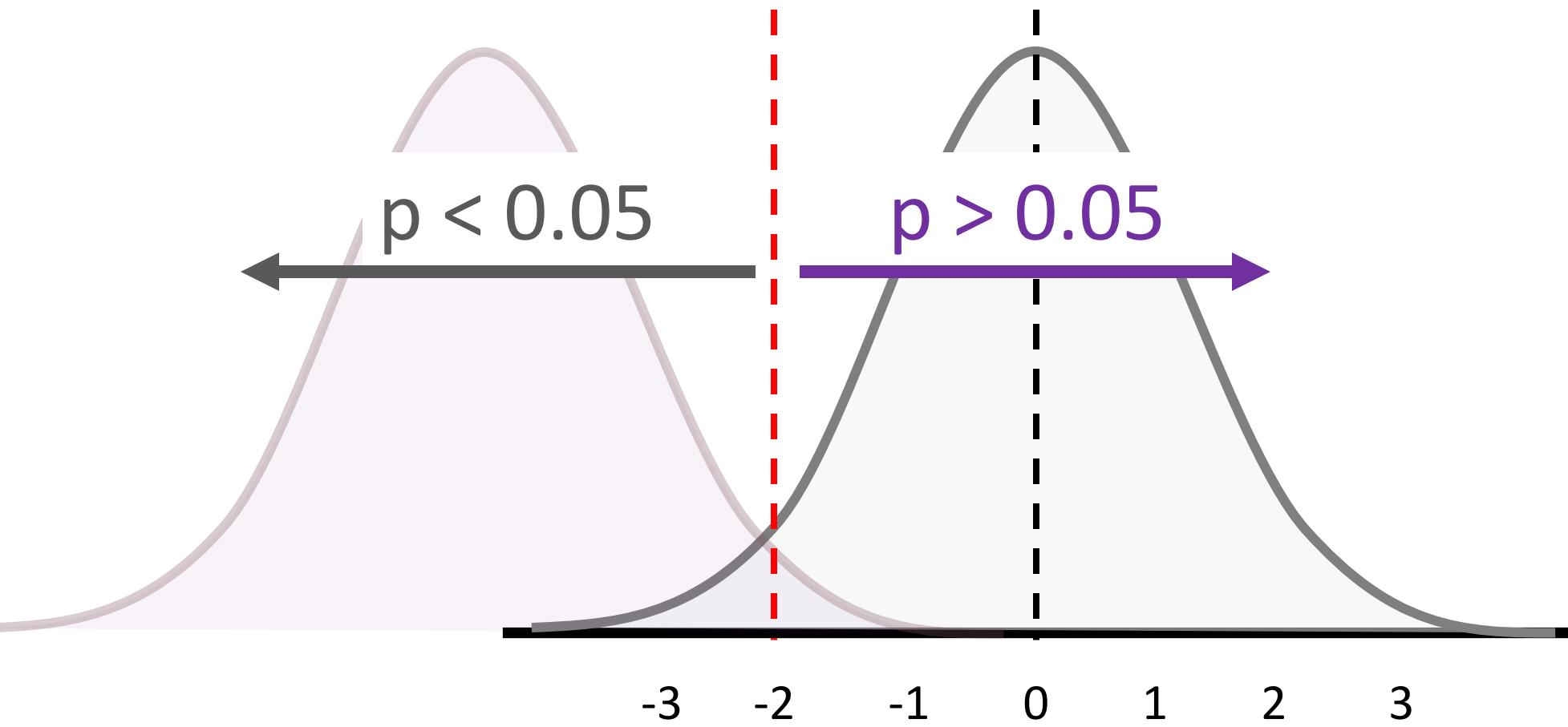
null hypothesis
 $\alpha = 0.05$ $\mu_1 - \mu_2 = 0?$



theoretical
differences

$$\mu_1 - \mu_2$$

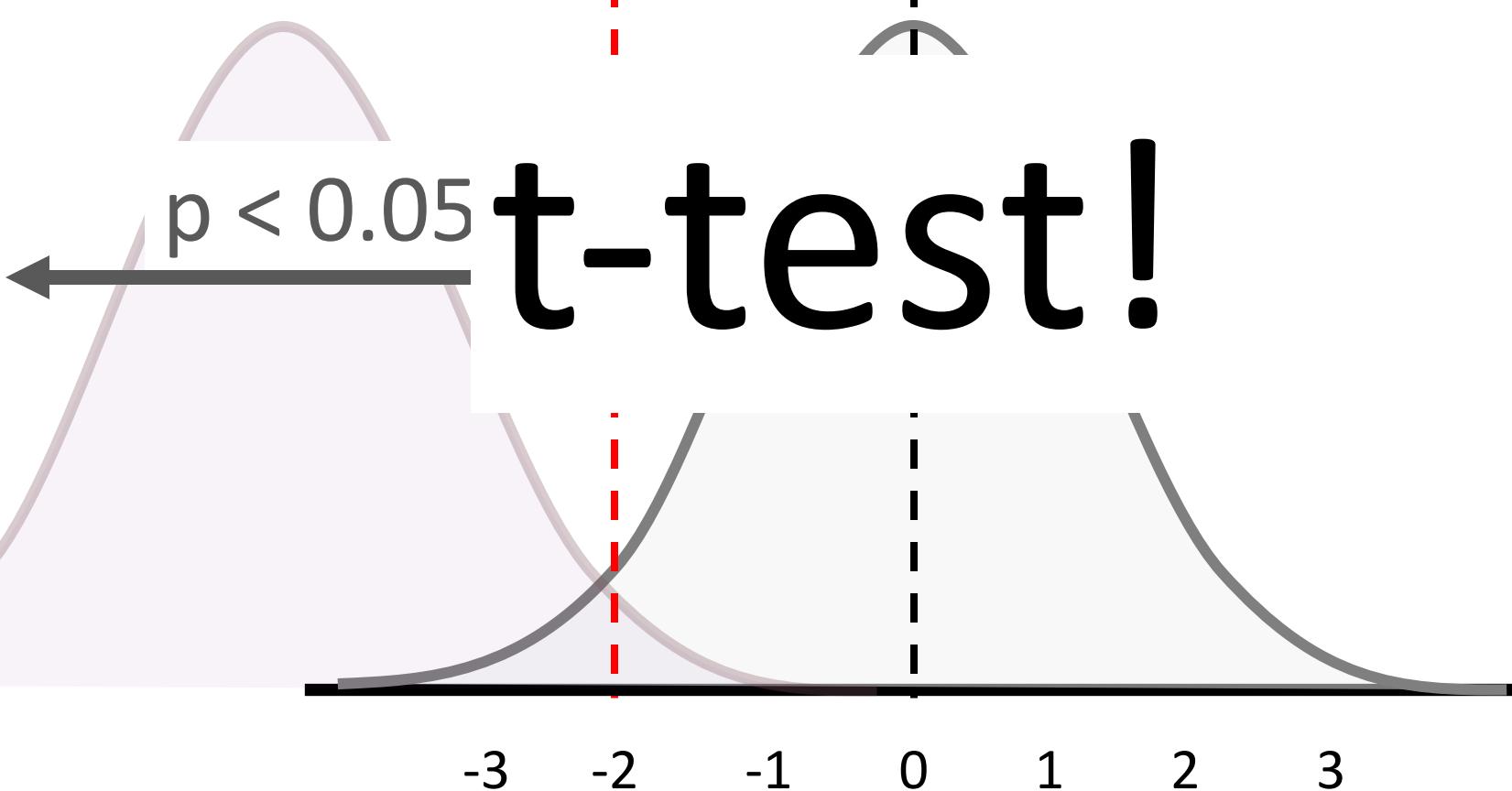
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theoretical
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$$\mu_1 - \mu_2$$

null hypothesis
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t-test!

$$\mu_1 - \mu_2 ?$$

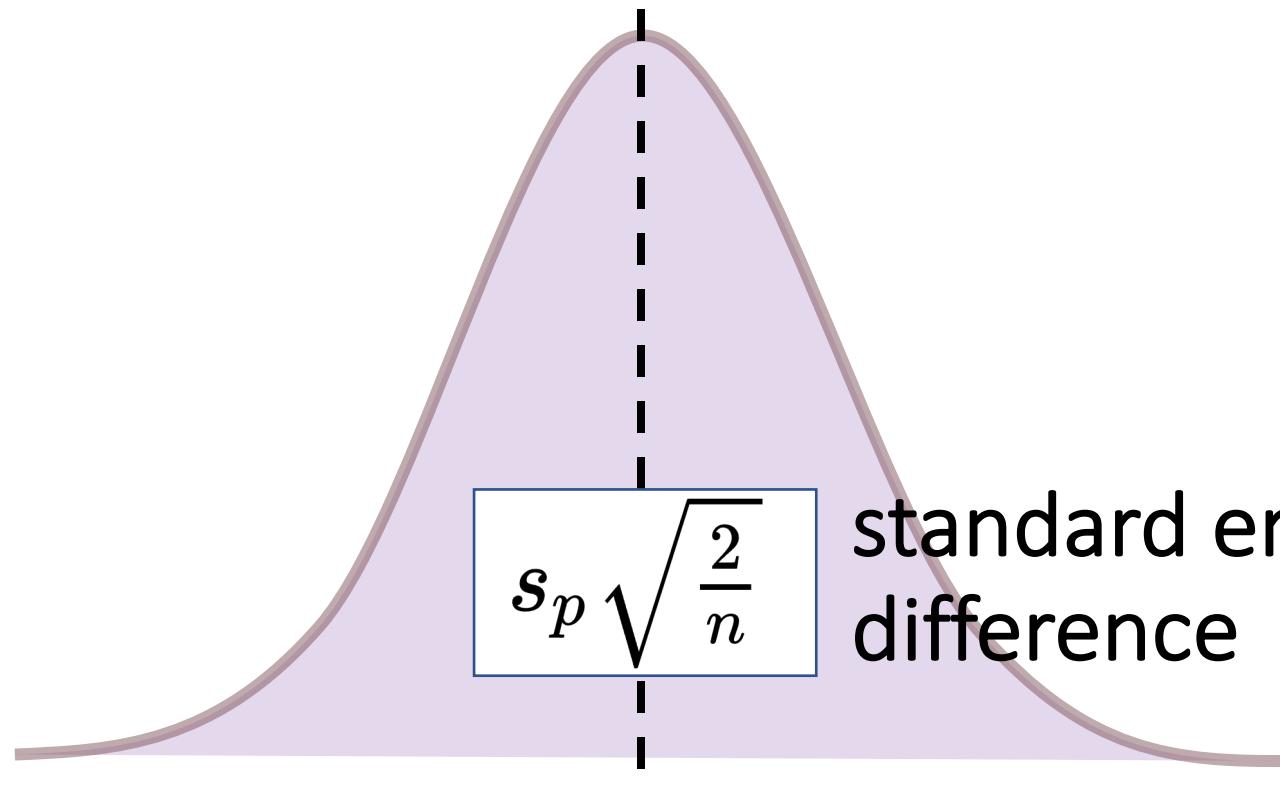
$$t = \frac{\bar{X}_1 - \bar{X}_2}{s_p \sqrt{\frac{2}{n}}}$$

\bar{X} : sample mean

$s_p \sqrt{\frac{2}{n}}$: standard error of the difference between
two means

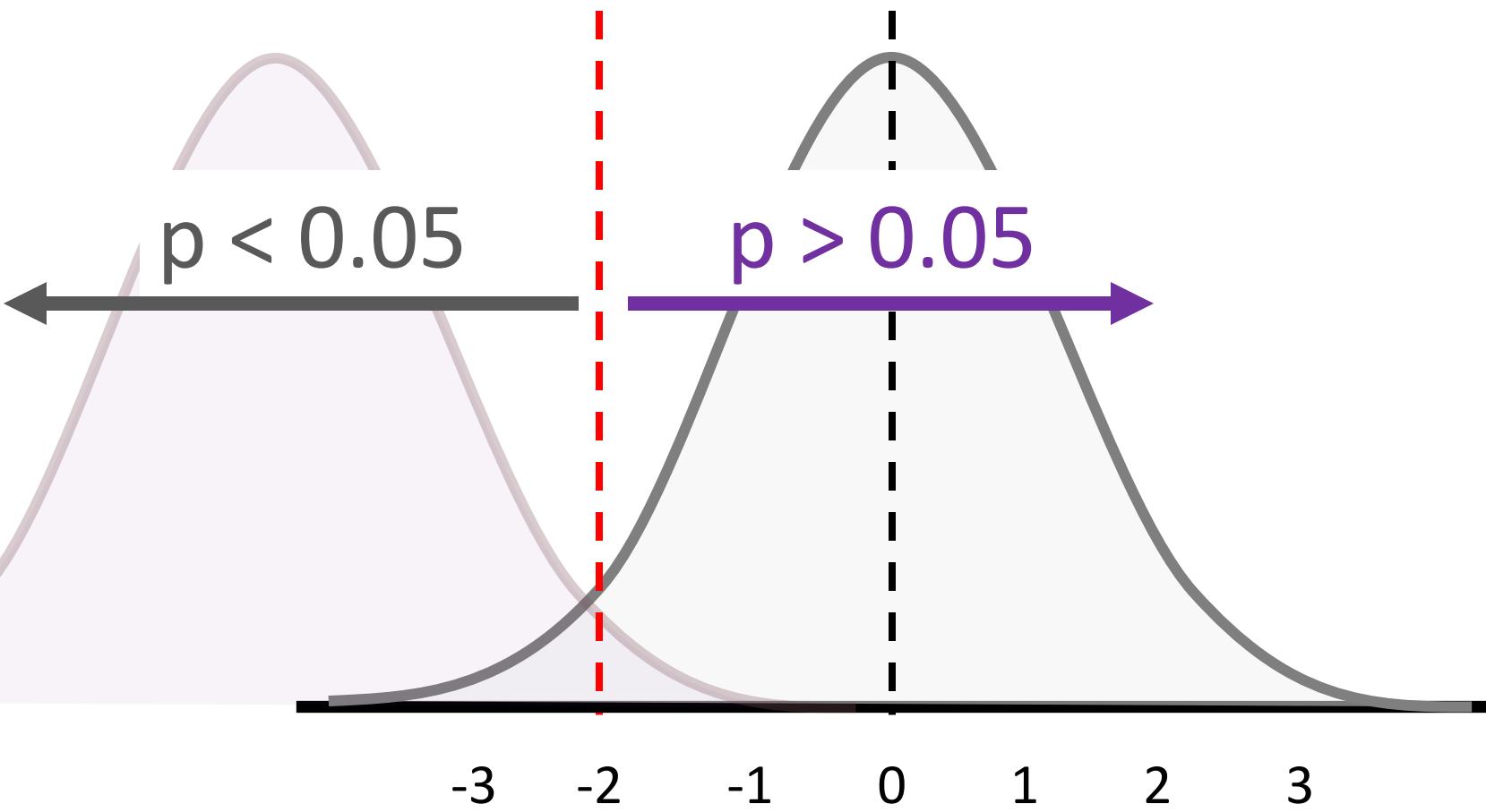
observed
differences

$$\bar{X}_1 - \bar{X}_2$$



standard error of the
difference

$$\alpha = 0.05$$



TYPE I & II ERRORS

		Reality	
		H_0 is true	H_0 is false
Decision	Reject H_0	Wrong Type I Error	Correct
	Fail to reject H_0	Correct	Wrong Type II Error

TYPE I & II ERRORS

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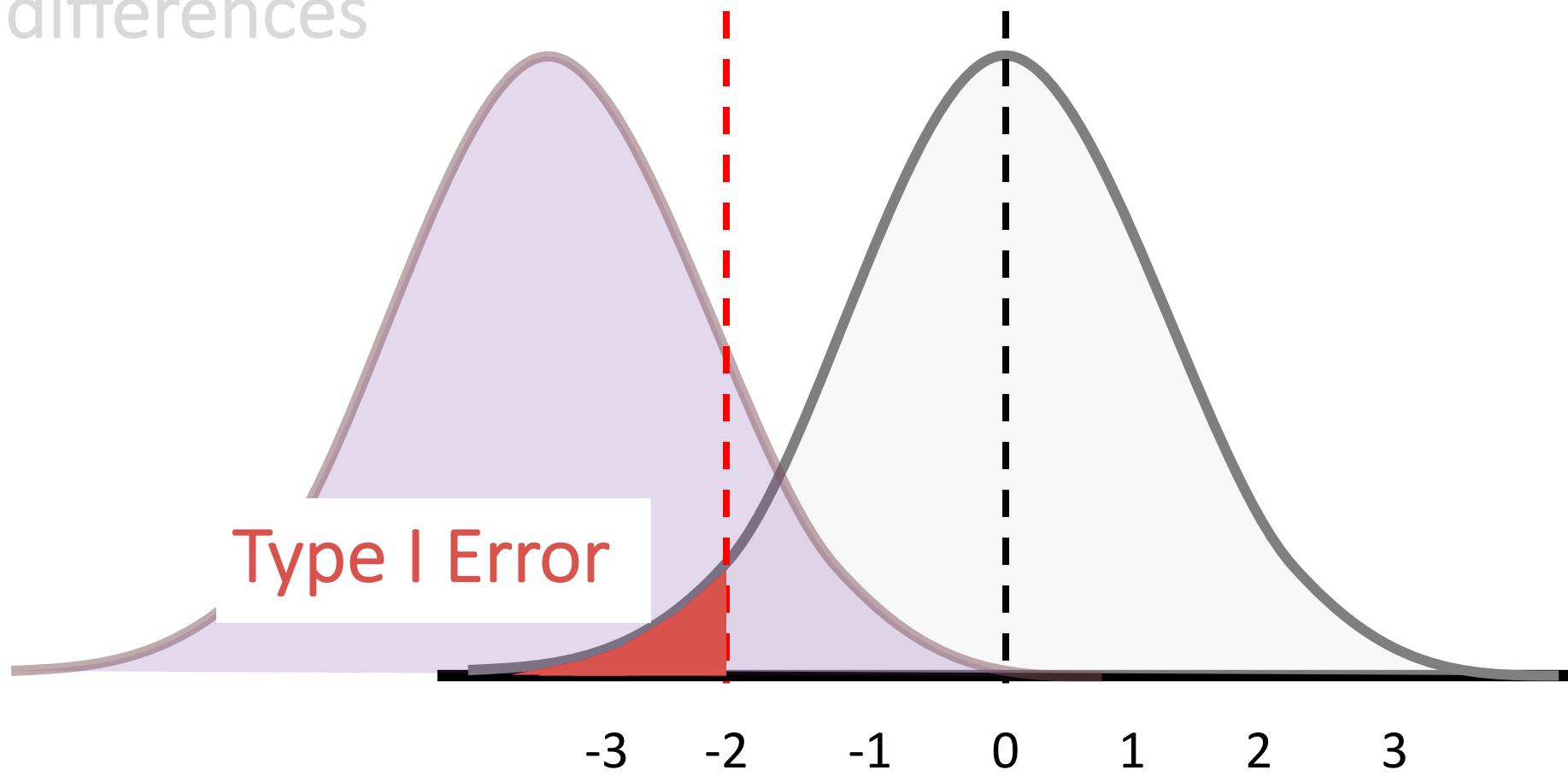
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theoretical
differences

null hypothesis

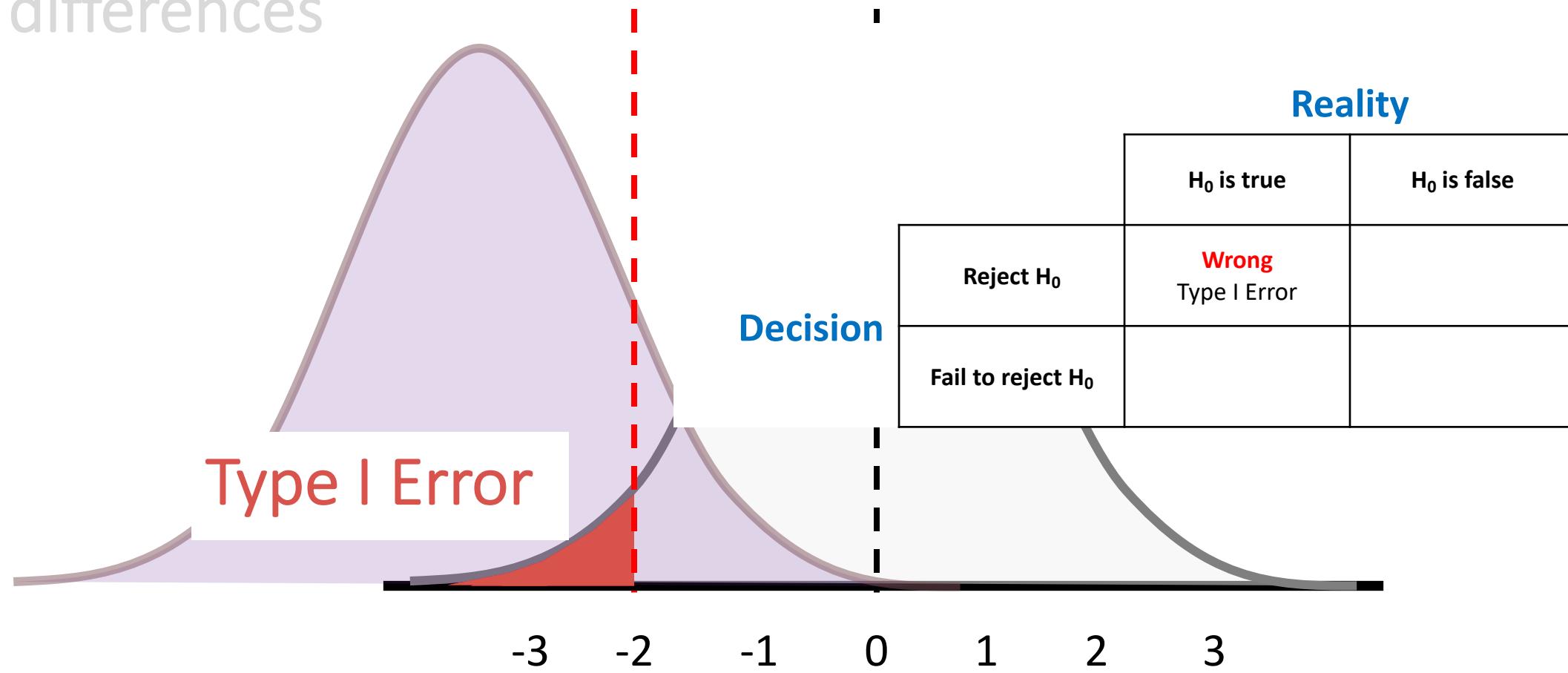
$$\mu_1 - \mu_2 \quad \alpha = 0.05 \quad \mu_1 - \mu_2 = 0?$$



theoretical
differences

null hypothesis

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theoretical
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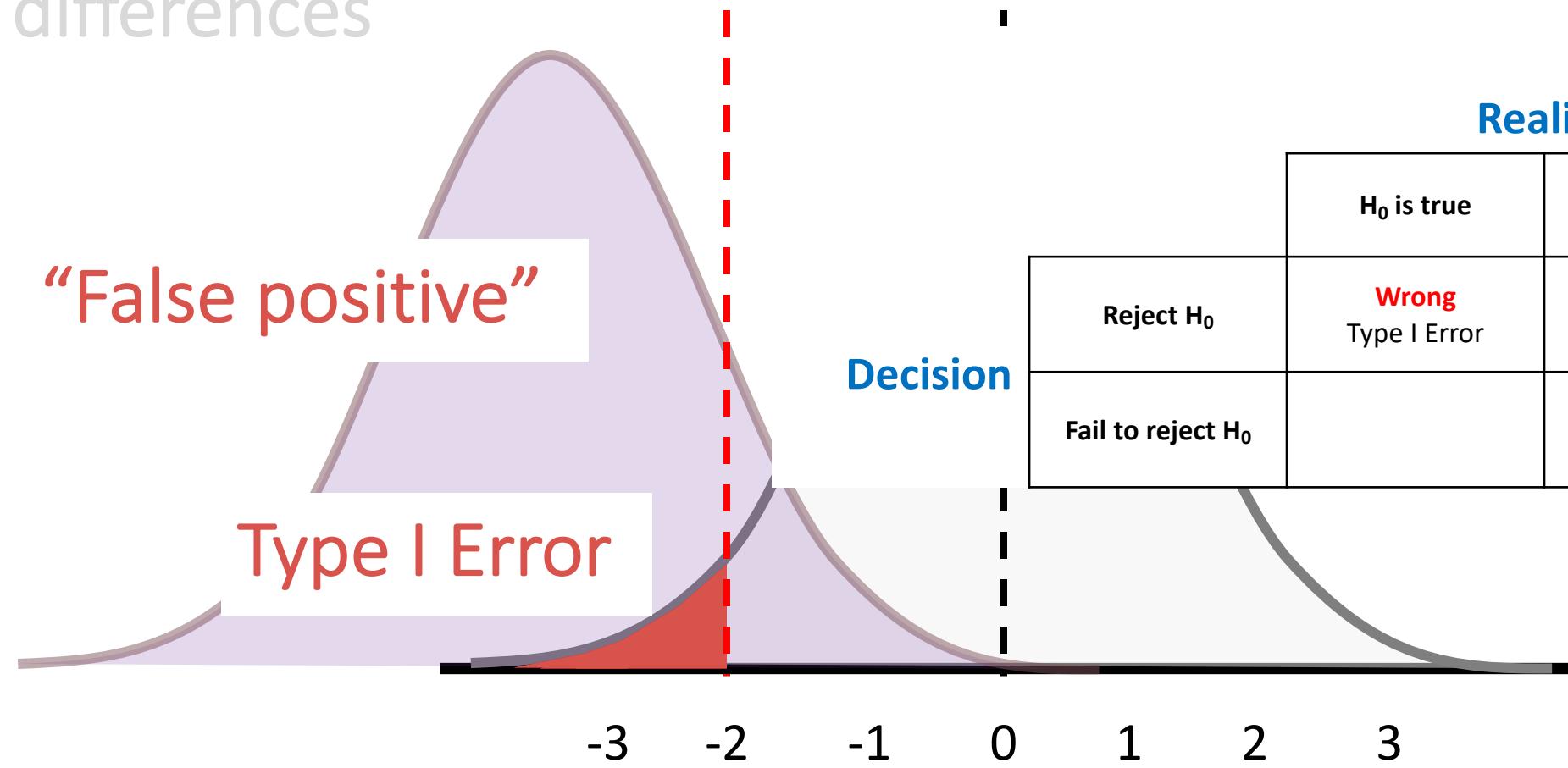
null hypothesis

$$\alpha = 0.05 \quad \mu_1 - \mu_2 = 0?$$

“False positive”

Type I Error

Decision



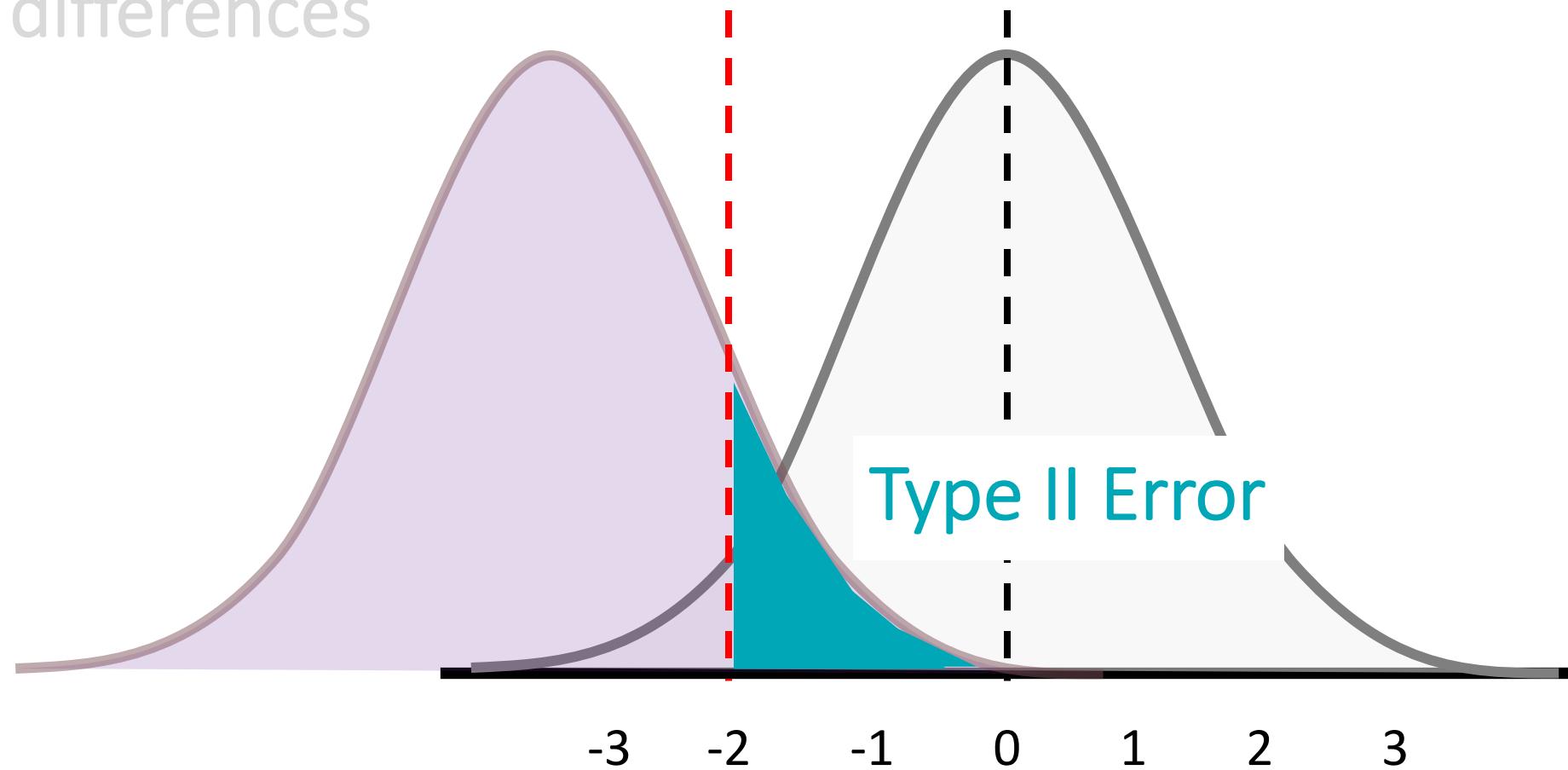
Reality

		H_0 is true	H_0 is false
Decision	Reject H_0	Wrong Type I Error	
	Fail to reject H_0		

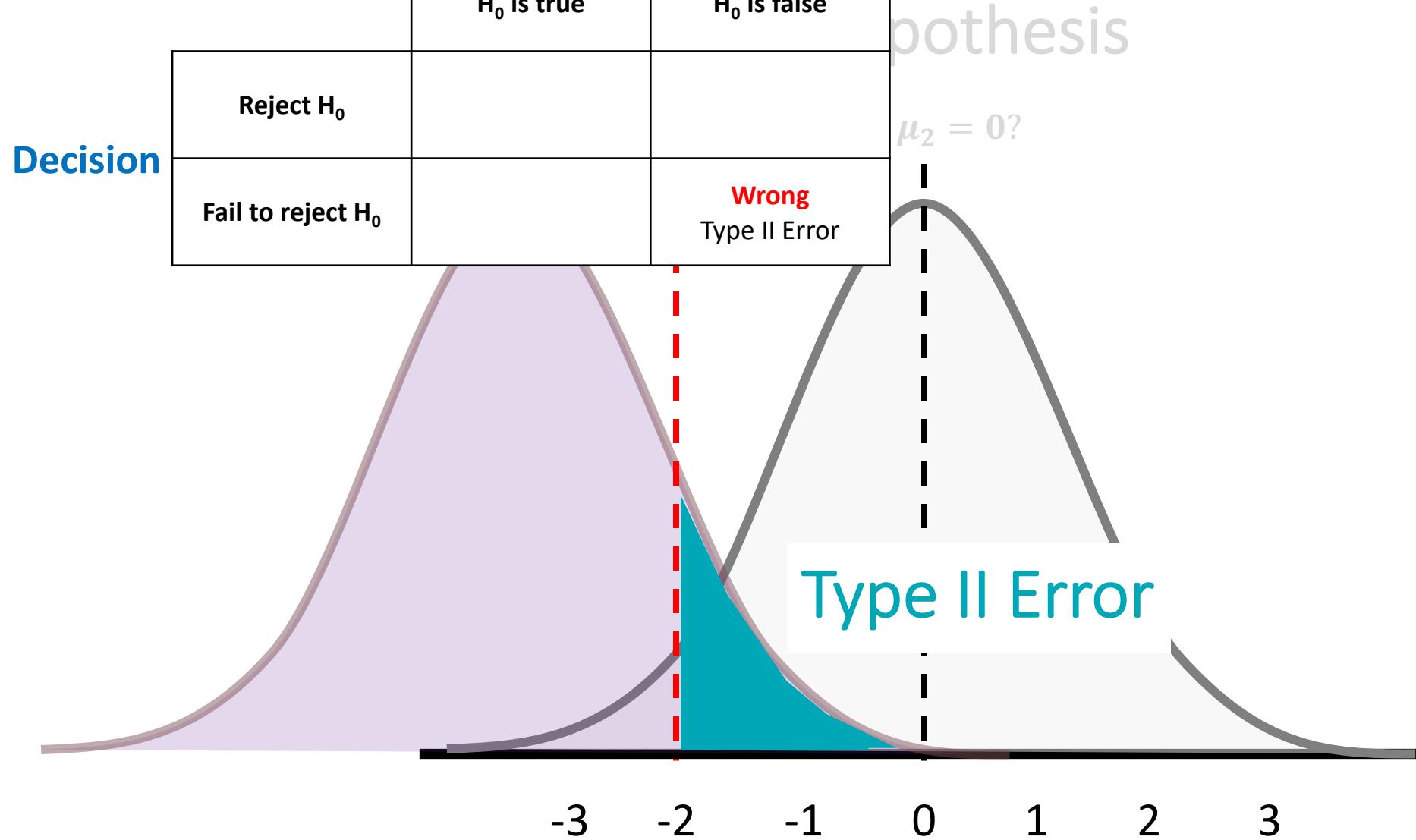
theoretical
differences

null hypothesis

$$\mu_1 - \mu_2 \quad \alpha = 0.05 \quad \mu_1 - \mu_2 = 0?$$



Reality



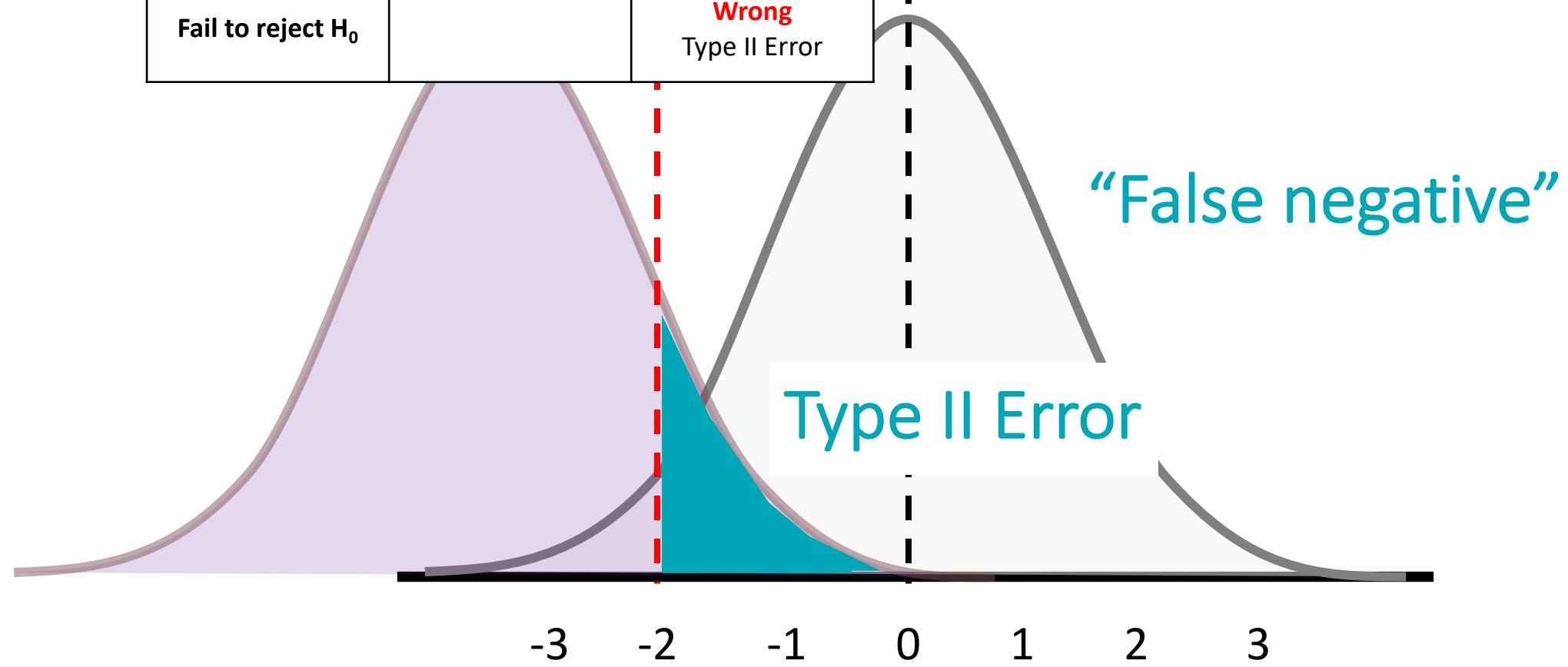
Reality

		H ₀ is true		H ₀ is false
		Reject H ₀		
Decision	Reject H ₀			
	Fail to reject H ₀			Wrong Type II Error

hypothesis

$$\mu_2 = 0?$$

Decision



theoretical
differences

null hypothesis

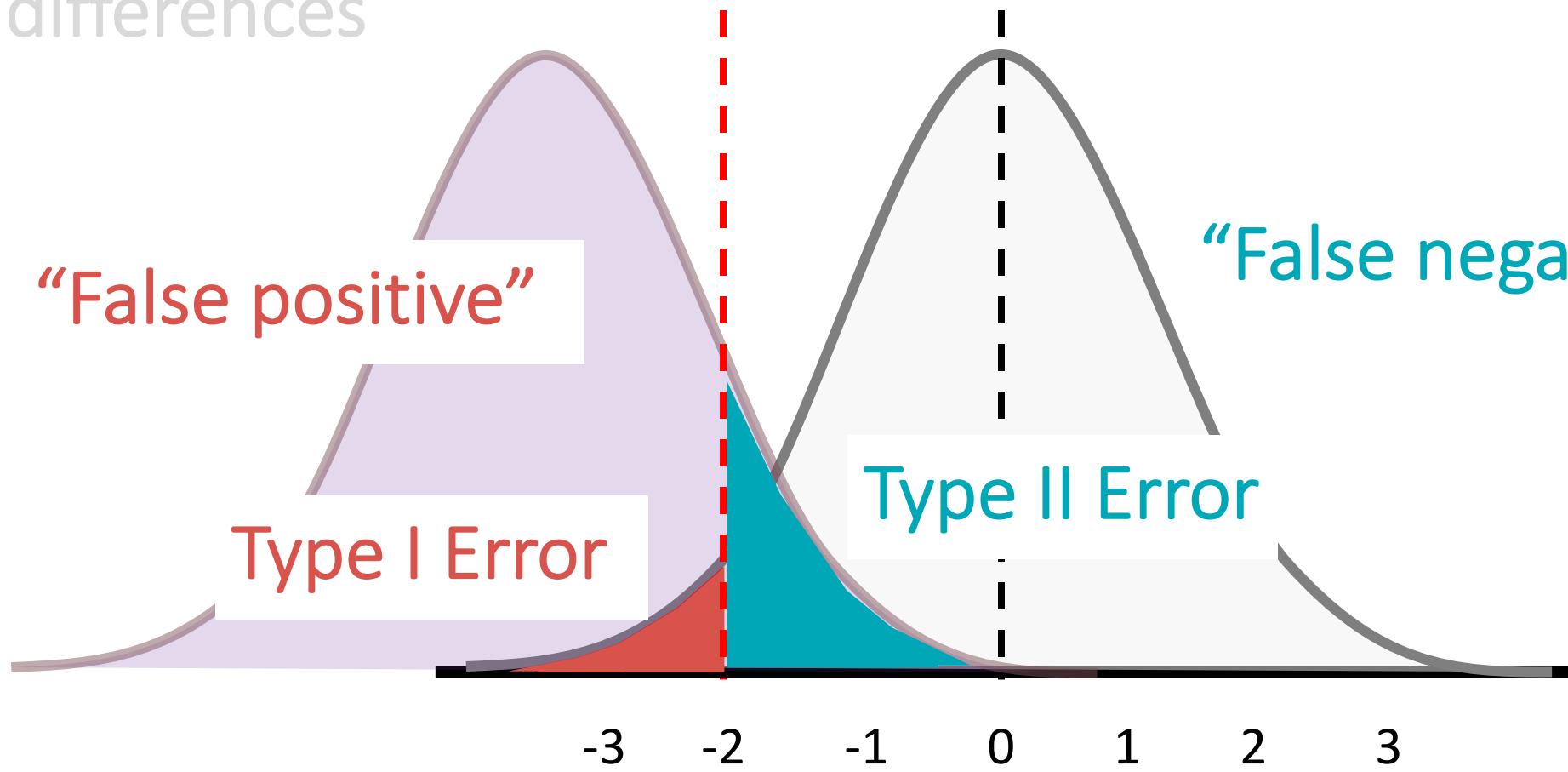
$$\alpha = 0.05 \quad \mu_1 - \mu_2 = 0?$$

“False positive”

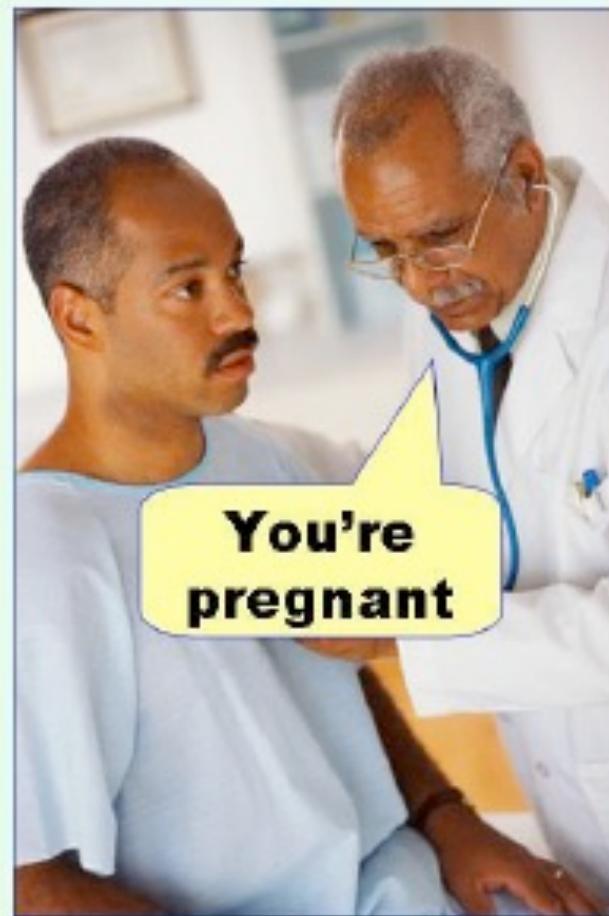
Type I Error

“False negative”

Type II Error

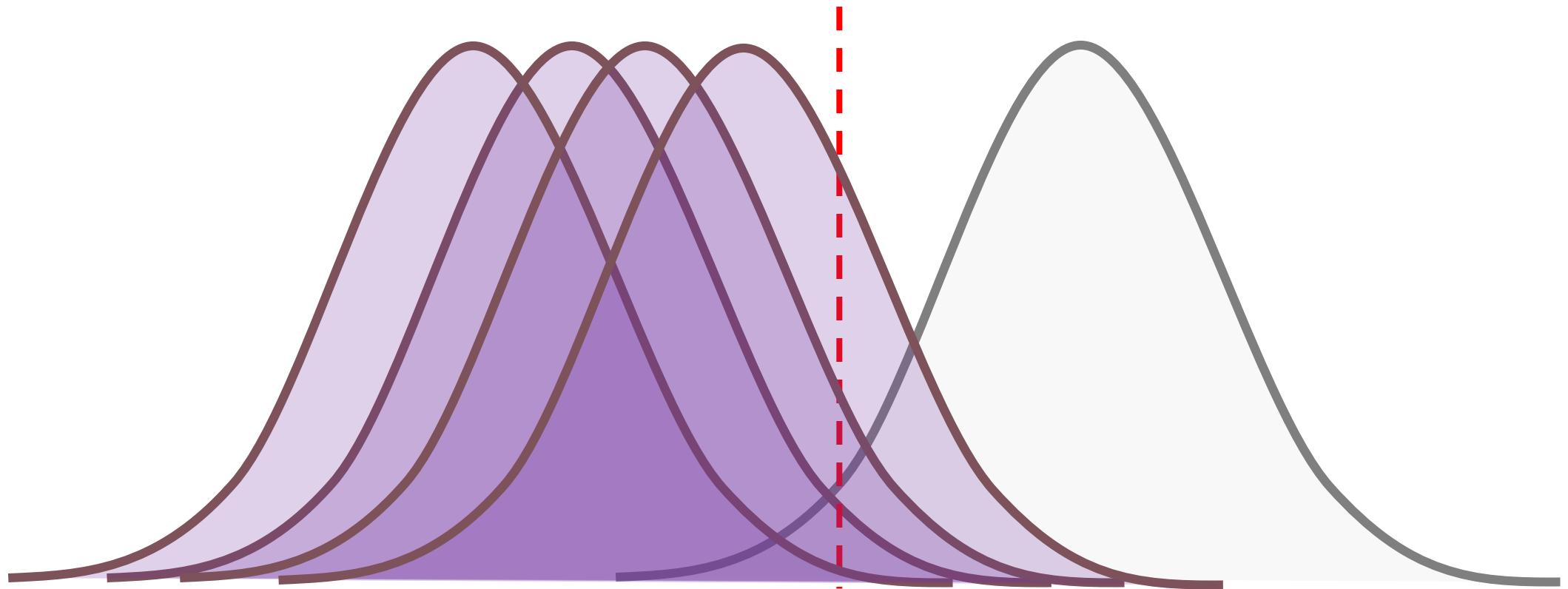


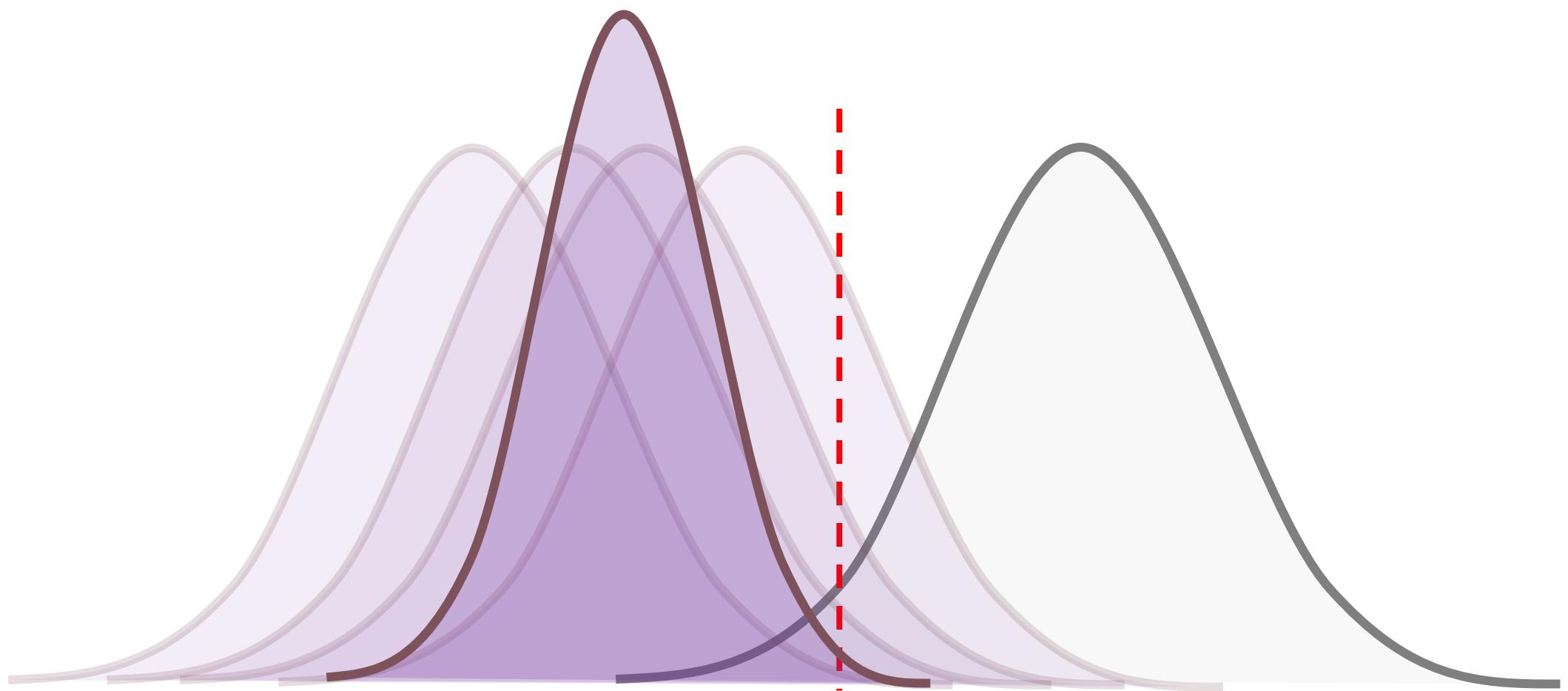
Type I error
(false positive)



Type II error
(false negative)







Summary I

- Mean & Standard deviation
- Null Hypothesis & Alternative Hypothesis
- α (alpha) & p-value
- Type I & Type II Error
- t-test

Introduction to R:

Part I

- R & RStudio environment
- Basic math operations:
 - addition, subtraction, multiplication, division, power, square-root
- Mean
- Standard deviation
- T-test

iris setosa



petal

iris versicolor



petal

iris virginica



petal

sepal

R:

<https://cran.r-project.org/bin/windows/base/>

RStudio

<https://posit.co/products/open-source/rstudio/>

```
packages <-  
c("tidyverse","emmeans","ggeffects","lme4","lmerTest")
```

```
install.packages(packages)
```

t-test : comparison between two means $\rightarrow \mu_1 - \mu_2$

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$\mu_1 = \mu_2 = \mu_3?$

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Species: Setosa = Versicolor = Virginica ?

$\mu_1 = \mu_2 = \mu_3 ?$

t-test : comparison between two means $\rightarrow \mu_1 - \mu_2$

$\mu_{A1} = \mu_{A2} = \mu_{A3} = \mu_{B1} = \mu_{B2} = \mu_{B3} ? ?$

t-test : comparison between two means $\rightarrow \mu_1 - \mu_2$

A: Species

A1: Setosa

A2: Versicolor

A3: Virginica

$\mu_{A1} = \mu_{A2} = \mu_{A3} = \mu_{B1} = \mu_{B2} = \mu_{B3} ? ?$

t-test : comparison between two means $\rightarrow \mu_1 - \mu_2$

A: Species

A1: Setosa

A2: Versicolor

A3: Virginica

B: Place

B1: Your home

B2: Your neighbor's home

B3: Your grandma's home

$\mu_{A1} = \mu_{A2} = \mu_{A3} = \mu_{B1} = \mu_{B2} = \mu_{B3}$??

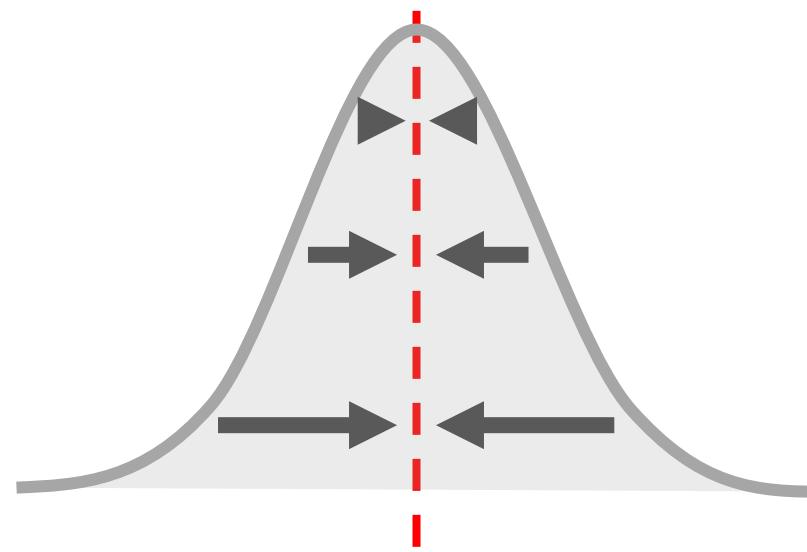
ANOVA: Analysis of variance

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variance: “spread” of the data

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ANOVA: Analysis of variance

$$\text{Variance} = \frac{\text{Sum of squared deviations, } SS}{\text{Degrees of freedom, } df}$$

ANOVA: Analysis of variance

variance between groups

variance within group

ANOVA: Analysis of variance

$$\frac{\text{variance between groups}}{\text{variance within group}} =$$

$$\frac{MS_A}{MS_R} =$$

F-ratio

$$\text{Variance} = \frac{\text{Sum of squared deviations, } SS}{\text{Degrees of freedom, } df}$$

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Squared deviation values are typically referred to as **sums of squares**, and abbreviated **SS**

Variance = $\frac{\text{Sum of squared deviations, } SS}{f}$

$$\frac{\text{variance between groups}}{\text{variance within group}}$$

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$$\frac{\text{variance between groups}}{\text{variance within group}}$$

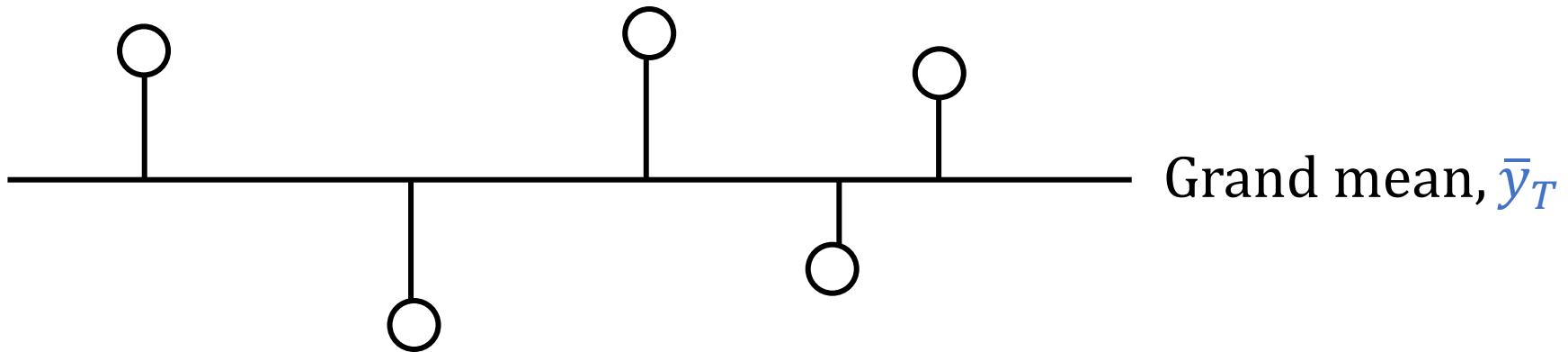
- Between-groups: $SS_{between} = SS_A = \sum_A s \cdot (\bar{y}_A - \bar{y}_T)^2$
- Within-groups: $SS_{within} = SS_R = \sum_{A,i} (y_{A,i} - \bar{y}_A)^2$
- Total: $SS_{total} = SS_T = \sum_{A,i} (y_{A,i} - \bar{y}_T)^2$

$$\frac{\text{variance between groups}}{\text{variance within group}}$$

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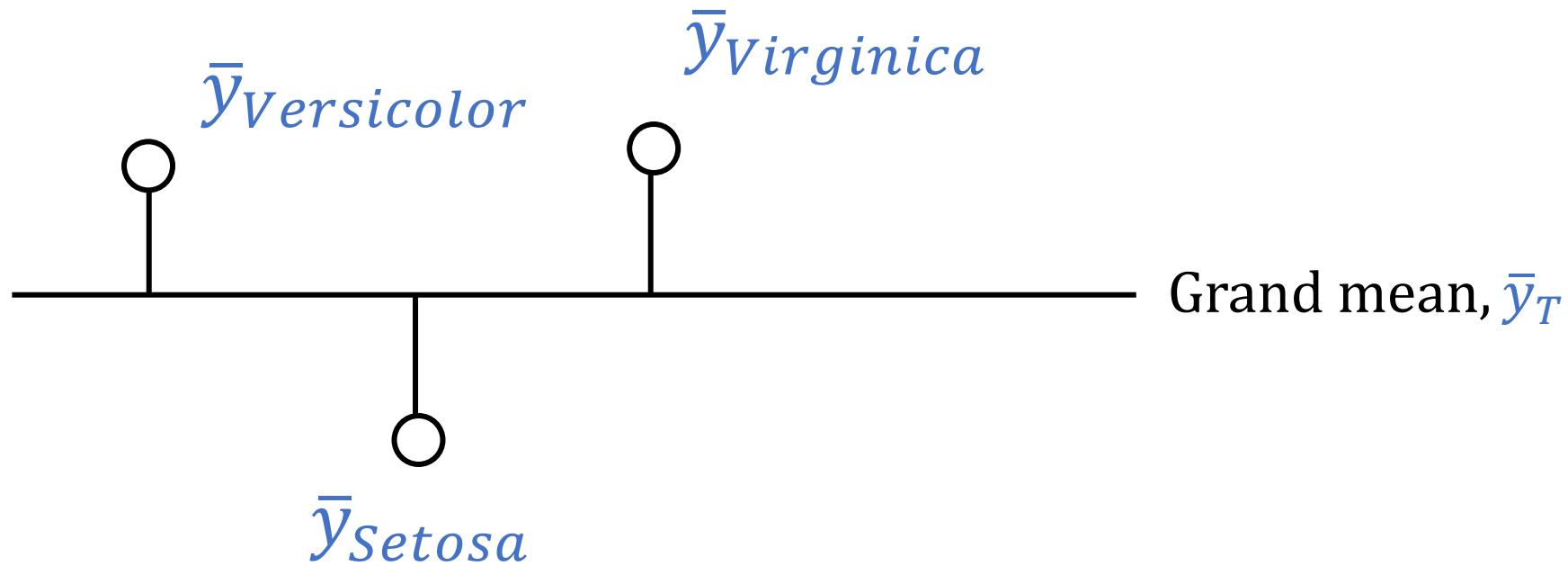
Between-groups: $SS_{between} = SS_A = \sum_A s \cdot (\bar{y}_A - \bar{y}_T)^2$

Treatment means, \bar{y}_A



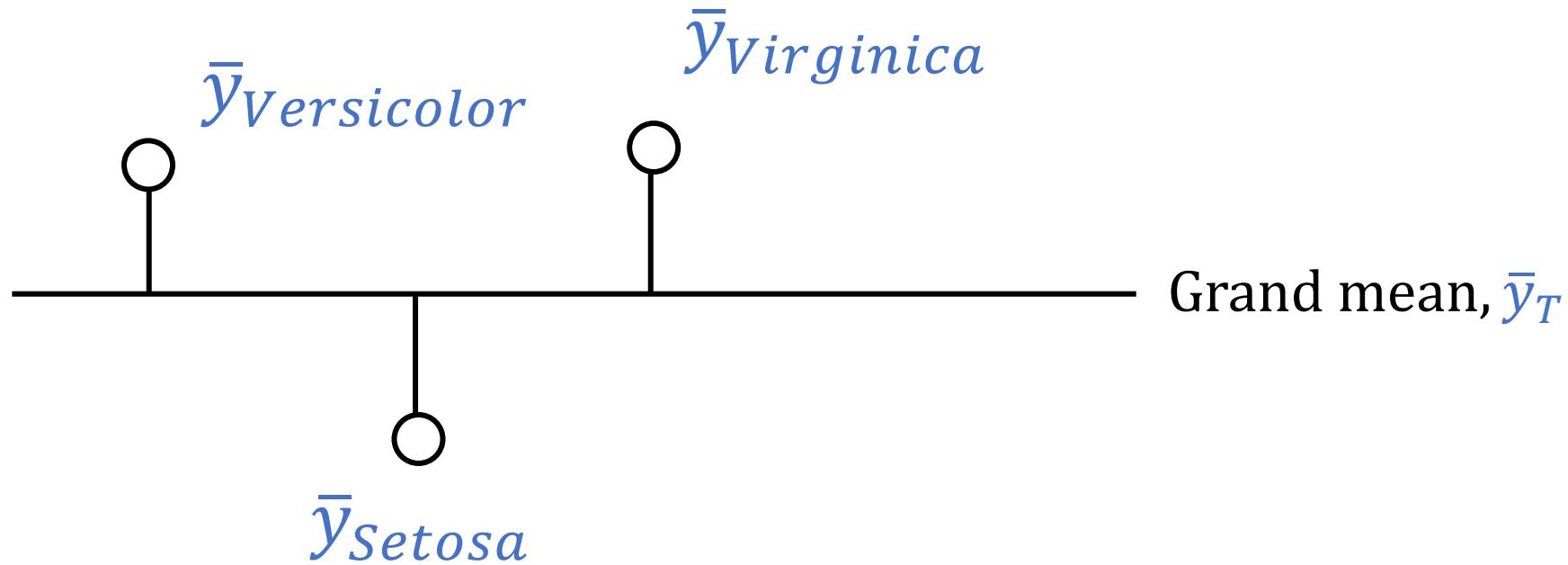
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Between-groups: $SS_{between} = SS_A = \sum_A s \cdot (\bar{y}_A - \bar{y}_T)^2$



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For sample size s in each group

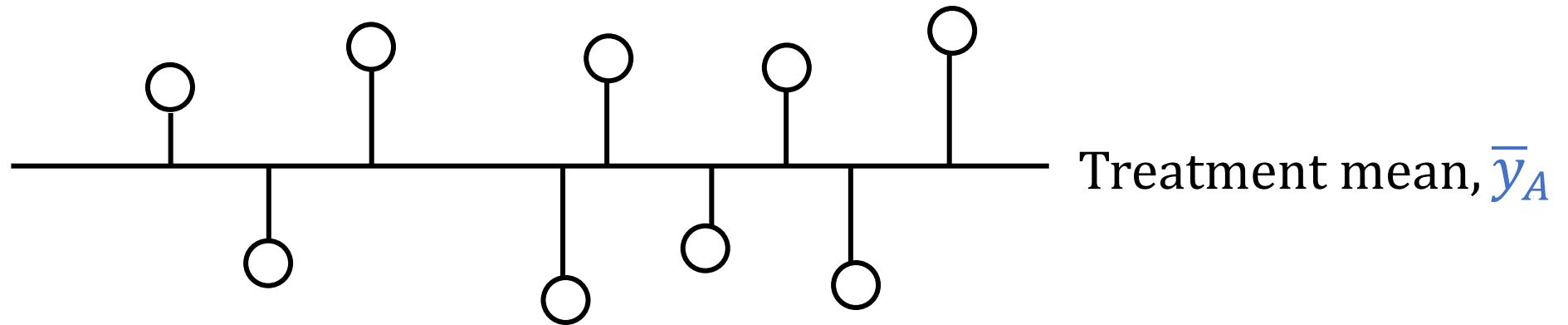


$$\frac{\text{variance between groups}}{\text{variance within group}}$$

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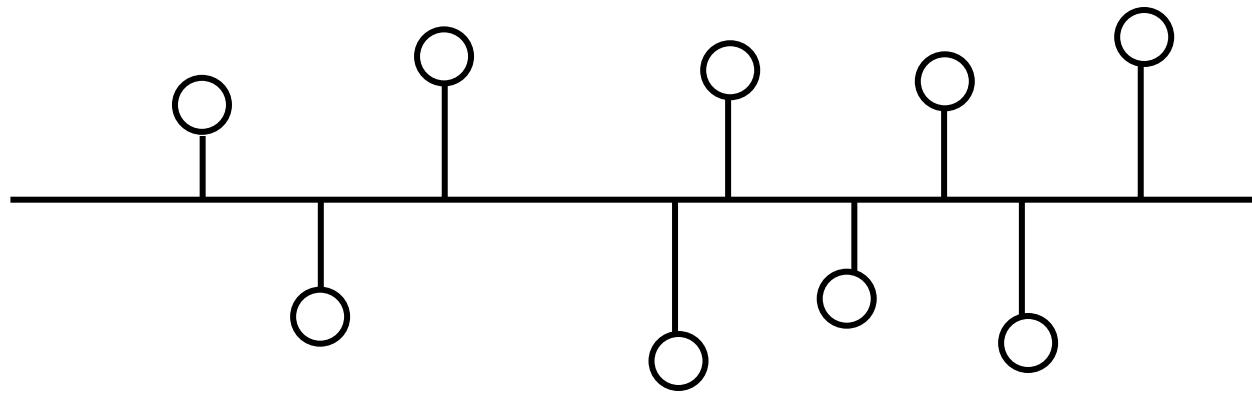
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Individual data points, $y_{A,i}$



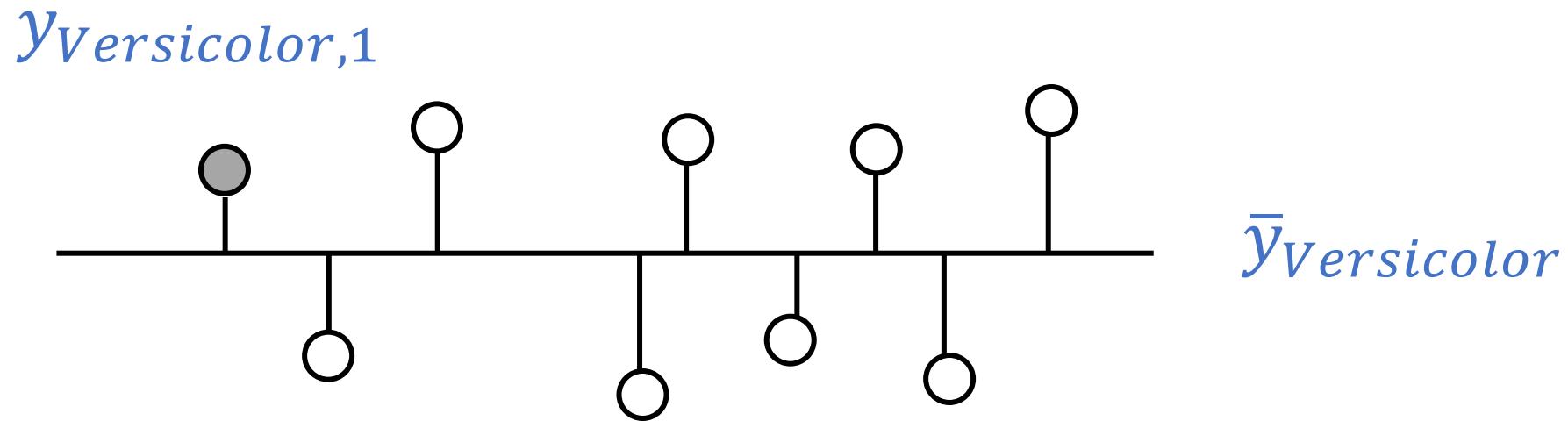
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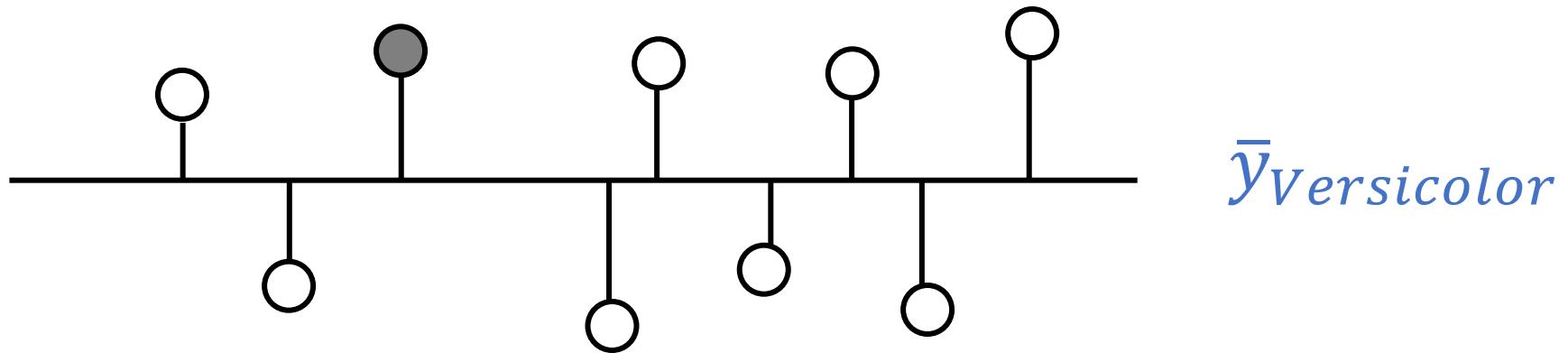
$$\bar{y}_{Versicolor}$$

Within-groups: $SS_{within} = SS_R = \sum_{A,i} (y_{A,i} - \bar{y}_A)^2$



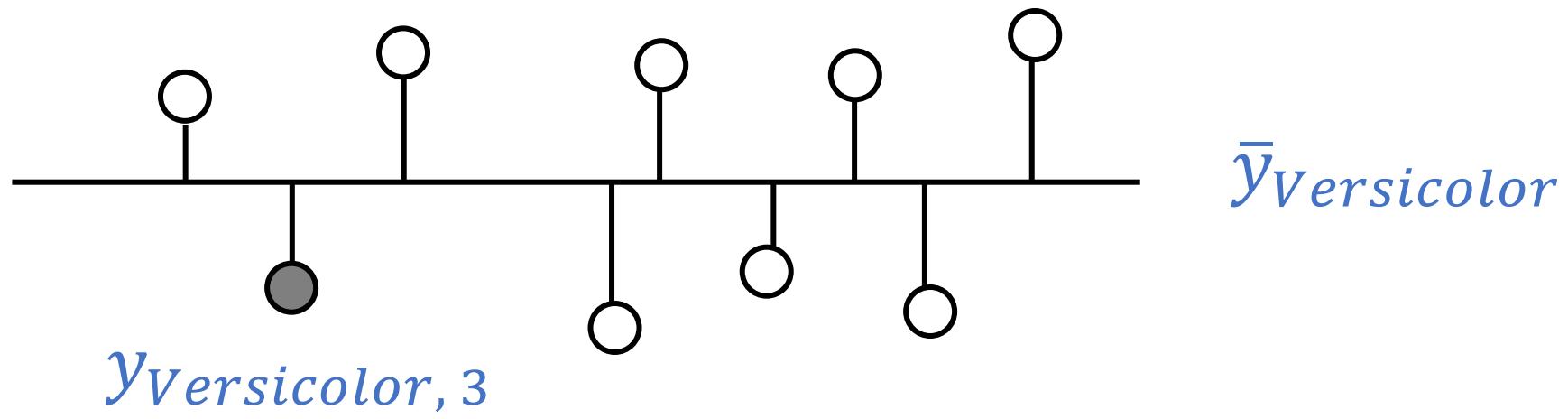
Within-groups: $SS_{within} = SS_R = \sum_{A,i} (y_{A,i} - \bar{y}_A)^2$

$y_{Versicolor, 2}$

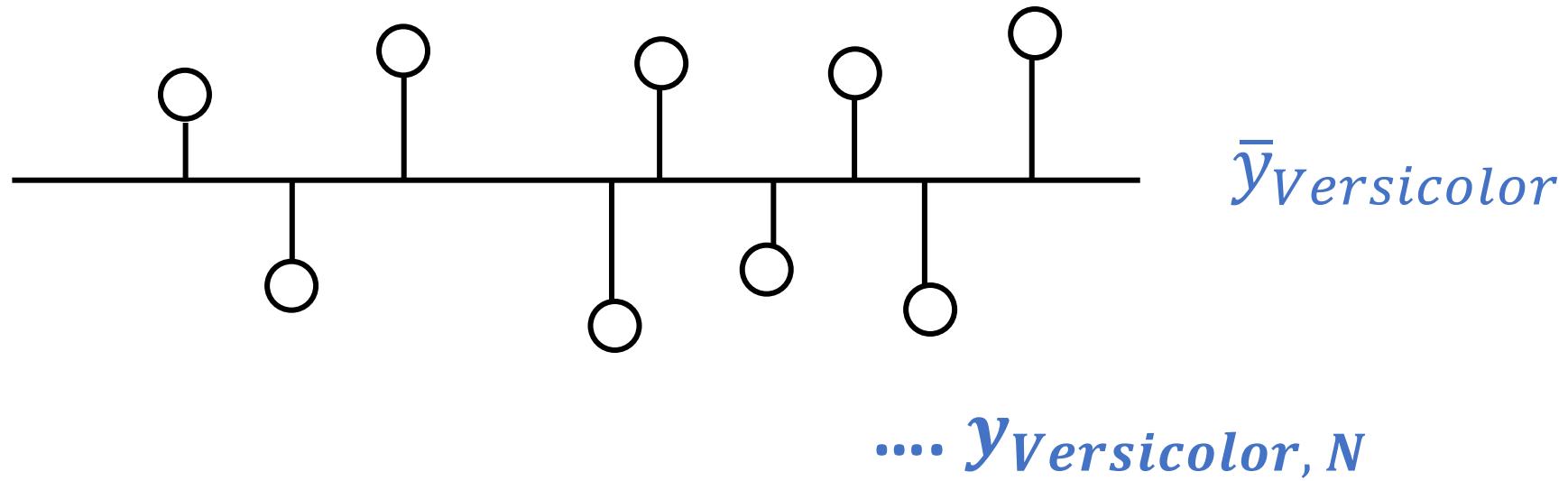


$\bar{y}_{Versicolor}$

Within-groups: $SS_{within} = SS_R = \sum_{A,i} (y_{A,i} - \bar{y}_A)^2$



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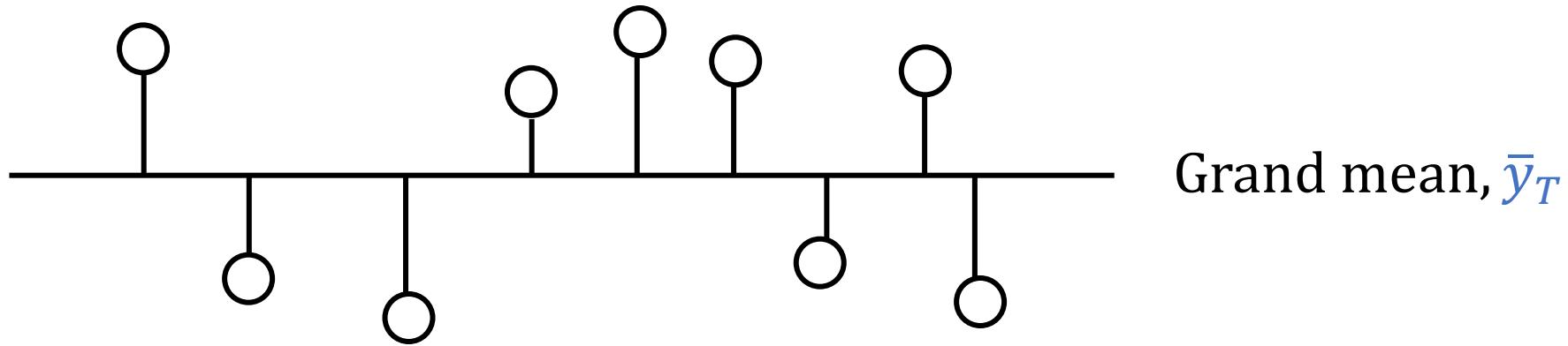
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Total:

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Individual data points, $y_{A,i}$

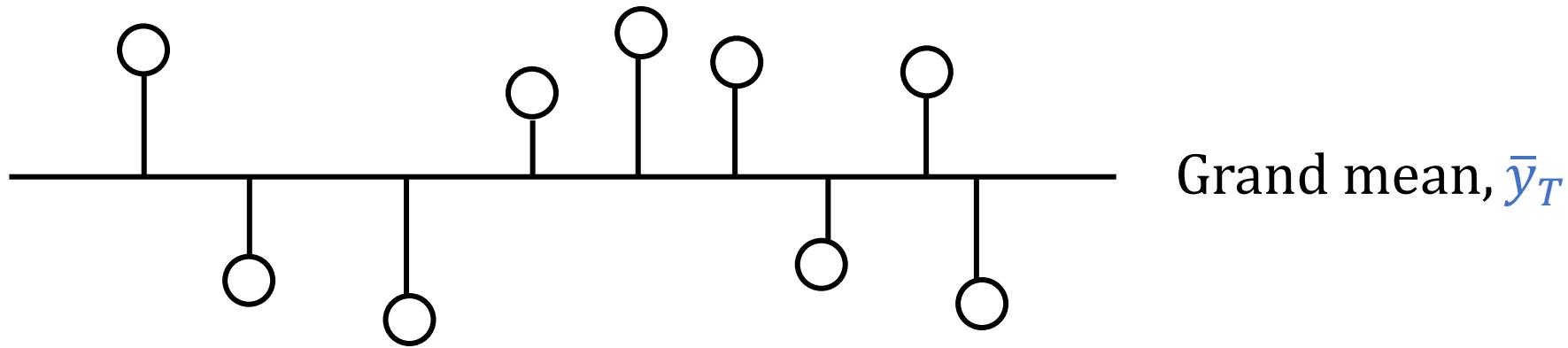


Individual data points, $y_{A,i}$

Total:

$$SS_{total} = SS_T = \sum_{A,i} (y_{A,i} - \bar{y}_T)^2$$

Individual data points, $y_{A,i}$



Individual data points, $y_{A,i}$

$$SS_{between} + SS_{within}$$

Total:

$$SS_{total} = SS_T = \sum_{A,i} (y_{A,i} - \bar{y}_T)^2$$

Useful to obtain ratio of variance explained by the treatment against noise (within-group variance)

$$SS_{between} + SS_{within}$$

Total:

$$SS_{total} = SS_T = \sum_{A,i} (y_{A,i} - \bar{y}_T)^2$$

Useful to obtain ratio of variance explained by the treatment against noise (within-group variance)

simplified e.g.,

$SS_{between}$

$SS_{between} + SS_{within}$

Mean Squared Error → F-ratio

Between-group Variance:

$$MS_A = \frac{SS_A}{df_A}$$



$$\frac{MS_A}{MS_R} = \text{F-ratio}$$

Within-group Variance:

$$MS_R = \frac{SS_R}{df_R}$$

Summary II

- ANOVA
- Variance
- F-ratio
- Sum of squares deviation
- Mean square error

Introduction to R: Part II

- ANOVA
- emmeans()
- plot()

DAY 2

Winter Workshop: **Basic and Intermediate Statistics with R**

Chai Jun Ho, PhD



Schedule

Day 1	Day 2	Day 3
Introduction to Statistics	Linear Model I	Linear Model II
Introduction to R	Data Visualization	Mixed-Effect Model

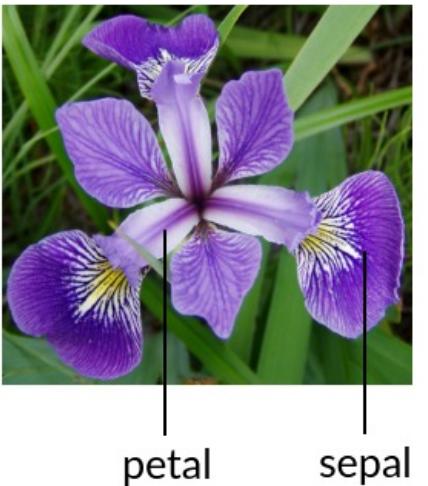
high calorie vs low calorie



Categorical differences

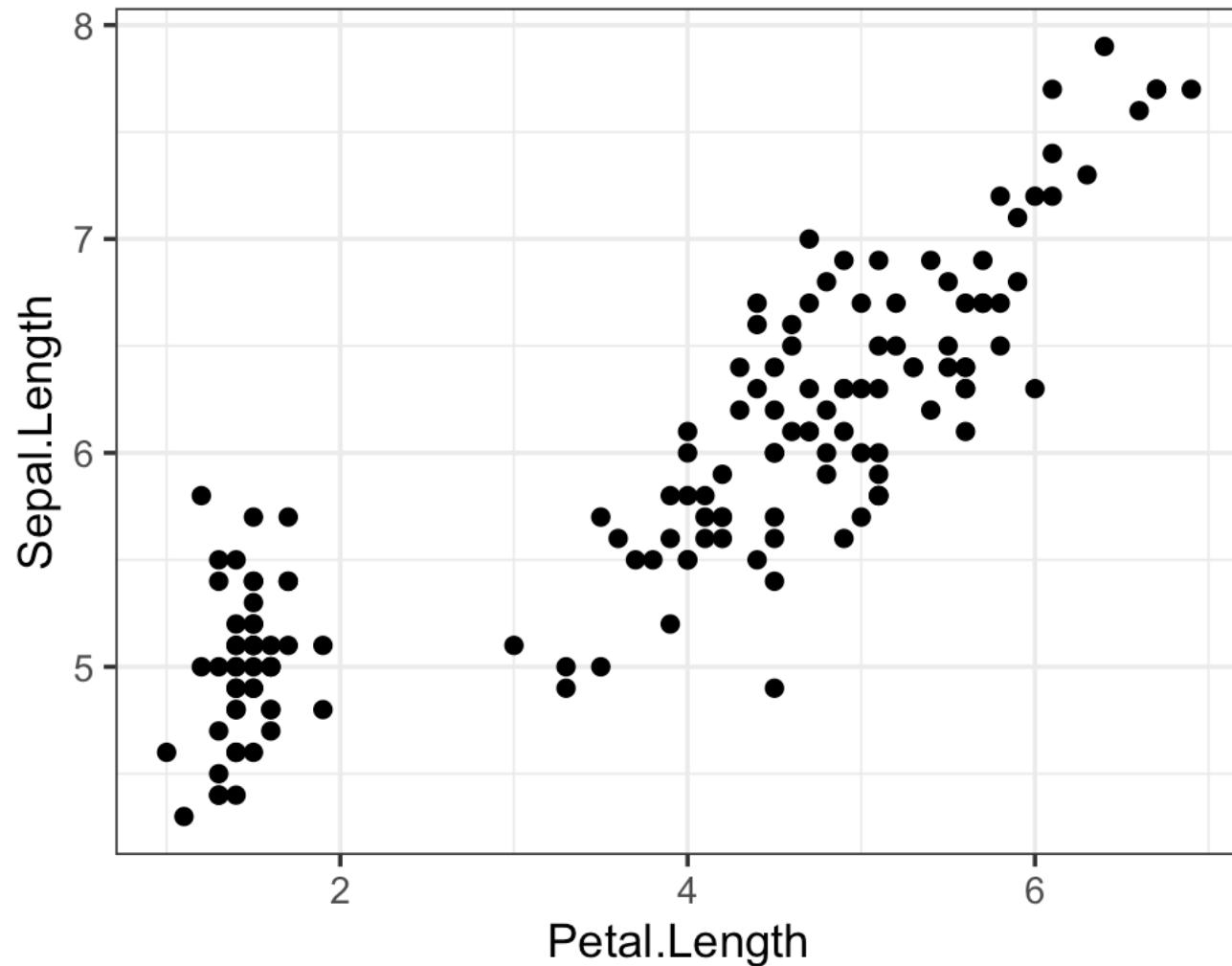
high calorie vs **low calorie**



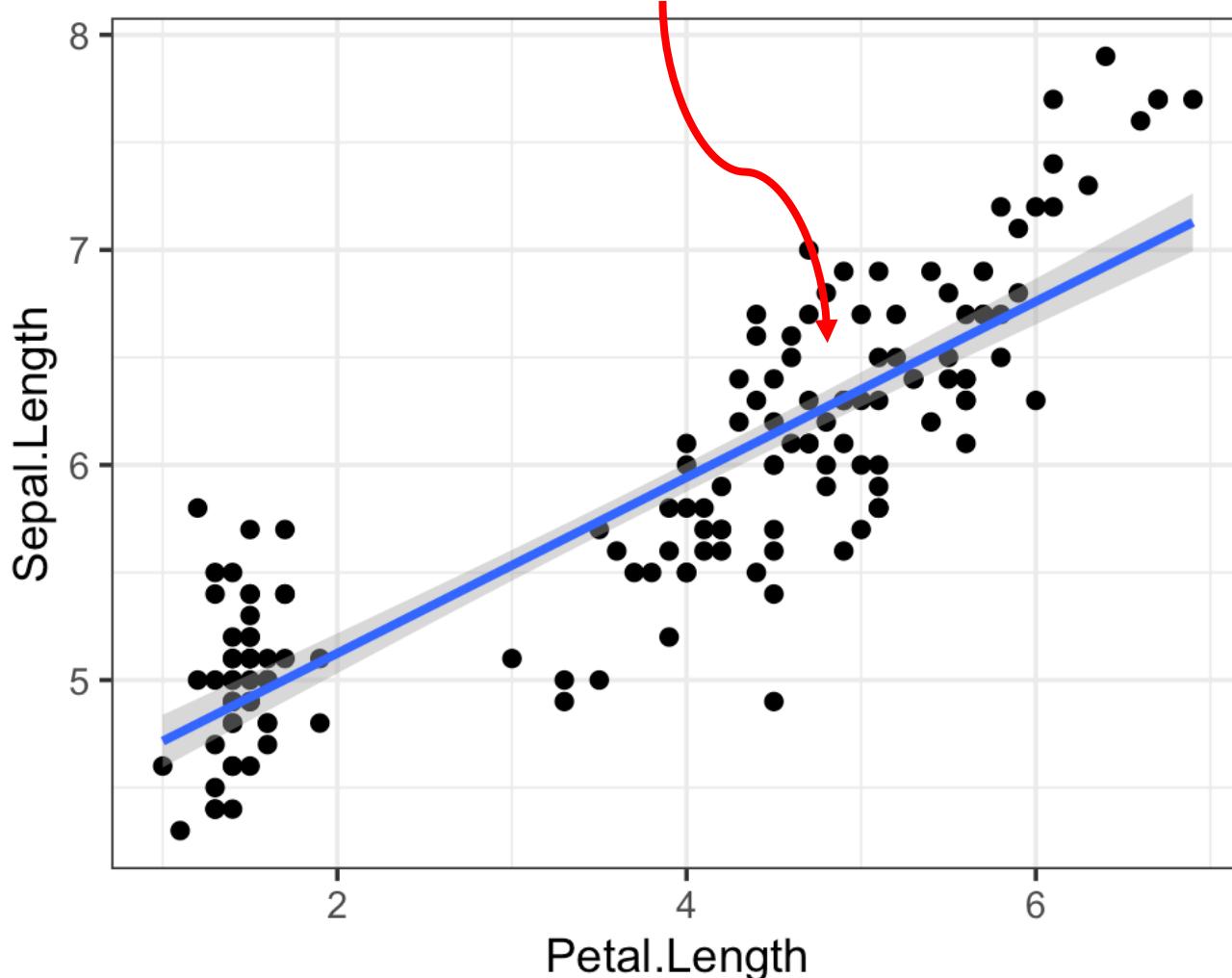


Long petal, long sepal?
Long petal, short sepal?
Short petal, long sepal?
Short petal, short sepal?

Relationships

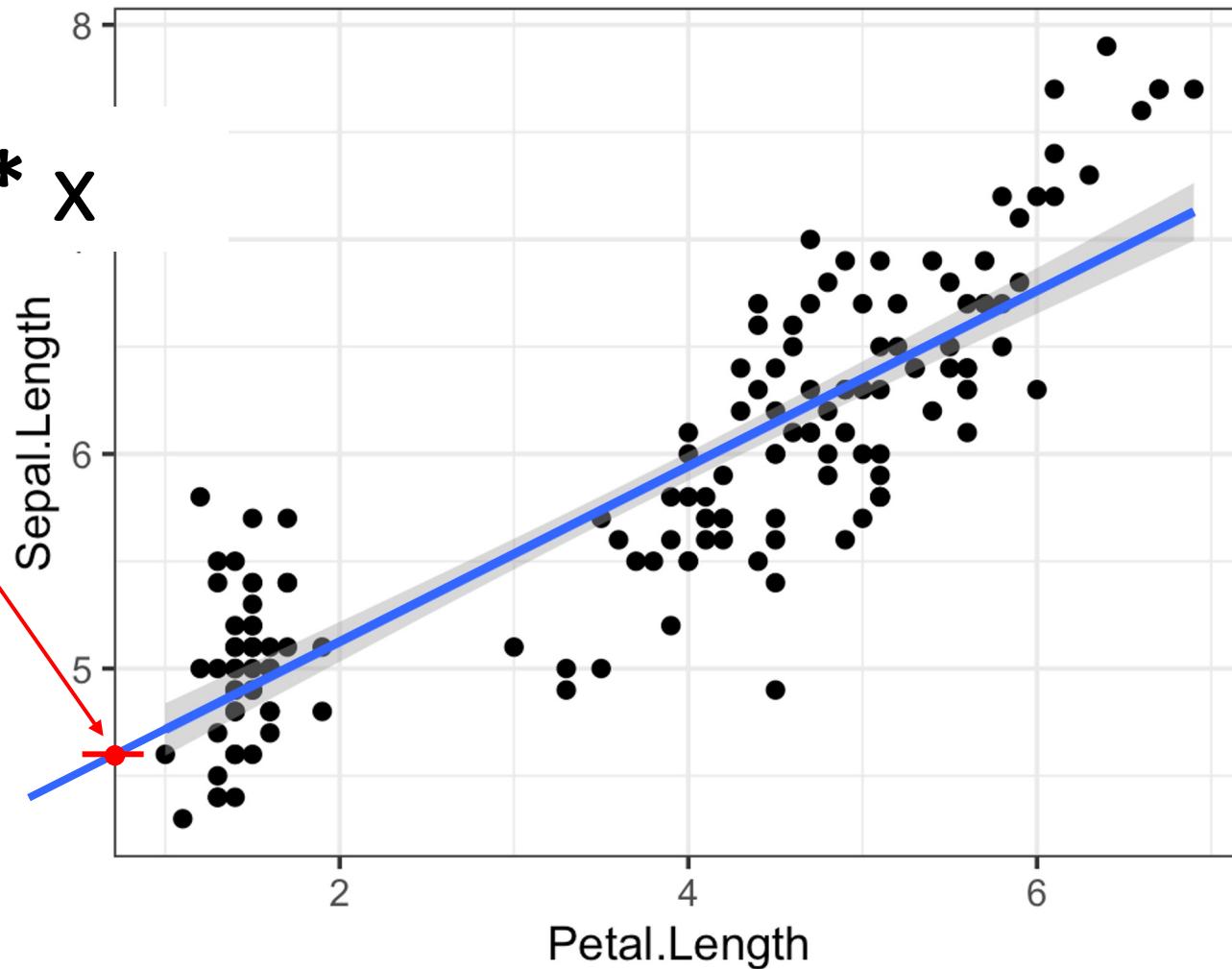


Linear model represented
by the **regression line**



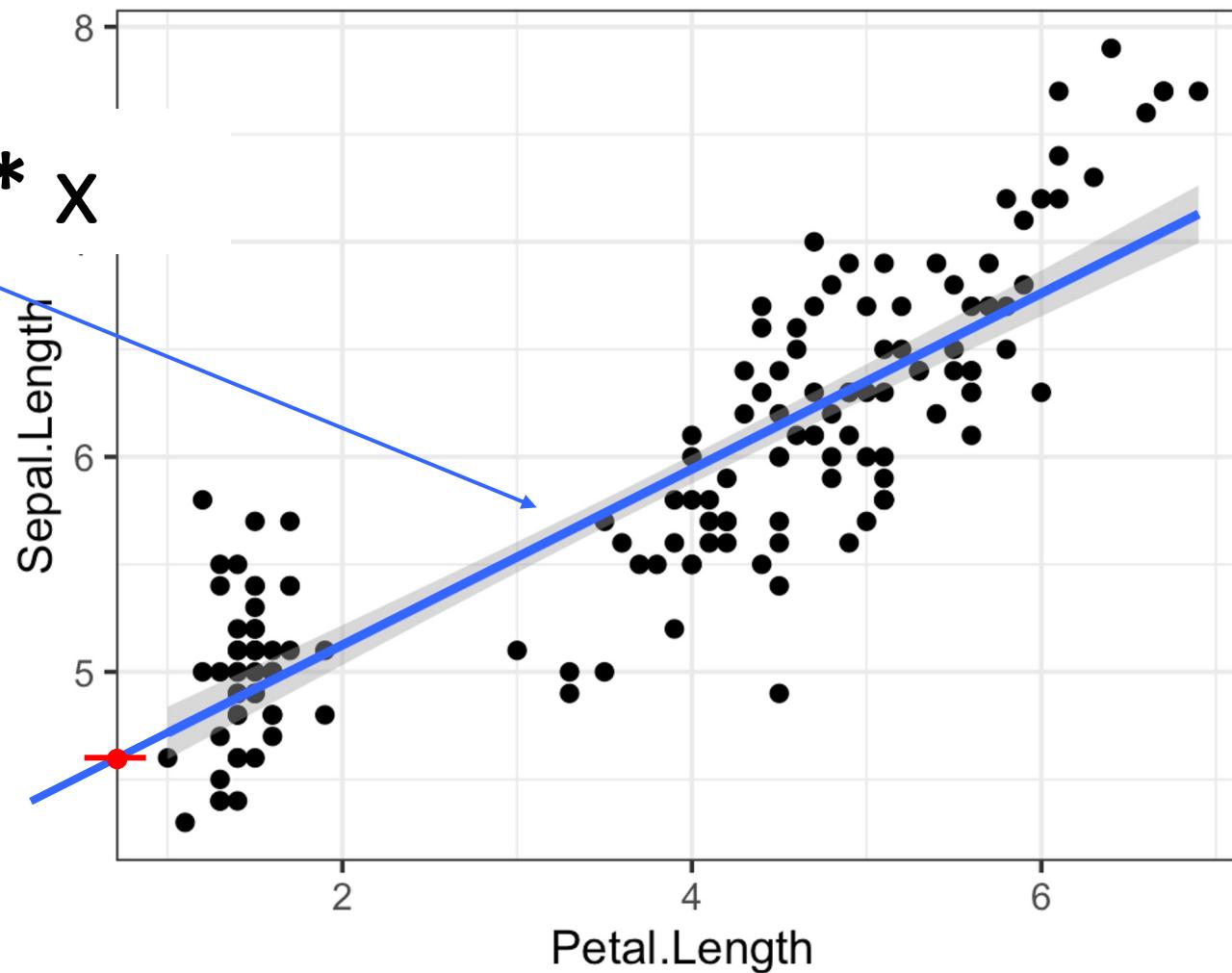
regression line

$$y = C + m * x$$



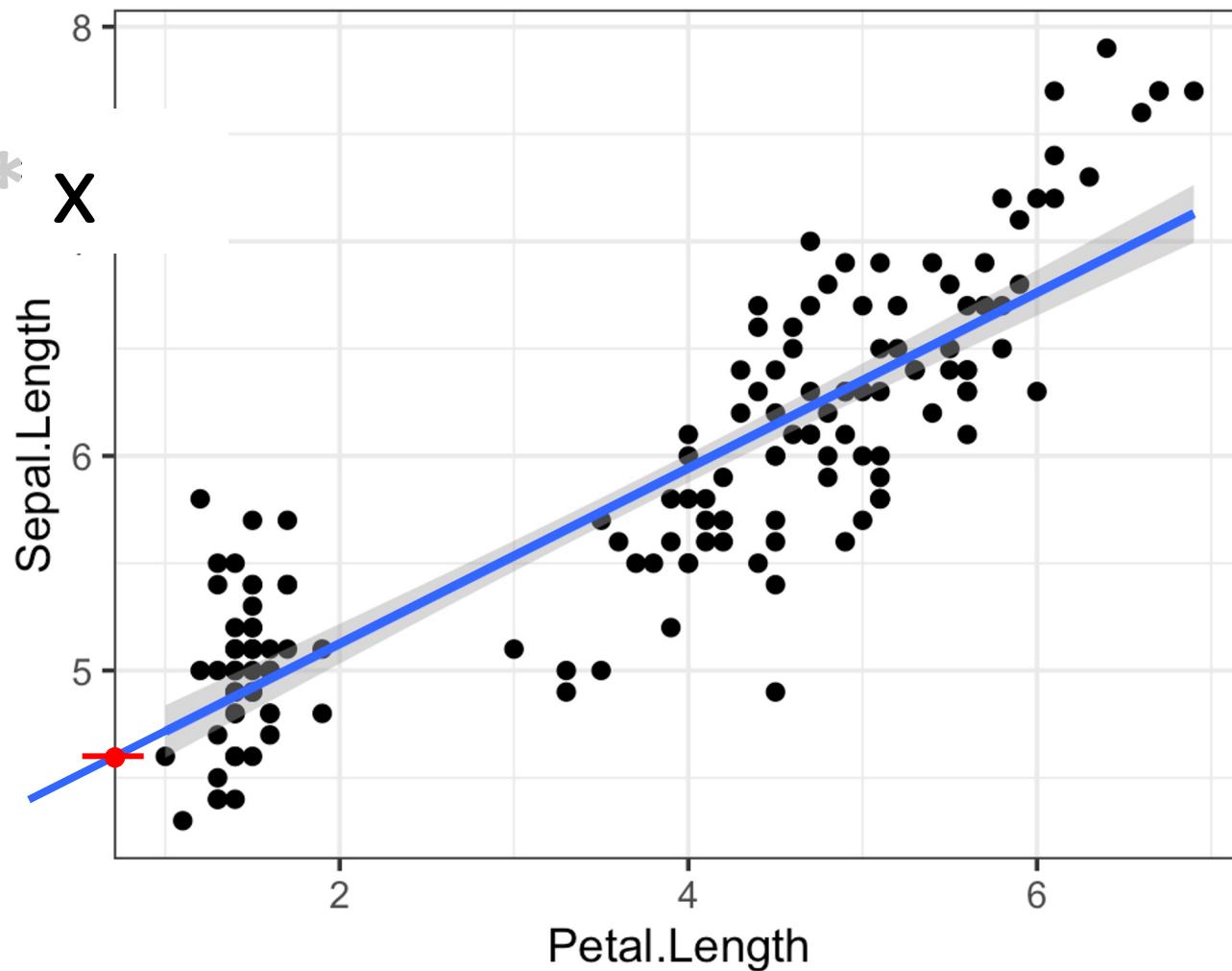
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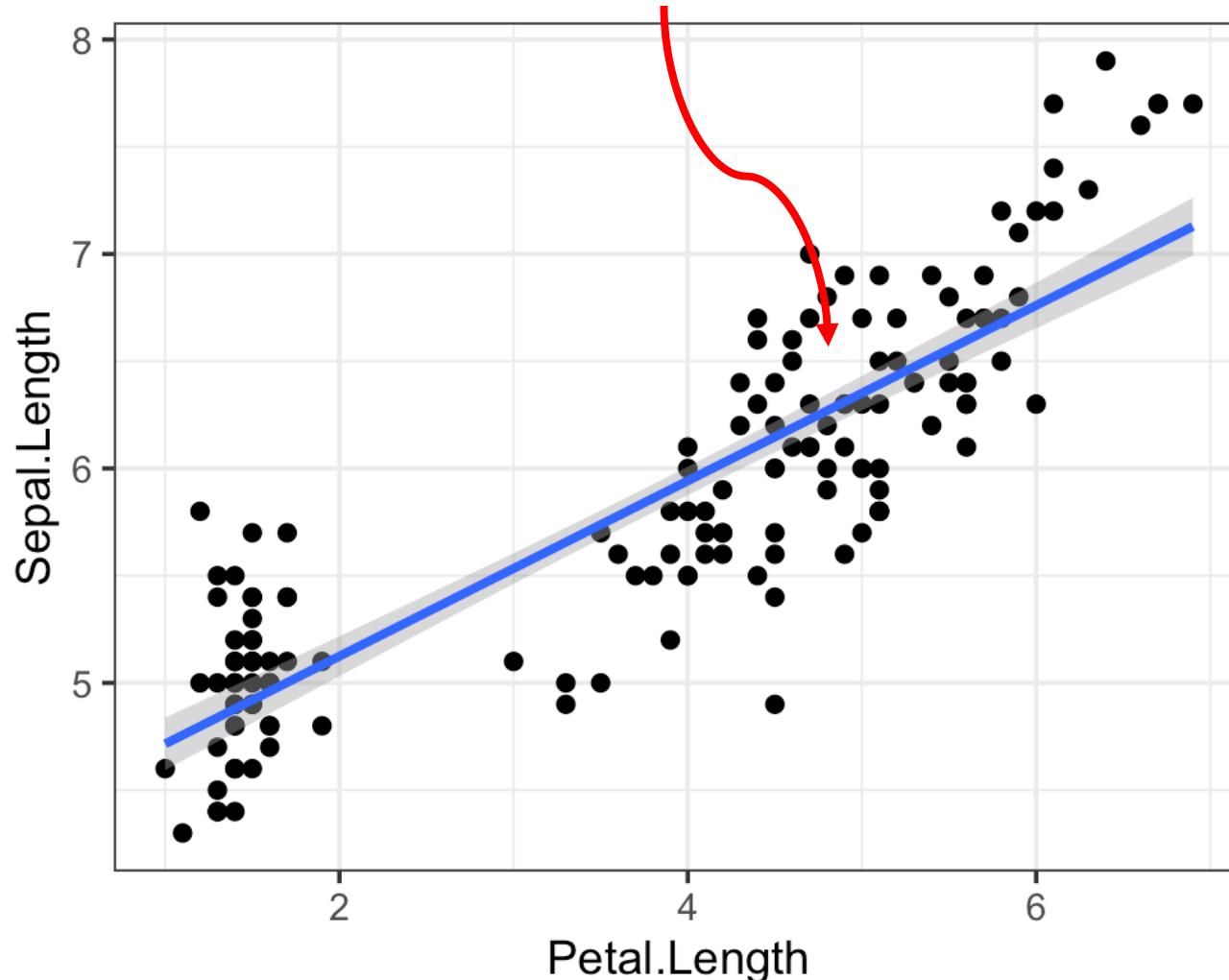


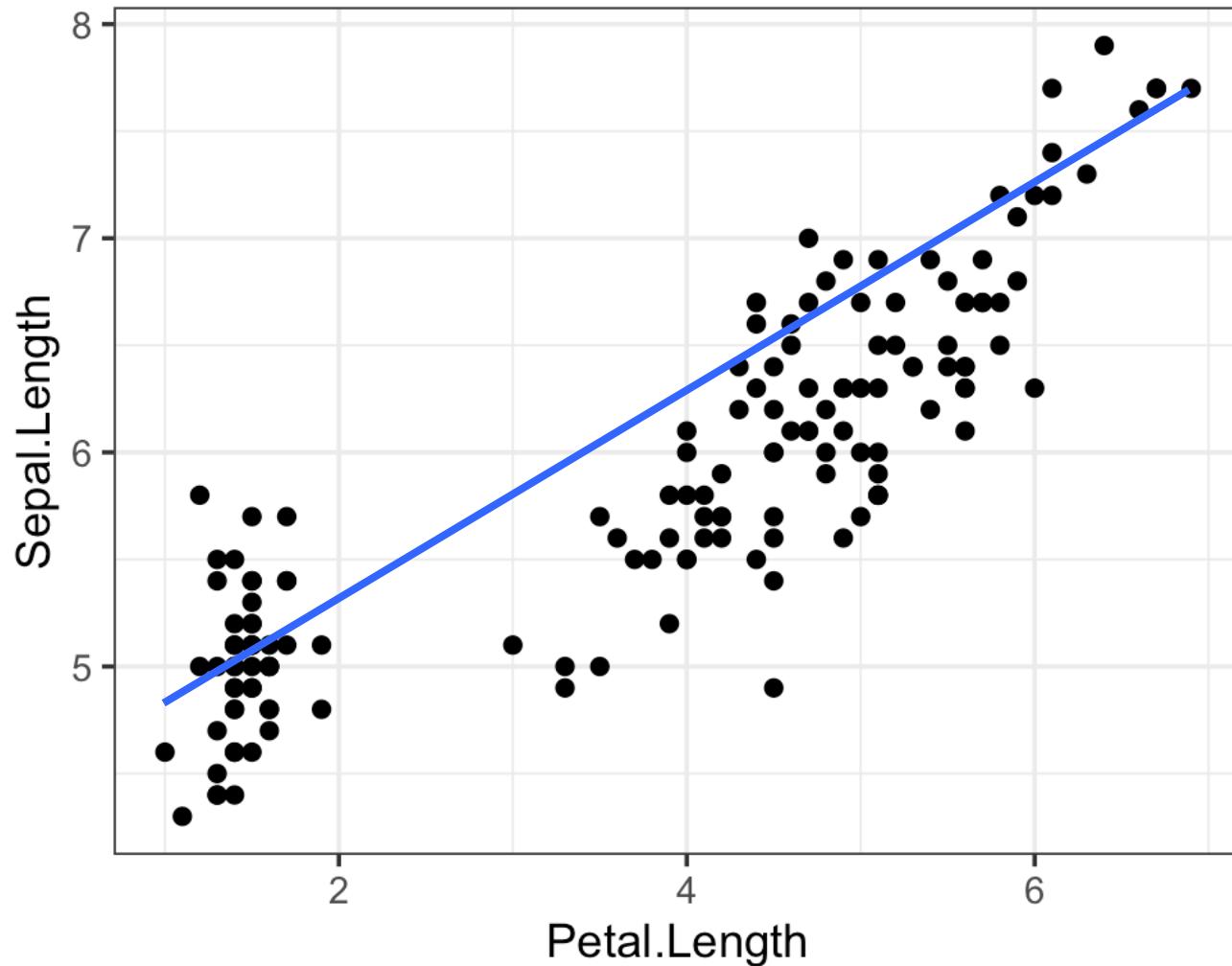
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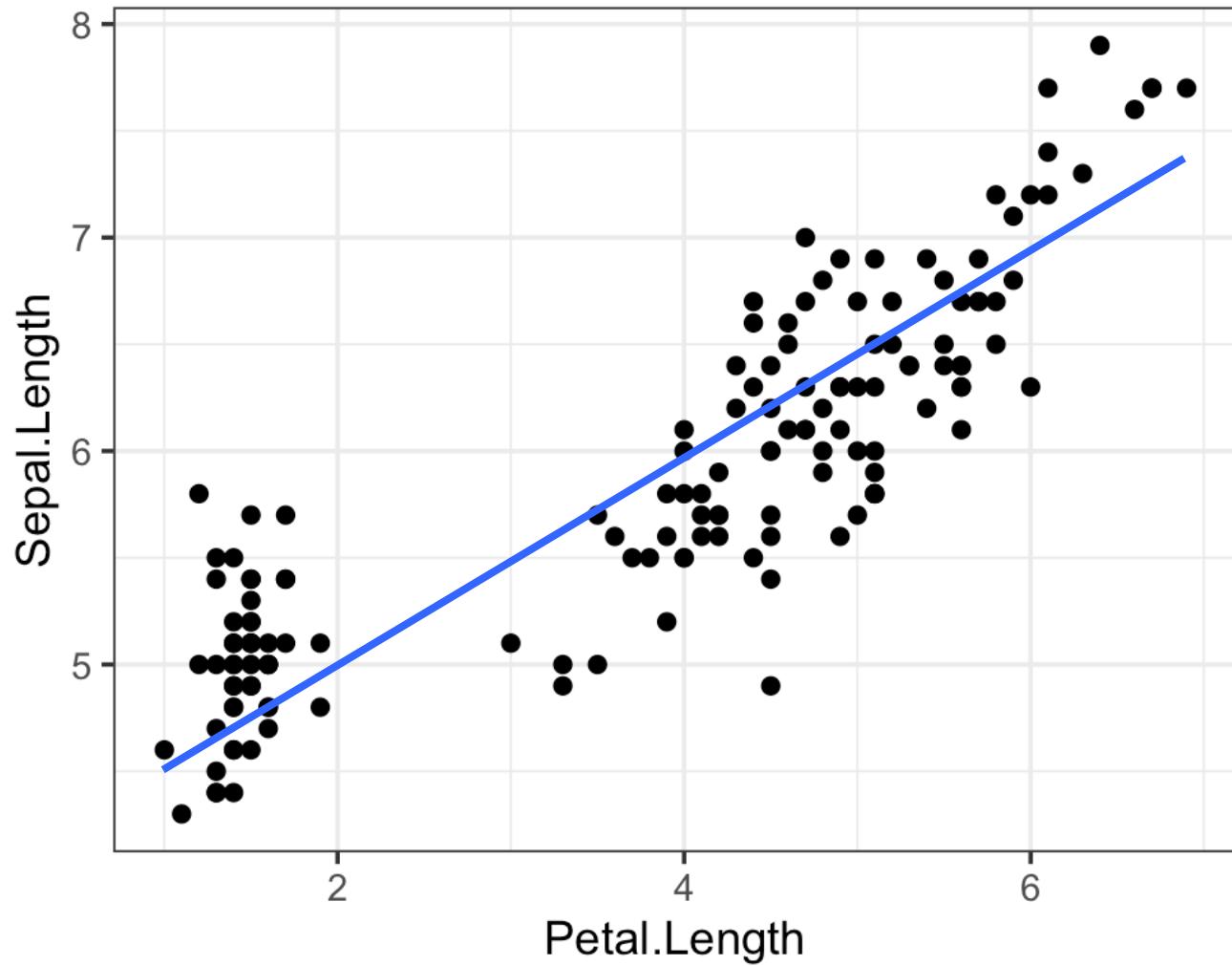
$$y = c + m * x$$

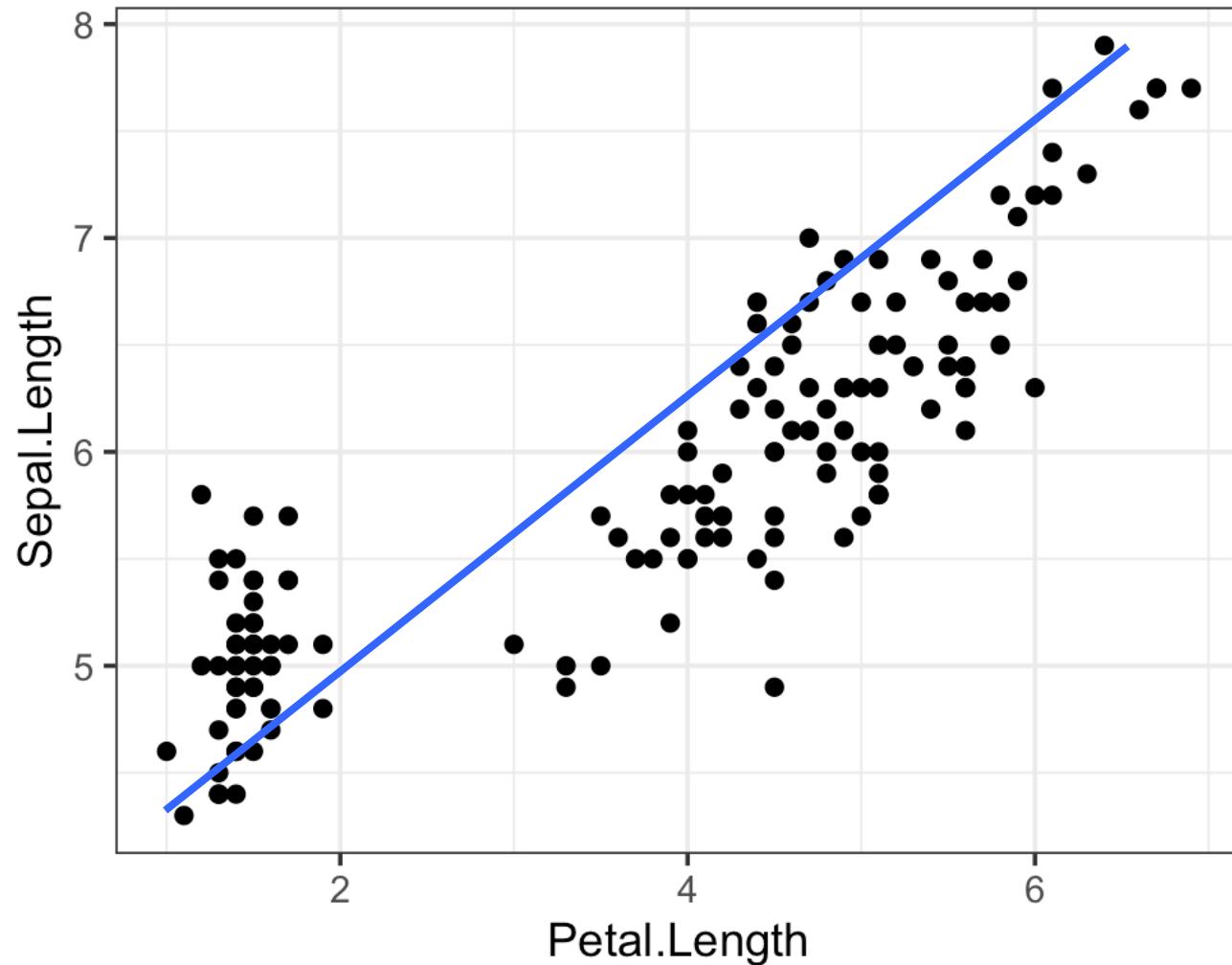


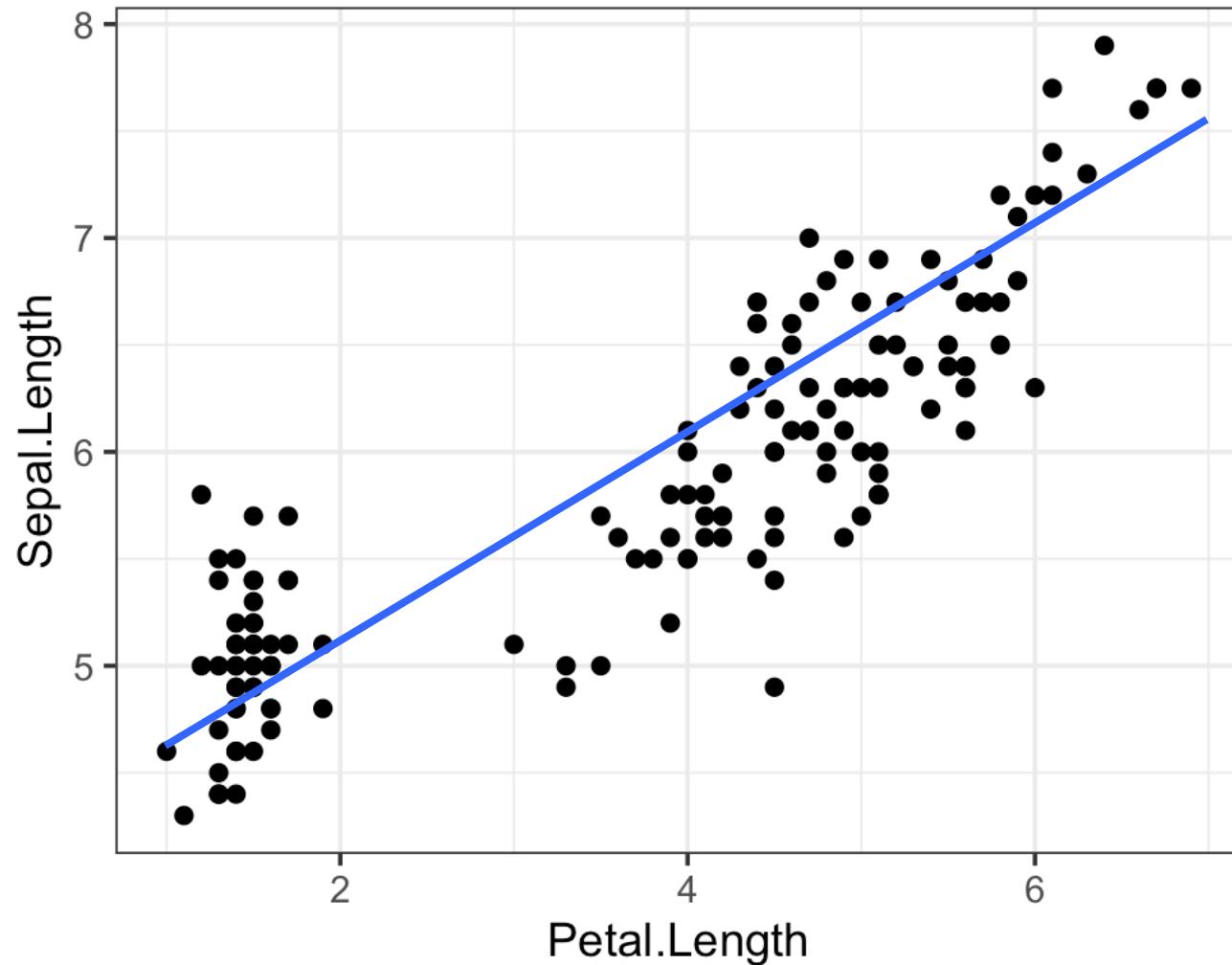
why this?

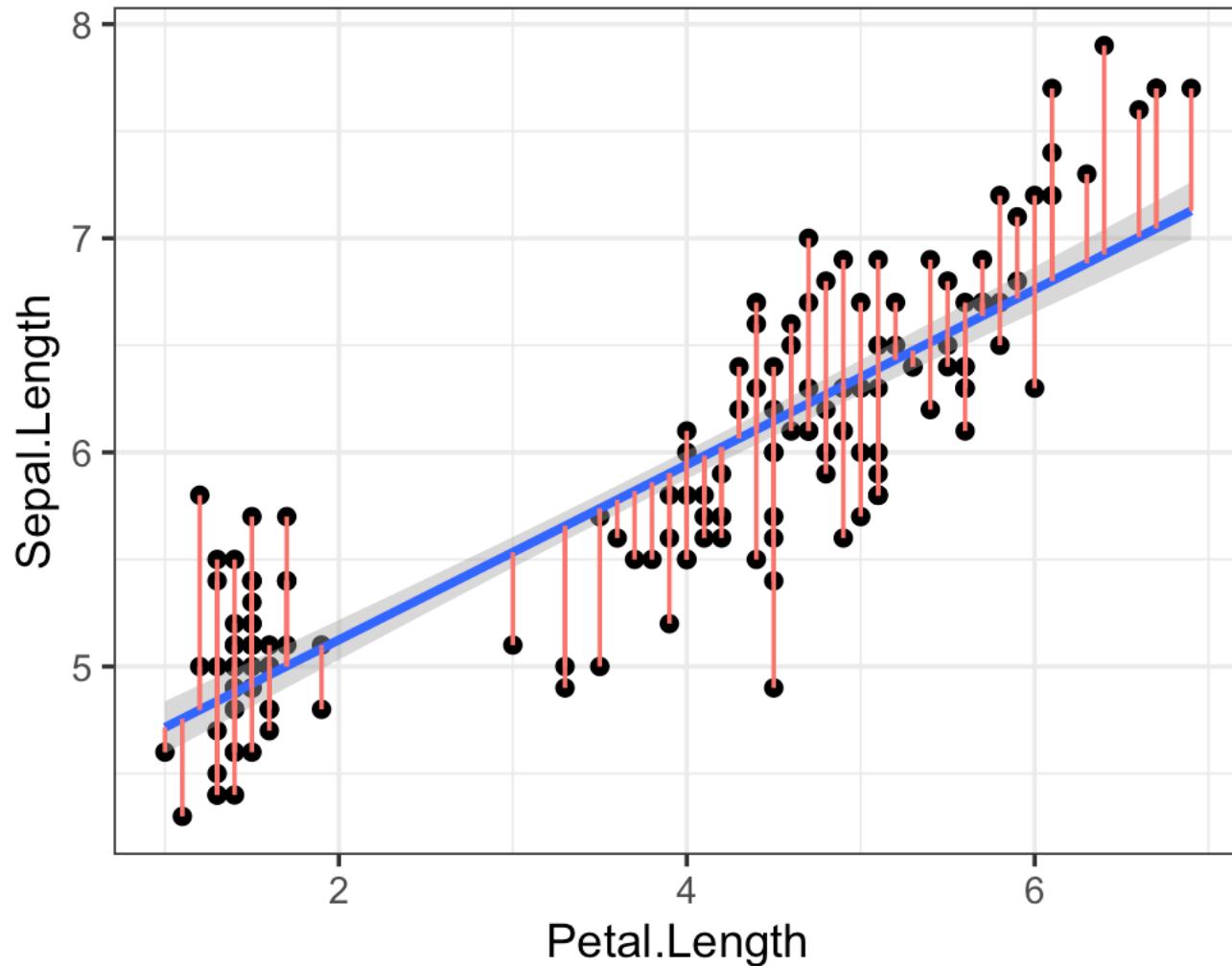




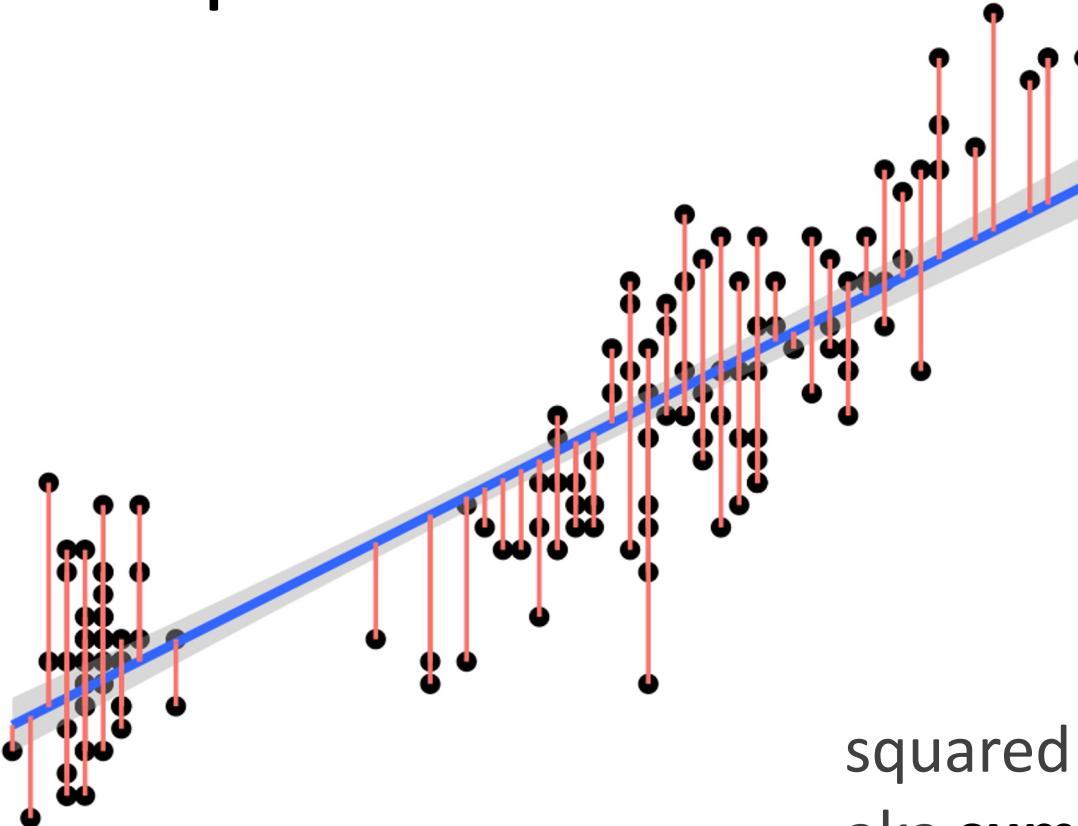




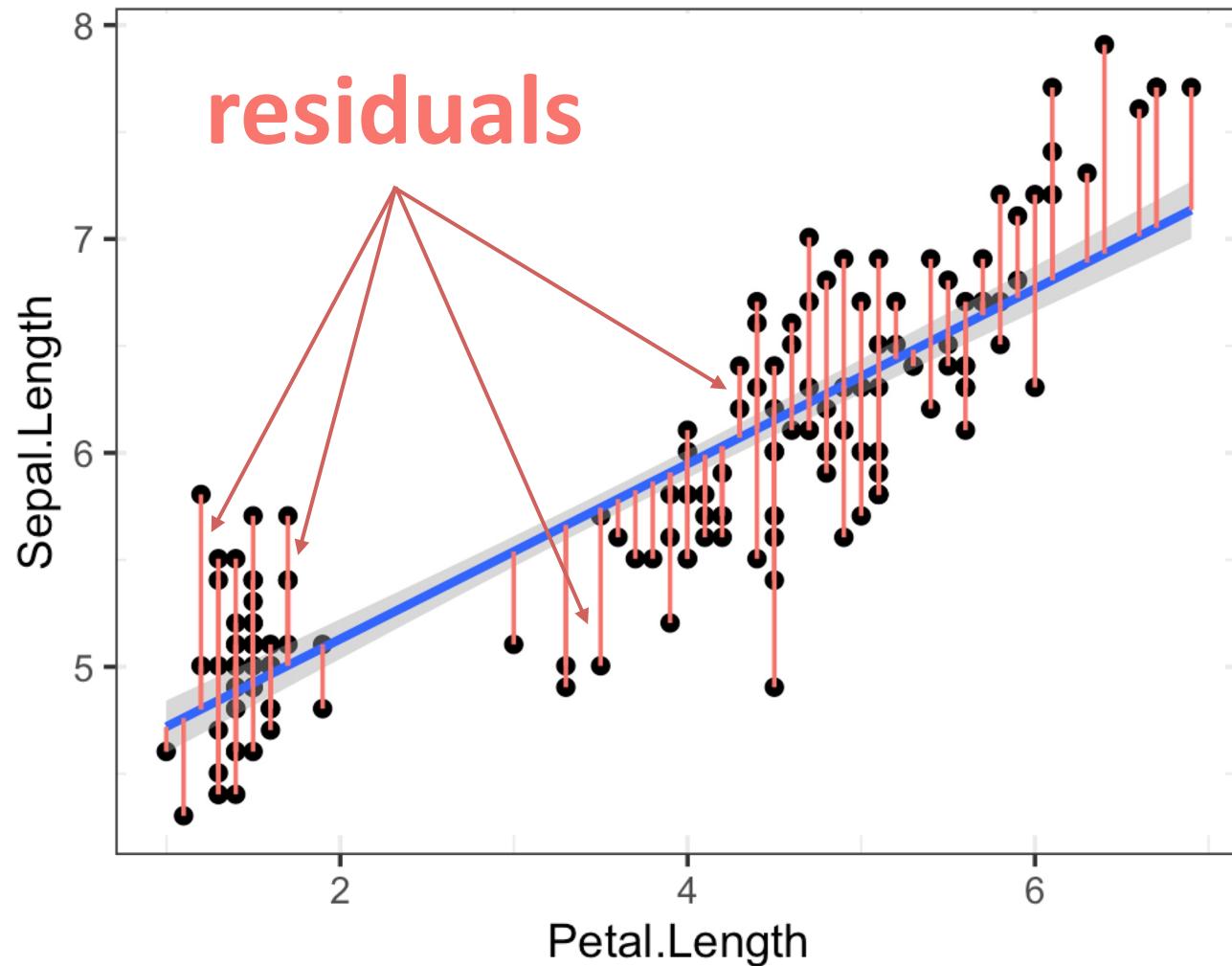




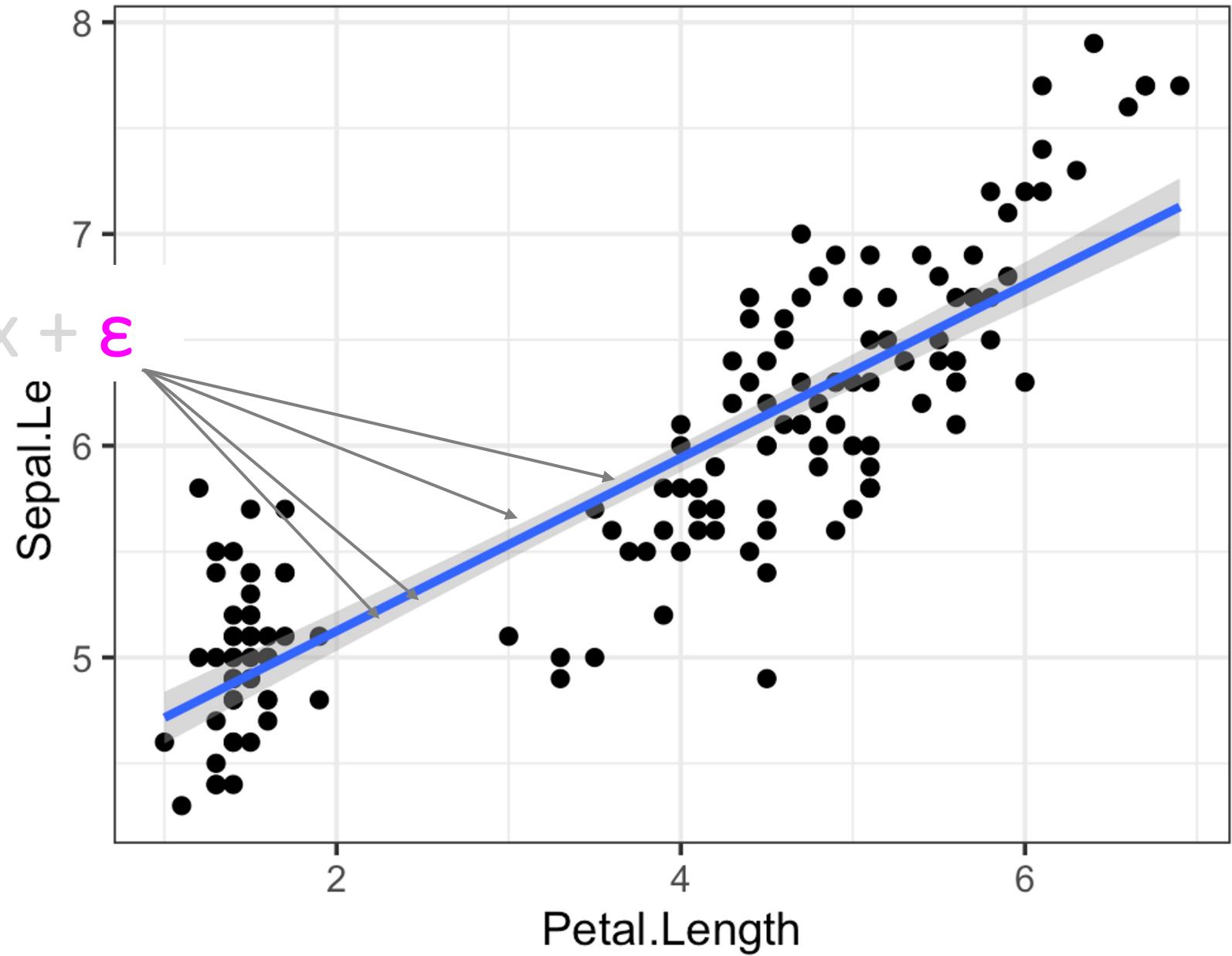
Minimizing squared deviation/distance
between **individual data point** and the
regression line



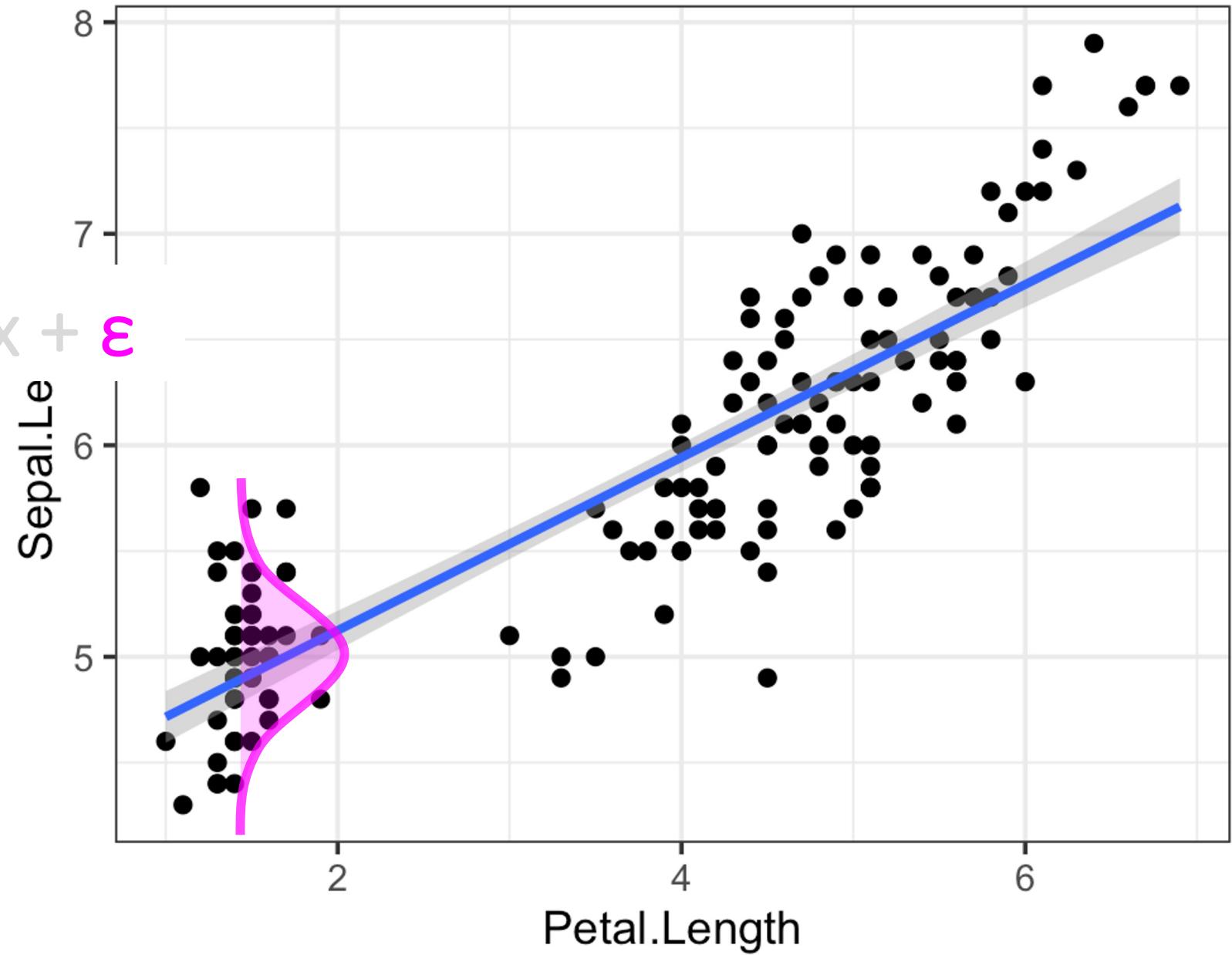
squared deviation/distance
aka **sums of squares!**



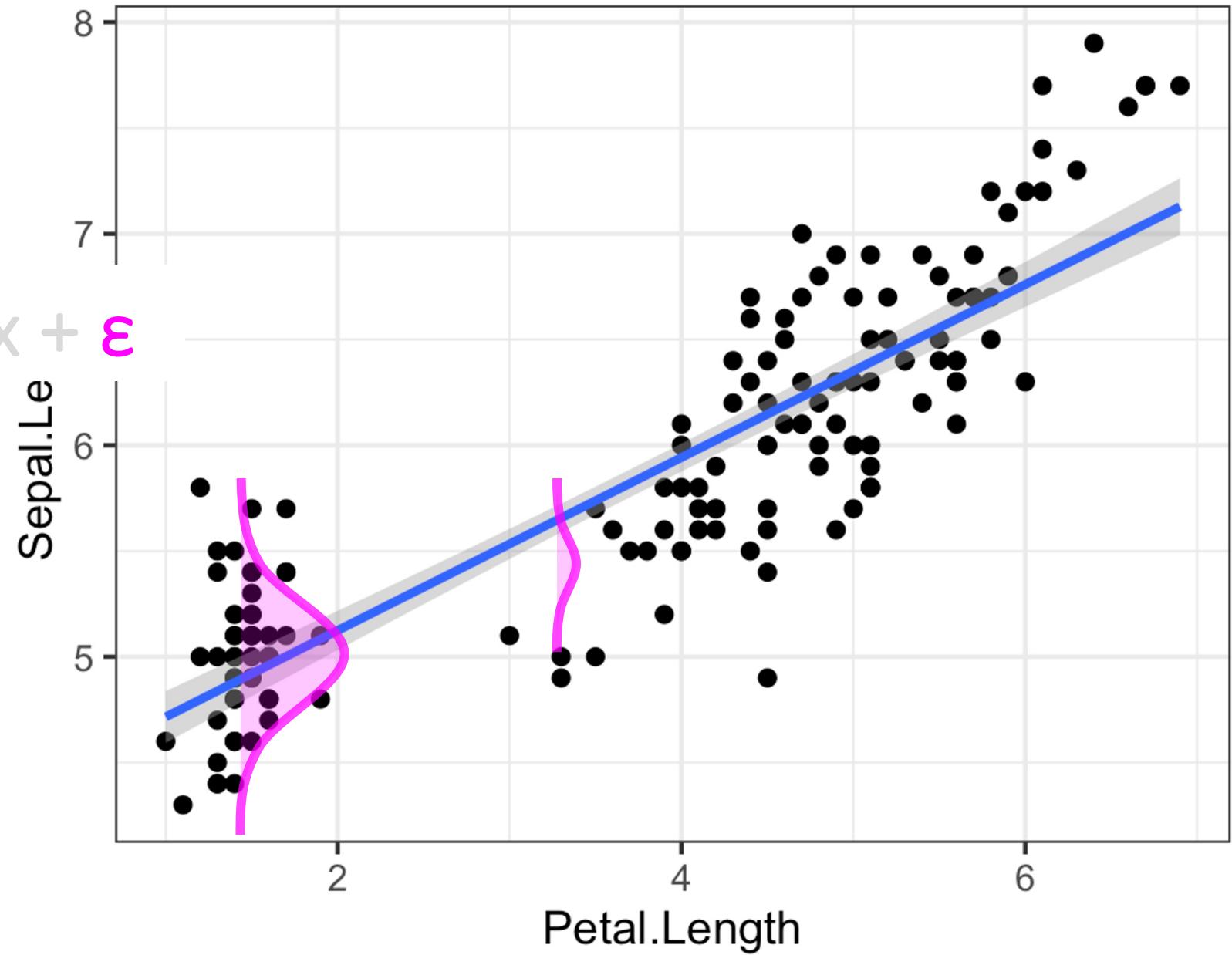
$$y = c + m * x + \varepsilon$$



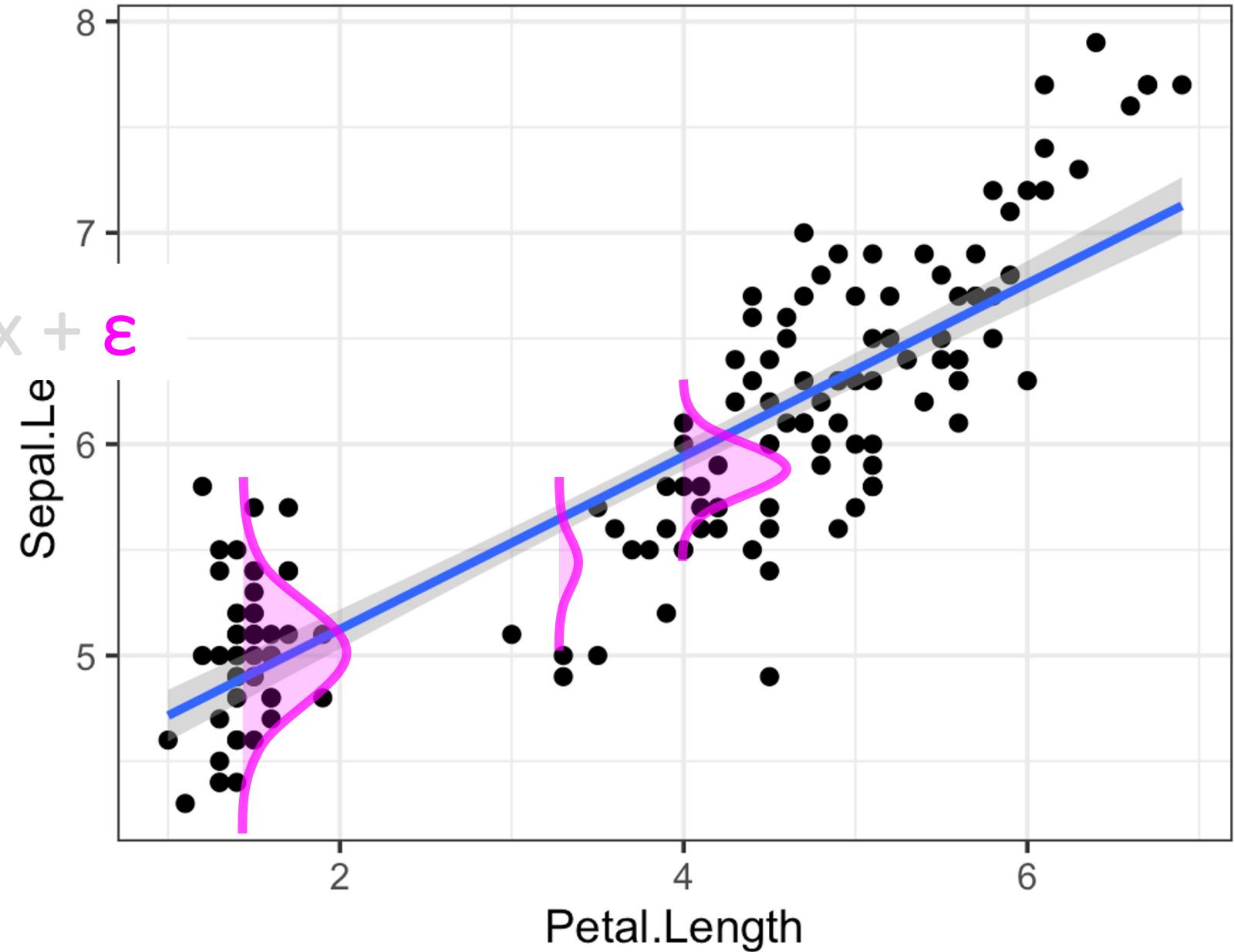
$$y = c + m * x + \varepsilon$$



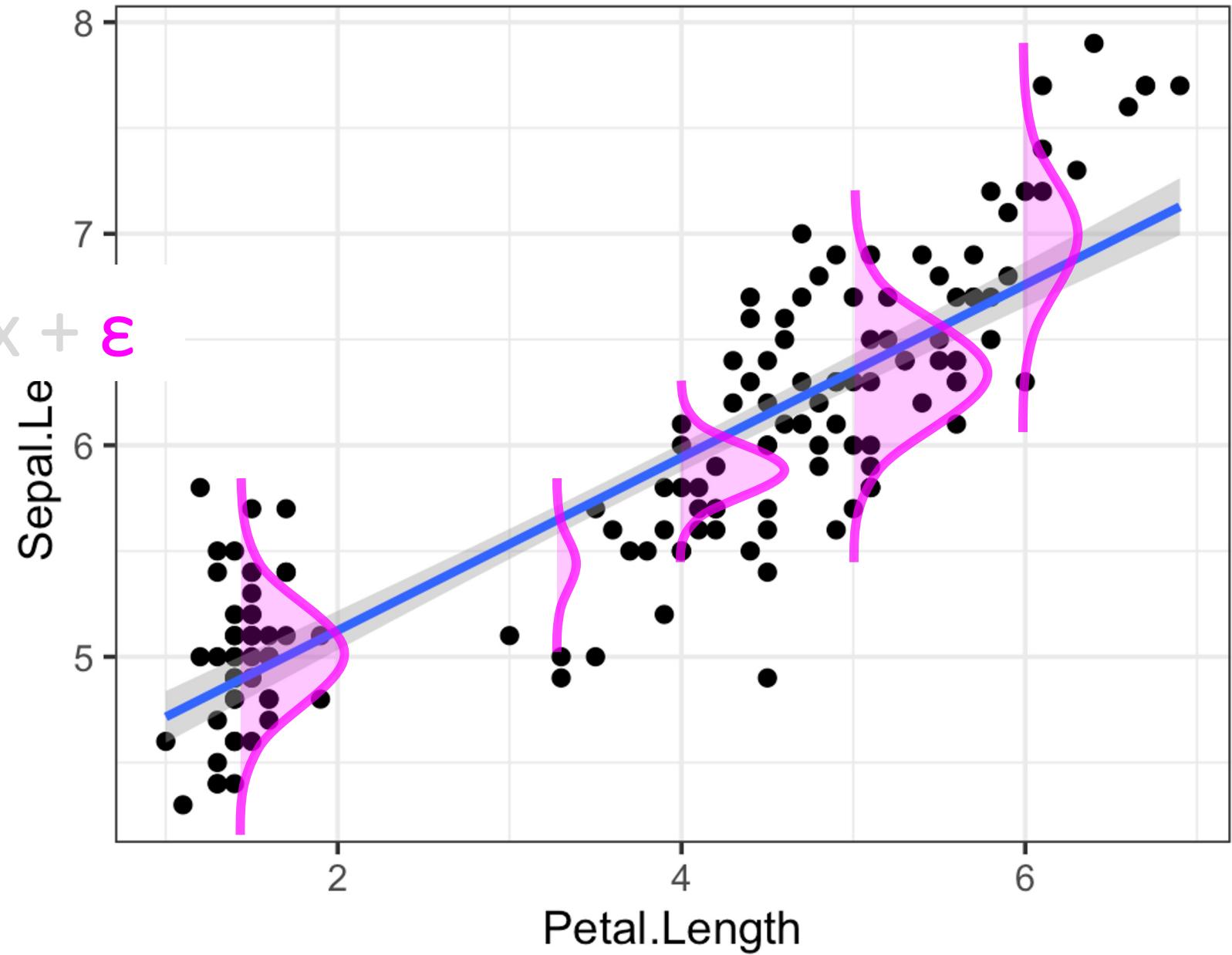
$$y = c + m * x + \varepsilon$$



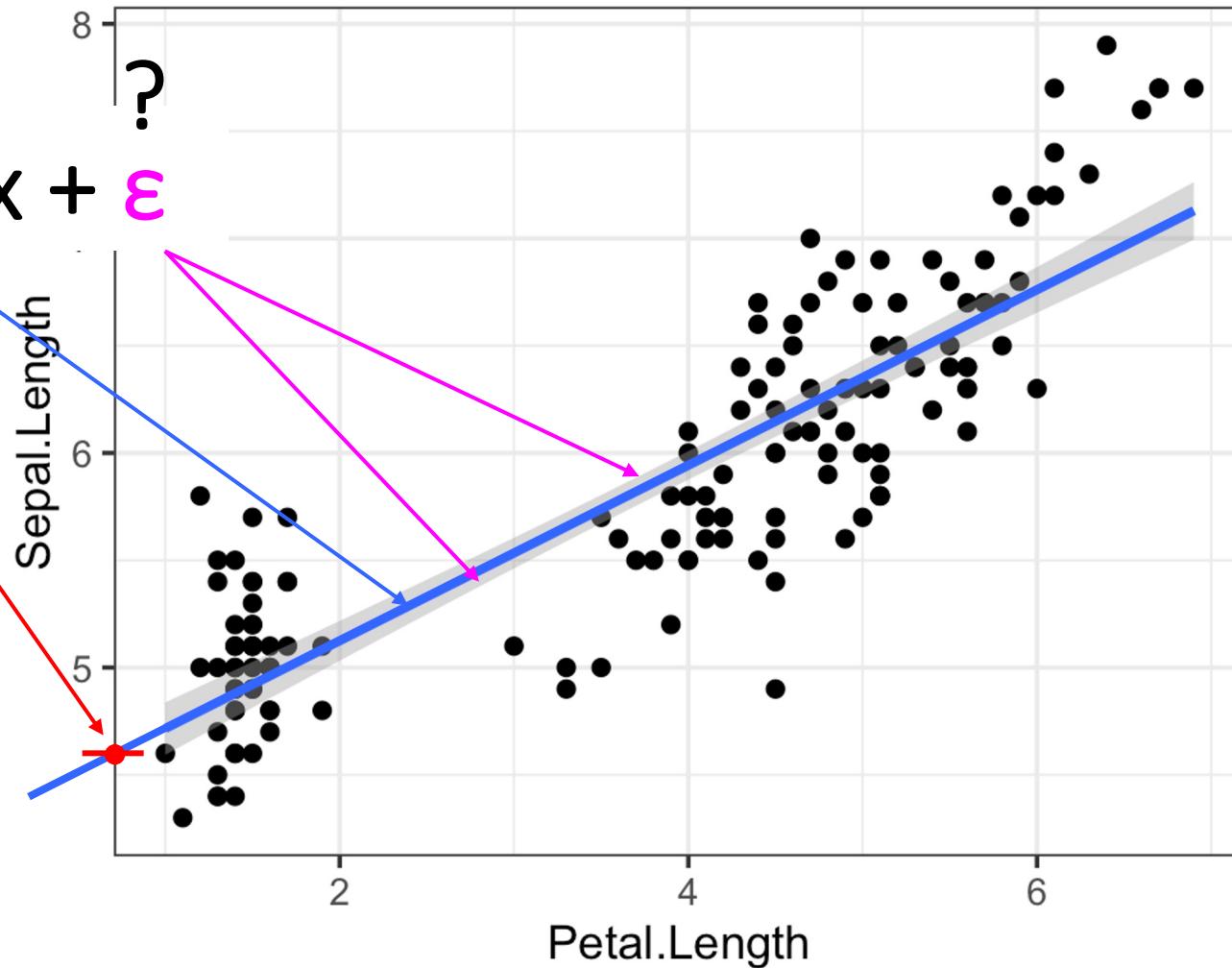
$$y = c + m * x + \varepsilon$$



$$y = c + m * x + \varepsilon$$



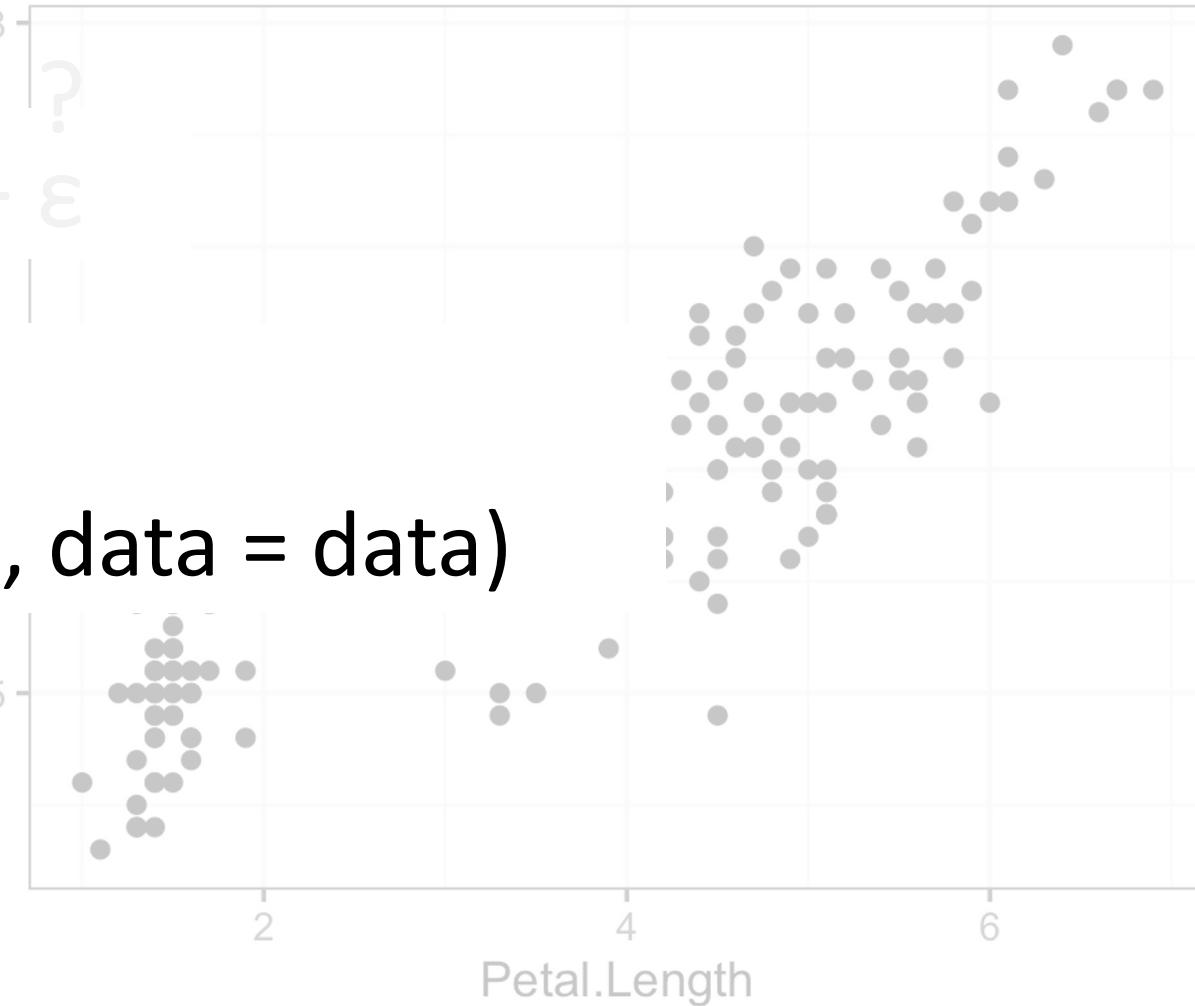
$$y = \color{red}{c} + \color{blue}{m} * \color{black}{x} + \color{magenta}{\epsilon}$$

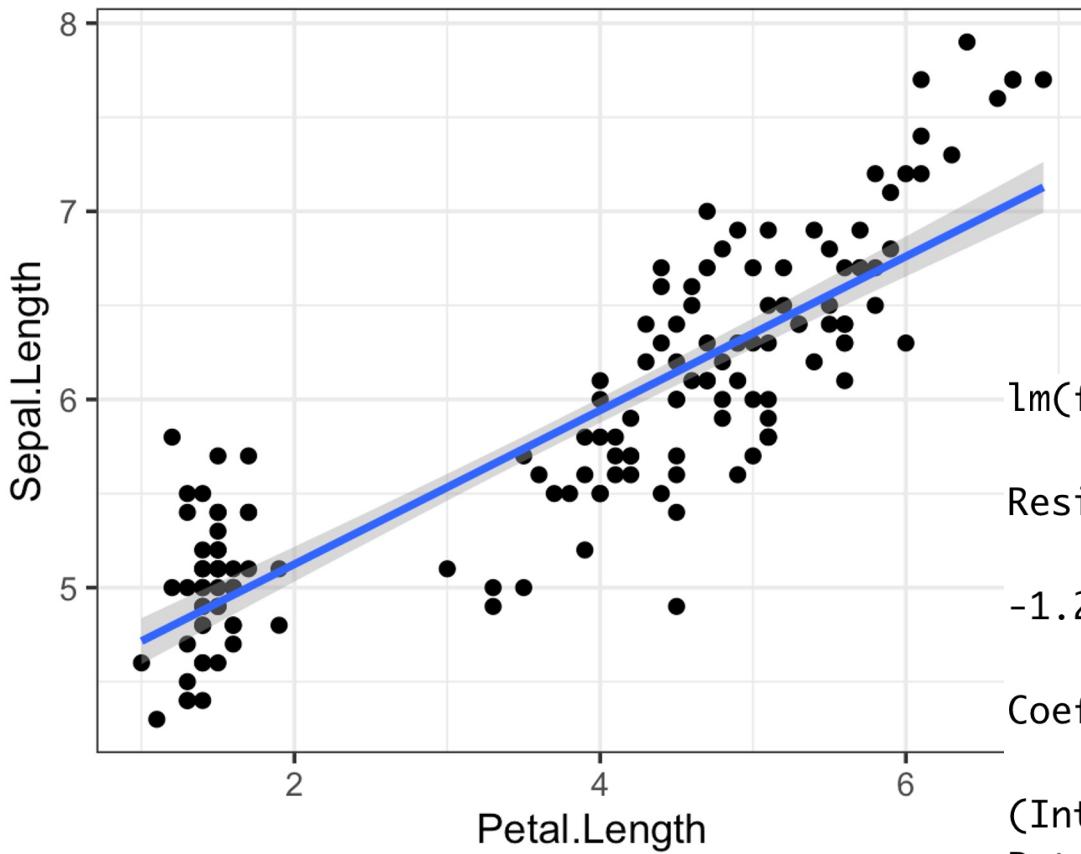


$$y \sim c + m * x + \epsilon$$

notation in R:

```
lmod = lm(y ~ x, data = data)
```





```
lm(formula = Sepal.Length ~ Petal.Length, data = iris)
```

Residuals:

Min	1Q	Median	3Q	Max
-1.24675	-0.29657	-0.01515	0.27676	1.00269

Coefficients:

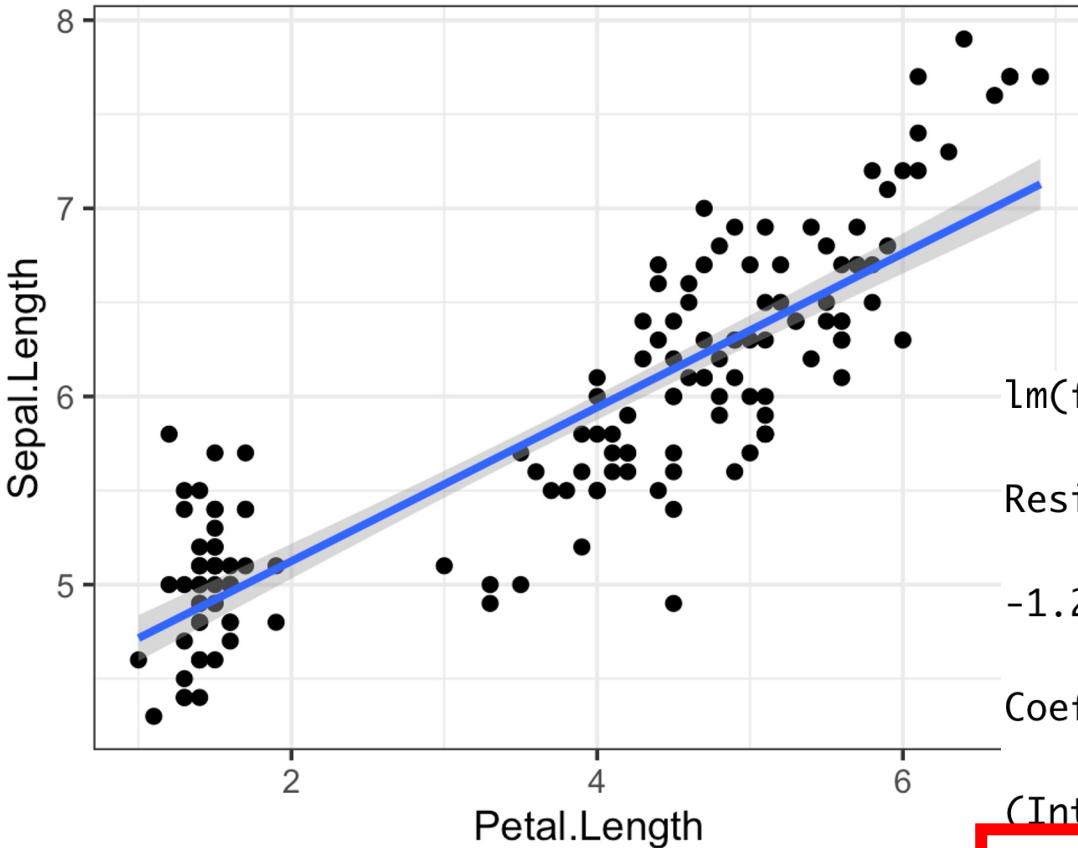
	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	4.30660	0.07839	54.94	<2e-16 ***
Petal.Length	0.40892	0.01889	21.65	<2e-16 ***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4071 on 148 degrees of freedom

Multiple R-squared: 0.76, Adjusted R-squared: 0.7583

F-statistic: 468.6 on 1 and 148 DF, p-value: < 2.2e-16



```
lm(formula = Sepal.Length ~ Petal.Length, data = iris)
```

Residuals:

Min	1Q	Median	3Q	Max
-1.24675	-0.29657	-0.01515	0.27676	1.00269

Coefficients:

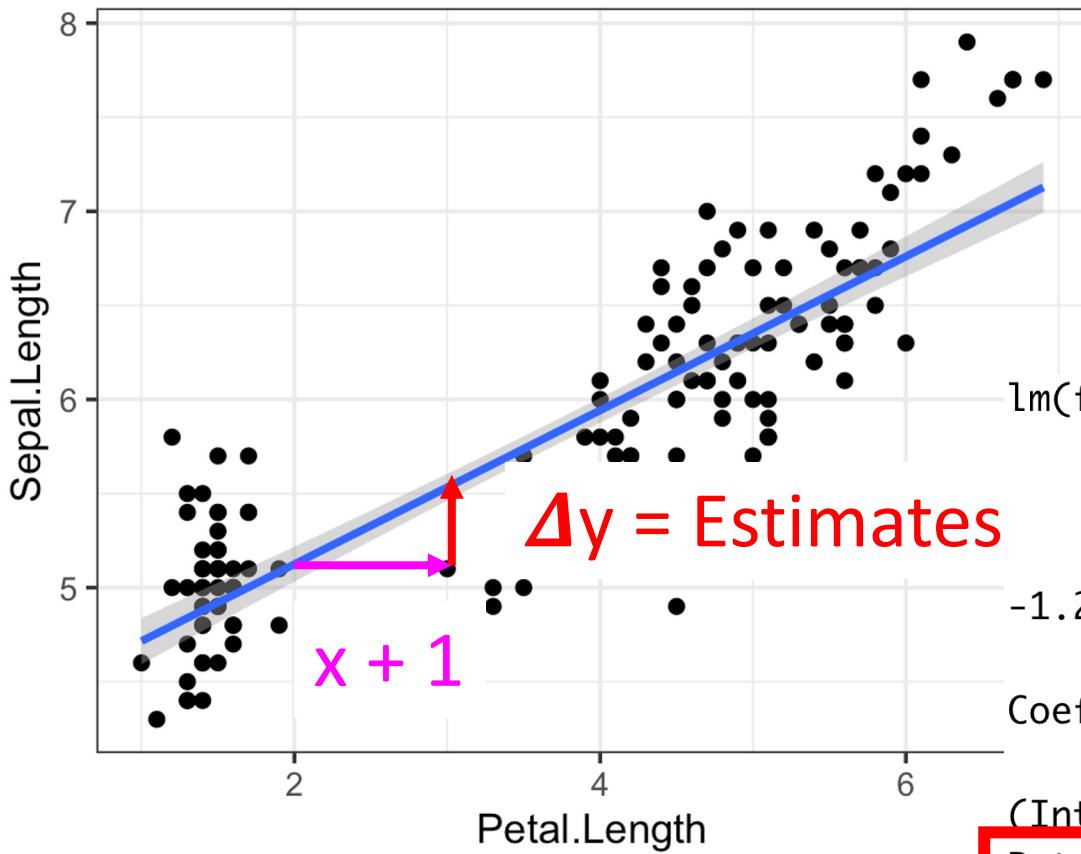
	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	4.30660	0.07839	54.94	<2e-16 ***
Petal.Length	0.40892	0.01889	21.65	<2e-16 ***

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```
lm(formula = Sepal.Length ~ Petal.Length, data = iris)
```

	Median	3Q	Max
-1.24675	-0.29657	-0.01515	0.27676
			1.00269

Coefficients:

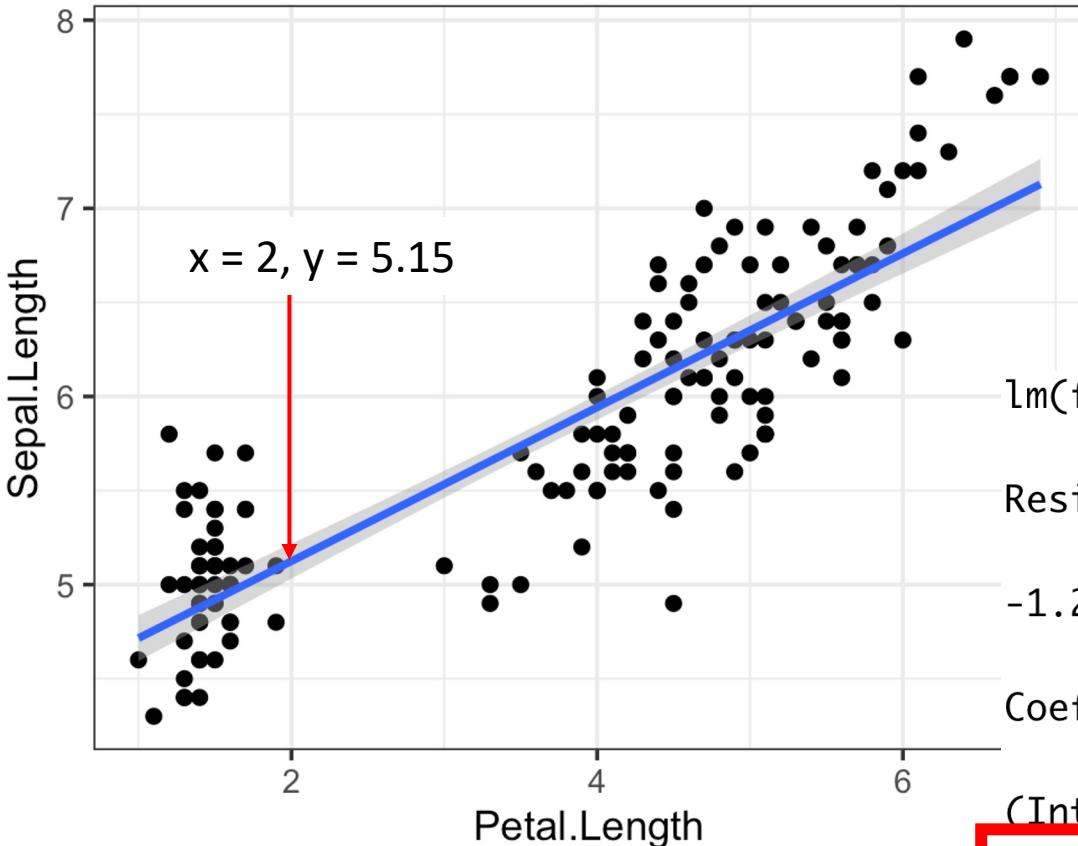
	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	4.30660	0.07839	54.94	<2e-16 ***
Petal.Length	0.40892	0.01889	21.65	<2e-16 ***

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```

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Min	1Q	Median	3Q	Max
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Coefficients:

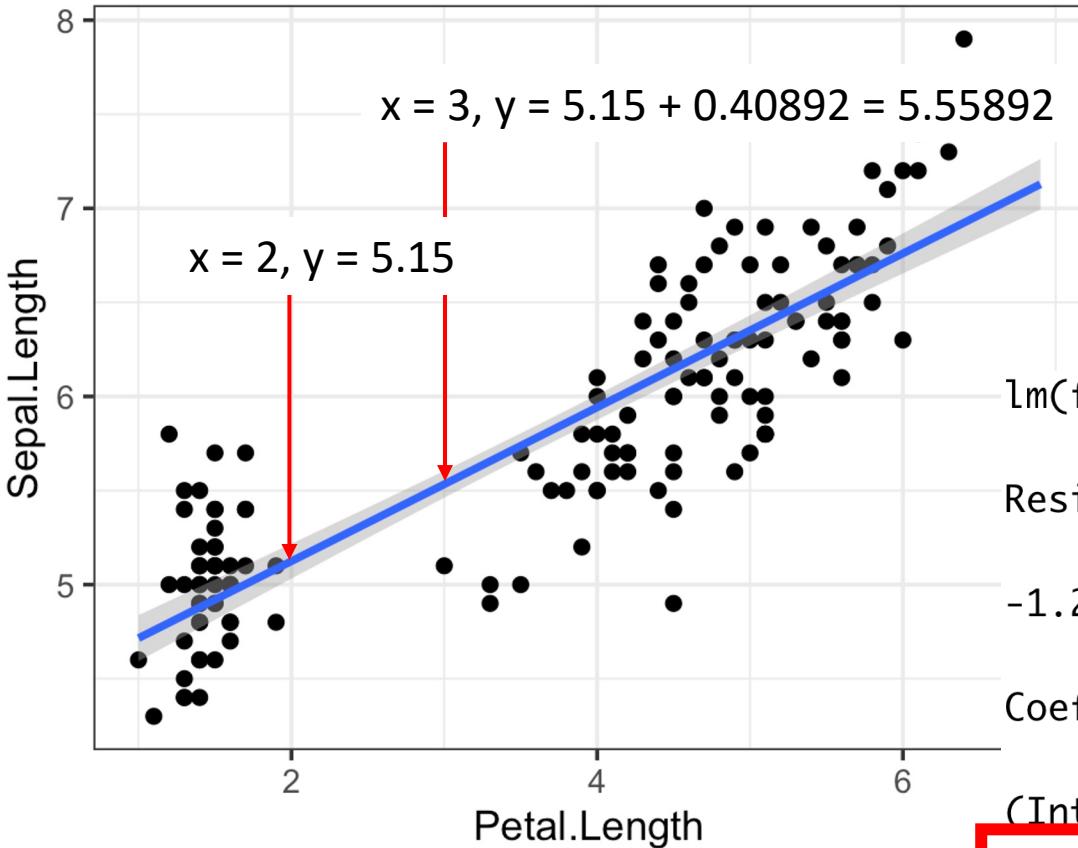
	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	4.30660	0.07839	54.94	<2e-16 ***
Petal.Length	0.40892	0.01889	21.65	<2e-16 ***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

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```
lm(formula = Sepal.Length ~ Petal.Length, data = iris)
```

Residuals:

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Summary I

- Linear regression
- Regression line
- Slope & intercept
- Residual
- Standard error
- $y = c + m * x + \epsilon$

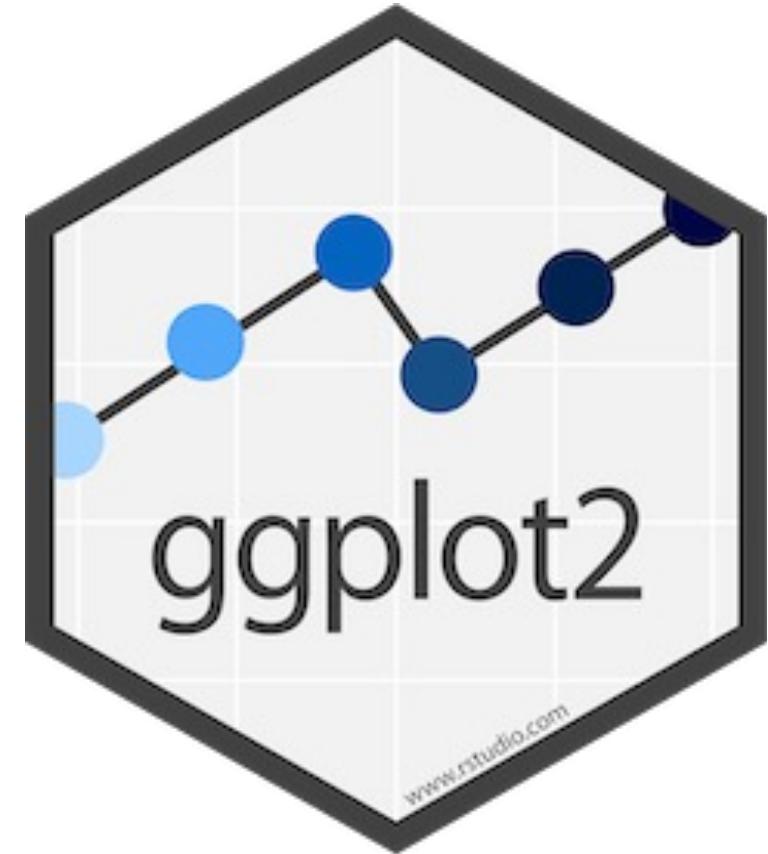
Linear modeling using R: Part I

- linear modeling, lm()
- summary()
- car::Anova()
- ggeffects::ggemmeans()

<https://osf.io/35htc/>

Data Visualization

- ggplot2 useful for creating graphics
 - based on The Grammar of Graphics
1. Provide data,
 2. Map variables to aesthetics,
 3. Declare what graphical geometries to use
 4. ggplot2 generate the graphics!



1. Provide data



```
ggplot(data = iris,  
aes(y = Sepal.Length, x = Petal.Length)) +  
geom_point()
```

1. Provide data

2. Map variables to aesthetics

```
ggplot(data = iris,  
aes(y = Sepal.Length, x = Petal.Length)) +  
geom_point()
```



1. Provide data

2. Map variables to aesthetics

```
ggplot(data = iris,  
aes(y = Sepal.Length, x = Petal.Length)) +  
geom_point()
```



3. Declare what graphical geometries to use

1. Provide data

2. Map variables to aesthetics

```
ggplot(data = iris,  
aes(y = Sepal.Length, x = Petal.Length)) +  
geom_point()
```



3. Declare what graphical geometries to use

`aes(x, y, color, fill, shape, etc.)`

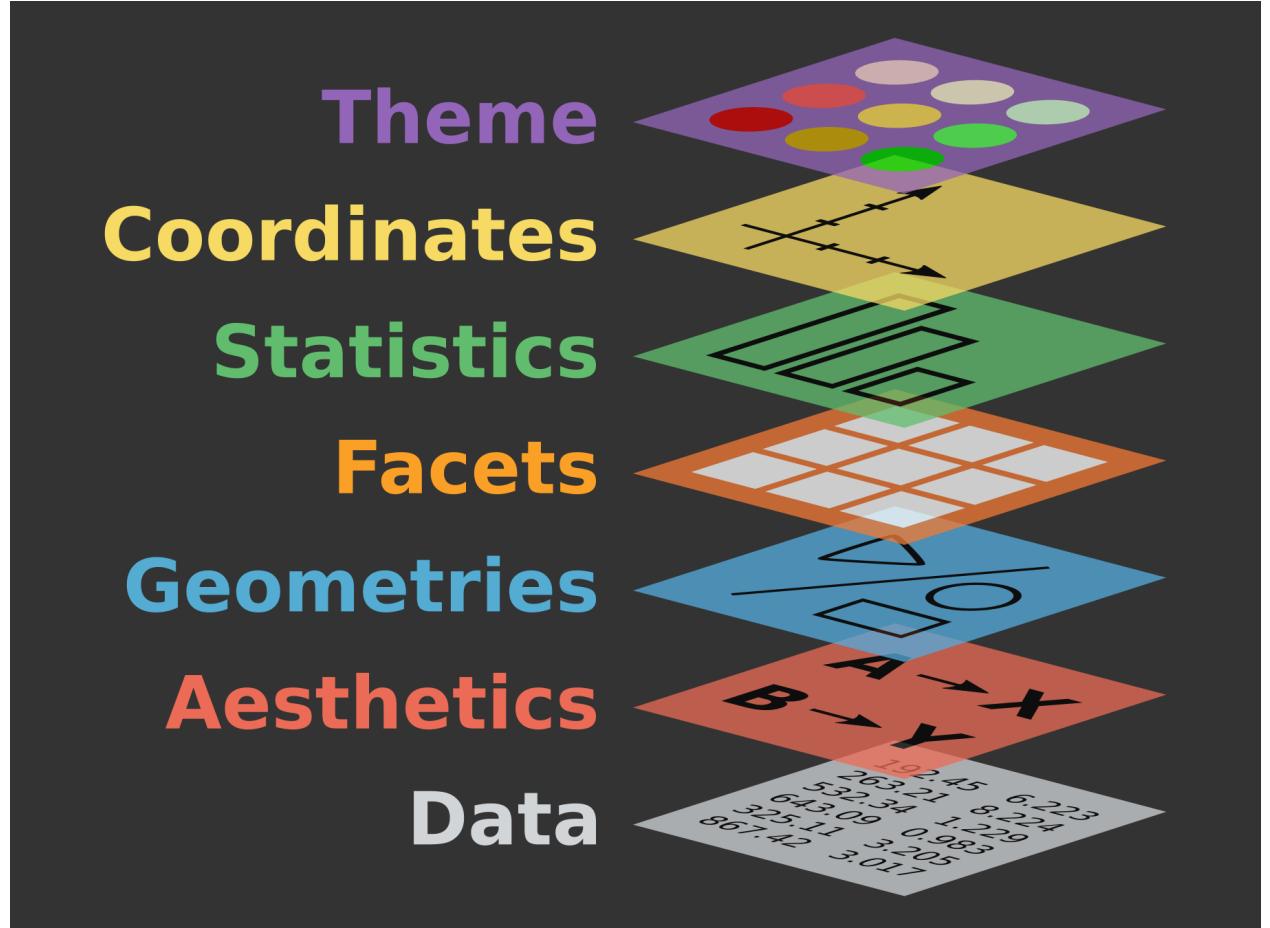
`geom_[point(), smooth(), bar(), line(), ribbon(),
boxplot(), histogram(), etc]`

Minimum to ggplot!

1. Provide data
2. Map variables to aesthetics
3. Declare what graphical geometries to use

1. Provide data
2. Map variables to aesthetics
3. Declare what graphical geometries to use

Theme
Coordinates
Statistics
Facets
Geometries
Aesthetics
Data



Define overall visuals

Set limits for graph

Summarise data

Plot data into facets

3. Declare what graphical

geometries to use

2. Map variables to aesthetics

1. Provide data

Theme

Coordinates

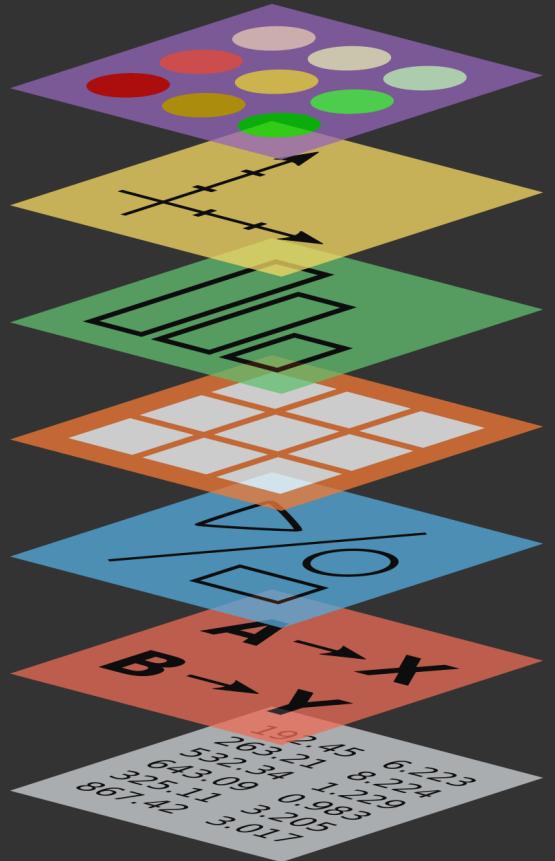
Statistics

Facets

Geometries

Aesthetics

Data



Google!



adjust axis limit ggplot in r



All

Videos

Images

Books

News

More

Tools

About 548,000 results (0.48 seconds)

<https://ggplot2.tidyverse.org> › reference › lims

⋮

Set scale limits — lims • ggplot2

This is a shortcut for supplying the **limits** argument to the individual scales. By default, any values outside the **limits** specified are replaced with NA.

[Scale_x_continuous](#) · [Coord_cartesian](#) · [Scale_x_discrete](#) · [Expand_limits](#)

People also ask ⋮

How to set limits for axes in ggplot2 R plots?



How do I change the axis limit in R?



How to specify y axis range in ggplot2?

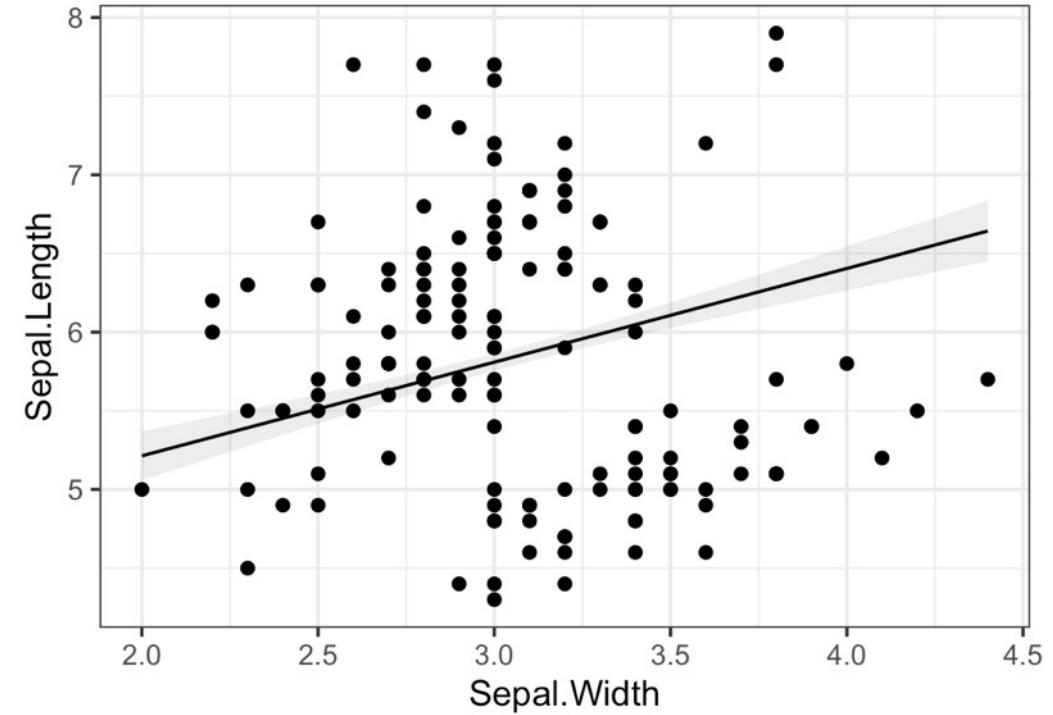
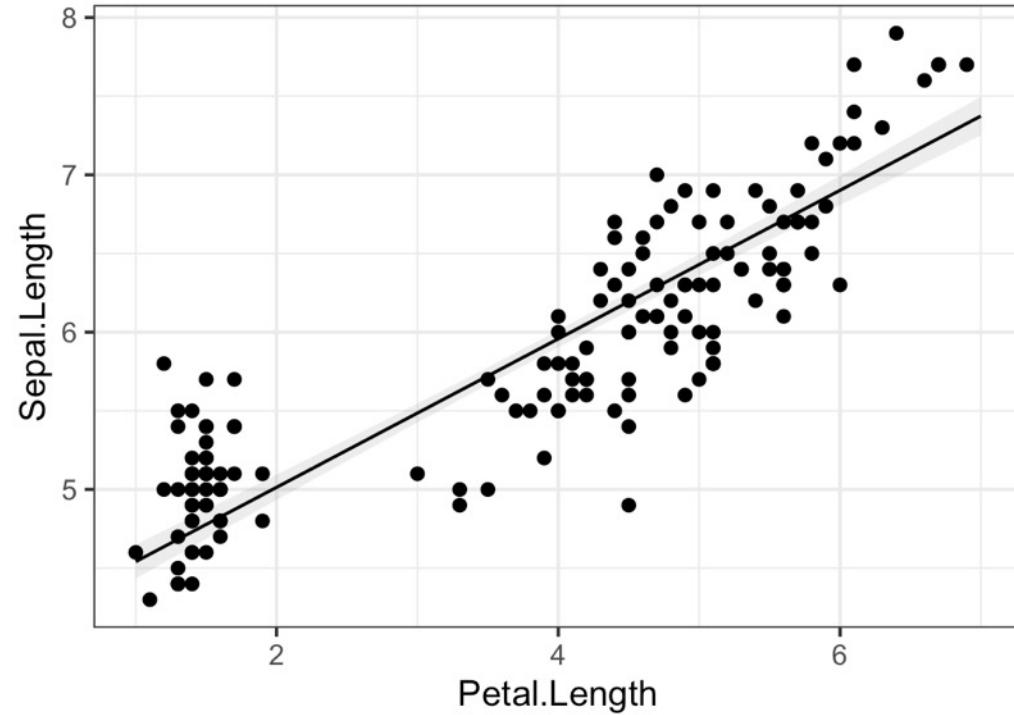


Which function used for setting axis limits in any graph in R?



Feedback

```
mlmod <- lm(Sepal.Length ~ Petal.Length + Sepal.Width, data = iris)
```



multiple linear regression

DAY 3

Winter Workshop: **Basic and Intermediate Statistics with R**

Chai Jun Ho, PhD



Schedule

Day 1	Day 2	Day 3
Introduction to Statistics	Linear Model I	Linear Model II
Introduction to R	Data Visualization	Mixed-Effect Model

Call:

summary(lmod)

Sepal.Length ~ Sepal.Width, data = iris)

Residuals:

Min	1Q	Median	3Q	Max
-1.5561	-0.6333	-0.1120	0.5579	2.2226

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	6.5262	0.4789	13.63	<2e-16 ***
Sepal.Width	-0.2234	0.1551	-1.44	0.152

Signif. codes:

0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.8251 on 148 degrees of freedom

Multiple R-squared: 0.01382, Adjusted R-squared: 0.007159

F-statistic: 2.074 on 1 and 148 DF, p-value: 0.1519

Call:

```
lm(formula = Sepal.Length ~ Sepal.Width, data = iris)
```

Resid

slope

p-value

Min

TQ

Median

3Q

Max

-1.5561

-0.6333

-0.1120

0.5579

2.2226

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
--	----------	------------	---------	----------

(Intercept)	6.5262	0.4789	13.63	<2e-16 ***
-------------	--------	--------	-------	------------

Sepal.Width	-0.2234	0.1551	-1.44	0.152
-------------	---------	--------	-------	-------

Signif. codes:

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Residual standard error: 0.8251 on 148 degrees of freedom

Multiple R-squared: 0.01382, Adjusted R-squared: 0.007159

F-statistic: 2.074 on 1 and 148 DF, p-value: 0.1519

Call:

```
lm(formula = Sepal.Length ~ Species, data = iris)
```

summary() duals:

	Min	1Q	Median	3Q	Max
	-1.6880	-0.3285	-0.0060	0.3120	1.3120

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	5.0060	0.0728	68.762	< 2e-16 ***
Speciesversicolor	0.9300	0.1030	9.033	8.77e-16 ***
Speciesvirginica	1.5820	0.1030	15.366	< 2e-16 ***

Signif. codes:

0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.5148 on 147 degrees of freedom

Multiple R-squared: 0.6187, Adjusted R-squared: 0.6135

F-statistic: 119.3 on 2 and 147 DF, p-value: < 2.2e-16

Call:

```
lm(formula = Sepal.Length ~ Species, data = iris)
```

Residuals:

Min	1Q	Median	3Q	Max
-1.6880	-0.3285	-0.0060	0.3120	1.3120

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	5.0060	0.0728	68.762	< 2e-16 ***
Speciesversicolor	0.9300	0.1030	9.033	8.77e-16 ***
Speciesvirginica	1.5820	0.1030	15.366	< 2e-16 ***

Signif. codes:

0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

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Call:

```
lm(formula = Sepal.Length ~ Species, data = iris)
```

Residuals:

Min	1Q	Median	3Q	Max
-1.6880	-0.3285	-0.0060	0.3120	1.3120

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	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	5.0060	0.0728	68.762	< 2e-16 ***
Speciesversicolor	0.9300	0.1030	9.033	8.77e-16 ***
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Signif. codes:

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F-statistic: 119.3 on 2 and 147 DF, p-value: < 2.2e-16

Call:
lm(formula = Sepal.Length ~ Species, data = iris)

Residuals: ???

	Min	IQ	Median	3Q	Max
	-1.6880	-0.3285	-0.0060	0.3120	1.3120

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	5.0060	0.0728	68.762	< 2e-16 ***
Speciesversicolor	0.9300	0.1030	9.033	8.77e-16 ***
Speciesvirginica	1.5820	0.1030	15.366	< 2e-16 ***

Signif. codes:

0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.5148 on 147 degrees of freedom
Multiple R-squared: 0.6187, Adjusted R-squared: 0.6135
F-statistic: 119.3 on 2 and 147 DF, p-value: < 2.2e-16

Call:

```
lm(formula = Sepal.Length ~ Species, data = iris)
```

Species

setosa	????	3Q	Max
...
...	120	1.31	20

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	5.0060	0.0728	68.762	< 2e-16 ***
Species	versicolor	0.9300	0.1030	9.033 8.77e-16 ***
Species	virginica	1.5820	0.1030	15.366 < 2e-16 ***

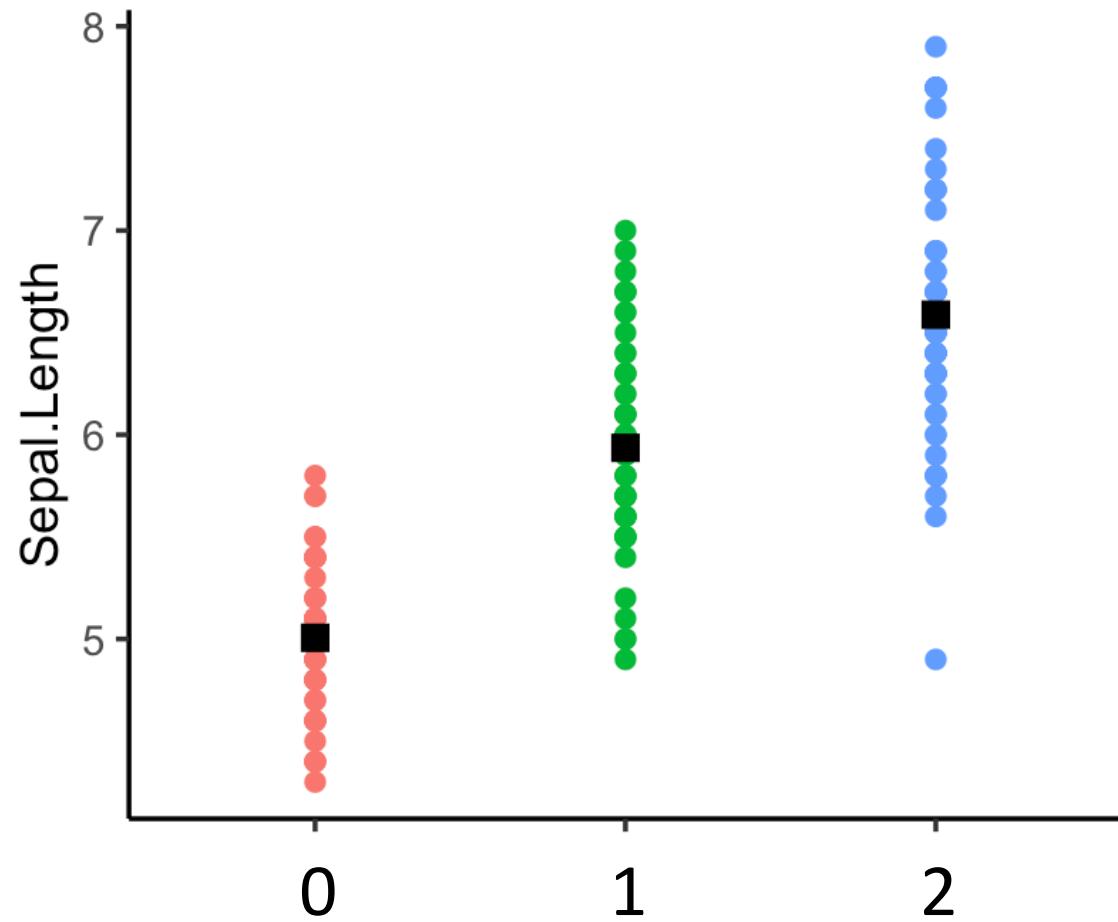
Signif. codes:

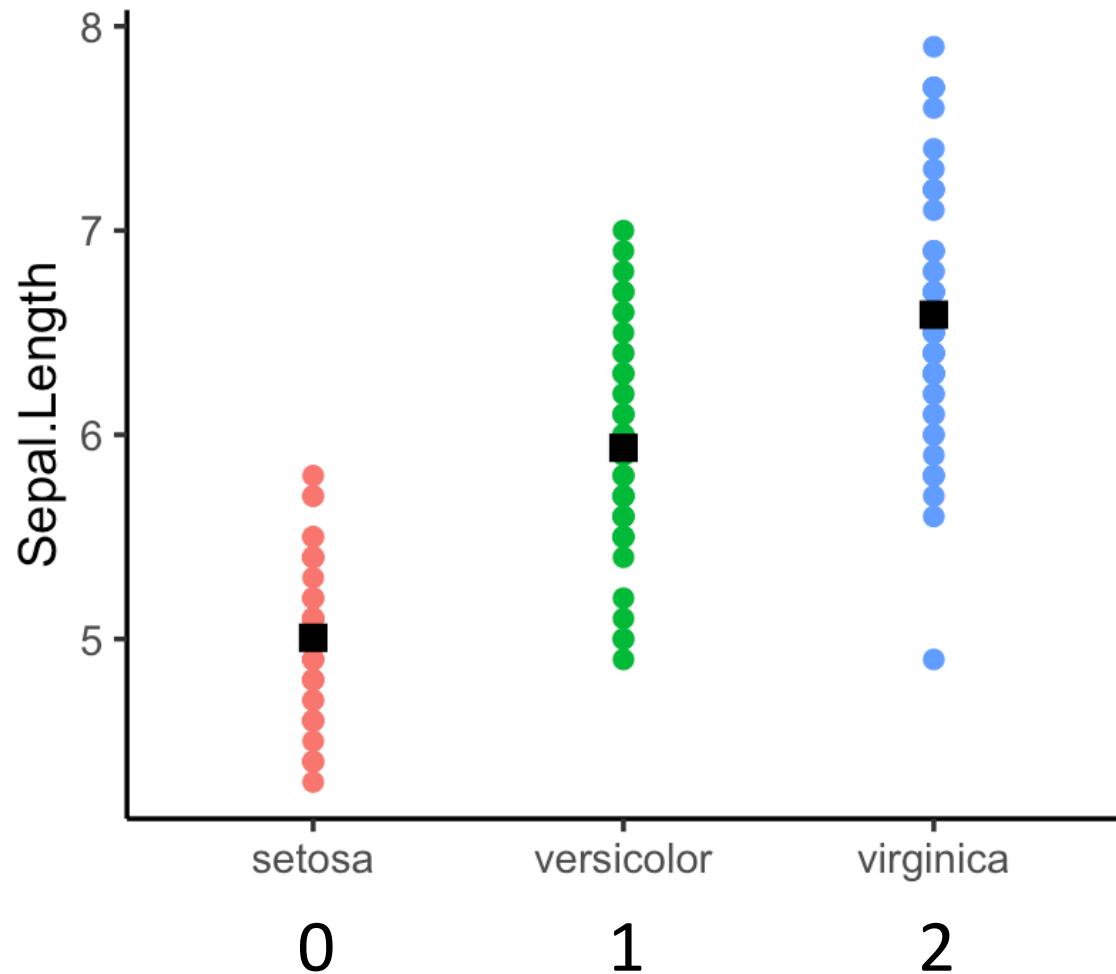
0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.5148 on 147 degrees of freedom

Multiple R-squared: 0.6187, Adjusted R-squared: 0.6135

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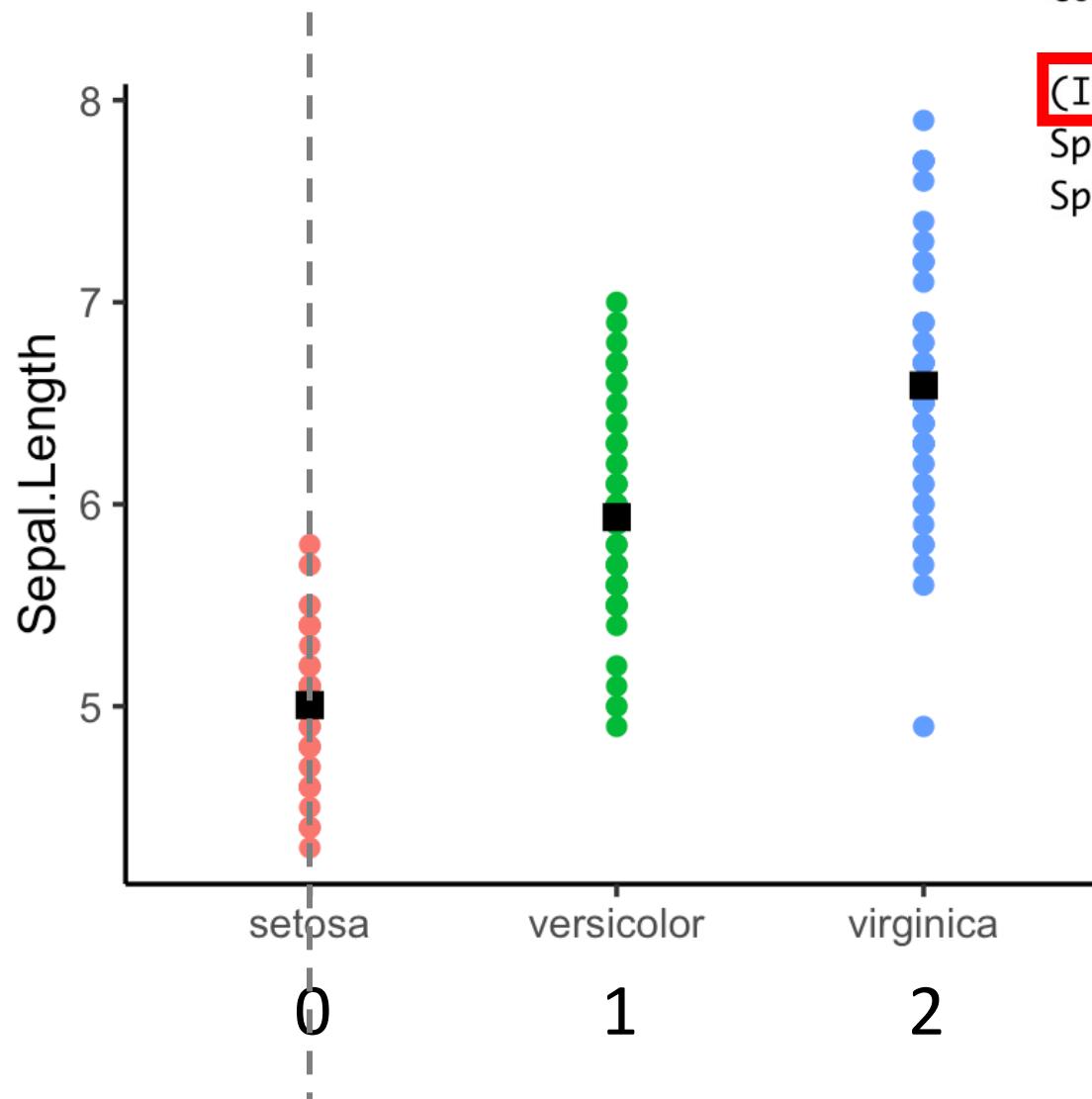
Coefficients:

(Intercept)
Speciesversicolor
Speciesvirginica

	Estimate	Std. Error	t
(Intercept)	5.0060	0.0728	68.8
Speciesversicolor	0.9300	0.1030	9.0
Speciesvirginica	1.5820	0.1030	15.3

"intercept"

point of reference

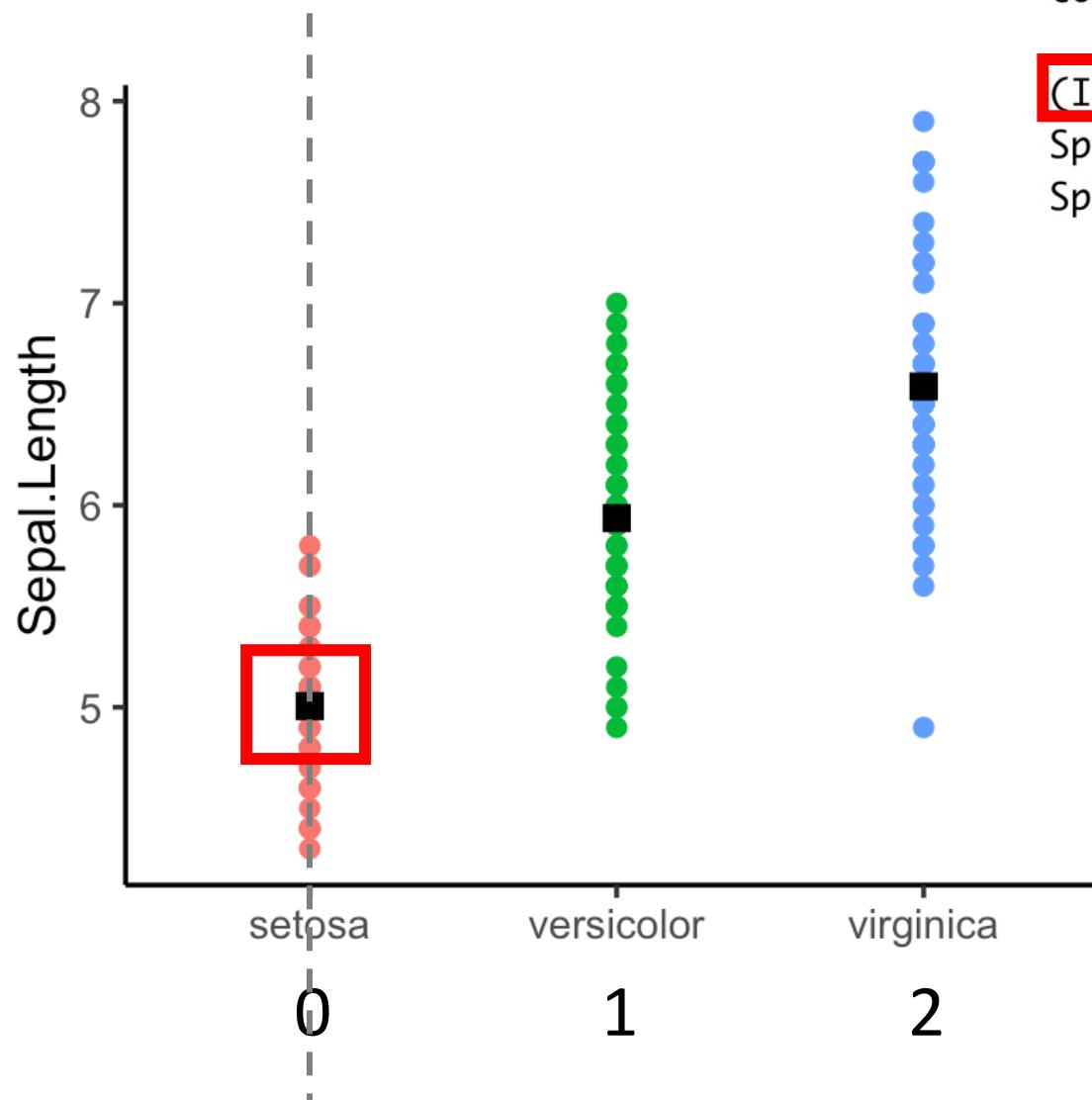


Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	5.0060	0.0728	68.762	< 2e-16	***
Speciesversicolor	0.9300	0.1030	9.033	8.77e-16	***
Speciesvirginica	1.5820	0.1030	15.366	< 2e-16	***

"intercept"

point of reference

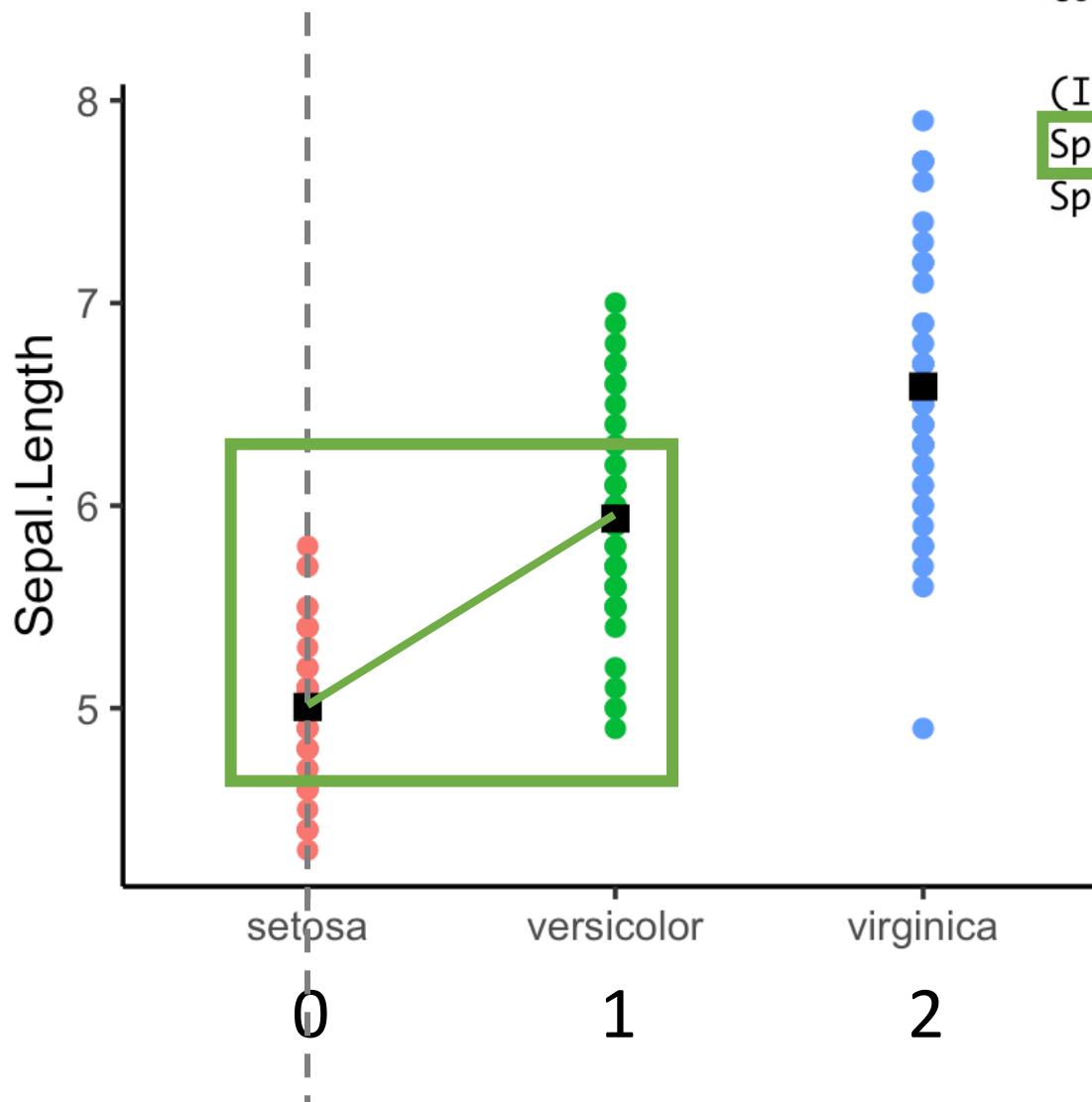


Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	5.0060	0.0728	68.762	< 2e-16	***
Speciesversicolor	0.9300	0.1030	9.033	8.77e-16	***
Speciesvirginica	1.5820	0.1030	15.366	< 2e-16	***

"intercept"

point of reference



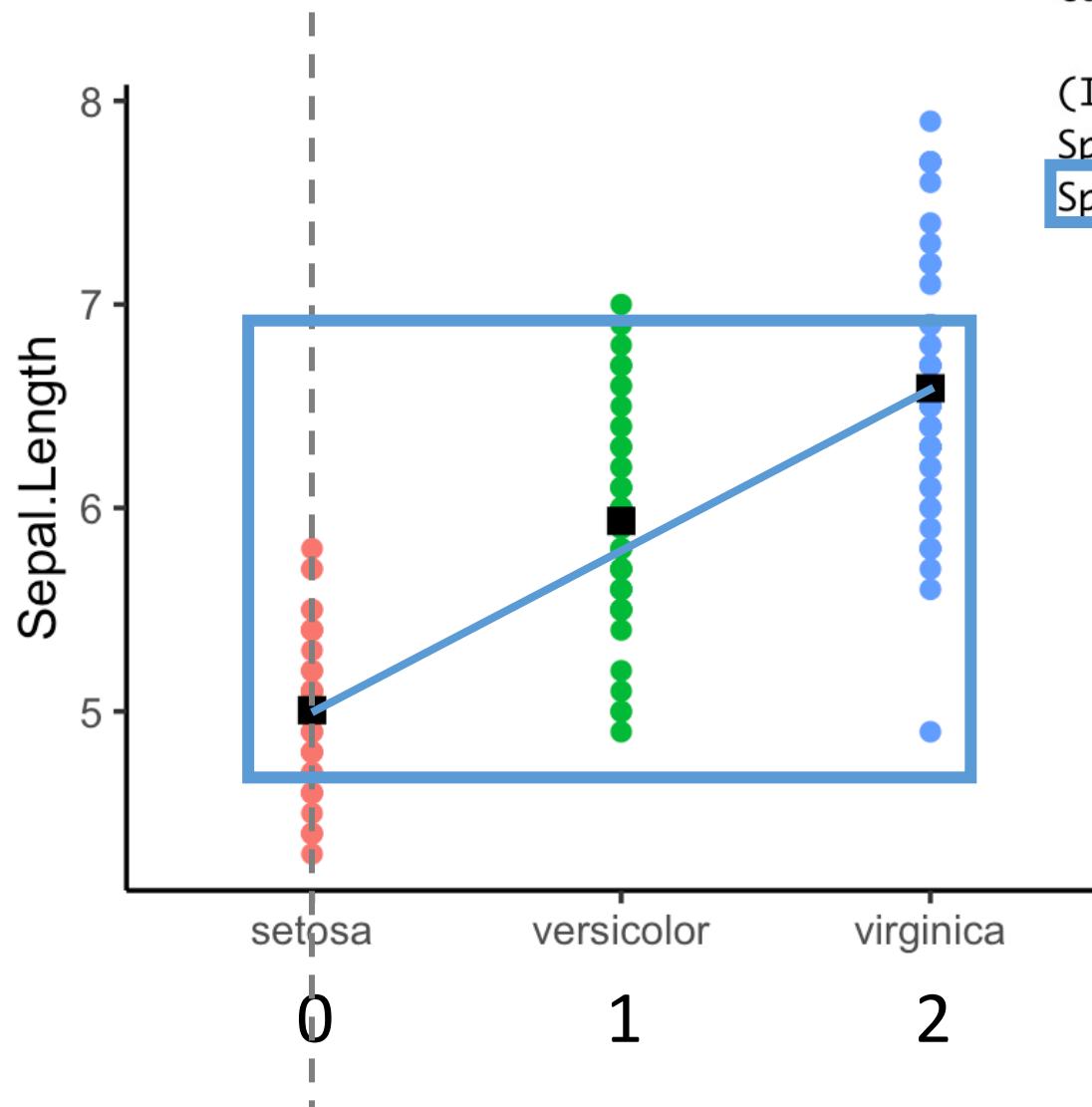
Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	5.0060	0.0728	68.762	< 2e-16	***
Speciesversicolor	0.9300	0.1030	9.033	8.77e-16	***
Speciesvirginica	1.5820	0.1030	15.366	< 2e-16	***

$$5.0060 + \\ 0.9300 = \\ 5.9360$$

"intercept"

point of reference



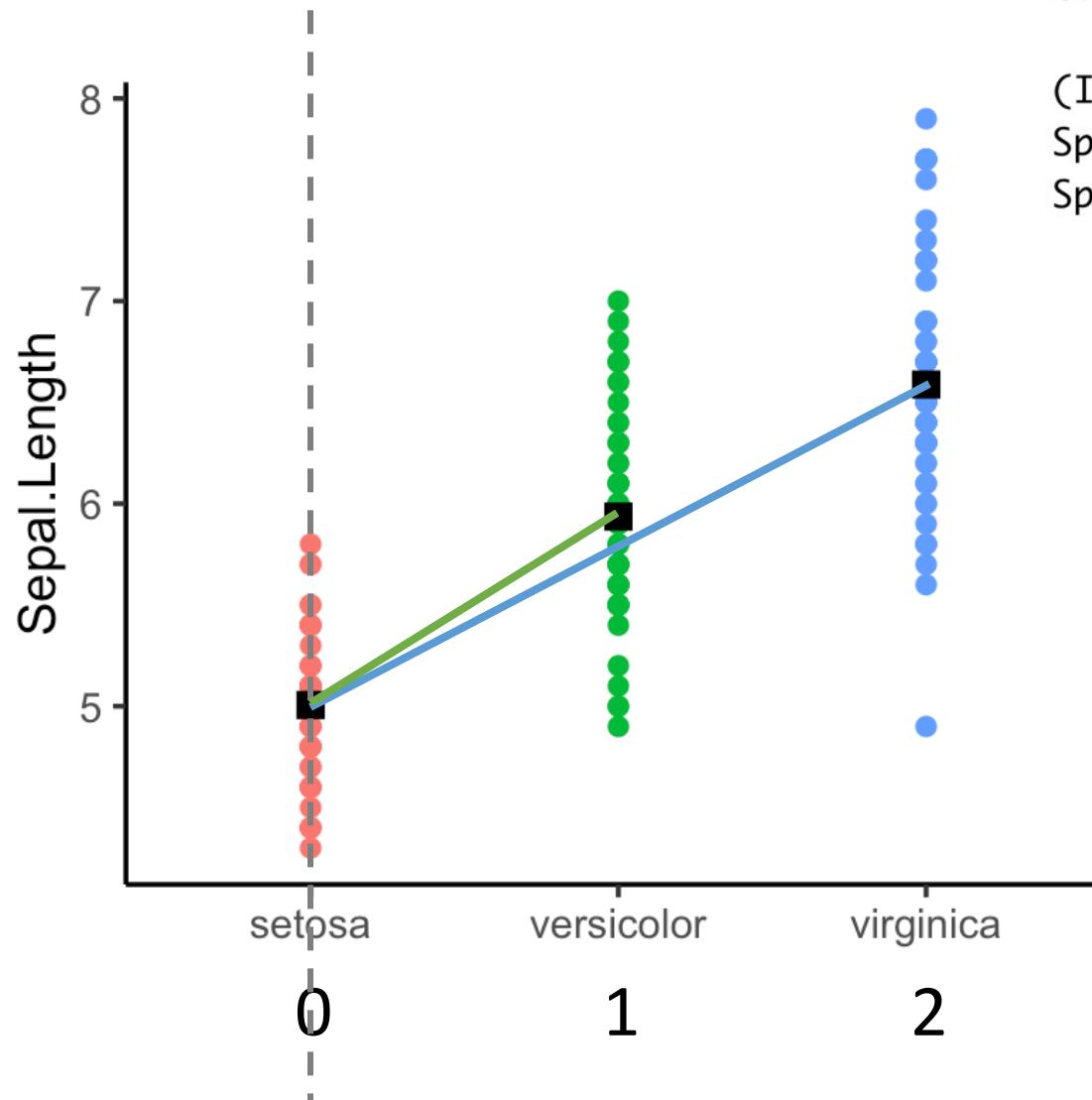
Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	5.0060	0.0728	68.762	< 2e-16	***
Speciesversicolor	0.9300	0.1030	9.033	8.77e-16	***
Speciesvirginica	1.5820	0.1030	15.366	< 2e-16	***

$$5.0060 + \\ 1.5820 = \\ 6.5880$$

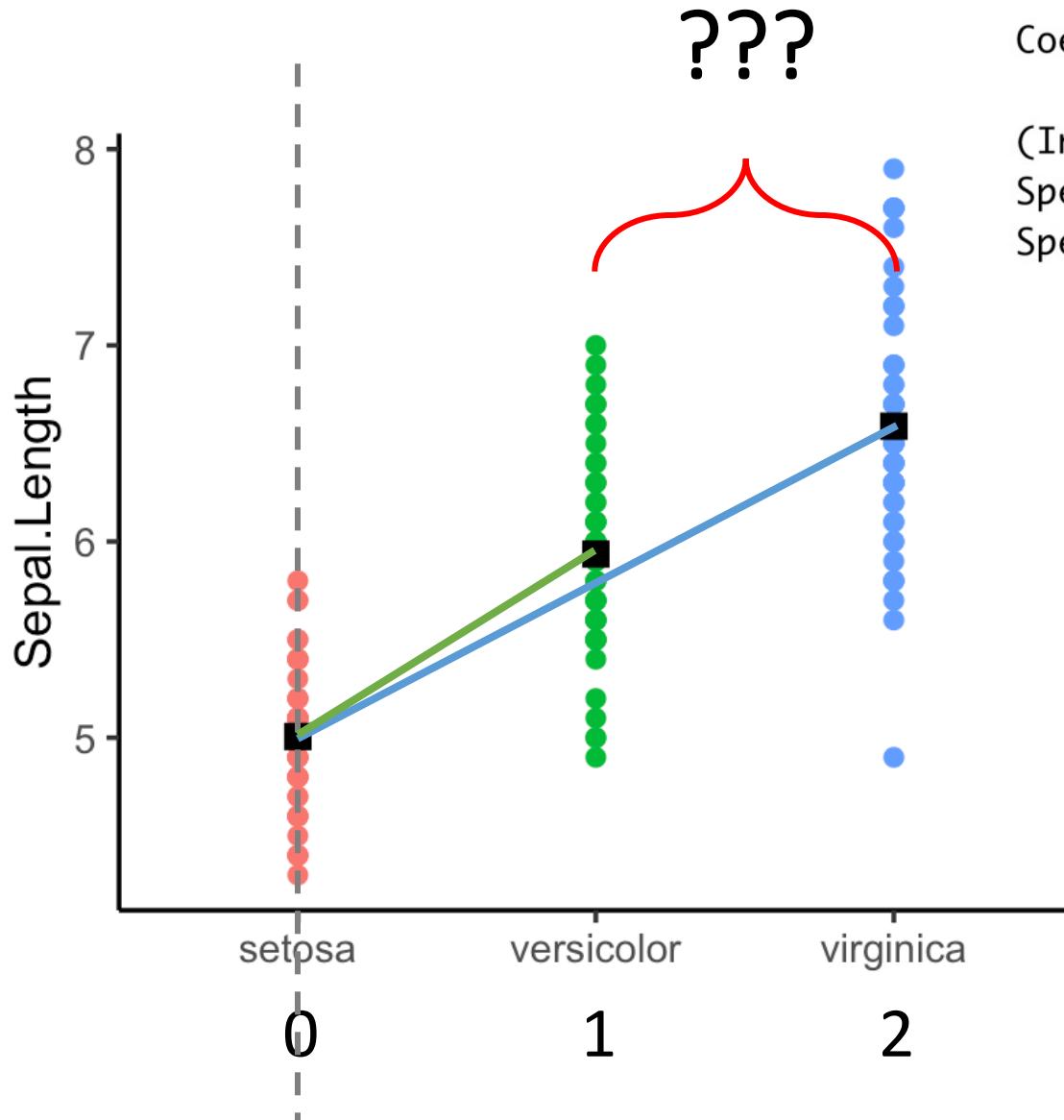
“intercept”

point of reference



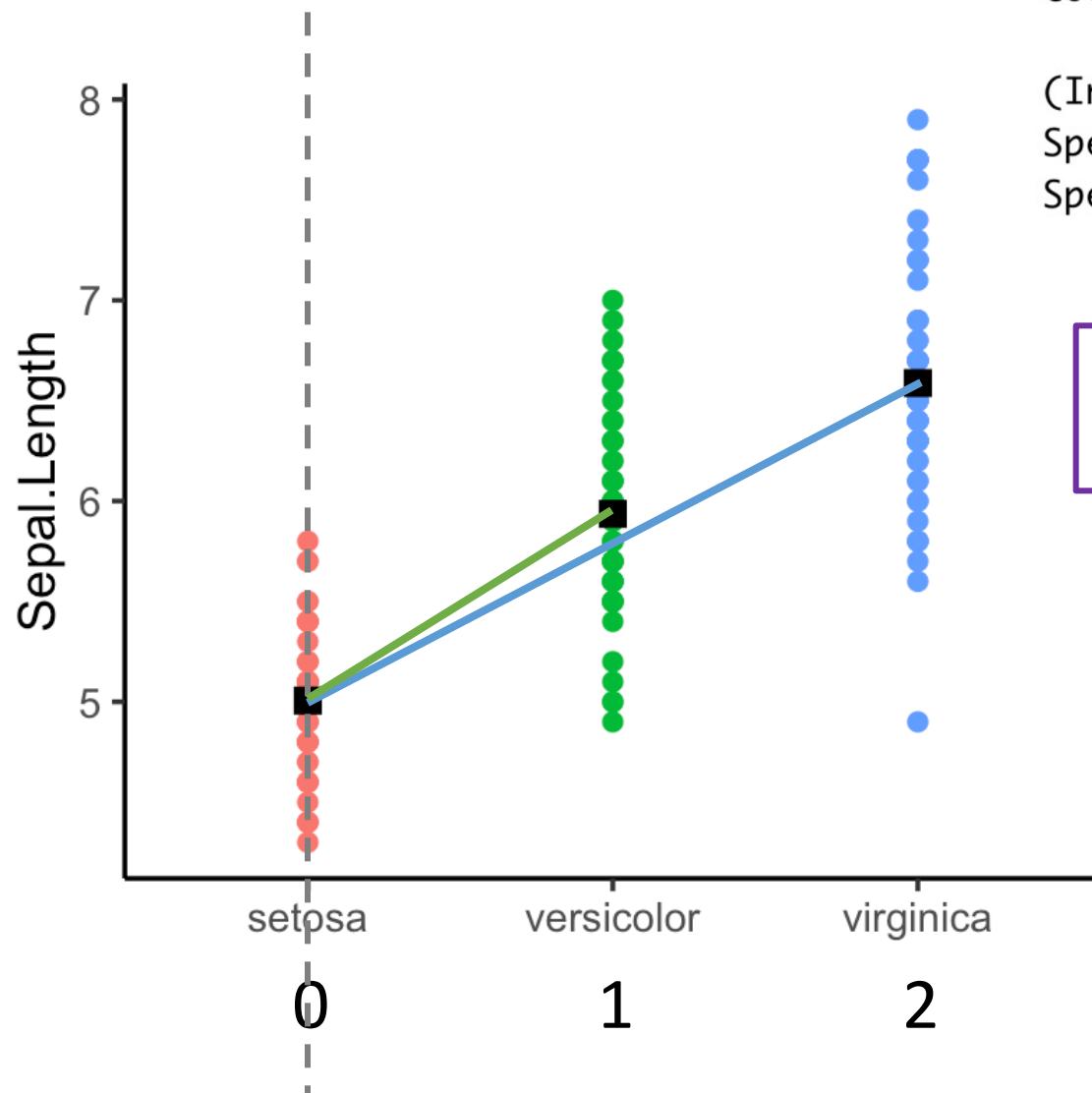
Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	5.0060	0.0728	68.762	< 2e-16 ***
Speciesversicolor	0.9300	0.1030	9.033	8.77e-16 ***
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Coefficients:

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(Intercept)	5.0060	0.0728	68.762	< 2e-16	***
Speciesversicolor	0.9300	0.1030	9.033	8.77e-16	***
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Coefficients:

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Speciesversicolor	0.9300	0.1030	9.033	8.77e-16 ***
Speciesvirginica	1.5820	0.1030	15.366	< 2e-16 ***

summary()

vs

car::Anova()

```
lmcat <- lm(Sepal.Length ~ Species, data = iris)
```



```
> car:::Anova(lmcat, type = "III")
```

Anova Table (Type III tests)

Response: Sepal.Length

	Sum Sq	Df	F value	Pr(>F)	
(Intercept)	1253.00	1	4728.16	< 2.2e-16	***
Species	63.21	2	119.26	< 2.2e-16	***
Residuals	38.96	147			

Signif. codes:

0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

```
> car::Anova(lmcat, type = "III")
```

Anova Table (Type III tests)

Response: Sepal.Length

	Sum Sq	Df	F value	
(Intercept)	1253.00	1	4728.10	
Species	63.21	2	119.26	< 2.2e-16 ***
Residuals	38.96	147		

Signif. codes:

0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Significant main effect of Species,
 $F(2, 147) = 119.26, p < .001$

Setosa – Versicolor = ???

Versicolor – Virginia = ???

Setosa – Virginia = ???

Response:

	Sum Sq	Df	F value	Pr(>F)	
(Intercept)	1253.00	1	4728.16	< 2.2e-16	***
Species	63.21	2	119.26	< 2.2e-16	***
Residuals	38.96	147			

Signif. codes:					
0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1					

$$\frac{\text{variance between groups}}{\text{variance within group}} = \text{F-ratio}$$

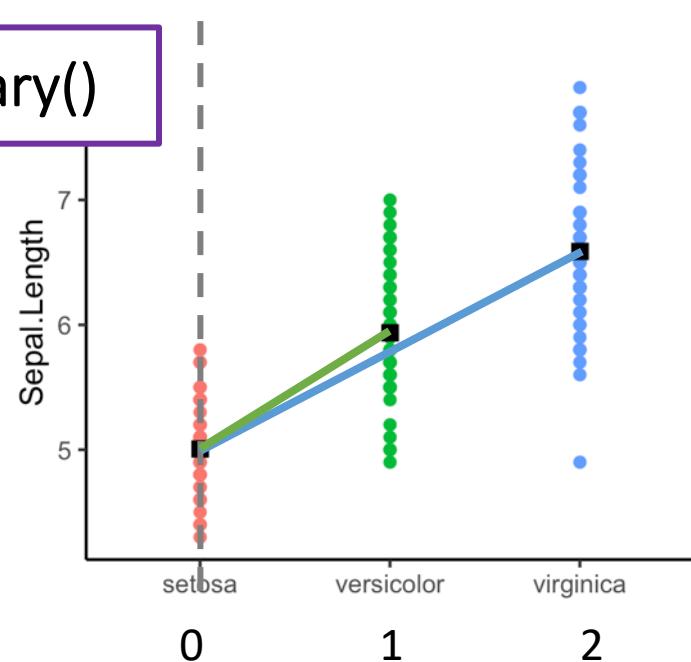
Response: Sepal.Length

	Sum Sq	Df	F value	Pr(>F)
(Intercept)	1253.00	1	4728.16	< 2.2e-16 ***
Species	63.21	2	119.26	< 2.2e-16 ***
Residuals	38.96	147		

Signif. codes:

0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

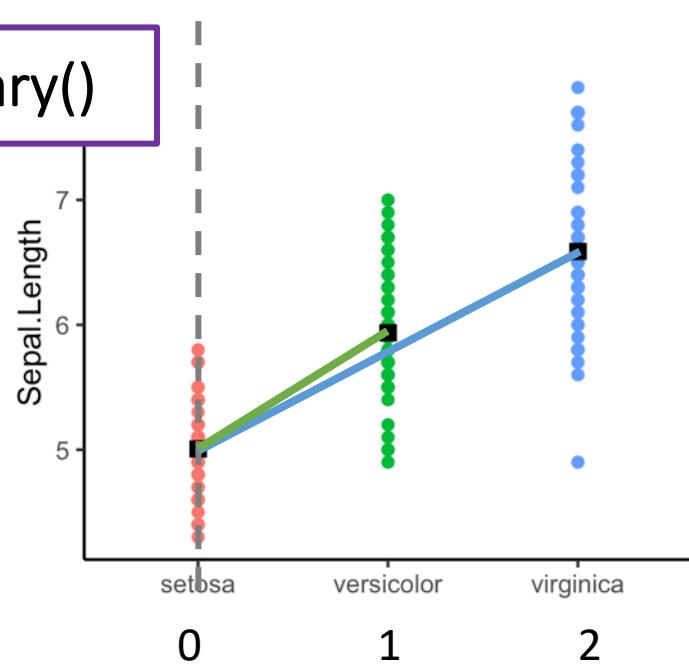
summary()



Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	5.0060	0.0728	68.762	< 2e-16 ***
Speciesversicolor	0.9300	0.1030	9.033	8.77e-16 ***
Speciesvirginica	1.5820	0.1030	15.366	< 2e-16 ***

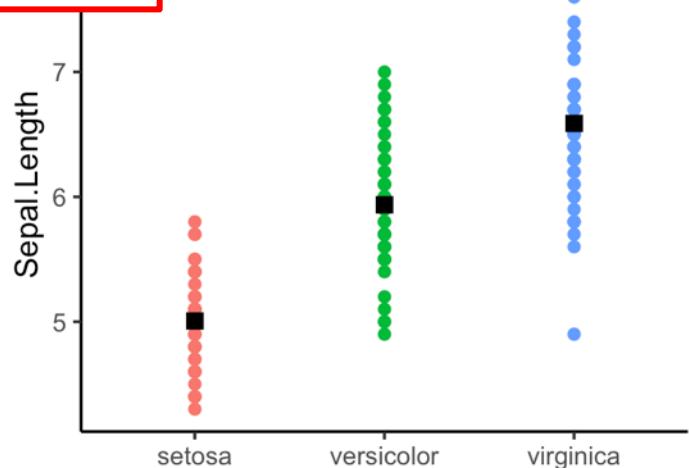
`summary()`



Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	5.0060	0.0728	68.762	< 2e-16 ***
Speciesversicolor	0.9300	0.1030	9.033	8.77e-16 ***
Speciesvirginica	1.5820	0.1030	15.366	< 2e-16 ***

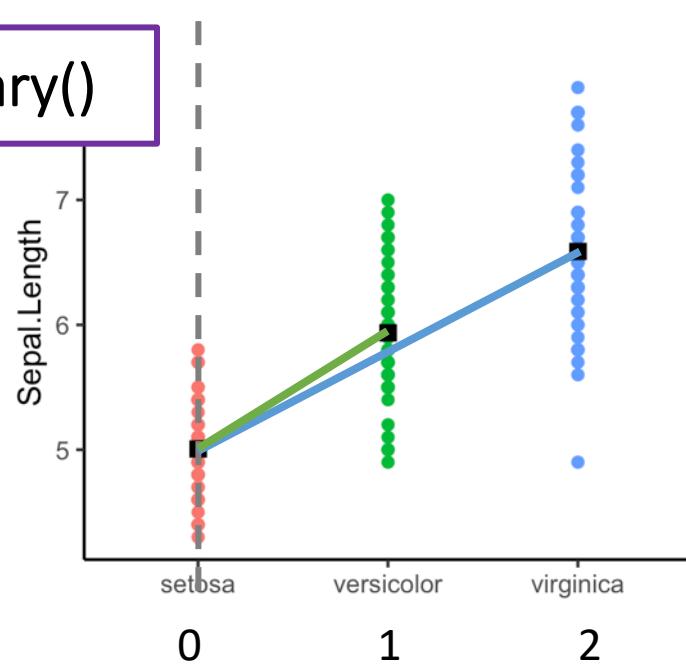
`car::Anova()`



Response: Sepal.Length

	Sum Sq	Df	F value	Pr(>F)
(Intercept)	1253.00	1	4728.16	< 2.2e-16 ***
Species	63.21	2	119.26	< 2.2e-16 ***
Residuals	38.96	147		

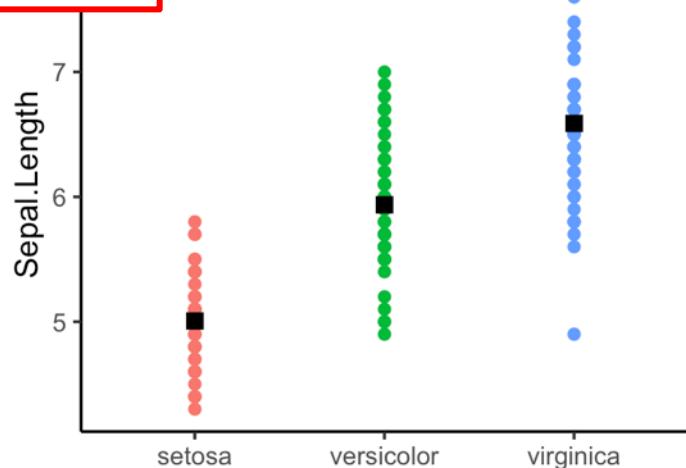
`summary()`



Coefficients:

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(Intercept)	5.0060	0.0728	68.762	< 2e-16 ***
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`car::Anova()`

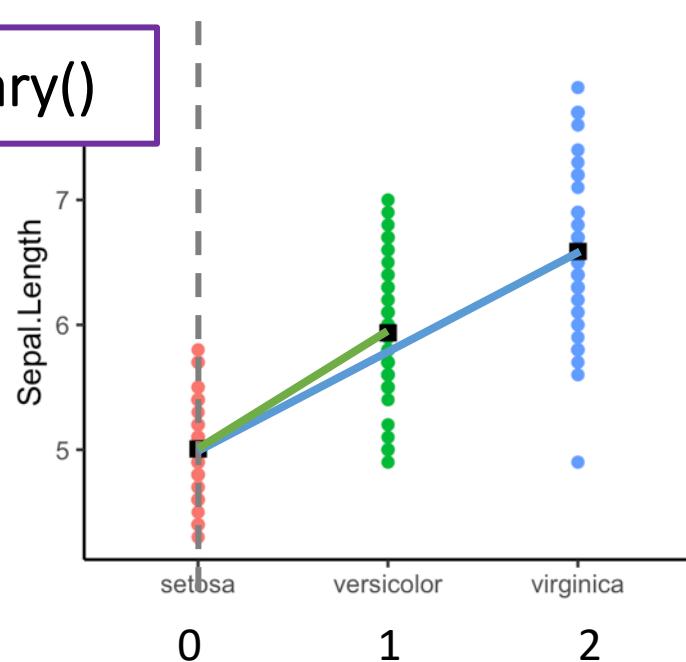


Response: Sepal.Length

	Sum Sq	Df	F value	Pr(>F)
(Intercept)	1253.00	1	4728.16	< 2.2e-16 ***
Species	63.21	2	119.26	< 2.2e-16 ***
Residuals	38.96	147		

$$\frac{\text{variance between groups}}{\text{variance within group}} = \text{F-ratio}$$

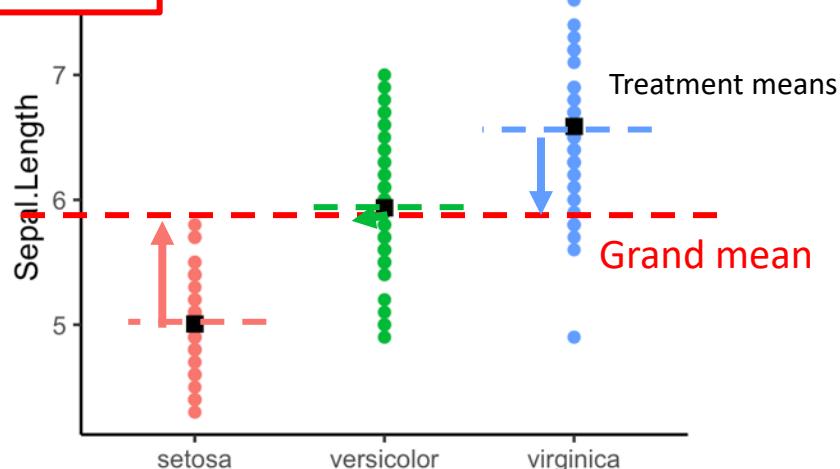
summary()



Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
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car::Anova()

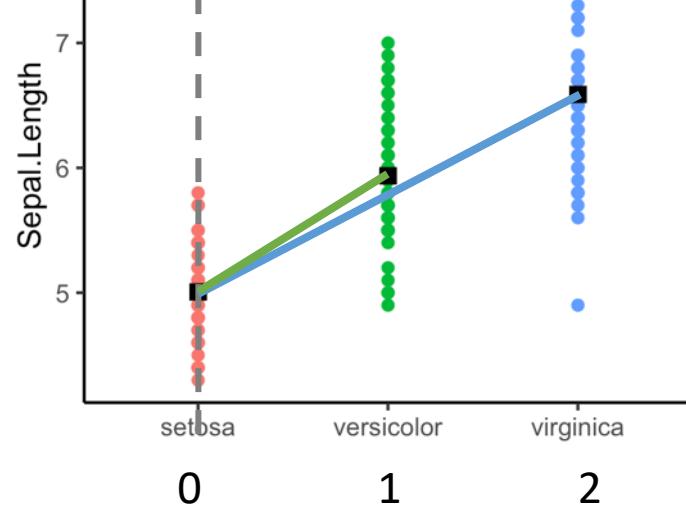


Response: Sepal.Length

	Sum Sq	Df	F value	Pr(>F)
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Species	63.21	2	119.26	< 2.2e-16 ***
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$$\frac{\text{variance between groups}}{\text{variance within group}} = \text{F-ratio}$$

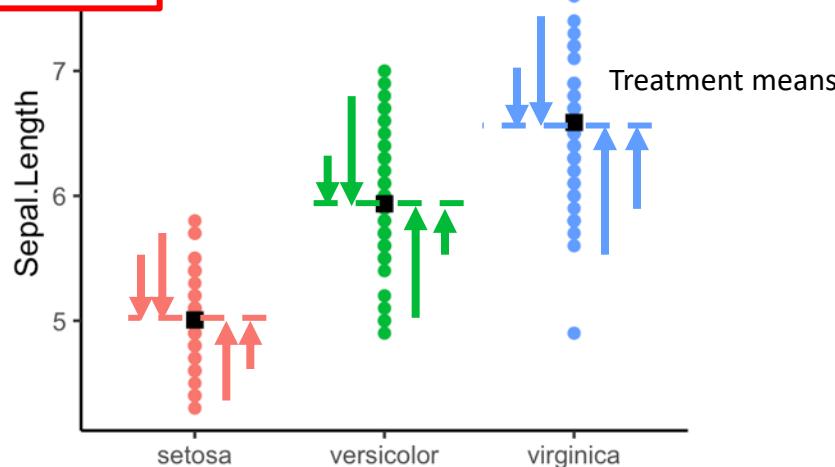
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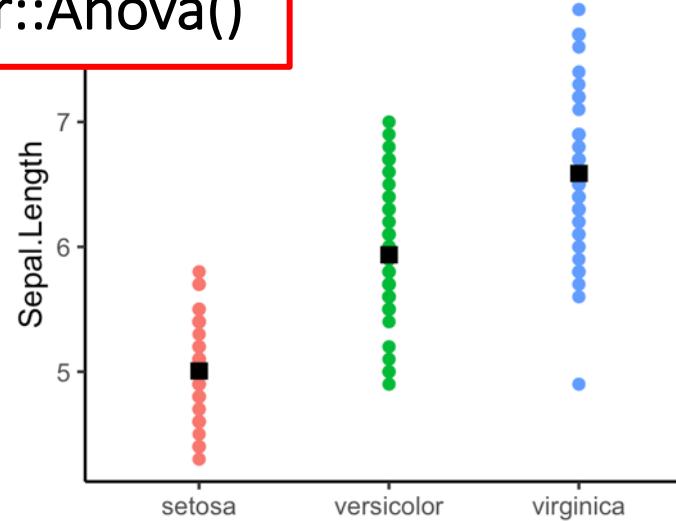


Response: Sepal.Length

	Sum Sq	Df	F value	Pr(>F)
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$$\frac{\text{variance between groups}}{\text{variance within group}} = \text{F-ratio}$$

car::Anova()

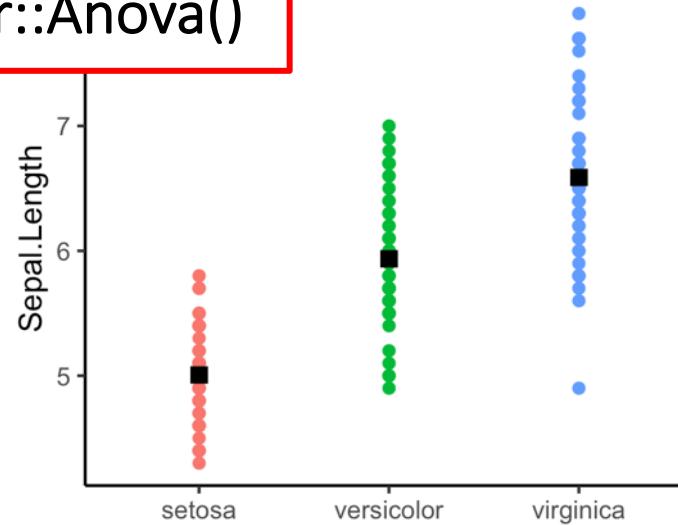


Response: Sepal.Length

	Sum Sq	Df	F value	Pr(>F)	
(Intercept)	1253.00	1	4728.16	< 2.2e-16	***
Species	63.21	2	119.26	< 2.2e-16	***
Residuals	38.96	147			



car::Anova()

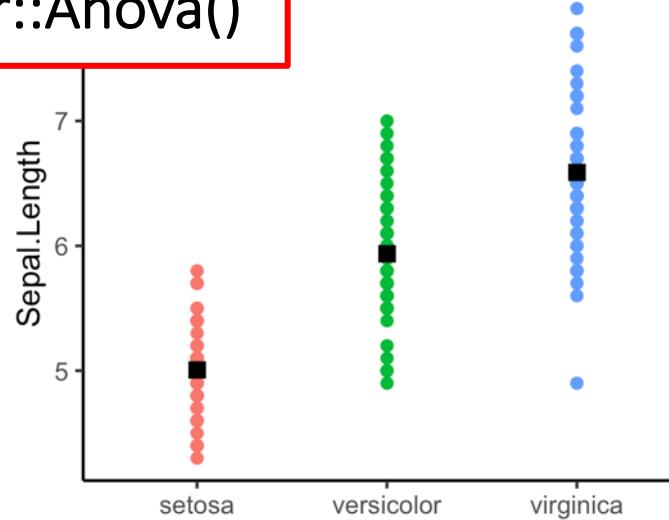


Response: Sepal.Length

	Sum Sq	Df	F value	Pr(>F)	
(Intercept)	1253.00	1	4728.16	< 2.2e-16	***
Species	63.21	2	119.26	< 2.2e-16	***
Residuals	38.96	147			

variance between groups was sufficiently huge while accounting for individual variance within group

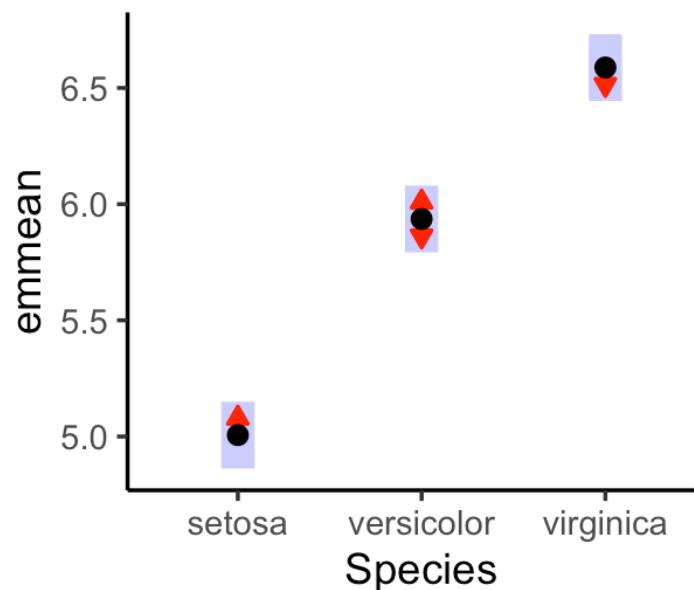
car::Anova()



Response: Sepal.Length

	Sum Sq	Df	F value	Pr(>F)	
(Intercept)	1253.00	1	4728.16	< 2.2e-16	***
Species	63.21	2	119.26	< 2.2e-16	***
Residuals	38.96	147			

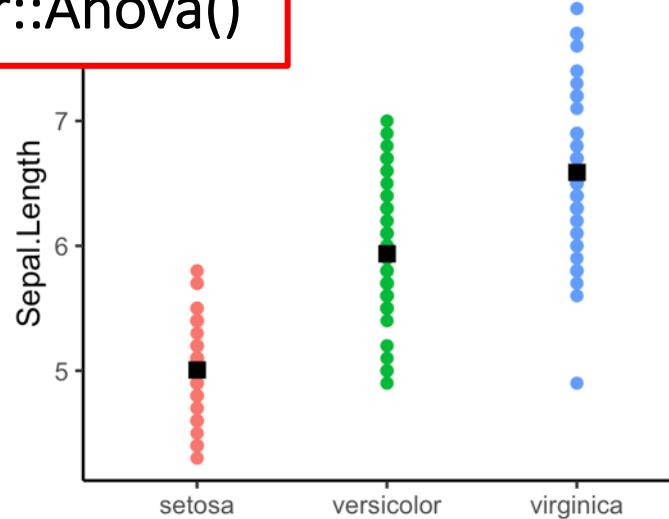
emmeans()



\$contrasts

contrast	estimate	SE	df	t.ratio	p.value
setosa - versicolor	-0.930	0.103	147	-9.033	<.0001
setosa - virginica	-1.582	0.103	147	-15.366	<.0001
versicolor - virginica	-0.652	0.103	147	-6.333	<.0001

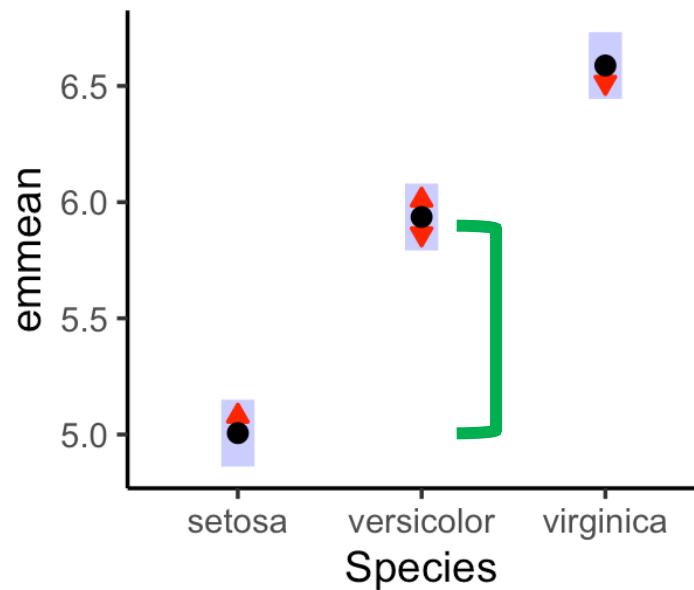
car::Anova()



Response: Sepal.Length

	Sum Sq	Df	F value	Pr(>F)	
(Intercept)	1253.00	1	4728.16	< 2.2e-16	***
Species	63.21	2	119.26	< 2.2e-16	***
Residuals	38.96	147			

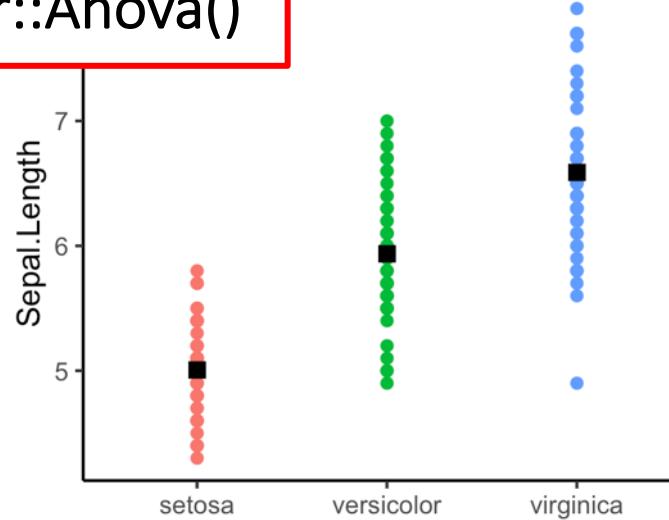
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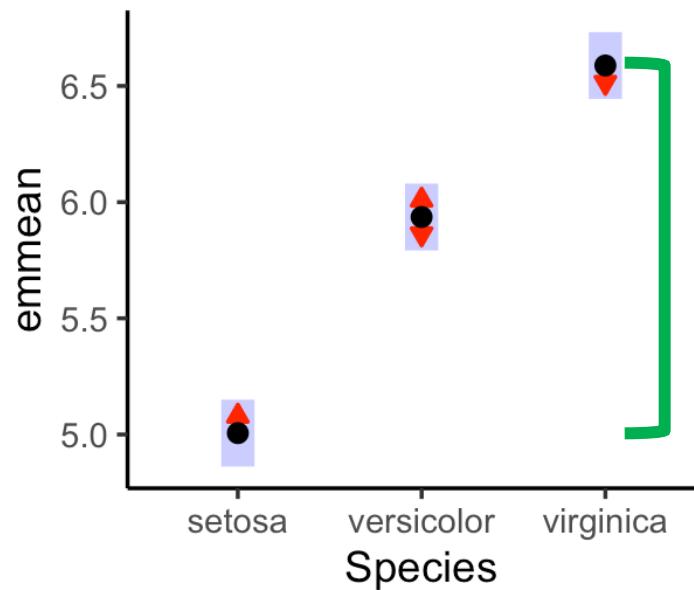
car::Anova()



Response: Sepal.Length

	Sum Sq	Df	F value	Pr(>F)	
(Intercept)	1253.00	1	4728.16	< 2.2e-16	***
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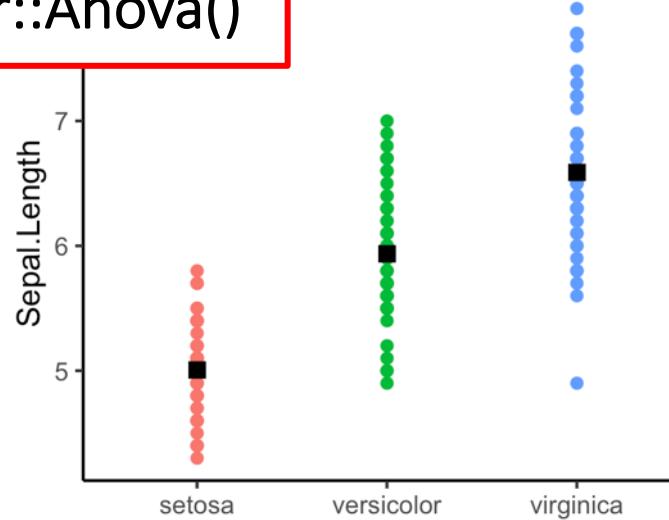
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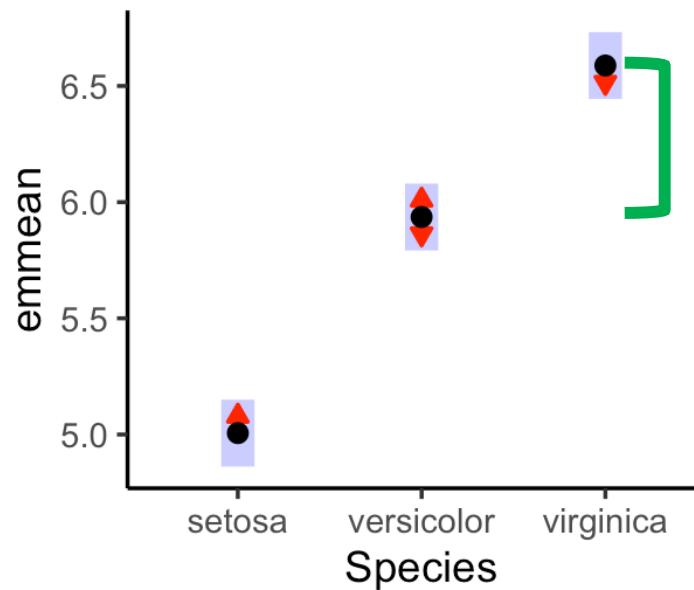
car::Anova()



Response: Sepal.Length

	Sum Sq	Df	F value	Pr(>F)	
(Intercept)	1253.00	1	4728.16	< 2.2e-16	***
Species	63.21	2	119.26	< 2.2e-16	***
Residuals	38.96	147			

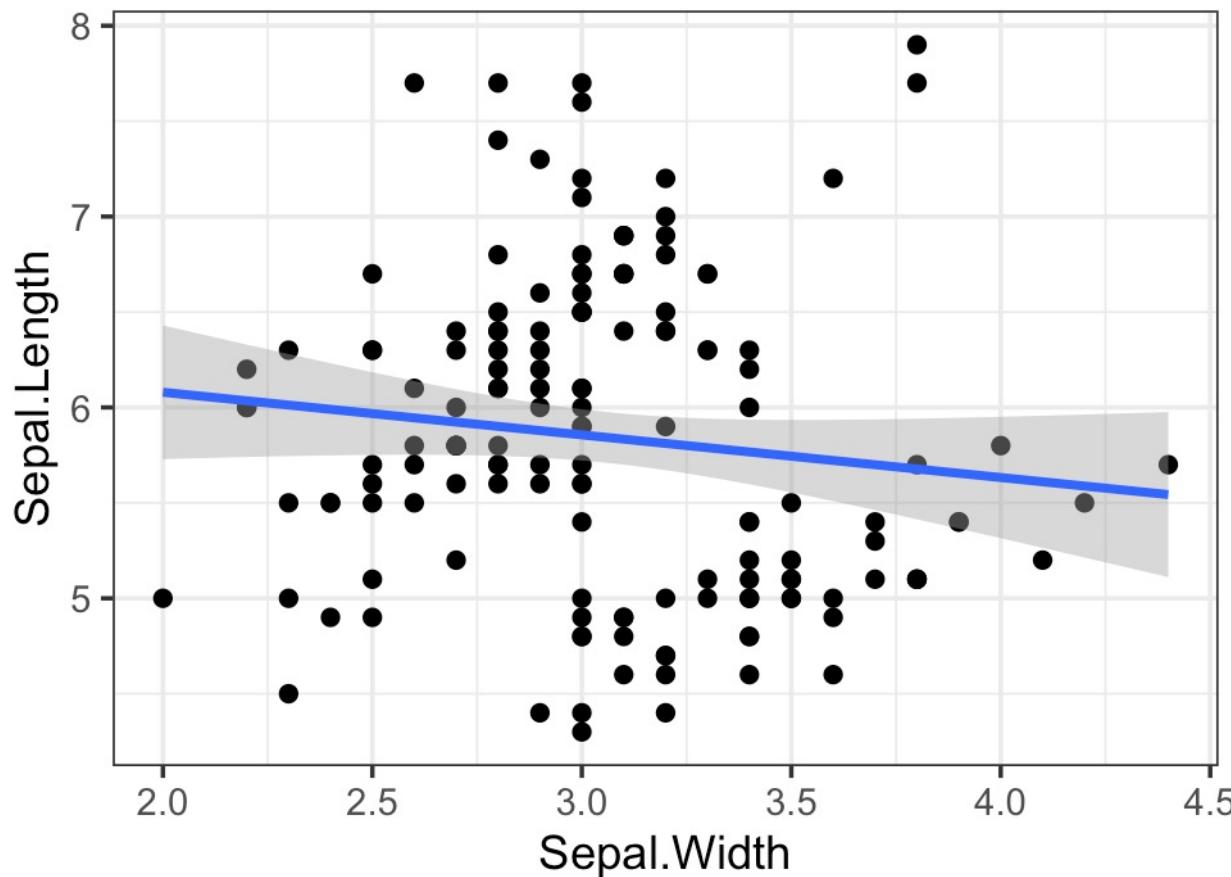
emmeans()



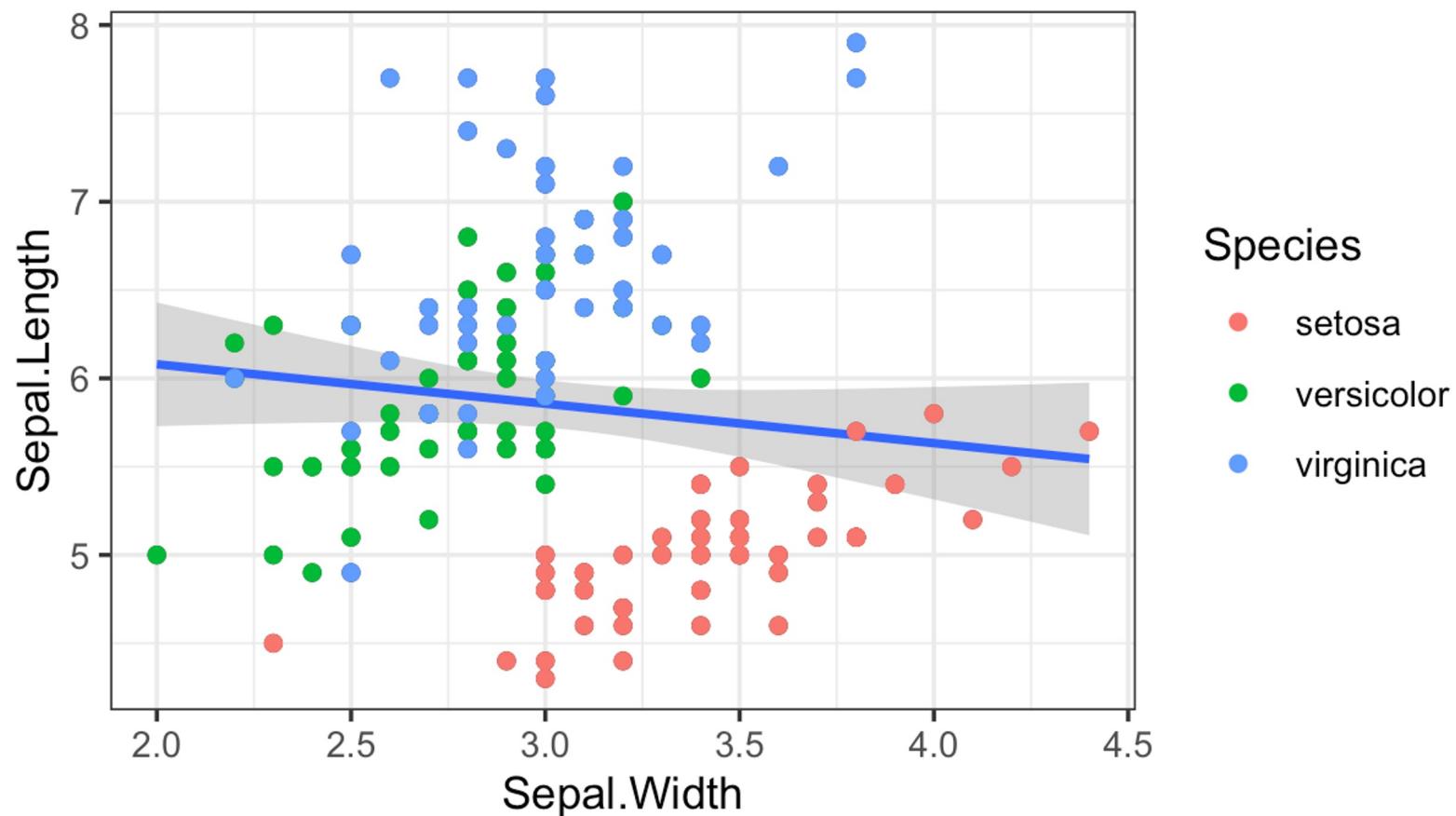
\$contrasts

contrast	estimate	SE	df	t.ratio	p.value
setosa - versicolor	-0.930	0.103	147	-9.033	<.0001
setosa - virginica	-1.582	0.103	147	-15.366	<.0001
versicolor - virginica	-0.652	0.103	147	-6.333	<.0001

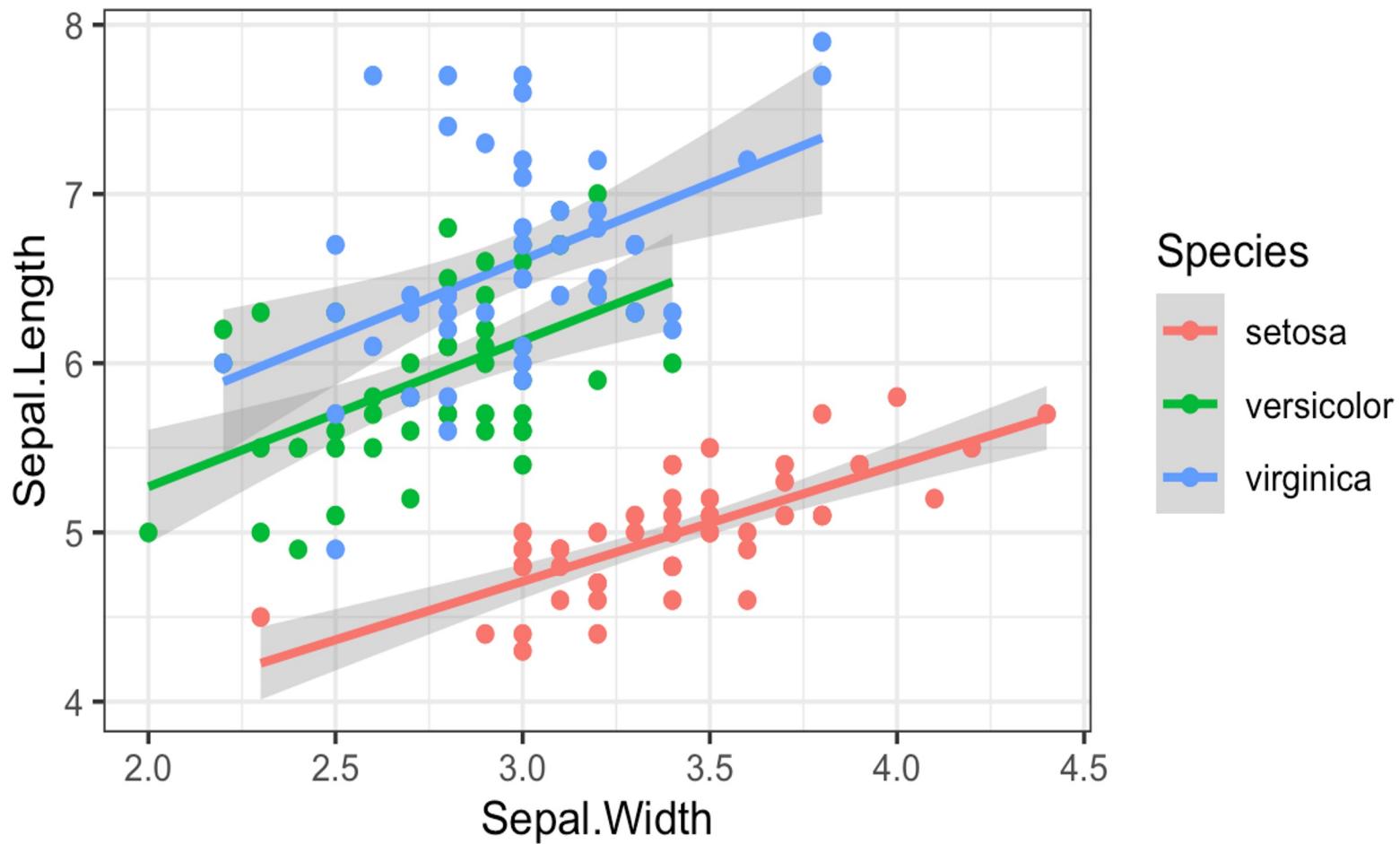
`lm(Sepal.Length ~ Sepal.Width, data = iris)`



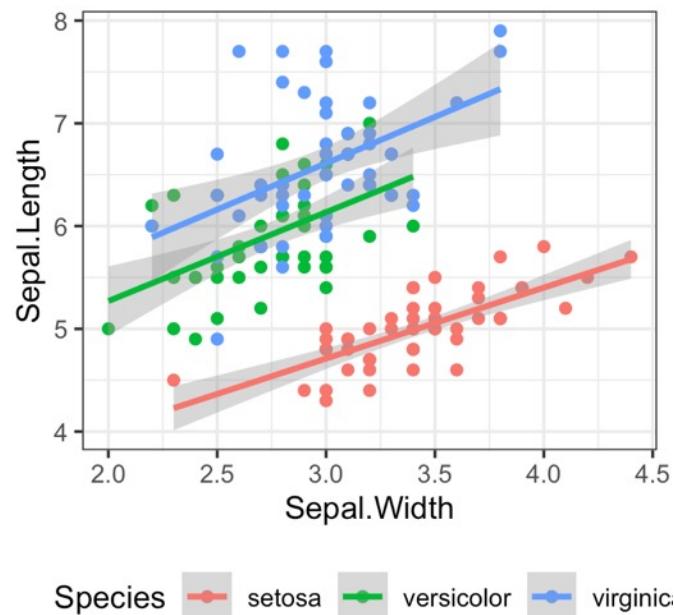
`Im(Sepal.Length ~ Sepal.Width, data = iris)`



`lm(Sepal.Length ~ Sepal.Width + Species, data = iris)`



`lm(Sepal.Length ~ Sepal.Width + Species, data = iris)`



Species setosa versicolor virginica

Call:

`lm(formula = Sepal.Length ~ Sepal.Width + Species, data = iris)`

Residuals:

Min	1Q	Median	3Q	Max
-1.30711	-0.25713	-0.05325	0.19542	1.41253

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	2.2514	0.3698	6.089	9.57e-09	***
Sepal.Width	0.8036	0.1063	7.557	4.19e-12	***
Speciesversicolor	1.4587	0.1121	13.012	< 2e-16	***
Speciesvirginica	1.9468	0.1000	19.465	< 2e-16	***

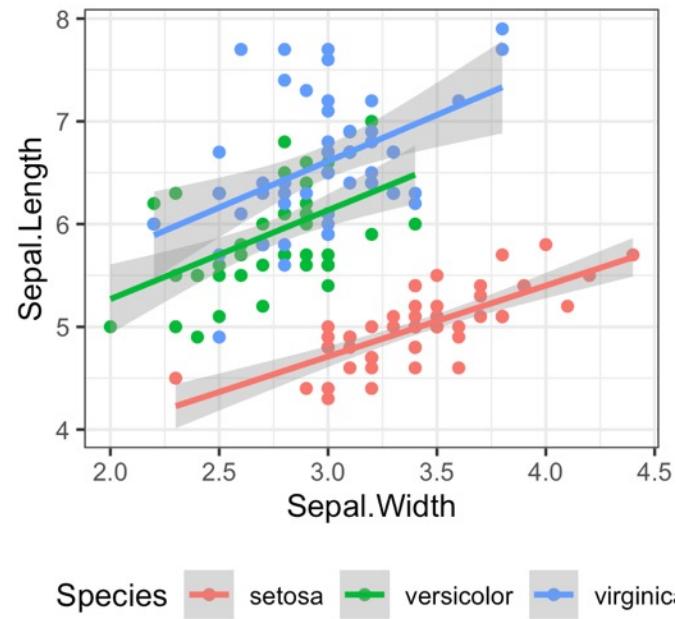
Signif. codes:	0 ***	0.001 **	0.01 *	0.05 .	0.1 ' 1

Residual standard error: 0.438 on 146 degrees of freedom

Multiple R-squared: 0.7259, Adjusted R-squared: 0.7203

F-statistic: 128.9 on 3 and 146 DF, p-value: < 2.2e-16

lm(Sepal.Length ~ Sepal.Width + Species, data = iris)



Anova Table (Type III tests)

Response: Sepal.Length

	Sum Sq	Df	F value	Pr(>F)	
(Intercept)	7.111	1	37.075	9.568e-09	***
Sepal.Width	10.953	1	57.102	4.187e-12	***
Species	72.752	2	189.651	< 2.2e-16	***
Residuals	28.004	146			

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

interactions in linear model



vs



interactions in linear model



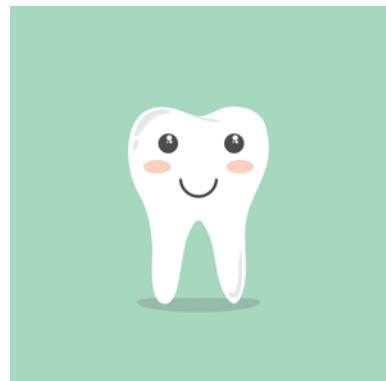
vs

type of
supplement



interactions in linear model

dosages



vs



```
lmint <- lm(len ~ supp * dose, data = ToothGrowth)
```

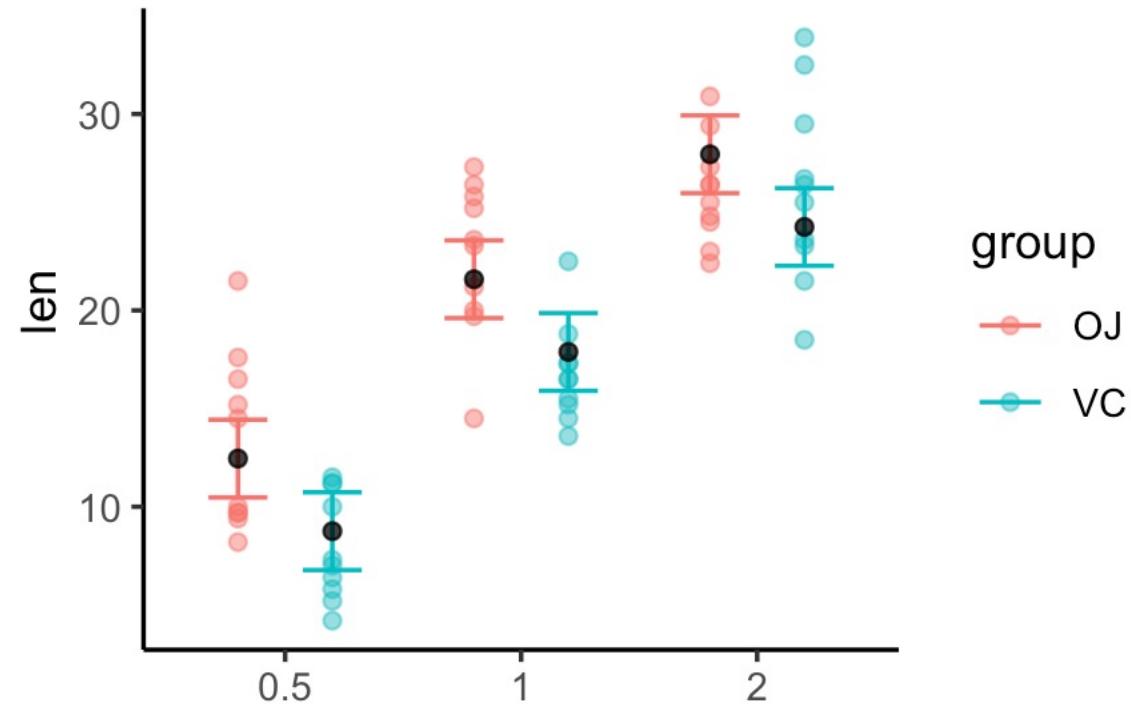


VS

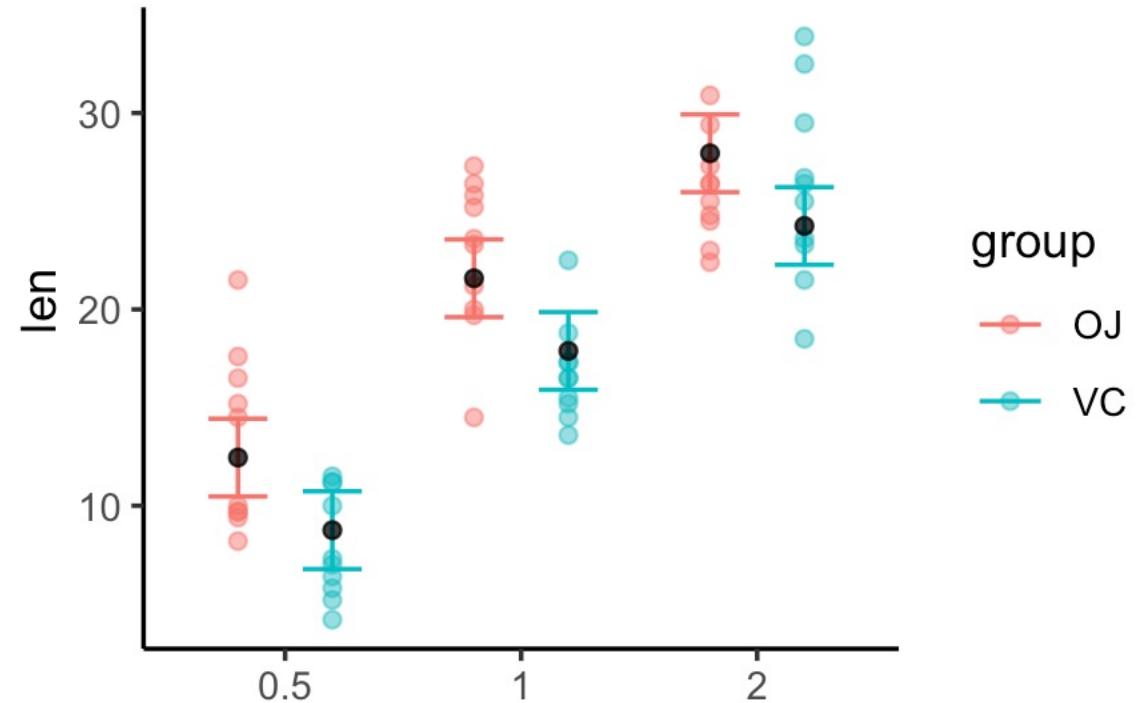




```
lmint <- lm(len ~ supp + dose, data = ToothGrowth)
```



```
lmint <- lm(len ~ supp + dose, data = ToothGrowth)
```

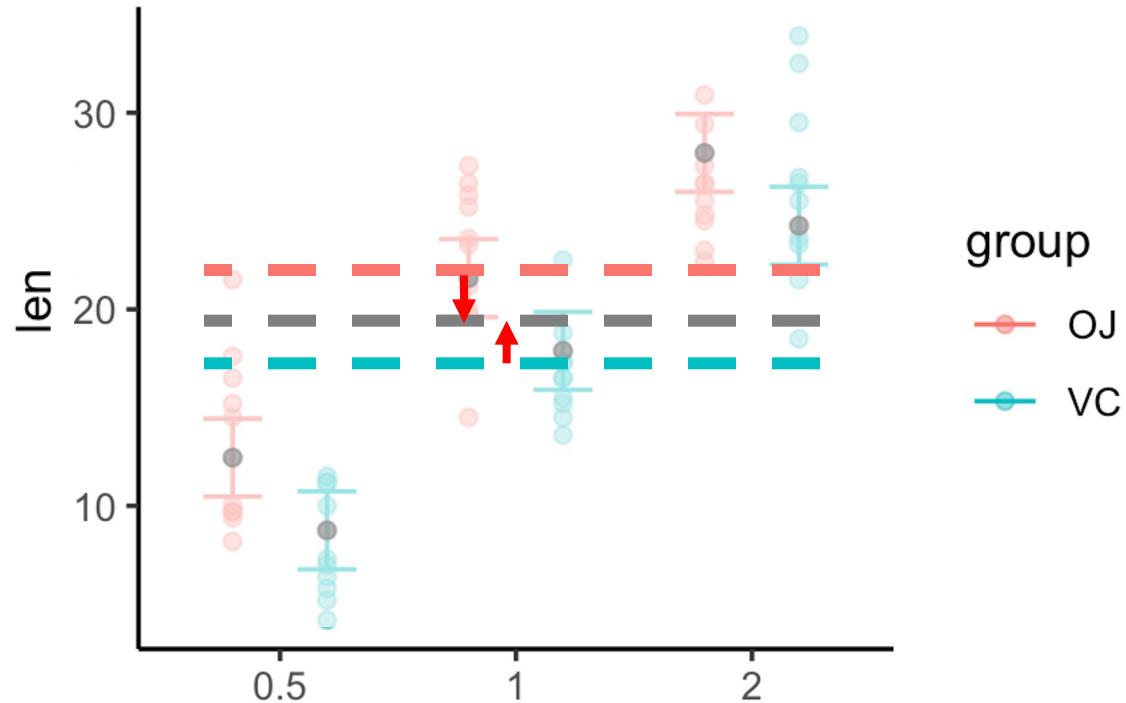


Anova Table (Type III tests)

Response: len

	Sum Sq	Df	F value	Pr(>F)
(Intercept)	2326.91	1	158.828	< 2.2e-16 *
supp	205.35	1	14.017	0.0004293 *
dose	2426.43	2	82.811	< 2.2e-16 *
Residuals	820.43	56		

```
lmint <- lm(len ~ supp + dose, data = ToothGrowth)
```



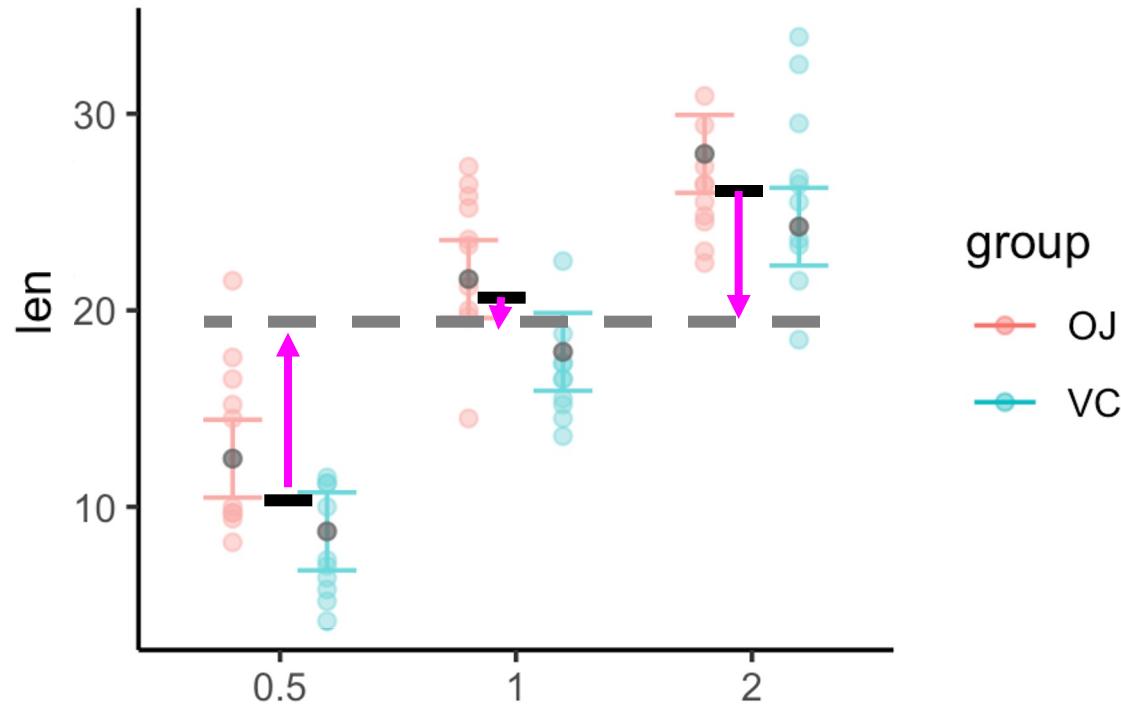
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Response: len

	Sum Sq	Df	F value	Pr(>F)
(Intercept)	2326.91	1	158.828	< 2.2e-16 *
supp	205.35	1	14.017	0.0004293 *
dose	2426.43	2	82.811	< 2.2e-16 *
Residuals	820.43	56		

Redo: Suppose to compare treatment mean to grand mean

```
lmint <- lm(len ~ supp + dose, data = ToothGrowth)
```



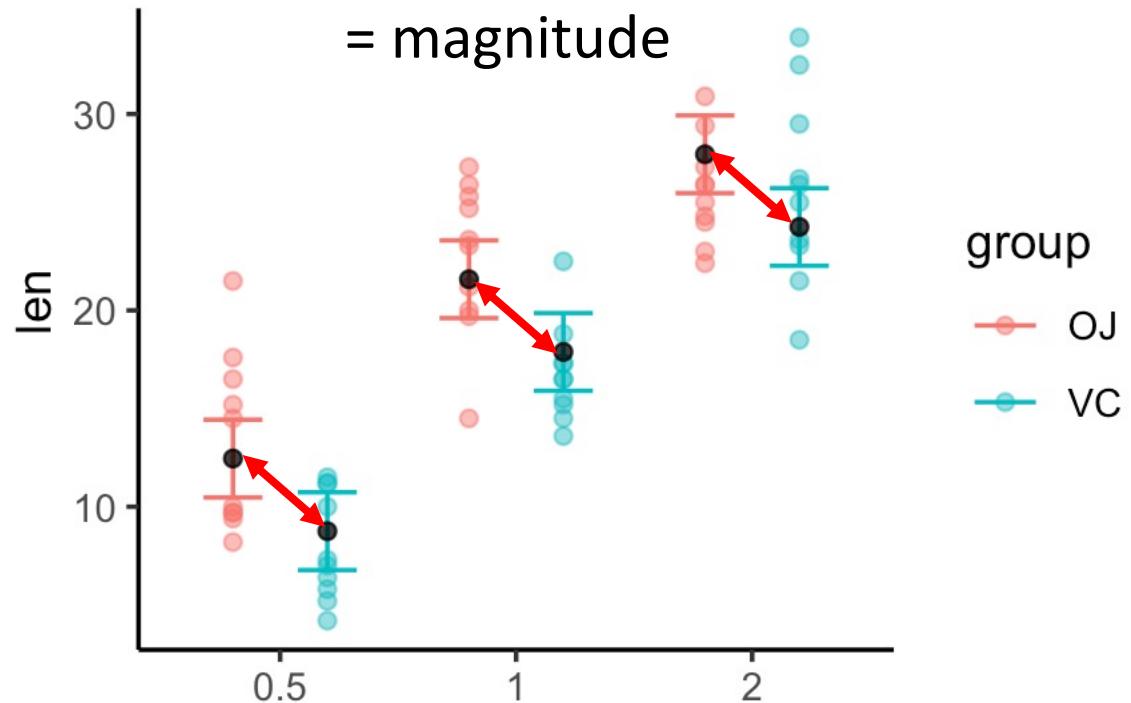
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Response: len

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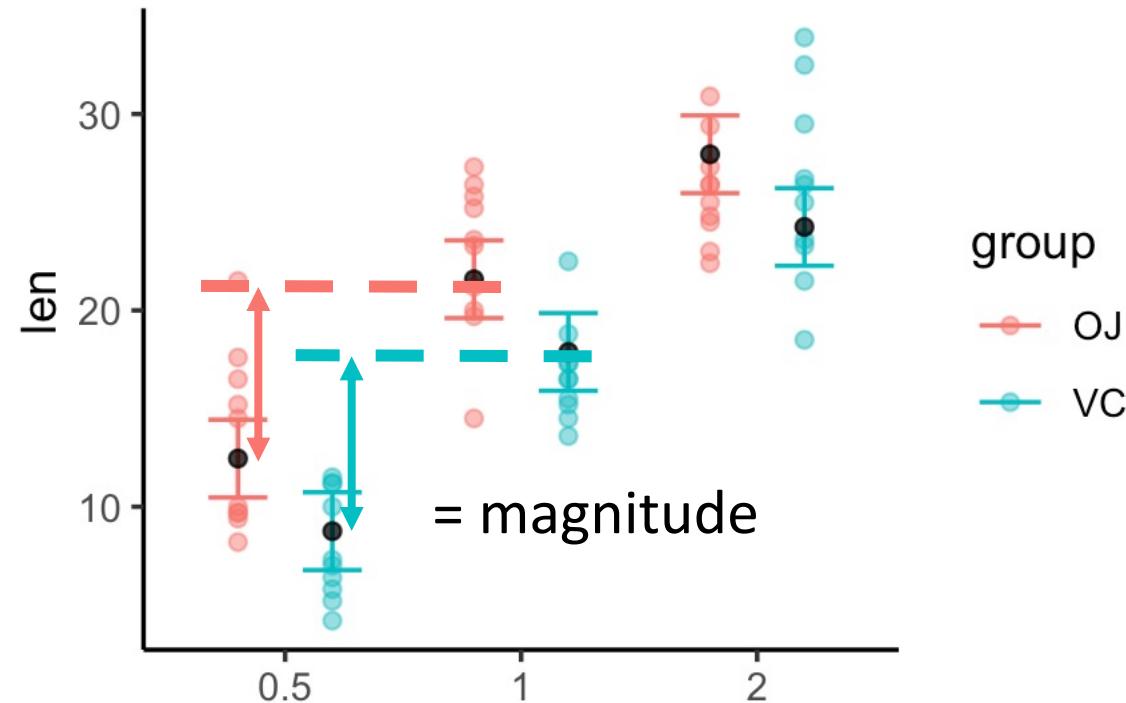


Anova Table (Type III tests)

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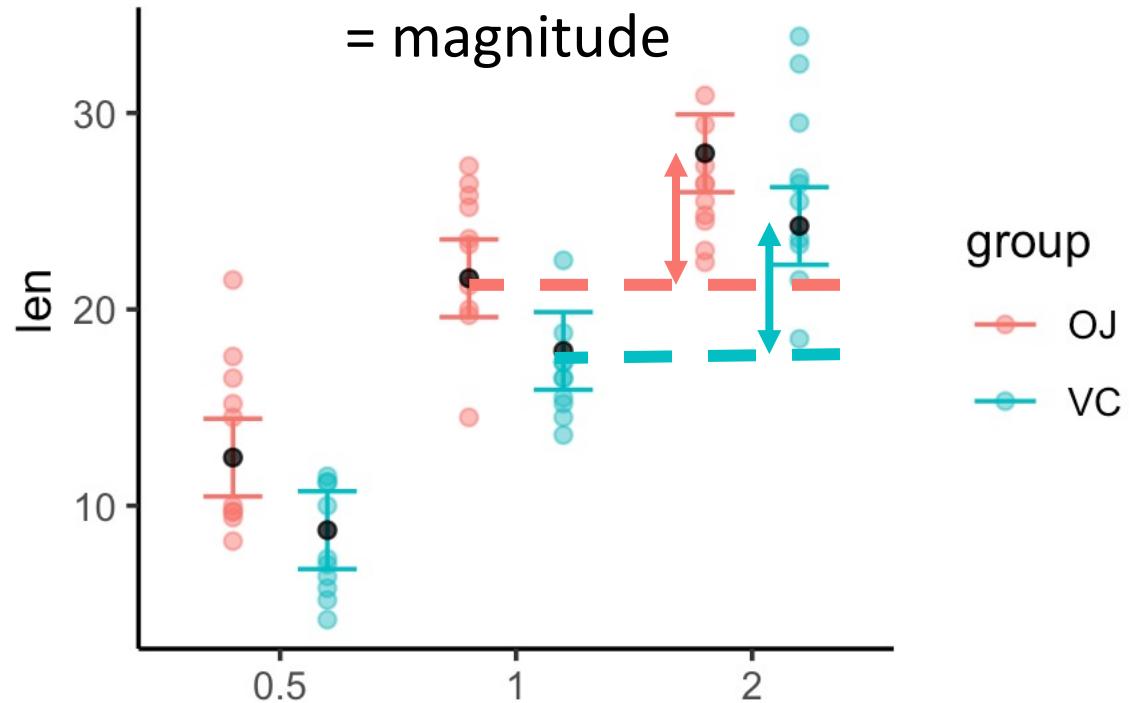


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```

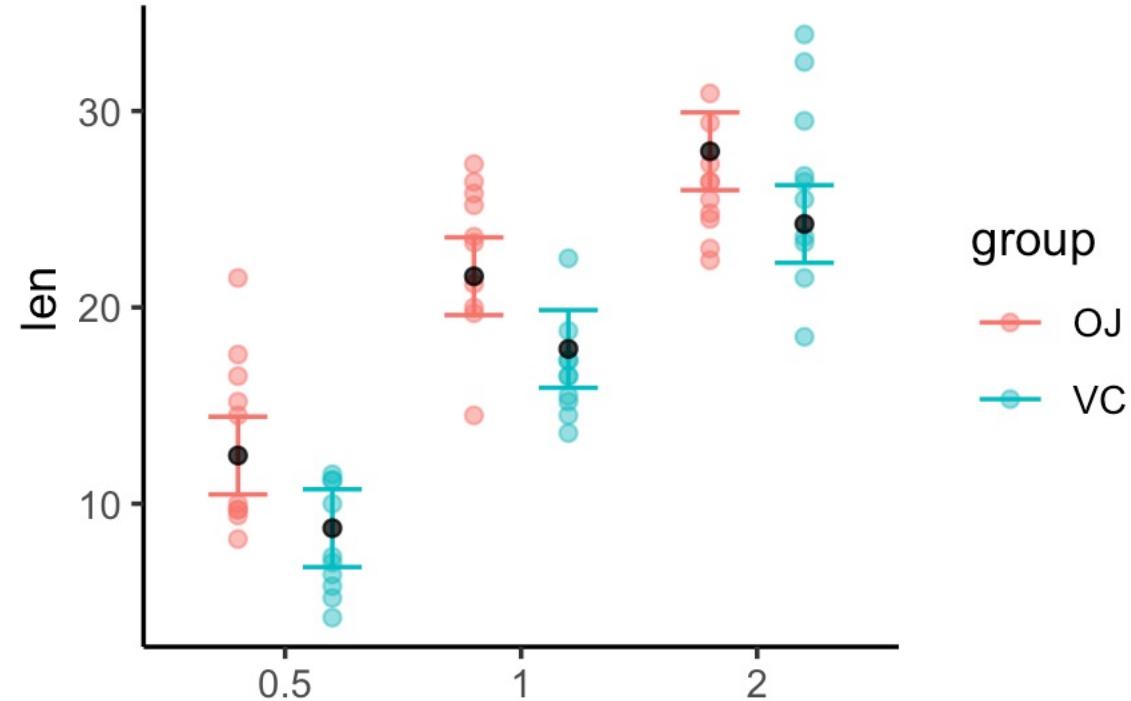


Anova Table (Type III tests)

Response: len

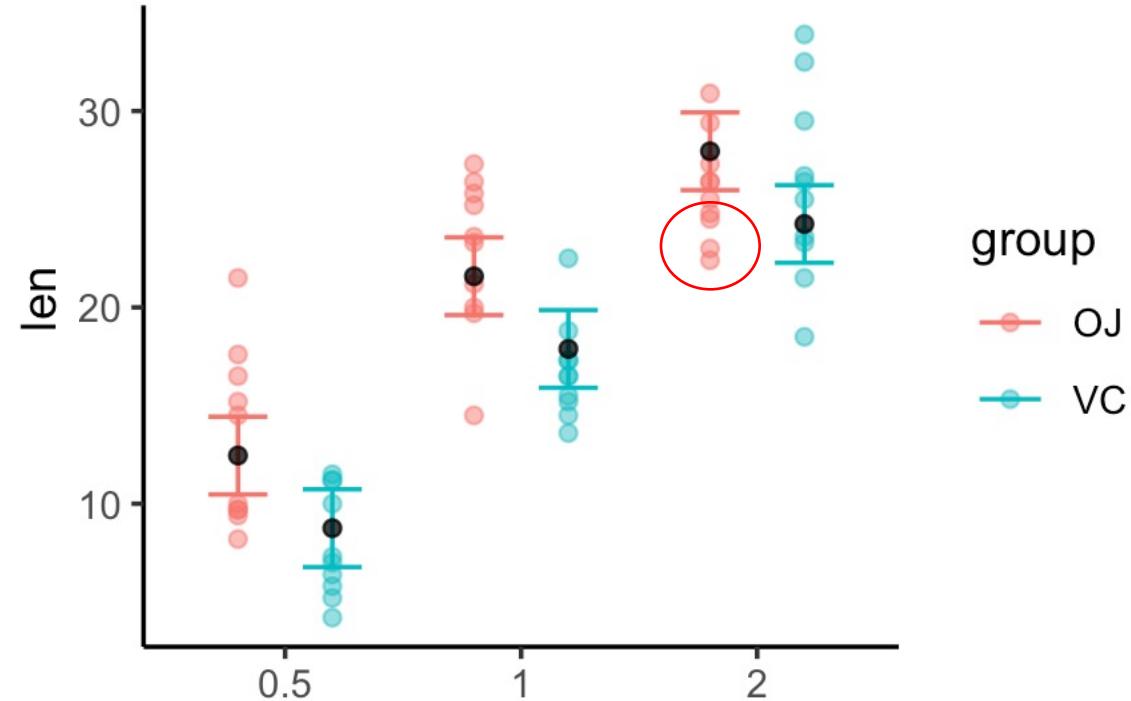
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```
lmint <- lm(len ~ supp + dose, data = ToothGrowth)
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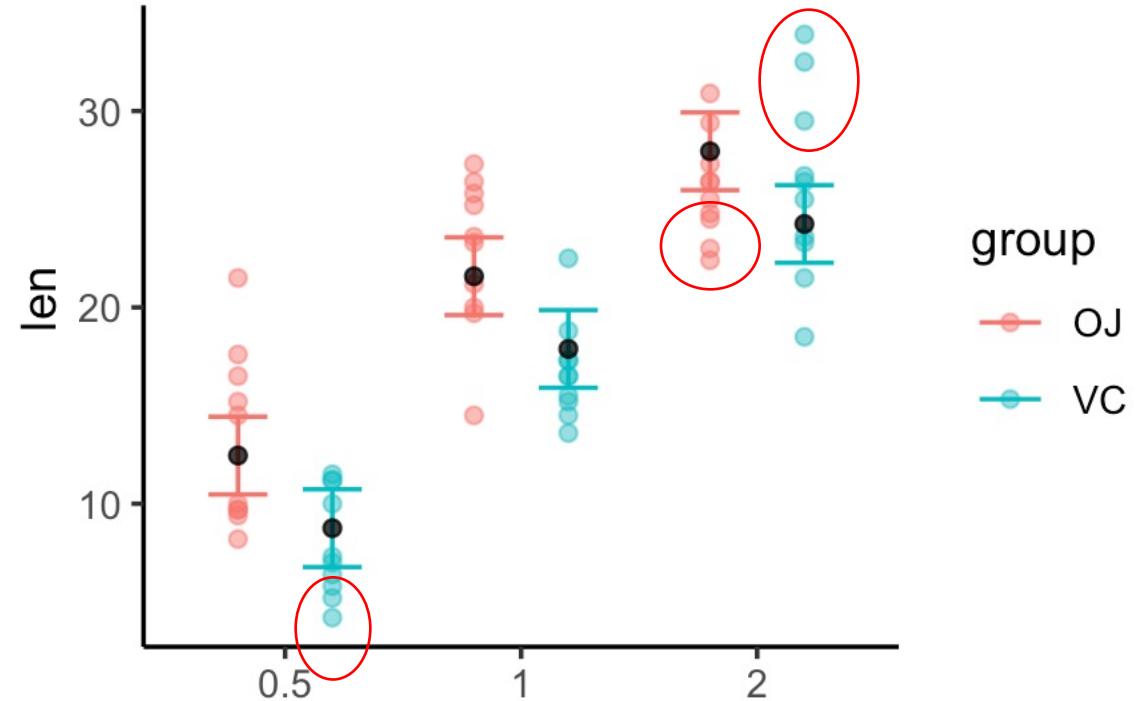
However!

```
lmint <- lm(len ~ supp + dose, data = ToothGrowth)
```



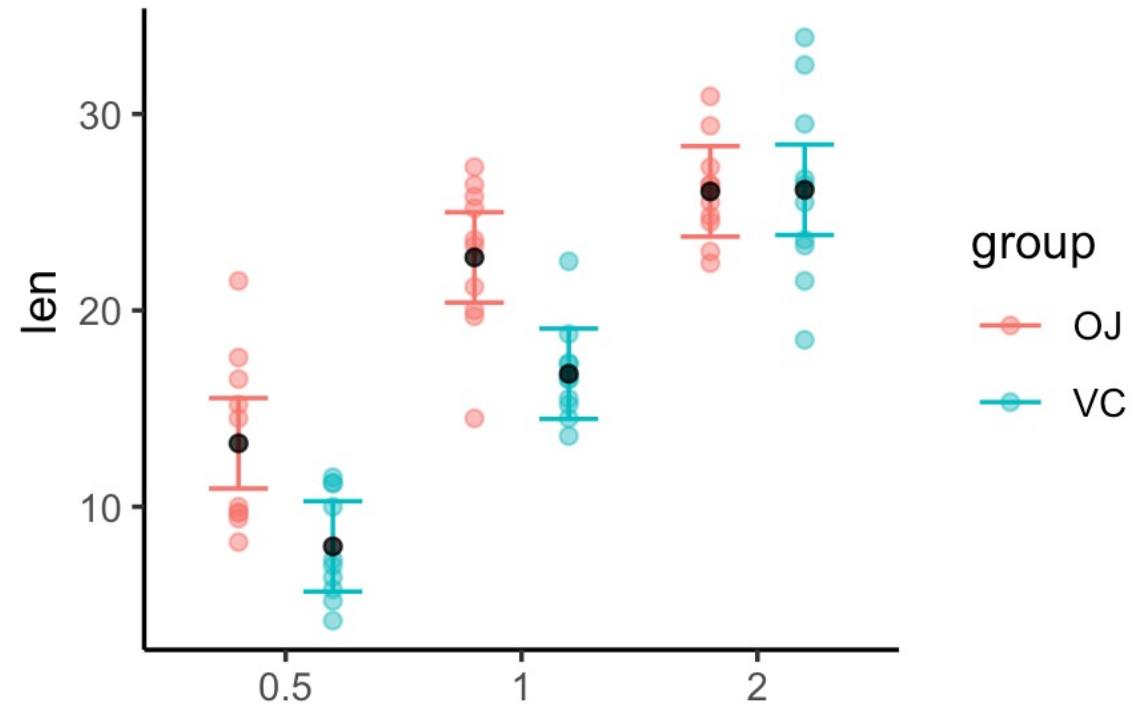
However!

```
lmint <- lm(len ~ supp + dose, data = ToothGrowth)
```

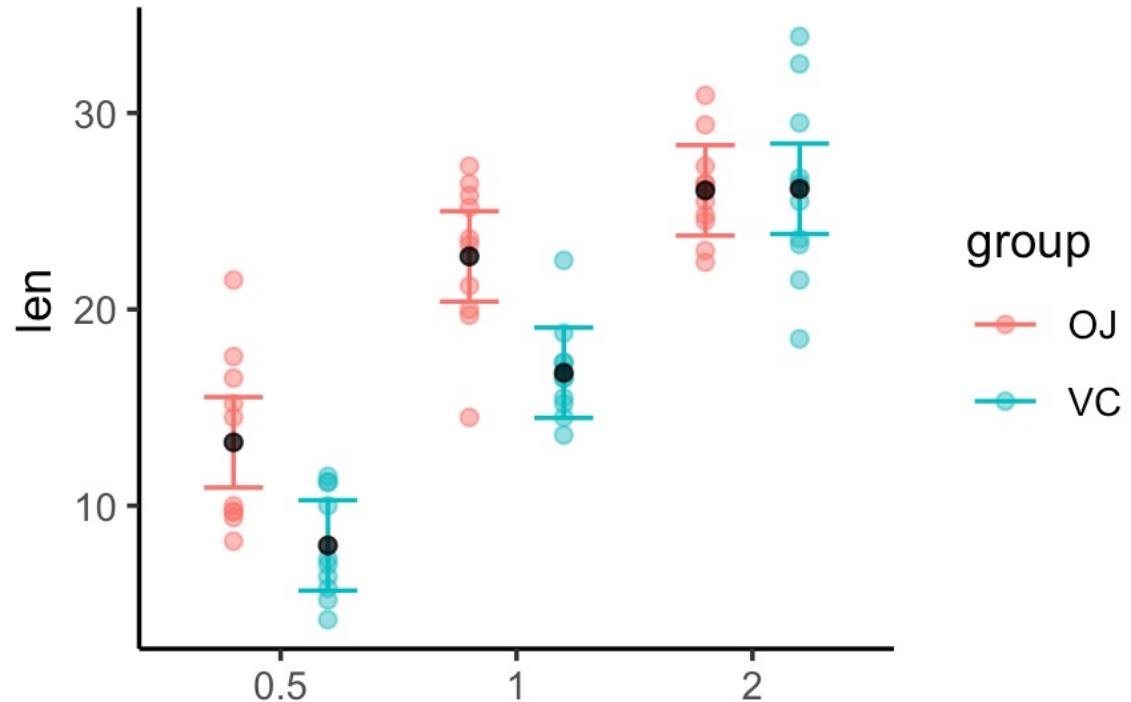


However!

```
lmint <- lm(len ~ supp * dose, data = ToothGrowth)
```



```
lmint <- lm(len ~ supp * dose, data = ToothGrowth)
```

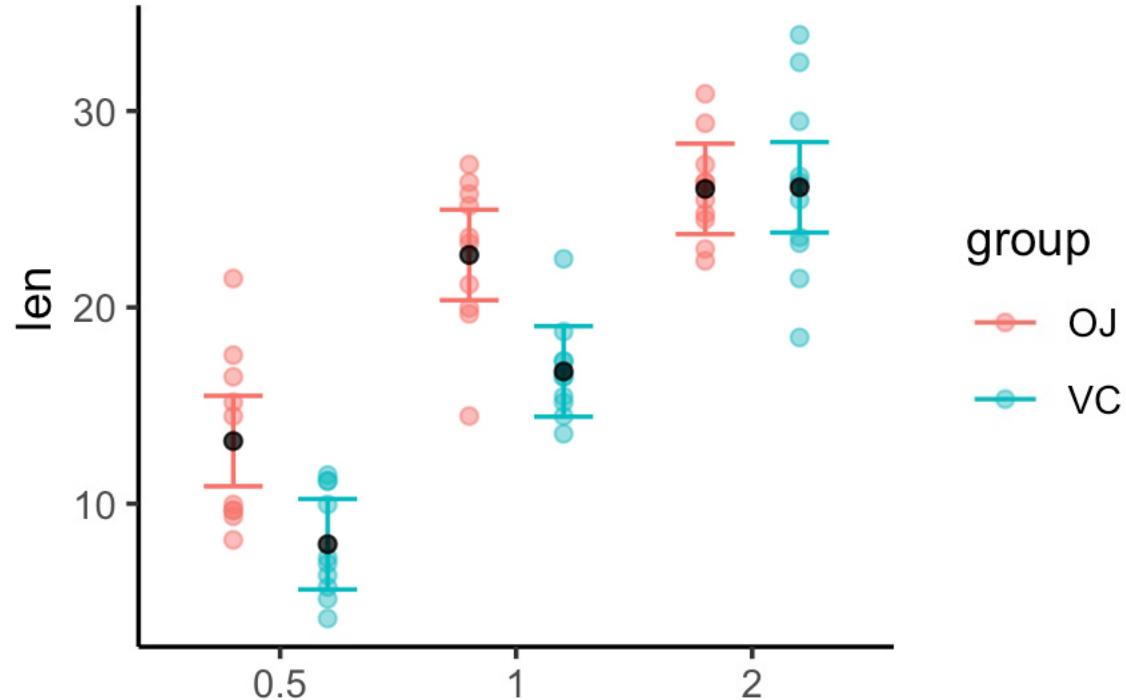


Anova Table (Type III tests)

Response: len

	Sum Sq	Df	F value	Pr(>F)
(Intercept)	1750.33	1	132.730	3.603e-16 **
supp	137.81	1	10.450	0.002092 **
dose	885.26	2	33.565	3.363e-10 **
supp:dose	108.32	2	4.107	0.021860 *
Residuals	712.11	54		

```
lmint <- lm(len ~ supp * dose, data = ToothGrowth)
```



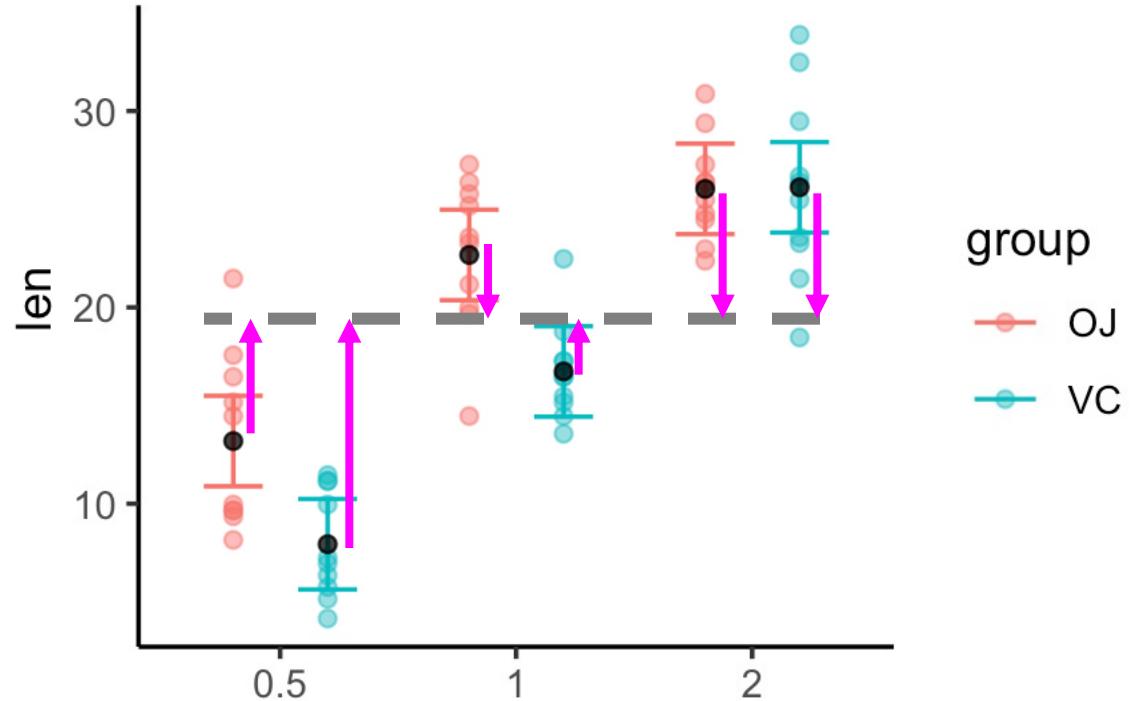
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supp:dose	108.32	2	4.107	0.021860 *
Residuals	712.11	54		

$$(\bar{y}_{AB} - \bar{y}_T) - (\bar{y}_A - \bar{y}_T) - (\bar{y}_B - \bar{y}_T)$$

```
lmint <- lm(len ~ supp * dose, data = ToothGrowth)
```



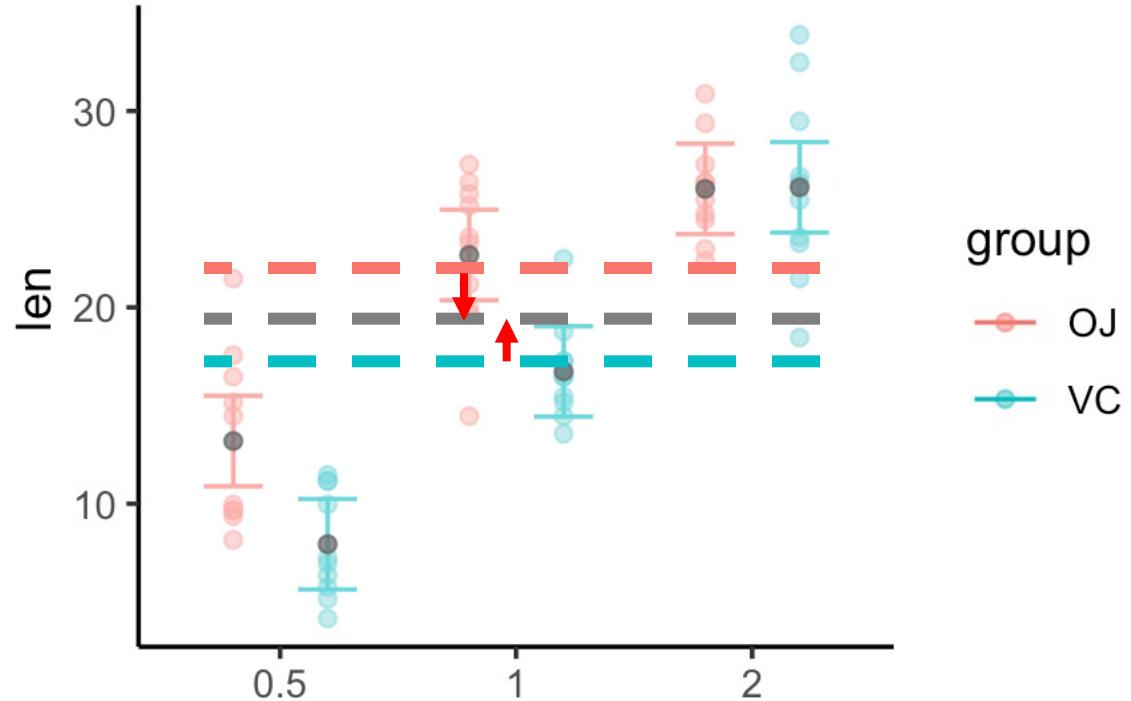
Anova Table (Type III tests)

Response: len

	Sum Sq	Df	F value	Pr(>F)
(Intercept)	1750.33	1	132.730	3.603e-16 *
supp	137.81	1	10.450	0.002092 *
dose	885.26	2	33.565	3.363e-10 *
supp:dose	108.32	2	4.107	0.021860 *
Residuals	712.11	54		

$$(\bar{y}_{AB} - \bar{y}_T) - (\bar{y}_A - \bar{y}_T) - (\bar{y}_B - \bar{y}_T)$$

```
lmint <- lm(len ~ supp * dose, data = ToothGrowth)
```



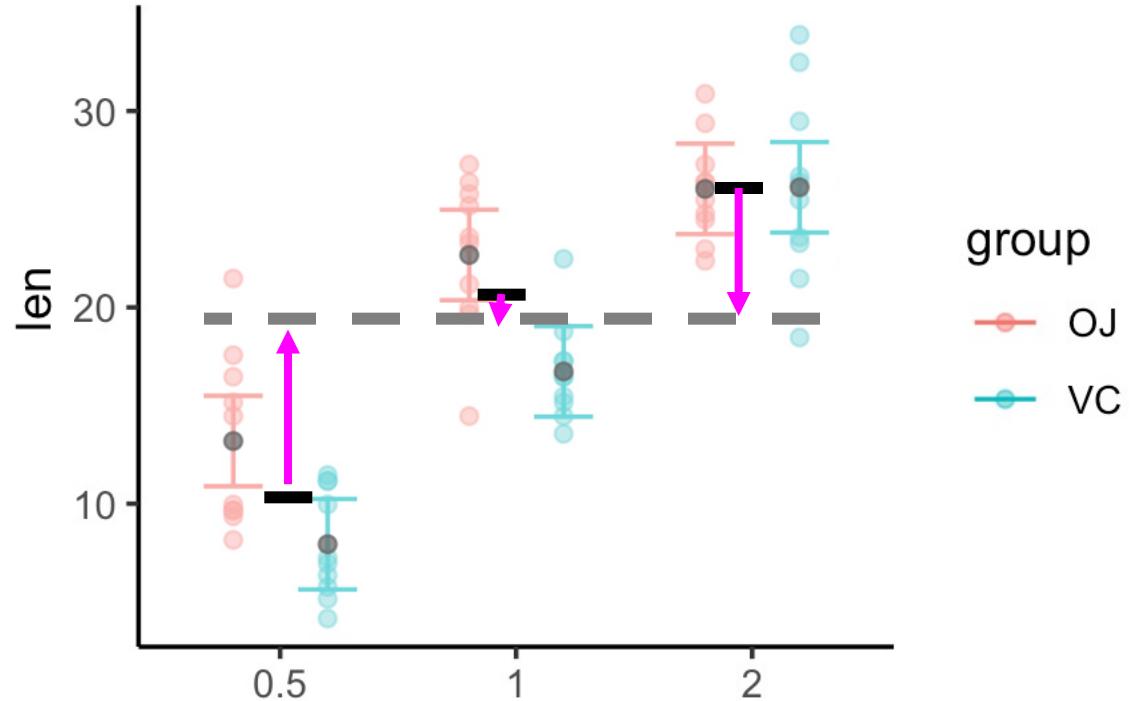
Anova Table (Type III tests)

Response: len

	Sum Sq	Df	F value	Pr(>F)
(Intercept)	1750.33	1	132.730	3.603e-16 **
supp	137.81	1	10.450	0.002092 **
dose	885.26	2	33.565	3.363e-10 **
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Residuals	712.11	54		

$$(\bar{y}_{AB} - \bar{y}_T) - (\bar{y}_A - \bar{y}_T) - (\bar{y}_B - \bar{y}_T)$$

```
lmint <- lm(len ~ supp * dose, data = ToothGrowth)
```



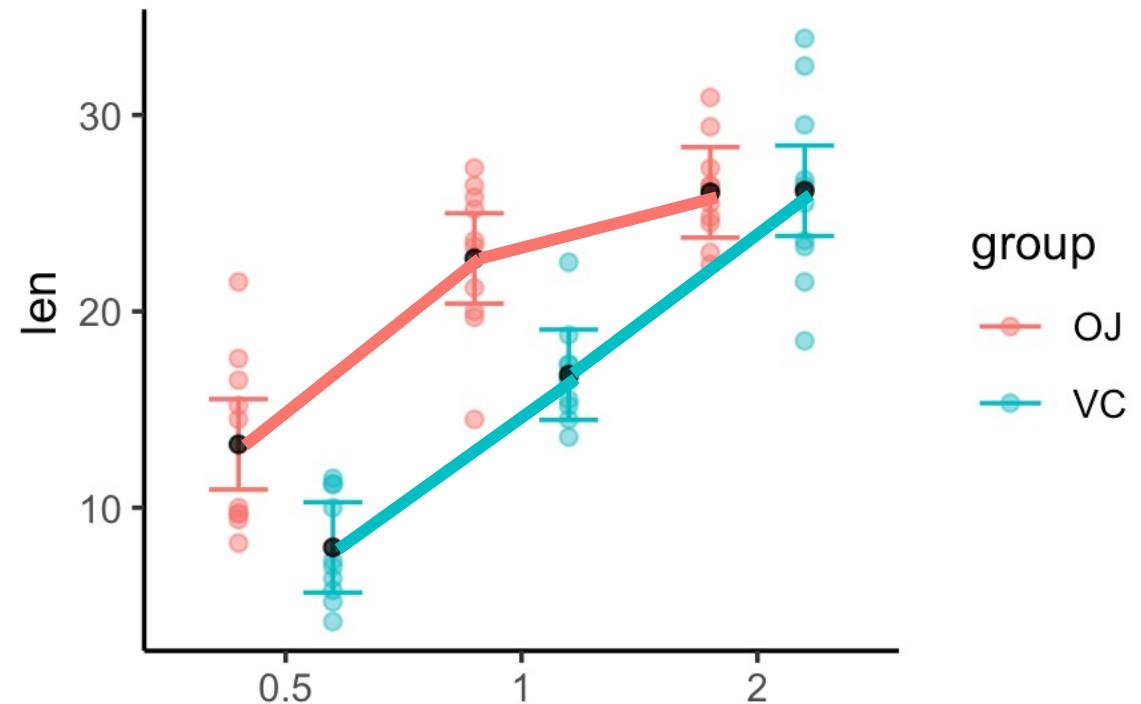
Anova Table (Type III tests)

Response: len

	Sum Sq	Df	F value	Pr(>F)
(Intercept)	1750.33	1	132.730	3.603e-16 *
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Residuals	712.11	54		

$$(\bar{y}_{AB} - \bar{y}_T) - (\bar{y}_A - \bar{y}_T) - (\bar{y}_B - \bar{y}_T)$$

```
lmint <- lm(len ~ supp * dose, data = ToothGrowth)
```



Anova Table (Type III tests)

Response: len

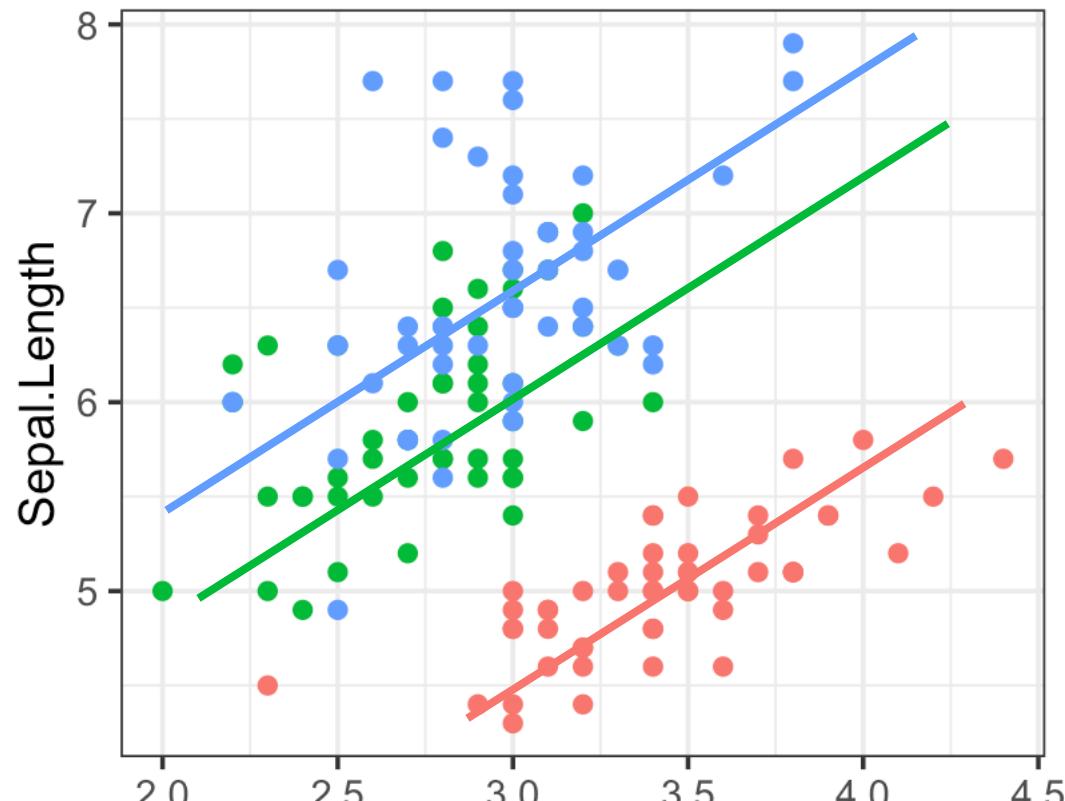
	Sum Sq	Df	F value	Pr(>F)
(Intercept)	1750.33	1	132.730	3.603e-16 **
supp	137.81	1	10.450	0.002092 **
dose	885.26	2	33.565	3.363e-10 **
supp:dose	108.32	2	4.107	0.021860 *
Residuals	712.11	54		

type of interactions

- categorical x categorical
- categorical x continuous
- continuous x continuous



`lm(Sepal.Length ~ Sepal.Width + Species, data = iris)`

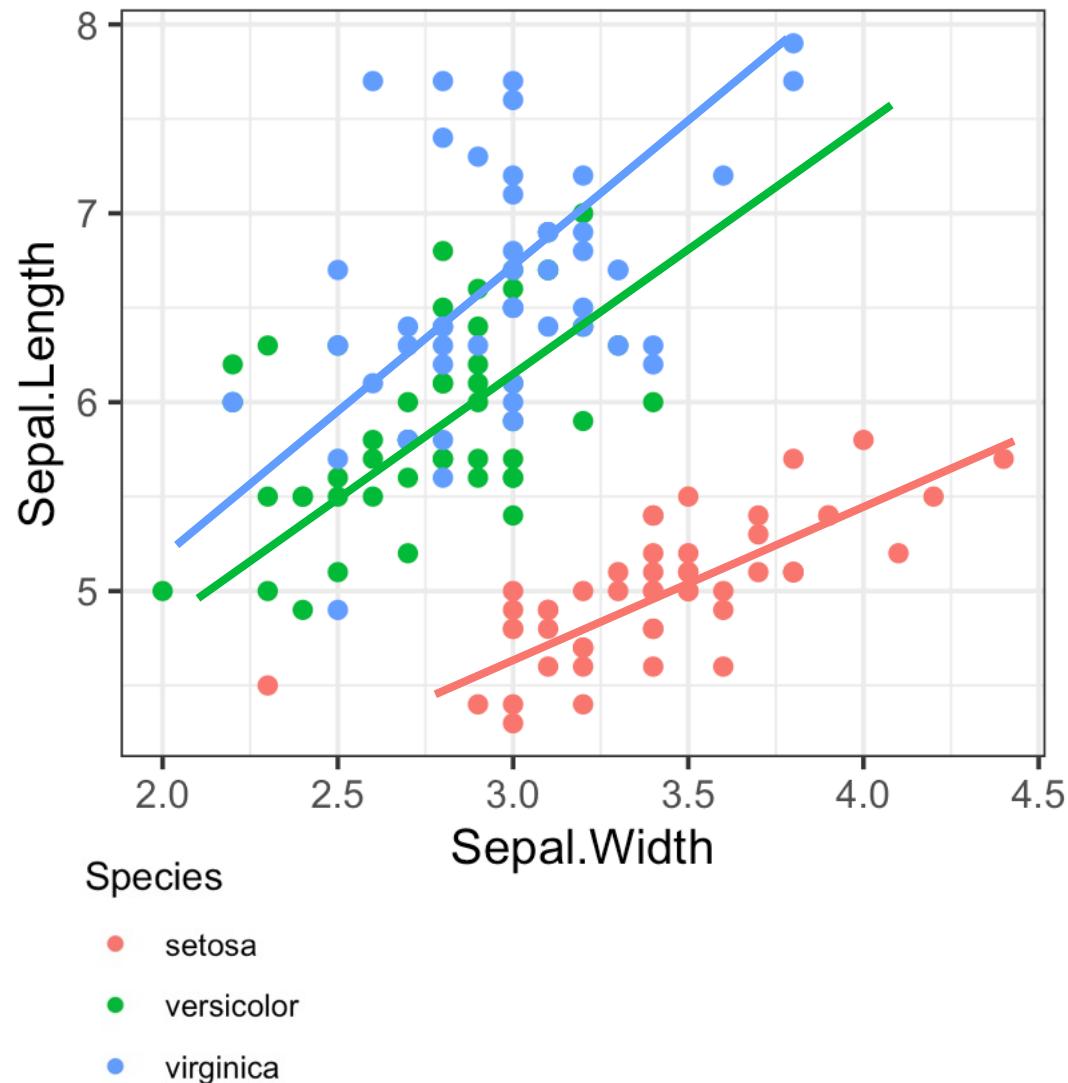


Species

- setosa
- versicolor
- virginica

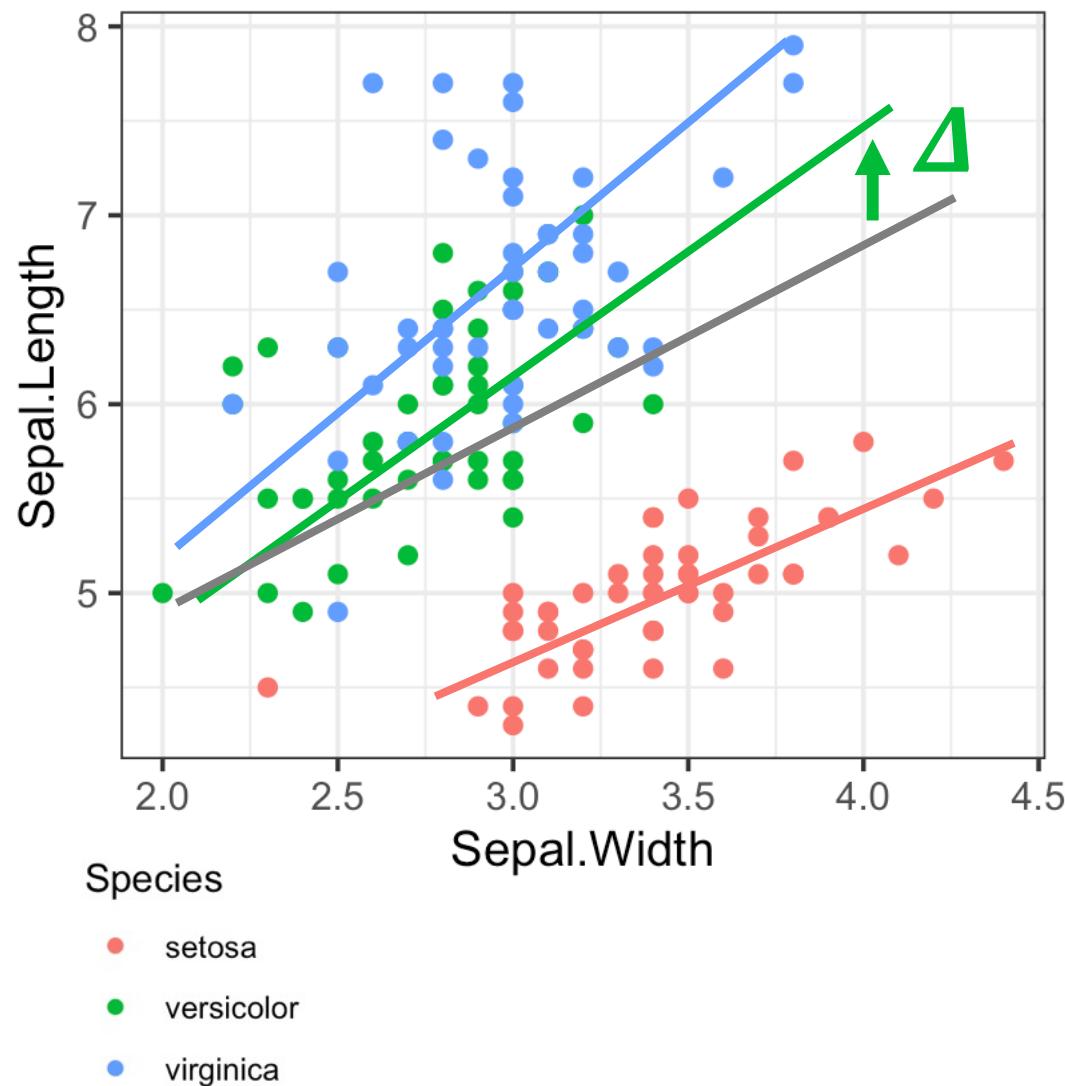
	Estimate
(Intercept)	2.2514
Sepal.Width	0.8036
Speciesversicolor	1.4587
Speciesvirginica	1.9468

`lm(Sepal.Length ~ Sepal.Width * Species, data = iris)`



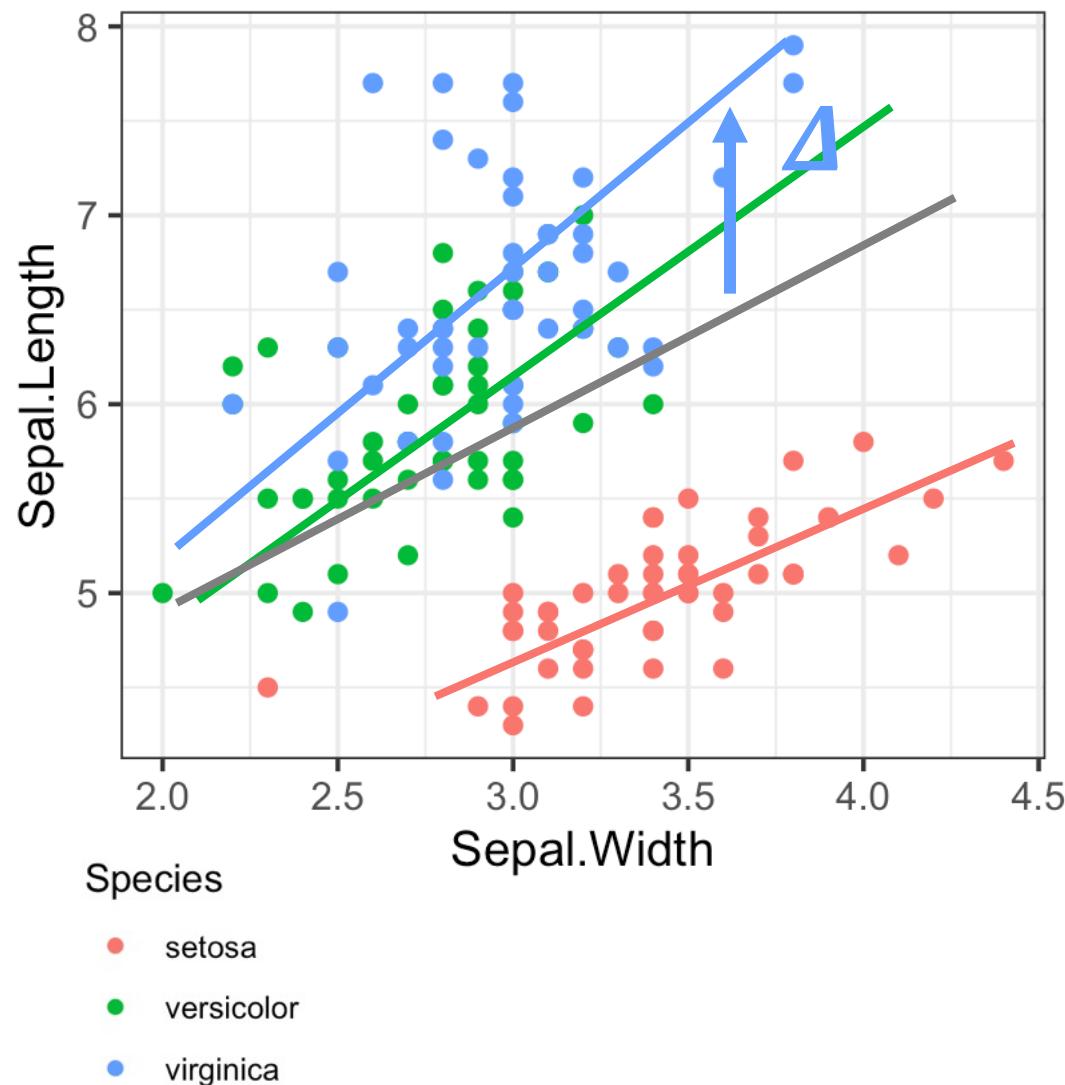
	Estimate
(Intercept)	2.6390
Sepal.Width	0.6905
Speciesversicolor	0.9007
Speciesvirginica	1.2678
Sepal.Width:Speciesversicolor	0.1746
Sepal.Width:Speciesvirginica	0.2110

`lm(Sepal.Length ~ Sepal.Width * Species, data = iris)`



	Estimate
(Intercept)	2.6390
Sepal.Width	0.6905
Speciesversicolor	0.9007
Speciesvirginica	1.2678
Sepal.Width:Speciesversicolor	0.1746
Sepal.Width:Speciesvirginica	0.2110

`lm(Sepal.Length ~ Sepal.Width * Species, data = iris)`



	Estimate
(Intercept)	2.6390
Sepal.Width	0.6905
Speciesversicolor	0.9007
Speciesvirginica	1.2678
Sepal.Width:Speciesversicolor	0.1746
Sepal.Width:Speciesvirginica	0.2110

type of interactions

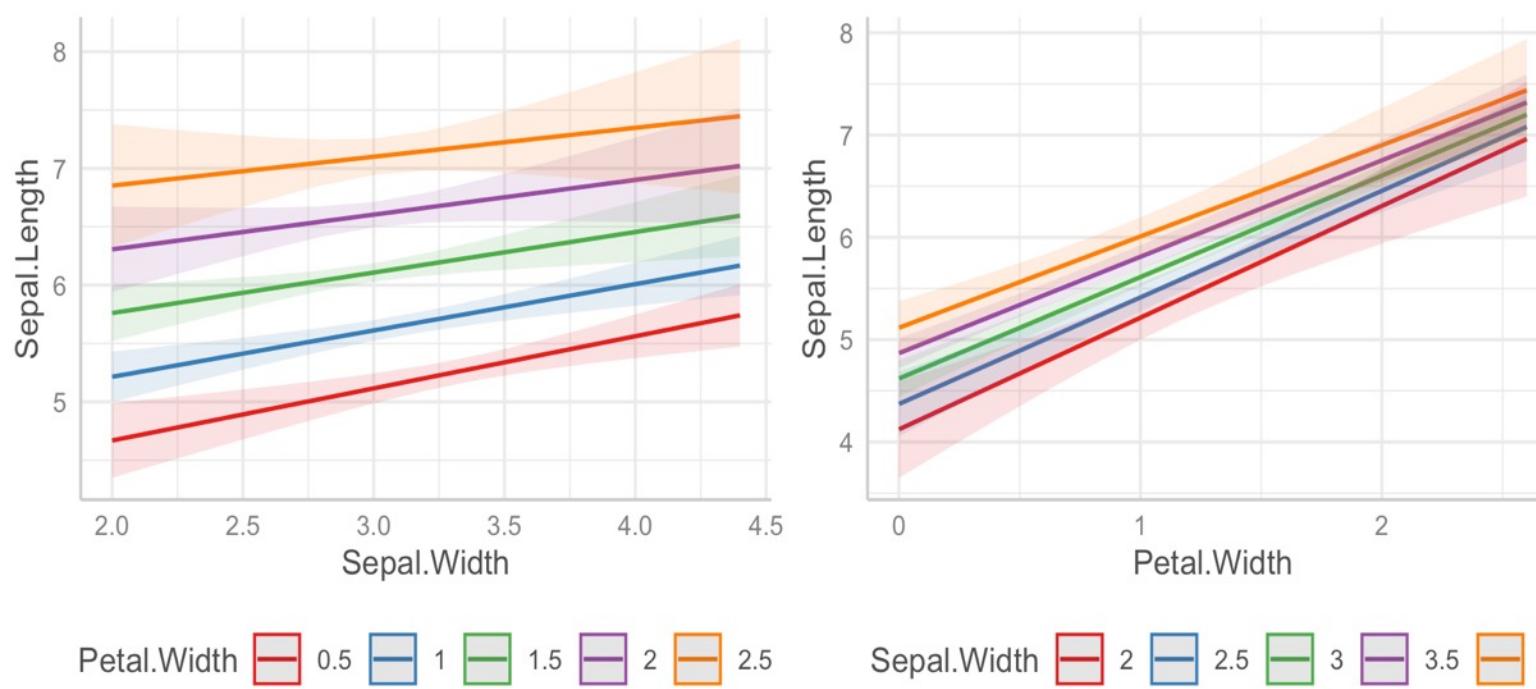
- categorical x categorical



- categorical x continuous

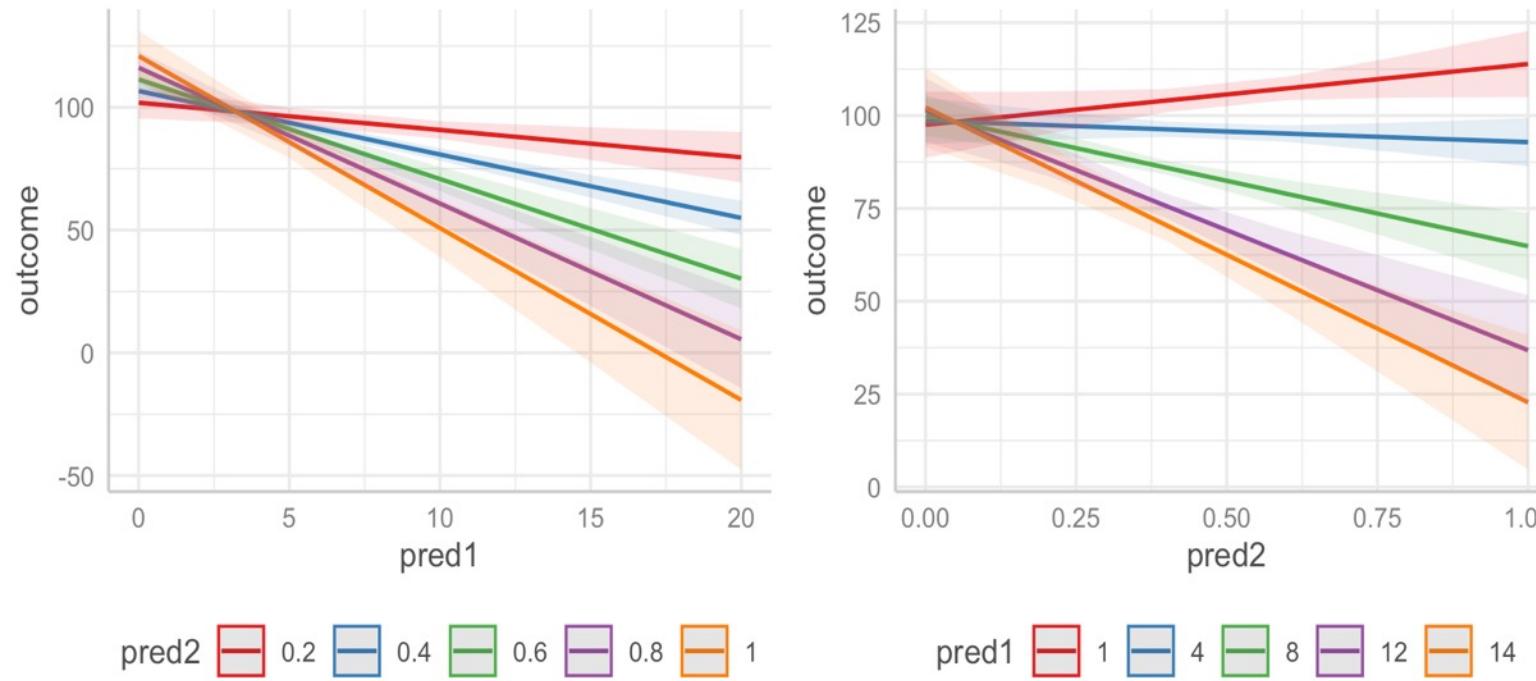


- continuous x continuous



Petal.Width
 0.5 (red)
 1 (blue)
 1.5 (green)
 2 (purple)
 2.5 (orange)

Sepal.Width
 2 (red)
 2.5 (blue)
 3 (green)
 3.5 (purple)
 4 (orange)

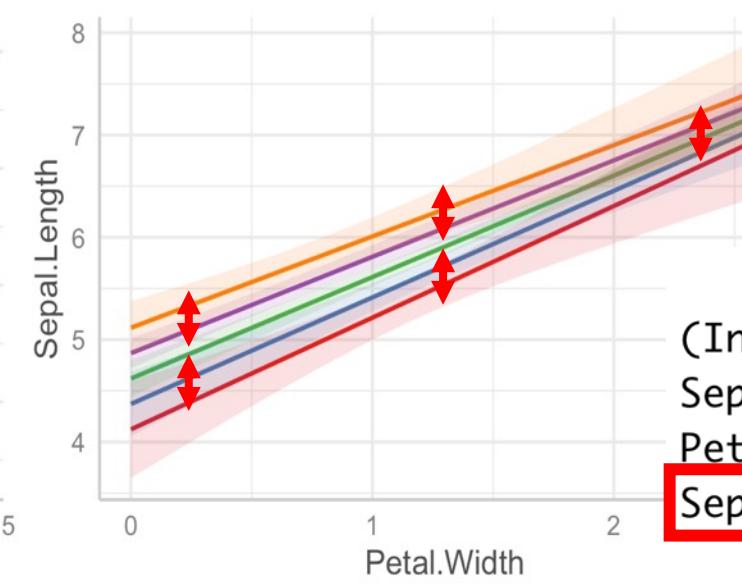
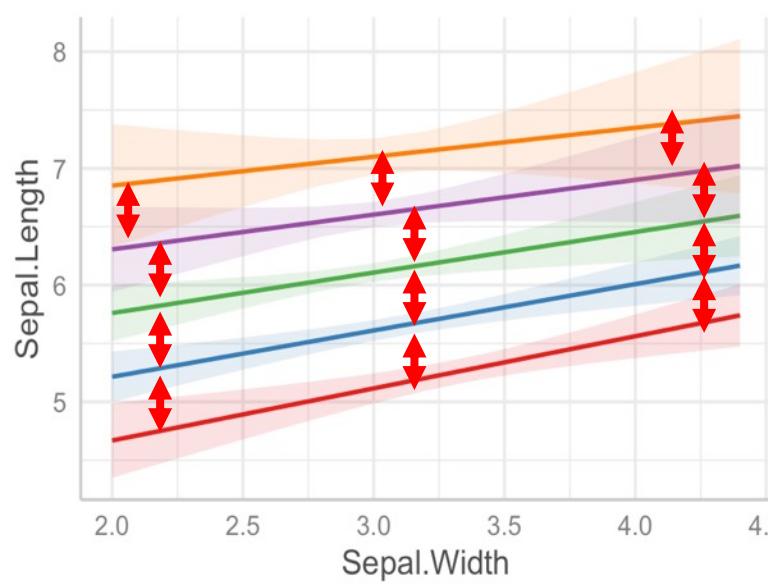


pred2
 0.2 (red)
 0.4 (blue)
 0.6 (green)
 0.8 (purple)
 1 (orange)

pred1
 1 (red)
 4 (blue)
 8 (green)
 12 (purple)
 14 (orange)

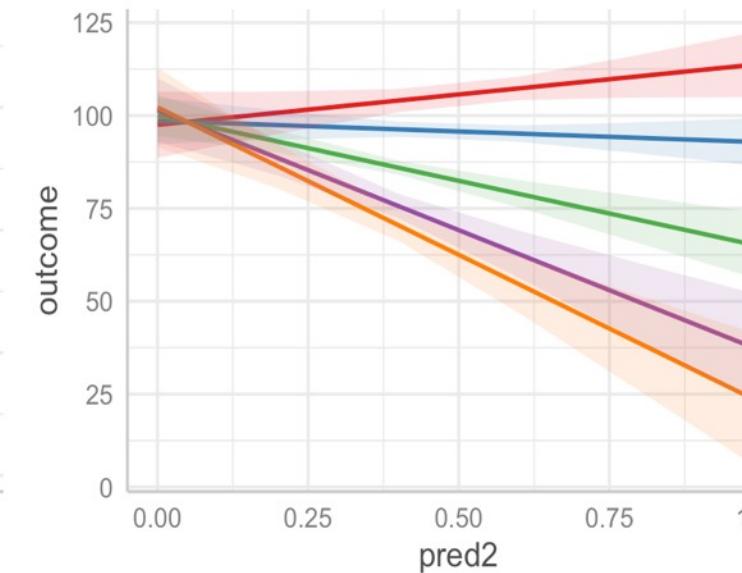
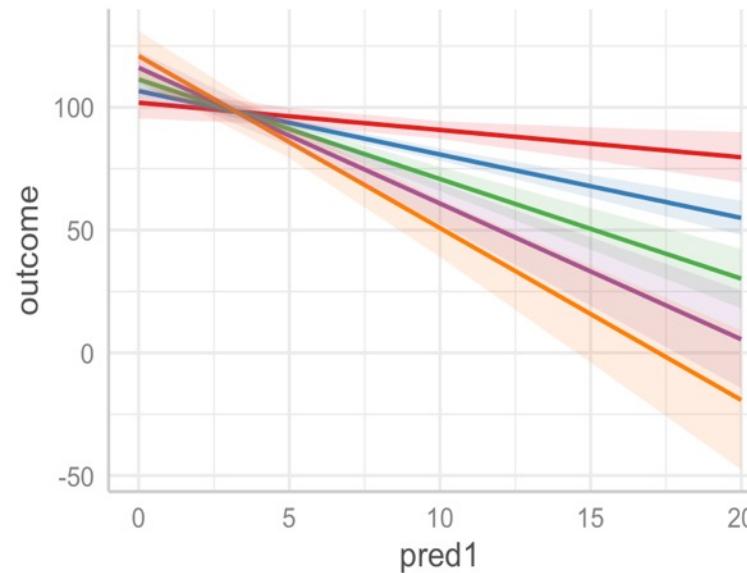
Sepal.length ~ Sepal.width * Petal.width

outcome ~ pred1 * pred2

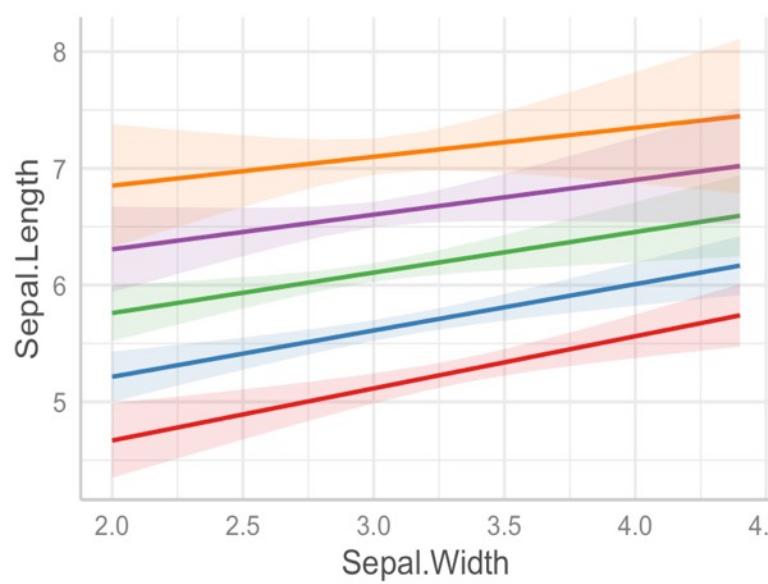


Sepal.length ~ Sepal.width * Petal.width

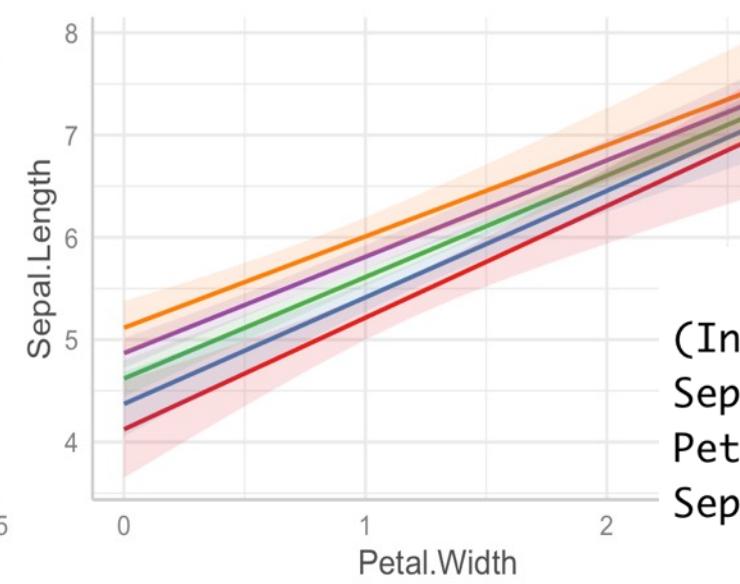
	Estimate	Pr(> t)
(Intercept)	3.13046	2.1e-07 ***
Sepal.Width	0.49642	0.00418 **
Petal.Width	1.29057	0.00729 **
Sepal.Width:Petal.Width	-0.09946	0.50038



outcome ~ pred1 * pred2

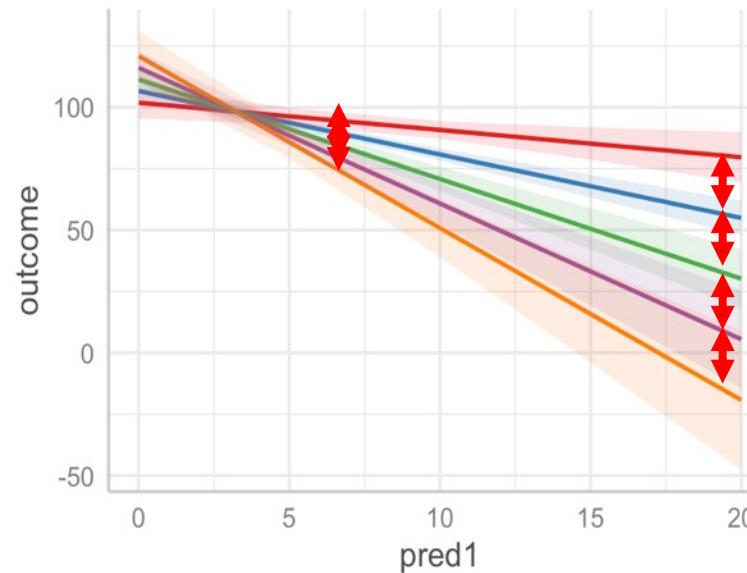


Petal.Width
■ 0.5 □ 1 □ 1.5 □ 2 □ 2.5

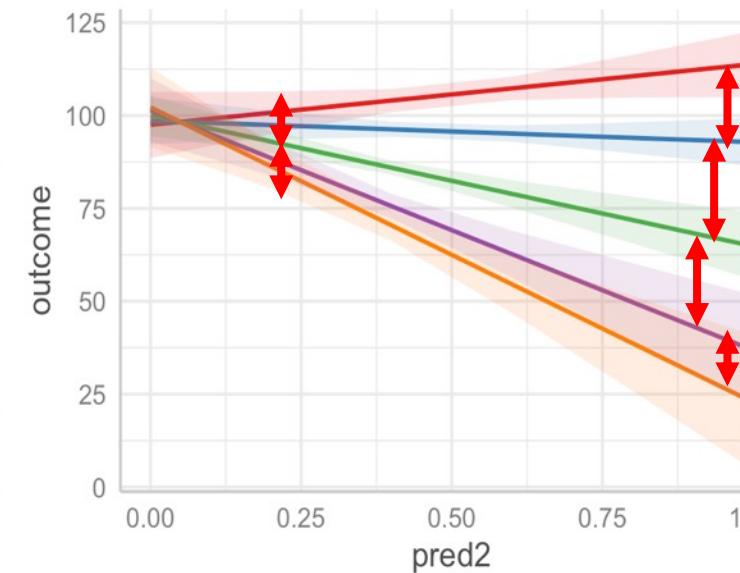


(Intercept)
 Sepal.Width
 Petal.Width
 Sepal.Width:Petal.Width

	Estimate	Pr(> t)
(Intercept)	3.13046	2.1e-07 ***
Sepal.Width	0.49642	0.00418 **
Petal.Width	1.29057	0.00729 **
Sepal.Width:Petal.Width	-0.09946	0.50038



pred2
■ 0.2 □ 0.4 □ 0.6 □ 0.8 □ 1



pred1
■ 1 □ 4 □ 8 □ 12 □ 14

$\text{Sepal.length} \sim \text{Sepal.width} * \text{Petal.width}$

outcome ~ pred1 * pred2

	Estimate	Pr(> t)
(Intercept)	97.1423	< 2e-16 ***
pred1	0.3617	0.5743
pred2	23.7294	0.0155 *
pred1:pred2	-7.3663	9.6e-07 ***

type of interactions

- categorical x categorical



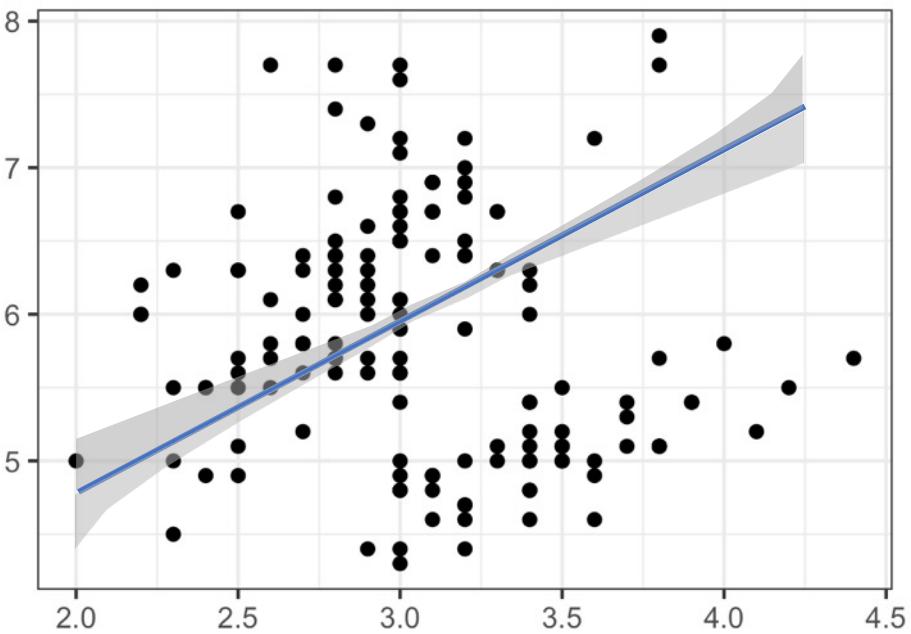
- categorical x continuous



- continuous x continuous

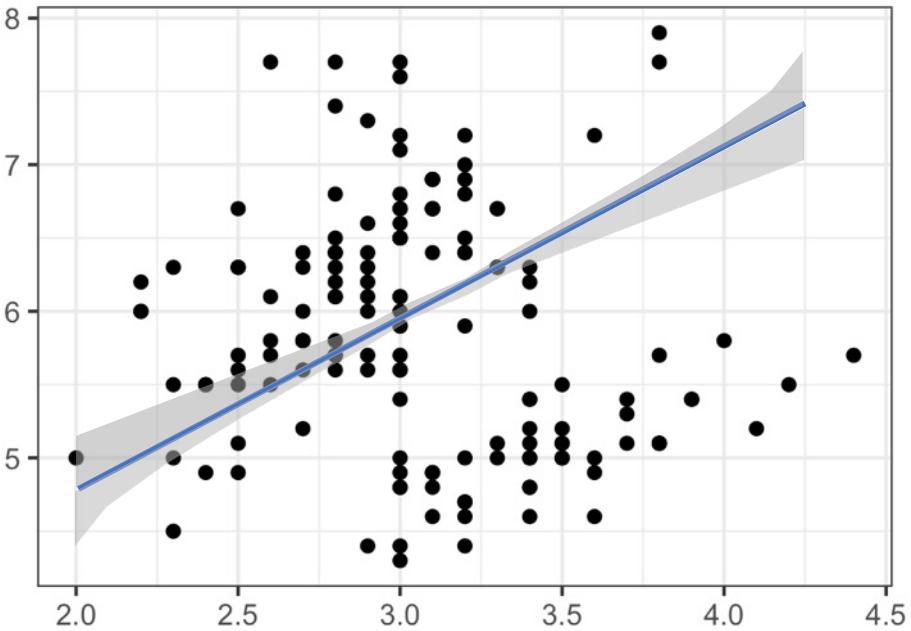


Mixed Model



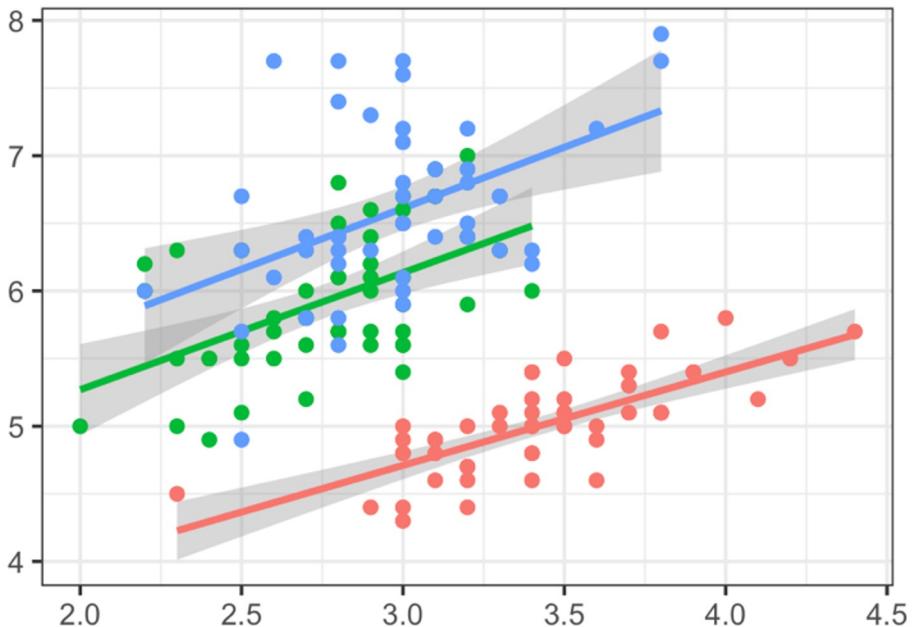
Simple linear regression

$$y \sim \beta_0 + \beta x + \varepsilon$$



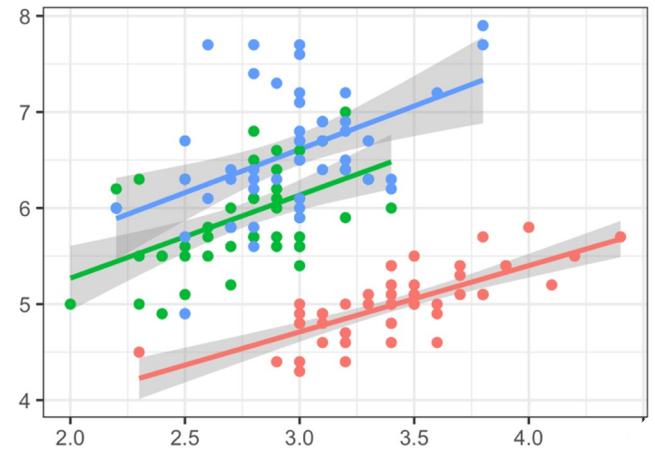
Simple linear regression

$$y \sim \beta_0 + \beta x + \varepsilon$$



Multiple linear regression

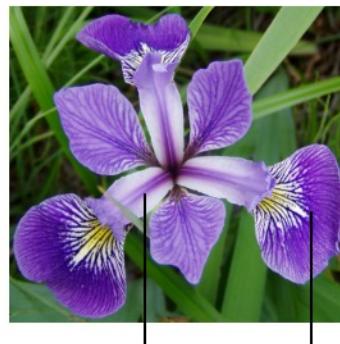
$$y \sim \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_N x_N + \varepsilon$$



iris setosa

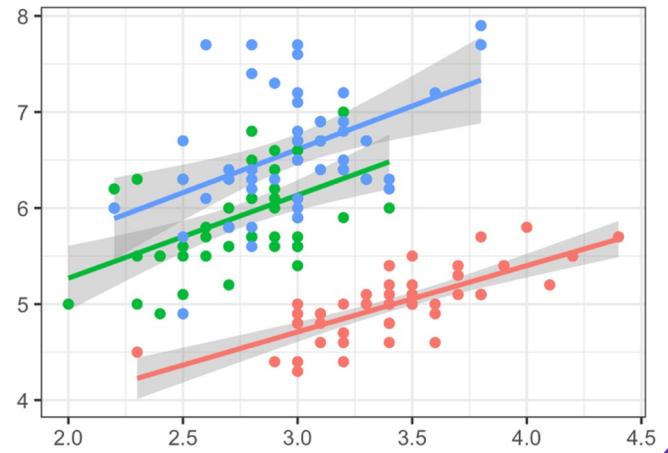


iris versicolor



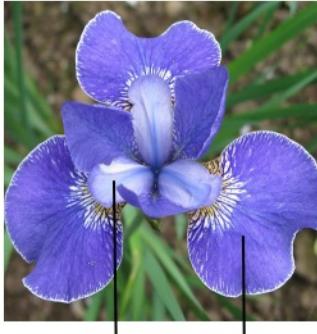
iris virginica



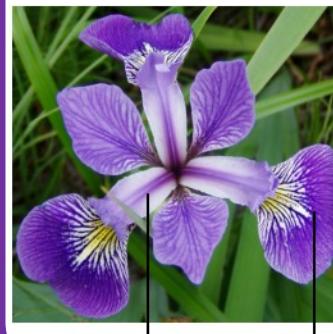


Species

iris setosa

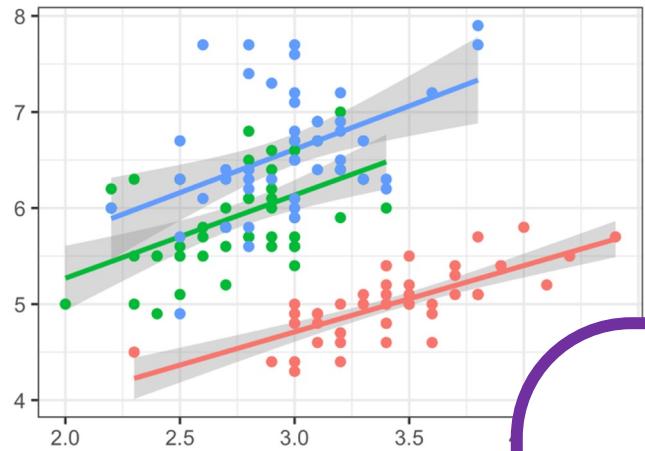


iris versicolor



iris virginica





Genus Iris

Species

iris setosa



iris versicolor



iris virginica





Species as
Fixed Effects



iris setosa



iris versicolor



iris virginica

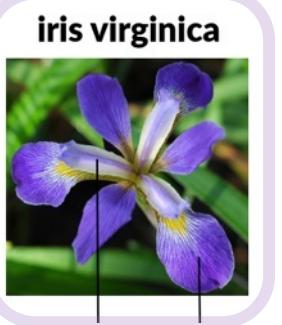
Species as
Fixed Effects



iris setosa



iris versicolor



iris virginica

Species as
Random Effects



iris setosa



iris versicolor



iris virginica

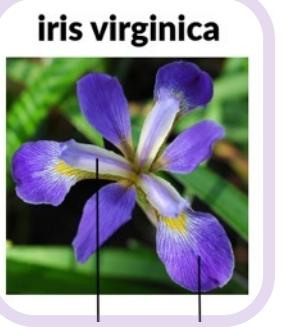
$$y \sim x + \text{Species}$$



iris setosa



iris versicolor



iris virginica

Species as
Random Effects



iris setosa



iris versicolor



iris virginica

$y \sim x + \text{Species}$



iris setosa



iris versicolor



iris virginica

$y \sim x + (1 \mid \text{Species})$

Sepal.Length ~ Petal.Length + (1 | Species)

Scaled residuals:

Min	1Q	Median	3Q	Max
-2.23334	-0.67332	-0.01684	0.67680	3.04429

Random effects:

Groups	Name	Variance	Std.Dev.
Species	(Intercept)	1.1617	1.0778
	Residual	0.1143	0.3381

Number of obs: 150, groups: Species, 3

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	2.50446	0.66743	2.45496	3.752	0.0463 *
Petal.Length	0.88847	0.06379	144.56089	13.927	<2e-16 ***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Sepal.Length ~ Petal.Length + (1 | Species)

Scaled residuals:

Min	1Q	Median	3Q	Max
-2.23334	-0.67332	-0.01684	0.67680	3.044

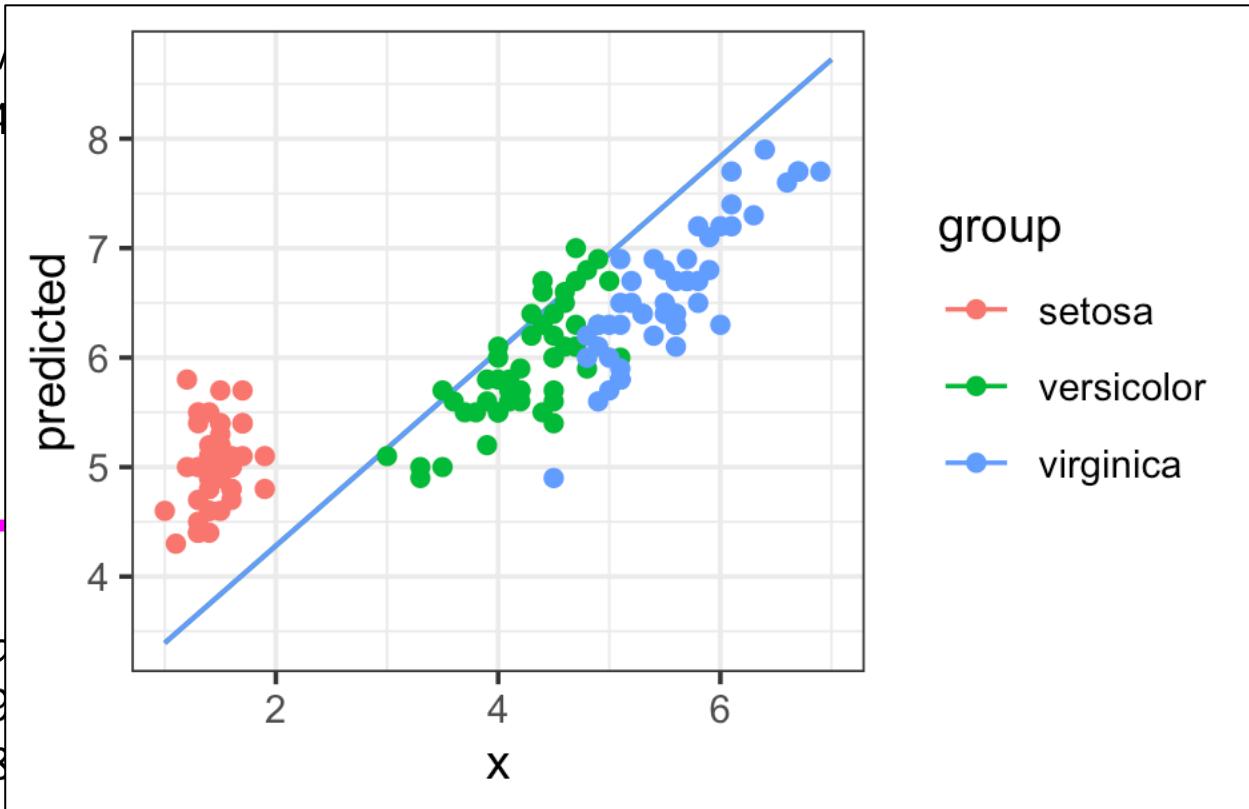
Random effects:

Groups	Name	Variance	Std.Dev.
Species	(Intercept)	1.1617	1.0778
Residual		0.1143	0.3381

Number of obs: 150, groups: Species, 3

Fixed effects:

	Estimate	Std. Error	df
(Intercept)	2.50446	0.66743	2.4549
Petal.Length	0.88847	0.06379	144.5608



Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Sepal.Length ~ Petal.Length + (1 | Species)

Scaled residuals:

Min	1Q	Median	3Q	Max
-2.23334	-0.67332	-0.01684	0.67680	3.04429

Random effects:

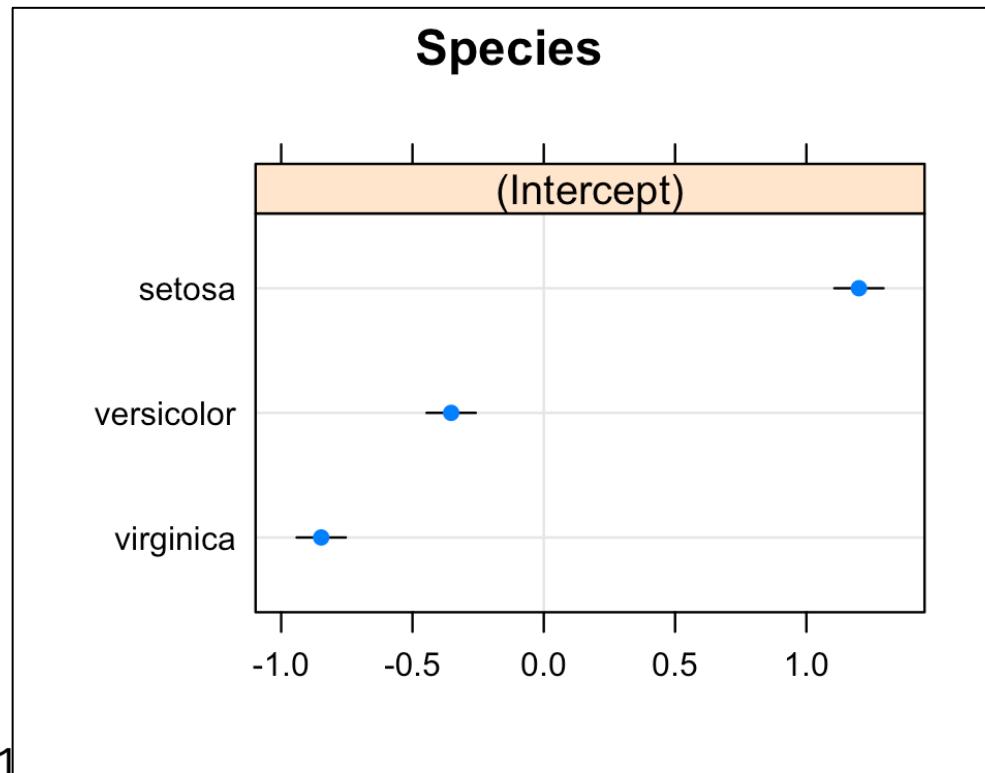
Groups	Name	Variance	Std.Dev.
Species	(Intercept)	1.1617	1.0778
	Residual	0.1143	0.3381

Number of obs: 150, groups: Species, 3

Fixed effects:

	Estimate	Std. Error	df	t
(Intercept)	2.50446	0.66743	2.45496	
Petal.Length	0.88847	0.06379	144.56089	1

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1



Sepal.Length ~ Petal.Length + (1 | Species)

Scaled residuals:

Min	1Q	Median	3Q	Max
-2.23334	-0.67332	-0.01684	0.67680	3.04429

Random effects:

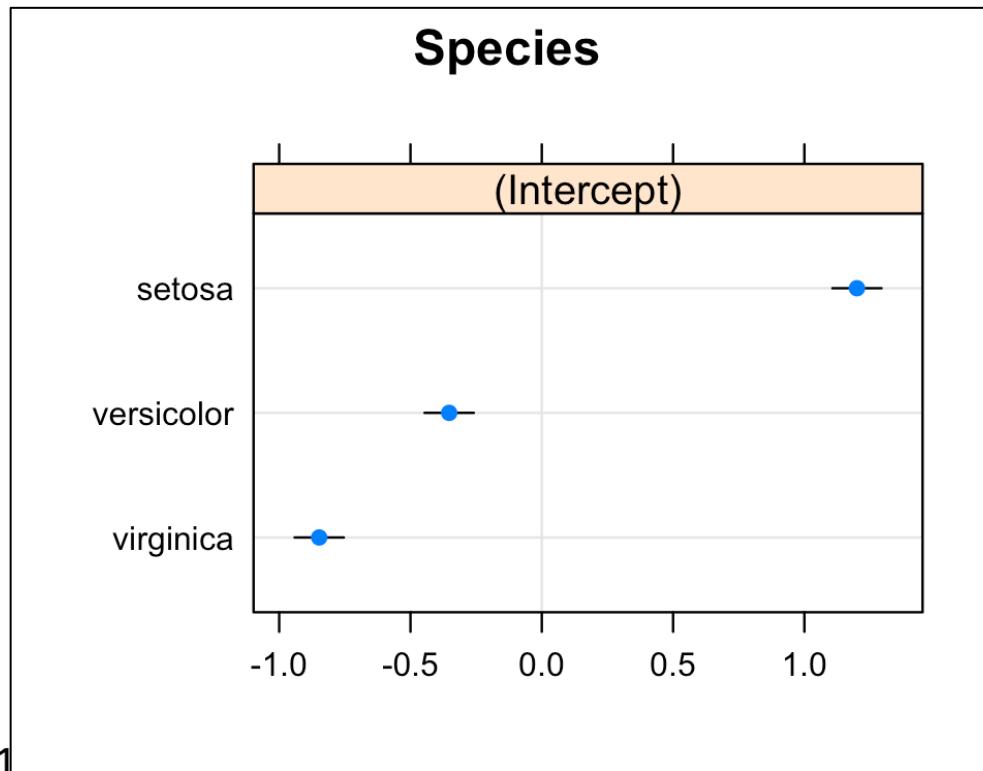
Groups	Name	Variance	Std.Dev.
Species	(Intercept)	1.1617	1.0778
	Residual	0.1143	0.3381

Number of obs: 150, groups: Species, 3

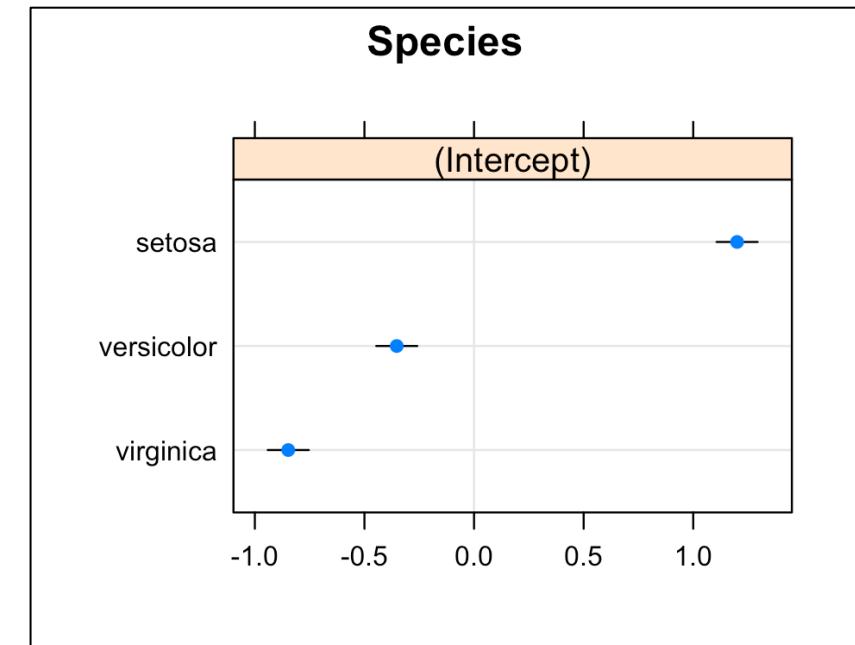
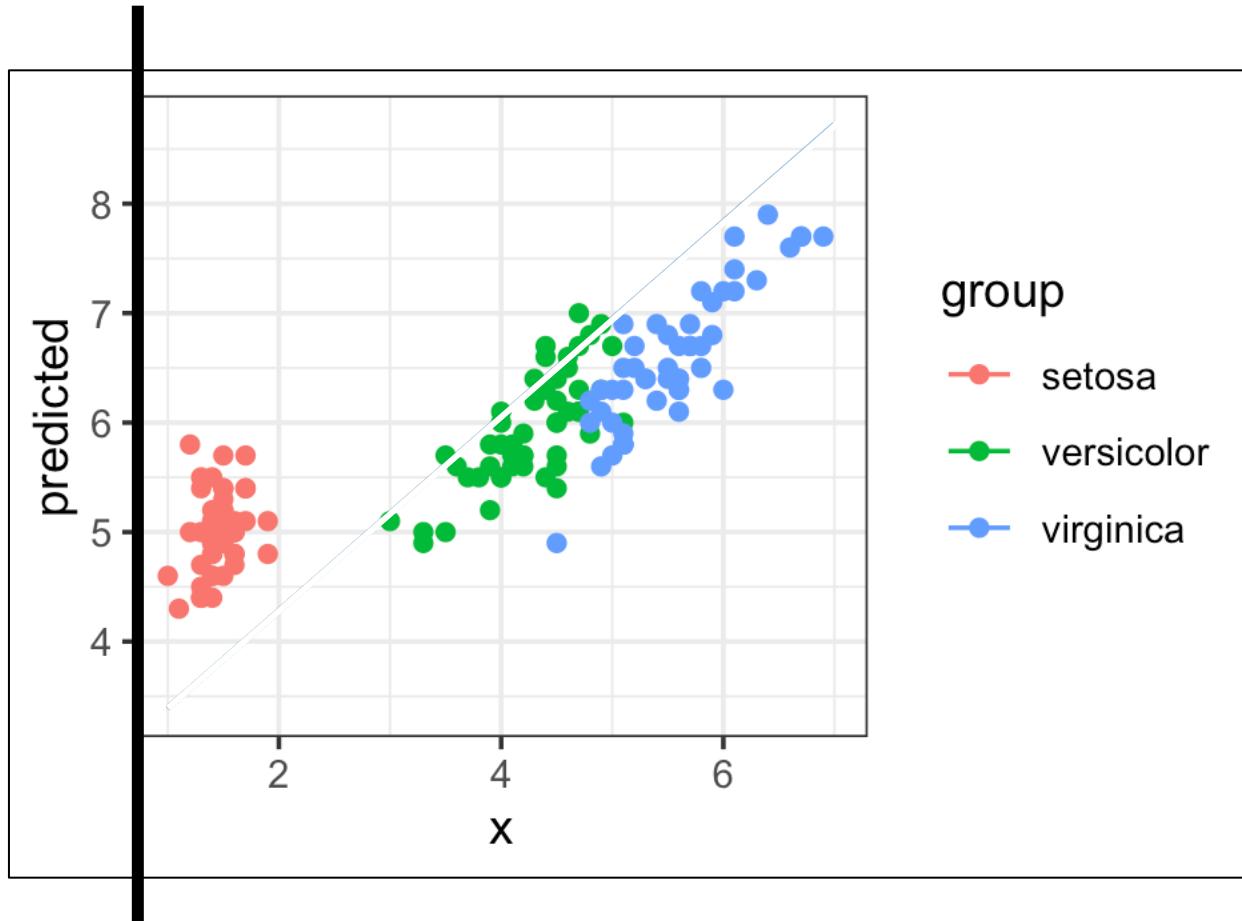
Fixed effects:

	Estimate	Std. Error	df	t
(Intercept)	2.50446	0.66743	2.45496	
Petal.Length	0.88847	0.06379	144.56089	1

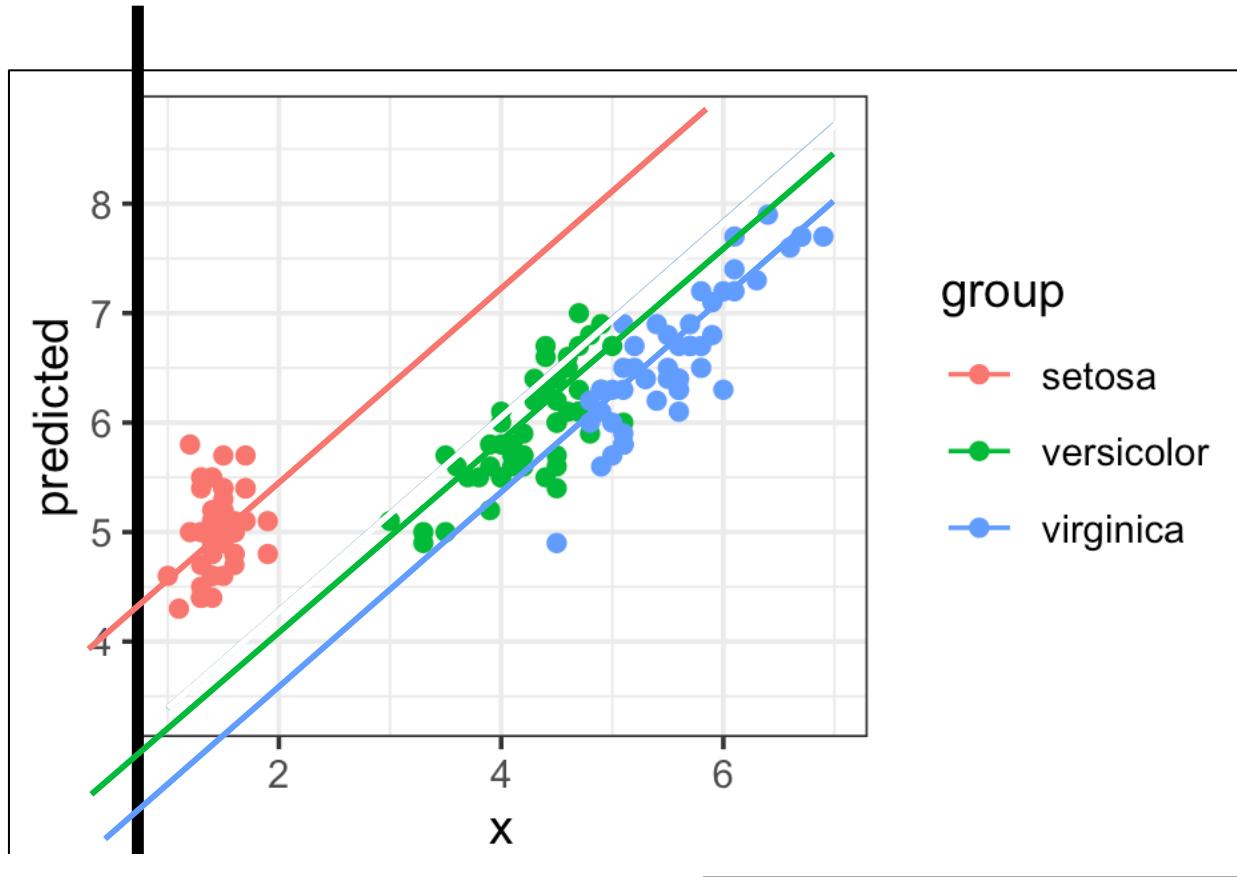
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1



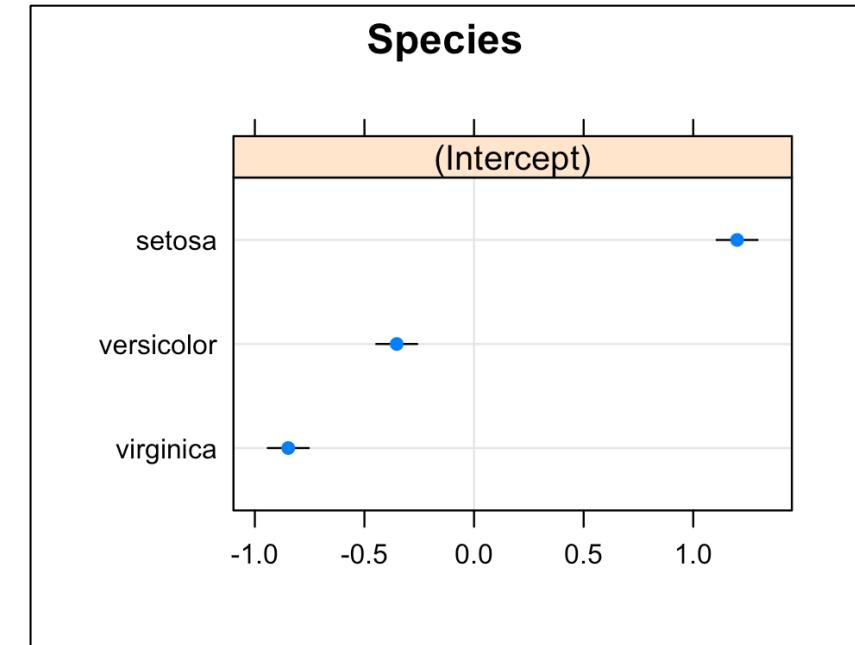
$\text{Sepal.Length} \sim \text{Petal.Length} + (1 \mid \text{Species})$



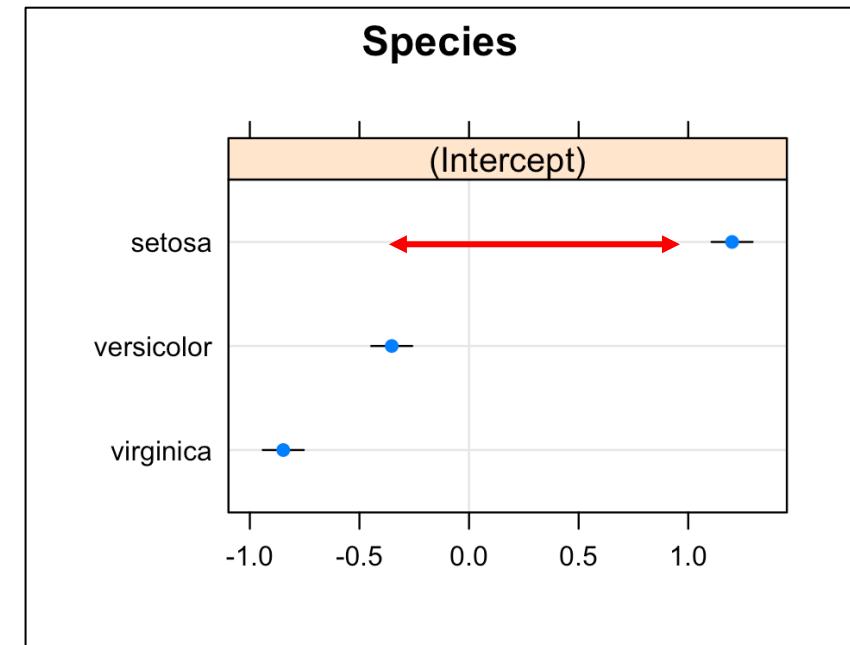
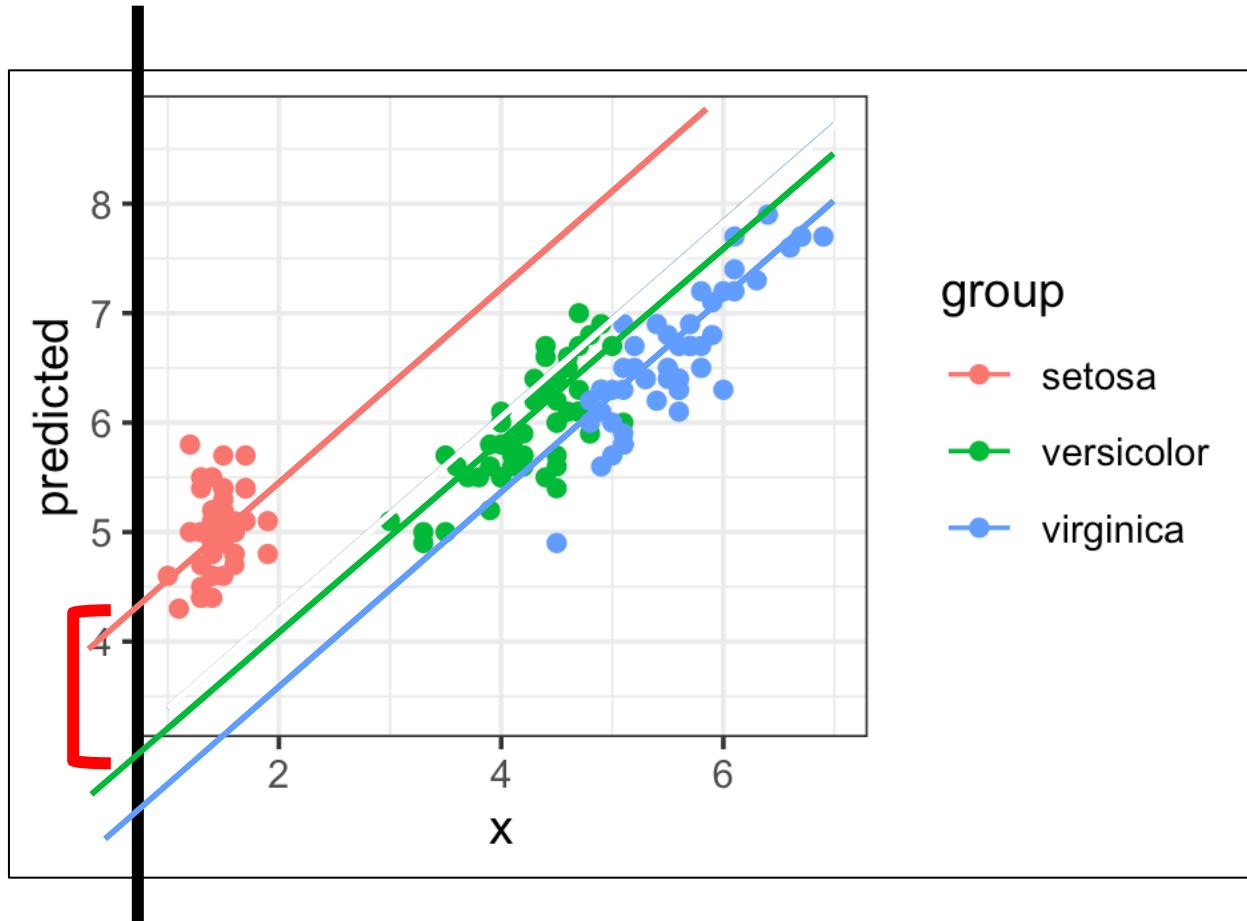
$\text{Sepal.Length} \sim \text{Petal.Length} + (1 | \text{Species})$



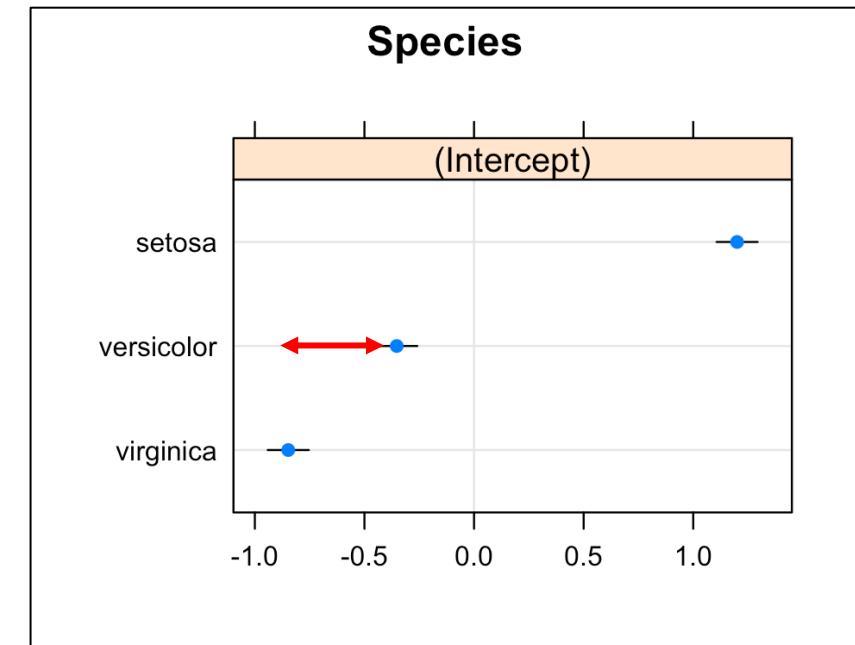
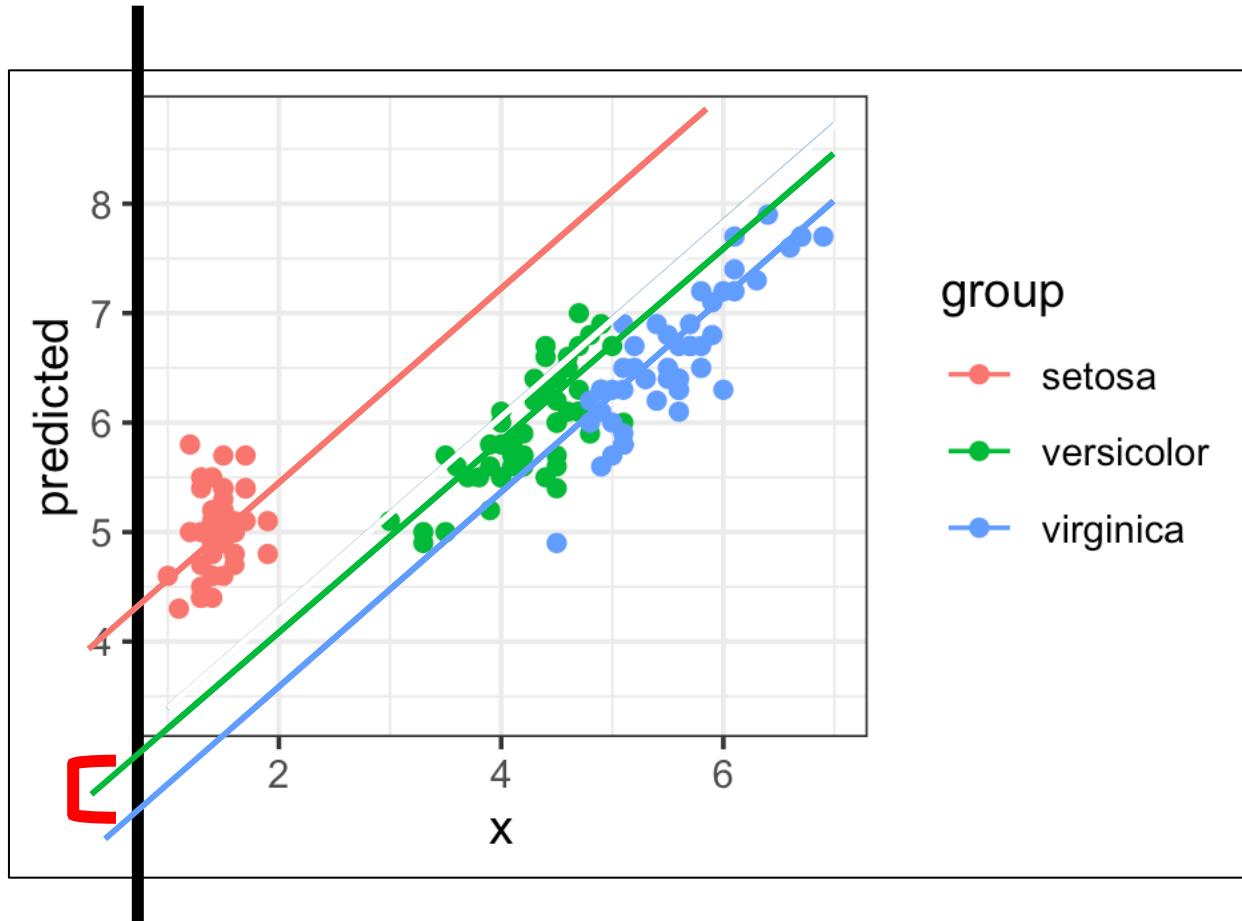
Random Intercepts



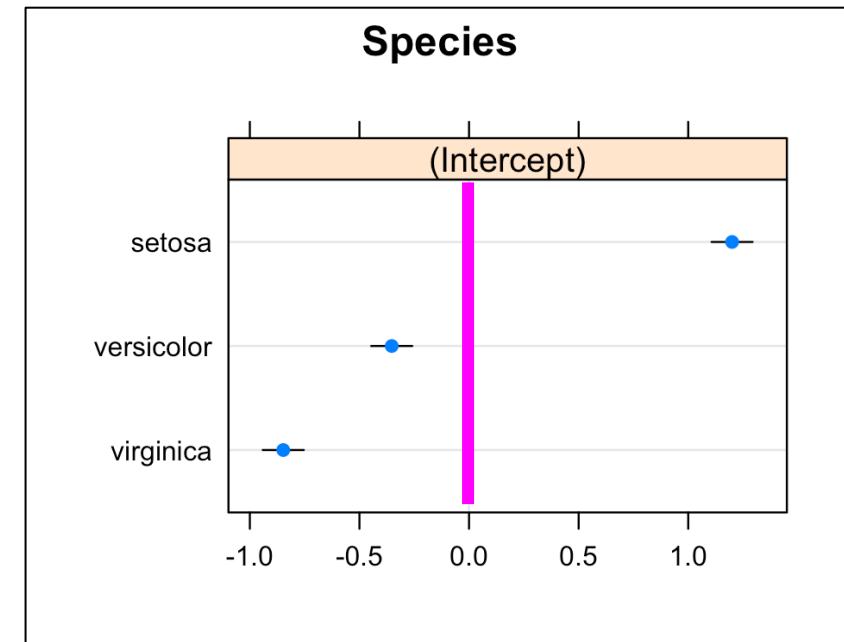
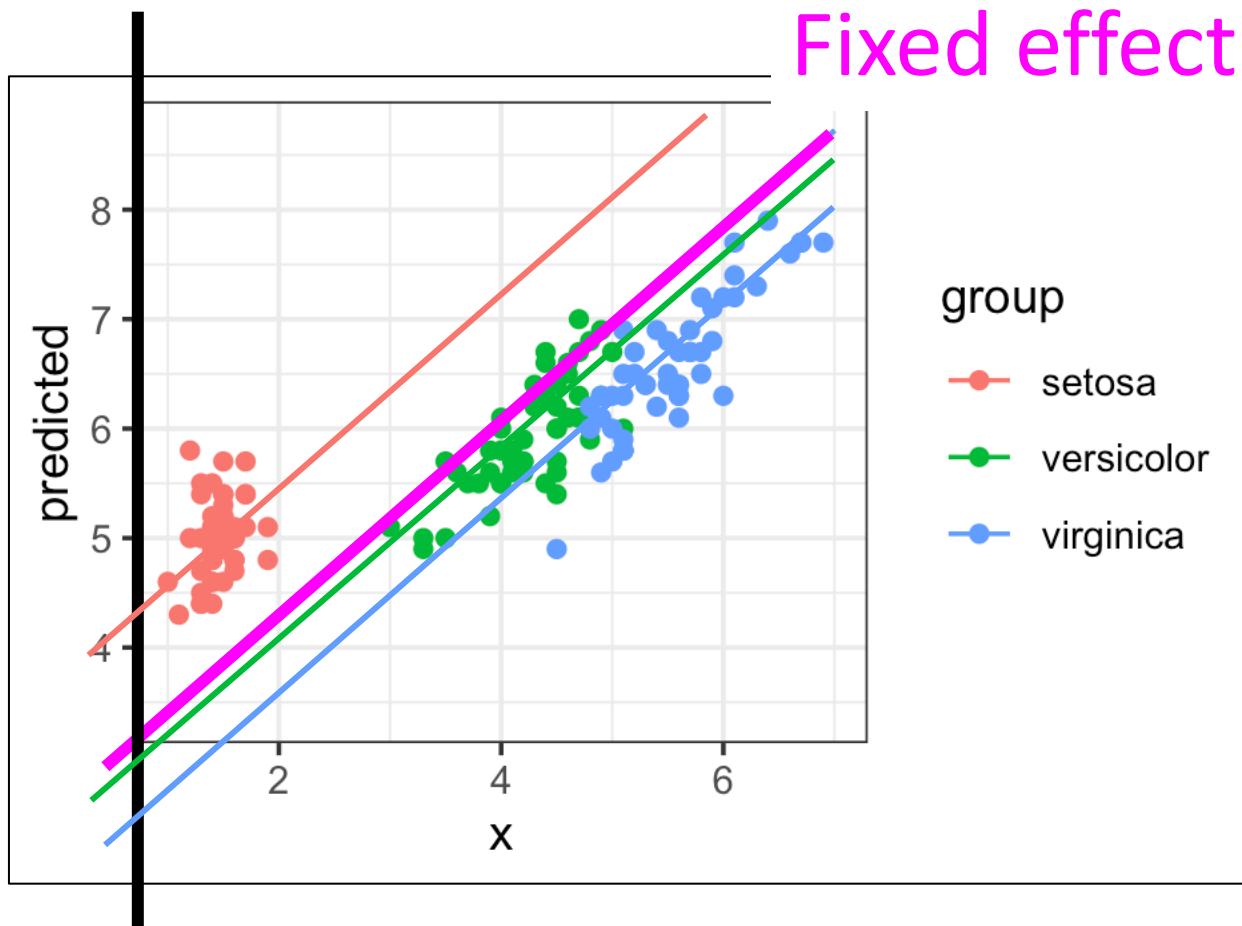
$\text{Sepal.Length} \sim \text{Petal.Length} + (1 | \text{Species})$



$\text{Sepal.Length} \sim \text{Petal.Length} + (1 \mid \text{Species})$



$\text{Sepal.Length} \sim \text{Petal.Length} + (1 | \text{Species})$



Random effects are variables based on **grouping definition**:

Random effects are variables based on grouping definition:

- Plant and plant fertilizer across areas
- Exam scores and SES across schools
- RT and condition across participants

Random effects are variables based on grouping definition:

- Plant and plant fertilizer across areas
- Exam scores and SES across schools
- RT and condition across participants

They are mostly for repeated measures:

- Repeatedly measure plant growth within each area
- Repeatedly measure exam scores within each school
- Repeatedly measure RT within each participant

Summary

- Linear regression with categorical variable
- Multiple linear regression with categorical variable
- Linear regression with interactions
- emmeans
- ggeffect
- Linear mixed model

Thank you!

junho.chai@chosun.ac.kr