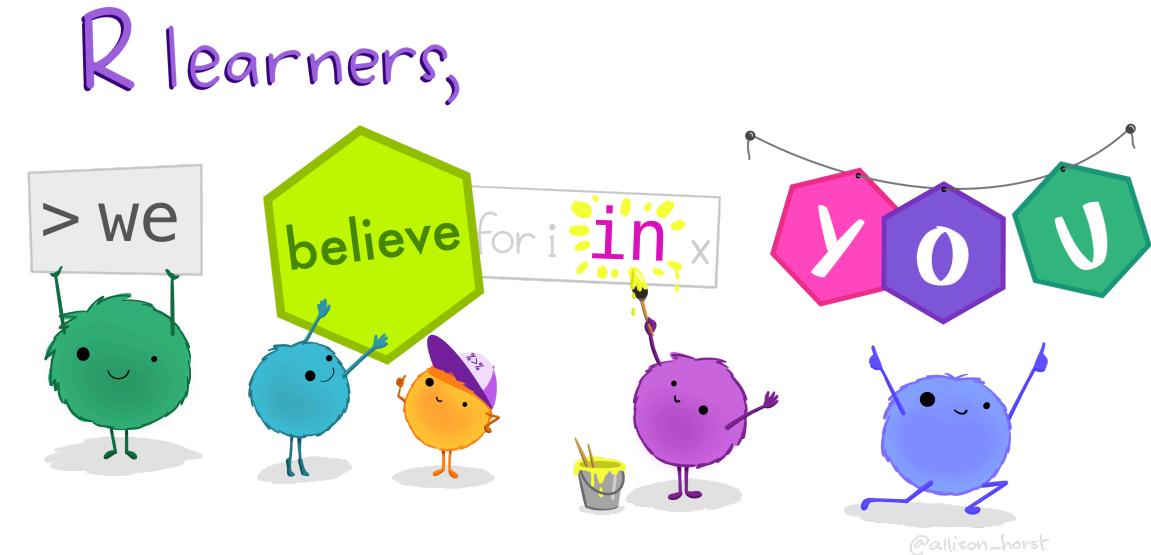


# Intro to Stats in R

## Linear Regression



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# You are not alone!



Alison Horst

# Getting started

1. Create and name a new folder
2. Open RStudio
3. Create R project
  - File -> New project -> Existing Directory
  - Browse to your folder
  - Select Create Project
4. Create new R script
  - File -> New File -> R Script

# Getting started

Make sure to load packages at the top:

```
1 library(tidyverse)
2 library(palmerpenguins)
```

# Getting started

We need one additional package:

`ggfortify` provides plotting tools for commonly used statistics

```
1 install.packages("ggfortify")
```

Add it to the top with the others

```
1 library(tidyverse)
2 library(palmerpenguins)
3 library(ggfortify)
```

# Getting started with stats in R

## 1. Always start with a picture!

- Stats should support your figures
- Do you see the expected pattern?

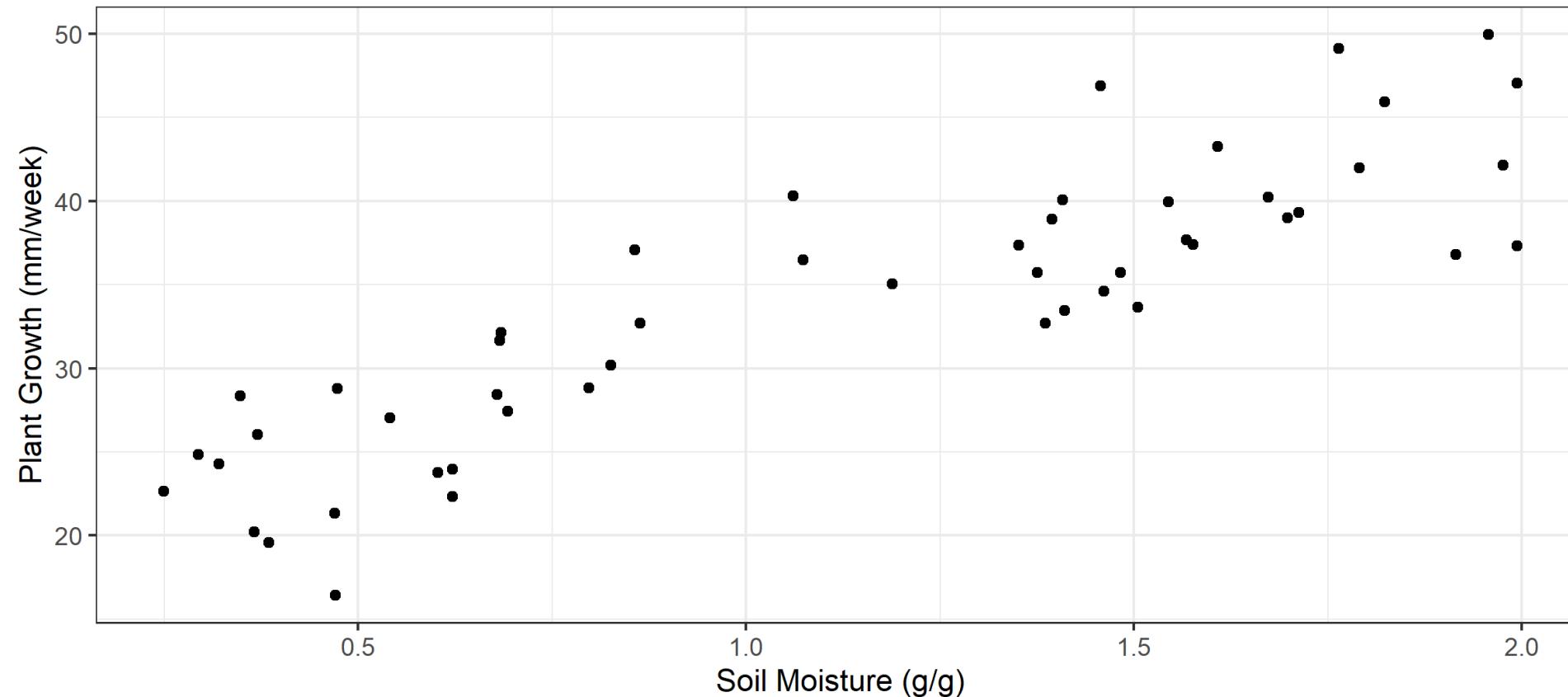
## 2. Translate your hypothesis into a statistical model

- Becomes easier with experience

## 3. Translate your statistical model in R language

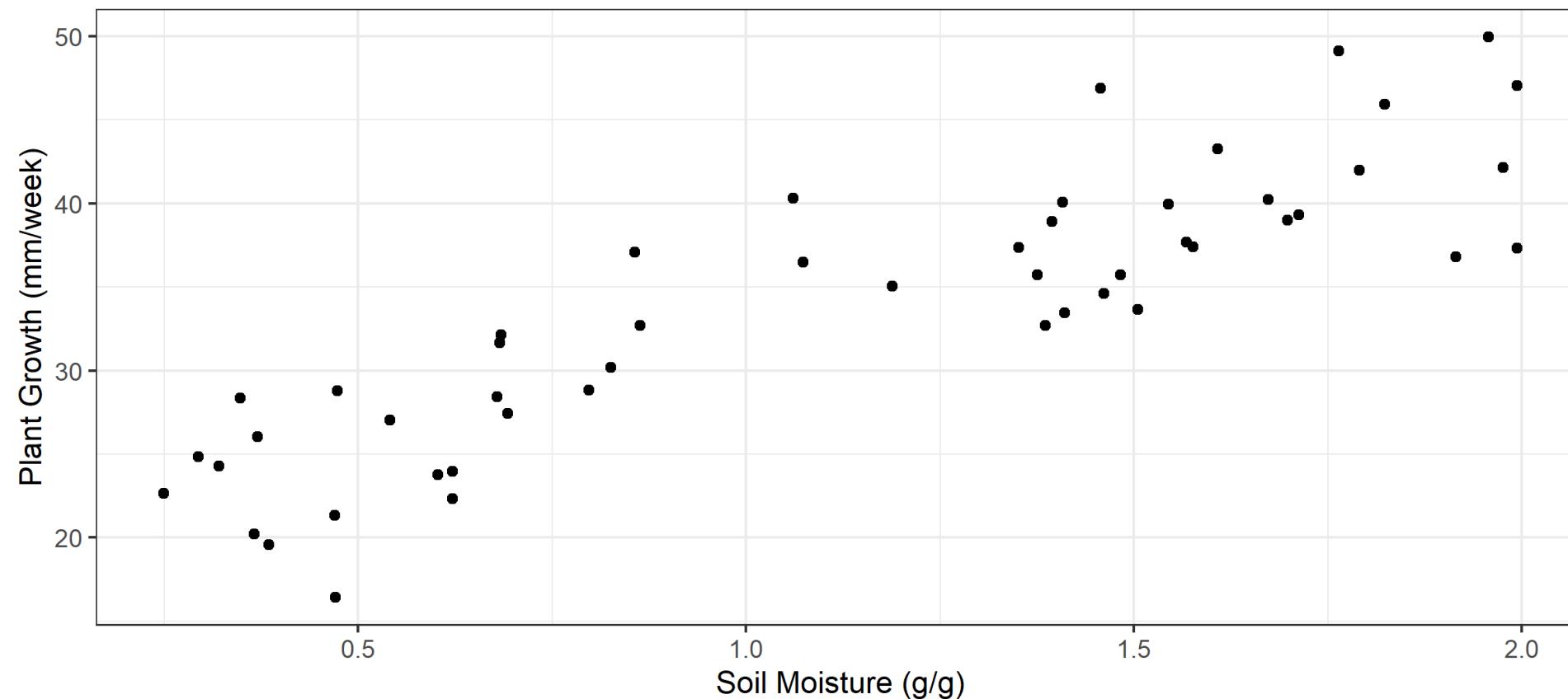
# Picture

- You are all familiar with how to use `ggplot2` to create a figure
  - Go back to your previous scripts and notes



# Picture

- We see a positive relationship (slope)
  - More soil moisture results in higher plant growth (as expected)



# Hypothesis into a statistical model

Hypothesis is that more moisture allows for higher growth rates

- Need to identify
  - Response (dependent, y) variable
  - Explanatory (independent, x) variable
  - Continuous or discrete/categorical



Allison Horst

# Hypothesis into a statistical model

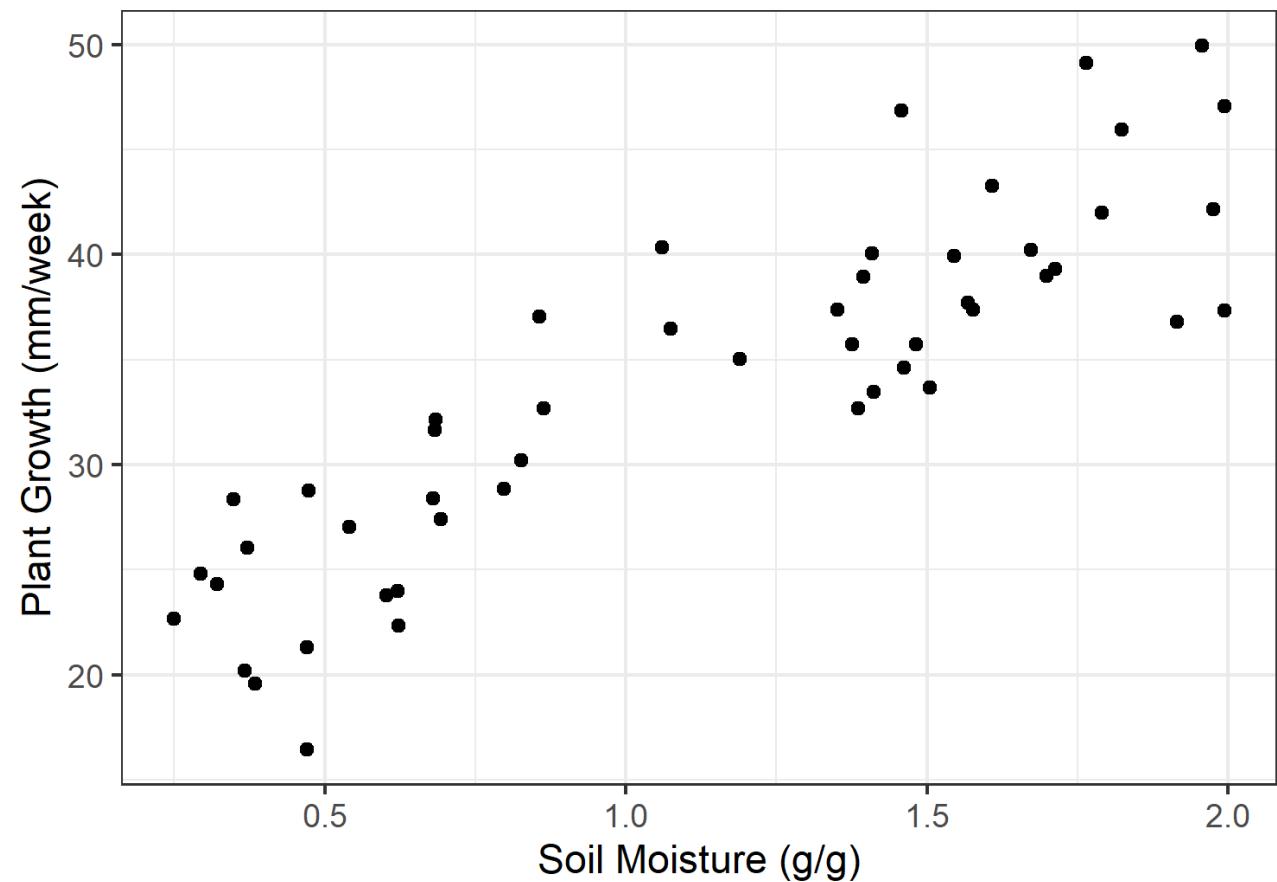
When both  $x$  and  $y$  are continuous we have a simple linear regression

Response variable ( $y$ )

- Plant growth
- Continuous

Explanatory variable ( $x$ )

- Soil Moisture
- Continuous



# Linear regression

## Running model in R

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

- **y** is the **response** variable (**dependent**)
- **x** is the **explanatory** variable (**independent, predictor**)

# Linear regression

## Running models in R

```
1 lm(y ~ x1 + x2 + ..., data = data)
```

- You can have multiple explanatory variables
- Can be all continuous, all discrete, or a mix
  - But these are often called: ANOVA, ANCOVA, Multiple regression, etc.

# Linear regression

## Running models in R

```
1 lm(plant.growth.rate ~ soil.moisture.content, data = plant_gr)
```

- This reads as: Fit a linear model, where we hypothesize that plant growth rate is a function of soil moisture content, using data from the `plant_gr` data frame.

# Assumptions first!

1. Assumption of equal variance
2. Assumption of normality of residuals
3. Evaluate leverage (influential data points) - technically not an assumption

# What are residuals?

- Residuals are difference between the observed value of the dependent variable ( $y$ ) and the value predicted by the model ( $\hat{y}$ )
  - A measure of how well the model fits the data

# Assumptions first!

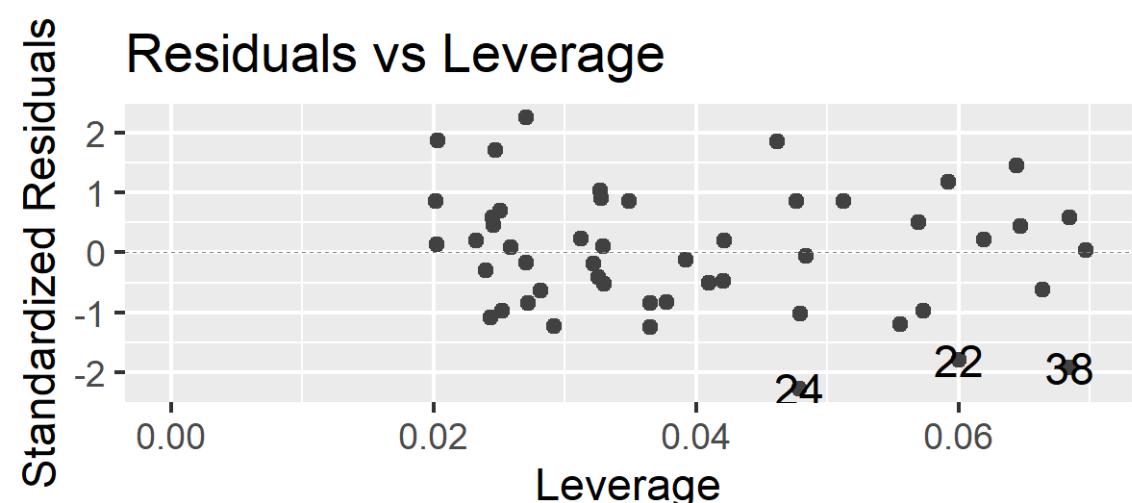
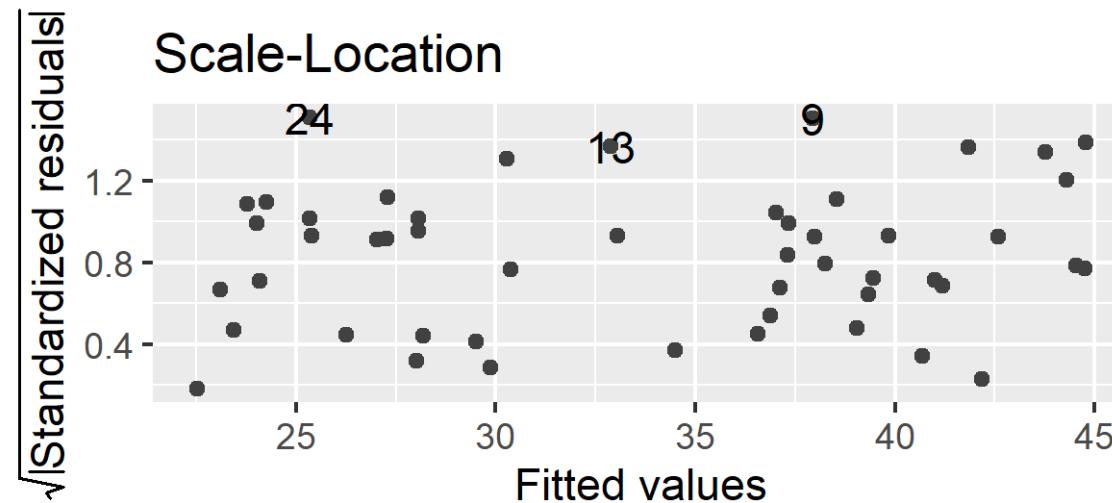
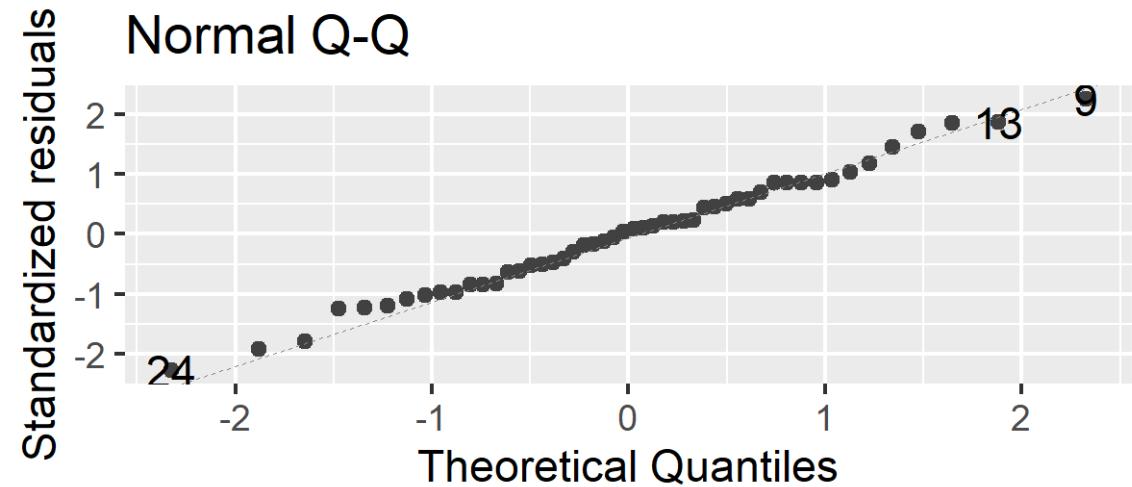
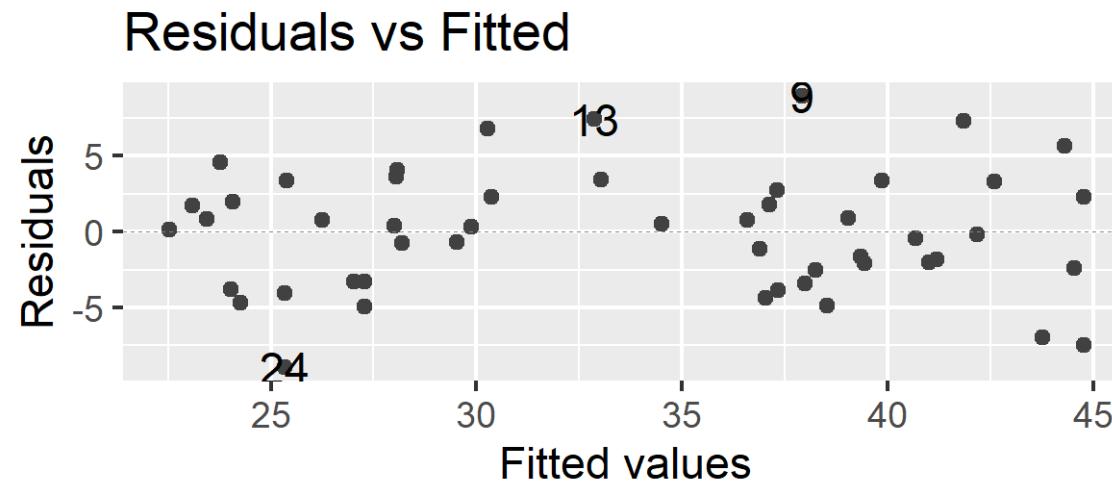
```
1 model_pgr <- lm(plant.growth.rate ~ soil.moisture.content,  
2                   data = plant_gr)
```

```
1 autoplot(model_pgr, smooth.colour = NA)
```

- The `autoplot()` function is part of the `ggfortify` package
- The `smooth.colour = NA` argument suppresses the “wiggly” line that is a locally weighted regression line.
  - Some argue the line can be unhelpful as one tends to look at the line and not the data

# Assumptions first!

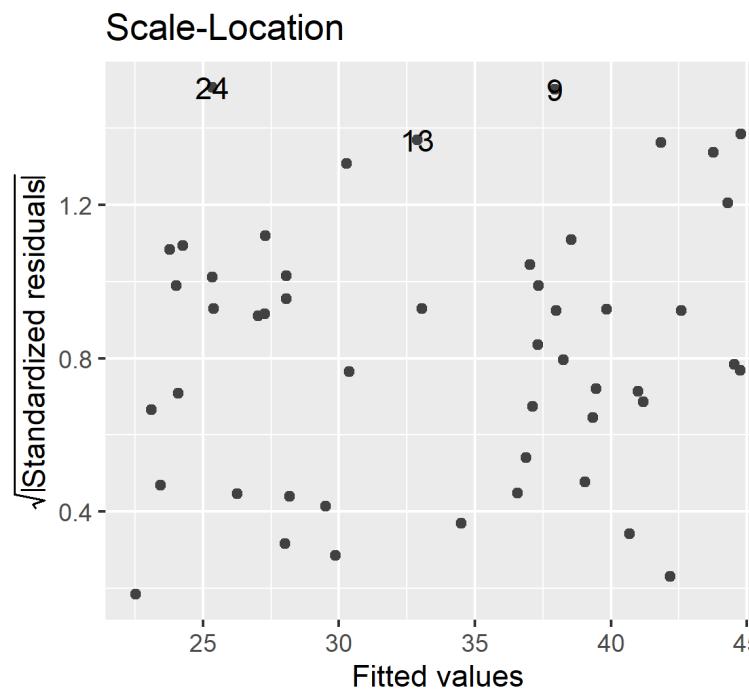
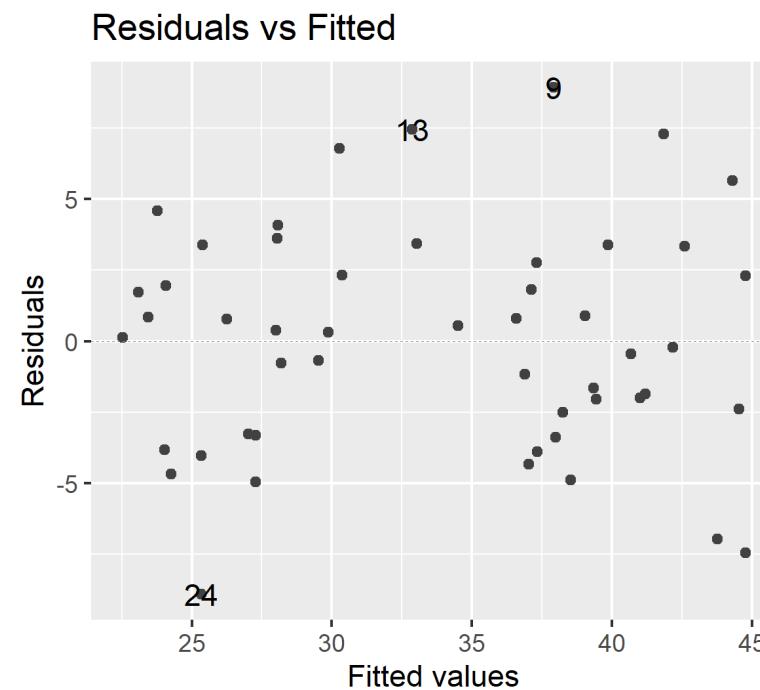
```
1 autoplot(model_pgr, smooth.colour = NA)
```



# Equal variance

## Homoscedasticity

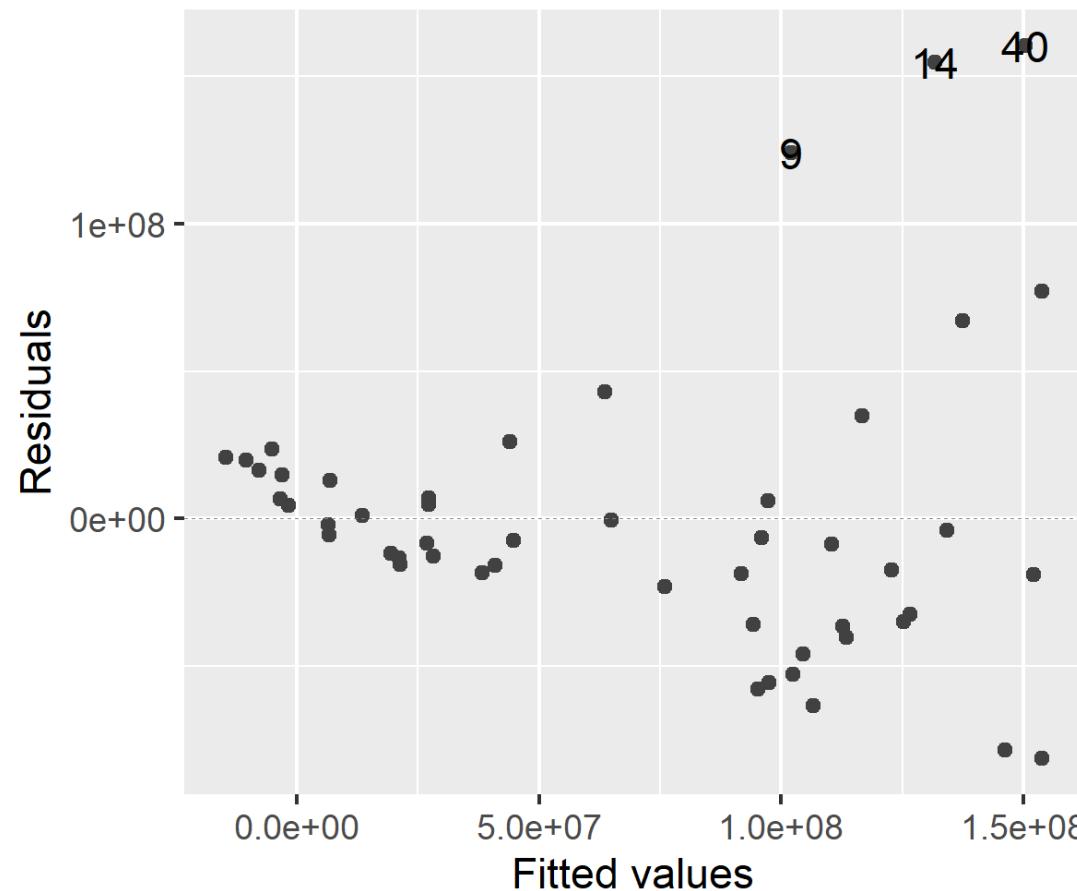
- The spread of residuals does not systematically increase or decrease as the predictor values change



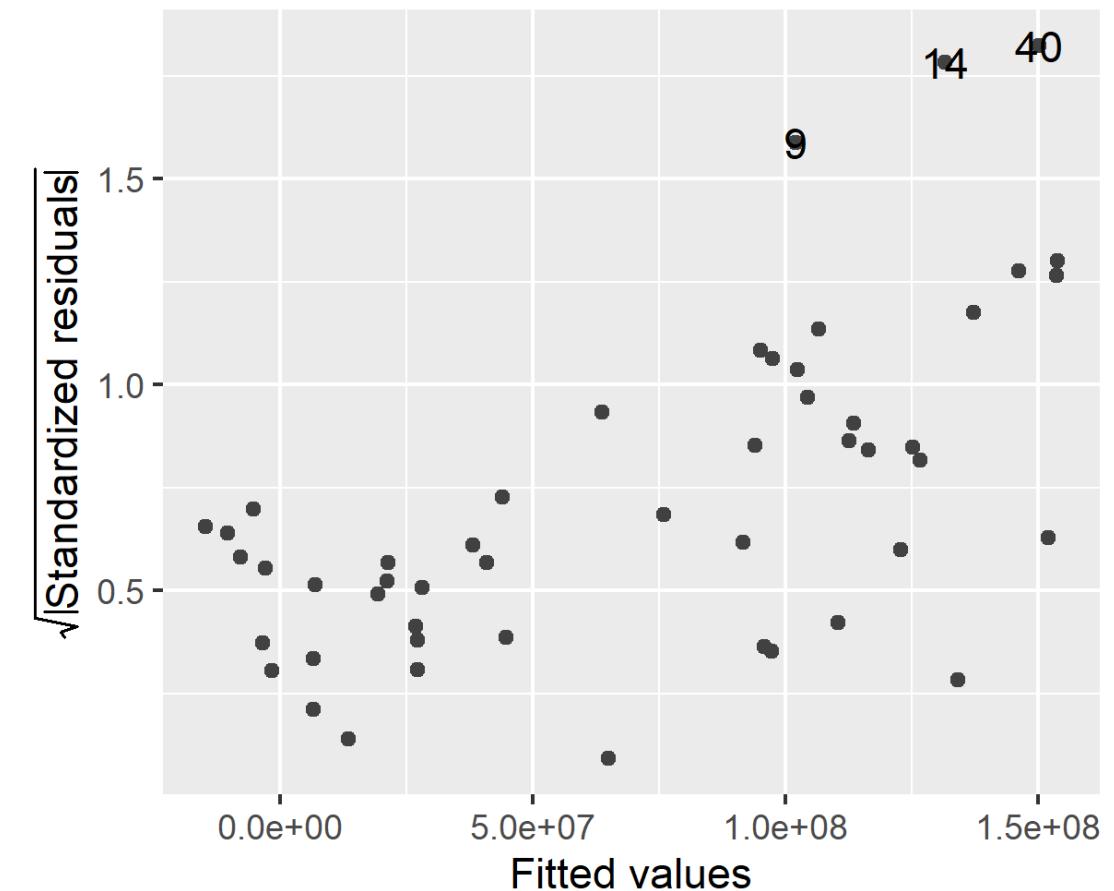
# Unequal variance

## Heteroscedasticity

Residuals vs Fitted

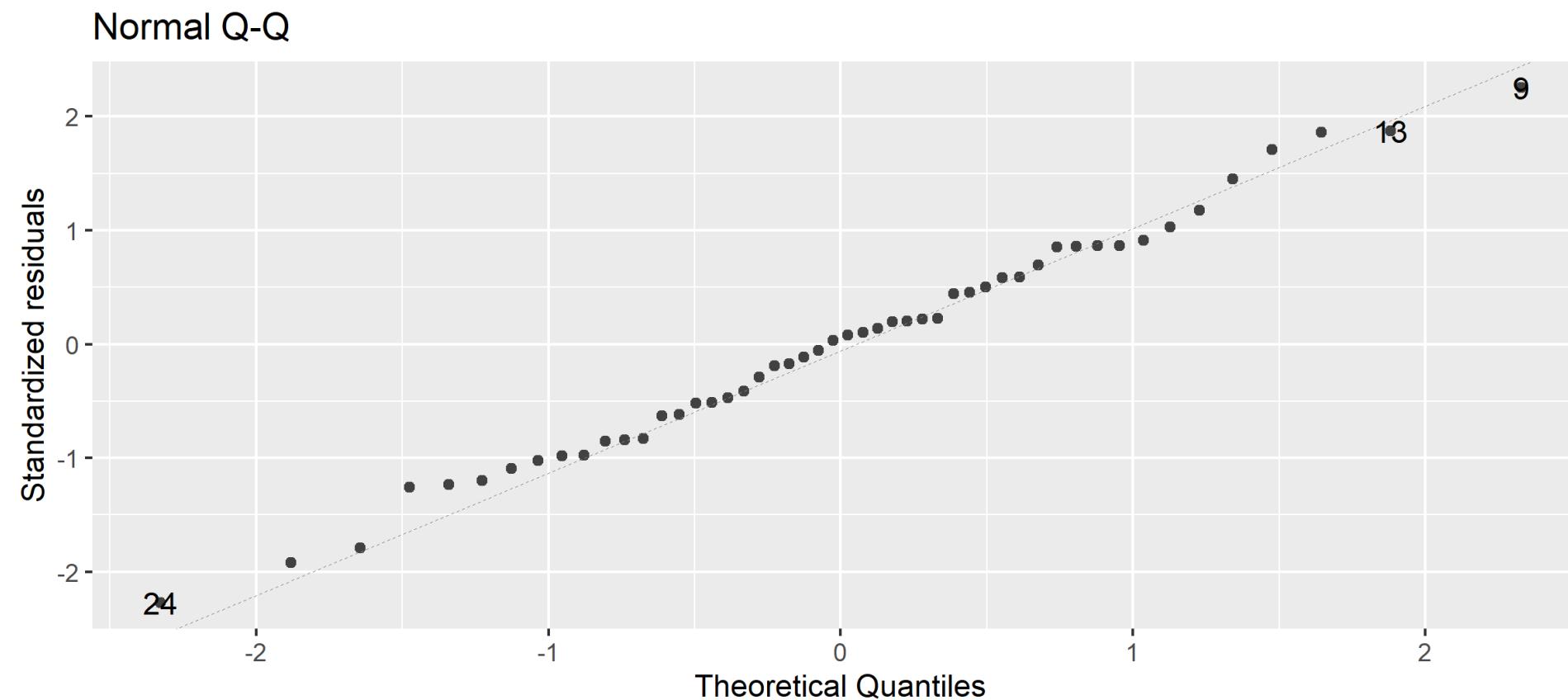


Scale-Location



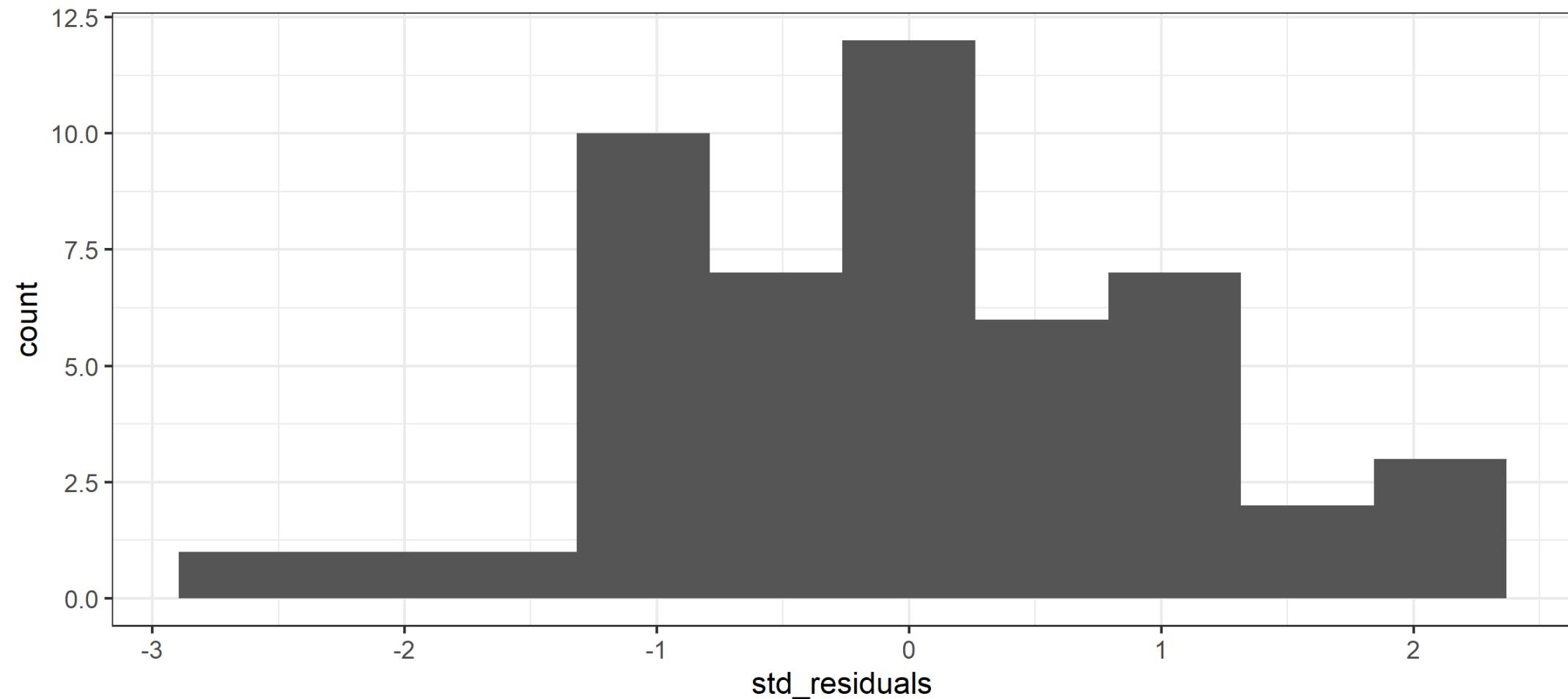
# Normal distribution of residuals

- Assess the distribution of residuals - looking for a normal distribution
  - Ensures the validity of conclusions made



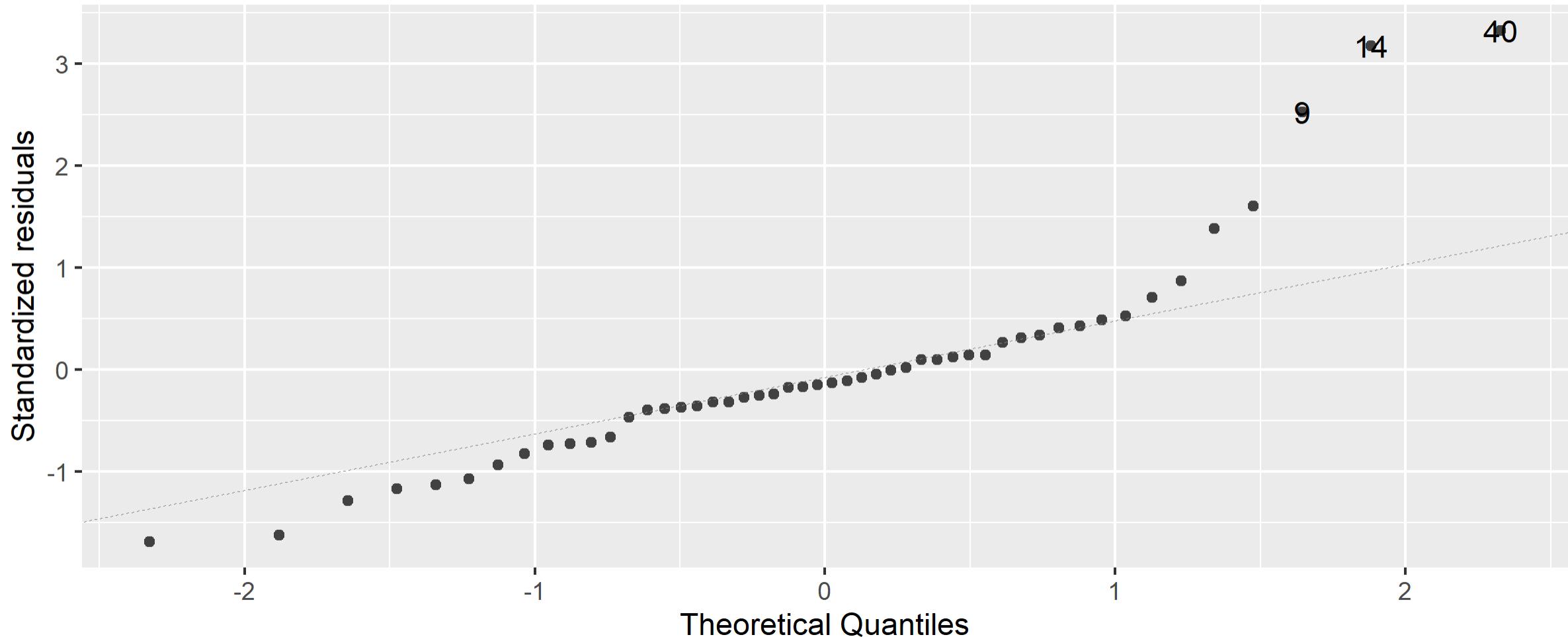
# Normal distribution of residuals

- Q-Q plots are a better tool when you have a sample size < 100



# Non-normal distribution

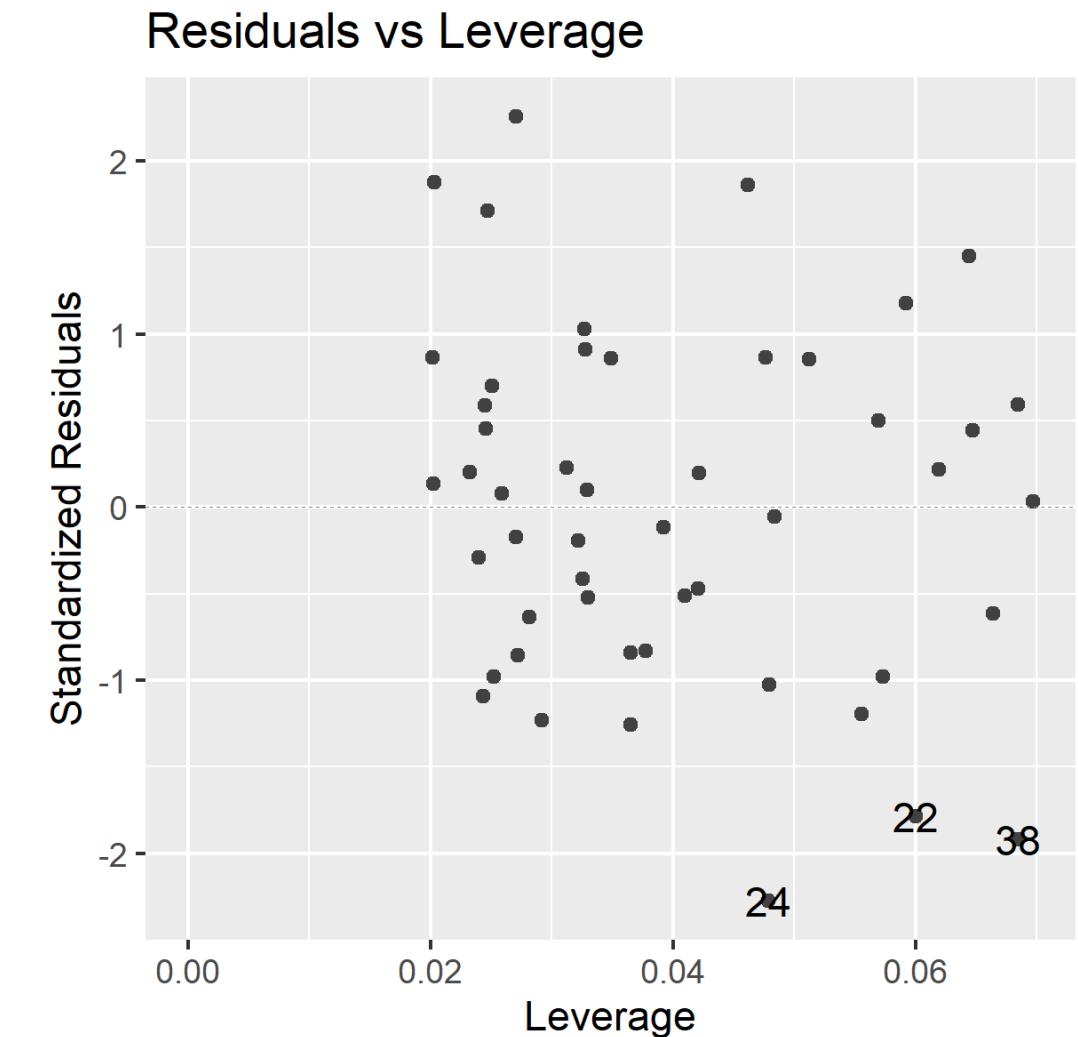
Normal Q-Q



# Leverage

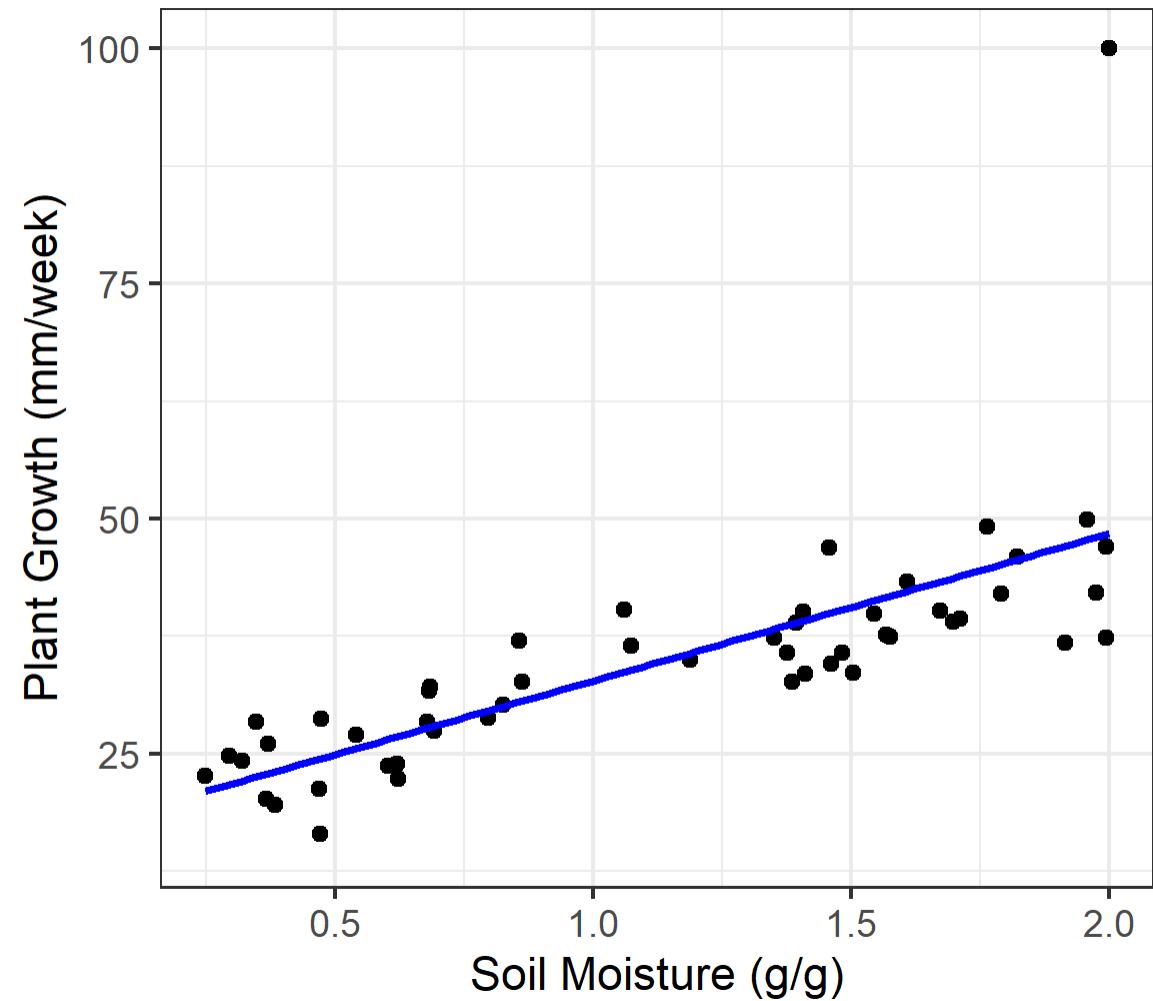
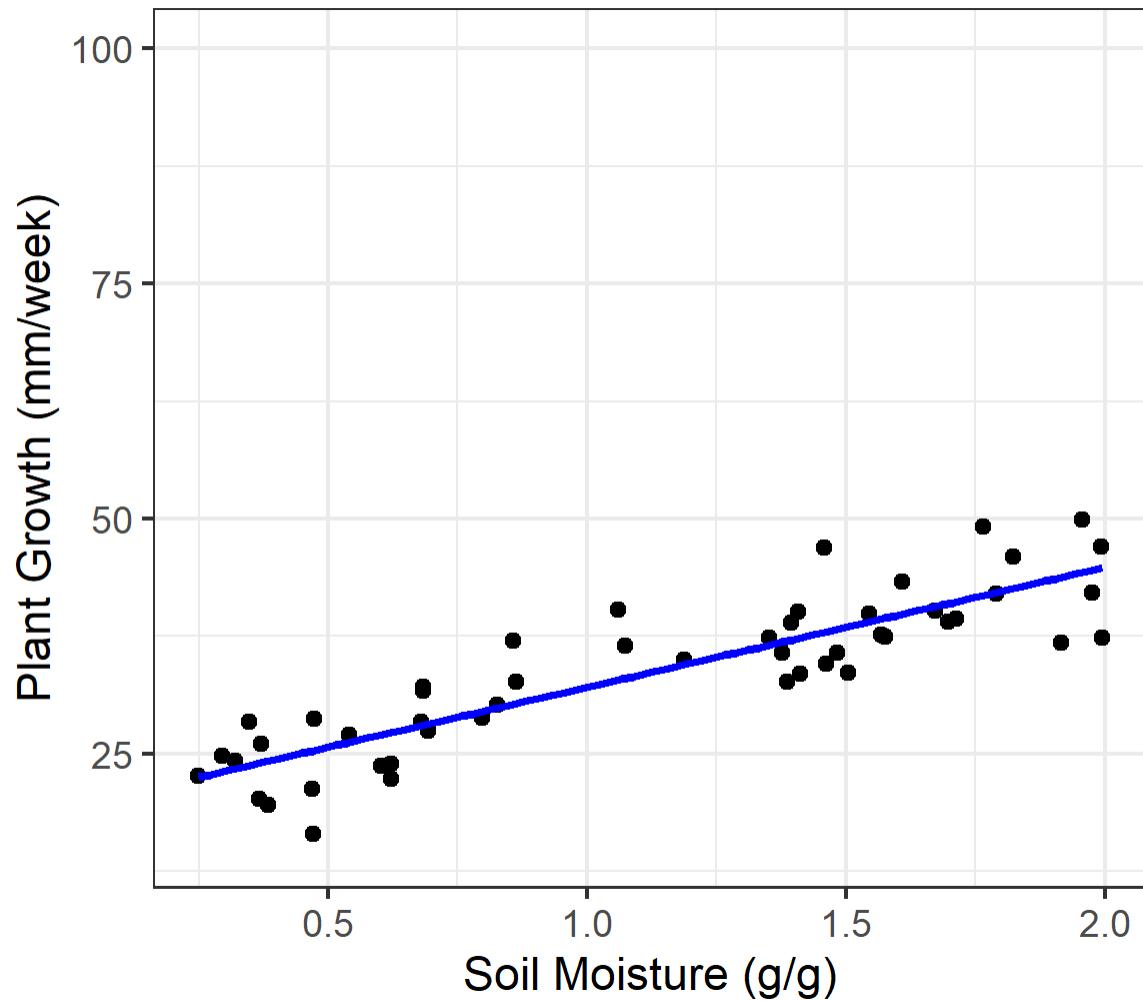
**Be very careful here!**

- Data points whose response variable (y) does not follow the general trend
  - Can skew results
- Do not throw out data because you don't like it!
- Outlier, or meaningful aspect of your data?





# Leverage



# Model assumptions

You can use formal tests for assumptions

(e.g., Bartlett, Levene, Shapiro-Wilk, Kolmogorov-Smirnov, Anderson-Darling...)

I generally recommend NOT doing this

- Small meaningless differences may lead to rejection
- Just look at your data!

# Model interpretation

**Everything is looking good!**

- Lets see if we can reject the null hypothesis
  - Soil moisture has no effect on plant growth rate
- We are going to use the `summary()` function to help us out

# Model interpretation

```
1 model_pgr <- lm(plant.growth.rate ~ soil.moisture.content, data = plant_gr)
```

```
1 summary(model_pgr)
```

Call:

```
lm(formula = plant.growth.rate ~ soil.moisture.content, data =  
plant_gr)
```

Residuals:

Min	1Q	Median	3Q	Max
-8.9089	-3.0747	0.2261	2.6567	8.9406

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	19.348	1.283	15.08	<2e-16 ***
soil.moisture.content	12.750	1.021	12.49	<2e-16 ***
---				
Signif. codes:	0 **** 0.001 ** 0.01 * 0.05 . 0.1 ' ' 1			

Residual standard error: 4.019 on 48 degrees of freedom

Multiple R-squared: 0.7648, Adjusted R-squared: 0.7599

F-statistic: 156.1 on 1 and 48 DF, p-value: < 2.2e-16

# Model interpretation

## Model

```
1
2 Call:
3 lm(formula = plant.growth.rate ~ soil.moisture.content, data = plant_gr)
4
5 Residuals:
6   Min     1Q Median     3Q    Max
7 -8.9089 -3.0747  0.2261  2.6567  8.9406
8
9 Coefficients:
10                      Estimate Std. Error t value Pr(>|t|)
11 (Intercept)            19.348     1.283   15.08 <2e-16 ***
12 soil.moisture.content 12.750      1.021   12.49 <2e-16 ***
13 ---
14 Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
15
16 Residual standard error: 4.019 on 48 degrees of freedom
17 Multiple R-squared:  0.7648,    Adjusted R-squared:  0.7599
18 F-statistic: 156.1 on 1 and 48 DF,  p-value: < 2.2e-16
```

# Model interpretation

## Effects

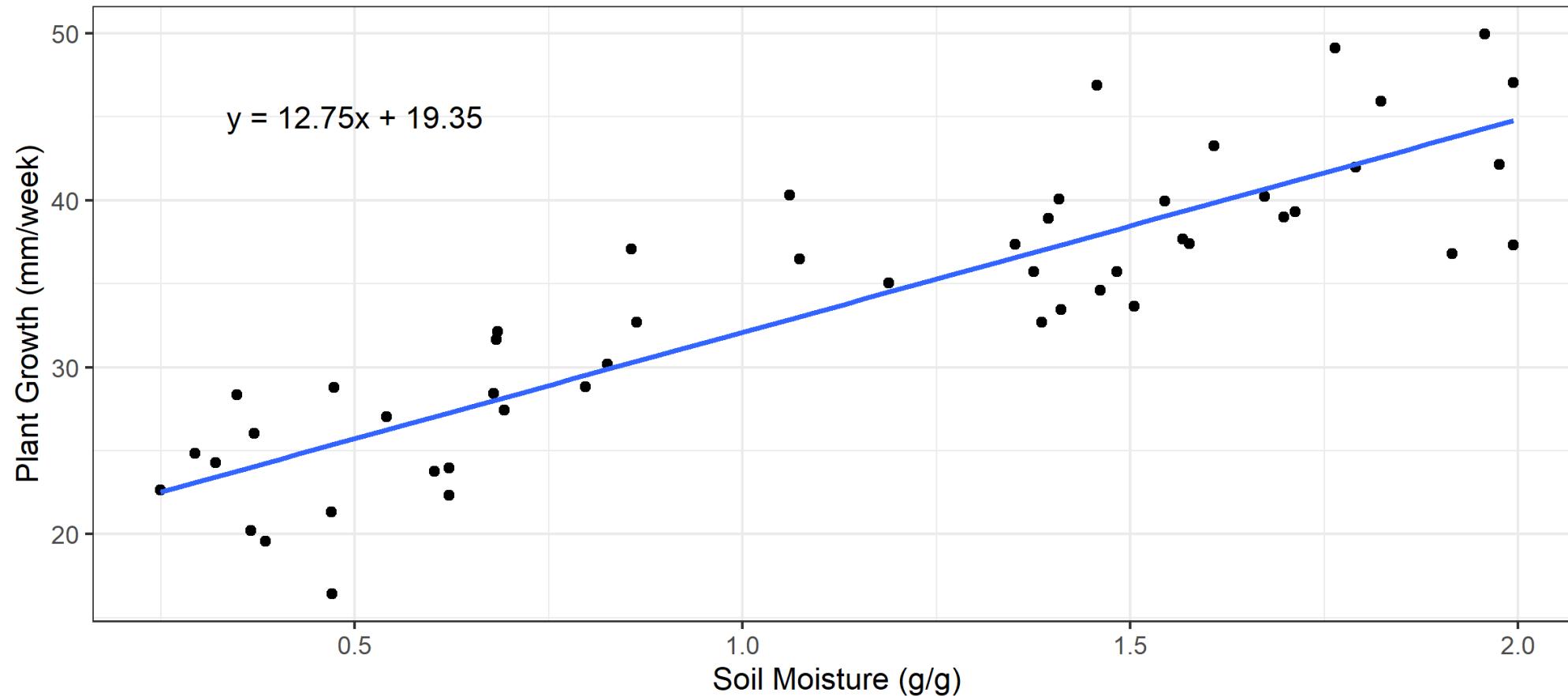
```
1
2 Call:
3 lm(formula = plant.growth.rate ~ soil.moisture.content, data = plant_gr)
4
5 Residuals:
6   Min     1Q Median     3Q    Max
7 -8.9089 -3.0747  0.2261  2.6567  8.9406
8
9 Coefficients:
10                      Estimate Std. Error t value Pr(>|t|)
11 (Intercept)            19.348     1.283   15.08 <2e-16 ***
12 soil.moisture.content 12.750      1.021   12.49 <2e-16 ***
13 ---
14 Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
15
16 Residual standard error: 4.019 on 48 degrees of freedom
17 Multiple R-squared:  0.7648,    Adjusted R-squared:  0.7599
18 F-statistic: 156.1 on 1 and 48 DF,  p-value: < 2.2e-16
```

# Model interpretation

# Back to the picture

$$y = a + bx$$

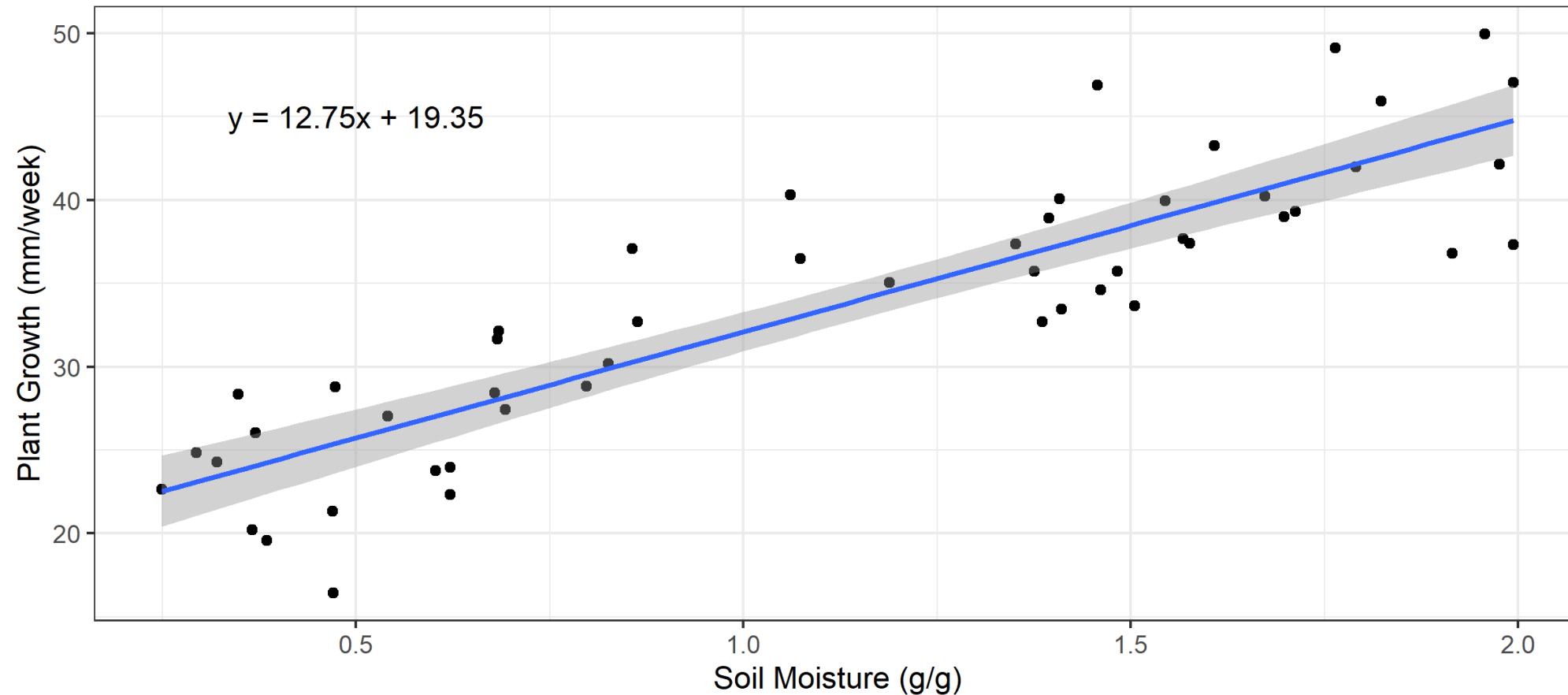
```
1 geom_smooth(method = "lm", se = FALSE)
```



# Back to the picture

Confidence interval

```
1 geom_smooth(method = "lm", se = TRUE)
```



# Confidence interval

- The range in which the mean (expected value) of the response variable is likely to fall for a given explanatory variable value

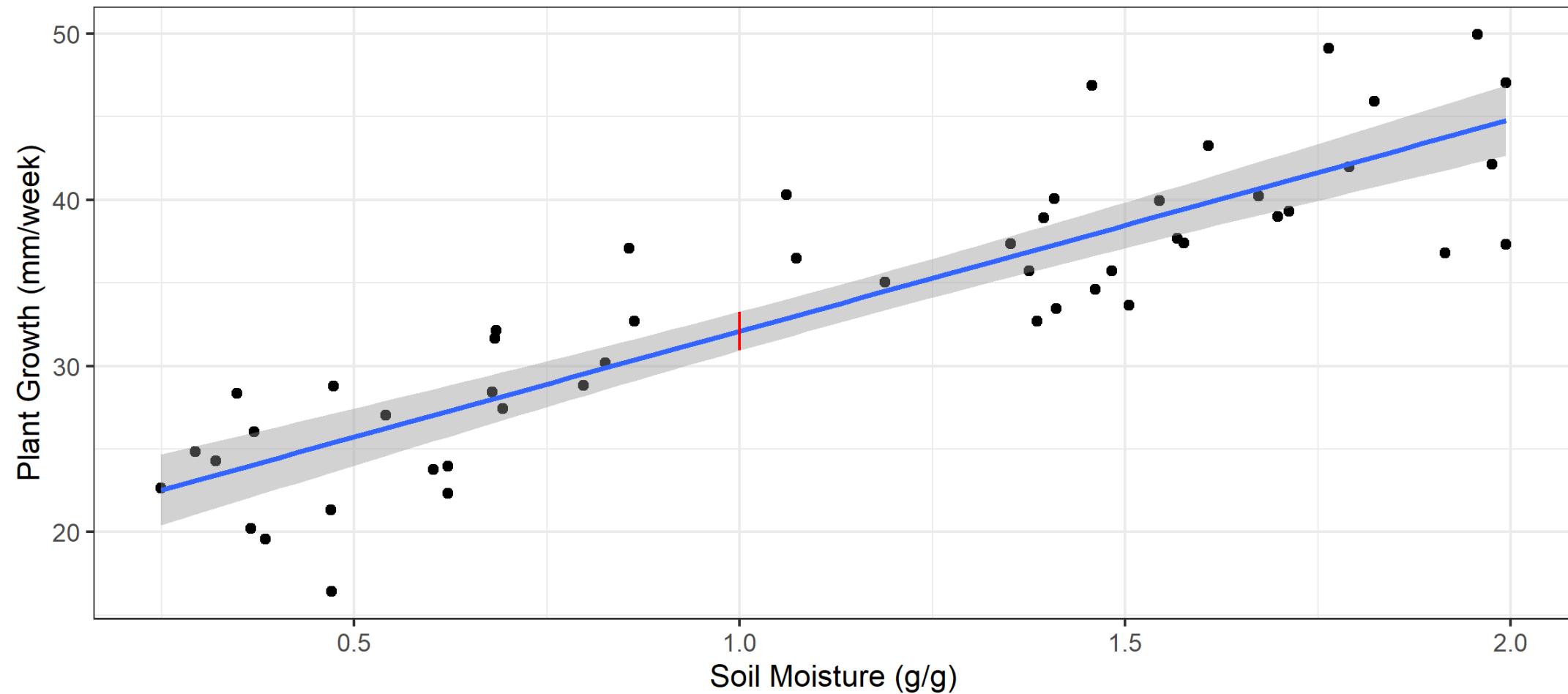
```
1 new_data <- data.frame(soil.moisture.content = 1)
2 predict(model_pgr, newdata = new_data,
3          interval = "confidence", level = 0.95)

      fit      lwr      upr
1 32.098 30.92568 33.27031
```

- A 95% confidence interval for plant growth rate at soil moisture content of 1 g/g would be 30.93 to 33.27 mm/week
- This means we are 95% confident that the **mean plant growth rate** falls within this range

# Confidence interval

- Double check



# Prediction interval

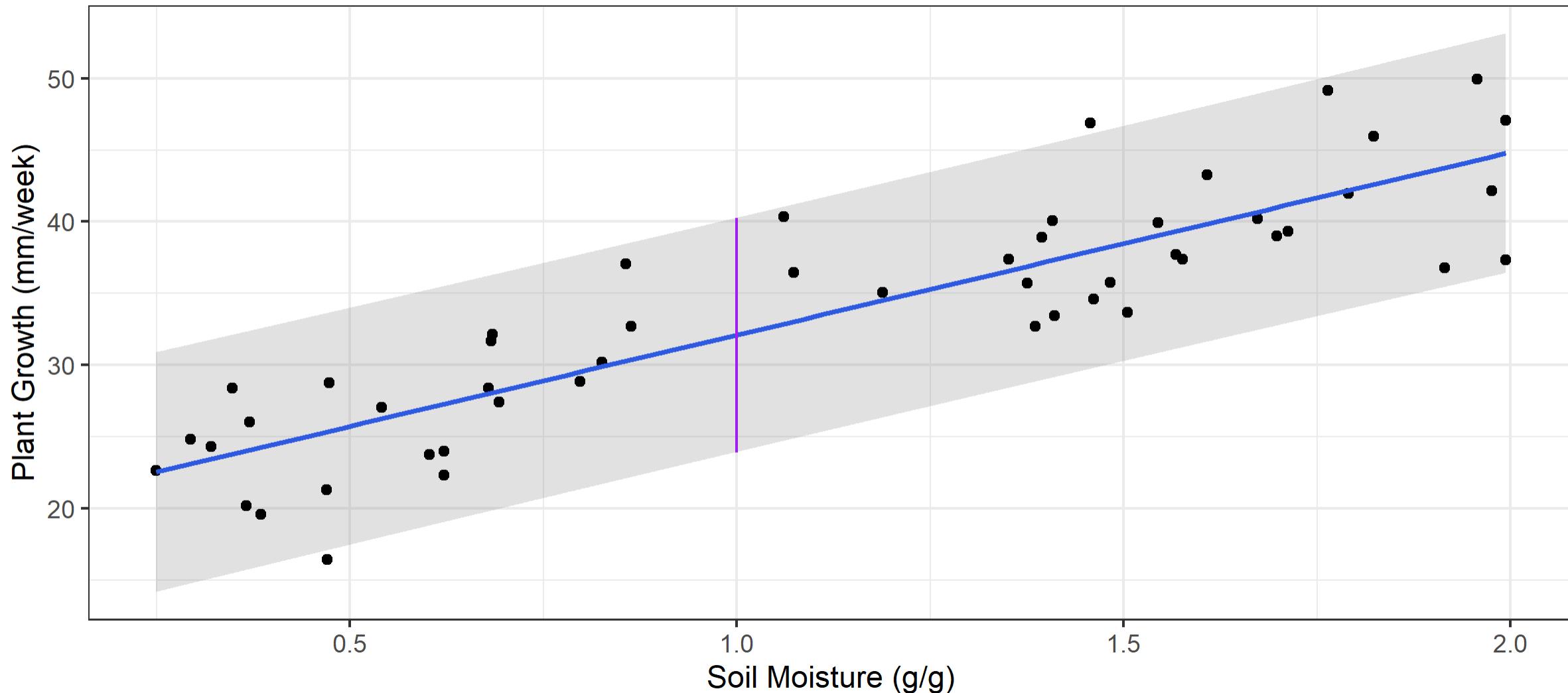
- The range in which an individual new observation is likely to fall for a given explanatory variable value

```
1 new_data <- data.frame(soil.moisture.content = 1)
2 predict(model_pgr, newdata = new_data,
3           interval = "predict", level = 0.95)

      fit      lwr      upr
1 32.098 23.93247 40.26352
```

- A 95% prediction interval for plant growth rate at soil moisture content of 1 g/g would be 23.93 to 40.26 mm/week
- This means we are 95% confident that if we take a **random** plant at that moisture content it will fall within this range

# Prediction interval



# Your turn!

Does flipper length, bill depth, and bill length in penguins vary with body mass?

Each student is going to do something slightly different!

1. bill length (Adelie)
2. bill depth (Adelie)
3. flipper length (Adelie)
4. bill length (Gentoo)
5. bill depth (Gentoo)
6. flipper length (Gentoo)

# Your turn!

We need to filter the data by penguin species

```
1 adelie_data <- filter(penguins, species == "Adelie")
```

or

```
1 gentoo_data <- filter(penguins, species == "Gentoo")
```

# Create your picture

```
1 ggplot(data = ___, aes(____)) +  
2   geom____() +  
3   theme____() +  
4   labs(y = ___, x = ____)
```

# Linear regression

```
1 _____ <- lm(____ ~ _____, data = _____)
```

# Assess your assumptions

```
1 autoplot(_____, smooth.colour = _____)
```

# Model interpretation

```
1 summary(____)
```

# Final picture

```
1 penguin_plot <- ggplot(data = ___, aes(____))  
2   geom____() +  
3   theme____() +  
4   labs(y = ___, x = ___) +  
5   ____(method = ___, se = ___)  
6 penguin_plot
```

Struggling to get your desired colours or text size? Please ask!

The plot preview may look different the the saved version.

```
1 ggsave(filename = ___, plot = ___, height = ___,  
2         width = ___, units = "mm", dpi =600)
```

# Assignment

**Complete the following and compile into a single well-formatted document**

- Include identifying information (name, date, title, etc)
- PDF format
- Figures are numbered and have meaningful captions
- Pay attention to spelling and grammar

Additionally

- Submit your R script file so I can reproduce your work!  
(not the .Rproj file)

# Assignment

1. Create a figure showing the relationship showing the relationship between body weight and flipper length, bill depth, or bill length for either Adelie or Chinstrap penguins. Include the standard error (95% confidence interval) about the regression line
2. Using the diagnostic plots for your linear regression model (do not include figure in the report), evaluate the assumptions of normality, equal variance, and influential points/outliers based on your output. Summarize any potential violations and their possible impact on the interpretation of the model

# Assignment

3. Determine the regression model (intercept and slope) and express the equation
4. Determine the  $r^2$  for the model
5. Test the significance of the modeled relationship (i.e., slope) using an  $\alpha$  of 0.05
6. Discuss the model's effectiveness in explaining bill depth, length, or flipper length using the coefficient of determination and significance test results

# Assignment

7. Explain what your  $r^2$  value indicates about the relationship between the independent and dependent variables in your model
8. If the  $r^2$  value is less than 100%, suggest another potential independent variables that could be added (i.e., multiple regression) to improve the model

# Wrapping up

- Stats can be confusing at the best of times!
- Be kind to yourself
- It takes practice!
- Your stats should support your figures (not the other way around)

Thank you!



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