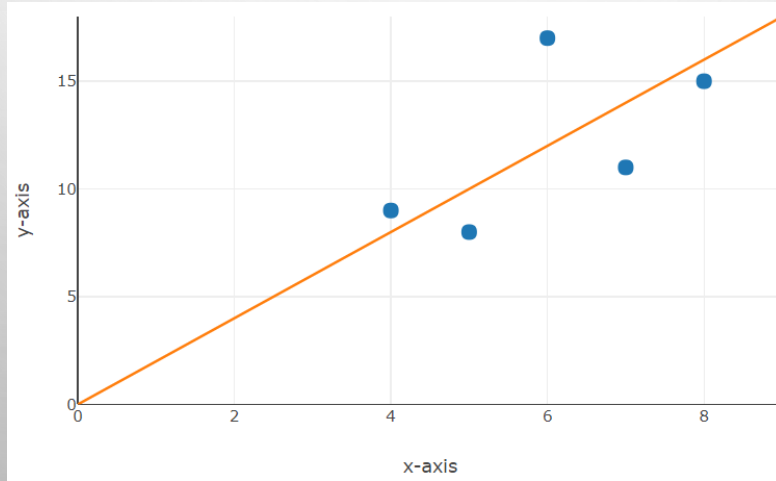


# CHAPTER 5 - LINEAR REGRESSION AND PLOTTINGS

## LINEAR REGRESSION

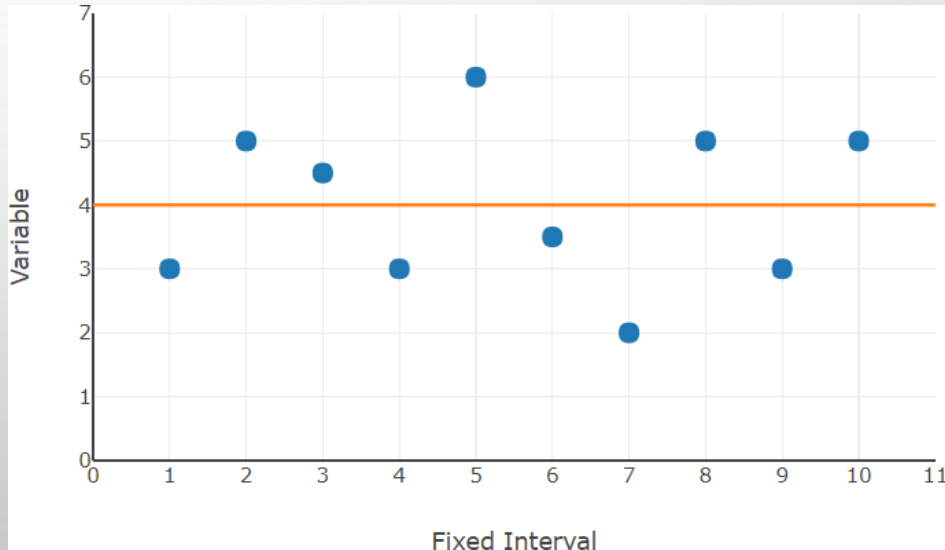
- The goal of **regression** is to develop an equation or formula that best describes the relationship between variables.



$$y = 2x$$

## LINEAR REGRESSION

- How do we find a best-fit line?
- Consider a dataset with only one variable
- The best-fit line is just the mean value of the data points



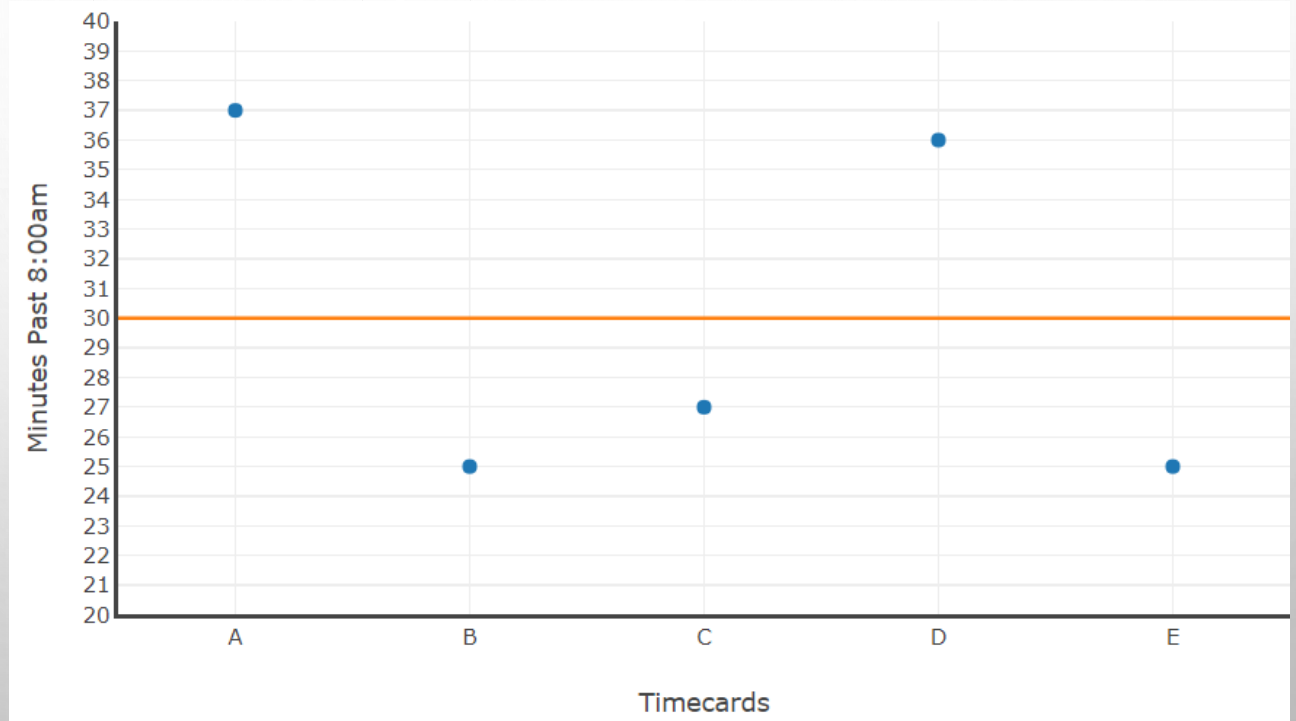
## UNDERSTANDING BEST FIT

- A plant manager wants to know when employees arrive at work
- The shift starts a 8:30am
- She takes five random timecards and plots the minutes of arrival on a chart



# UNDERSTANDING BEST FIT

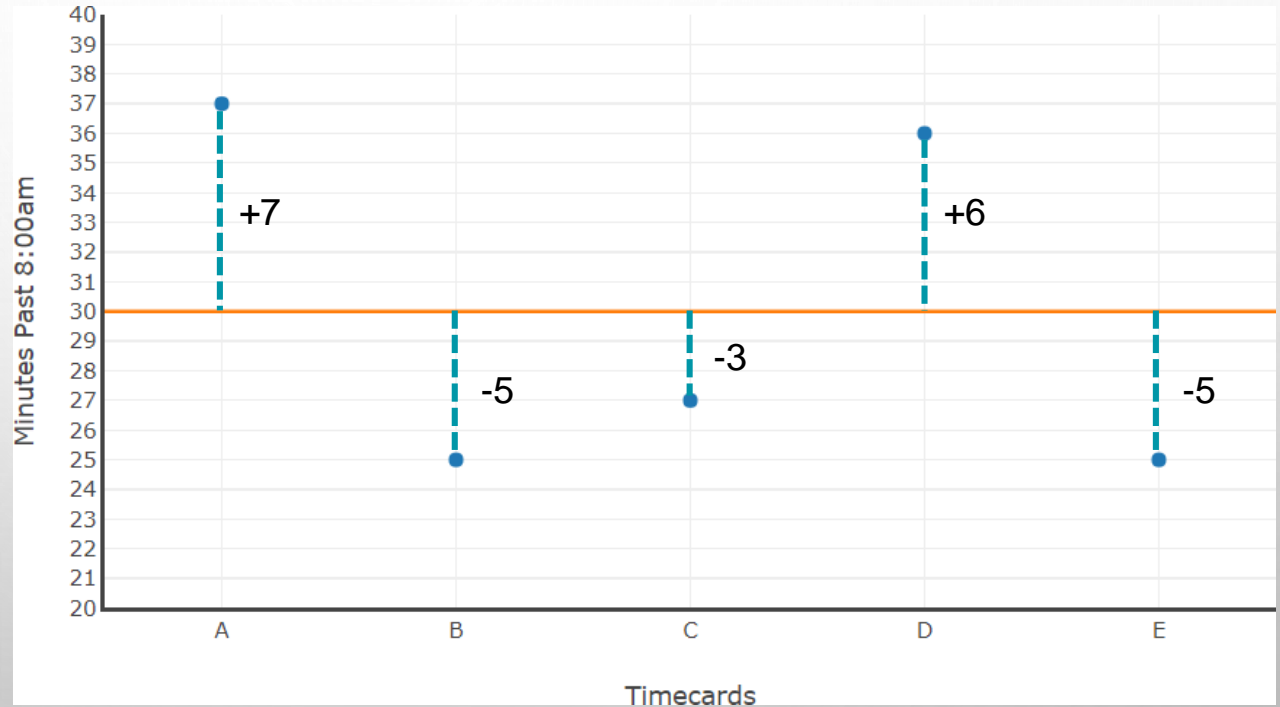
Timecard	Minutes past 8:00am
A	37
B	25
C	27
D	36
E	25
<b>Total:</b>	<b>150</b>
<b>Mean</b>	<b>30</b>



What makes  
 $y = 30$  a  
best-fit line?

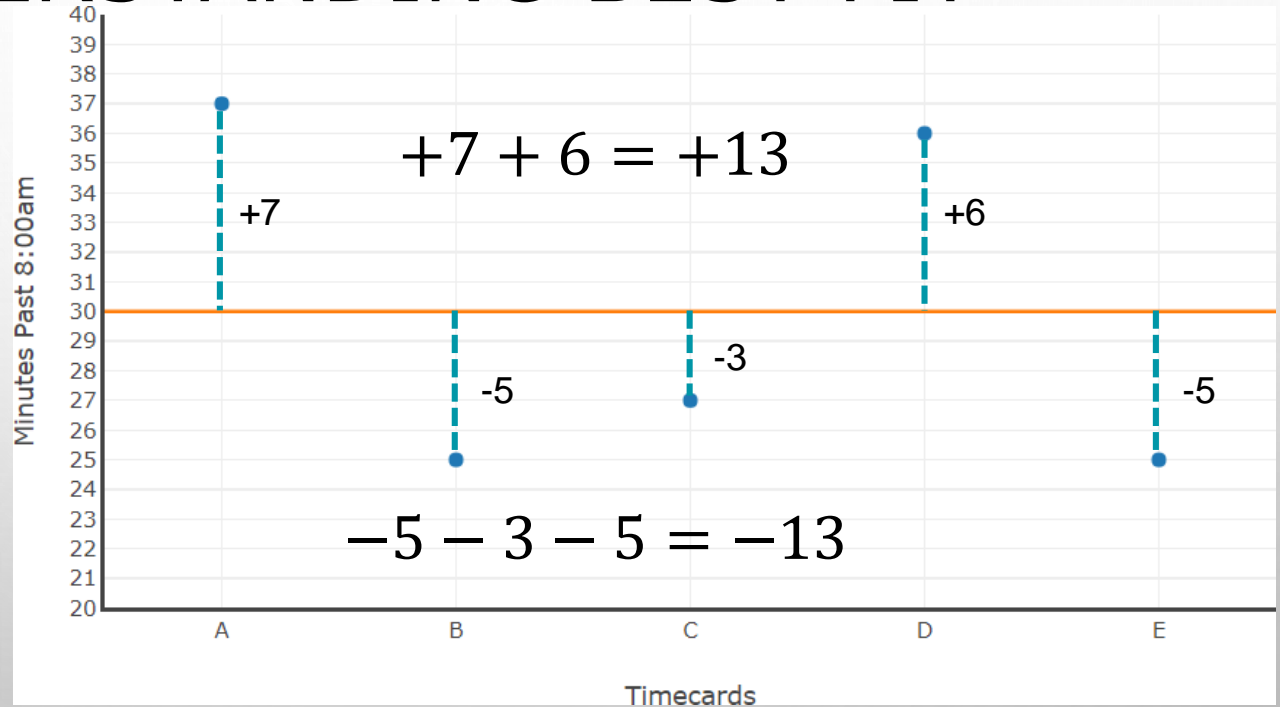
Consider the  
error

## UNDERSTANDING BEST FIT



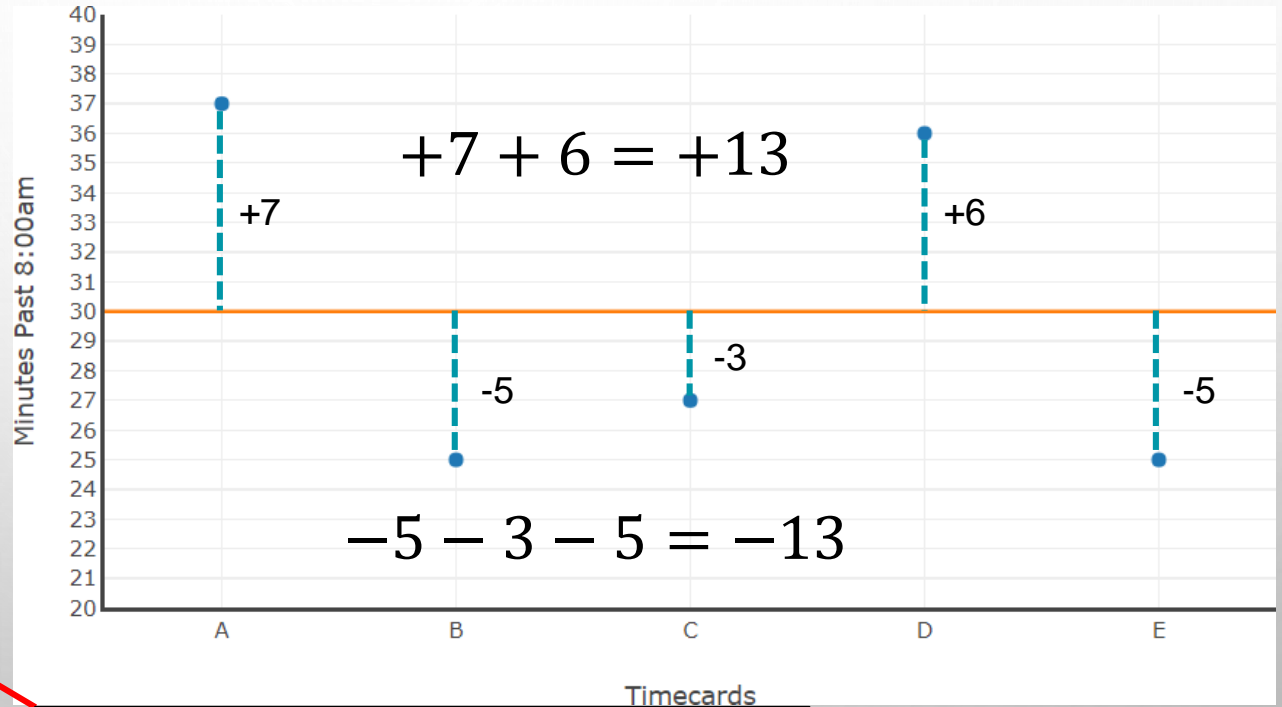
# UNDERSTANDING BEST FIT

See that the sum of the distances above the line balances the sum of those below the line



# UNDERSTANDING BEST FIT

Error (E)	Square Error (SE)
+7	49
-5	25
-3	9
+6	36
-5	25
<b>Sum of Squares Error (SSE)</b>	<b>144</b>



we want to MINIMIZE the SSE

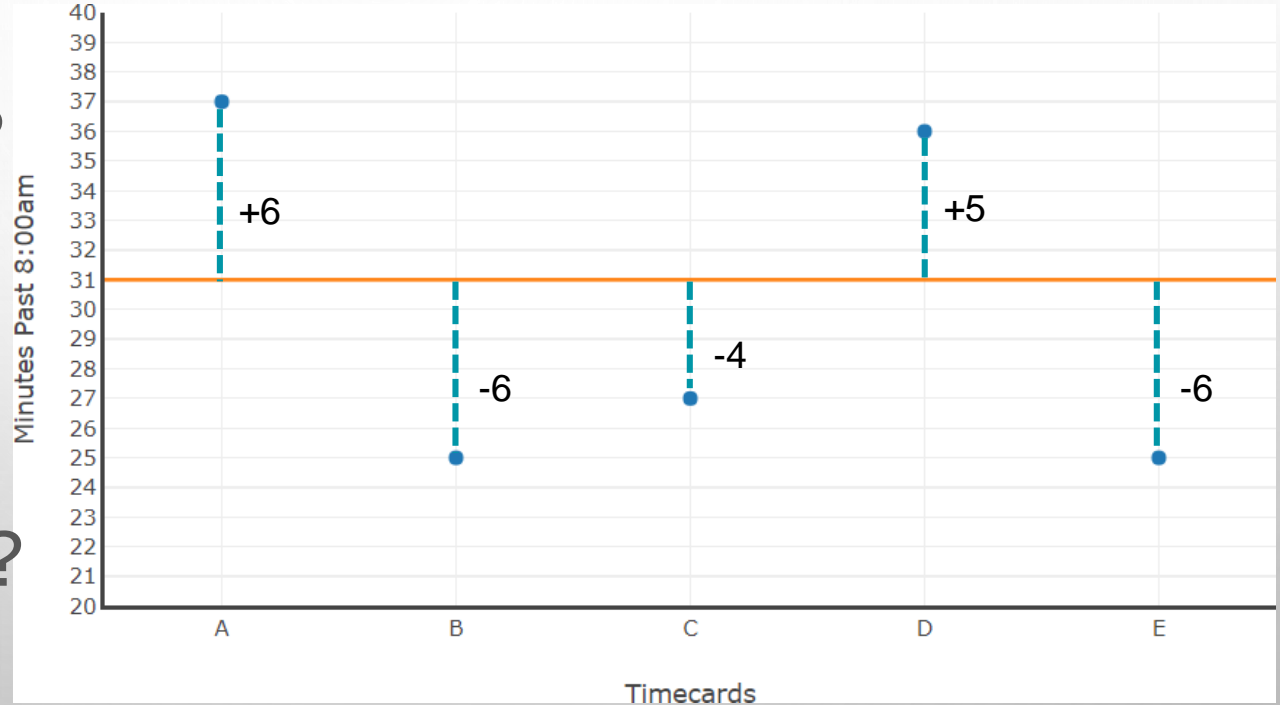


## UNDERSTANDING BEST FIT

What if we  
move the line?

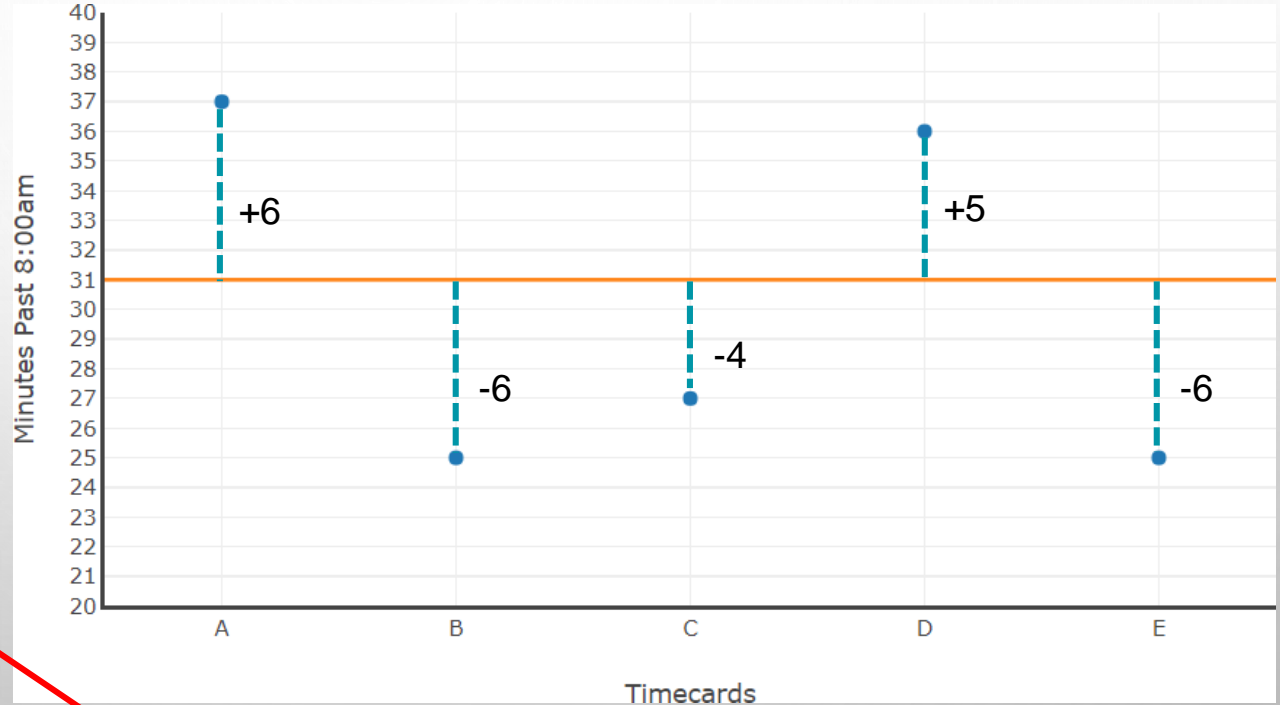
Let's set it to  
 $y = 31$  instead

How does it  
affect the SSE?



# UNDERSTANDING BEST FIT

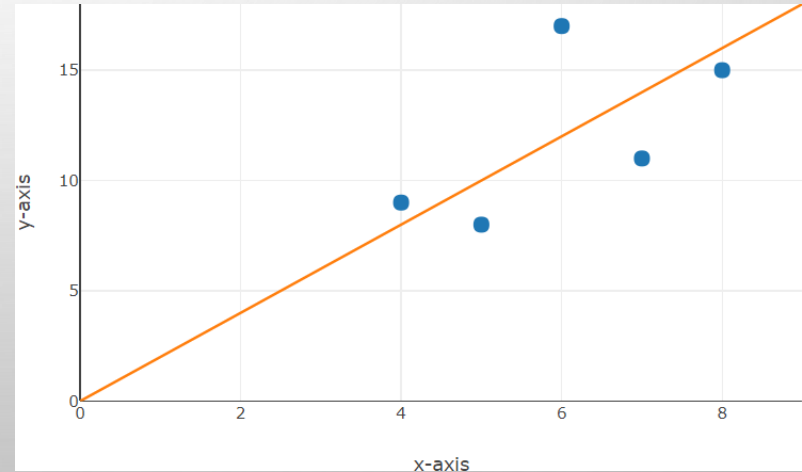
Error (E)		Square Error (SE)	
+7	+6	49	36
-5	-6	25	36
-3	-4	9	16
+6	+5	36	25
-5	-6	25	36
Sum of Squares Error (SSE)		144	149



moving the line INCREASED the SSE

## LINEAR REGRESSION

- That's it! The goal of regression is to find the line that best describes our data.
- Fortunately, we don't have to rely on trial-and-error.
- We have algebra!

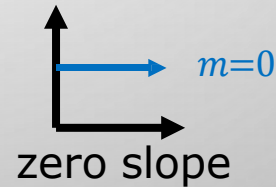
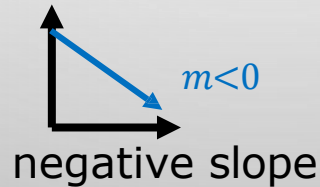
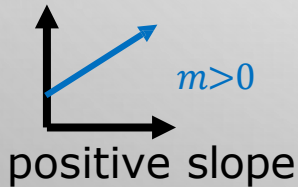


## LINEAR REGRESSION

- Recall that the equation of a line follows the form  $y = mx + b$  where

$m$  is the slope of the line, and

$b$  is where the line crosses the y-axis when  $x=0$  ( $b$  is the y-intercept)



## LINEAR REGRESSION

- In a linear regression, where we try to formulate the relationship between variables,  $y = mx + b$  becomes

$$\hat{y} = b_0 + b_1x$$

- Our goal is to predict the value of a **dependent variable** ( $y$ ) based on that of an **independent variable** ( $x$ ).

$$\hat{y} = b_0 + b_1x$$

## LINEAR REGRESSION

- How to derive  $b_1$  and  $b_0$ :

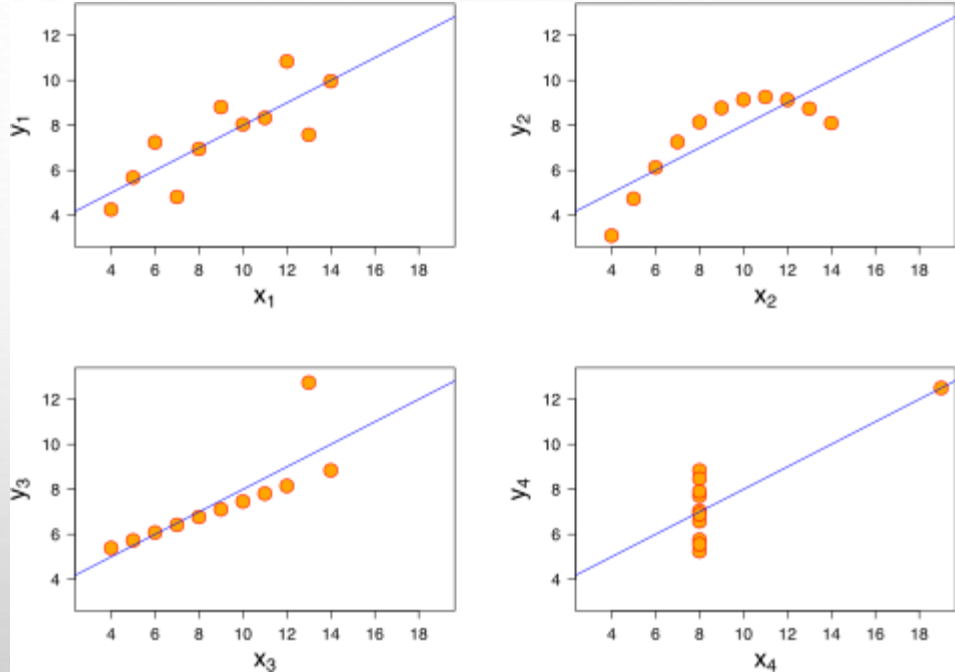
$$b_1 = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sum(x_i - \bar{x})^2}$$

$$b_0 = \bar{y} - b_1\bar{x}$$

# LIMITATIONS OF LINEAR REGRESSION

Anscombe's Quartet illustrates the pitfalls of relying on pure calculation.

Each graph results in the same calculated regression line.



## REGRESSION EXERCISE #1

- A manager wants to find the relationship between the number of hours that a plant is operational in a week and weekly production.





## REGRESSION EXERCISE #1

- Here the independent variable  $x$  is hours of operation, and the dependent variable  $y$  is production volume.



## REGRESSION EXERCISE #1

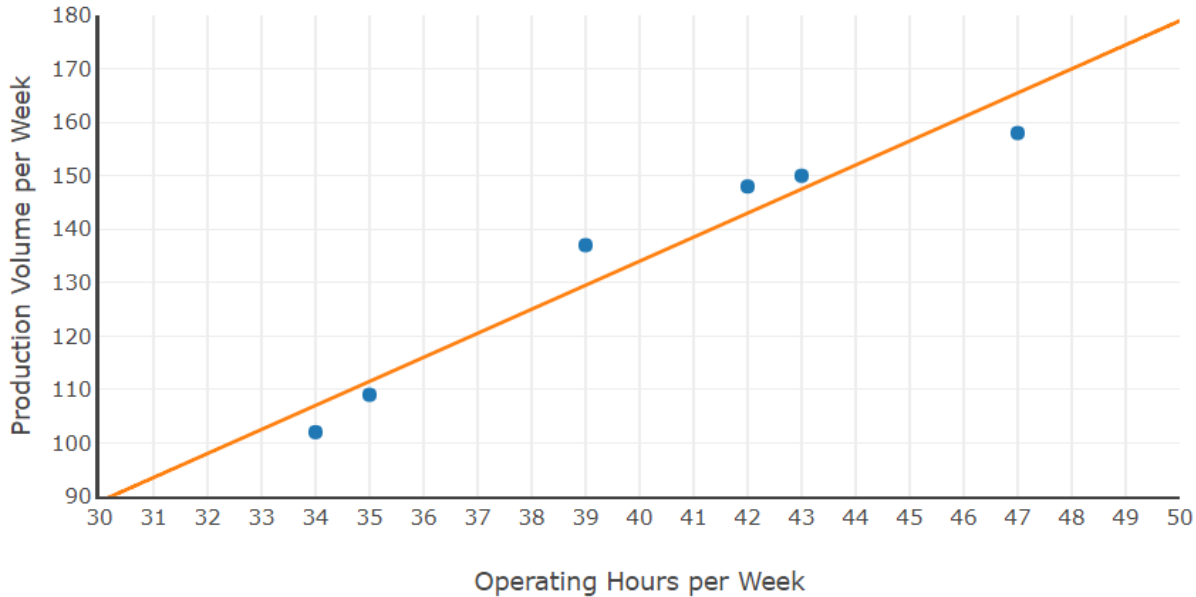
- The manager develops the following table:

Production Hours (x)	Production Volume (y)
34	102
35	109
39	137
42	148
43	150
47	158

# REGRESSION EXERCISE #1

- First, plot the data Is there a linear pattern?

Production Hours (x)	Production Volume (y)
34	102
35	109
39	137
42	148
43	150
47	158



# REGRESSION EXERCISE #1

- Run calculations:

$$\hat{y} = b_0 + b_1x$$

$$b_1 = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sum(x_i - \bar{x})^2}$$

$$b_0 = \bar{y} - b_1\bar{x}$$

Production Hours (x)	Production Volume (y)	$(x - \bar{x})$	$(y - \bar{y})$	$(x - \bar{x})(y - \bar{y})$	$(x - \bar{x})^2$
34	102	-6	-32	192	36
35	109	-5	-25	125	25
39	137	-1	3	-3	1
42	148	2	14	28	4
43	150	3	16	48	9
47	158	7	24	168	49
$\bar{x}, \bar{y}$	<b>40</b>			<b>Sum: 558</b>	<b>124</b>
				$\Sigma(x - \bar{x})(y - \bar{y})$	$\Sigma(x - \bar{x})^2$

# REGRESSION EXERCISE #1

- Run calculations:

Production Hours (x)	Production Volume (y)
34	102
35	109
39	137
42	148
43	150
47	158
$\bar{x}, \bar{y}$	40 134

$$b_1 = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sum(x_i - \bar{x})^2}$$

$$= \frac{558}{124} = 4.5$$

$$b_0 = \bar{y} - b_1 \bar{x} = 134 - (4.5 \times 40) = -46$$

$$\hat{y} = b_0 + b_1 x$$
$$b_1 = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sum(x_i - \bar{x})^2}$$
$$b_0 = \bar{y} - b_1 \bar{x}$$

Sum:	558	124
	$\sum(x - \bar{x})(y - \bar{y})$	$\sum(x - \bar{x})^2$

## REGRESSION EXERCISE #1

Based on the formula, if the manager wants to produce 125 units per week, the plant should run for:

Production Hours (x)	Production Volume (y)
34	102
35	109
39	137
42	148
43	150
47	158

$$\hat{y} = b_0 + b_1x$$

$$125 = -46 + 4.5x$$

$$171$$

$$x = \frac{171}{4.5} = \mathbf{38 \text{ hours per week}}$$

The background features a light gray gradient with several realistic water droplets of varying sizes scattered in the corners. The droplets have highlights and shadows, giving them a three-dimensional appearance. The text is centered in a bold, black, sans-serif font.

# MULTIPLE REGRESSION

## LINEAR VS MULTIPLE REGRESSION

- In linear regression we have one independent variable that may relate to a dependent variable with the formula

$$\hat{y} = b_0 + b_1x$$



## LINEAR VS MULTIPLE REGRESSION

- Multiple regression lets us compare several independent variables to one dependent variable at the same time.
- Each independent variable is assigned a subscript:  $x_1, x_2, x_3$  etc.

# LINEAR VS MULTIPLE REGRESSION

- The general formula is expanded:

linear regression

$$\hat{y} = b_0 + b_1x$$

multiple regression

$$\hat{y} = b_0 + b_1x_1 + b_2x_2 + \dots$$

- $b_1$  is the coefficient on  $x_1$
- $b_1$  reflects the change in  $\hat{y}$  for a given change in  $x_1$ , all else remaining constant

# LINEAR VS MULTIPLE REGRESSION

- The formulas for coefficients also expand:  
multiple regression

$$b_1 = \frac{\sum(x_2 - \bar{x}_2)^2 \sum(x_1 - \bar{x}_1)(y - \bar{y}) - \sum(x_1 - \bar{x}_1)(x_2 - \bar{x}_2) \sum(x_2 - \bar{x}_2)(y - \bar{y})}{\sum(x_1 - \bar{x}_1)^2 \sum(x_2 - \bar{x}_2)^2 - (\sum(x_1 - \bar{x}_1)(x_2 - \bar{x}_2))^2}$$

$$b_2 = \frac{\sum(x_1 - \bar{x}_1)^2 \sum(x_2 - \bar{x}_2)(y - \bar{y}) - \sum(x_1 - \bar{x}_1)(x_2 - \bar{x}_2) \sum(x_1 - \bar{x}_1)(y - \bar{y})}{\sum(x_1 - \bar{x}_1)^2 \sum(x_2 - \bar{x}_2)^2 - (\sum(x_1 - \bar{x}_1)(x_2 - \bar{x}_2))^2}$$

$$b_0 = \bar{y} - b_1 \bar{x}_1 - b_2 \bar{x}_2$$

## MULTIPLE REGRESSION

- For example, a used car lot may want to know what variables affect net profits
- They would create a list of predictors that might correlate with profit:

price      age      brand  
                 color      style



## MULTIPLE REGRESSION

- They would want to measure the correlation of each variable to net profit
- However, some predictors might correlate with each other:

price age brand  
color style



## MULTIPLE REGRESSION

- The age of a car would have a direct impact on its sales price
- You can't adjust one without affecting the other
- This is called **multicollinearity**

price age brand  
color style



## REGRESSION EXERCISE #2



- A pharmacy delivers medications to the surrounding community.
- Drivers can make several stops per delivery.
- The owner would like to predict the **length of time** a delivery will take based on one or two related variables.





## REGRESSION EXERCISE #2

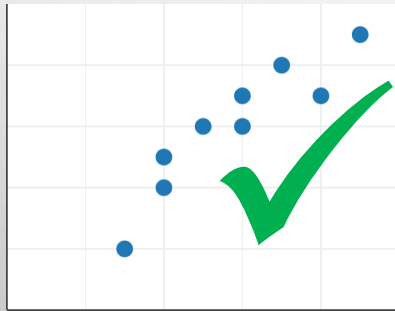
- First, consider what variables may have an effect on delivery time:
  - number of stops
  - driving distance
  - outside temperature
  - gasoline prices



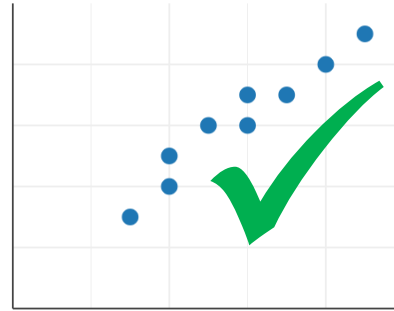


## REGRESSION EXERCISE #2

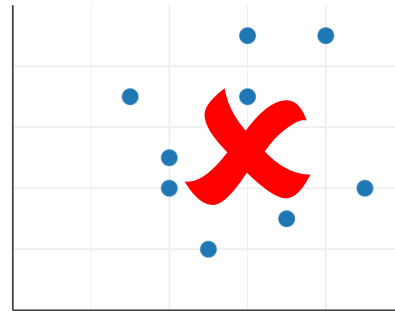
- Next, plot each variable against delivery time to see if there may be a relationship



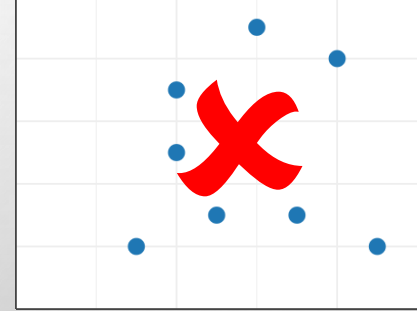
Time vs Distance



Time vs Stops



Time vs Temperature

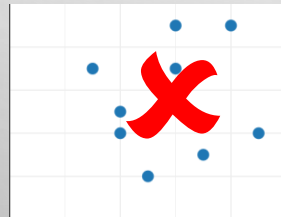


Time vs Gas Price

## REGRESSION EXERCISE #2



- Once we've chosen our variables  $x_1$  and  $x_2$ , we'll usually test for multicollinearity
- We want to know if our two independent variables are closely related to each other
- If they are, it makes sense to discard one!



Stops vs Distance

A delivery might go to one customer that lives far away, or to a group of stops close by

# REGRESSION EXERCISE #2



$y = \text{Delivery Time (minutes)}$

$x_1 = \text{Number of Stops}$

$x_2 = \text{Distance (miles)}$

$y$	$x_1$	$x_2$	$(y - \bar{y})$	$(x_1 - \bar{x}_1)$	$(x_1 - \bar{x}_1)^2$	$(x_2 - \bar{x}_2)$	$(x_2 - \bar{x}_2)^2$
29	1	8	-1	-1	1	2	4
31	3	4	1	1	1	-2	4
36	2	9	6	0	0	3	9
35	3	6	5	1	1	0	0
19	1	3	-11	-1	1	-3	9
$\bar{y}$	$\bar{x}_1$	$\bar{x}_2$			$\Sigma(x_1 - \bar{x}_1)^2$		$\Sigma(x_2 - \bar{x}_2)^2$
30	2	6			4		26

$(x_1 - \bar{x}_1)(y - \bar{y})$	$(x_2 - \bar{x}_2)(y - \bar{y})$	$(x_1 - \bar{x}_1)(x_2 - \bar{x}_2)$
1	-2	-2
1	-2	-2
0	18	0
5	0	0
11	33	3
$\Sigma(x_1 - \bar{x}_1)(y - \bar{y})$	$\Sigma(x_2 - \bar{x}_2)(y - \bar{y})$	$\Sigma(x_1 - \bar{x}_1)(x_2 - \bar{x}_2)$
18	47	-1

# REGRESSION EXERCISE #2



$y = \text{Delivery Time (minutes)}$

$x_1 = \text{Number of Stops}$

$x_2 = \text{Distance (miles)}$

$$b_1 = \frac{\sum(x_2 - \bar{x}_2)^2 \sum(x_1 - \bar{x}_1)(y - \bar{y}) - \sum(x_1 - \bar{x}_1)(x_2 - \bar{x}_2) \sum(x_2 - \bar{x}_2)(y - \bar{y})}{\sum(x_1 - \bar{x}_1)^2 \sum(x_2 - \bar{x}_2)^2 - (\sum(x_1 - \bar{x}_1)(x_2 - \bar{x}_2))^2}$$

$$b_2 = \frac{\sum(x_1 - \bar{x}_1)^2 \sum(x_2 - \bar{x}_2)(y - \bar{y}) - \sum(x_1 - \bar{x}_1)(x_2 - \bar{x}_2) \sum(x_1 - \bar{x}_1)(y - \bar{y})}{\sum(x_1 - \bar{x}_1)^2 \sum(x_2 - \bar{x}_2)^2 - (\sum(x_1 - \bar{x}_1)(x_2 - \bar{x}_2))^2}$$

$\bar{y}$	$\bar{x}_1$	$\bar{x}_2$
30	2	6

$\sum(x_1 - \bar{x}_1)^2$
4

$\sum(x_2 - \bar{x}_2)^2$
26

$\sum(x_1 - \bar{x}_1)(y - \bar{y})$
18

$\sum(x_2 - \bar{x}_2)(y - \bar{y})$
47

$\sum(x_1 - \bar{x}_1)(x_2 - \bar{x}_2)$
-1



$y = \text{Delivery Time (minutes)}$

$x_1 = \text{Number of Stops}$

$x_2 = \text{Distance (miles)}$

## REGRESSION EXERCISE #2

$$b_1 = \frac{(26)(18) - (-1)(47)}{(4)(26) - ((-1))^2} = \frac{515}{103} = 5$$

$$b_2 = \frac{(4)(47) - (-1)(18)}{(4)(26) - ((-1))^2} = \frac{206}{103} = 2$$

$\bar{y}$	$\bar{x}_1$	$\bar{x}_2$
30	2	6

$\Sigma(x_1 - \bar{x}_1)^2$
4

$\Sigma(x_2 - \bar{x}_2)^2$
26

$\Sigma(x_1 - \bar{x}_1)(y - \bar{y})$
18

$\Sigma(x_2 - \bar{x}_2)(y - \bar{y})$
47

$\Sigma(x_1 - \bar{x}_1)(x_2 - \bar{x}_2)$
-1

# REGRESSION EXERCISE #2



$y = \text{Delivery Time (minutes)}$

$x_1 = \text{Number of Stops}$

$x_2 = \text{Distance (miles)}$

$$\hat{y} = 8 + 5x_1 + 2x_2$$

$$b_1 = \frac{(26)(18) - (-1)(47)}{(4)(26) - ((-1))^2} = \frac{515}{103} = 5$$

$$b_2 = \frac{(4)(47) - (-1)(18)}{(4)(26) - ((-1))^2} = \frac{206}{103} = 2$$

$$\begin{aligned} b_0 &= \cancel{30} - b_1\bar{x}_1 - b_2\bar{x}_2 \\ &= 30 - (5)(2) - (2)(6) \\ &= 30 - 10 - 12 = 8 \end{aligned}$$

$\bar{y}$	$\bar{x}_1$	$\bar{x}_2$
30	2	6

$\Sigma(x_1 - \bar{x}_1)^2$
4

$\Sigma(x_2 - \bar{x}_2)^2$
26

$\Sigma(x_1 - \bar{x}_1)(y - \bar{y})$
18

$\Sigma(x_2 - \bar{x}_2)(y - \bar{y})$
47

$\Sigma(x_1 - \bar{x}_1)(x_2 - \bar{x}_2)$
-1

# REGRESSION EXERCISE #2



$y$  = Delivery Time (minutes)

$x_1$  = Number of Stops

$x_2$  = Distance (miles)

$$\hat{y} = 8 + 5x_1 + 2x_2$$

$y$	$x_1$	$x_2$
29	1	8
31	3	4
36	2	9
35	3	6
19	1	3

ON OUR ANALYSIS, PHARMACY DELIVERIES HAVE A FIXED TIME OF 8 MINUTES, PLUS 5 MINUTES FOR EACH STOP, AND 2 MINUTES FOR EACH MILE TRAVELED

# IMPLEMENTATION IN R




# USAGE OF LM()

Syntax: `lm(formula, data)`

Example:

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

```
R 4.4.1 . ~/ 
> data(mtcars)
> # Example dataset
> model <- lm(mpg ~ wt + hp, data = mtcars)
> summary(model)

Call:
lm(formula = mpg ~ wt + hp, data = mtcars)

Residuals:
    Min       1Q   Median       3Q      Max
-3.941 -1.600 -0.182  1.050  5.854

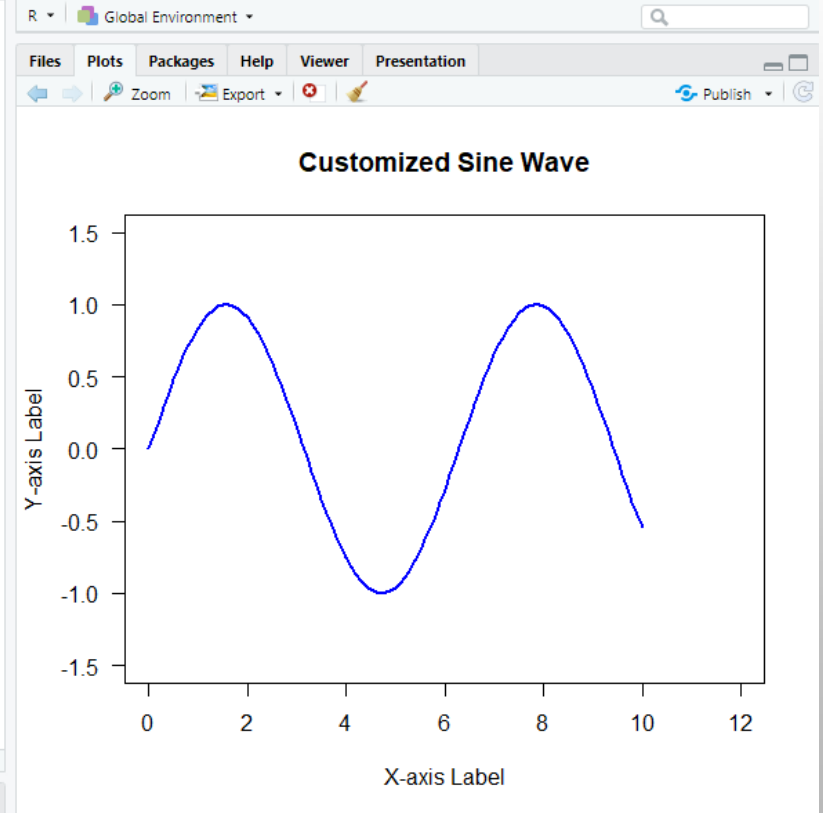
Coefficients:
            Estimate
(Intercept) 37.22727
          wt  -3.87783
          hp  -0.03177

            Std. Error
(Intercept)  1.59879
          wt   0.63273
          hp   0.00903
```

# ADVANCED PLOTTING

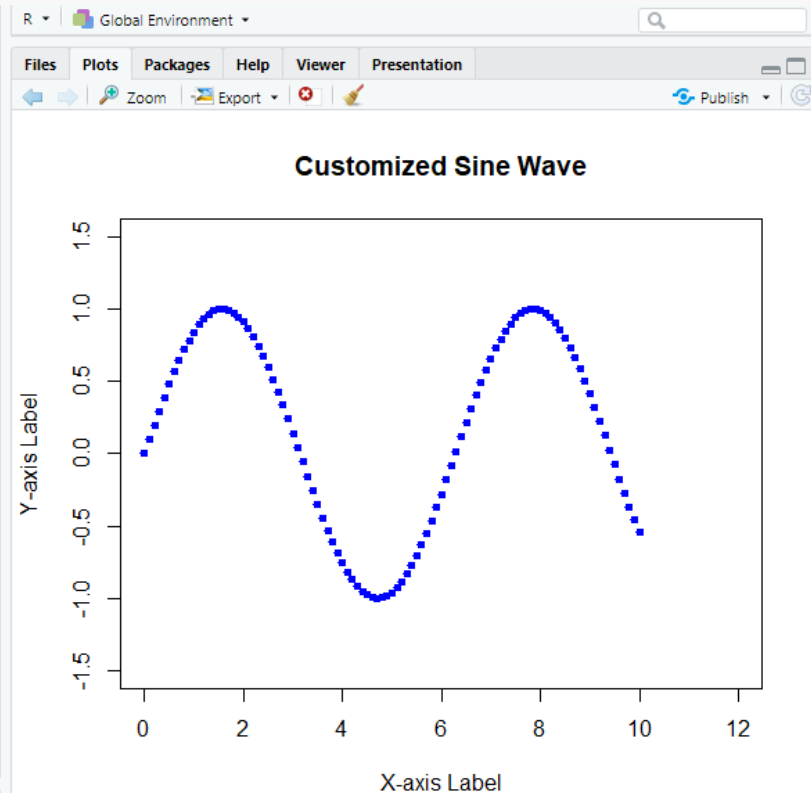
# SIMPLE PLOT

```
1 # Generate sample data
2 x <- seq(0, 10, by = 0.1)
3 y <- sin(x)
4
5 # Basic plot with customization
6 plot(
7   x, y,
8   type = "l",           # Line plot
9   col = "blue",        # Line color
10  lwd = 2,              # Line width
11  main = "Customized sine wave", # Title
12  xlab = "X-axis Label", # X-axis label
13  ylab = "Y-axis Label", # Y-axis label
14  xlim = c(0, 12),      # X-axis limits
15  ylim = c(-1.5, 1.5),  # Y-axis limits
16  las = 1               # Rotate axis labels
17 )
18
19
```



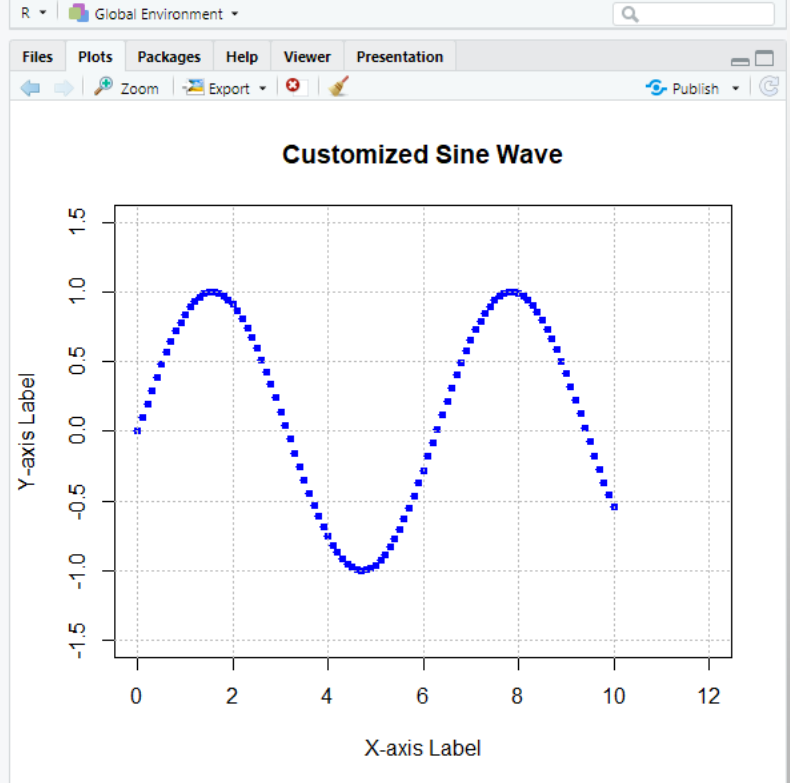
# USING PCH

```
1 # Generate sample data
2 x <- seq(0, 10, by = 0.1)
3 y <- sin(x)
4
5 # Basic plot with customization
6 plot(
7   x, y,
8   type = "p",           # Line plot
9   col = "blue",        # Line color
10  lwd = 2,              # Line width
11  main = "Customized sine wave", # Title
12  xlab = "X-axis Label", # X-axis label
13  ylab = "Y-axis Label", # Y-axis label
14  xlim = c(0, 12),     # X-axis limits
15  ylim = c(-1.5, 1.5), # Y-axis limits
16  pch = 20
17 )
18
19
```



# ADDING GRID LINES

```
1  
2 # Adding grid lines  
3 grid(col = "gray", lty = "dotted", lwd = 0.5)
```



3:46 (Top Level) ↕

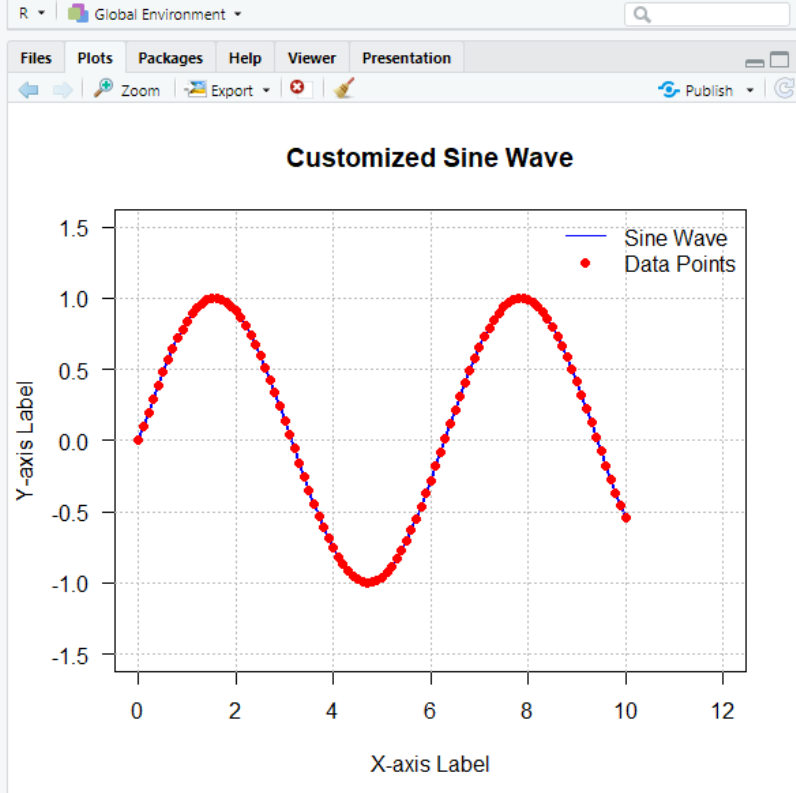
R Script ↕

Console



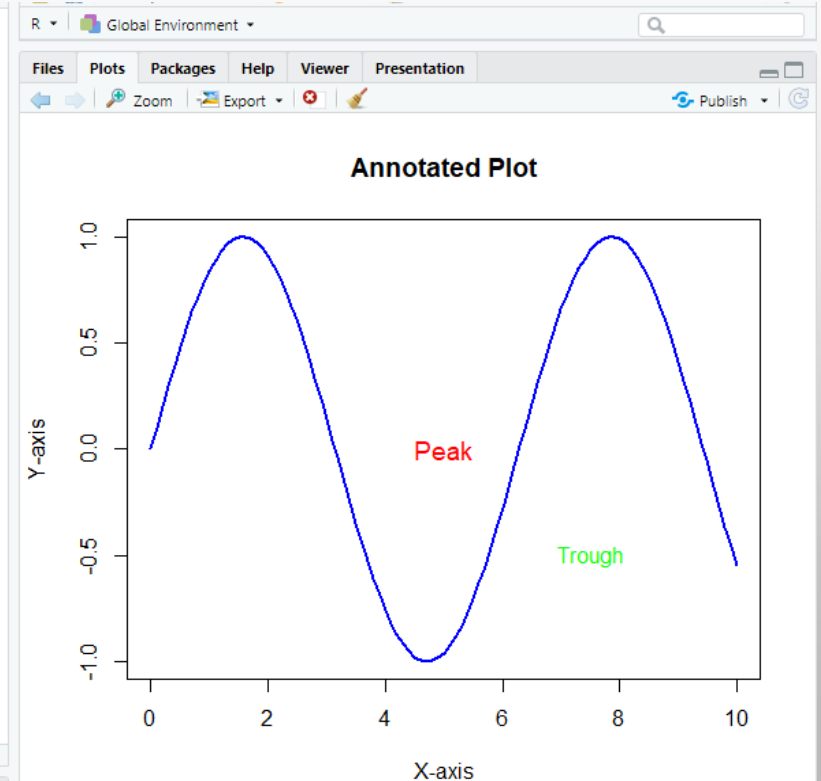
# ADDING A LEGEND

```
1 # Adding a legend
2 legend(
3   "topright",           # Position
4   legend = c("Sine Wave", "Data Points"), # Labels
5   col = c("blue", "red"), # colors
6   lty = c(1, NA),      # Line type (solid for sin
7   pch = c(NA, 16),     # Point type
8 )
9 |
```



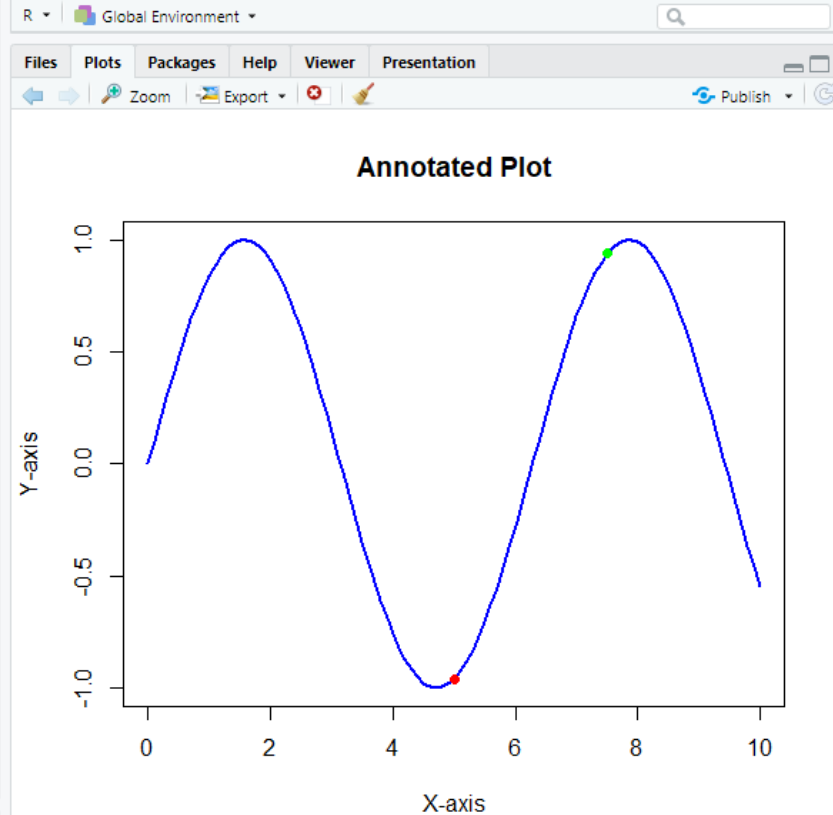
# ADDING A TEXT

```
1  
2 # Add text annotations  
3  
4 text(5, 0, "Peak", col = "red", cex = 1.2)  
5 # Add text at (7.5, -0.5)  
6 text(7.5, -0.5, "Trough", col = "green", cex = 1)
```



# LABEL SPECIFIC POINTS

```
1 # Label specific points
2
3 # Highlight point at x = 5
4 points(5, sin(5), col = "red", pch = 16)
5 # Highlight point at x = 7.5
6 points(7.5, sin(7.5), col = "green", pch = 16) |
```





# COLORS()

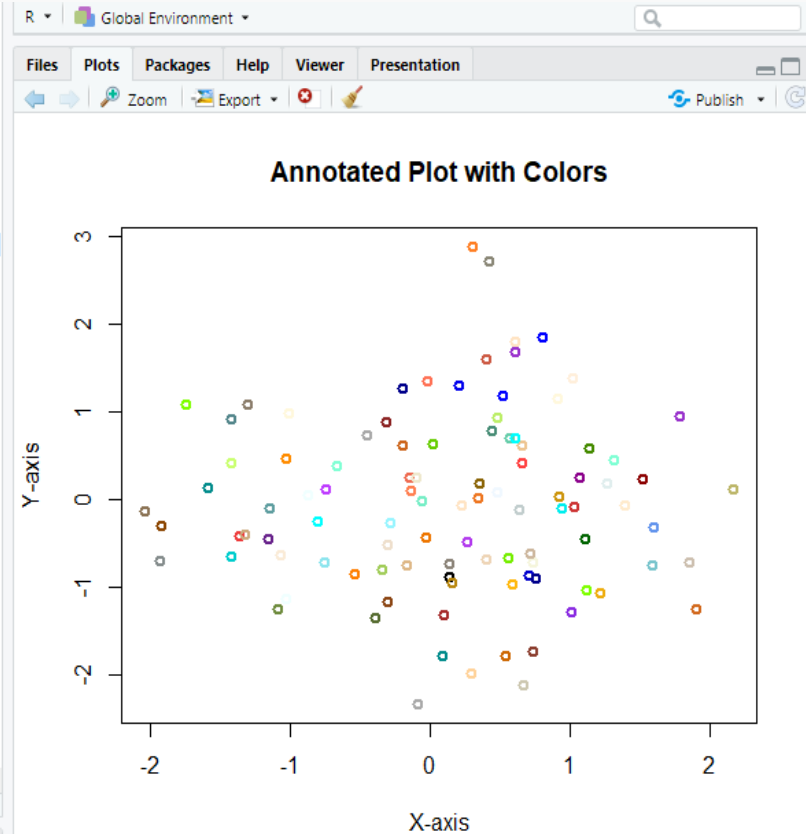
```
> colors(distinct = TRUE)
```

```
[1] "white"  
[2] "aliceblue"  
[3] "antiquewhite"  
[4] "antiquewhite1"  
[5] "antiquewhite2"  
[6] "antiquewhite3"  
[7] "antiquewhite4"  
[8] "aquamarine"  
[9] "aquamarine2"  
[10] "aquamarine3"  
[11] "aquamarine4"  
[12] "azure"  
[13] "azure2"  
[14] "azure3"  
[15] "azure4"  
[16] "beige"  
[17] "bisque"  
[18] "bisque2"  
[19] "bisque3"  
[20] "bisque4"  
[21] "black"  
[22] "blanchedalmond"
```

THE COLORS() FUNCTION  
GENERATES ALL BUILT IN  
COLORS IN R

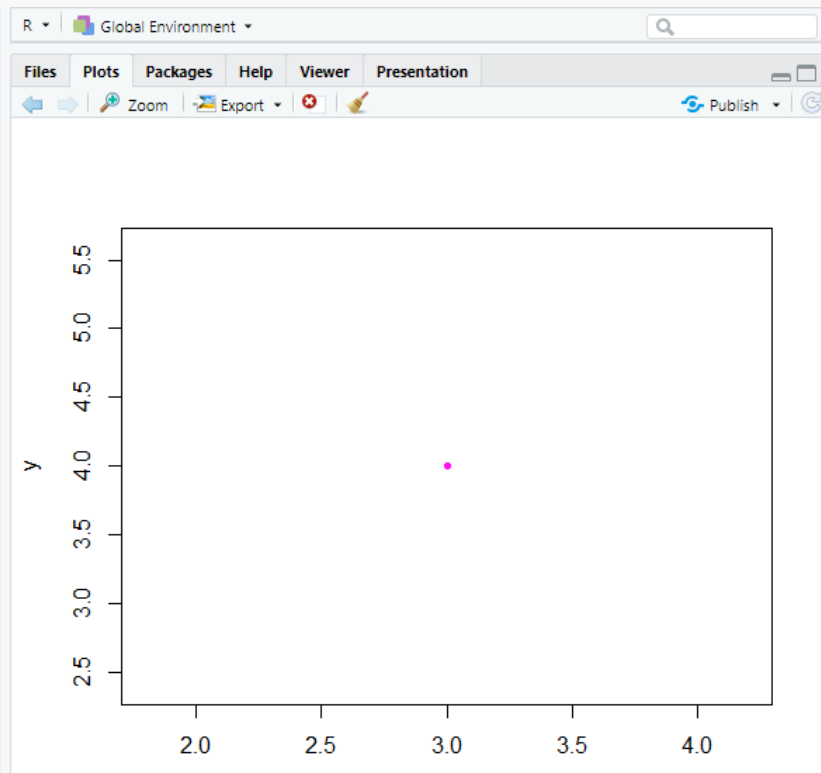
# THIS CAN BE USED LIKE:

```
1 # Generate sample data
2 x <- rnorm(100)
3 y <- rnorm(100)
4
5 # Basic plot with customized colors
6 plot(
7   x, y, type = "p", col = colors(), lwd = 2, # Hex cod
8   main = "Annotated Plot with Colors", xlab = "X-axis",
9 )
```



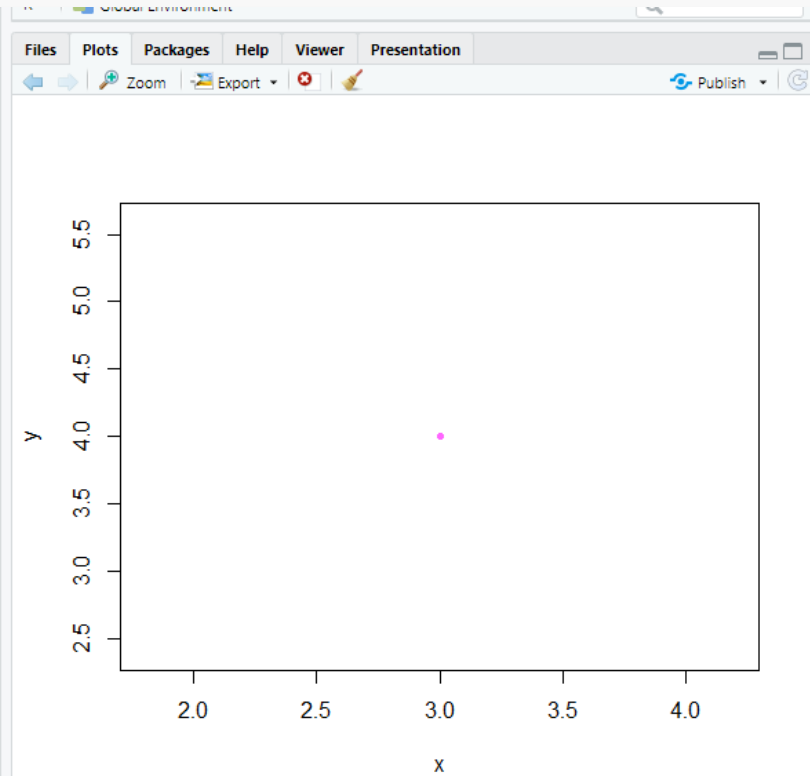
# YOU CAN ALSO USE HEX CODE TO COLOR

```
1 # Generate sample data
2 x <- 3
3 y <- 4
4
5 # Basic plot with customized colors
6 plot(
7   x, y, type = "p", col = "#FF11F3", pch=20
8 )
```



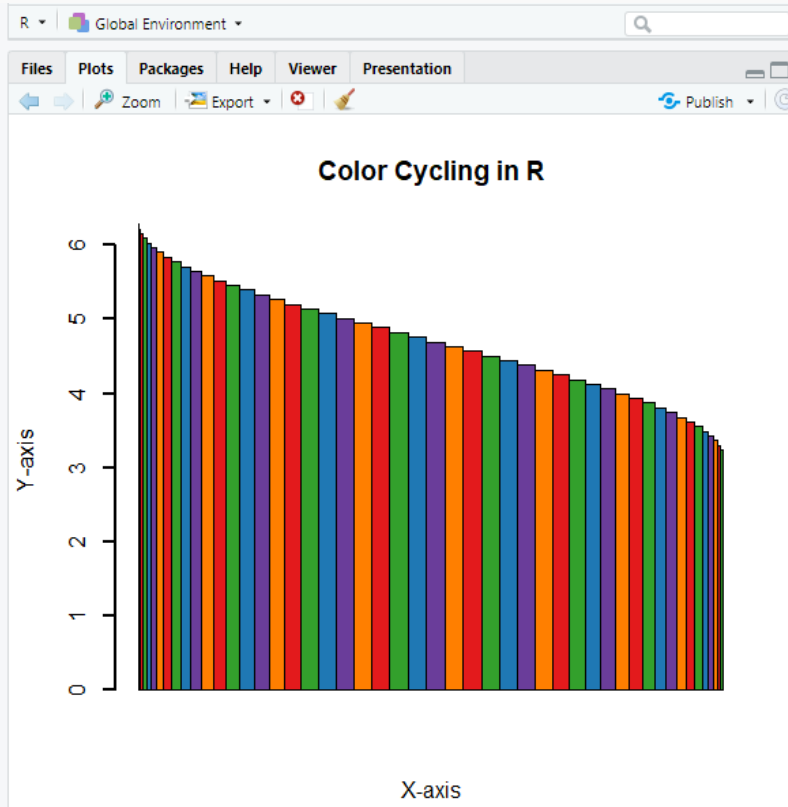
# YOU CAN ALSO USE RGB()

```
> rgb(1,0.4,1)
[1] "#FF66FF"
> plot(x,y,col=rgb(1,0.4,1),pch=20)
> |
```



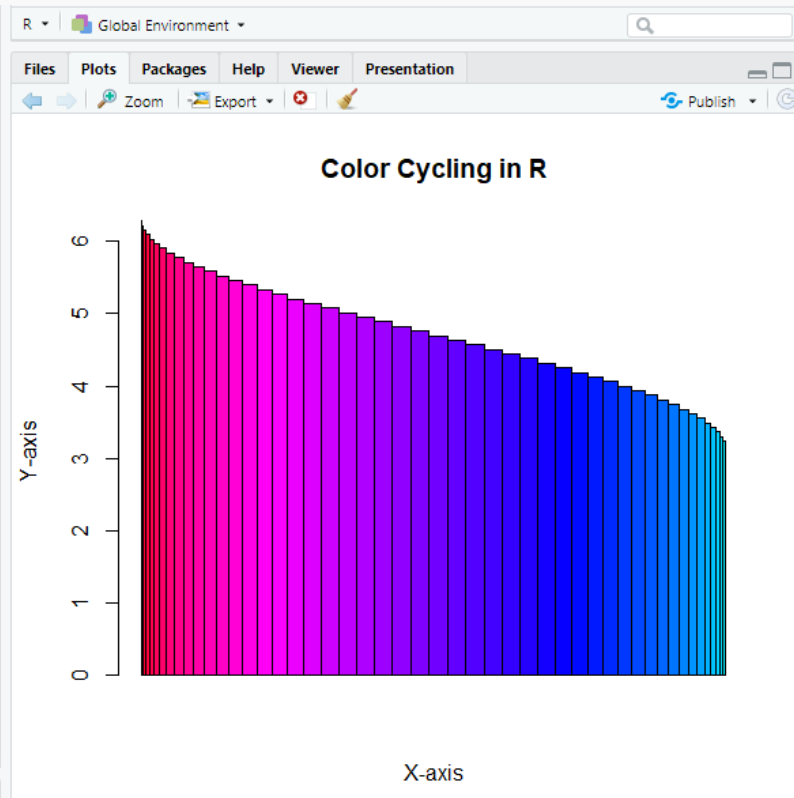
# COLOR CYCLING IN R

```
1 # Create a custom palette
2 custom_colors <- c("#1f78b4",
3                   "#33a02c",
4                   "#e31a1c",
5                   "#ff7f00",
6                   "#6a3d9a") # Hex colors
7 # Plot with color cycling
8 barplot(
9   x, y, type = "l", lty = 1, lwd = 2,
10  col = custom_colors, # Use custom color palette
11  xlab = "X-axis", ylab = "Y-axis", main = "Color cycl
12 )
```



# USING COLOR PALETTES – RAINBOW(N)

```
1  
2 # Plot with color palette  
3 barplot(  
4   x, y, col = rainbow(100),  
5   xlab = "X-axis", ylab = "Y-axis",  
6   main = "Color Cycling in R"  
7 )|
```



# OTHER COLOR PALETTES

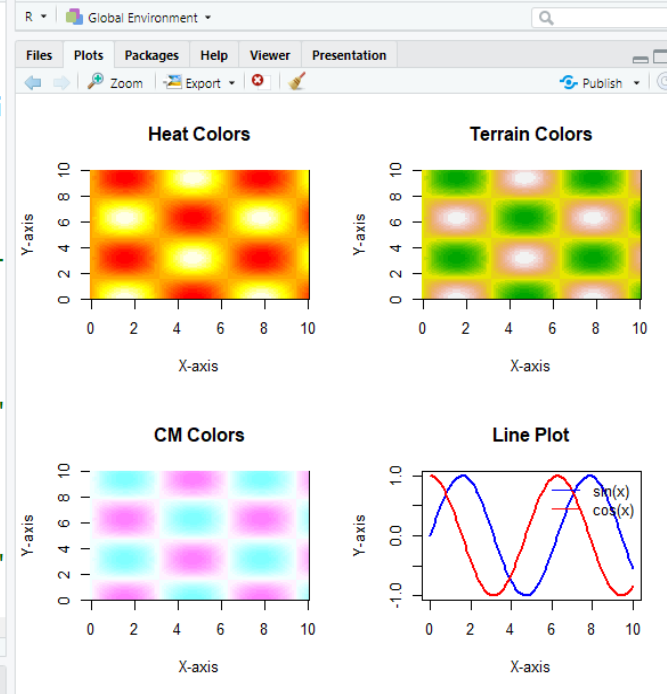
heat.colors()  
terrain.colors()  
cm.colors()

```
1 # Plot 1: Using heat.colors()
2 image(
3   x, x, z, col = heat.colors(20),
4   main = "Heat Colors", xlab = "X-axis", ylab = "Y-axis"
5 )
6 # Plot 2: Using terrain.colors()
7 image(
8   x, x, z, col = terrain.colors(20),
9   main = "Terrain Colors", xlab = "X-axis", ylab = "Y-axis"
10 )
11 # Plot 3: Using cm.colors()
12 image(
13   x, x, z, col = cm.colors(20),
14   main = "CM Colors", xlab = "X-axis", ylab = "Y-axis"
15 )
16 # Plot 4: Line plot for reference
17 plot(
18   x, y1, type = "l", col = "blue", lwd = 2,
19   main = "Line Plot", xlab = "X-axis", ylab = "Y-axis"
20 )
```

20:2 (Top Level) ↕

R Script ↕

Console



# 3D SCATTER PLOT

```
1 # Install the scatterplot3d package
2 install.packages("scatterplot3d")
3
4 # Load the package
5 library(scatterplot3d)
6
7 # Generate random data
8 x <- rnorm(50)
9 y <- rnorm(50)
10 z <- rnorm(50)
11
12 # Create a 3D scatterplot
13 scatterplot3d(
14   x, y, z, pch = 16, color = "blue", |
15   main = "3D scatterplot", xlab = "X-axis",
16   ylab = "Y-axis", zlab = "Z-axis"
17 )
18
```

