

# Chapter 14: Inference for Correlation

DSCC 462

Computational Introduction to Statistics

Anson Kahng

Fall 2022

# Final Project Announcements

# Final Project Announcements

- Teams are due by Friday: Use the Google Sheet (see Announcements) to sign up / find teammates

# Final Project Announcements

- Teams are due by Friday: Use the Google Sheet (see Announcements) to sign up / find teammates
- Final project description is up on Blackboard

# Final Project Announcements

- Teams are due by Friday: Use the Google Sheet (see Announcements) to sign up / find teammates
- Final project description is up on Blackboard
  - Setup: Ad dataset, company wants to understand their data...

# Final Project Announcements

- Teams are due by Friday: Use the Google Sheet (see Announcements) to sign up / find teammates
- Final project description is up on Blackboard
  - Setup: Ad dataset, company wants to understand their data...
  - Some open-ended questions, some less so (room for interpretation!)

# Final Project Announcements

- Teams are due by Friday: Use the Google Sheet (see Announcements) to sign up / find teammates
- Final project description is up on Blackboard
  - Setup: Ad dataset, company wants to understand their data...
  - Some open-ended questions, some less so (room for interpretation!)
- Datasets will be released once teams are formed (Friday)

# Plan for Today



# Plan for Today

- Introduce tools that allow us to go past our previous assumptions of independence when comparing random variables

# Plan for Today

- Introduce tools that allow us to go past our previous assumptions of independence when comparing random variables
- In particular, learn how to infer whether or not a linear relationship exists between two variables,  $X$  and  $Y$

# Correlation

# Correlation

- Recall that correlation tells us the degree to which two random variables are (linearly) associated or related

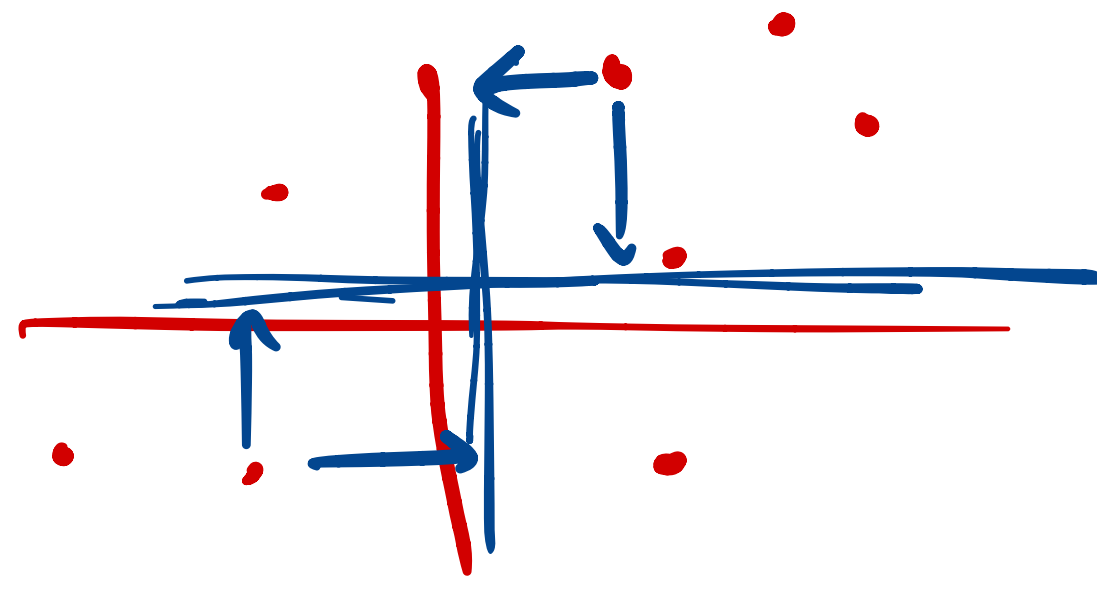
# Correlation

- Recall that correlation tells us the degree to which two random variables are (linearly) associated or related
- We denote the true population correlation of  $X$  and  $Y$  as  $\rho$  ("rho")

# Correlation

- Recall that correlation tells us the degree to which two random variables are (linearly) associated or related
- We denote the true population correlation of  $X$  and  $Y$  as  $\rho$  ("rho")
- We estimate  $\rho$  with Pearson's coefficient of correlation,  $r$  (Chapter 3)

# Correlation



- Recall that correlation tells us the degree to which two random variables are (linearly) associated or related
- We denote the true population correlation of  $X$  and  $Y$  as  $\rho$  ("rho")
- We estimate  $\rho$  with Pearson's coefficient of correlation,  $r$  (Chapter 3)

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\left[ \sum_{i=1}^n (x_i - \bar{x})^2 \right] \left[ \sum_{i=1}^n (y_i - \bar{y})^2 \right]}} = \frac{1}{(n-1)} \sum_{i=1}^n \left( \frac{x_i - \bar{x}}{s_x} \right) \left( \frac{y_i - \bar{y}}{s_y} \right)$$

# Correlation

- Recall that correlation tells us the degree to which two random variables are (linearly) associated or related
- We denote the true population correlation of  $X$  and  $Y$  as  $\rho$  ("rho")
- We estimate  $\rho$  with Pearson's coefficient of correlation,  $r$  (Chapter 3)

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\left[ \sum_{i=1}^n (x_i - \bar{x})^2 \right] \left[ \sum_{i=1}^n (y_i - \bar{y})^2 \right]}} = \frac{1}{(n-1)} \sum_{i=1}^n \left( \frac{x_i - \bar{x}}{s_x} \right) \left( \frac{y_i - \bar{y}}{s_y} \right)$$

- Note that  $-1 \leq r \leq 1$

$s_x \cdot (n-1)$



# Correlation: Example

# Correlation: Example

- Setup: Suppose we examine  $n = 7$  subjects for which we have age and weight measurements

# Correlation: Example

- Setup: Suppose we examine  $n = 7$  subjects for which we have age and weight measurements
- We want to determine whether a significant linear relationship exists between age ( $X$ ) and weight ( $Y$ )

# Correlation: Inference

# Correlation: Inference

- Question: Is the population correlation,  $\rho$ , between two variables,  $X$  and  $Y$ , different from 0?

# Correlation: Inference

- Question: Is the population correlation,  $\rho$ , between two variables,  $X$  and  $Y$ , different from 0?
- In other words, we're investigating whether a linear relationship exists between  $X$  and  $Y$  (age and weight)

# Correlation: Inference

- Question: Is the population correlation,  $\rho$ , between two variables,  $X$  and  $Y$ , different from 0?
- In other words, we're investigating whether a linear relationship exists between  $X$  and  $Y$  (age and weight)
- Use the sample correlation  $r$  for our statistic in hypothesis testing

# Correlation: Inference



# Correlation: Inference

- Hypotheses:  $H_0 : \rho = 0$  vs.  $H_1 : \rho \neq 0$

# Correlation: Inference

- Hypotheses:  $H_0 : \rho = 0$  vs.  $H_1 : \rho \neq 0$
- If pairs  $(x_i, y_i)$  come from normally distributed  $X$  and  $Y$ , then if we standardize  $r$ , we get a statistic that has a t distribution with  $n - 2$  degrees of freedom

# Correlation: Inference

- Hypotheses:  $H_0 : \rho = 0$  vs.  $H_1 : \rho \neq 0$
- If pairs  $(x_i, y_i)$  come from normally distributed  $X$  and  $Y$ , then if we standardize  $r$ , we get a statistic that has a t distribution with  $n - 2$  degrees of freedom
- Test statistic:  $t = \frac{r - \rho}{SE(r)}$ , where  $SE(r) = \sqrt{\frac{1 - r^2}{n - 2}}$

$$z = \frac{\bar{x} - \mu}{SE} \quad \sigma/\sqrt{n}$$

# Correlation: Inference

- Hypotheses:  $H_0 : \rho = 0$  vs.  $H_1 : \rho \neq 0$
- If pairs  $(x_i, y_i)$  come from normally distributed  $X$  and  $Y$ , then if we standardize  $r$ , we get a statistic that has a t distribution with  $n - 2$  degrees of freedom

- Test statistic:  $t = \frac{r - \rho}{SE(r)}$ , where  $SE(r) = \sqrt{\frac{1 - r^2}{n - 2}}$

- We thus get  $t = \frac{r - \rho}{SE(r)} = r \sqrt{\frac{n - 2}{1 - r^2}}$   
 $r \in [-1, 1]$

$$\frac{r - \rho}{SE(r)} = \frac{r}{\sqrt{\frac{1 - r^2}{n - 2}}}$$

# Correlation: Inference Example

# Correlation: Inference Example

- Returning to setup: Suppose we examine  $n = 7$  subjects for which we have age and weight measurements

# Correlation: Inference Example

- Returning to setup: Suppose we examine  $n = 7$  subjects for which we have age and weight measurements
- We want to determine whether a significant linear relationship exists between age ( $X$ ) and weight ( $Y$ )

# Correlation: Inference Example

- Returning to setup: Suppose we examine  $n = 7$  subjects for which we have age and weight measurements
- We want to determine whether a significant linear relationship exists between age ( $X$ ) and weight ( $Y$ )
  - $H_0 : \rho = 0$  vs.  $H_1 : \rho \neq 0$



# Correlation: Inference Example

- Returning to setup: Suppose we examine  $n = 7$  subjects for which we have age and weight measurements
- We want to determine whether a significant linear relationship exists between age ( $X$ ) and weight ( $Y$ )
  - $H_0 : \rho = 0$  vs.  $H_1 : \rho \neq 0$
- We know that the correlation between weight and age for this sample is  $r = 0.865$

# Correlation: Inference Example

- Returning to setup: Suppose we examine  $n = 7$  subjects for which we have age and weight measurements
- We want to determine whether a significant linear relationship exists between age ( $X$ ) and weight ( $Y$ )
  - $H_0 : \rho = 0$  vs.  $H_1 : \rho \neq 0$
- We know that the correlation between weight and age for this sample is  $r = 0.865$
- Test this null hypothesis at the  $\alpha = 0.05$  significance level

# Correlation: Inference Example

# Correlation: Inference Example

- $H_0 : \rho = 0$  vs.  $H_1 : \rho \neq 0$ , test at  $\alpha = 0.05$

# Correlation: Inference Example

- $H_0 : \rho = 0$  vs.  $H_1 : \rho \neq 0$ , test at  $\alpha = 0.05$
- The correlation between weight and age for this sample is  $r = 0.865$

# Correlation: Inference Example

- $H_0 : \rho = 0$  vs.  $H_1 : \rho \neq 0$ , test at  $\alpha = 0.05$
- The correlation between weight and age for this sample is  $r = 0.865$
- Test statistic:

# Correlation: Inference Example

- $H_0 : \rho = 0$  vs.  $H_1 : \rho \neq 0$ , test at  $\alpha = 0.05$
- The correlation between weight and age for this sample is  $r = 0.865$
- Test statistic:
- p-value:

# Correlation: Inference Example

- $H_0 : \rho = 0$  vs.  $H_1 : \rho \neq 0$ , test at  $\alpha = 0.05$   $df = 7 - 2 = 5$
- The correlation between weight and age for this sample is  $r = 0.865$
- Test statistic:

$$t = r \cdot \sqrt{\frac{n-2}{1-r^2}} = 0.865 \cdot \sqrt{\frac{7-2}{1-(0.865)^2}} = 3.856$$

- p-value:

$$p = 2 \cdot \Pr(T \geq 3.856) = 2 \cdot (1 - \text{pt}(3.856, df = 5)) = 0.012$$

- Conclusion:

Reject  $H_0$ , some correlation.



# Correlation: Inference in R

# Correlation: Inference in R

- We can also calculate directly in R using the `cor.test()` function

# Correlation: Inference in R

- We can also calculate directly in R using the `cor.test()` function

```
> x<-c(220,215,179,145,145,177,136)
> y<-c(68,58,43,37,20,58,36)
> cor.test(x,y)
```

Pearson's product-moment correlation

data: x and y

t = 3.856, df = 5, p-value = 0.01193

alternative hypothesis: true correlation is not equal to 0

95 percent confidence interval:

0.3213733 0.9798243

sample estimates:

cor

0.8650727

# Correlation Limitations

# Correlation Limitations

- Only describes linear relationships

# Correlation Limitations

- Only describes linear relationships
  - We could be missing a nonlinear relationship if we don't examine the scatterplot

# Correlation Limitations

- Only describes linear relationships
  - We could be missing a nonlinear relationship if we don't examine the scatterplot
- Hypothesis testing only works for the null hypothesis  $H_0 : \rho = 0$

# Correlation Limitations

- Only describes linear relationships
  - We could be missing a nonlinear relationship if we don't examine the scatterplot
- Hypothesis testing only works for the null hypothesis  $H_0 : \rho = 0$ 
  - For any  $\rho \neq 0$ , normality assumptions are not met and our hypothesis testing procedures are invalid



# Correlation Limitations

- Only describes linear relationships
  - We could be missing a nonlinear relationship if we don't examine the scatterplot
- Hypothesis testing only works for the null hypothesis  $H_0 : \rho = 0$ 
  - For any  $\rho \neq 0$ , normality assumptions are not met and our hypothesis testing procedures are invalid
- Correlation can be very sensitive to outliers and can thus give misleading results when outliers are present

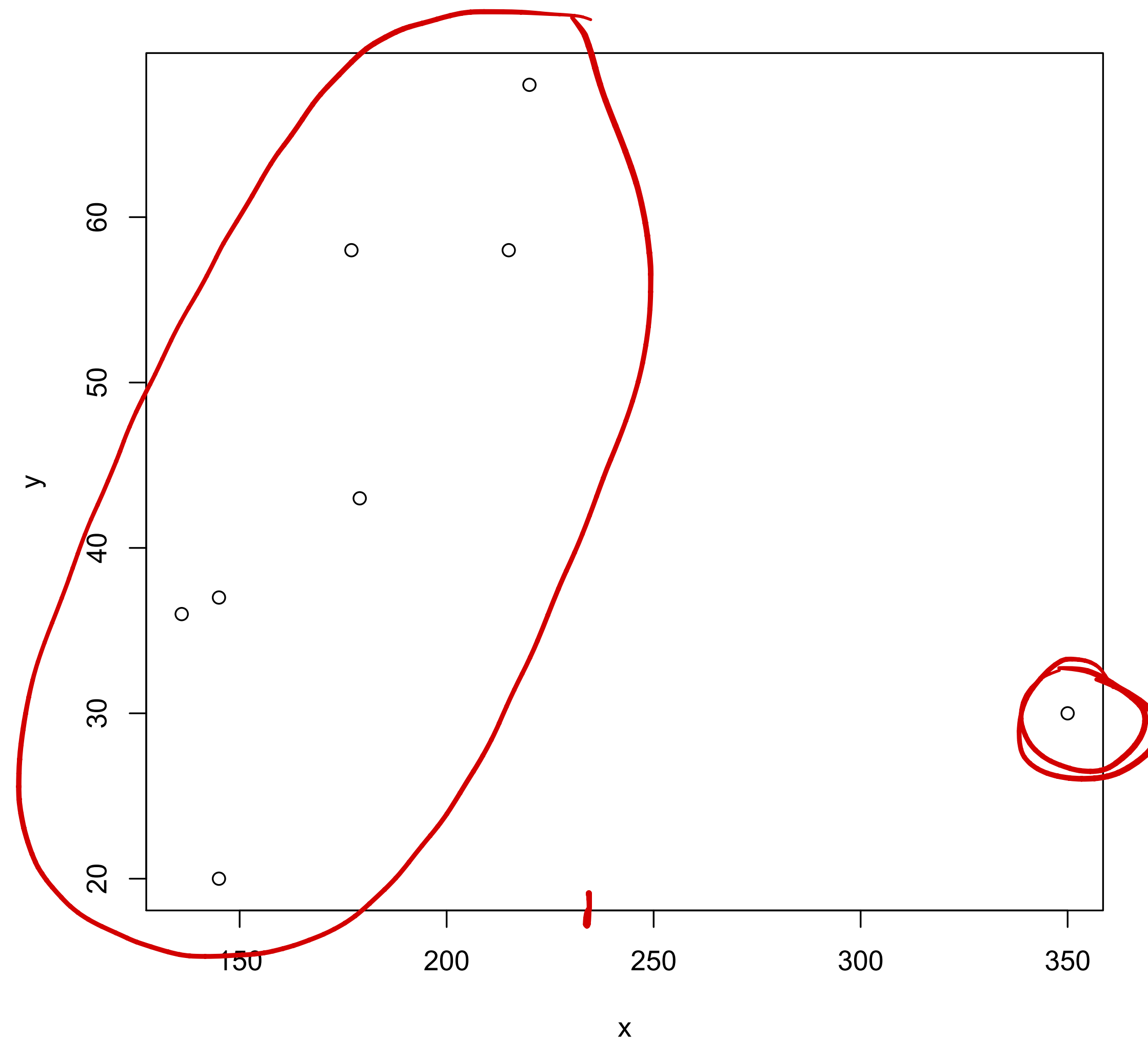
# Correlation Limitations

# Correlation Limitations

- Suppose we have another subject who is 30 years old with a weight of 350 pounds

# Correlation Limitations

- Suppose we have another subject who is 30 years old with a weight of 350 pounds



# Correlation Limitations

```
> x<-c(220,215,179,145,145,177,136, 350)  
> y<-c(68,58,43,37,20,58,36, 30)  
> plot(x,y)  
> cor(x,y)  
[1] 0.06260467
```

# Spearman's Rank Correlation Coefficient

# Spearman's Rank Correlation Coefficient

- Need a more robust measure that isn't as sensitive to outliers

# Spearman's Rank Correlation Coefficient

- Need a more robust measure that isn't as sensitive to outliers
- Instead of using the actual observations, we rank the data and then use the *ranks* as our data



# Spearman's Rank Correlation Coefficient

- Need a more robust measure that isn't as sensitive to outliers
- Instead of using the actual observations, we rank the data and then use the *ranks* as our data
  - If multiple values are the same, assign the average rank

# Spearman's Rank Correlation Coefficient

- Need a more robust measure that isn't as sensitive to outliers
- Instead of using the actual observations, we rank the data and then use the *ranks* as our data
  - If multiple values are the same, assign the average rank
- Rank all the  $x$  values, and call these ranks  $x_r$

# Spearman's Rank Correlation Coefficient

- Need a more robust measure that isn't as sensitive to outliers
- Instead of using the actual observations, we rank the data and then use the *ranks* as our data
  - If multiple values are the same, assign the average rank
- Rank all the  $x$  values, and call these ranks  $x_r$
- Rank all the  $y$  values, and call these ranks  $y_r$

# Spearman's Rank Correlation Coefficient

- Need a more robust measure that isn't as sensitive to outliers
- Instead of using the actual observations, we rank the data and then use the *ranks* as our data
  - If multiple values are the same, assign the average rank
- Rank all the  $x$  values, and call these ranks  $x_r$
- Rank all the  $y$  values, and call these ranks  $y_r$
- Compute the Pearson's correlation coefficient for this ranked data  $(x_r, y_r)$  instead of the actual data

# Spearman's Rank Correlation Coefficient

- Need a more robust measure that isn't as sensitive to outliers
- Instead of using the actual observations, we rank the data and then use the *ranks* as our data
  - If multiple values are the same, assign the average rank
- Rank all the  $x$  values, and call these ranks  $x_r$
- Rank all the  $y$  values, and call these ranks  $y_r$
- Compute the Pearson's correlation coefficient for this ranked data  $(x_r, y_r)$  instead of the actual data
- This is *Spearman's correlation coefficient*



# Spearman's Rank Correlation Coefficient

# Spearman's Rank Correlation Coefficient

- Calculate Spearman's correlation coefficient as follows:

# Spearman's Rank Correlation Coefficient

- Calculate Spearman's correlation coefficient as follows:

$$r_s = \frac{\sum_{i=1}^n (x_{ri} - \bar{x}_r)(y_{ri} - \bar{y}_r)}{\sqrt{\left[ \sum_{i=1}^n (x_{ri} - \bar{x}_r)^2 \right] \left[ \sum_{i=1}^n (y_{ri} - \bar{y}_r)^2 \right]}}$$

$X \rightarrow x_r$   
 $Y \rightarrow y_r$



# Spearman's Rank Correlation Coefficient

- Calculate Spearman's correlation coefficient as follows:

$$r_s = \frac{\sum_{i=1}^n (x_{ri} - \bar{x}_r)(y_{ri} - \bar{y}_r)}{\sqrt{\left[ \sum_{i=1}^n (x_{ri} - \bar{x}_r)^2 \right] \left[ \sum_{i=1}^n (y_{ri} - \bar{y}_r)^2 \right]}}$$

- Note that  $-1 \leq r_s \leq 1$

# Spearman's Rank Correlation Coefficient

- Calculate Spearman's correlation coefficient as follows:

$$r_s = \frac{\sum_{i=1}^n (x_{ri} - \bar{x}_r)(y_{ri} - \bar{y}_r)}{\sqrt{\left[ \sum_{i=1}^n (x_{ri} - \bar{x}_r)^2 \right] \left[ \sum_{i=1}^n (y_{ri} - \bar{y}_r)^2 \right]}}$$

- Note that  $-1 \leq r_s \leq 1$
- Same interpretations of association between  $X$  and  $Y$

# Spearman's Rank Correlation Coefficient

Patient	Weight	Rank	Age	Rank
1	220	7	68	7
2	215	6	<del>58</del>	5.5
3	179	5	<del>43</del>	4
4	[ 145	2.5	37	3
5	[ 145	2.5	- 20	1
6	- 177	4	58	5.5
7	- 136	1	36	2

# Spearman's Rank Correlation Coefficient

- Consider the following age and weight measurements for the 7 subjects

Patient	Weight	Rank	Age	Rank
1	220		68	
2	215		58	
3	179		43	
4	145		37	
5	145		20	
6	177		58	
7	136		36	

# Spearman's Rank Correlation Coefficient

# Spearman's Rank Correlation Coefficient

- Using this information, we can calculate  $r_s$  as follows:

# Spearman's Rank Correlation Coefficient

- Using this information, we can calculate  $r_s$  as follows:
  - $\bar{x}_r =$

# Spearman's Rank Correlation Coefficient

- Using this information, we can calculate  $r_s$  as follows:
  - $\bar{x}_r =$
  - $\bar{y}_r =$



# Spearman's Rank Correlation Coefficient

- Using this information, we can calculate  $r_s$  as follows:
  - $\bar{x}_r =$
  - $\bar{y}_r =$
  - $r_s =$

# Spearman's Rank Correlation Coefficient

1 2 3 4 5 6 7

$(x_i, y_i)$

- Using this information, we can calculate  $r_s$  as follows:

- $\bar{x}_r = 4$

- $\bar{y}_r = 4$

- $r_s = \frac{\sum_{i=1}^n (x_{ri} - 4)(y_{ri} - 4)}{\sqrt{[\sum (x_{ri} - 4)^2][\sum (y_{ri} - 4)^2]}} = \underline{0.873}$

- Recall that Pearson's correlation coefficient was given as 0.865. How does Spearman's rank correlation coefficient compare?

# Spearman's Rank Correlation Coefficient: R

```
> x<-c(220,215,179,145,145,177,136)
> y<-c(68,58,43,37,20,58,36)
> cor(x,y, method="spearman")
[1] 0.8727273
>
> x1 <- rank(x)
> y1 <- rank(y)
> x1; y1
[1] 7.0 6.0 5.0 2.5 2.5 4.0 1.0
[1] 7.0 5.5 4.0 3.0 1.0 5.5 2.0
> cor(x1,y1)
[1] 0.8727273
```

# Spearman's Rank Correlation Coefficient: R

- In R:

*shortcut*

```
> x<-c(220,215,179,145,145,177,136)
> y<-c(68,58,43,37,20,58,36)
> cor(x,y, method="spearman")
[1] 0.8727273
```

*long:*

```
> x1 <- rank(x)
> y1 <- rank(y)
> x1; y1
[1] 7.0 6.0 5.0 2.5 2.5 4.0 1.0
[1] 7.0 5.5 4.0 3.0 1.0 5.5 2.0
> cor(x1,y1)
[1] 0.8727273
```

# Spearman's Rank Correlation Coefficient: Interpretation

# Spearman's Rank Correlation Coefficient: Interpretation

- Spearman's rank correlation coefficient is a measure of concordance of ranks for the outcomes  $x$  and  $y$

# Spearman's Rank Correlation Coefficient: Interpretation

- Spearman's rank correlation coefficient is a measure of concordance of ranks for the outcomes  $x$  and  $y$
- If measurements of  $X$  and  $Y$  are ranked in the same order for each variable, then  $r_s = 1$

# Spearman's Rank Correlation Coefficient: Interpretation

- Spearman's rank correlation coefficient is a measure of concordance of ranks for the outcomes  $x$  and  $y$
- If measurements of  $X$  and  $Y$  are ranked in the same order for each variable, then  $r_s = 1$
- If measurements of  $X$  and  $Y$  are ranked in the reverse order from each other, then  $r_s = -1$



# Spearman's Rank Correlation Coefficient: Interpretation

- Spearman's rank correlation coefficient is a measure of concordance of ranks for the outcomes  $x$  and  $y$
- If measurements of  $X$  and  $Y$  are ranked in the same order for each variable, then  $r_s = 1$
- If measurements of  $X$  and  $Y$  are ranked in the reverse order from each other, then  $r_s = -1$
- If there is no linear correspondence between the ranks, then  $r_s = 0$

# Spearman's Rank Correlation Coefficient: Outliers

# Spearman's Rank Correlation Coefficient: Outliers

- What is the Spearman rank correlation coefficient when we have an outlier in our data?

# Spearman's Rank Correlation Coefficient: Outliers

- What is the Spearman rank correlation coefficient when we have an outlier in our data?

Pearson [  $\frac{r - \rho}{SE} = t$

```
> x<-c(220,215,179,145,145,177,136,350)  
> y<-c(68,58,43,37,20,58,36,30)  
> cor(x,y)  
[1] 0.06260467  
> cor(x,y, method="spearman")  
[1] 0.373494
```

Sp

# Spearman's Rank Correlation Coefficient: Inference

# Spearman's Rank Correlation Coefficient: Inference

- We can similarly perform hypothesis tests for  $\rho$  based on  $r_s$

# Spearman's Rank Correlation Coefficient: Inference

- We can similarly perform hypothesis tests for  $\rho$  based on  $r_s$
- If the sample size is large enough (generally  $n \geq 10$ ) and if we can assume that pairs of ranks  $(x_{ri}, y_{ri})$  are chosen randomly, then we can test the null hypothesis  $H_0 : \rho = 0$  vs. the alternative hypothesis  $H_1 : \rho \neq 0$

Pearson  $t_s = \frac{r_s - \rho}{\sqrt{\frac{1 - r_s^2}{n - 2}}}$

# Spearman's Rank Correlation Coefficient: Inference

- We can similarly perform hypothesis tests for  $\rho$  based on  $r_s$
- If the sample size is large enough (generally  $n \geq 10$ ) and if we can assume that pairs of ranks  $(x_{ri}, y_{ri})$  are chosen randomly, then we can test the null hypothesis  $H_0 : \rho = 0$  vs. the alternative hypothesis  $H_1 : \rho \neq 0$
- Use a similar test statistic:  $t_s = r_s \cdot \sqrt{\frac{n-2}{1-r_s^2}}$



# Spearman's Rank Correlation Coefficient: Inference

- We can similarly perform hypothesis tests for  $\rho$  based on  $r_s$
- If the sample size is large enough (generally  $n \geq 10$ ) and if we can assume that pairs of ranks  $(x_{ri}, y_{ri})$  are chosen randomly, then we can test the null hypothesis  $H_0 : \rho = 0$  vs. the alternative hypothesis  $H_1 : \rho \neq 0$
- Use a similar test statistic:  $t_s = r_s \cdot \sqrt{\frac{n-2}{1-r_s^2}}$
- Compare  $t_s$  to a t distribution with  $n - 2$  degrees of freedom

# Spearman's Rank Correlation Coefficient: Inference

# Spearman's Rank Correlation Coefficient: Inference

- Although we only have  $n = 7$ , let's test  $H_0 : \rho = 0$  vs.  $H_1 : \rho \neq 0$  at  $\alpha = 0.05$

# Spearman's Rank Correlation Coefficient: Inference

- Although we only have  $n = 7$ , let's test  $H_0 : \rho = 0$  vs.  $H_1 : \rho \neq 0$  at  $\alpha = 0.05$
- Calculating our t-statistic:

# Spearman's Rank Correlation Coefficient: Inference

- Although we only have  $n = 7$ , let's test  $H_0 : \rho = 0$  vs.  $H_1 : \rho \neq 0$  at  $\alpha = 0.05$
- Calculating our t-statistic:
- Calculating the p-value:

# Spearman's Rank Correlation Coefficient: Inference

- Although we only have  $n = 7$ , let's test  $H_0 : \rho = 0$  vs.  $H_1 : \rho \neq 0$  at  $\alpha = \underline{0.05}$

- Calculating our t-statistic:

$$r_s = 0.873$$

$$t_s = r_s \sqrt{\frac{n-2}{1-r_s^2}} = 0.873 \sqrt{\frac{7-2}{1-0.873^2}} = 3.997$$

- Calculating the p-value:

$$p = 2 \cdot \Pr(T > 3.997) = \dots = 0.0103$$

- Conclusion:

$$p < \alpha \rightarrow \text{Reject } H_0$$

# Spearman's Rank Correlation Coefficient: R

```
> x<-c(220,215,179,145,145,177,136)
> y<-c(68,58,43,37,20,58,36)
> cor.test(x,y,method="spearman",exact=FALSE)
```

"n ≥ 10"

Spearman's rank correlation rho

data: x and y

S = 7.1273, p-value = 0.01035

alternative hypothesis: true rho is not equal to 0

sample estimates:

rho

$r_s \rightarrow 0.8727273$