Gov 50: 11. Summarizing Bivariate Relationships

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Harvard University

- 1. Z-scores and standardization
- 2. Correlation
- 3. Writing our own functions

1/ Z-scores and standardization

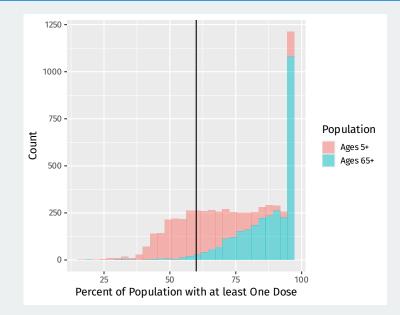
COVID vaccination rates and votes

<pre>library(tidyverse)</pre>	
library(gov50data)	
covid_votes	

## #	# A	tibble:	3,114	x 8	
------	-----	---------	-------	-----	--

##		fips	county	state	one_dose_5plus_pct	one_dose_65plus_pct		
##		<chr></chr>	<chr></chr>	<chr></chr>	<dbl></dbl>	<dbl></dbl>		
##	1	26039	Crawf~	MI	55.7	77.3		
##	2	40015	Caddo~	ОК	83.3	95		
##	3	17007	Boone~	IL	71.1	94.5		
##	4	12055	Highl~	FL	68.9	93.7		
##	5	34029	Ocean~	NJ	71	95		
##	6	01067	Henry~	AL	58.5	85.5		
##	7	27037	Dakot~	MN	81	95		
##	8	27115	Pine ~	MN	56.5	85		
##	9	51750	Radfo~	VA	41.5	73.8		
##	10	22009	Avoye~	LA	59.7	80.1		
## # i 3,104 more rows								
##	## # i 3 more variables: booster_5plus_pct <dbl>,</dbl>							
##	## # dem_pct_2000 <dbl>, dem_pct_2020 <dbl></dbl></dbl>							

Is 60% vaccinated a lot?



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 - Middling for the 5+ group, but very low for the 65+ group.

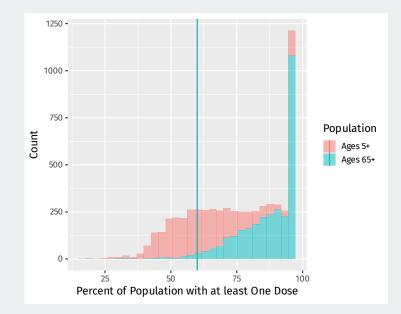
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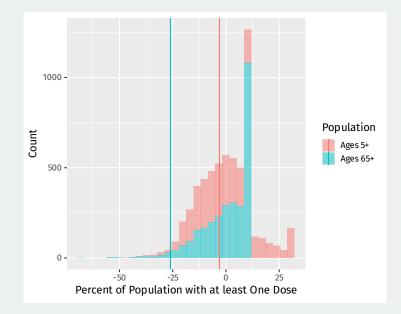
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- Can we transform the values of our variables to be **common units**?
- Yes, with two transformations:
 - **Centering**: subtract the mean of the variable from each value.
 - Scaling: dividing deviations from the mean by the standard deviation.

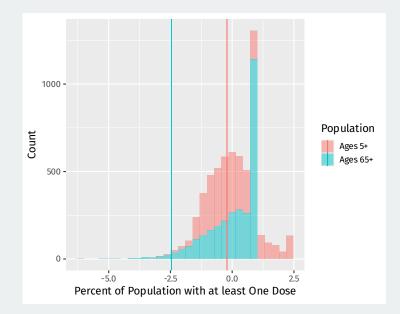
Original distributions



Centered distributions



Centered and scaled distributions



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• Useful heuristic: data more than 3 SDs away from mean are rare.

z-score example

covid_votes >
<pre>mutate(one_dose_centered = one_dose_5plus_pct -</pre>
<pre>mean(one_dose_5plus_pct, na.rm = TRUE)) ></pre>
<pre>select(fips:state, one_dose_5plus_pct, one_dose_centered)</pre>

##	# 4	A tibb]	le: 3,114	x 5		
##		fips	county	state	<pre>one_dose_5plus_pct</pre>	one_dose_centered
##		<chr></chr>	<chr></chr>	<chr></chr>	<dbl></dbl>	<dbl></dbl>
##	1	26039	Crawfor~	MI	55.7	-7.35
##	2	40015	Caddo C~	ОК	83.3	20.2
##	3	17007	Boone C~	IL	71.1	8.05
##	4	12055	Highlan~	FL	68.9	5.85
##	5	34029	Ocean C~	NJ	71	7.95
##	6	01067	Henry C~	AL	58.5	-4.55
##	7	27037	Dakota ~	MN	81	17.9
##	8	27115	Pine Co~	MN	56.5	-6.55
##	9	51750	Radford~	VA	41.5	-21.6
##	10	22009	Avoyell~	LA	59.7	-3.35
## # i 3,104 more rows						

z-score example

```
covid_votes |>
  mutate(
    one_dose_z =
        (one_dose_5plus_pct - mean(one_dose_5plus_pct, na.rm = TRUE)) /
        sd(one_dose_5plus_pct, na.rm = TRUE)) |>
        select(fips:state, one_dose_5plus_pct, one_dose_z)
```

##	# /	A tibbl	le: 3,114 x 5			
##		fips	county	state	<pre>one_dose_5plus_pct</pre>	one_dose_z
##		<chr></chr>	<chr></chr>	<chr></chr>	<dbl></dbl>	<dbl></dbl>
##	1	26039	Crawford County	MI	55.7	-0.508
##	2	40015	Caddo County	OK	83.3	1.40
##	3	17007	Boone County	IL	71.1	0.556
##	4	12055	Highlands Coun~	FL	68.9	0.404
##	5	34029	Ocean County	NJ	71	0.549
##	6	01067	Henry County	AL	58.5	-0.314
##	7	27037	Dakota County	MN	81	1.24
##	8	27115	Pine County	MN	56.5	-0.452
##	9	51750	Radford city	VA	41.5	-1.49
##	10	22009	Avoyelles Pari~	LA	59.7	-0.231
##	# :	i 3,104	+ more rows			

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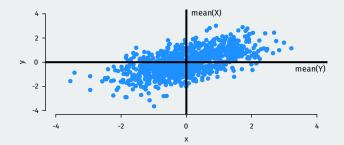
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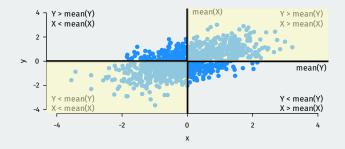
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- Interpretation:
 - Correlation is between -1 and 1
 - Correlation of 0 means no linear association.
 - Positive correlations \rightsquigarrow positive associations.
 - Negative correlations \rightsquigarrow negative associations.
 - Closer to -1 or 1 means stronger association.

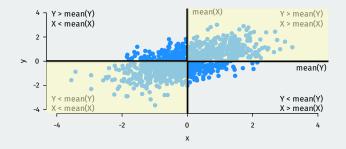
Correlation intuition



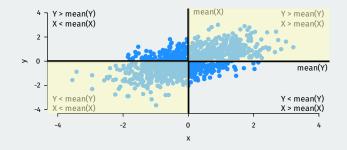
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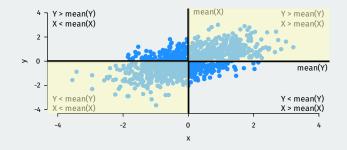
• Large values of X tend to occur with large values of Y:



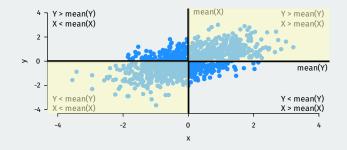
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 - (z-score for x_i) × (z-score for y_i) = (pos. num.) × (pos. num) = +



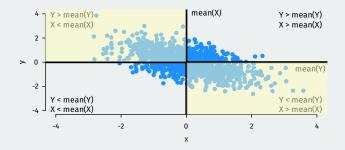
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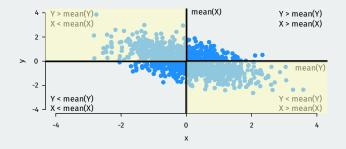
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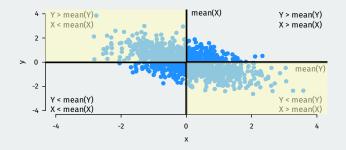
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- If these dominate \rightsquigarrow positive correlation.



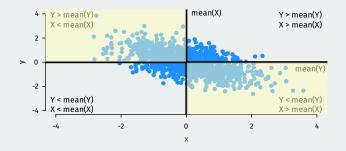
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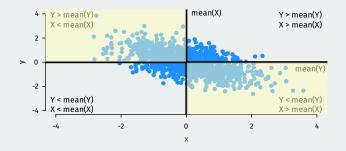
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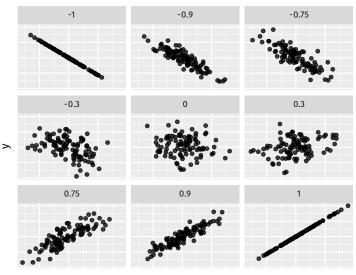


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 - (z-score for x_i) × (z-score for y_i) = (neg. num.) × (pos. num) = -
- If these dominate \leadsto negative correlation.

Correlation examples



х

• Correlation measures **linear** association.

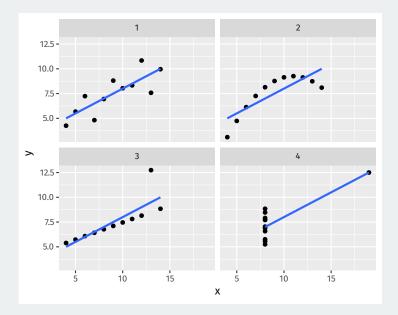
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 - cor(x,y) = cor(ax+b, cy+d)
 - Celsius vs. Fahreneheit; dollars vs. pesos; cm vs. in.

All 4 relationships have 0.816 correlation



Use the cor() function:

cor(covid_votes\$one_dose_5plus_pct, covid_votes\$dem_pct_2020)

[1] NA

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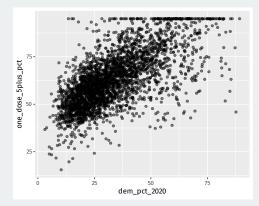
[1] NA

Missing values: set the use = "pairwise" \rightarrow available case analysis

cor(covid_votes\$one_dose_5plus_pct, covid_votes\$dem_pct_2020, use = "pairwise")

Comparing correlations

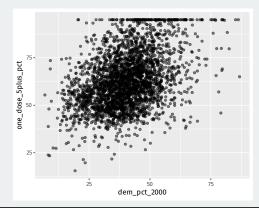
covid_votes |>
 ggplot(aes(x = dem_pct_2020, y = one_dose_5plus_pct)) +
 geom_point(alpha = 0.5)



cor(covid_votes\$one_dose_5plus_pct, covid_votes\$dem_pct_2020, use = "pairwise")

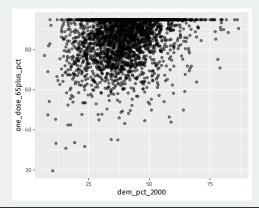
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covid_votes |>
 ggplot(aes(x = dem_pct_2000, y = one_dose_5plus_pct)) +
 geom point(alpha = 0.5)



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covid_votes |>
 ggplot(aes(x = dem_pct_2000, y = one_dose_65plus_pct)) +
 geom_point(alpha = 0.5)



cor(covid_votes\$one_dose_65plus_pct, covid_votes\$dem_pct_2000, use = "pairwise")

3/ Writing our own functions

Why write functions?

Copy-pasting code tedious and prone to failure:

```
covid_votes |>
 mutate(
    one dose 5p z =
      (one_dose_5plus_pct - mean(one_dose_5plus_pct, na.rm = TRUE)) /
      sd(one dose 5plus pct, na.rm = TRUE),
    one dose 65p z =
      (one_dose_65plus_pct - mean(one_dose_65plus_pct, na.rm = TRUE)) /
      sd(one dose 65plus pct, na.rm = TRUE),
    booster z =
      (booster 5plus pct - mean(booster 5plus pct, na.rm = TRUE)) /
      sd(booster 5plus pct, na.rm = TRUE),
    dem pct 2000 z =
      (dem pct 2000 - mean(dem pct 2000, na.rm = TRUE)) /
      sd(dem pct 2000, na.rm = TRUE),
    dem pct_2020_z =
      (dem_pct_2020 - mean(dem_pct_2020, na.rm = TRUE)) /
      sd(dem_pct_2020, na.rm = TRUE)
```

Notice that all of the mutations follow the same template:

(- mean(, na.rm = TRUE)) / sd(, na.rm = TRUE)

Only one thing varies: the column of data, represented with

We create functions like so:

<pre>name <- function(arguments) {</pre>	
body	
}	

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body		
}		

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- Name: the name of the function that we'll use to call it. Maybe z_score?
- 2. **Arguments**: things that we want to vary across calls of our function. We'll use x.
- 3. Body: the code that the function performs.

Convert our template to a function:

z_score <- function(x) {
 (x - mean(x, na.rm = TRUE)) / sd(x, na.rm = TRUE)
}</pre>

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 (x - mean(x, na.rm = TRUE)) / sd(x, na.rm = TRUE)
}</pre>

Check that it seems to work:

z_score(c(1,2, 3, 4, 5))

[1] -1.265 -0.632 0.000 0.632 1.265

```
covid_votes |>
mutate(
    one_dose_5p_z = z_score(one_dose_5plus_pct),
    one_dose_65p_z = z_score(one_dose_65plus_pct),
    booster_z = z_score(booster_5plus_pct),
    dem_pct_2000_z = z_score(dem_pct_2000),
    dem_pct_2020_z = z_score(dem_pct_2020)
)
```

across() function

If we want to replace our variables with z-scores, we can use the across() function to perform many mutations at once:

covid_votes |>
 mutate(across(one_dose_5plus_pct:dem_pct_2020, z_score))

## # A tibble: 3,114 x 8						
##	fips	county stat	e one_dose_5plus_pct	one_dose_65plus_pct		
##	<chr></chr>	<chr> <chr< td=""><td>> <dbl></dbl></td><td><dbl></dbl></td></chr<></chr>	> <dbl></dbl>	<dbl></dbl>		
##	1 26039	Crawf~ MI	-0.508	-0.829		
##	2 40015	Caddo~ OK	1.40	0.843		
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##	10 22009	Avoye~ LA	-0.231	-0.564		
## # i 3,104 more rows						
<pre>## # i 3 more variables: booster_5plus_pct <dbl>,</dbl></pre>						
## # dem_pct_2000 <dbl>, dem_pct_2020 <dbl></dbl></dbl>						

Alternative approach

We could also target all the numeric variables:

covid_votes |>
 mutate(across(where(is.numeric), z_score))

## # A tibble: 3,114 x 8						
##		fips	county	state	<pre>one_dose_5plus_pct</pre>	one_dose_65plus_pct
##		<chr></chr>	<chr></chr>	<chr></chr>	<dbl></dbl>	<dbl></dbl>
##	1	26039	Crawf~	MI	-0.508	-0.829
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##	9	51750	Radfo~	VA	-1.49	-1.16
##	10	22009	Avoye~	LA	-0.231	-0.564
##	# 3	i 3,104	4 more 1	OWS		
##	## # i 3 more variables: booster_5plus_pct <dbl>,</dbl>					
##	#	dem p	oct 2000) <dbl:< td=""><td>>, dem pct 2020 <db]< td=""><td>L></td></db]<></td></dbl:<>	>, dem pct 2020 <db]< td=""><td>L></td></db]<>	L>

Alternative approach

We could also target only the first dose variables:

covid_votes |>
 mutate(across(starts_with("one_dose"), z_score))

## # A tibble: 3,114 x 8						
##		fips	county	state	<pre>one_dose_5plus_pct</pre>	one_dose_65plus_pct
##		<chr></chr>	<chr></chr>	<chr></chr>	<dbl></dbl>	<dbl></dbl>
##	1	26039	Crawf~	MI	-0.508	-0.829
##	2	40015	Caddo~	OK	1.40	0.843
##	3	17007	Boone~	IL	0.556	0.795
##	4	12055	Highl~	FL	0.404	0.720
##	5	34029	Ocean~	NJ	0.549	0.843
##	6	01067	Henry~	AL	-0.314	-0.0545
##	7	27037	Dakot~	MN	1.24	0.843
##	8	27115	Pine ~	MN	-0.452	-0.102
##	9	51750	Radfo~	VA	-1.49	-1.16
##	10	22009	Avoye~	LA	-0.231	-0.564
##	# 3	i 3,104	4 more 1	rows		
##	## # i 3 more variables: booster_5plus_pct <dbl>,</dbl>					
##	#	dem (oct 2000	∂ <dbl:< td=""><td>>, dem pct 2020 <db]< td=""><td>L></td></db]<></td></dbl:<>	>, dem pct 2020 <db]< td=""><td>L></td></db]<>	L>

What if we want to be able to control na.rm in the calls to mean() and sd() in our z_score function? Add an argument!

z_score2 <- function(x, na.rm = FALSE) {
 (x - mean(x, na.rm = na.rm)) / sd(x, na.rm = na.rm)
</pre>

head(z_score2(covid_votes\$one_dose_5plus_pct))

[1] NA NA NA NA NA NA

head(z_score2(covid_votes\$one_dose_5plus_pct, na.rm = TRUE))

[1] -0.508 1.398 0.556 0.404 0.549 -0.314