

Gov 50: 10. Summarizing Bivariate Relationships

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Roadmap

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

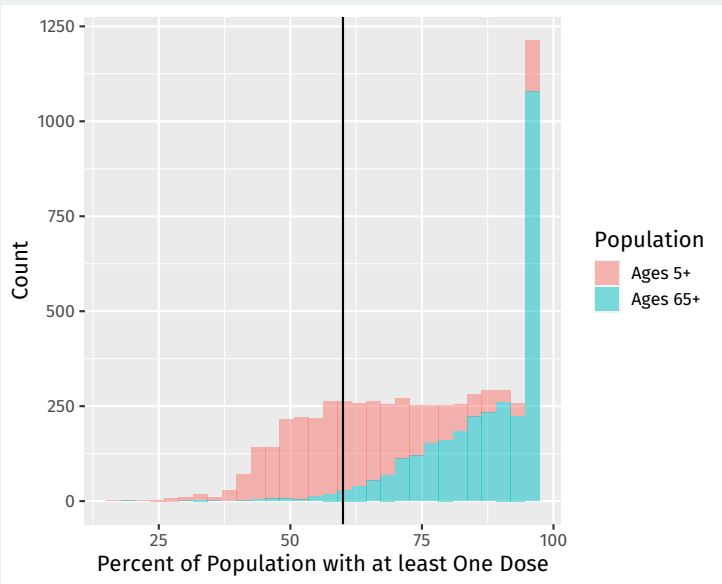
1/ Z-scores and standardization

COVID vaccination rates and votes

```
library(tidyverse)
library(gov50data)
covid_votes
```

```
## # A tibble: 3,114 x 8
##   fips county      state one_d~1 one_d~2 boost~3 dem_p~4
##   <chr> <chr>      <chr> <dbl> <dbl> <dbl> <dbl>
## 1 26039 Crawford Cou~ MI      55.7  77.3  31.2  43.8
## 2 40015 Caddo County OK       83.3  95    30.3  46.4
## 3 17007 Boone County IL       71.1  94.5  35.1  41.8
## 4 12055 Highlands Co~ FL       68.9  93.7  24.7  40.3
## 5 34029 Ocean County NJ        71    95    32.1  47.2
## 6 01067 Henry County AL       58.5  85.5  18.2  40.1
## 7 27037 Dakota County MN        81    95    49.5  46.9
## 8 27115 Pine County MN       56.5  85    31.7  47.0
## 9 51750 Radford city VA       41.5  73.8  1.79  46.4
## 10 22009 Avoyelles Pa~ LA       59.7  80.1  21.9  45.7
## # ... with 3,104 more rows, 1 more variable:
## #   dem_pct_2020 <dbl>, and abbreviated variable names
## #   1: one_dose_5plus_pct, 2: one_dose_65plus_pct,
## #   3: booster_5plus_pct, 4: dem_pct_2000
```

Is 60% vaccinated a lot?



How large is large?

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- Yes, with two transformations:

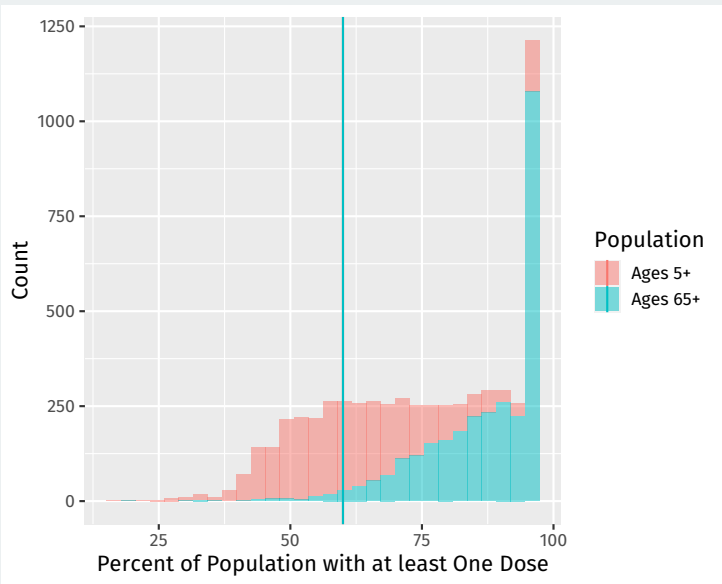
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- Yes, with two transformations:
 - **Centering**: subtract the mean of the variable from each value.

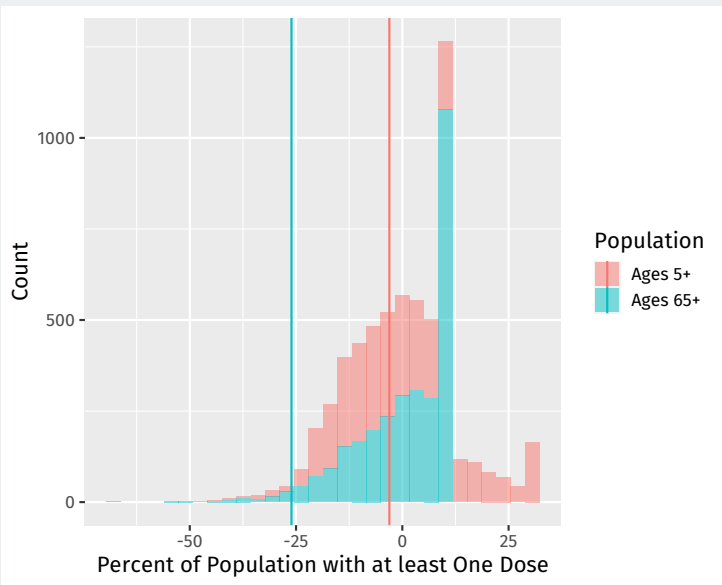
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- How large 60% vaccinated is depends on the distribution!
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 - Middling for the 5+ group, but very low for the 65+ group.
- Can we transform the values of our variables to be **common units**?
- Yes, with two transformations:
 - **Centering**: subtract the mean of the variable from each value.
 - **Scaling**: dividing deviations from the mean by the standard deviation.

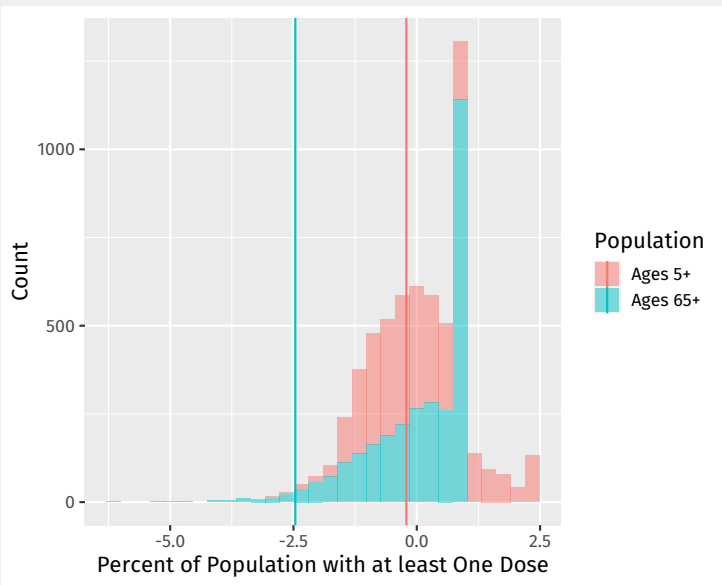
Original distributions



Centered distributions



Centered and scaled distributions



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$$\text{z-score of } x_i = \frac{x_i - \text{mean of } x}{\text{standard deviation of } x}$$

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

z-score example

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

```
## # A tibble: 3,114 x 5
##   fips county          state one_dose_5plus_pct one_dos~1
##   <chr> <chr>          <chr>          <dbl>          <dbl>
## 1 26039 Crawford County MI              55.7           -7.35
## 2 40015 Caddo County    OK              83.3            20.2
## 3 17007 Boone County  IL              71.1             8.05
## 4 12055 Highlands County FL              68.9             5.85
## 5 34029 Ocean County  NJ              71                7.95
## 6 01067 Henry County  AL              58.5            -4.55
## 7 27037 Dakota County MN              81               17.9
## 8 27115 Pine County  MN              56.5            -6.55
## 9 51750 Radford city VA              41.5            -21.6
## 10 22009 Avoyelles Parish LA              59.7            -3.35
## # ... with 3,104 more rows, and abbreviated variable name
## #   1: one_dose_centered
```

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 tibble: 3,114 x 5
##   fips county          state one_dose_5plus_pct one_dos~1
##   <chr> <chr>          <chr>          <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 County 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 Parish LA             59.7      -0.231
## # ... with 3,104 more rows, and abbreviated variable name
## #   1: one_dose_z
```

2/ Correlation

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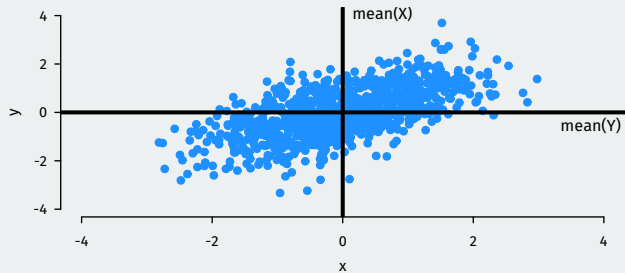
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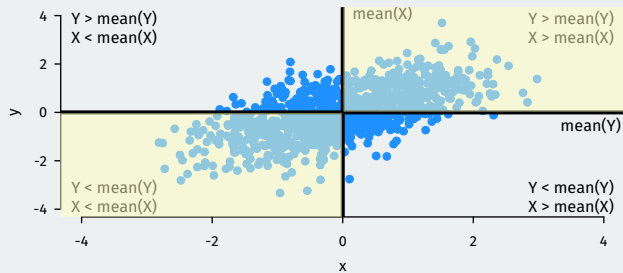
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- Interpretation:
 - Correlation is between -1 and 1
 - Correlation of 0 means no linear association.
 - Positive correlations \rightsquigarrow positive associations.
 - Negative correlations \rightsquigarrow negative associations.
 - Closer to -1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

Correlation intuition

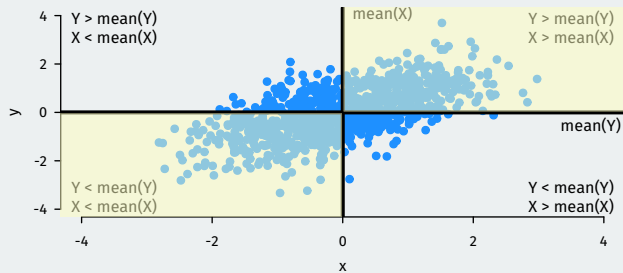


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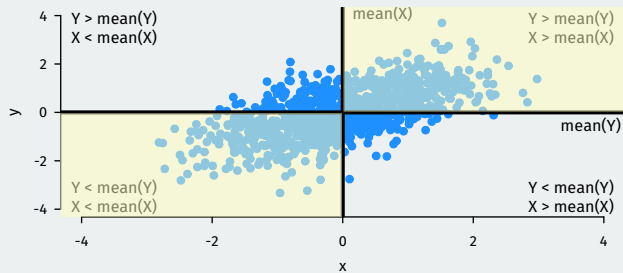
- Large values of X tend to occur with large values of Y:

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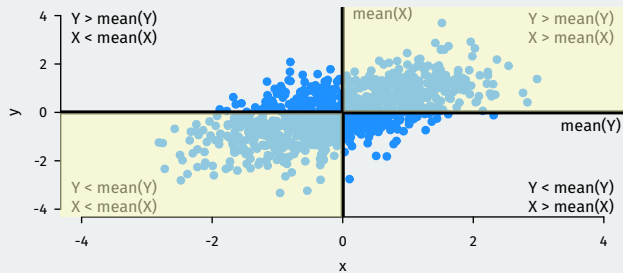
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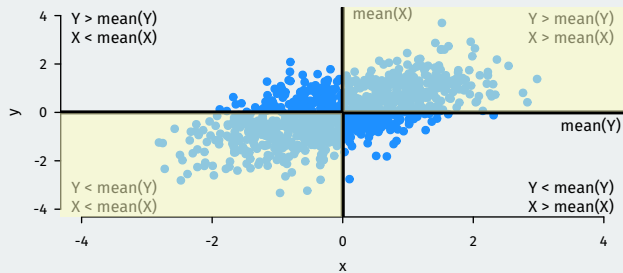
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Correlation intuition



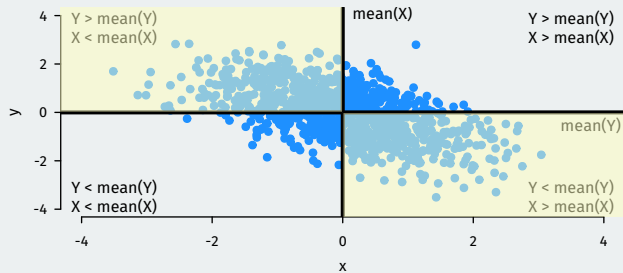
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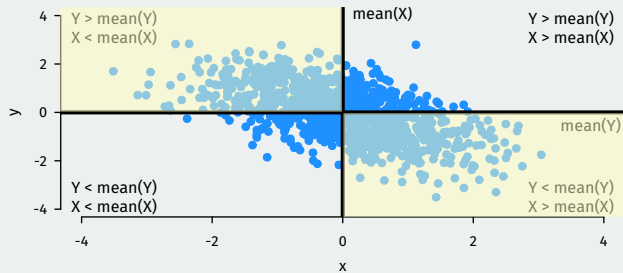
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- If these dominate \rightsquigarrow positive correlation.

Correlation intuition



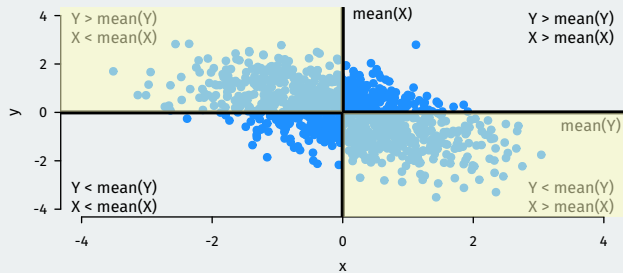
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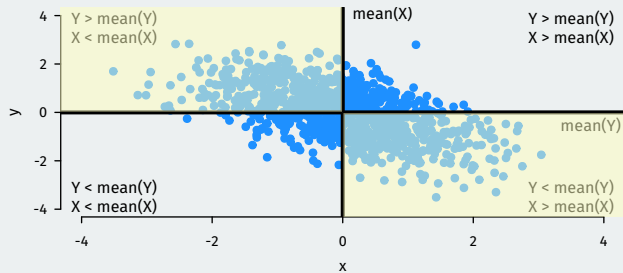
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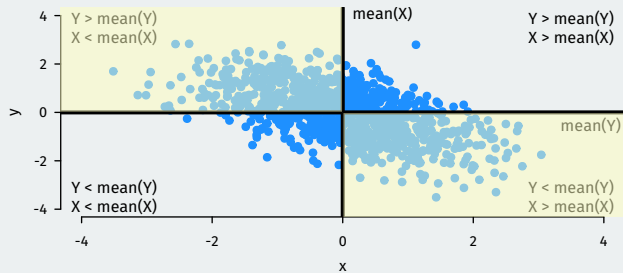
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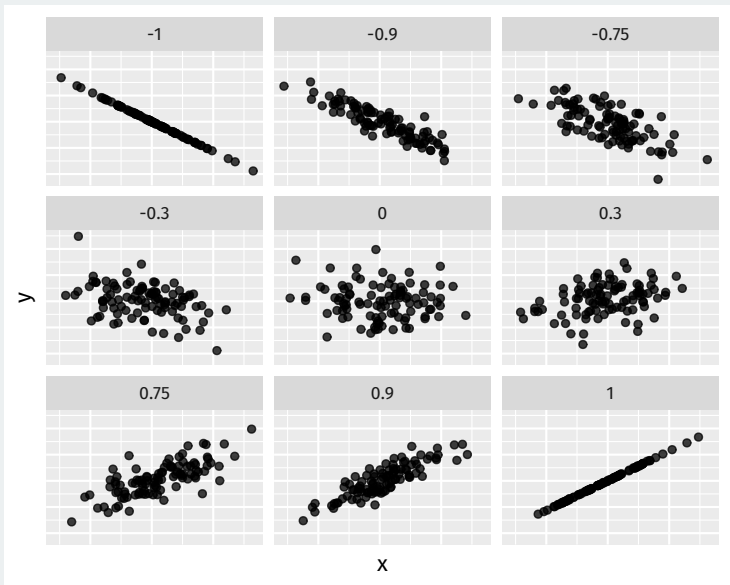
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- If these dominate \rightsquigarrow negative correlation.

Correlation examples



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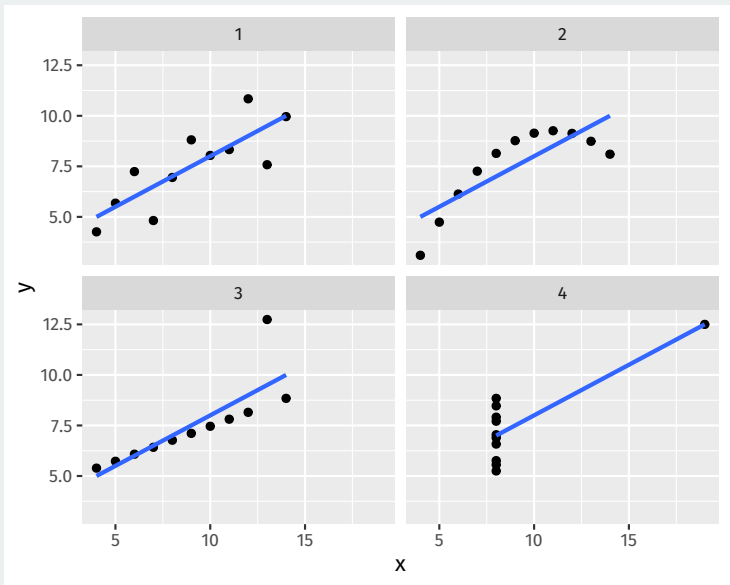
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- Not affected by changes of scale:
 - $\text{cor}(x, y) = \text{cor}(ax+b, cy+d)$
 - Celsius vs. Fahrenheit; dollars vs. pesos; cm vs. in.

All 4 relationships have 0.816 correlation



Correlation in R

Use the `cor()` function:

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

```
## [1] NA
```

Correlation in R

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```
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```

```
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```

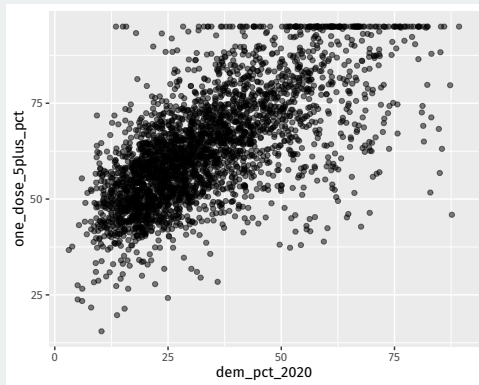
Missing values: set the `use = "pairwise"` → available case analysis

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

```
## [1] 0.666
```

Comparing correlations

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

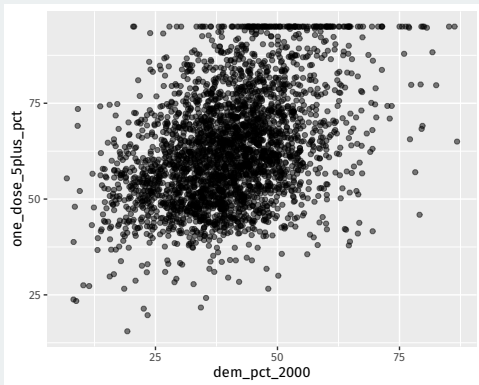


```
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     use = "pairwise")
```

```
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```

Comparing correlations

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

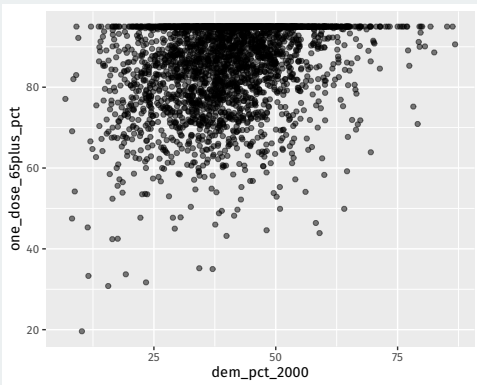


```
cor(covid_votes$one_dose_5plus_pct, covid_votes$dem_pct_2000,  
     use = "pairwise")
```

```
## [1] 0.394
```


Comparing correlations

```
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")
```

```
## [1] 0.263
```

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)
  )
```

Writing a new function

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 `█`

Components of a function

We create functions like so:

```
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1. **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.

Our first function

Convert our template to a function:

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

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z_score <- function(x) {  
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}
```

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
```

Cleaning up our code

```
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      state one_d~1 one_d~2 boost~3 dem_p~4
##   <chr> <chr>      <chr> <dbl> <dbl> <dbl> <dbl>
## 1 26039 Crawford Cou~ MI     -0.508 -0.829  0.531 0.340
## 2 40015 Caddo County OK      1.40  0.843  0.439 0.556
## 3 17007 Boone County IL      0.556 0.795  0.927 0.163
## 4 12055 Highlands Co~ FL      0.404 0.720 -0.135 0.0402
## 5 34029 Ocean County NJ      0.549 0.843  0.623 0.624
## 6 01067 Henry County AL     -0.314 -0.0545 -0.799 0.0255
## 7 27037 Dakota County MN      1.24  0.843  2.40  0.598
## 8 27115 Pine County MN     -0.452 -0.102  0.577 0.612
## 9 51750 Radford city VA     -1.49 -1.16  -2.47 0.556
## 10 22009 Avoyelles Pa~ LA     -0.231 -0.564 -0.424 0.501
## # ... with 3,104 more rows, 1 more variable:
## #   dem_pct_2020 <dbl>, and abbreviated variable names
## #   1: one_dose_5plus_pct, 2: one_dose_65plus_pct,
```

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 one_d~1 one_d~2 boost~3 dem_p~4  
##   <chr> <chr>      <chr> <dbl> <dbl> <dbl> <dbl>  
## 1 26039 Crawford Cou~ MI    -0.508 -0.829  0.531  0.340  
## 2 40015 Caddo County OK     1.40  0.843  0.439  0.556  
## 3 17007 Boone County IL     0.556 0.795  0.927  0.163  
## 4 12055 Highlands Co~ FL     0.404 0.720 -0.135 0.0402  
## 5 34029 Ocean County NJ     0.549 0.843  0.623  0.624  
## 6 01067 Henry County AL    -0.314 -0.0545 -0.799 0.0255  
## 7 27037 Dakota County MN     1.24  0.843  2.40  0.598  
## 8 27115 Pine County MN    -0.452 -0.102  0.577  0.612  
## 9 51750 Radford city VA    -1.49 -1.16  -2.47  0.556  
## 10 22009 Avoyelles Pa~ LA    -0.231 -0.564 -0.424 0.501  
## # ... with 3,104 more rows, 1 more variable:  
## #   dem_pct_2020 <dbl>, and abbreviated variable names  
## #   1: one_dose_5plus_pct, 2: one_dose_65plus_pct,  
## #   3: booster_5plus_pct, 4: dem_pct_2000
```

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 one_d~1 one_d~2 boost~3 dem_p~4
##   <chr> <chr>      <chr> <dbl> <dbl> <dbl> <dbl>
## 1 26039 Crawford Cou~ MI     -0.508 -0.829 31.2 43.8
## 2 40015 Caddo County OK      1.40 0.843 30.3 46.4
## 3 17007 Boone County IL      0.556 0.795 35.1 41.8
## 4 12055 Highlands Co~ FL      0.404 0.720 24.7 40.3
## 5 34029 Ocean County NJ      0.549 0.843 32.1 47.2
## 6 01067 Henry County AL     -0.314 -0.0545 18.2 40.1
## 7 27037 Dakota County MN      1.24 0.843 49.5 46.9
## 8 27115 Pine County MN     -0.452 -0.102 31.7 47.0
## 9 51750 Radford city VA     -1.49 -1.16 1.79 46.4
## 10 22009 Avoyelles Pa~ LA     -0.231 -0.564 21.9 45.7
## # ... with 3,104 more rows, 1 more variable:
## #   dem_pct_2020 <dbl>, and abbreviated variable names
## #   1: one_dose_5plus_pct, 2: one_dose_65plus_pct,
## #   3: booster_5plus_pct, 4: dem_pct_2000
```

Adding arguments to our function

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)  
}
```

```
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
```