Summerizing relationships and tidying and joining data

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Agenda

- Housekeeping
- Z-scores and standardization
- Correlation
- Writing our own functions
- Causality review
- Pivoting data longer
- Joining data sets

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Here is the link for the another example from Gruber on the powerful DiD tool

- This link will expire in a couple of weeks

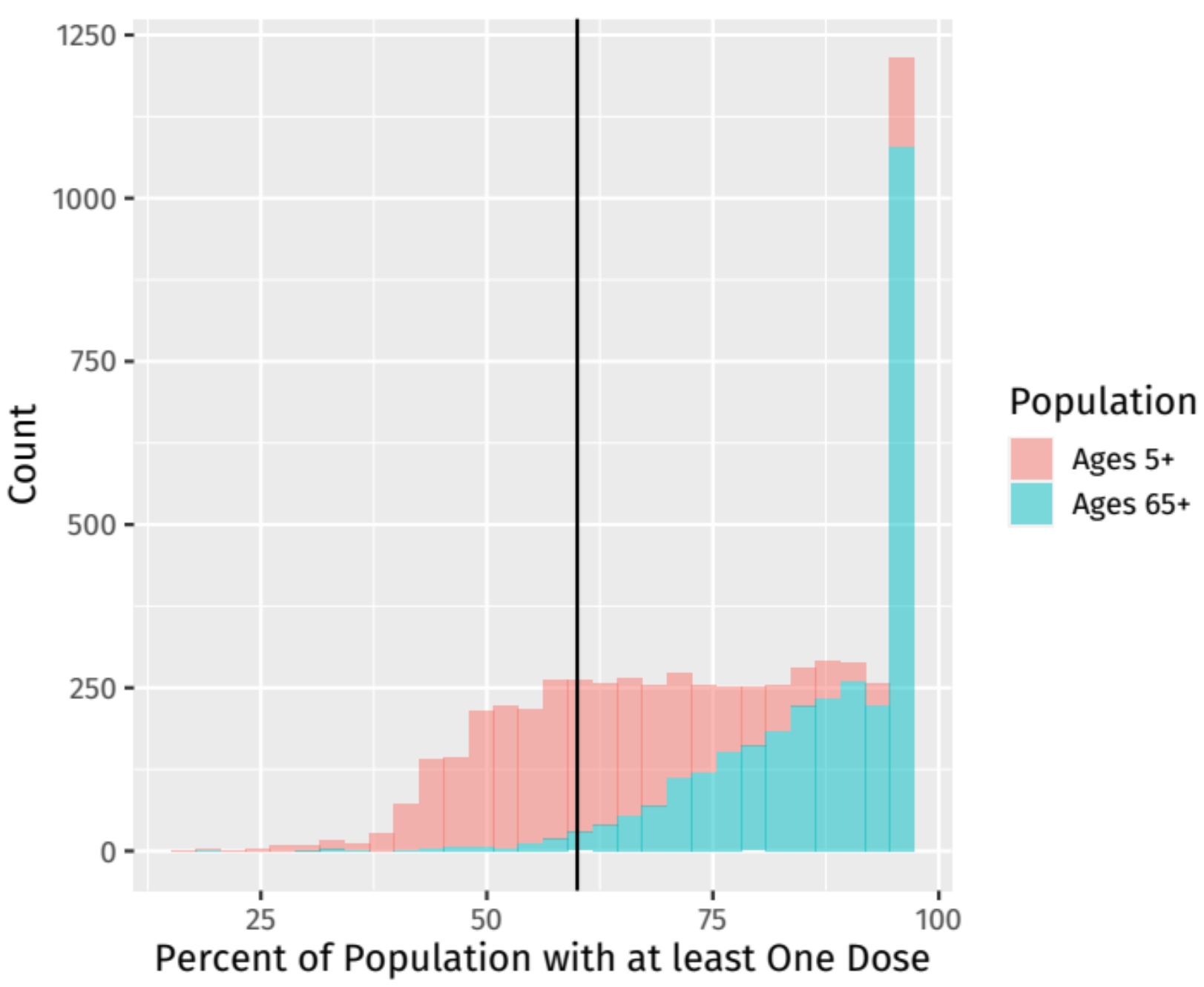
1. Z-scores and standardization

COVID vaccination rates and votes

```
library(tidyverse)
library(TPDdata)
covid_votes
```

```
## # A tibble: 3,114 x 8
##    fips  county           state one_dose_5plus~1 one_d~2 boost~3 dem_p~4 dem_p~5
##    <chr> <chr>            <chr>            <dbl>   <dbl>   <dbl>   <dbl>   <dbl>
##  1 26039 Crawford County  MI                55.7    77.3   31.2     43.8    34.0
##  2 40015 Caddo County     OK                83.3    95     30.3     46.4    27.1
##  3 17007 Boone County     IL                71.1    94.5   35.1     41.8    42.2
##  4 12055 Highlands County FL                68.9    93.7   24.7     40.3    32.5
##  5 34029 Ocean County     NJ                71      95     32.1     47.2    35.0
##  6 01067 Henry County     AL                58.5    85.5   18.2     40.1    28.0
##  7 27037 Dakota County    MN                81      95     49.5     46.9    55.7
##  8 27115 Pine County      MN                56.5    85     31.7     47.0    33.9
##  9 51750 Radford city     VA                41.5    73.8    1.79    46.4    53.1
## 10 22009 Avoyelles Parish LA                59.7    80.1   21.9     45.7    28.8
## # ... with 3,104 more rows, and abbreviated variable names
## #   1: one_dose_5plus_pct, 2: one_dose_65plus_pct, 3: booster_5plus_pct,
## #   4: dem_pct_2000, 5: dem_pct_2020
```

Is 60% vaccnated a lot?



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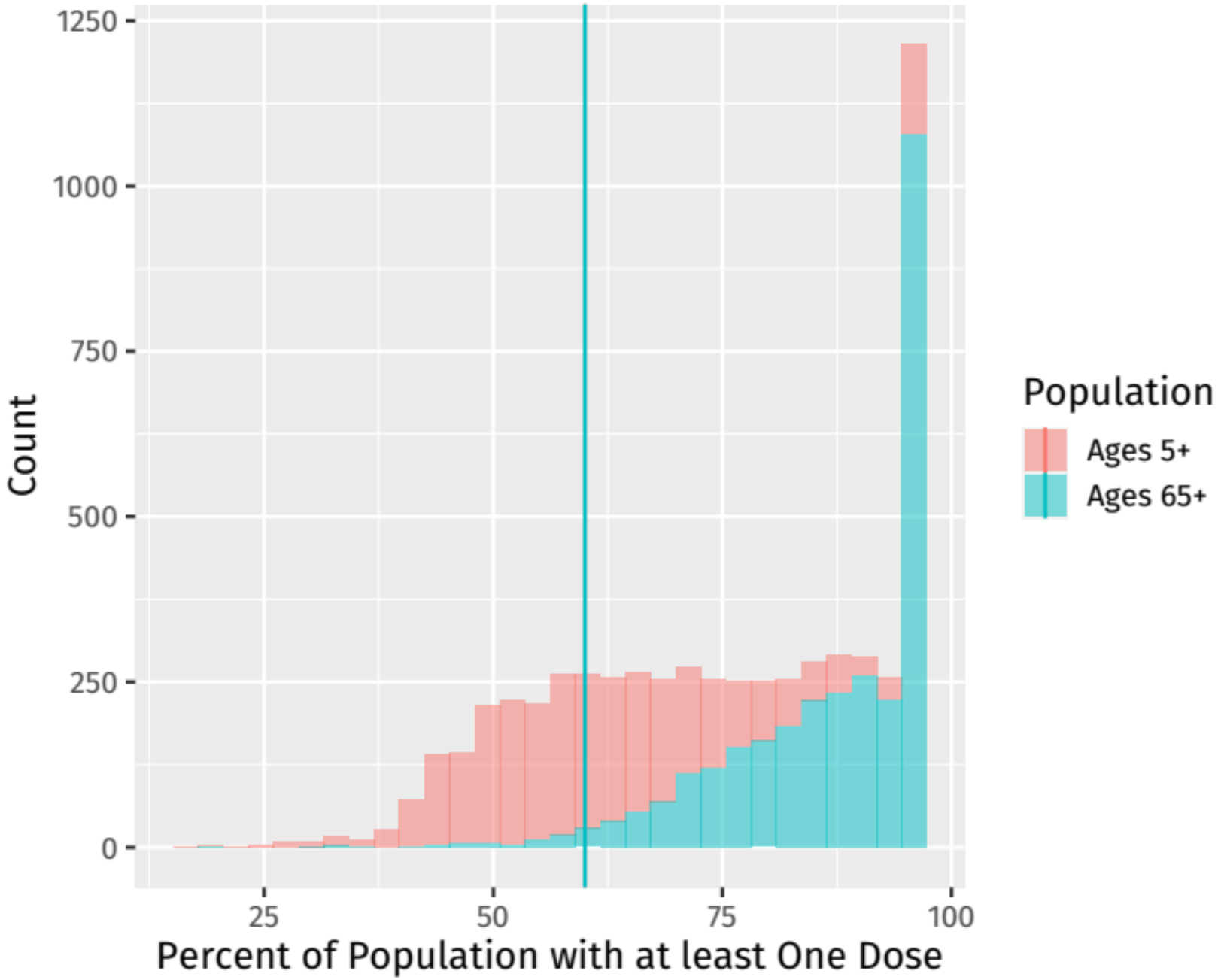
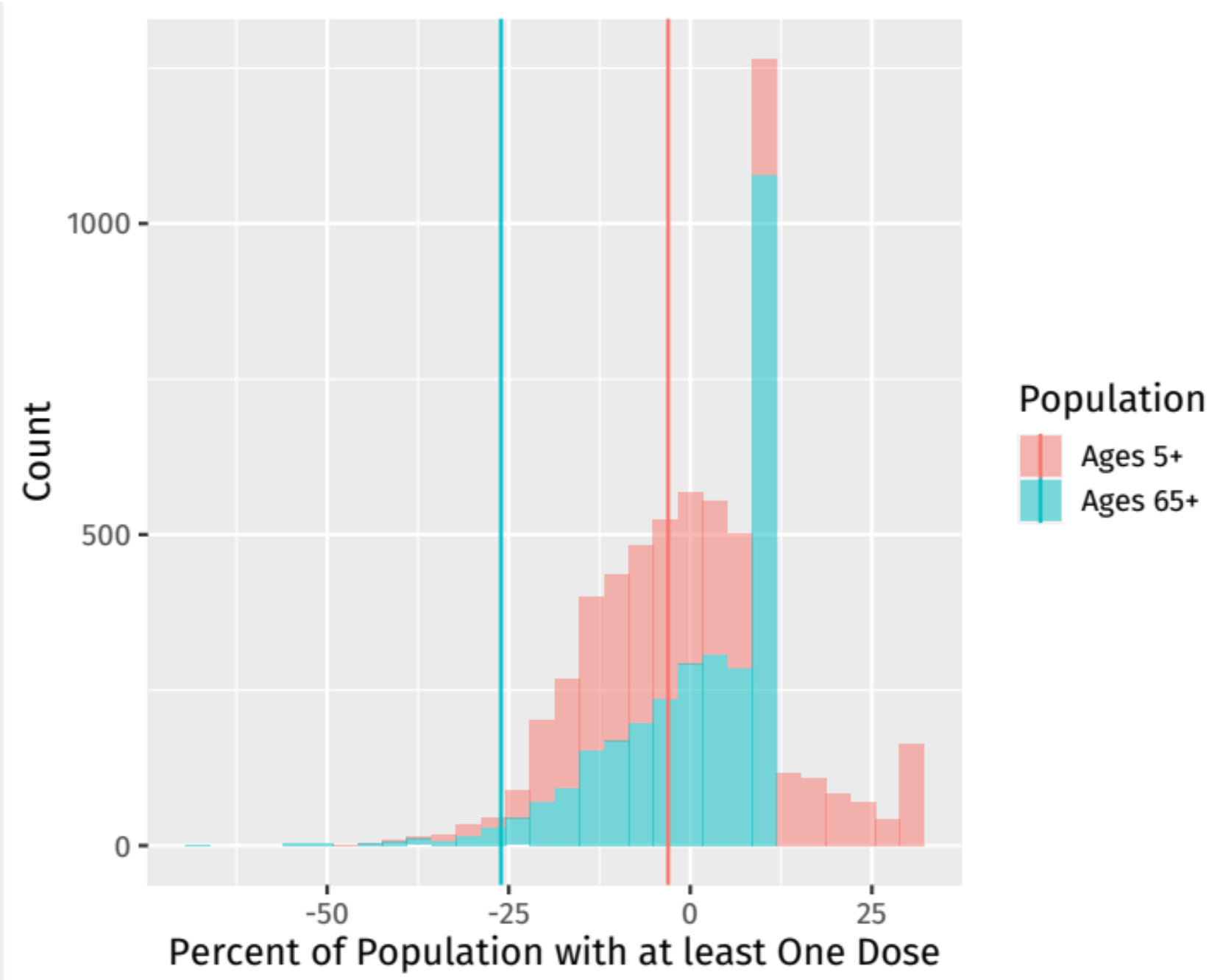
  - **Centering**: subtract the mean of the variable from each value
  - **Scaling**: dividing deviations from the mean by the standard deviation

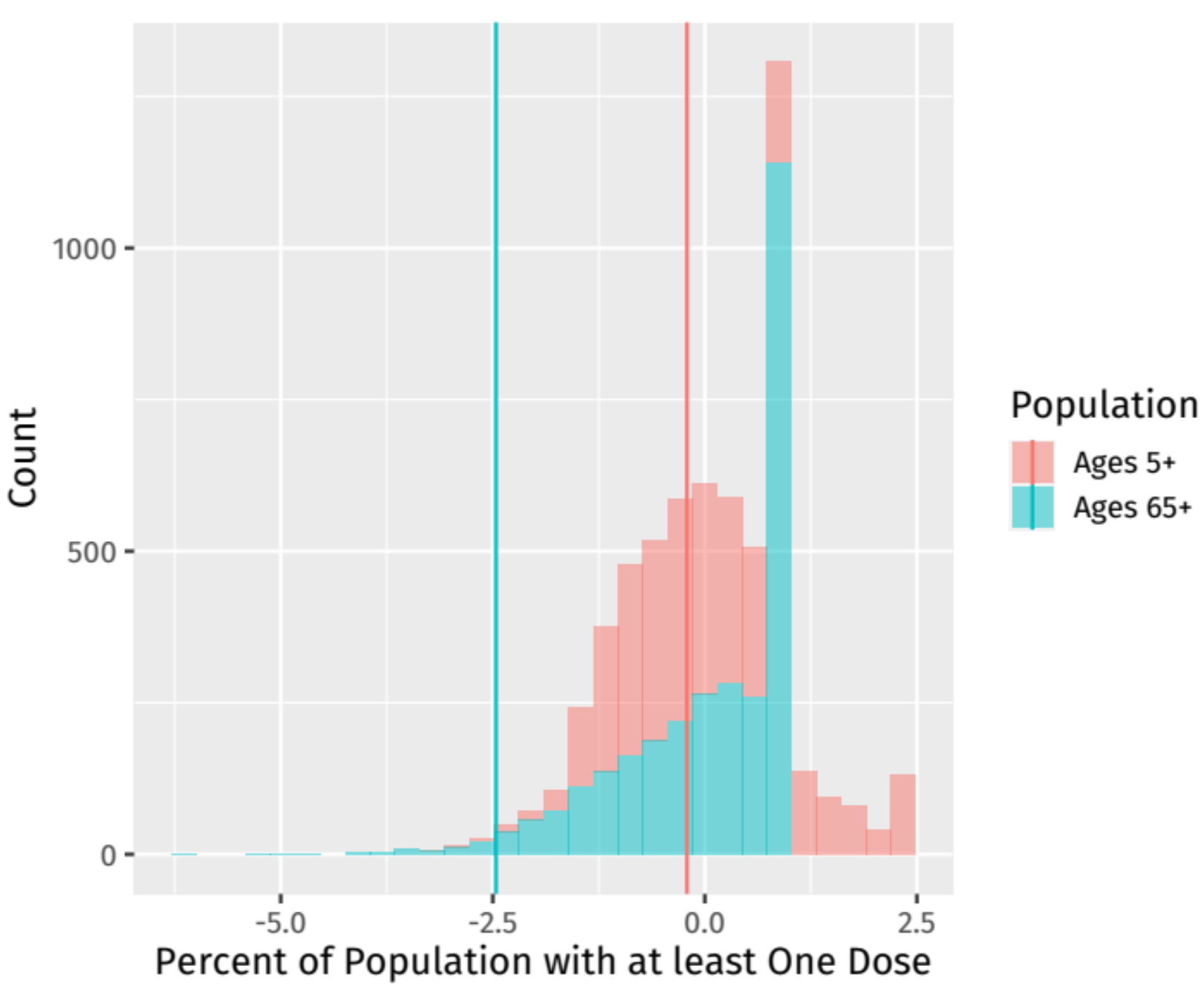
Original distributions



Centered distributions



Centered and scaled distributions



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- Combine them with the **z-score** transformation:

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

- Useful heuristic: data more than 3 SDs away from its 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_dose_centered
##    <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
```

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_dose_z
##    <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
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2. Correlation

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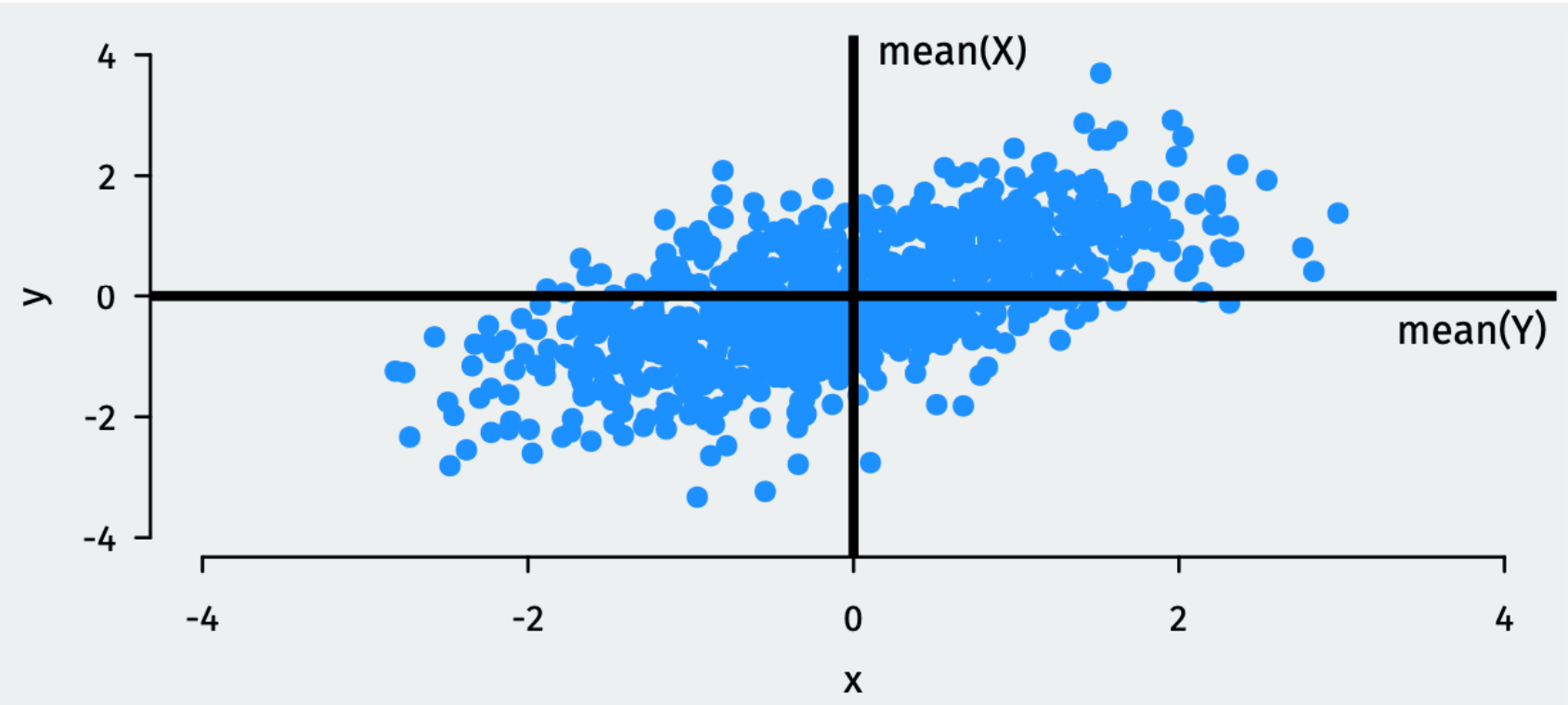
  - Closer to -1 or 1 means stronger association

Correlation intuition



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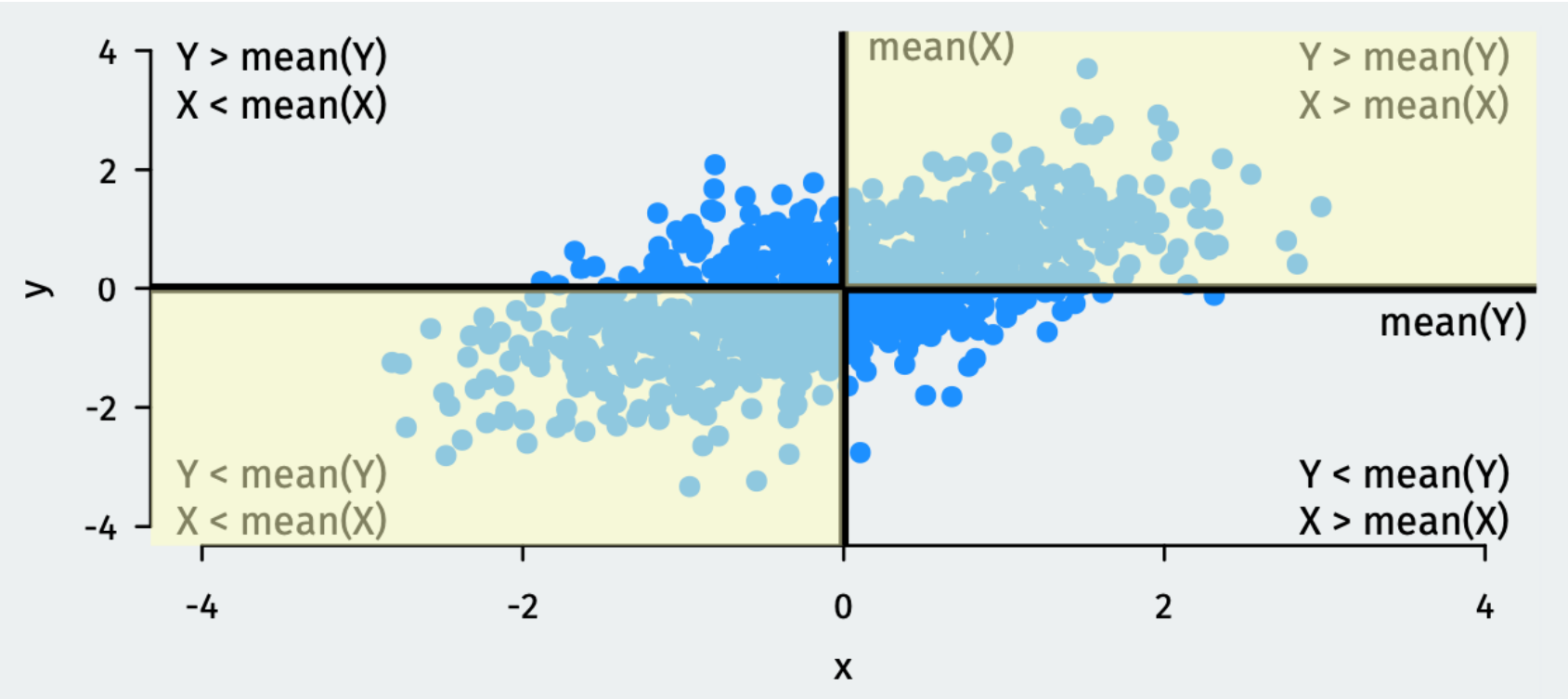

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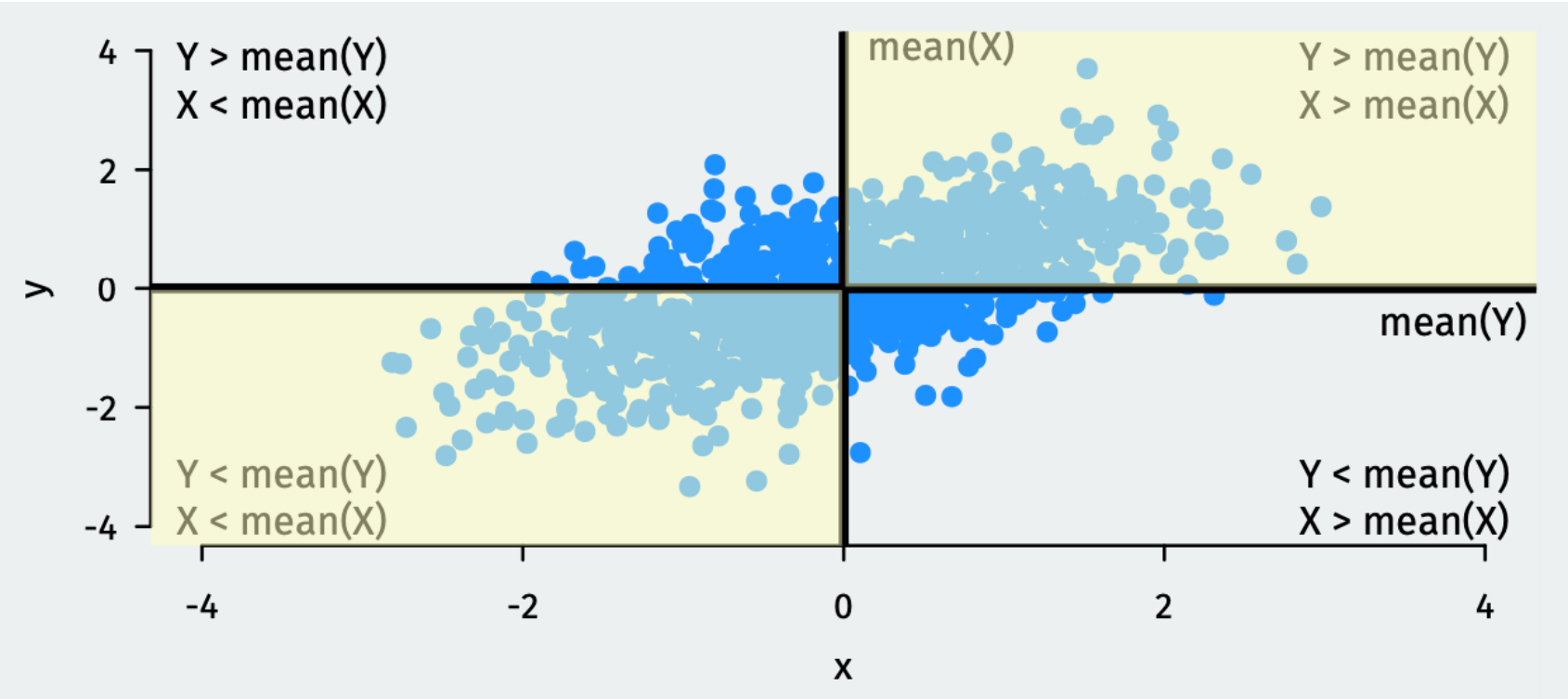

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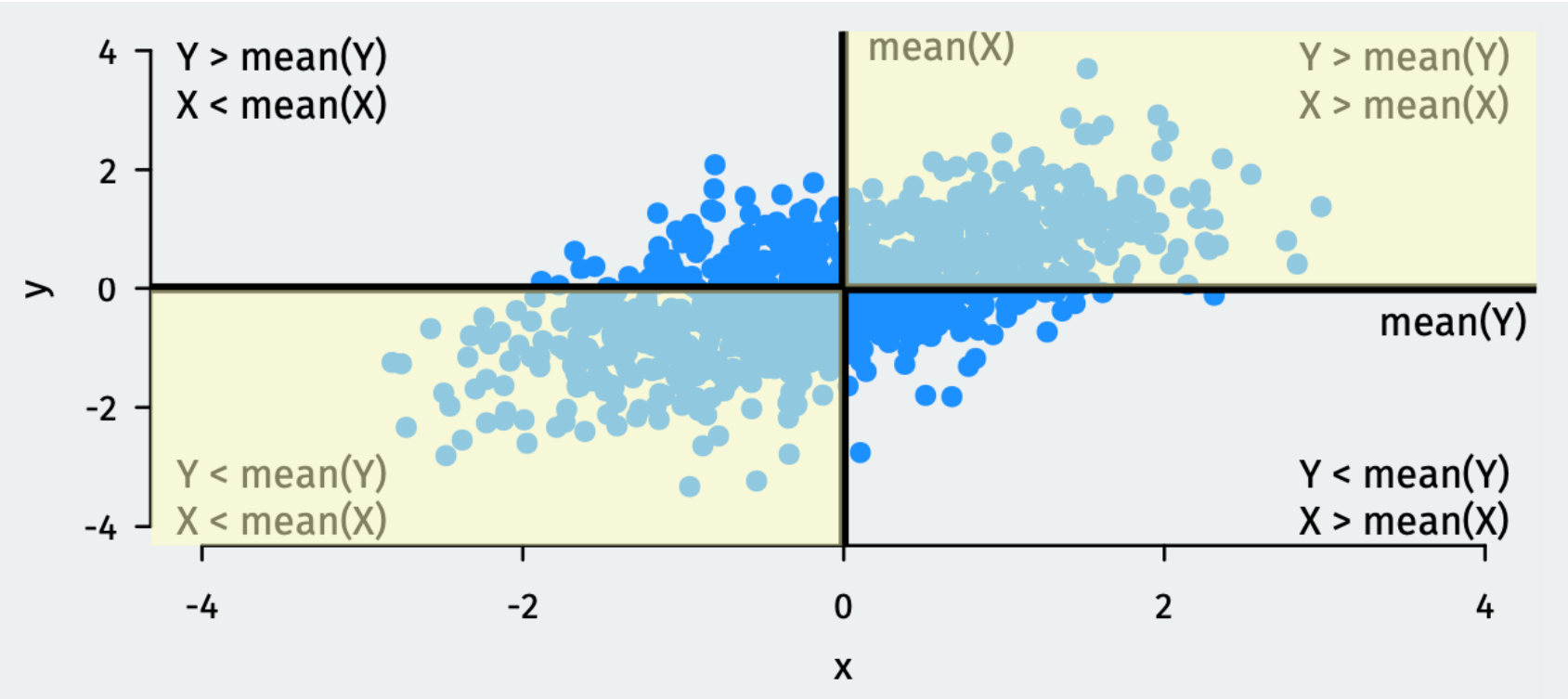

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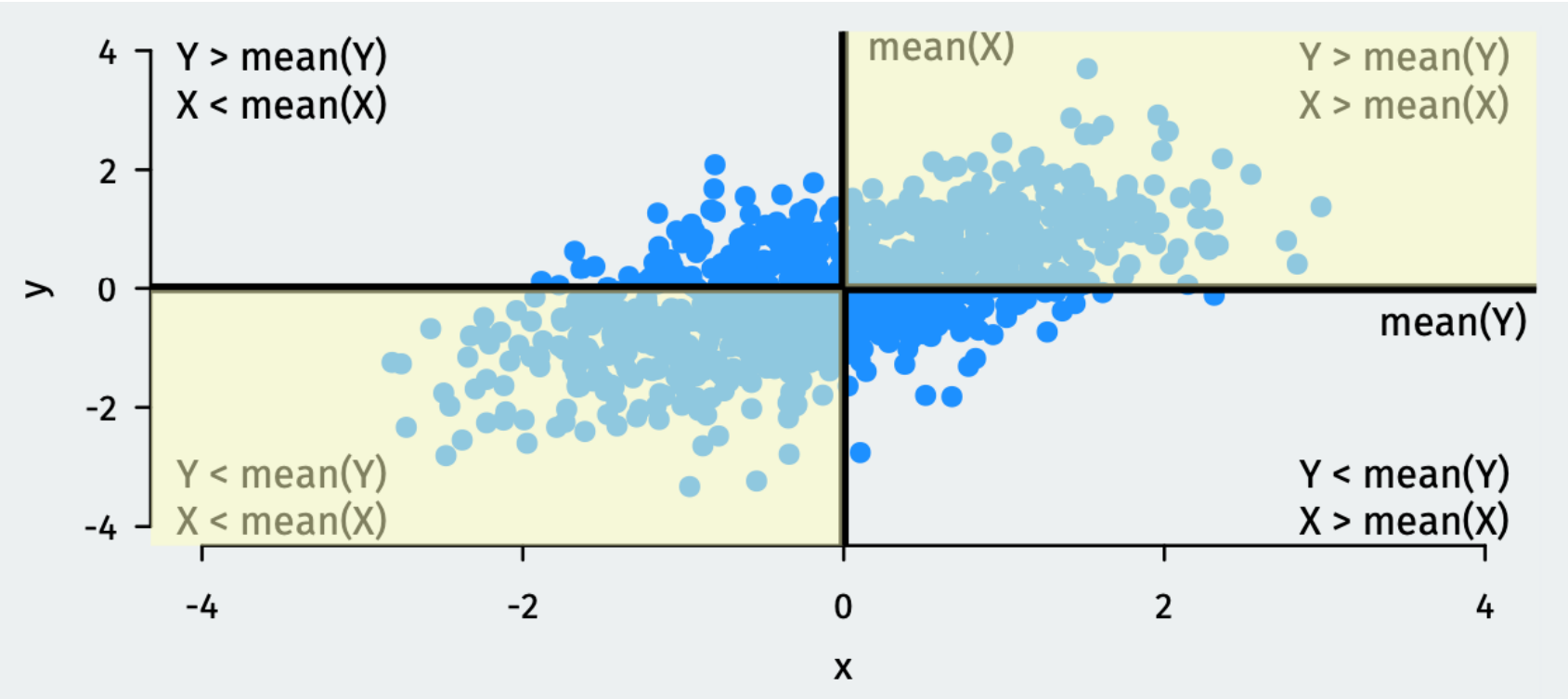

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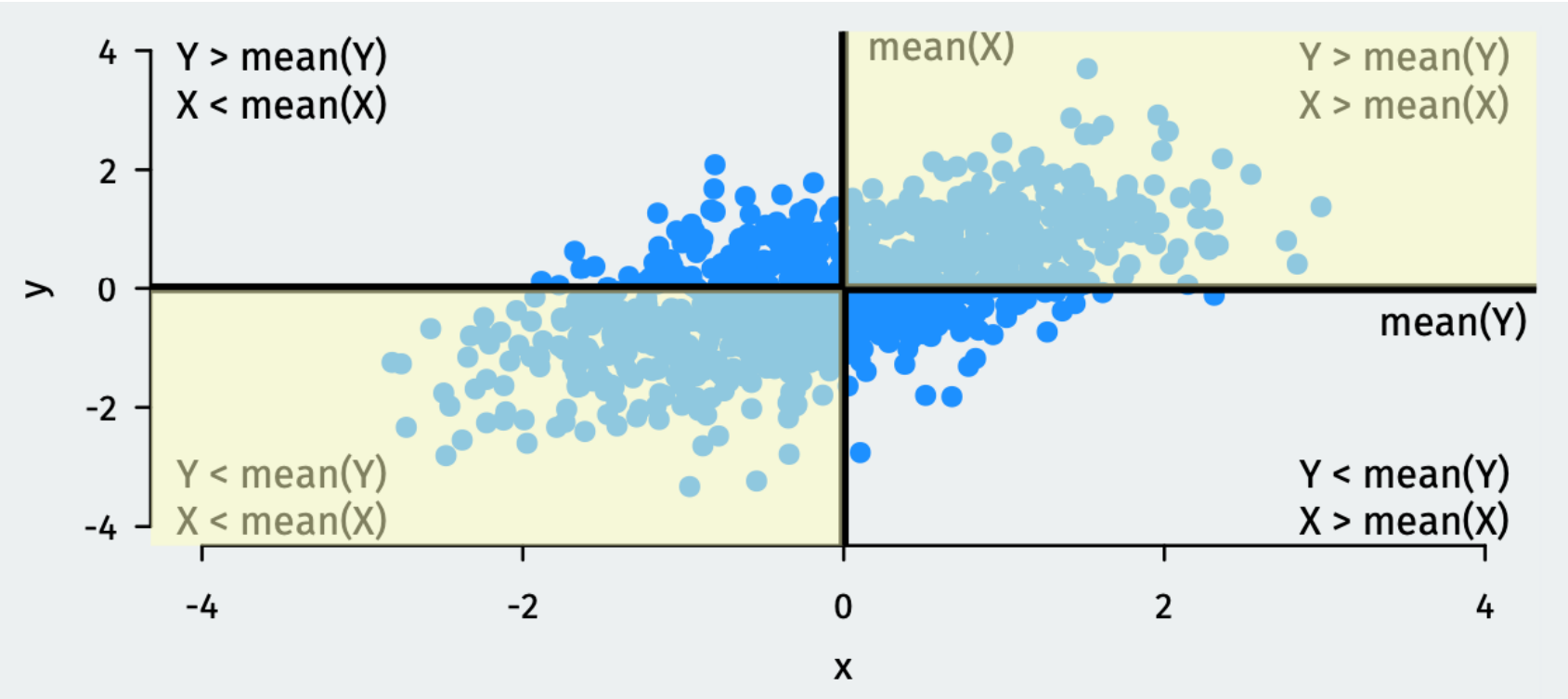

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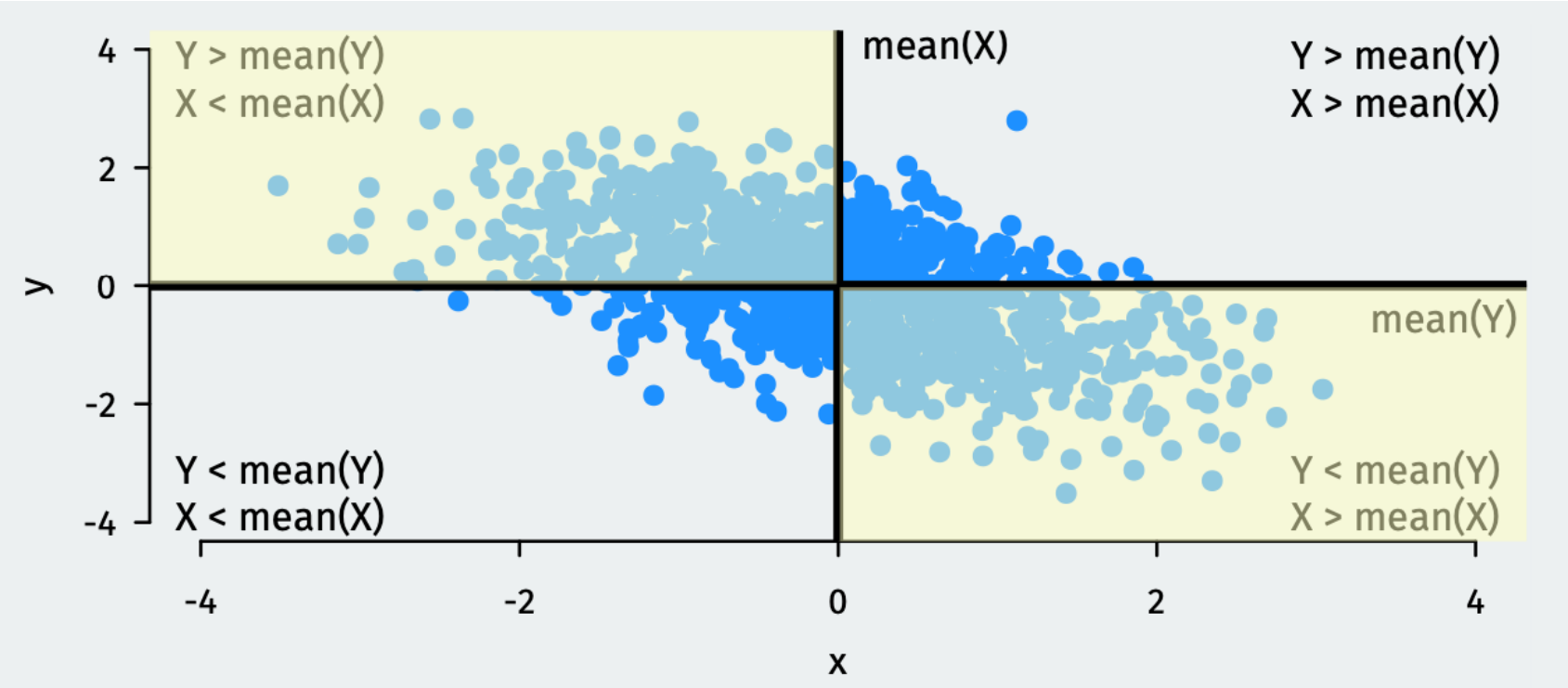

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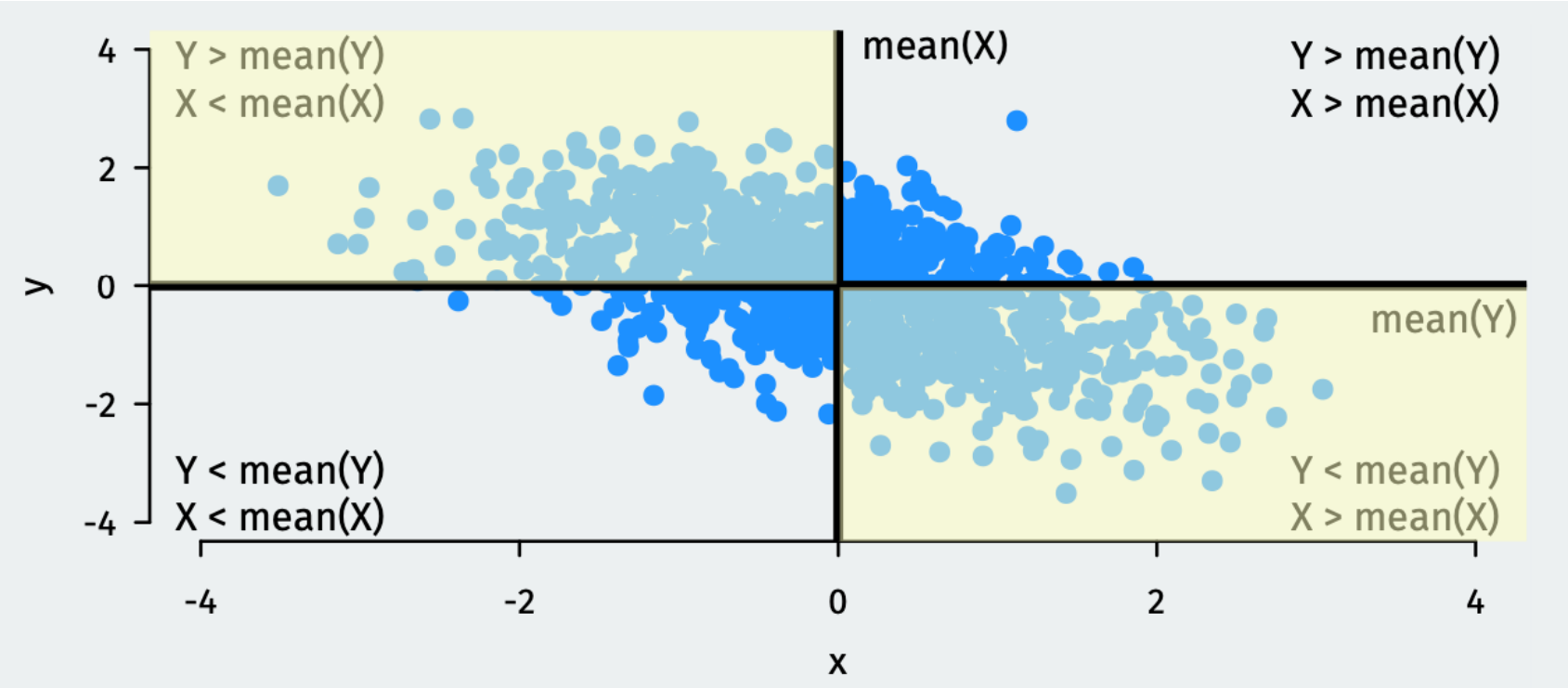

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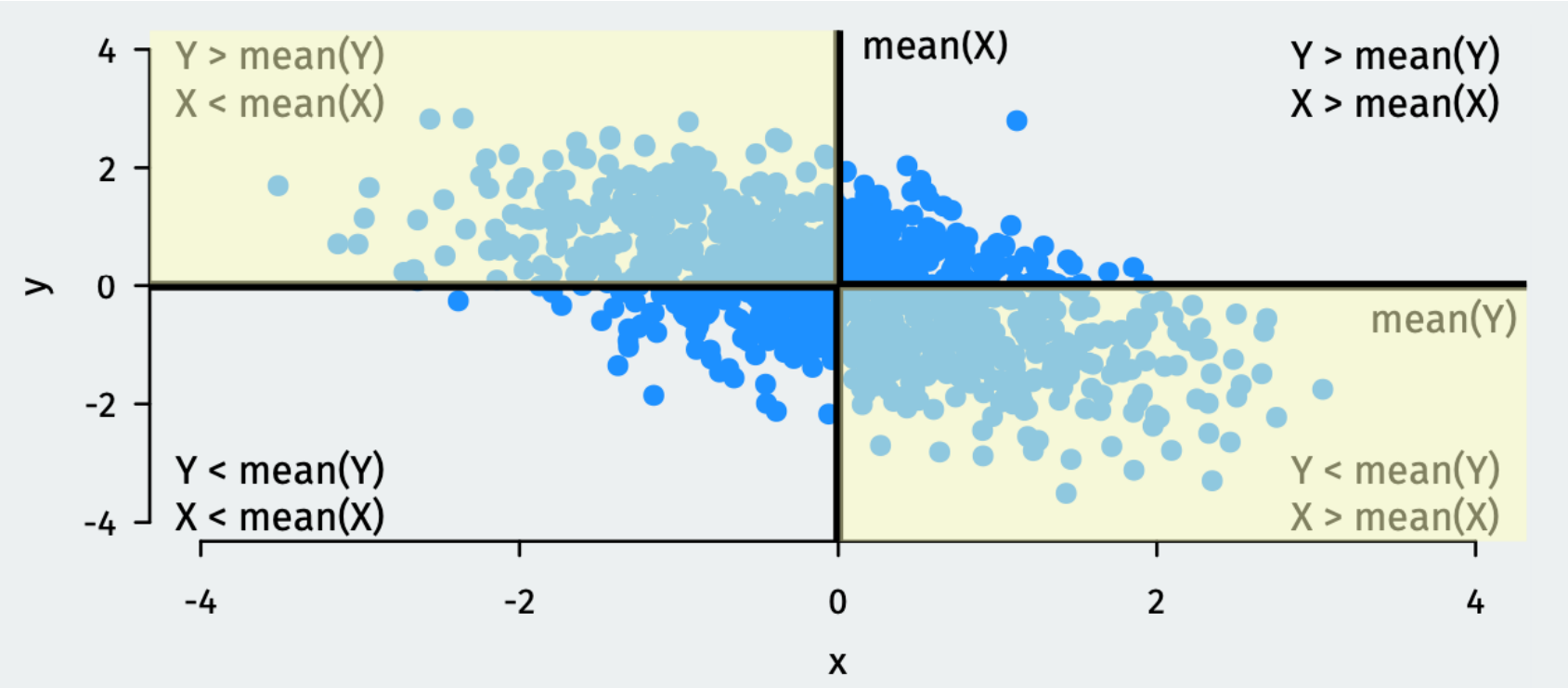

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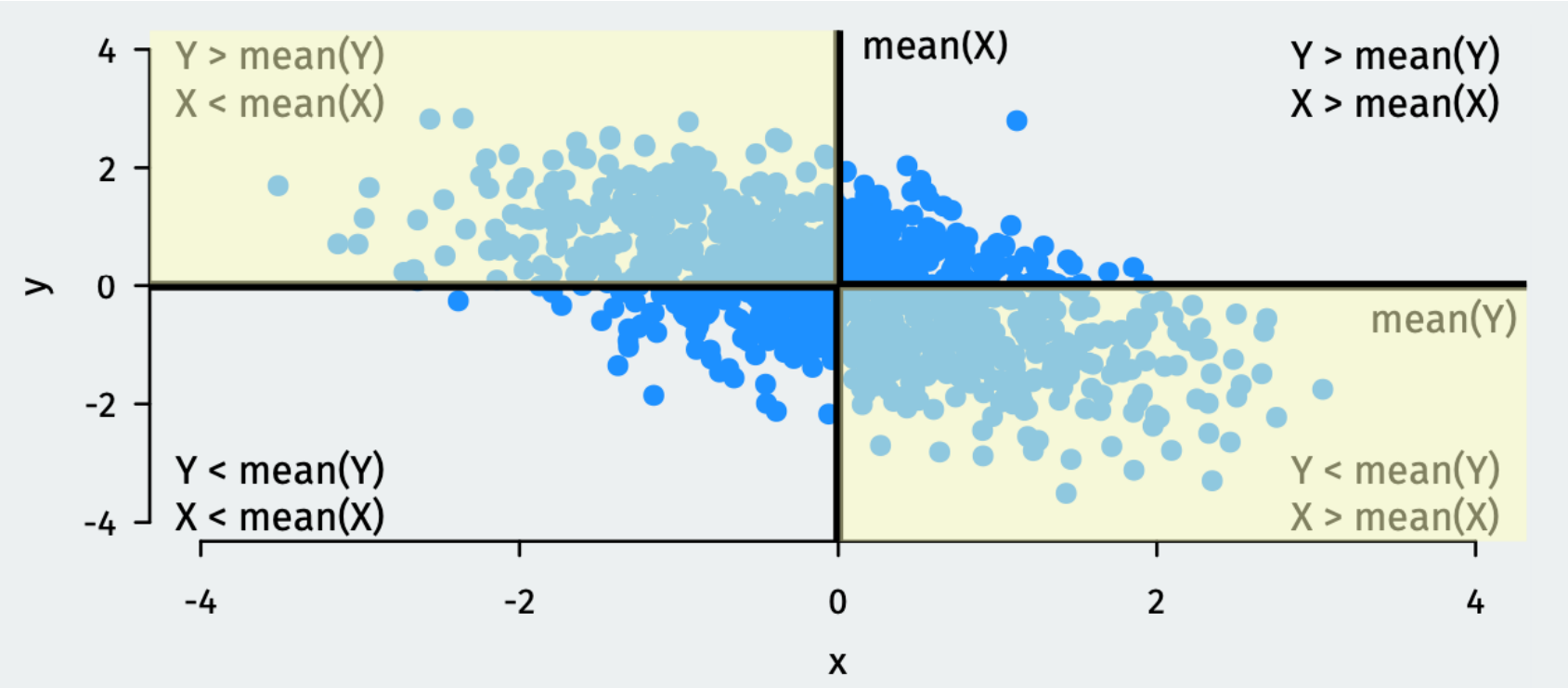

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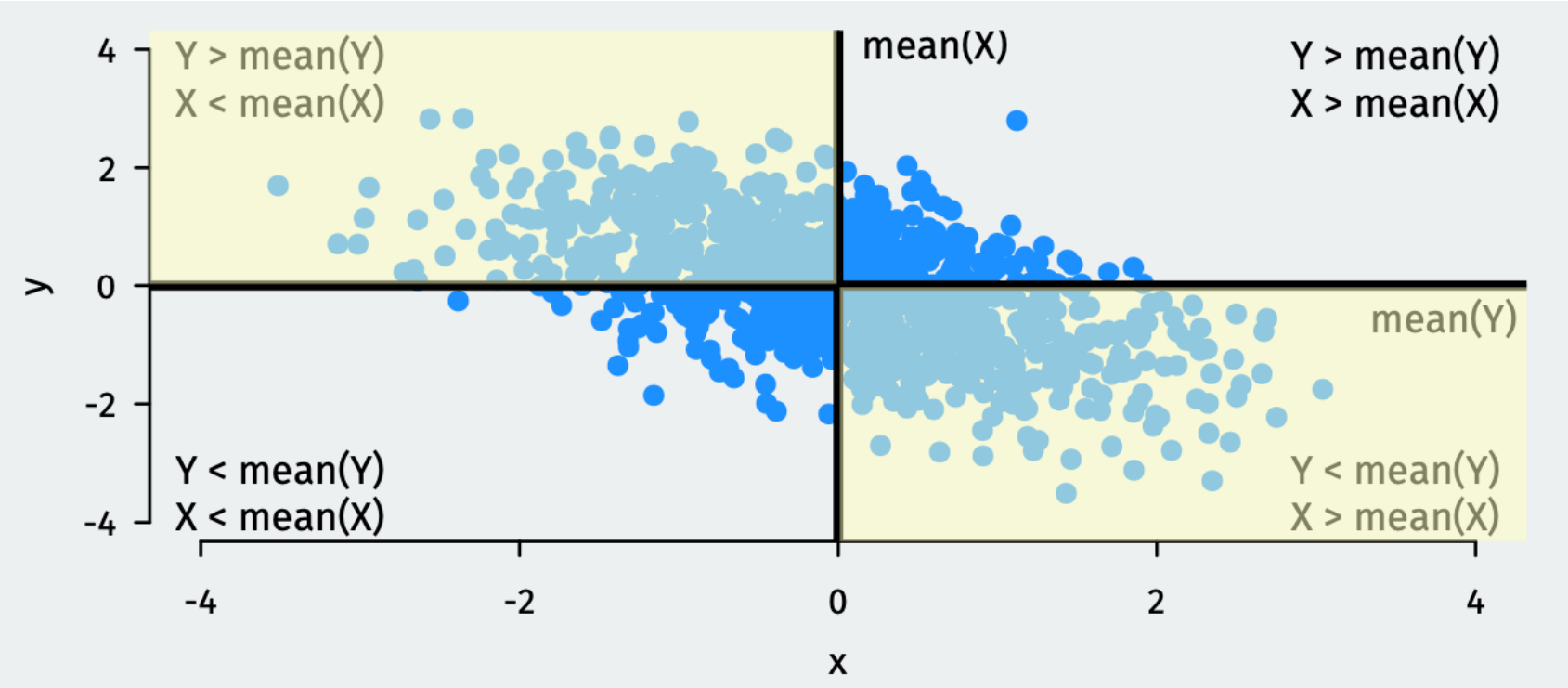

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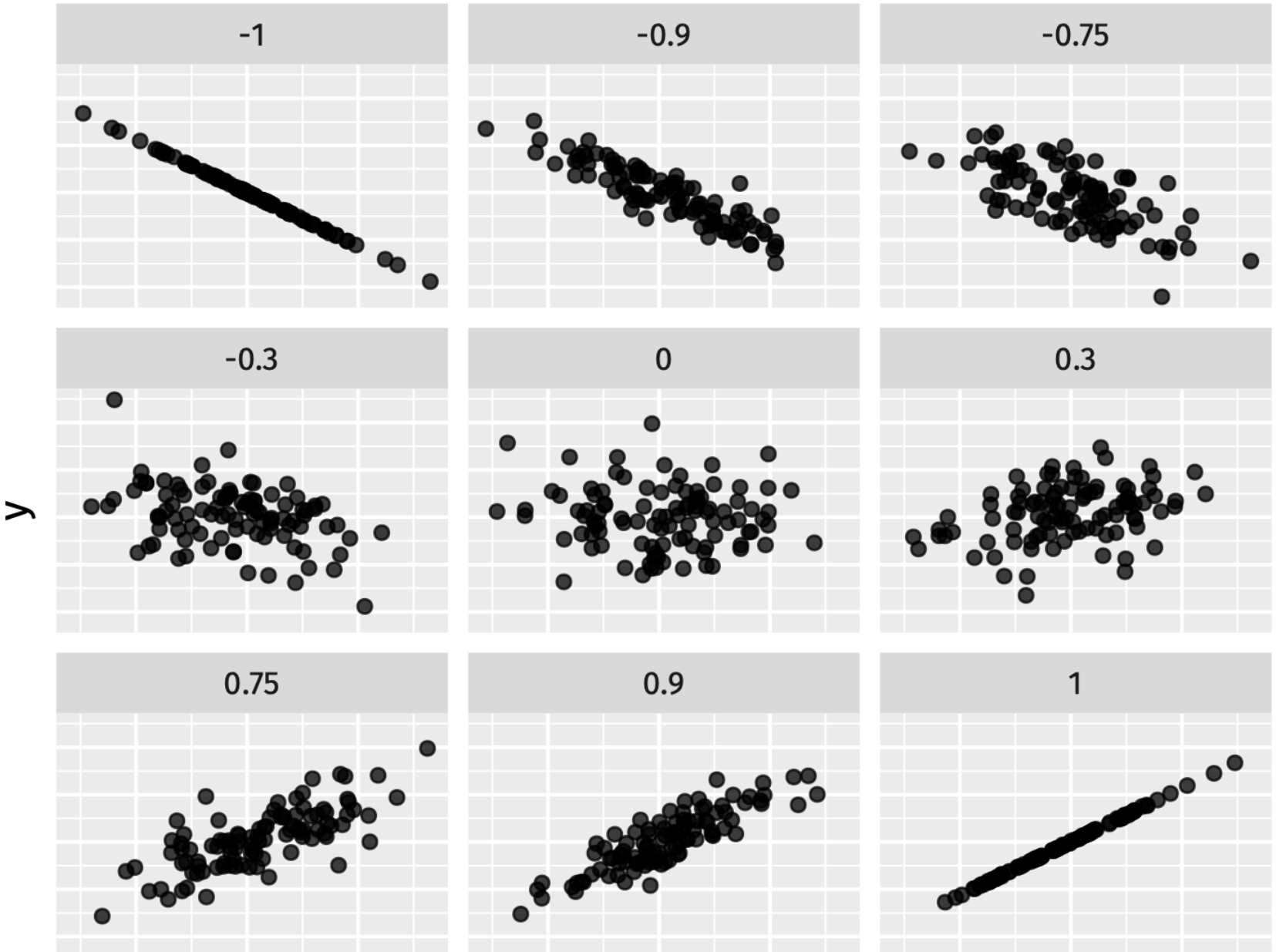
Correlation examples



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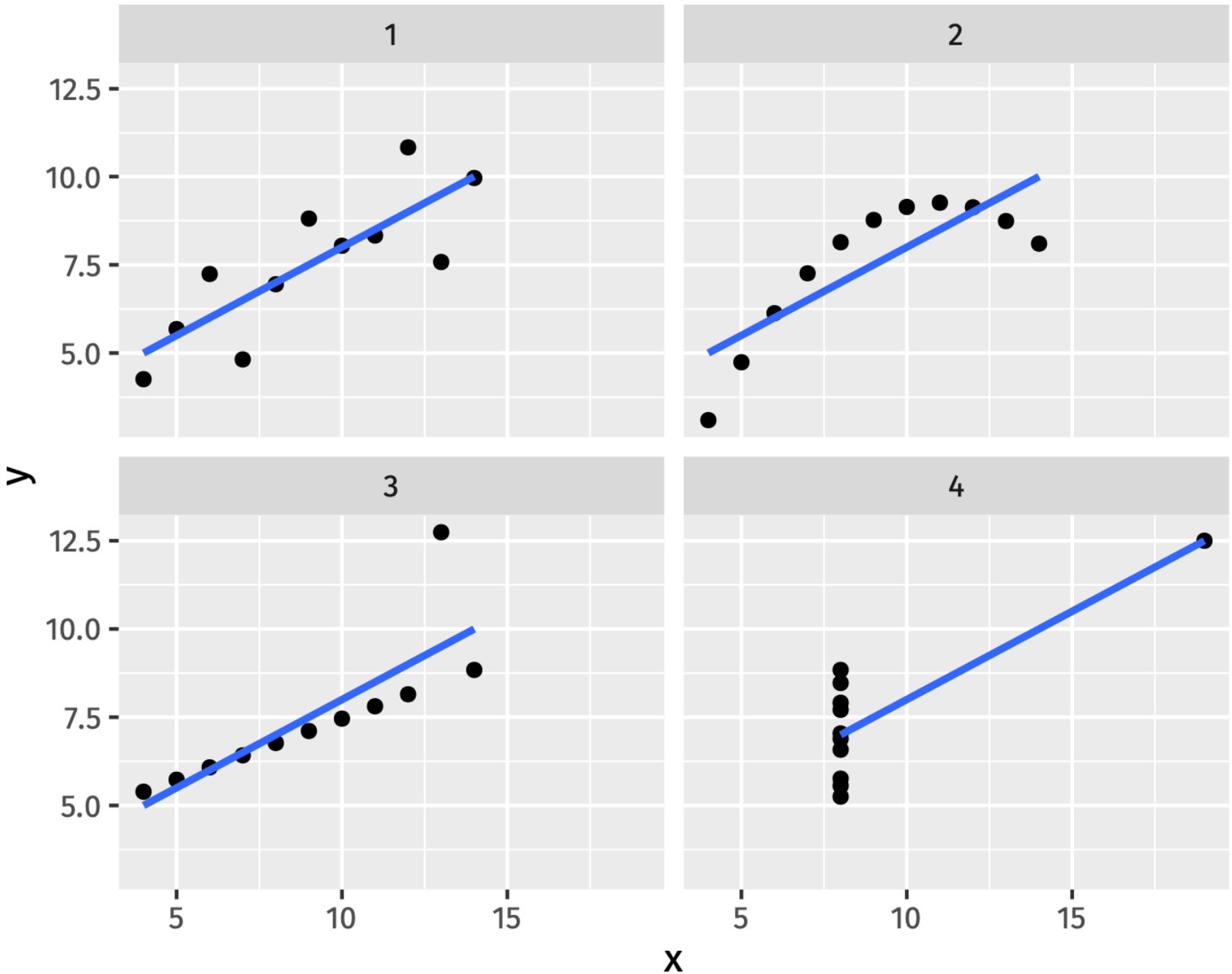
- Order doesn't matter: `cor(x,y) = cor(y,x)`
- Not affected by changes of scale:
  - `cor(x,y) = cor(ax+b, cy+d)`
  - Celsius vs. Fahrenheit: dollars vs. pesos; cm vs. in.

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
```

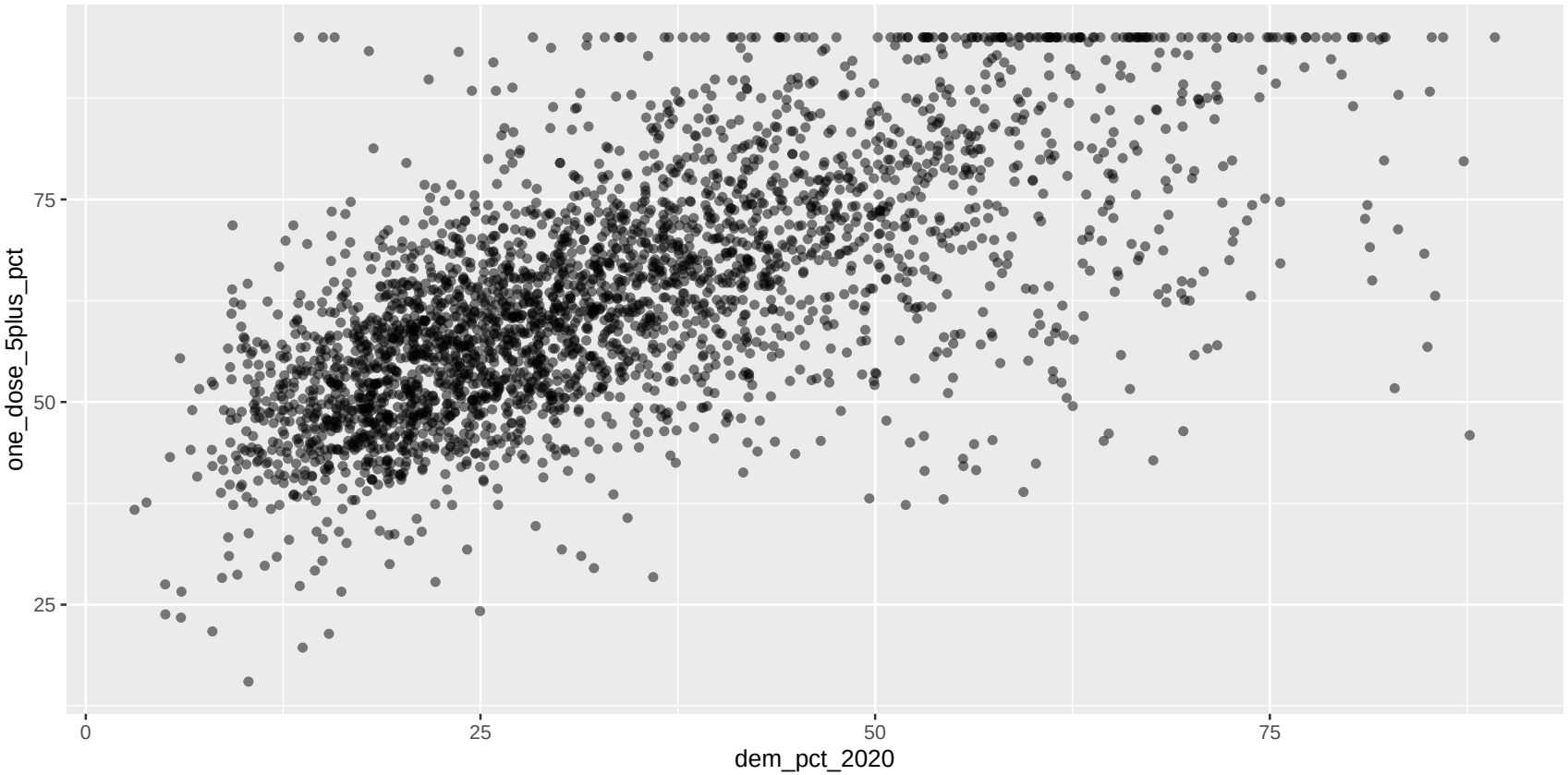
Missing values: set the use ="pairwise" -> available case analysis

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

```
## [1] 0.6664387
```

Comparing correlations

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

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

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## [1] 0.6664387
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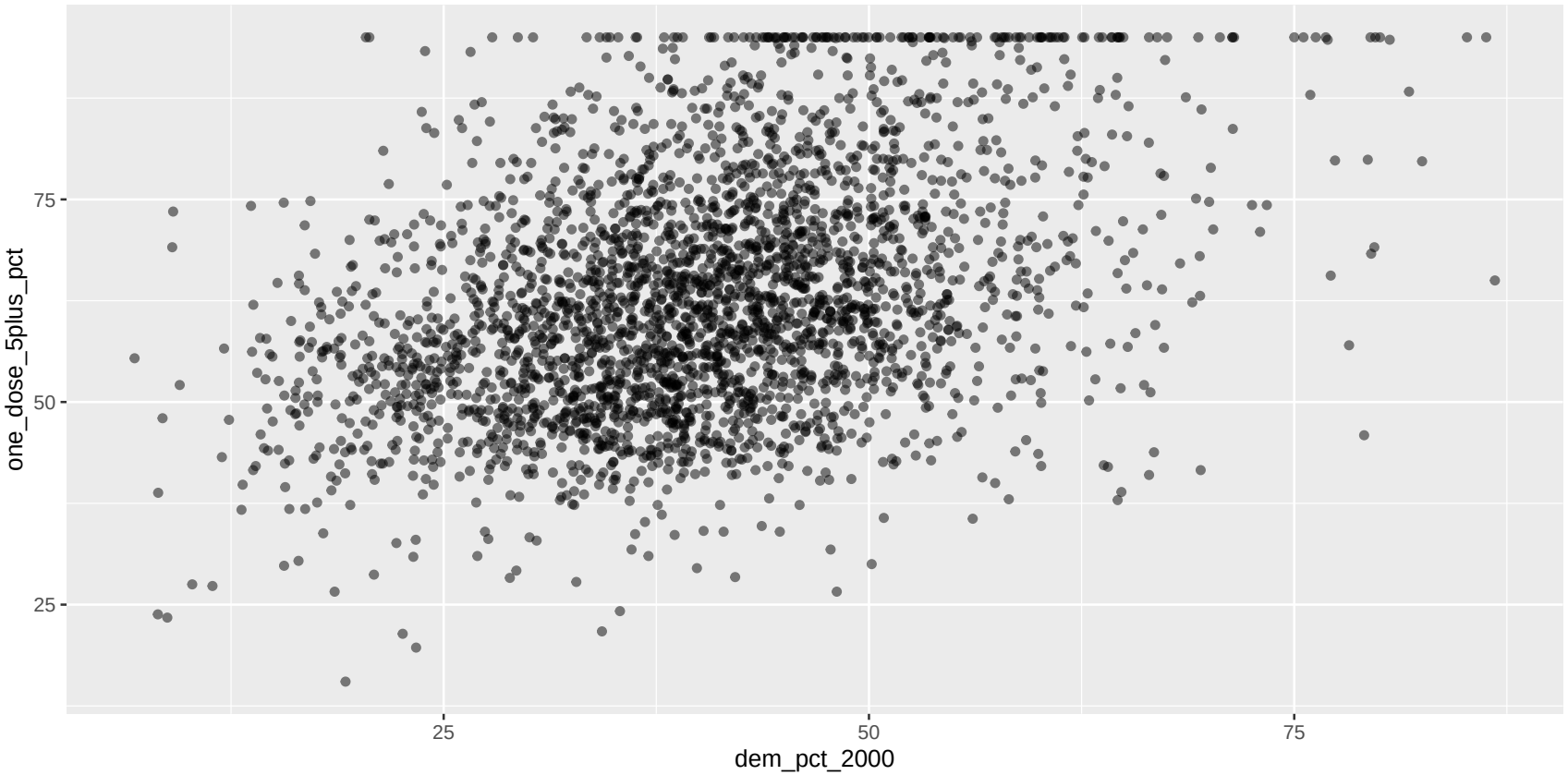
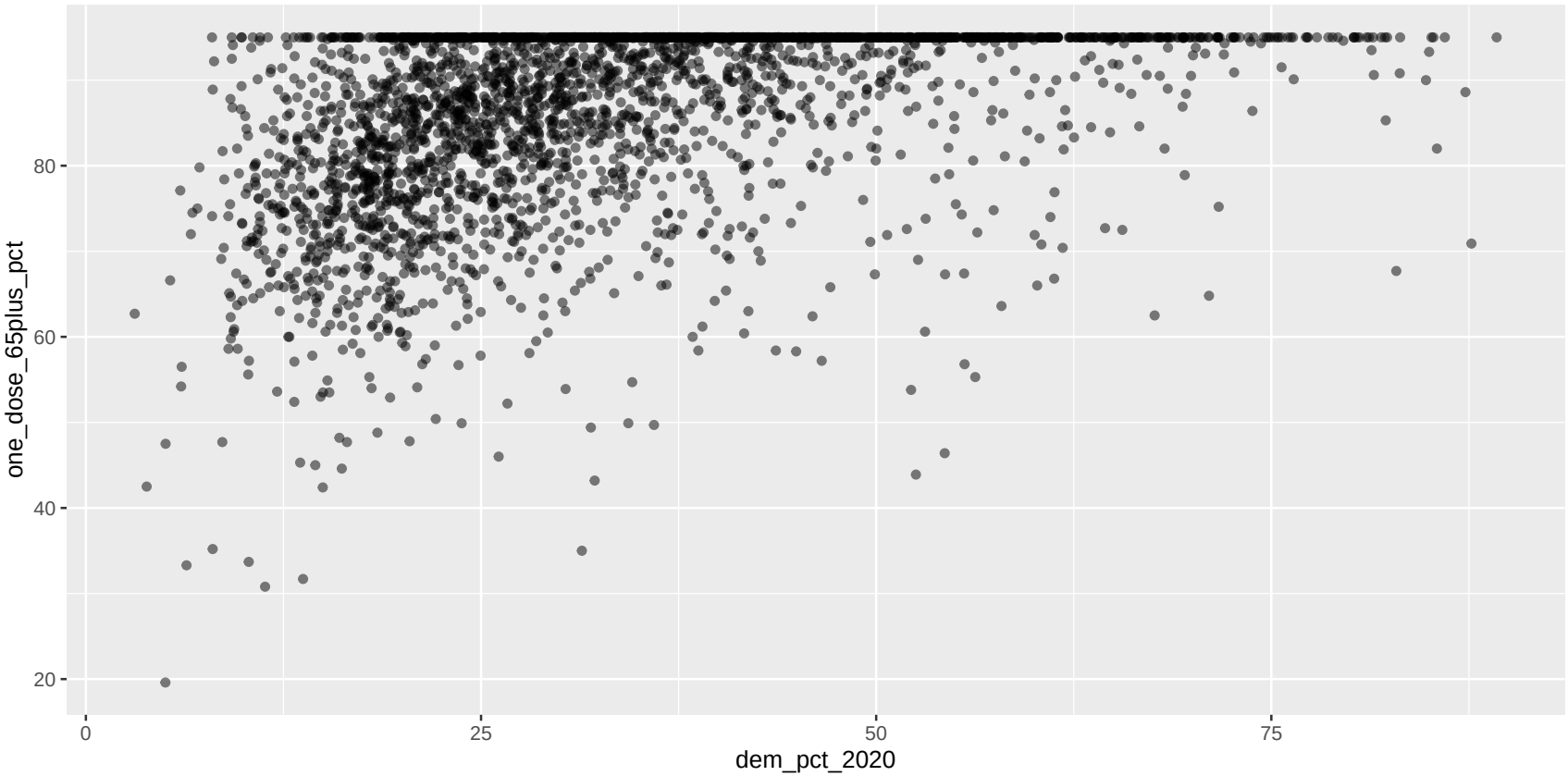



```
cor(covid_votes$one_dose_5plus_pct, covid_votes$dem_pct_2000, use="pairwise")
```

```
## [1] 0.3941203
```

Comparing correlations

```
covid_votes |>
  ggplot(aes(x = dem_pct_2020, y = one_dose_65plus_pct)) +
  geom_point(alpha = 0.5)
```




```
cor(covid_votes$one_dose_65plus_pct, covid_votes$dem_pct_2020, use="pairwise")
```

```
## [1] 0.447203
```

3. Writing our own functions.

Why write functions?

copy-pasting codes is 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:

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

Only one thing varies: the column (or the vector) of data (variable), represented with `x`

We create functions like so:

```
name <- function(arguments) {
  body
}
```

Components of a function

We create functions like so:

```
name <- function(arguments) {
  body
}
```

Three components:

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```
name <- function(arguments) {
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Components of a function

We create functions like so:

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```

Three components:

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 will 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)
}
```

Convert our template to a function:

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

Let's check this if it works:

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

```
## [1] -1.2649111 -0.6324555  0.0000000  0.6324555  1.2649111
```

Now, 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)
  )
```

```
## # A tibble: 3,114 x 13
##    fips  county    state one_d~1 one_d~2 boost~3 dem_p~4 dem_p~5 one_d~6 one_d~7
##    <chr> <chr>     <chr>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>
##  1 26039 Crawford~ MI       55.7    77.3   31.2     43.8    34.0  -0.508 -0.829
##  2 40015 Caddo Co~ OK       83.3    95     30.3     46.4    27.1   1.40   0.843
##  3 17007 Boone Co~ IL       71.1    94.5   35.1     41.8    42.2   0.556  0.795
##  4 12055 Highland~ FL       68.9    93.7   24.7     40.3    32.5   0.404  0.720
##  5 34029 Ocean Co~ NJ       71      95     32.1     47.2    35.0   0.549  0.843
##  6 01067 Henry Co~ AL       58.5    85.5   18.2     40.1    28.0  -0.314 -0.0545
##  7 27037 Dakota C~ MN       81      95     49.5     46.9    55.7   1.24   0.843
##  8 27115 Pine Cou~ MN       56.5    85     31.7     47.0    33.9  -0.452 -0.102
##  9 51750 Radford ~ VA       41.5    73.8    1.79    46.4    53.1  -1.49  -1.16
## 10 22009 Avoyelle~ LA       59.7    80.1   21.9     45.7    28.8  -0.231 -0.564
## # ... with 3,104 more rows, 3 more variables: booster_z <dbl>,
## #   dem_pct_2000_z <dbl>, dem_pct_2020_z <dbl>, and abbreviated variable names
## #   1: one_dose_5plus_pct, 2: one_dose_65plus_pct, 3: booster_5plus_pct,
## #   4: dem_pct_2000, 5: dem_pct_2020, 6: one_dose_5p_z, 7: one_dose_65p_z
```

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_dose_5plus~1 one_d~2 boost~3 dem_p~4 dem_p~5
##    <chr> <chr>            <chr>            <dbl>   <dbl>   <dbl>   <dbl>   <dbl>
##  1 26039 Crawford County  MI              -0.508 -0.829    0.531  0.340   0.0471
##  2 40015 Caddo County     OK               1.40   0.843    0.439  0.556  -0.387
##  3 17007 Boone County     IL               0.556  0.795    0.927  0.163   0.563
##  4 12055 Highlands County FL               0.404  0.720   -0.135  0.0402 -0.0487
##  5 34029 Ocean County     NJ               0.549  0.843    0.623  0.624   0.109
##  6 01067 Henry County     AL              -0.314 -0.0545  -0.799  0.0255 -0.328
##  7 27037 Dakota County    MN               1.24   0.843    2.40   0.598   1.41
##  8 27115 Pine County      MN              -0.452 -0.102    0.577  0.612   0.0393
##  9 51750 Radford city     VA              -1.49  -1.16    -2.47   0.556   1.25
## 10 22009 Avoyelles Parish LA              -0.231 -0.564   -0.424  0.501  -0.280
## # ... with 3,104 more rows, and abbreviated variable names
## #   1: one_dose_5plus_pct, 2: one_dose_65plus_pct, 3: booster_5plus_pct,
## #   4: dem_pct_2000, 5: dem_pct_2020
```

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_dose_5plus~1 one_d~2 boost~3 dem_p~4 dem_p~5
##    <chr> <chr>            <chr>            <dbl>   <dbl>   <dbl>   <dbl>   <dbl>
##  1 26039 Crawford County  MI              -0.508 -0.829    0.531  0.340   0.0471
##  2 40015 Caddo County     OK               1.40   0.843    0.439  0.556  -0.387
##  3 17007 Boone County     IL               0.556  0.795    0.927  0.163   0.563
##  4 12055 Highlands County FL               0.404  0.720   -0.135  0.0402 -0.0487
##  5 34029 Ocean County     NJ               0.549  0.843    0.623  0.624   0.109
##  6 01067 Henry County     AL              -0.314 -0.0545  -0.799  0.0255 -0.328
##  7 27037 Dakota County    MN               1.24   0.843    2.40   0.598   1.41
##  8 27115 Pine County      MN              -0.452 -0.102    0.577  0.612   0.0393
##  9 51750 Radford city     VA              -1.49  -1.16    -2.47   0.556   1.25
## 10 22009 Avoyelles Parish LA              -0.231 -0.564   -0.424  0.501  -0.280
## # ... with 3,104 more rows, and abbreviated variable names
## #   1: one_dose_5plus_pct, 2: one_dose_65plus_pct, 3: booster_5plus_pct,
## #   4: dem_pct_2000, 5: dem_pct_2020
```

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_dose_5plus~1 one_d~2 boost~3 dem_p~4 dem_p~5
##    <chr> <chr>            <chr>            <dbl>   <dbl>   <dbl>   <dbl>   <dbl>
##  1 26039 Crawford County  MI              -0.508 -0.829    31.2     43.8    34.0
##  2 40015 Caddo County     OK               1.40   0.843    30.3     46.4    27.1
##  3 17007 Boone County     IL               0.556  0.795    35.1     41.8    42.2
##  4 12055 Highlands County FL               0.404  0.720    24.7     40.3    32.5
##  5 34029 Ocean County     NJ               0.549  0.843    32.1     47.2    35.0
##  6 01067 Henry County     AL              -0.314 -0.0545   18.2     40.1    28.0
##  7 27037 Dakota County    MN               1.24   0.843    49.5     46.9    55.7
##  8 27115 Pine County      MN              -0.452 -0.102    31.7     47.0    33.9
##  9 51750 Radford city     VA              -1.49  -1.16      1.79    46.4    53.1
## 10 22009 Avoyelles Parish LA              -0.231 -0.564    21.9     45.7    28.8
## # ... with 3,104 more rows, and abbreviated variable names
## #   1: one_dose_5plus_pct, 2: one_dose_65plus_pct, 3: booster_5plus_pct,
## #   4: dem_pct_2000, 5: dem_pct_2020
```

Notes on `starts_with`

`starts_with` is a tidyway (`tidyselect`)

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`ends_with()`: ends with an exact suffix

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There are other functions too such as:

`ends_with()`: ends with an exact suffix

`contains()`: contains a literal string

`matches()`: matches a regular expression

Notes on `starts_with`

`starts_with` is a tidyway (`tidyselect`)

It looks for an exact match from the beginning of characters

There are other functions too such as:

`ends_with()`: ends with an exact suffix

`contains()`: contains a literal string

`matches()`: matches a regular expression

`num_range()`: matches a numerical range like x01, x02, x03, etc.

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] -0.5076545  1.3982427  0.5557809  0.4038615  0.5488754 -0.3143026
```

4. Causality review

Potential outcomes:

- $Y_i(1)$ is the value that the outcome would take if gave unit i **treatment** and changed nothing else about them

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- $Y_i(1)$ is the value that the outcome would take if gave unit i **treatment** and changed nothing else about them
- $Y_i(0)$ is the value that the outcome would take if gave unit i **no treatment** and changed nothing else about them

Potential outcomes:

- $Y_i(1)$ is the value that the outcome would take if gave unit i **treatment** and changed nothing else about them
- $Y_i(0)$ is the value that the outcome would take if gave unit i **no treatment** and changed nothing else about them
- Not the **possible values** of the outcome

Treatment: $T_i = 1$ if vaccinated, $T_i = 0$ if not

Outcome: $Y_i = 1$ if acquired COVID after 12 weeks, $Y_i = 0$ if not

- What are the potential outcomes $Y_i(0)$ and $Y_i(1)$?
- Why not compare early volunteers for the vaccine to the overall population?

5. Pivoting data longer

Mortality data

```
library(TPDdata)
mortality
```

```
## # A tibble: 217 x 52
##    country      count~1 indic~2 `1972` `1973` `1974` `1975` `1976` `1977` `1
##    <chr>        <chr>   <chr>    <dbl>  <dbl>  <dbl>  <dbl>  <dbl>  <dbl>  <
##  1 Aruba        ABW     Mortal~   NA     NA     NA     NA     NA     NA
##  2 Afghanistan  AFG     Mortal~  291    285.   280.   274.   268    262.   2
##  3 Angola       AGO     Mortal~   NA     NA     NA     NA     NA     NA
##  4 Albania      ALB     Mortal~   NA     NA     NA     NA     NA     NA
##  5 Andorra      AND     Mortal~   NA     NA     NA     NA     NA     NA
##  6 United Arab~ ARE     Mortal~   80.1   72.6   65.7   59.4   53.6   48.3
##  7 Argentina    ARG     Mortal~   69.7   68.2   66.1   63.3   59.8   55.7
##  8 Armenia      ARM     Mortal~   NA     NA     NA     NA     87.1   83.6
##  9 American Sa~ ASM     Mortal~   NA     NA     NA     NA     NA     NA
## 10 Antigua and~ ATG     Mortal~   26.9   25.1   23.5   22.1   20.8   19.5
## # ... with 207 more rows, 42 more variables: `1979` <dbl>, `1980` <dbl>,
## #   `1981` <dbl>, `1982` <dbl>, `1983` <dbl>, `1984` <dbl>, `1985` <dbl>,
## #   `1986` <dbl>, `1987` <dbl>, `1988` <dbl>, `1989` <dbl>, `1990` <dbl>,
## #   `1991` <dbl>, `1992` <dbl>, `1993` <dbl>, `1994` <dbl>, `1995` <dbl>,
## #   `1996` <dbl>, `1997` <dbl>, `1998` <dbl>, `1999` <dbl>, `2000` <dbl>,
## #   `2001` <dbl>, `2002` <dbl>, `2003` <dbl>, `2004` <dbl>, `2005` <dbl>,
## #   `2006` <dbl>, `2007` <dbl>, `2008` <dbl>, `2009` <dbl>, `2010` <dbl>, ..
```

Pivoting longer

Mortality data in a "wide" format (years in columns)

We can convert this to country-year rows with `pivot_longer()`

```
mydata |>
  pivot_longer(
    cols = <variables to pivot>>,
    names_to = <new variable to put column names>,
    values_to = <new variable to put column values>
  )
```

Pivoting the mortality data

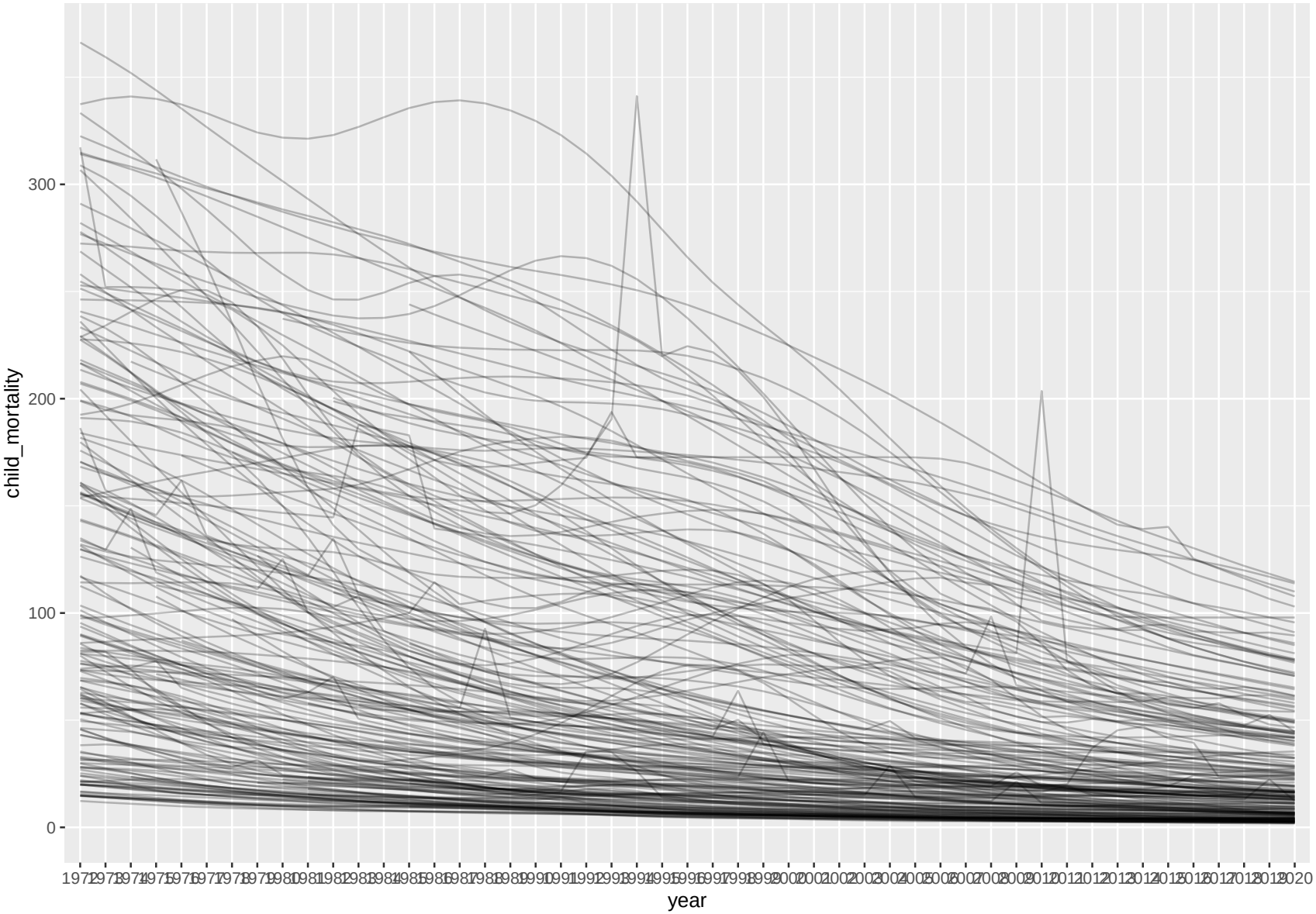
```
mortality |>
  select(-indicator) |>
  pivot_longer(
    cols=`1972`:`2020`,
    names_to = "year",
    values_to = "child_mortality"
  )
```

```
## # A tibble: 10,633 x 4
##    country country_code year  child_mortality
##    <chr>   <chr>        <chr>             <dbl>
##  1 Aruba   ABW          1972                 NA
##  2 Aruba   ABW          1973                 NA
##  3 Aruba   ABW          1974                 NA
##  4 Aruba   ABW          1975                 NA
##  5 Aruba   ABW          1976                 NA
##  6 Aruba   ABW          1977                 NA
##  7 Aruba   ABW          1978                 NA
##  8 Aruba   ABW          1979                 NA
##  9 Aruba   ABW          1980                 NA
## 10 Aruba   ABW          1981                 NA
## # ... with 10,623 more rows
```

Let's do line plots!

```
mortality |>
  select(-indicator) |>
  pivot_longer(
    cols=`1972`:`2020`,
    names_to = "year",
    values_to = "child_mortality"
  ) |>
  ggplot(mapping = aes(x = year, y = child_mortality, group
  geom_line(alpha = 0.25)
```

Hmm, what's going on?



Making sure year is numeric

By default, pivoted column names are characters, but we can transform them:

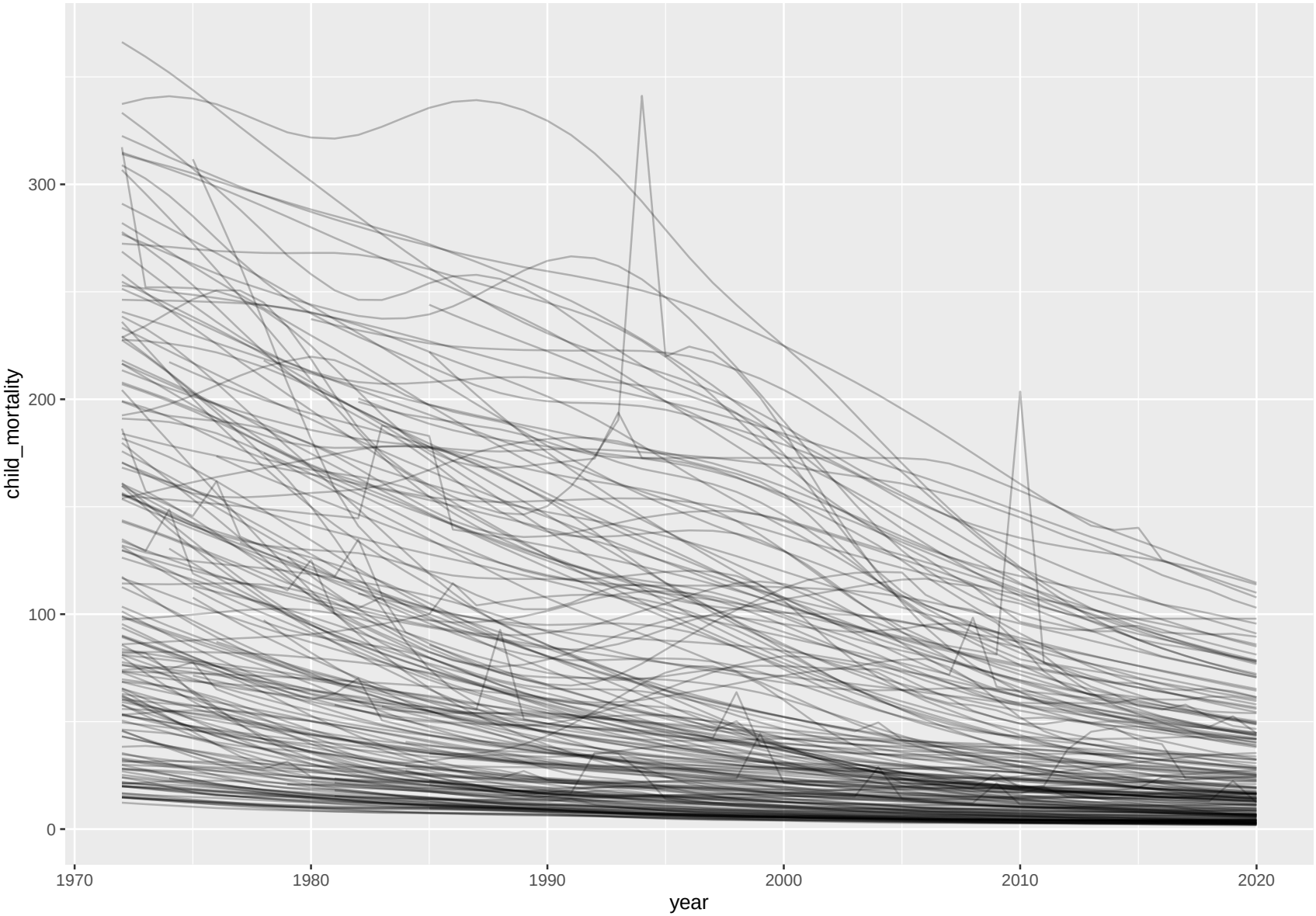
```
mortality_long <- mortality |>
  select(-indicator) |>
  pivot_longer(
    cols=`1972`:`2020`,
    names_to = "year",
    values_to = "child_mortality"
  ) |>
  mutate(year = as.integer(year))
mortality_long
```

```
## # A tibble: 10,633 x 4
##    country country_code  year child_mortality
##    <chr>   <chr>        <int>           <dbl>
##  1 Aruba   ABW           1972              NA
##  2 Aruba   ABW           1973              NA
##  3 Aruba   ABW           1974              NA
##  4 Aruba   ABW           1975              NA
##  5 Aruba   ABW           1976              NA
##  6 Aruba   ABW           1977              NA
##  7 Aruba   ABW           1978              NA
##  8 Aruba   ABW           1979              NA
##  9 Aruba   ABW           1980              NA
```

Let's (re)do line plots!

```
mortality_long |>
  ggplot(mapping = aes(x = year, y = child_mortality, group= country)) +
  geom_line(alpha=0.25)
```

There we go


child_mortality
300
200
100
0
1970
1980
1990
2000
2010
2020
year

Spotify data

```
library(TPDdata)
spotify
```

```
## # A tibble: 490 x 54
##    Track N~1 Artist week1 week2 week3 week4 week5 week6 week7 week8 week9 week10
##    <chr>     <chr>  <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 The Box   Roddy~     1     1     1     1     1     1     1     1     1      1
##  2 ROXANNE   Arizo~     2     4     5     4     4     4     6     7     9     21
##  3 Yummy     Justi~     3     6    17    17    17    24    15    32    NA     NA
##  4 Circles   Post ~     4     7     9    10     7    10    11    10    17     26
##  5 BOP       DaBaby     5     5     7     5    11    12    18    18    32     47
##  6 Falling   Trevo~     6     8    10     7     6     8    10    11    18     28
##  7 Dance Mo~ Tones~     7    13    13    12    12    13    17    13    21     33
##  8 Bandit (~ Juice~     8    11    14    14    15    20    27    26    42     NA
##  9 Futsal S~ Lil U~     9     9    19    21    24    32    40    49    NA     NA
## 10 everythi~ Billi~    10    17    28     9     8    11    14    17    29     NA
## # ... with 480 more rows, 42 more variables: week11 <dbl>, week12 <dbl>,
## #   week13 <dbl>, week14 <dbl>, week15 <dbl>, week16 <dbl>, week17 <dbl>,
## #   week18 <dbl>, week19 <dbl>, week20 <dbl>, week21 <dbl>, week22 <dbl>,
## #   week23 <dbl>, week24 <dbl>, week25 <dbl>, week26 <dbl>, week27 <dbl>,
## #   week28 <dbl>, week29 <dbl>, week30 <dbl>, week31 <dbl>, week32 <dbl>,
## #   week33 <dbl>, week34 <dbl>, week35 <dbl>, week36 <dbl>, week37 <dbl>,
## #   week38 <dbl>, week39 <dbl>, week40 <dbl>, week41 <dbl>, week42 <dbl>, ...
```

Pivoting not ideal

Last approach isn't ideal because of the week prefix:

```
spotify |>
  pivot_longer(
    cols = c(-`Track Name`, -Artist),
    names_to = "week_of_year",
    values_to = "rank"
  )
```

```
## # A tibble: 25,480 x 4
##    `Track Name` Artist      week_of_year  rank
##    <chr>        <chr>       <chr>        <dbl>
##  1 The Box      Roddy Ricch week1            1
##  2 The Box      Roddy Ricch week2            1
##  3 The Box      Roddy Ricch week3            1
##  4 The Box      Roddy Ricch week4            1
##  5 The Box      Roddy Ricch week5            1
##  6 The Box      Roddy Ricch week6            1
##  7 The Box      Roddy Ricch week7            1
##  8 The Box      Roddy Ricch week8            1
##  9 The Box      Roddy Ricch week9            1
## 10 The Box      Roddy Ricch week10           1
## # ... with 25,470 more rows
```

Removing a column name prefix

```
spotify |>
  pivot_longer(
    cols = c(-`Track Name`, -Artist),
    names_to = "week_of_year",
    values_to = "rank",
    names_prefix = "week"
  ) |>
  mutate(
    week_of_year = as.integer(week_of_year)
  )
```

Removing a column name prefix

```
## # A tibble: 25,480 x 4
##    `Track Name` Artist      week_of_year  rank
##    <chr>        <chr>              <int> <dbl>
##  1 The Box      Roddy Ricch            1     1
##  2 The Box      Roddy Ricch            2     1
##  3 The Box      Roddy Ricch            3     1
##  4 The Box      Roddy Ricch            4     1
##  5 The Box      Roddy Ricch            5     1
##  6 The Box      Roddy Ricch            6     1
##  7 The Box      Roddy Ricch            7     1
##  8 The Box      Roddy Ricch            8     1
##  9 The Box      Roddy Ricch            9     1
## 10 The Box      Roddy Ricch           10     1
## # ... with 25,470 more rows
```

6. Joining datasets

Gapminder data

```
library(gapminder)
gapminder
```

```
## # A tibble: 1,704 x 6
##    country     continent  year lifeExp      pop gdpPercap
##    <fct>       <fct>     <int>   <dbl>    <int>     <dbl>
##  1 Afghanistan Asia       1952    28.8  8425333      779.
##  2 Afghanistan Asia       1957    30.3  9240934      821.
##  3 Afghanistan Asia       1962    32.0 10267083      853.
##  4 Afghanistan Asia       1967    34.0 11537966      836.
##  5 Afghanistan Asia       1972    36.1 13079460      740.
##  6 Afghanistan Asia       1977    38.4 14880372      786.
##  7 Afghanistan Asia       1982    39.9 12881816      978.
##  8 Afghanistan Asia       1987    40.8 13867957      852.
##  9 Afghanistan Asia       1992    41.7 16317921      649.
## 10 Afghanistan Asia       1997    41.8 22227415      635.
## # ... with 1,694 more rows
```

What if we want to add the `child_motality` variable to the `gapminder` data?

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Just add the columns?

What if we want to add the `child_motality` variable to the `gapminder` data?

Just add the columns?

```
gapminder |>
  select(country, year) |>
  head()
```

```
## # A tibble: 6 x 2
##   country      year
##   <fct>       <int>
## 1 Afghanistan  1952
## 2 Afghanistan  1957
## 3 Afghanistan  1962
## 4 Afghanistan  1967
## 5 Afghanistan  1972
## 6 Afghanistan  1977
```

```
mortality_long |>
  select(country, year) |>
  head()
```

```
## # A tibble: 6 x 2
##   country  year
##   <chr>   <int>
## 1 Aruba    1972
## 2 Aruba    1973
## 3 Aruba    1974
## 4 Aruba    1975
## 5 Aruba    1976
## 6 Aruba    1977
```

Rows are not aligned properly!

Key variables

A **primary key** is a variable or set of variables that uniquely identifies rows in the data

- `{country, year}` in the `gapminder` data

Key variables

A **primary key** is a variable or set of variables that uniquely identifies rows in the data

- `{country, year}` in the `gapminder` data

A `foreign key` is the corresponding variable(s) in another table

- `{country, year}` in the `mortality_long` data

Key variables

A **primary key** is a variable or set of variables that uniquely identifies rows in the data

- `{country, year}` in the `gapminder` data

A `foreign key` is the corresponding variable(s) in another table

- `{country, year}` in the `mortality_long` data

If we align the two tables based on these variables, we can add variables from one to the other

Checking that the keys are unique

Things get weird if these keys are not unique. Let's check.

Checking primary key is unique

```
gapminder |>
  count(country, year) |>
  filter(n>1)
```

```
## # A tibble: 0 x 3
```

Checking foreign key is unique

```
mortality_long |>
  count(country, year) |>
  filter(n>1)
```

```
## # A tibble: 0 x 3
```

left_join(): add variables to primary table

left_join() keeps all rows from the first argument/piped data:

```
gapminder |>
  left_join(mortality_long) |>
  select(country, year, lifeExp, pop, gdpPercap, child_mortality) |>
  head(n = 6)
```

```
## Joining with `by = join_by(country, year)`
```

```
## # A tibble: 6 x 6
##   country      year lifeExp      pop gdpPercap child_mortality
##   <chr>       <int>   <dbl>    <int>     <dbl>           <dbl>
## 1 Afghanistan  1952    28.8  8425333      779.             NA
## 2 Afghanistan  1957    30.3  9240934      821.             NA
## 3 Afghanistan  1962    32.0 10267083      853.             NA
## 4 Afghanistan  1967    34.0 11537966      836.             NA
## 5 Afghanistan  1972    36.1 13079460      740.            291
## 6 Afghanistan  1977    38.4 14880372      786.            262.
```

Rows in primary table not in foreign table: new values are NA

inner_join(): add and filter

inner_join() adds the variables from the foreign table and dilters to rows in both tables:

```
gapminder |>
  inner_join(mortality_long) |>
  select(country, year, lifeExp, pop, gdpPercap, child_mortality) |>
  head(n=6)
```

```
## Joining with `by = join_by(country, year)`
```

```
## # A tibble: 6 x 6
##   country      year lifeExp      pop gdpPercap child_mortality
##   <chr>       <int>   <dbl>    <int>     <dbl>           <dbl>
## 1 Afghanistan  1972    36.1 13079460      740.            291
## 2 Afghanistan  1977    38.4 14880372      786.            262.
## 3 Afghanistan  1982    39.9 12881816      978.            231.
## 4 Afghanistan  1987    40.8 13867957      852.            198.
## 5 Afghanistan  1992    41.7 16317921      649.            166.
## 6 Afghanistan  1997    41.8 22227415      635.            142.
```

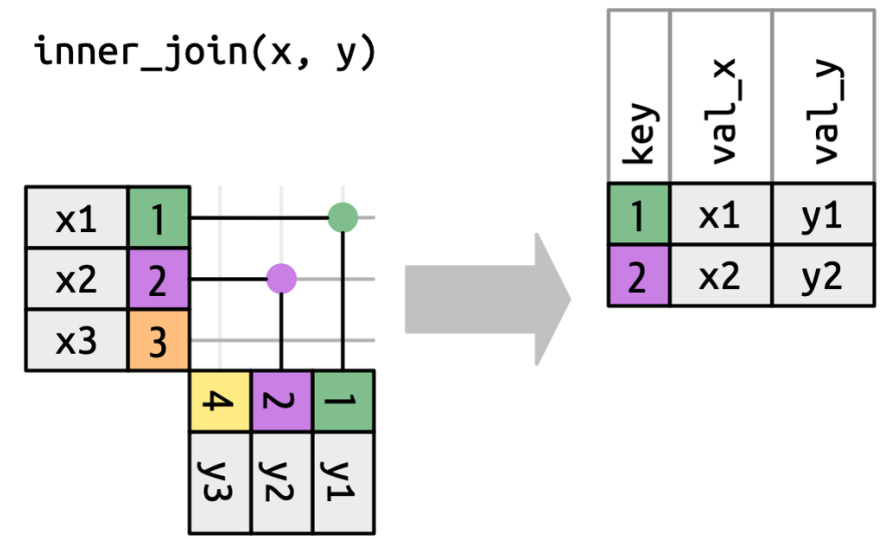
How inner joins work

Two data sets:

x	
1	x1
2	x2
3	x3

y	
1	y1
2	y2
4	y3

Finding matching keys:

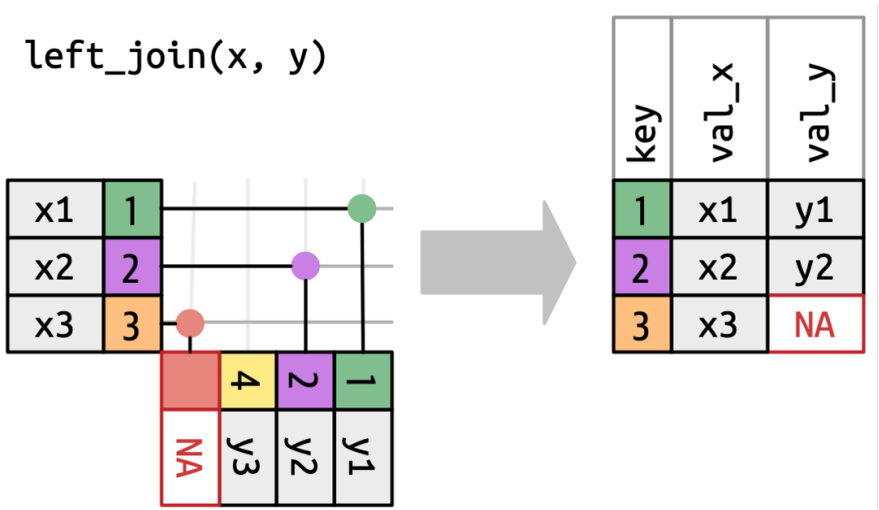


How left joins work

Two data sets:

	x		y
1	x1	1	y1
2	x2	2	y2
3	x3	4	y3

Keep all x keys:



More complicated example

```
library(nycflights13)
flights2 <- flights |>
  select(year, time_hour, origin, dest, tailnum, carrier)
flights2
```

```
## # A tibble: 336,776 x 6
##     year time_hour           origin dest  tailnum carrier
##    <int> <dttm>              <chr>  <chr> <chr>   <chr>
##  1  2013 2013-01-01 05:00:00 EWR    IAH   N14228  UA
##  2  2013 2013-01-01 05:00:00 LGA    IAH   N24211  UA
##  3  2013 2013-01-01 05:00:00 JFK    MIA   N619AA  AA
##  4  2013 2013-01-01 05:00:00 JFK    BQN   N804JB  B6
##  5  2013 2013-01-01 06:00:00 LGA    ATL   N668DN  DL
##  6  2013 2013-01-01 05:00:00 EWR    ORD   N39463  UA
##  7  2013 2013-01-01 06:00:00 EWR    FLL   N516JB  B6
##  8  2013 2013-01-01 06:00:00 LGA    IAD   N829AS  EV
##  9  2013 2013-01-01 06:00:00 JFK    MCO   N593JB  B6
## 10  2013 2013-01-01 06:00:00 LGA    ORD   N3ALAA  AA
## # ... with 336,766 more rows
```

Planes data

```
planes2 <- planes |>
  select(tailnum, year, type, engine, seats)
planes2
```

```
## # A tibble: 3,322 x 5
##    tailnum  year type                    engine    seats
##    <chr>   <int> <chr>                   <chr>     <int>
##  1 N10156   2004 Fixed wing multi engine Turbo-fan    55
##  2 N102UW   1998 Fixed wing multi engine Turbo-fan   182
##  3 N103US   1999 Fixed wing multi engine Turbo-fan   182
##  4 N104UW   1999 Fixed wing multi engine Turbo-fan   182
##  5 N10575   2002 Fixed wing multi engine Turbo-fan    55
##  6 N105UW   1999 Fixed wing multi engine Turbo-fan   182
##  7 N107US   1999 Fixed wing multi engine Turbo-fan   182
##  8 N108UW   1999 Fixed wing multi engine Turbo-fan   182
##  9 N109UW   1999 Fixed wing multi engine Turbo-fan   182
## 10 N110UW   1999 Fixed wing multi engine Turbo-fan   182
## # ... with 3,312 more rows
```

What happens with naive join?

```
flights2 |>
  left_join(planes2)
```

```
## Joining with `by = join_by(year, tailnum)`
```

```
## # A tibble: 336,776 x 9
##     year time_hour           origin dest  tailnum carrier type  engine seats
##    <int> <dttm>              <chr>  <chr> <chr>   <chr>   <chr> <chr>  <int>
##  1  2013 2013-01-01 05:00:00 EWR    IAH   N14228  UA      <NA>  <NA>      NA
##  2  2013 2013-01-01 05:00:00 LGA    IAH   N24211  UA      <NA>  <NA>      NA
##  3  2013 2013-01-01 05:00:00 JFK    MIA   N619AA  AA      <NA>  <NA>      NA
##  4  2013 2013-01-01 05:00:00 JFK    BQN   N804JB  B6      <NA>  <NA>      NA
##  5  2013 2013-01-01 06:00:00 LGA    ATL   N668DN  DL      <NA>  <NA>      NA
##  6  2013 2013-01-01 05:00:00 EWR    ORD   N39463  UA      <NA>  <NA>      NA
##  7  2013 2013-01-01 06:00:00 EWR    FLL   N516JB  B6      <NA>  <NA>      NA
##  8  2013 2013-01-01 06:00:00 LGA    IAD   N829AS  EV      <NA>  <NA>      NA
##  9  2013 2013-01-01 06:00:00 JFK    MCO   N593JB  B6      <NA>  <NA>      NA
## 10  2013 2013-01-01 06:00:00 LGA    ORD   N3ALAA  AA      <NA>  <NA>      NA
## # ... with 336,766 more rows
```

Specify the joining variables

```
flights2 |>
  left_join(planes2, by = "tailnum")
```

```
## # A tibble: 336,776 x 10
##    year.x time_hour           origin dest  tailnum carrier year.y type    engine
##     <int> <dttm>              <chr>  <chr> <chr>   <chr>    <int> <chr>   <chr>
##  1   2013 2013-01-01 05:00:00 EWR    IAH   N14228  UA        1999 Fixed ~ Turbo~
##  2   2013 2013-01-01 05:00:00 LGA    IAH   N24211  UA        1998 Fixed ~ Turbo~
##  3   2013 2013-01-01 05:00:00 JFK    MIA   N619AA  AA        1990 Fixed ~ Turbo~
##  4   2013 2013-01-01 05:00:00 JFK    BQN   N804JB  B6        2012 Fixed ~ Turbo~
##  5   2013 2013-01-01 06:00:00 LGA    ATL   N668DN  DL        1991 Fixed ~ Turbo~
##  6   2013 2013-01-01 05:00:00 EWR    ORD   N39463  UA        2012 Fixed ~ Turbo~
##  7   2013 2013-01-01 06:00:00 EWR    FLL   N516JB  B6        2000 Fixed ~ Turbo~
##  8   2013 2013-01-01 06:00:00 LGA    IAD   N829AS  EV        1998 Fixed ~ Turbo~
##  9   2013 2013-01-01 06:00:00 JFK    MCO   N593JB  B6        2004 Fixed ~ Turbo~
## 10   2013 2013-01-01 06:00:00 LGA    ORD   N3ALAA  AA          NA <NA>    <NA>
## # ... with 336,766 more rows, and 1 more variable: seats <int>
```

Change variables names

```
flights2 |>
  left_join(planes2 |> rename(manufacture_year = year))
```

```
## Joining with `by = join_by(tailnum)`
```

```
## # A tibble: 336,776 x 10
##     year time_hour           origin dest  tailnum carrier manufac~1 type  engine
##    <int> <dttm>              <chr>  <chr> <chr>   <chr>       <int> <chr> <chr>
##  1  2013 2013-01-01 05:00:00 EWR    IAH   N14228  UA           1999 Fixe~ Turbo~
##  2  2013 2013-01-01 05:00:00 LGA    IAH   N24211  UA           1998 Fixe~ Turbo~
##  3  2013 2013-01-01 05:00:00 JFK    MIA   N619AA  AA           1990 Fixe~ Turbo~
##  4  2013 2013-01-01 05:00:00 JFK    BQN   N804JB  B6           2012 Fixe~ Turbo~
##  5  2013 2013-01-01 06:00:00 LGA    ATL   N668DN  DL           1991 Fixe~ Turbo~
##  6  2013 2013-01-01 05:00:00 EWR    ORD   N39463  UA           2012 Fixe~ Turbo~
##  7  2013 2013-01-01 06:00:00 EWR    FLL   N516JB  B6           2000 Fixe~ Turbo~
##  8  2013 2013-01-01 06:00:00 LGA    IAD   N829AS  EV           1998 Fixe~ Turbo~
##  9  2013 2013-01-01 06:00:00 JFK    MCO   N593JB  B6           2004 Fixe~ Turbo~
## 10  2013 2013-01-01 06:00:00 LGA    ORD   N3ALAA  AA             NA <NA>  <NA>
## # ... with 336,766 more rows, 1 more variable: seats <int>, and abbreviated
## #   variable name 1: manufacture_year
```