Data Visualization Principles

Summer Institute in Data Science

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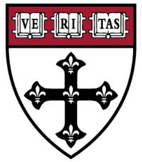

HARVARD
SCHOOL OF PUBLIC HEALTH

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@RJANunez

What to expect today

- Today we will show some bad examples of data visualization, discuss how we can improve on them, and use these as motivation for a list of principles
- The principles we will discuss today are mostly based on research related to how humans detect patterns and make visual comparisons
- Things to consider:
    1. Choose a visualization technique that best fit the way our brains process visual information
    2. Have a goal in mind
    3. Know your audience

Encoding data using visual cues

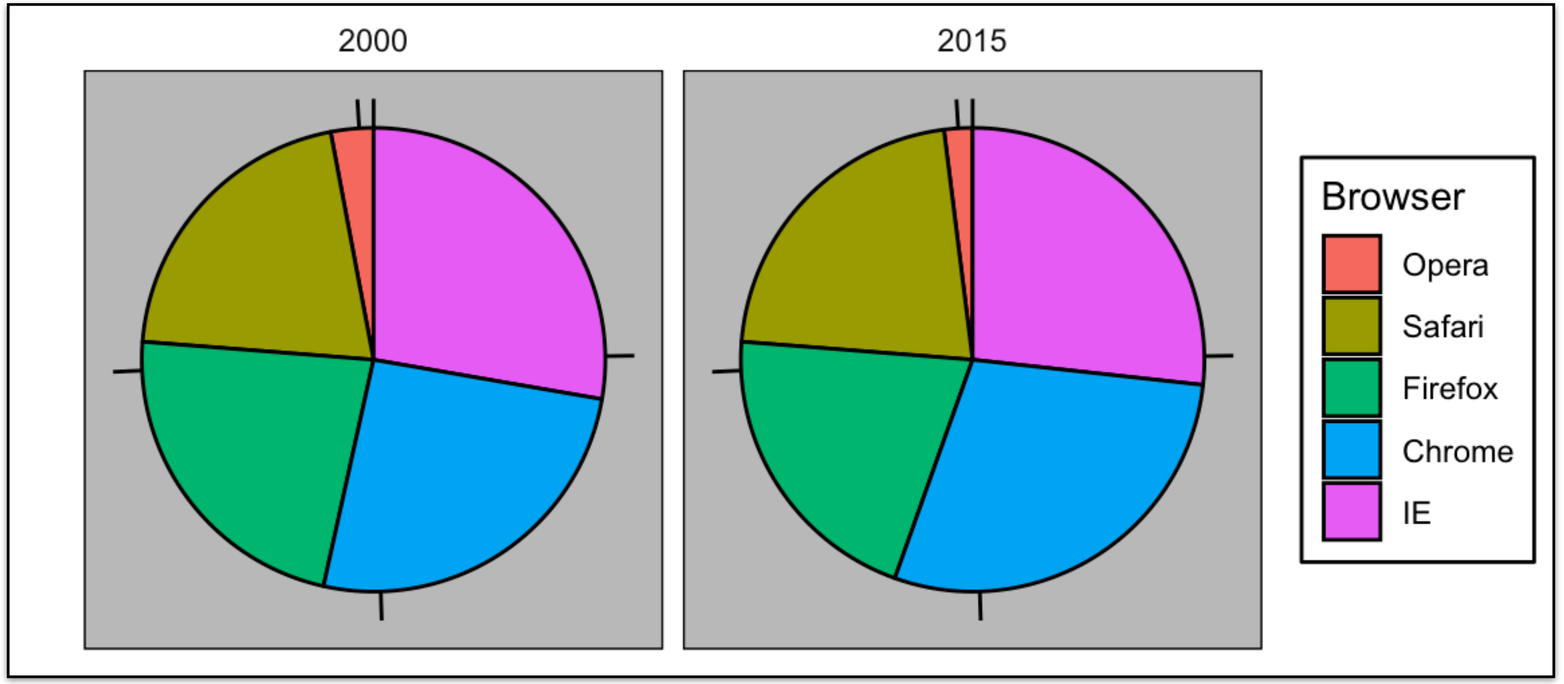
- There are several approaches at our disposal including:
    1. Position
    2. Aligned lengths
    3. Angles
    4. Area
    5. Brightness
    6. Color hue

First example

- Suppose we want to report the results from two hypothetical regarding browser preference taken in 2000 and then 2015
- The options were:
    1. Opera
    2. Safari
    3. Firefox
    4. Chrome
    5. Internet explorer
- Note that for each year we are simply comparing 5 quantities (the 5 percentages)

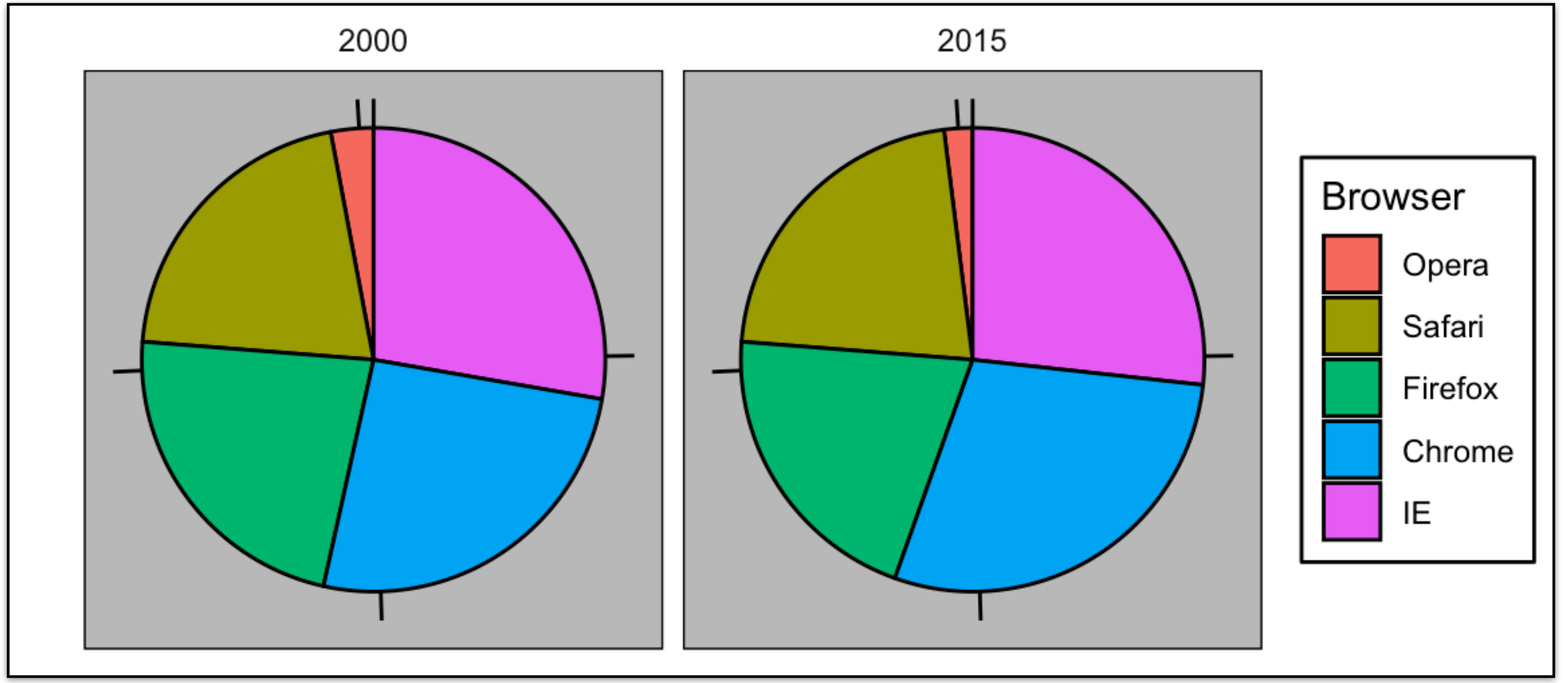
First example

- A common representation of percentages, popularized by Microsoft Excel, is the pie chart:



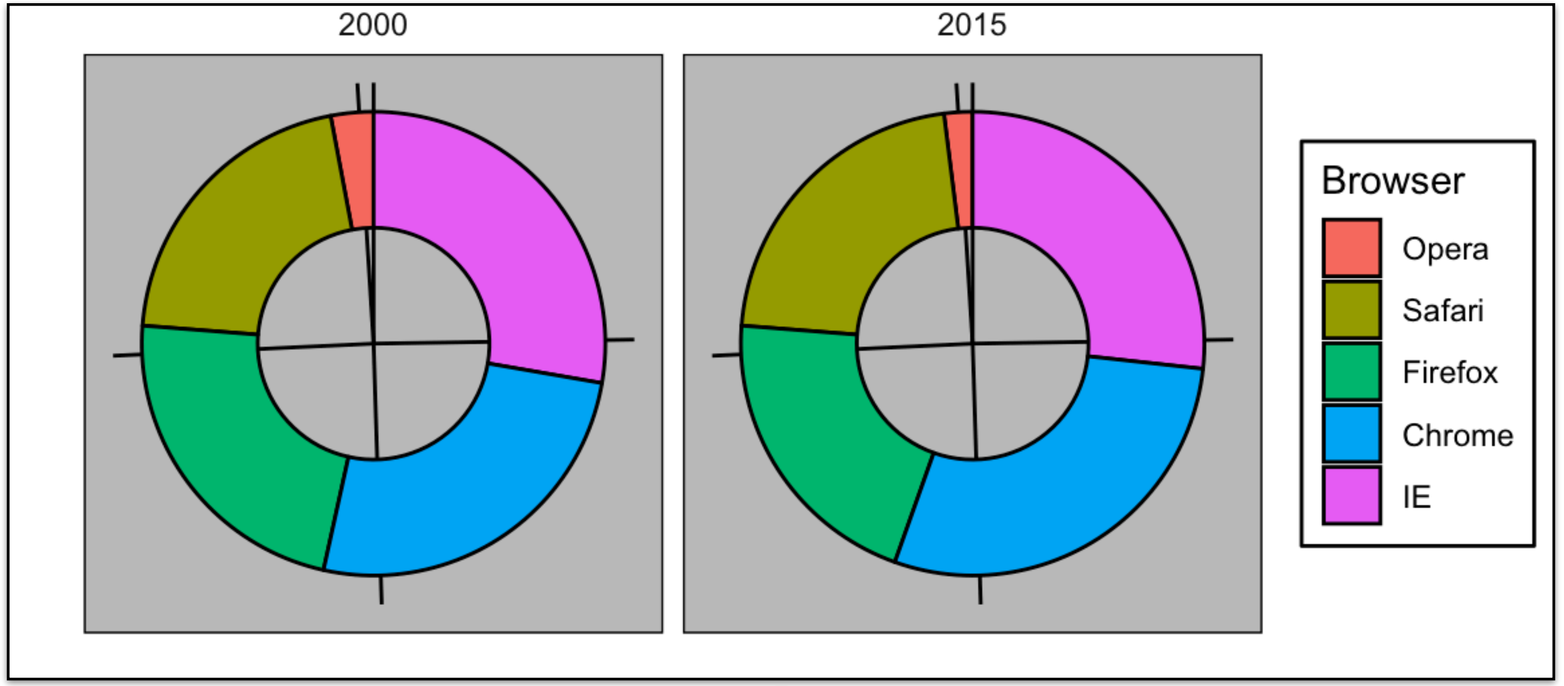
First example

- Here we are representing quantities using both areas and angles, since both the angle and area of each slice is proportional to the percentage it represents
- It turns out that perception studies conclude that humans are not good at quantifying angles and even worse at quantifying areas



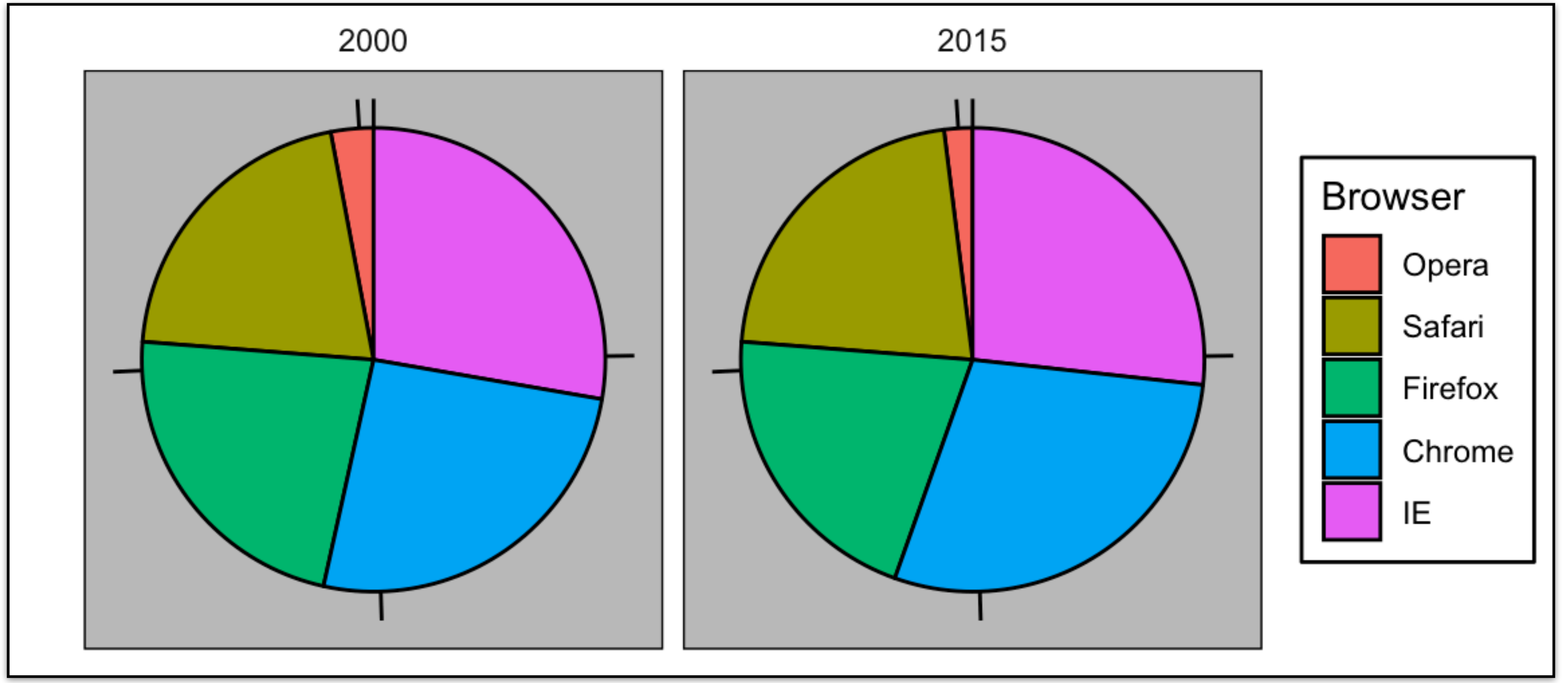
First example

- The donut chart is an example that only uses areas



First example

- To see how bad we are at visually quantifying angles and areas let's try to estimate the percentage of respondents that prefer Firefox
- Any guesses?



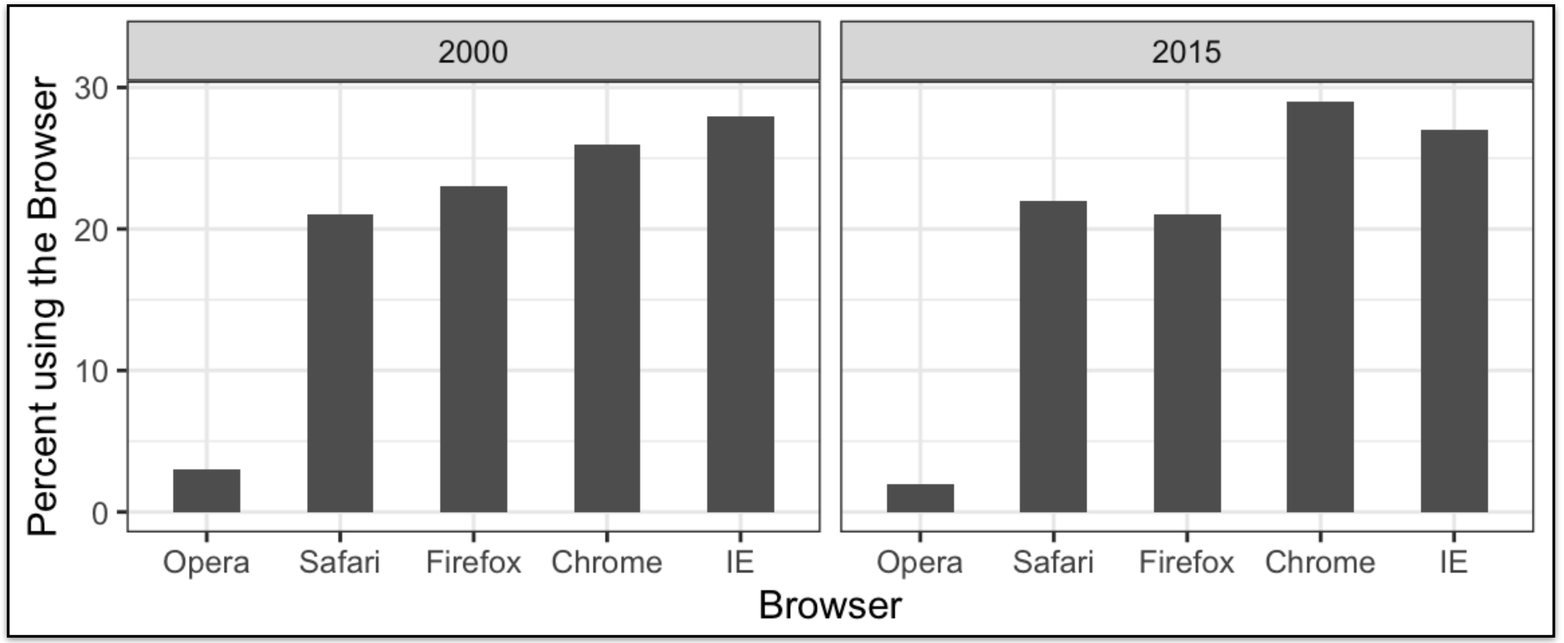
First example

- Here is the data
- In this case, its better to just present a table

Browser	2000	2010
Opera	3	2
Safari	21	22
Firefox	23	21
Chrome	26	29
Internet explorer	28	27

First example

- The preferred way to plot these data is with a barplot
- Here we use length and position as visual cues



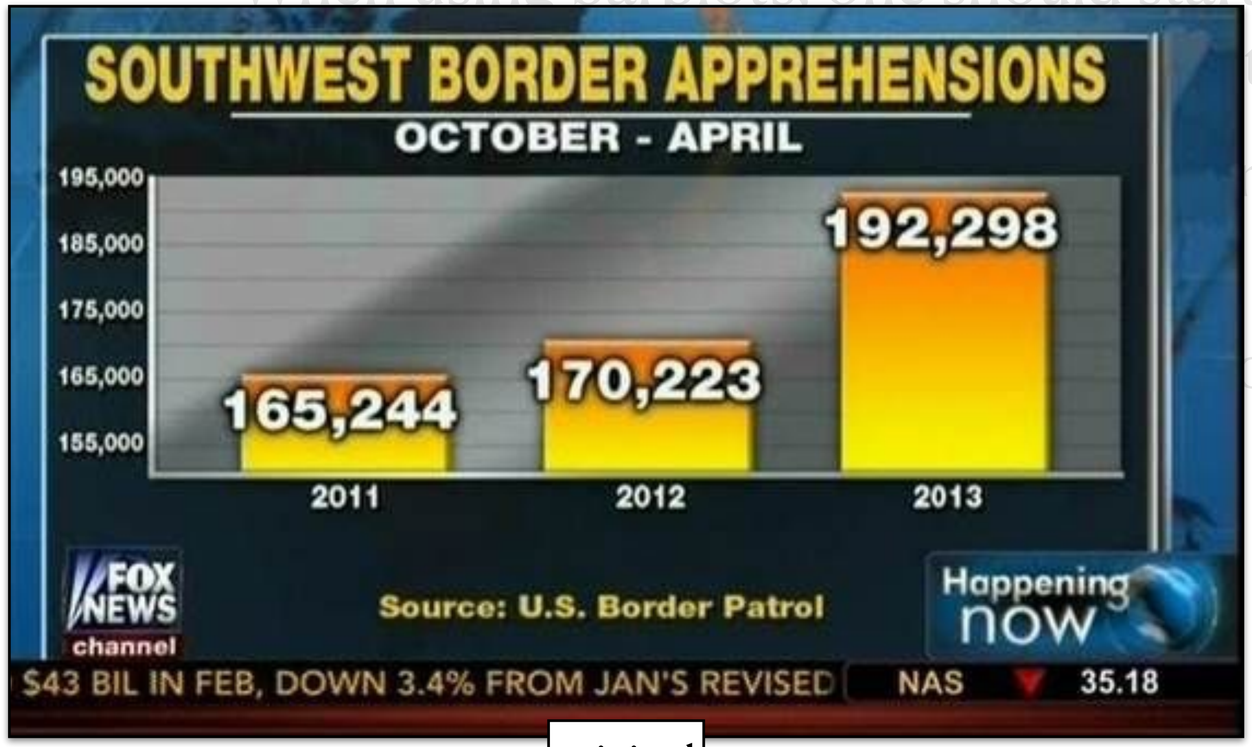
- If for some reason you have to use pie charts, label each slice with the corresponding numerical value

Know when to include 0

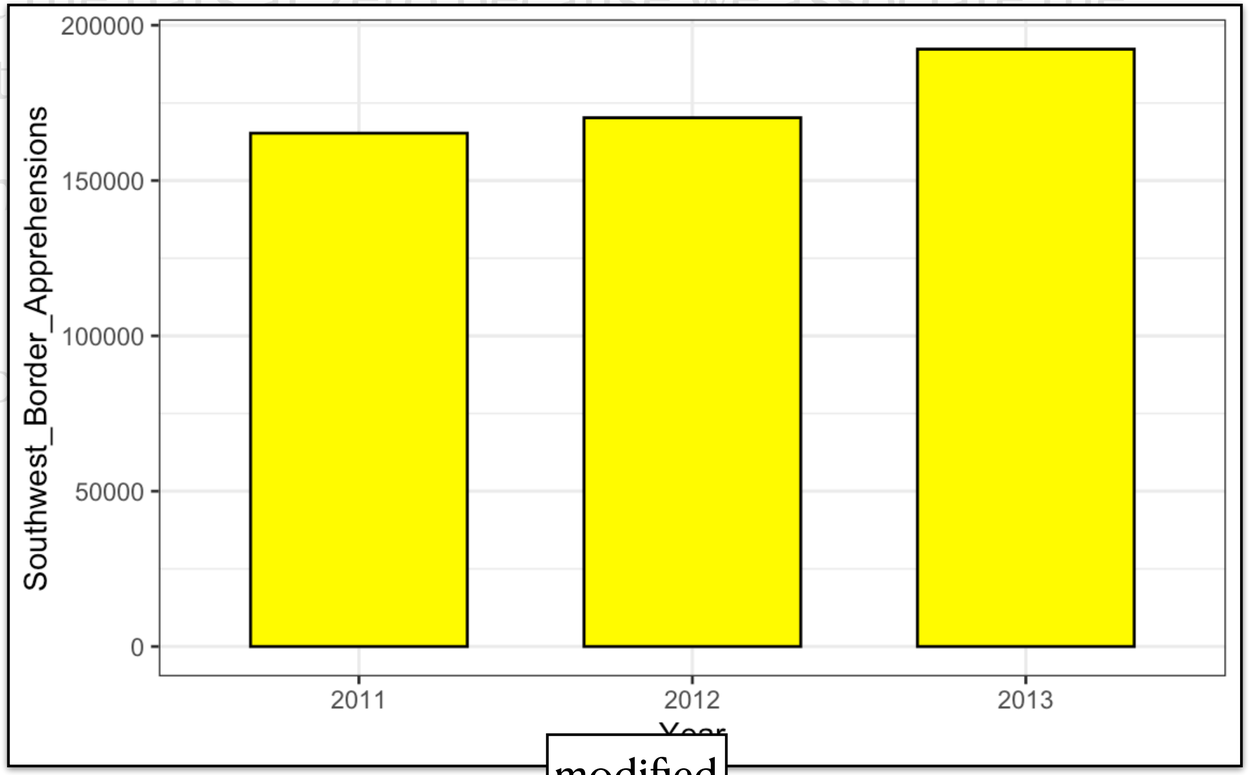
- When using barplots, one should start the bars at zero because we associate the length to be proportional to the quantities being displayed
- By avoiding zero, small differences can be made to look bigger than they actually are
- Take this example used by Peter Aldhous here

Know when to include 0

- When using barplots, one should start the bars at zero because we associate the



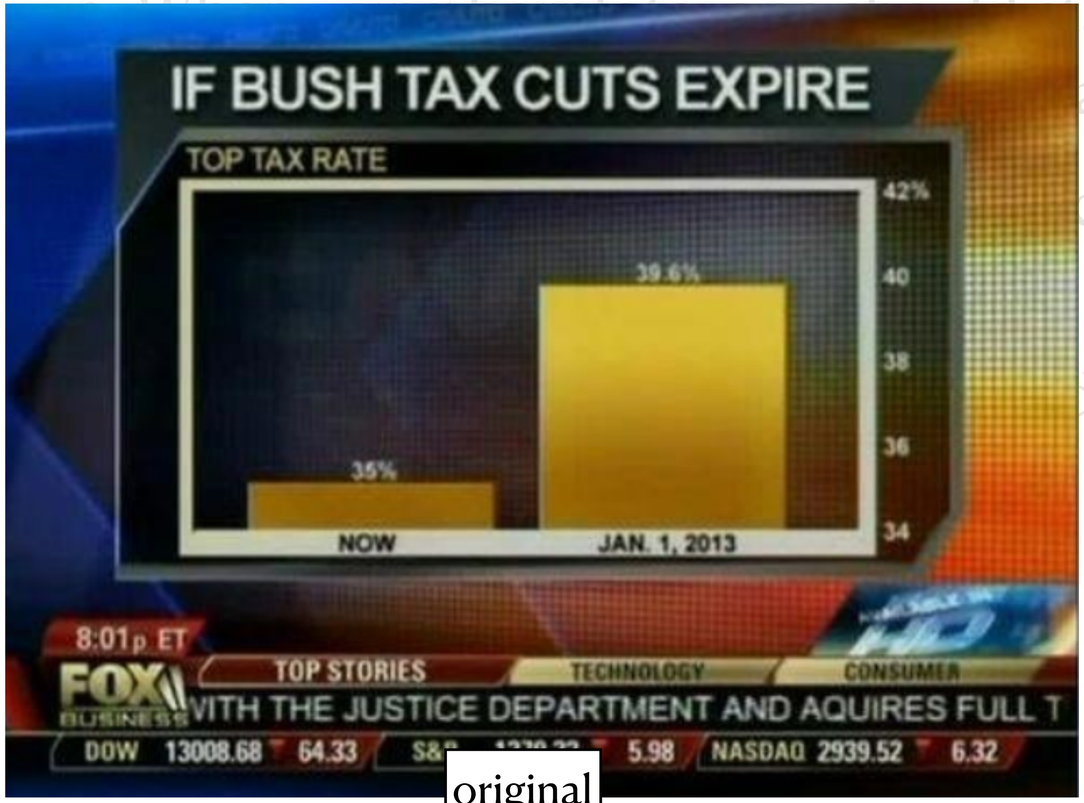
original



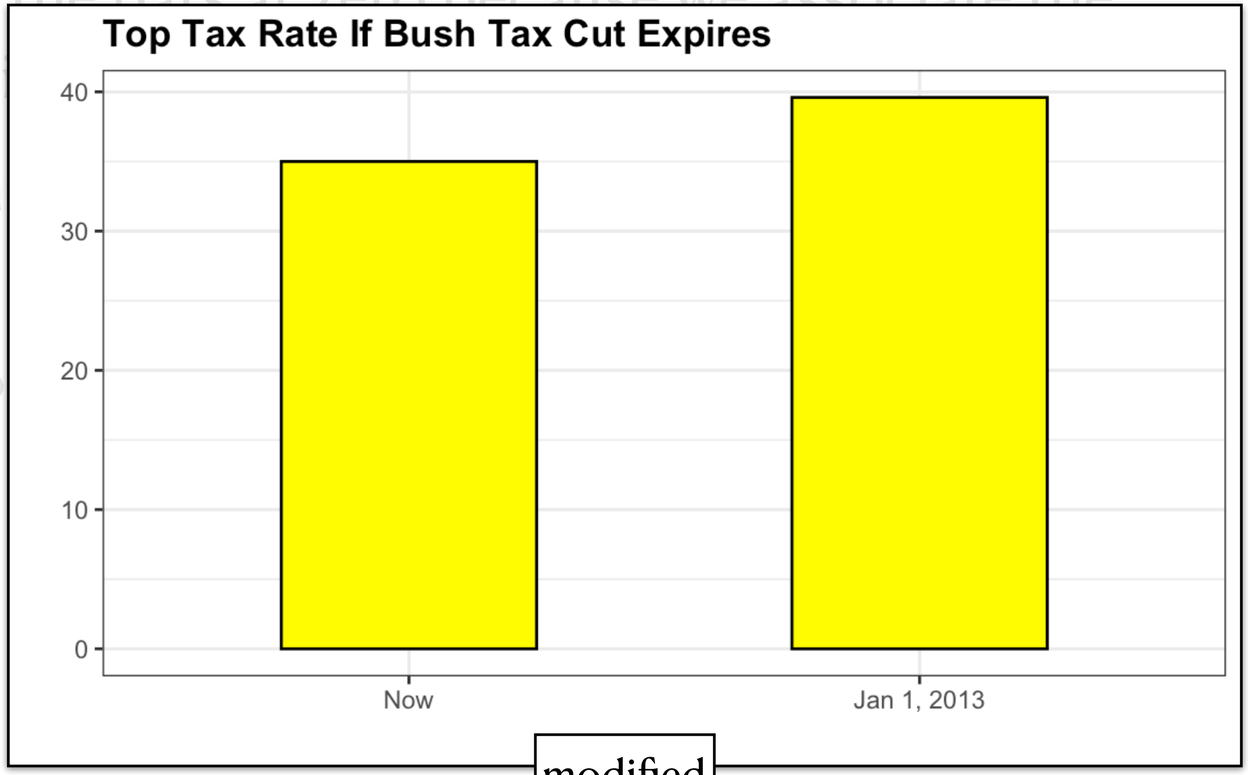
modified

- The original figure makes a 16% increase look a 3-fold change

Know when to include 0



original

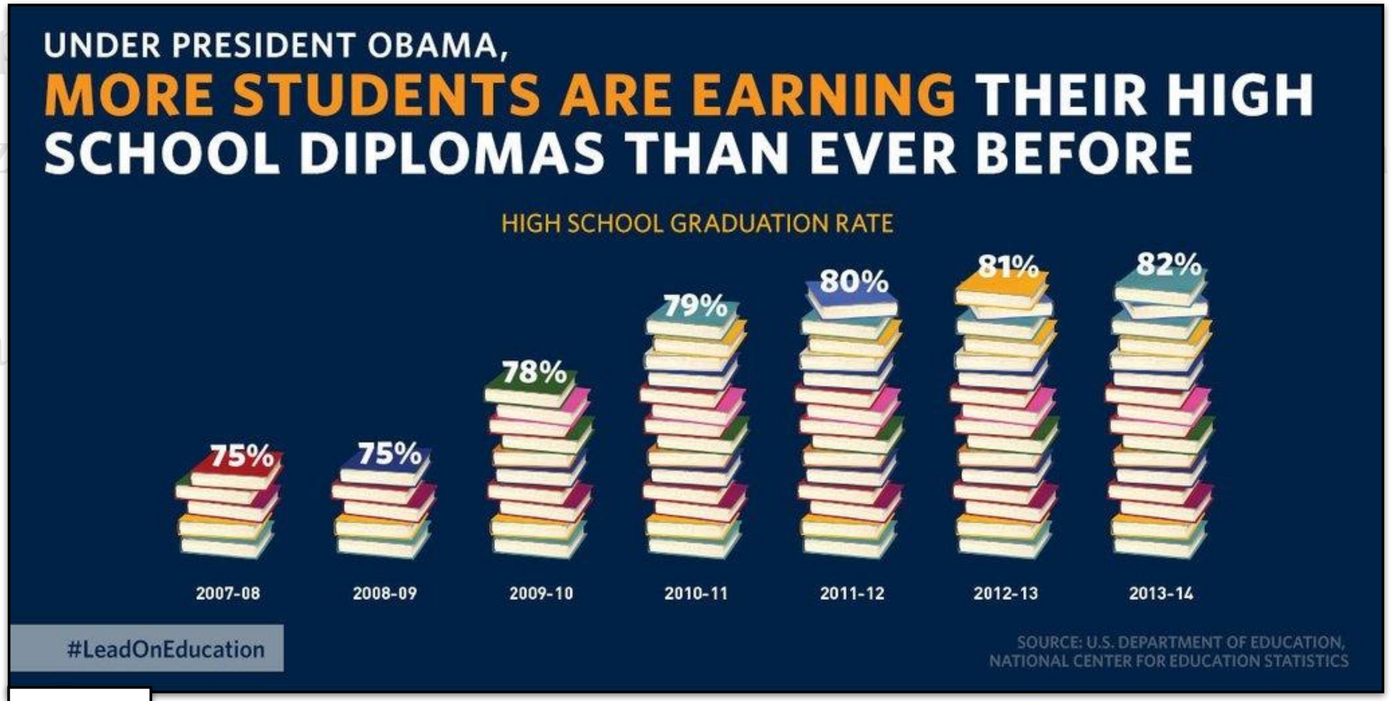


modified

- This one makes a 13% increase look like a 5-fold change!

Know when to include 0

- When using barplots, one should start the bars at zero because we associate the length to be
- By avoiding z an they actually are
- Take this exa

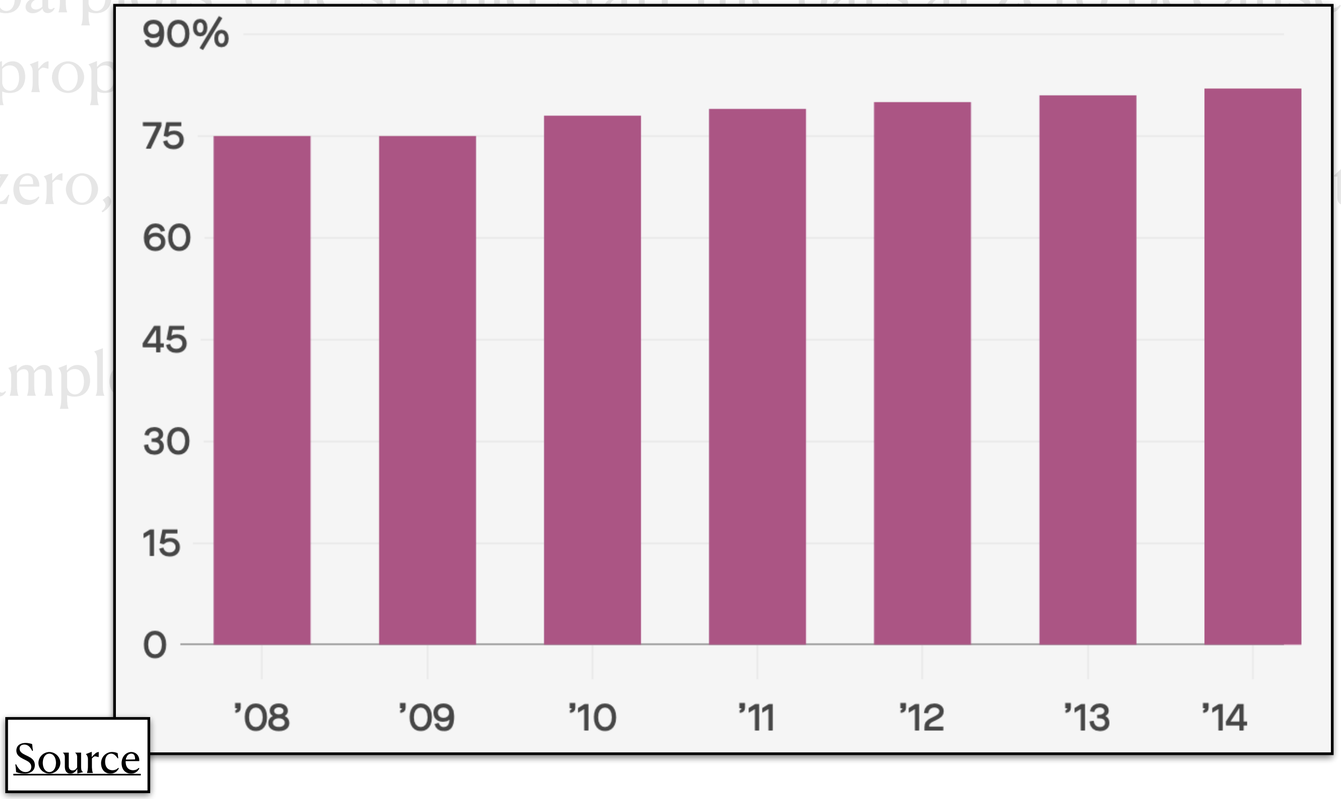


Source

- What does 5 books (75%) mean? What about 16 books(82%)?

Know when to include 0

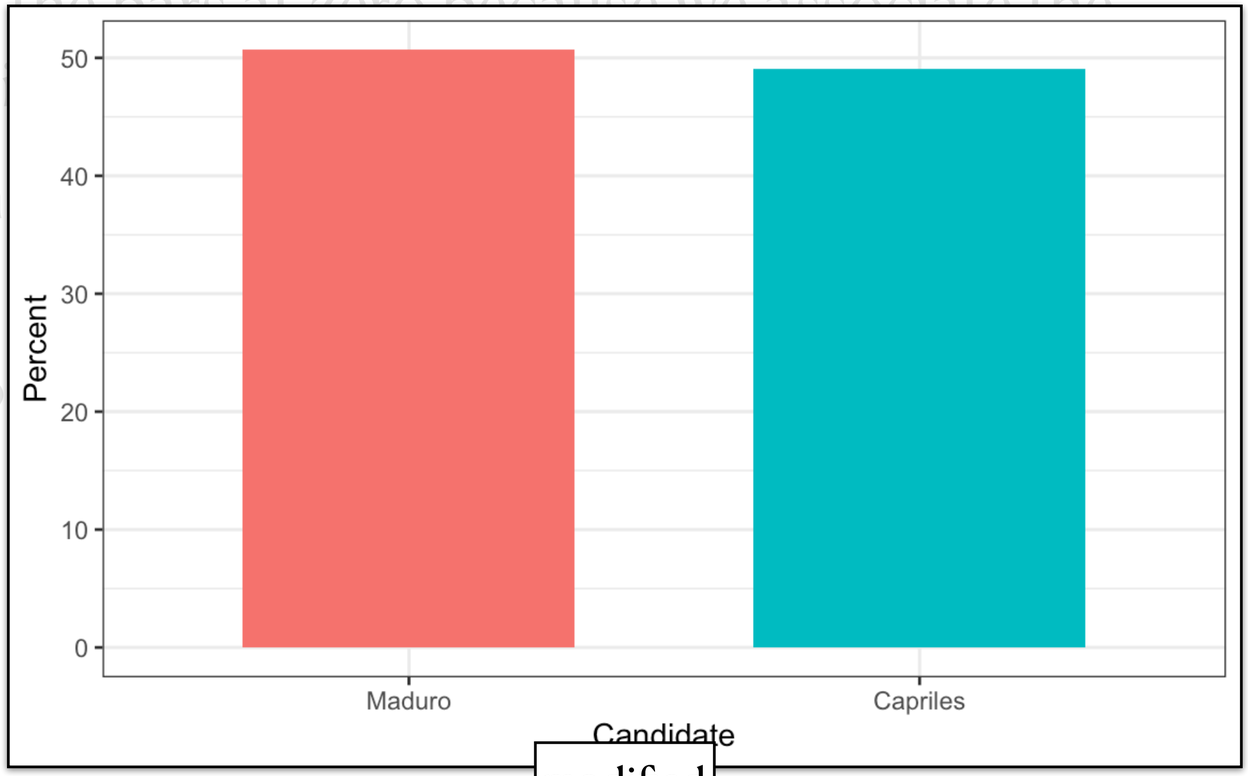
- When using barplots, one should start the bars at zero because we associate the length to be prop
- By avoiding zero, than they actually are
- Take this exampl



- A better version

Know when to include 0

original

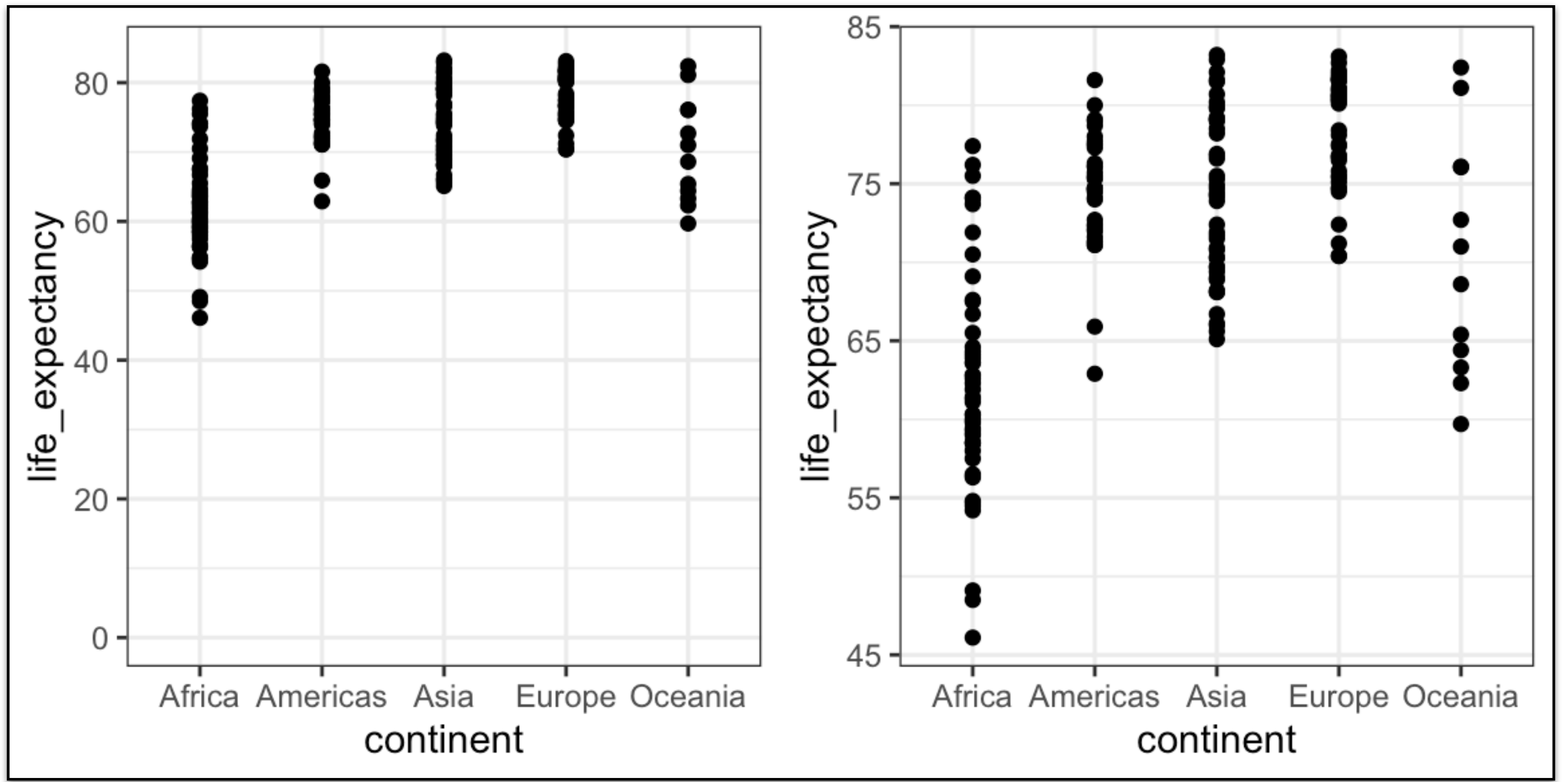


modified

- This one makes a 3% increase look like all of Venezuela voted for Maduro

Know when to include 0

- If, for example, one uses position instead of length as a visual cue then its not necessary to include 0
- This is particularly the case when we want to compare between-group to within-group variability



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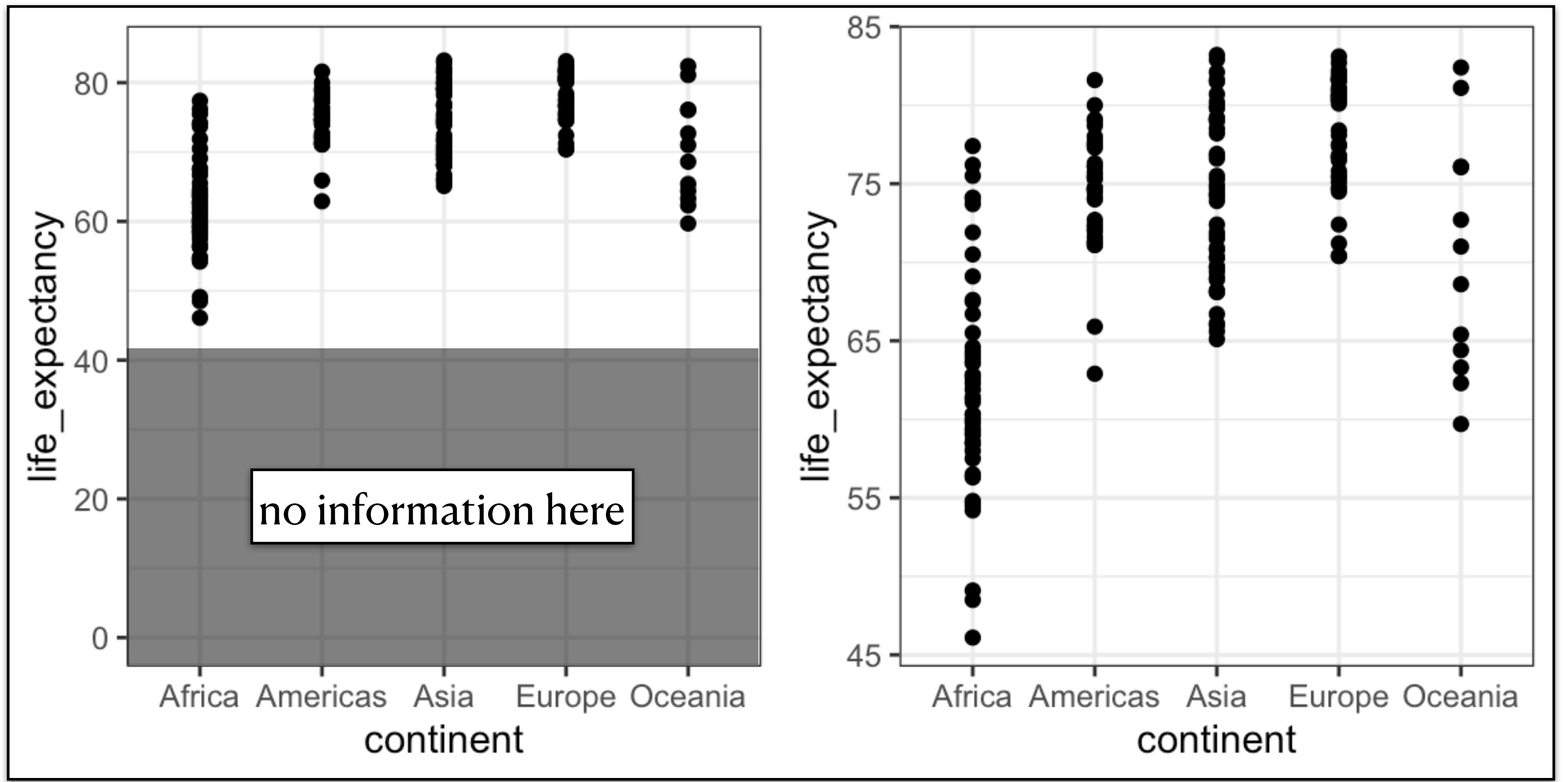


Do not distort quantities

- During President Obama's 2011 State of the Union Address, the following chart was used to show the US GDP against four competing nations
- Judging by the area of the circles, it seems that the US has an economy over five times larger than China's economy over 20 plus times that of France

Do not distort quantities

- But look at the numbers:

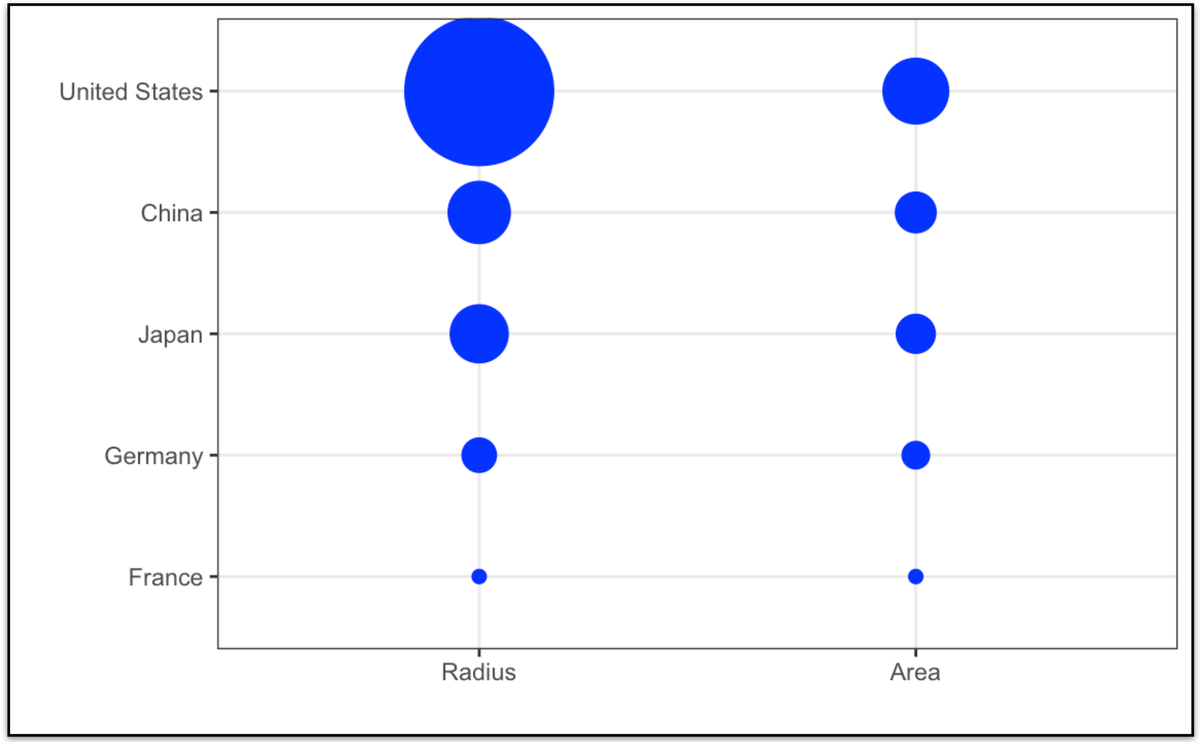
$$\text{US/China } 14.6/5.7 = 2.6$$

$$\text{US/France } 14.6/2.5 = 5.8$$

- Why the distortion? It turns out that the radius of the circle, instead of the area, is proportional to the quantity

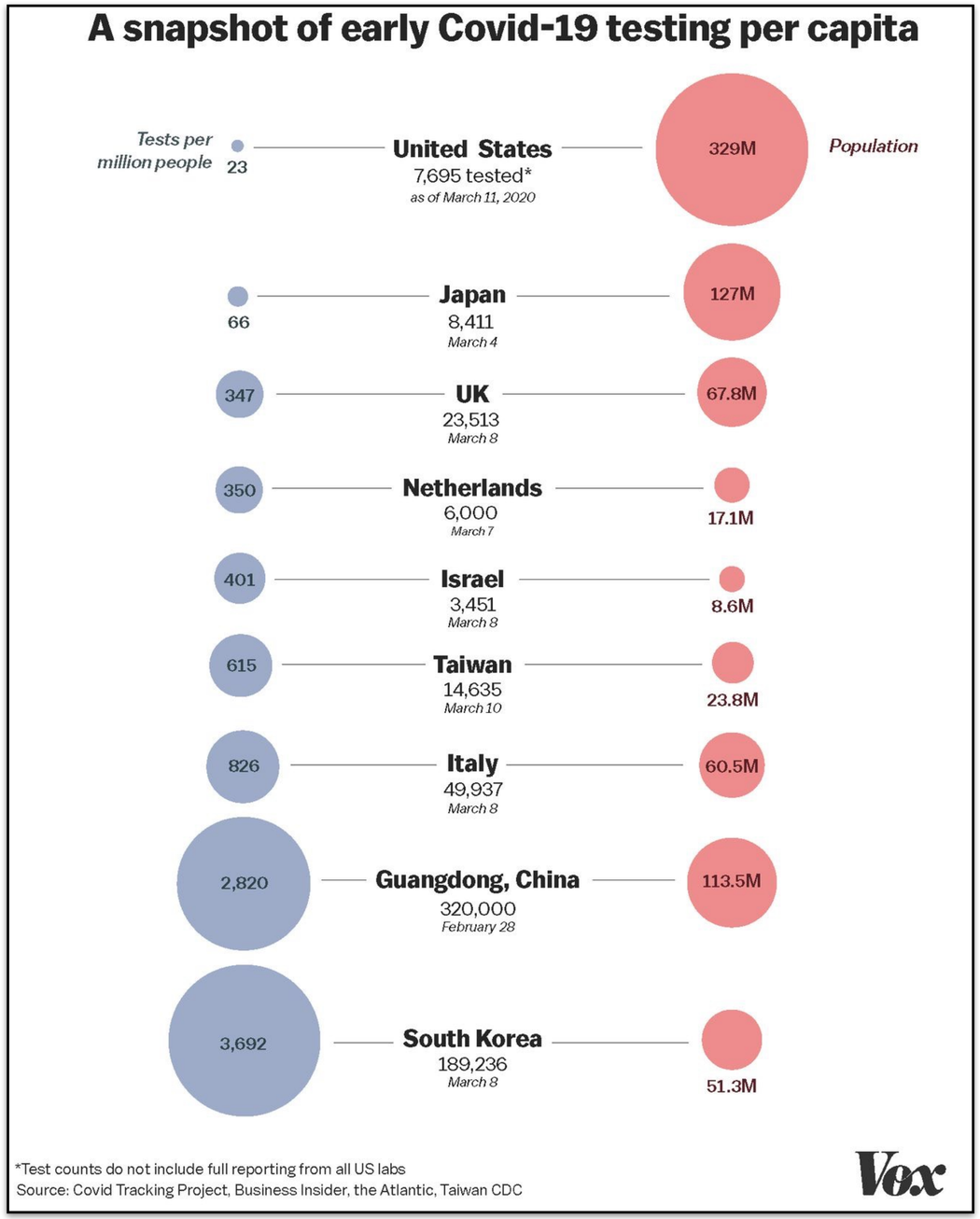
Do not distort quantities

- Creating a better version

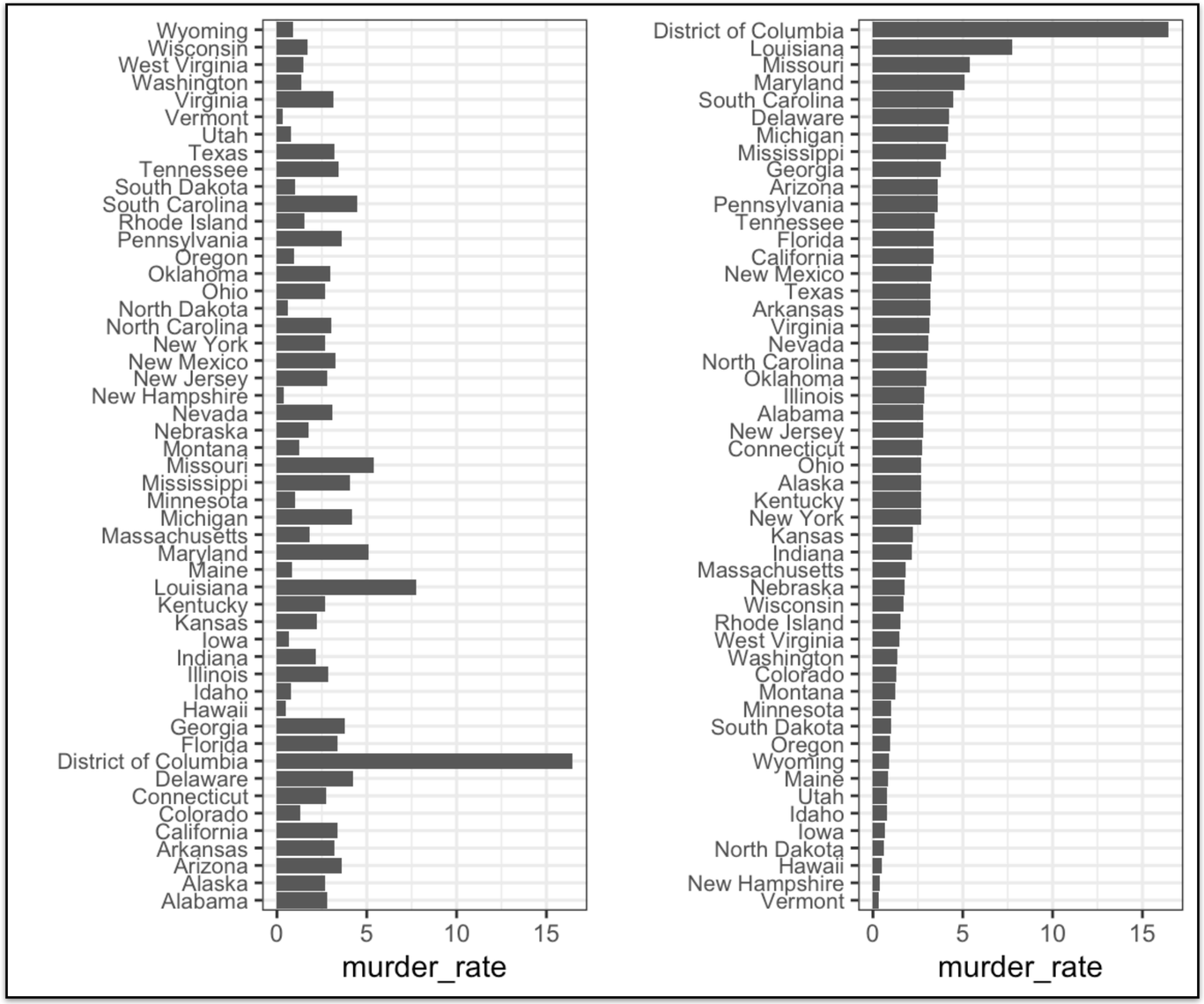


Do not distort quantities

- Here is a good example from Vox

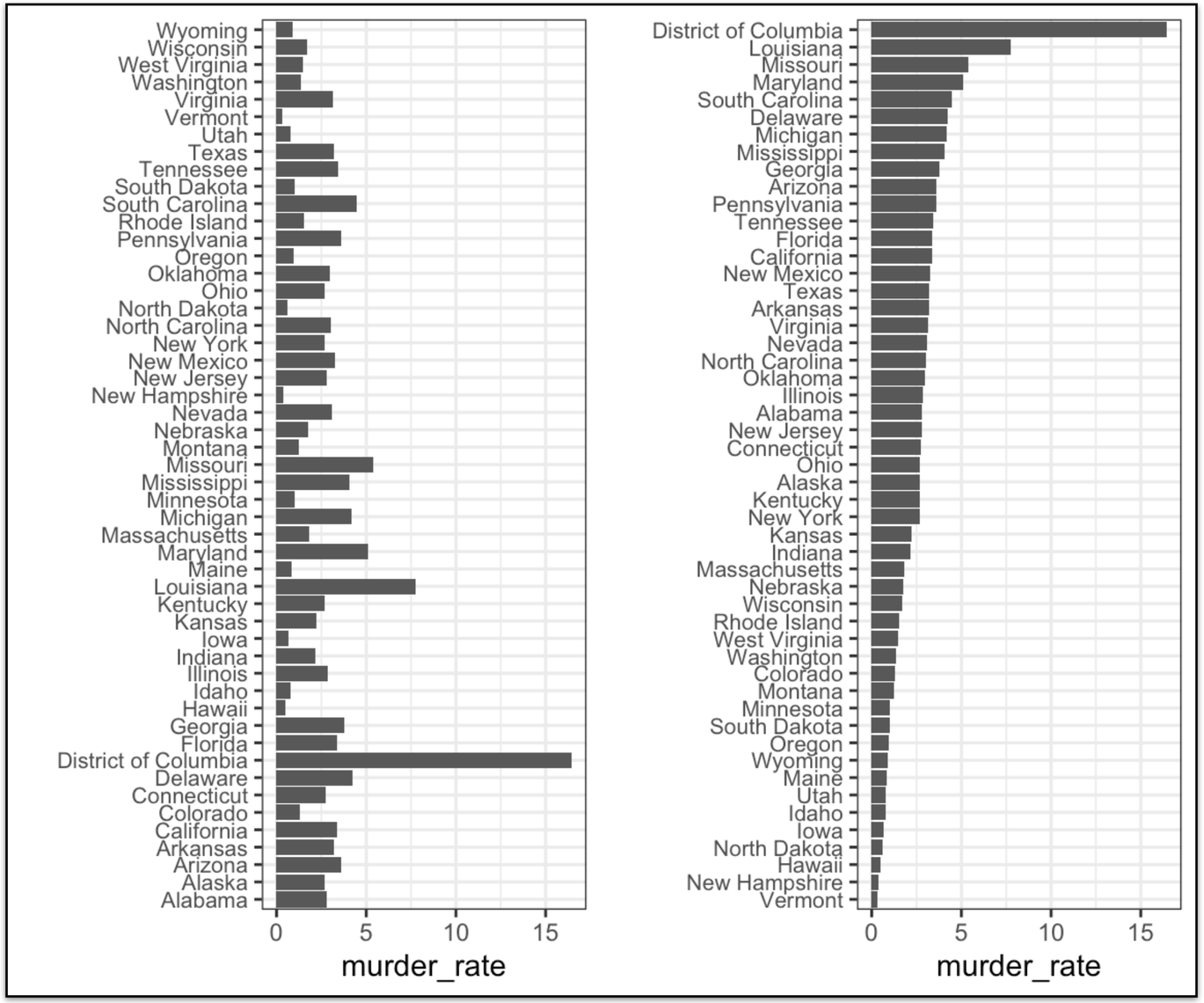


Order categories by a meaningful value



Order categories by a meaningful value

Ordered alphabetically



Ordered by rate

Show the data

- To motivate this principle, here is an example from the heights dataset

```
library(tidyverse)
library(dslabs)
data("heights")

heights %>%
   group_by(sex) %>%
   summarize(a = mean(height),
             s = sd(height)) %>%
   ungroup() %>%
   ggplot(aes(sex, a)) +
   geom_errorbar(aes(ymin=a-s, ymax=a+s), width = 0.10) +
   geom_col(width = 0.50, color="black") +
   ylab("Height (inches)") +
   xlab("Sex") +
   theme_bw()
```

Show the data

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   geom_errorbar(aes(ym
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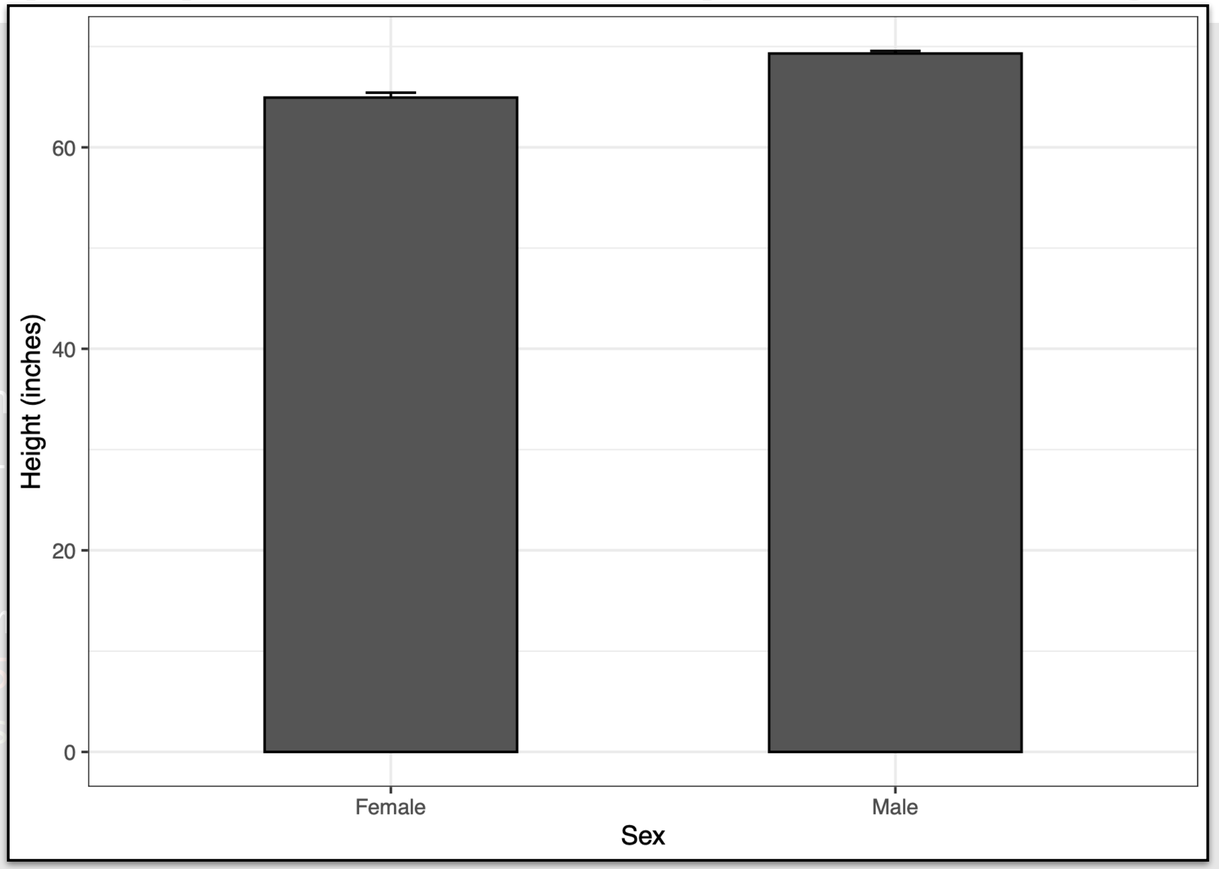
```



- This is known as a dynamite plot

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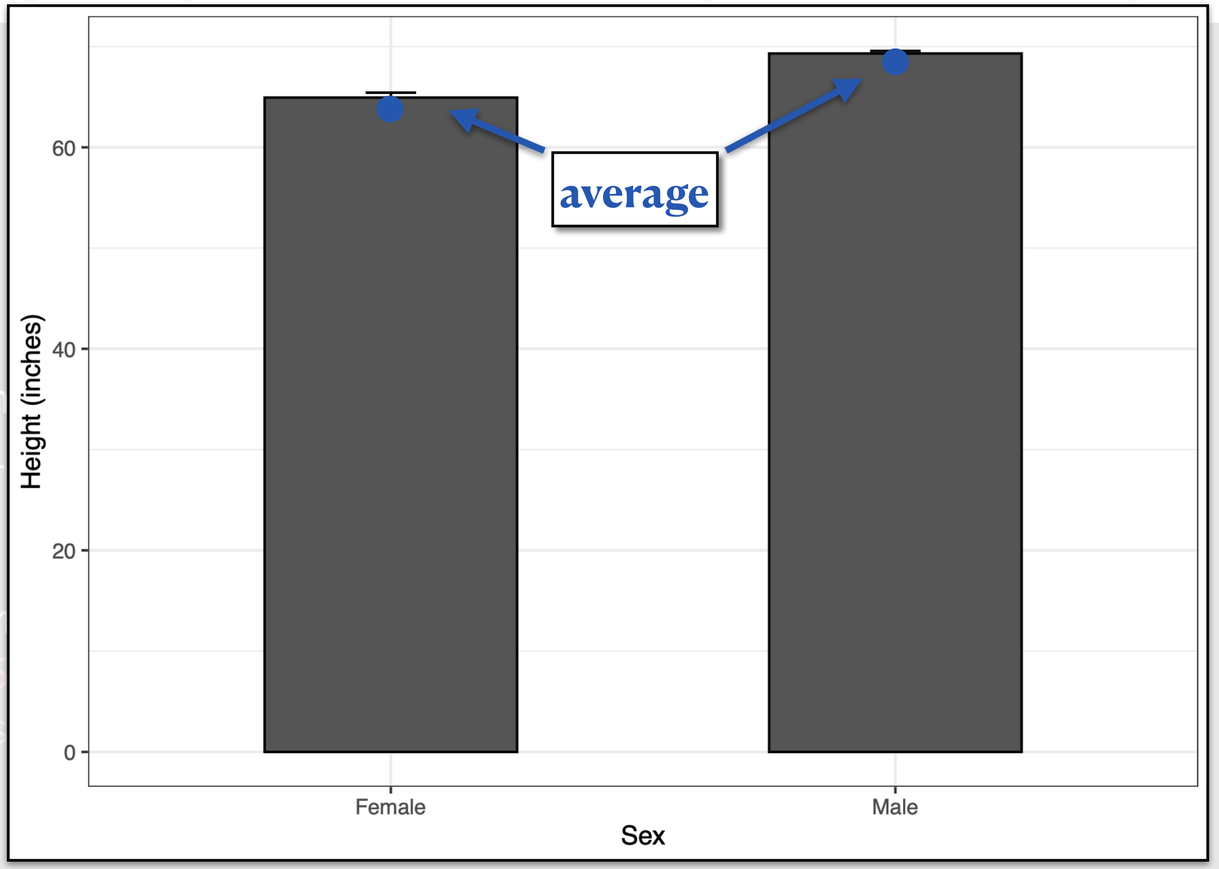

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Show the data

- To motivate this principle, h[illegible] the heights dataset

```
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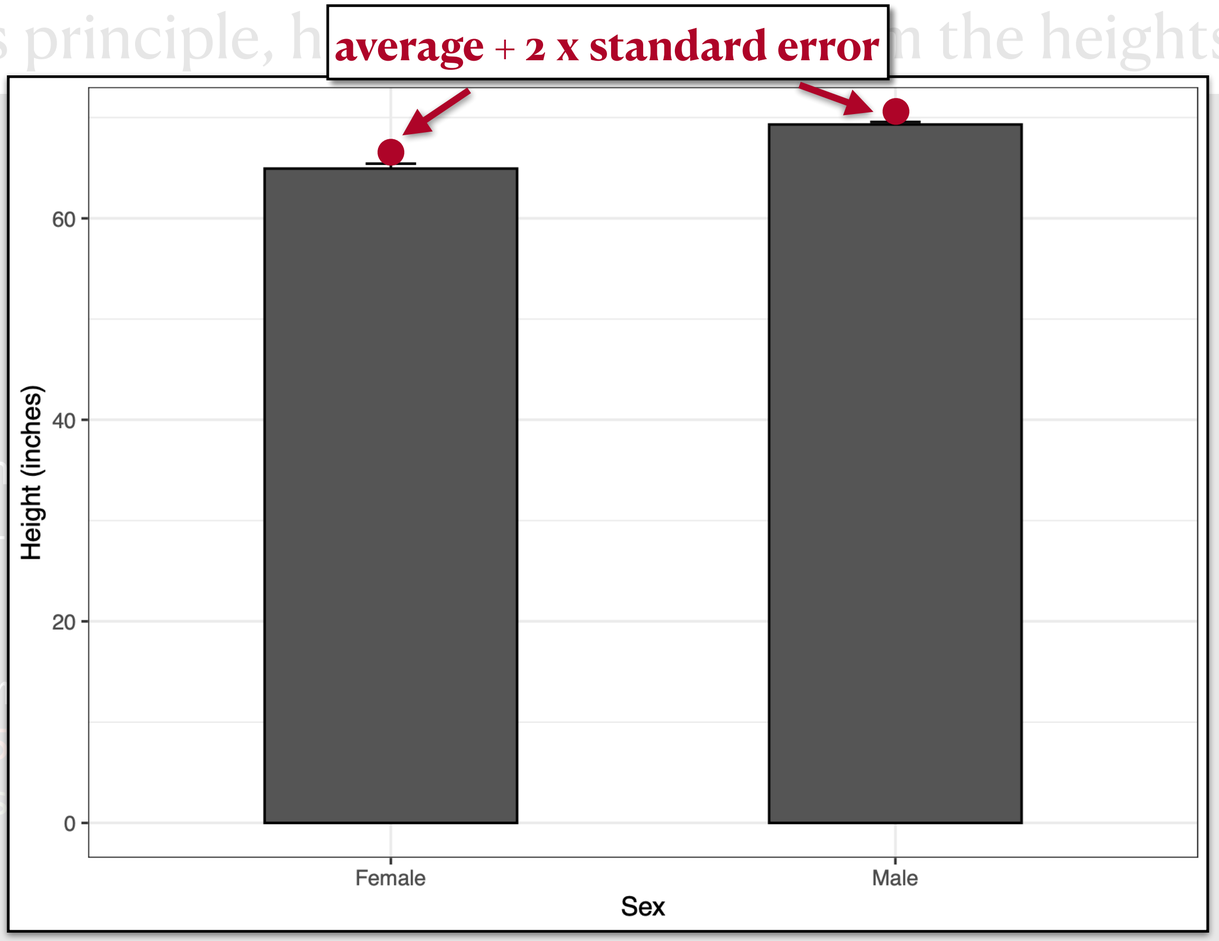

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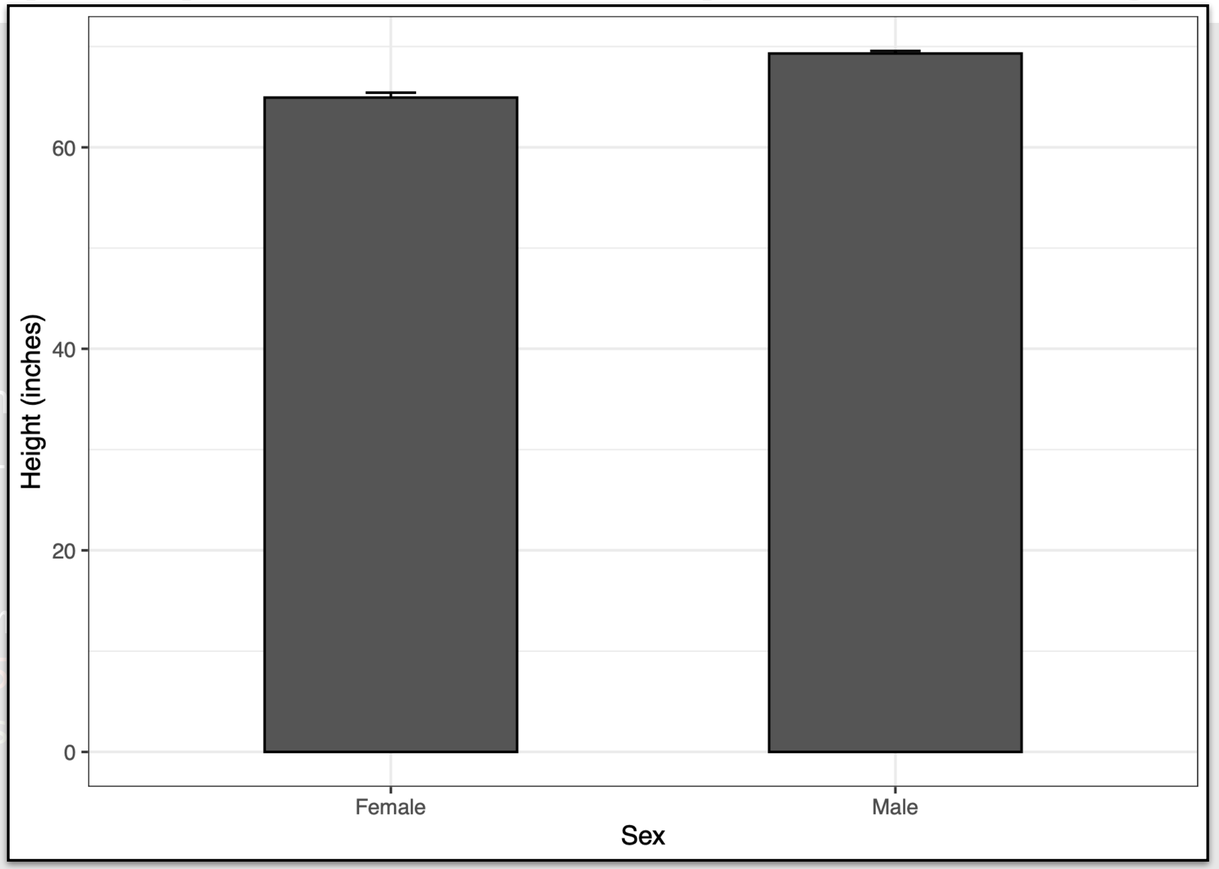

- This figure says very little about the data.
- All we can see is the mean for each group and the corresponding standard errors

Show the data

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   ylab("Height (inches
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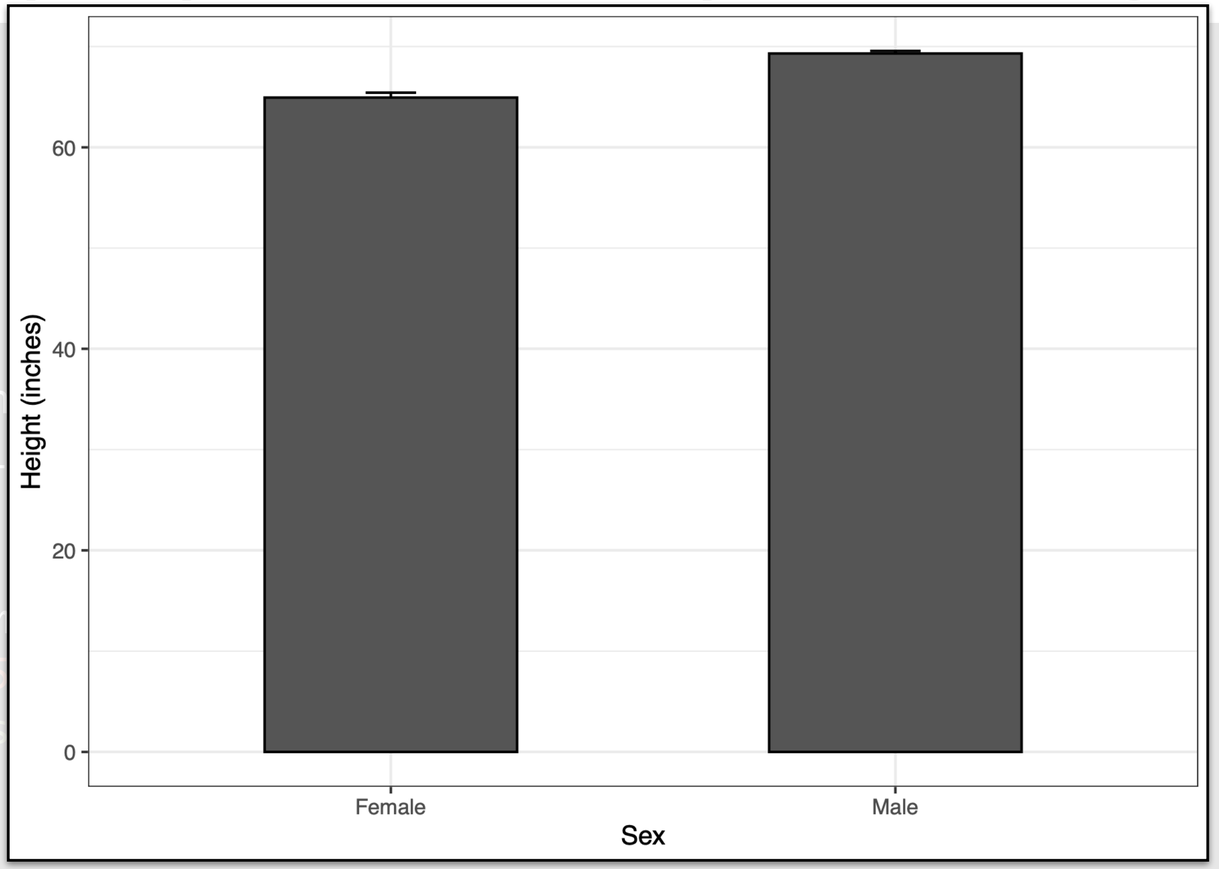
```



- Let's go back to our principle, show the data!

Show the data

- This simple code generates a more informative figure:

```
heights %>%
   ggplot(aes(sex, height)) +
   geom_point() +
   theme_bw()
```

Show the data

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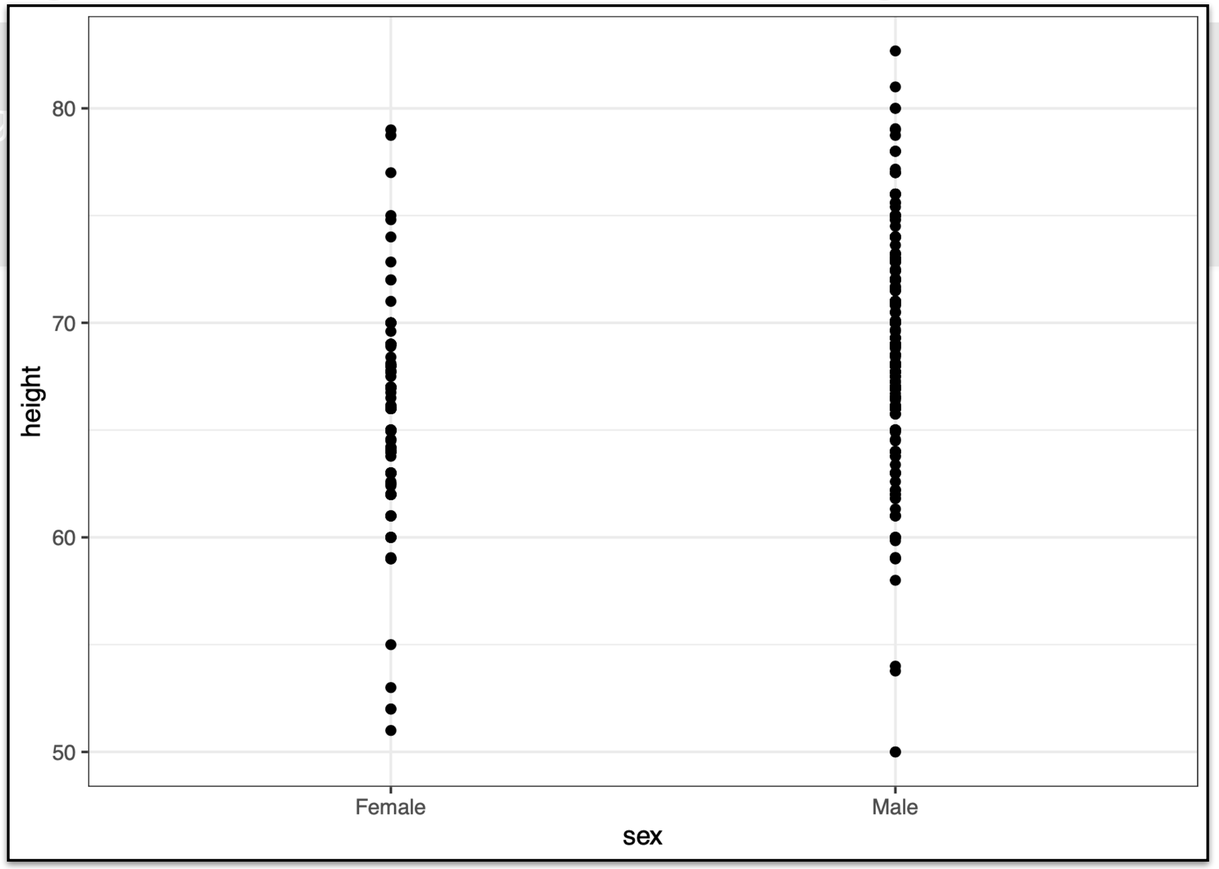


- From this we can see the range of the data
- Let's improve on this

Show the data

- This simple code generates a more informative figure:

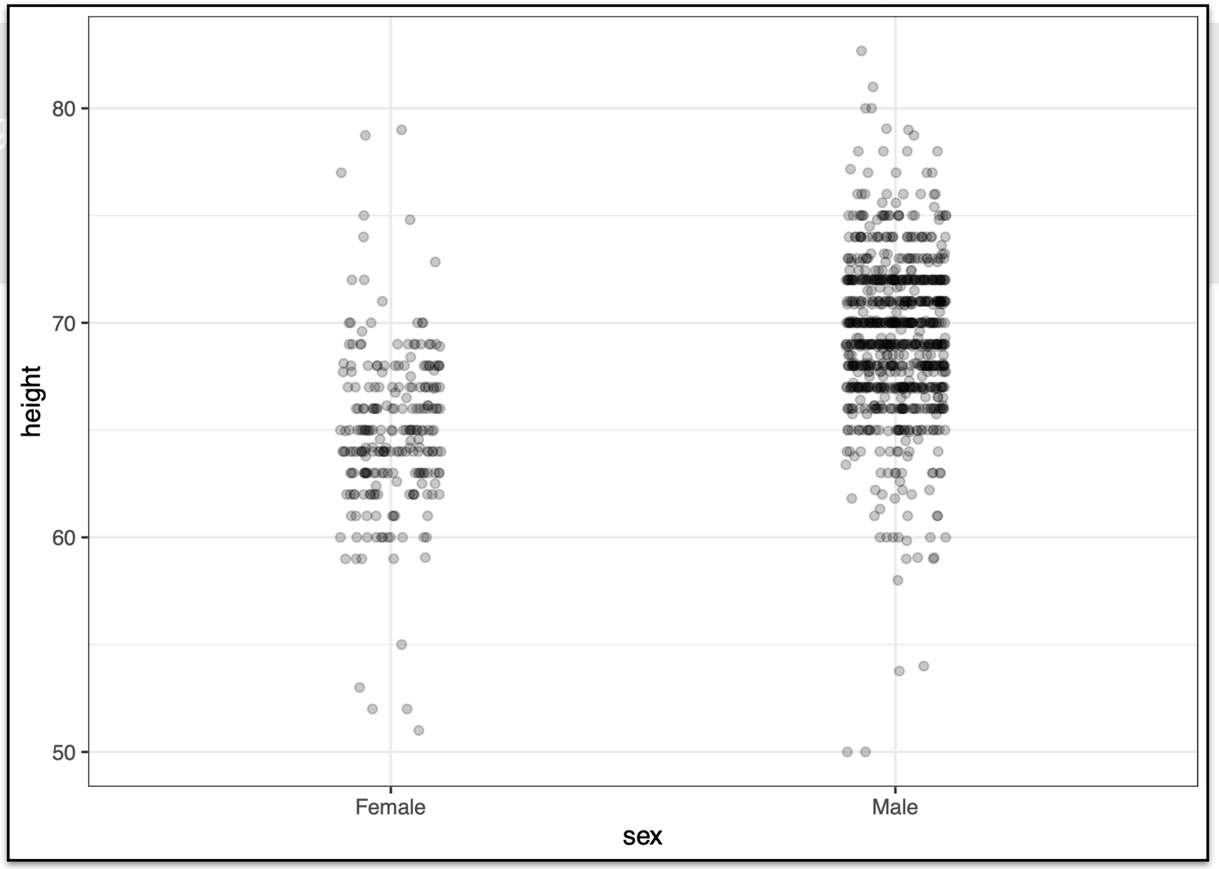
```
heights %>%
   ggplot(aes(sex, height)) +
   geom_jitter(width = 0.1, alpha = 0.2) +
   theme_bw()
```

- Here we add a *jitter* — a small random shift to each point

Show the data

- This simple code generates a more informative figure:

```
heights %>%
   ggplot(aes(sex, heig
   geom_jitter(width =
   theme_bw()
```



- Note that we add a horizontal *jitter*, which does not affect the interpretation

Show the data

- This simple code generates a more informative figure:

```
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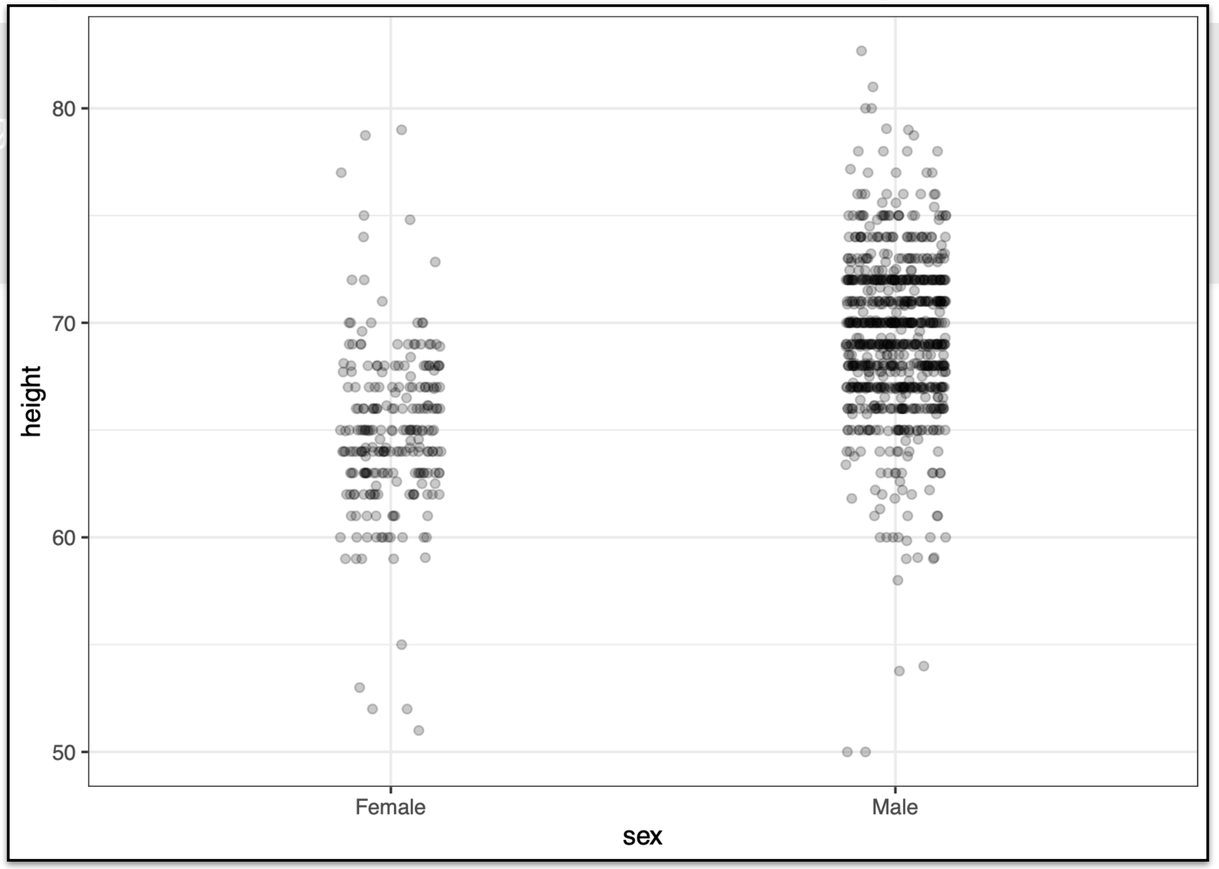
   theme_bw()
```



- Further, the alpha-blend gives us a better understanding of the distributions

Use common axes

- There are a lot of points, let's use histograms instead:

```
heights %>%
  ggplot(aes(x=height, y=..density..)) +
  geom_histogram(color="black") +
  theme_bw() +
  facet_wrap(~sex, scales = “free_x”)
```

Use common axes

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```
heights %>%
  ggplot(aes(x=height,
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  theme_bw() +
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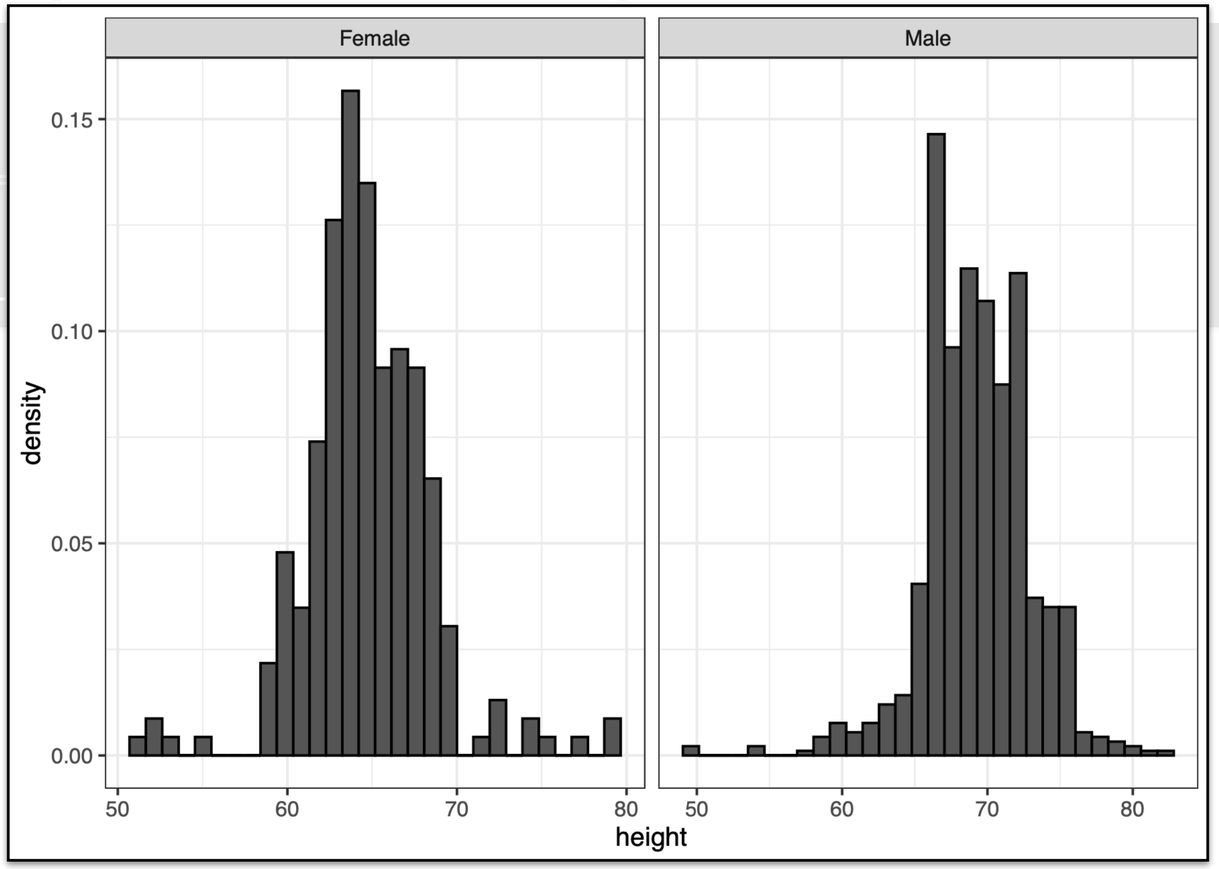

- Its not immediately clear that males, on average, are taller than females
- The *x-axis* is not the same for the two groups

Use common axes

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```
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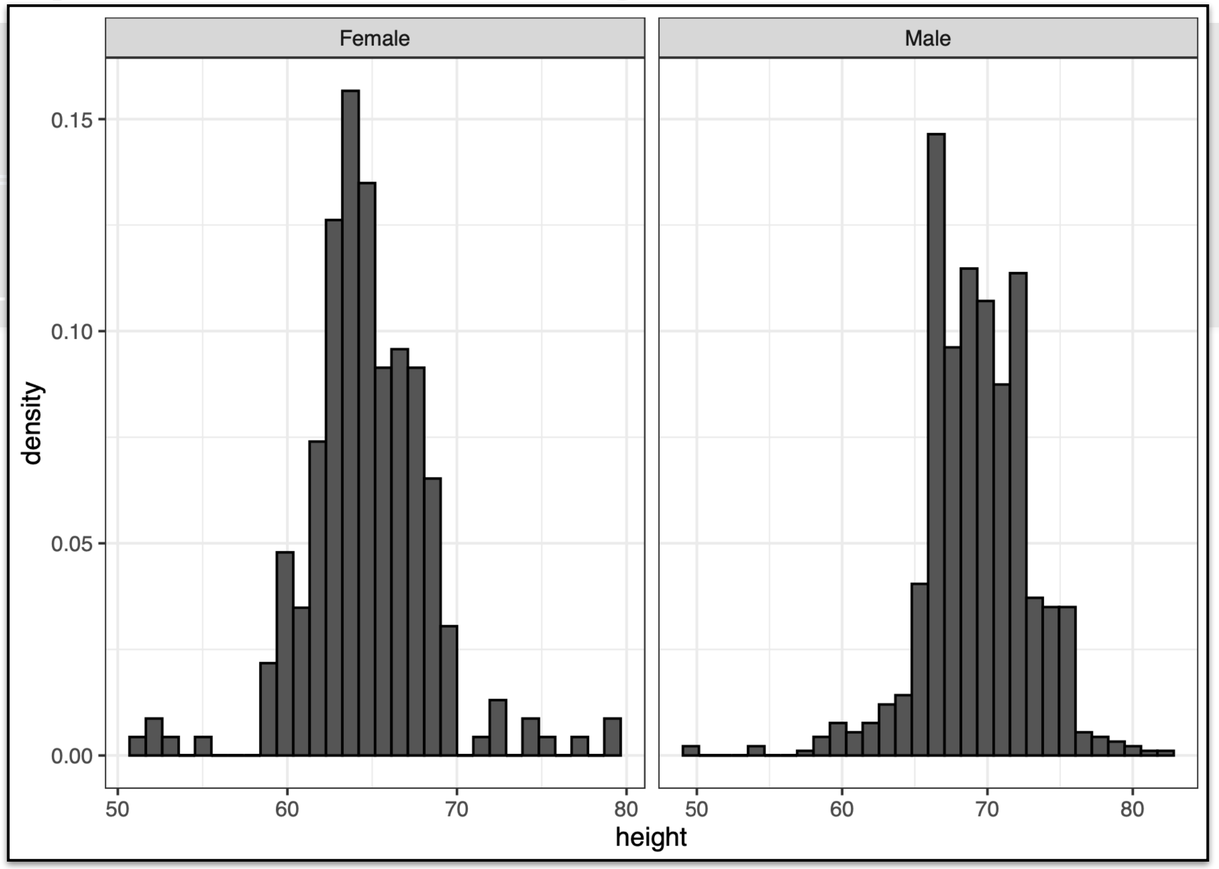

- Use common *x* axes!

Use common axes

- The default in `facet_wrap` is to have common axes

```
heights %>%
  ggplot(aes(x=height, y=..density..)) +
  geom_histogram(color="black") +
  theme_bw() +
  facet_wrap(~sex)
```

Use common axes

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```
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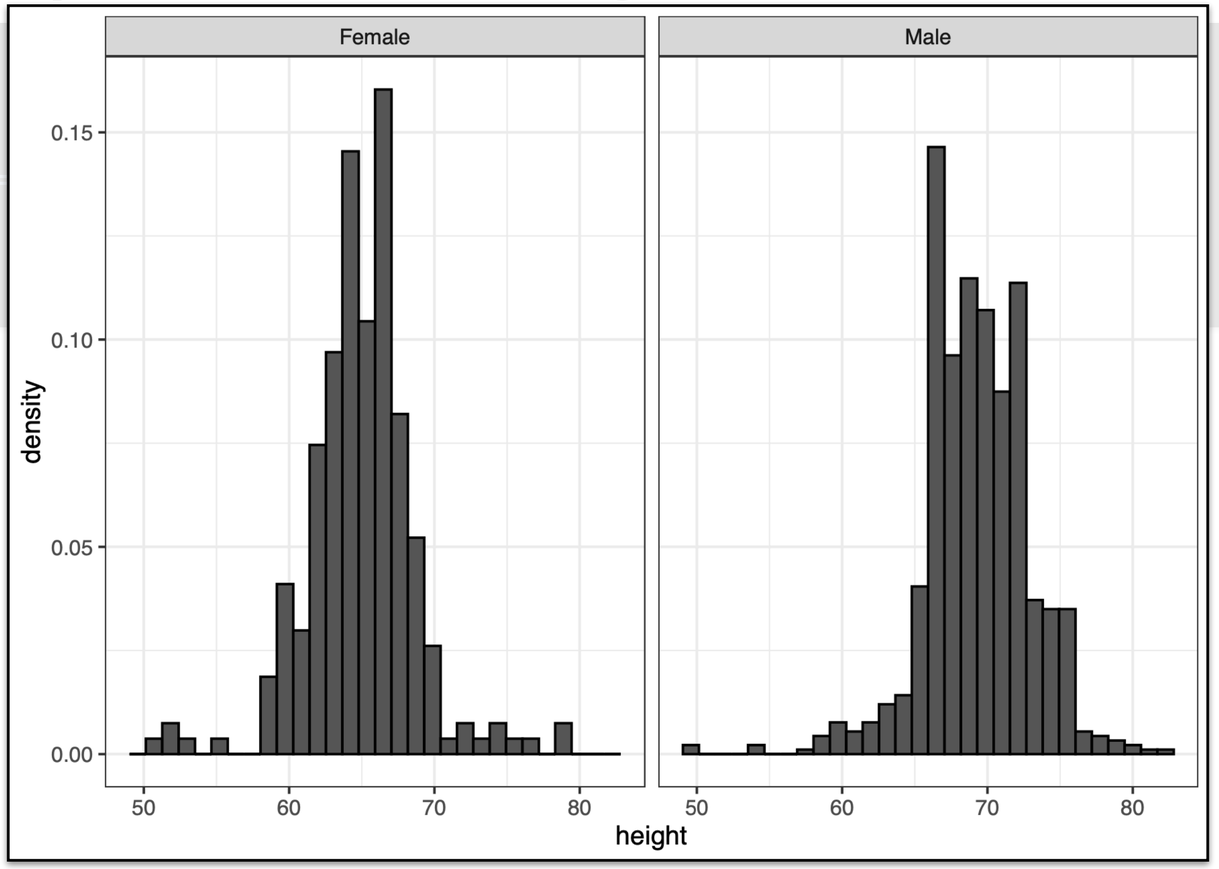


- This is better

Use common axes

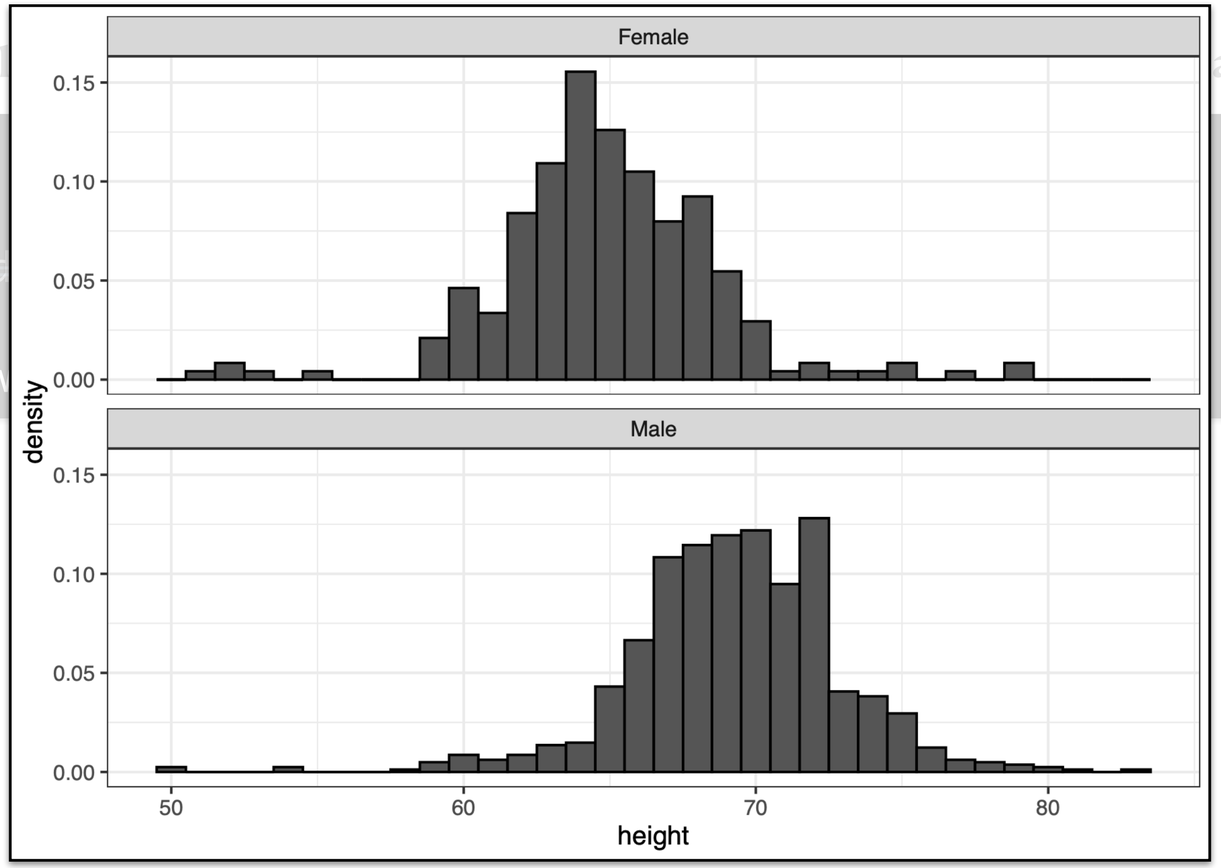
- Another principle:
  - **Align plots vertically to see horizontal changes and horizontally to see vertical changes**

```
heights %>%
  ggplot(aes(x=height, y=..density..)) +
  geom_histogram(binwidth=1,color="black") +
  theme_bw() +
  facet_wrap(~sex, nrow=2)
```

Use common axes

- Another principle:
  - Align plots vertically to see relationships in the data when they are changes

```
heights %>%
  ggplot(aes(x=height,
  geom_histogram(binwi
  theme_bw() +
  facet_wrap(~sex, nrow
```



- This makes it easier to see the difference

Use common axes

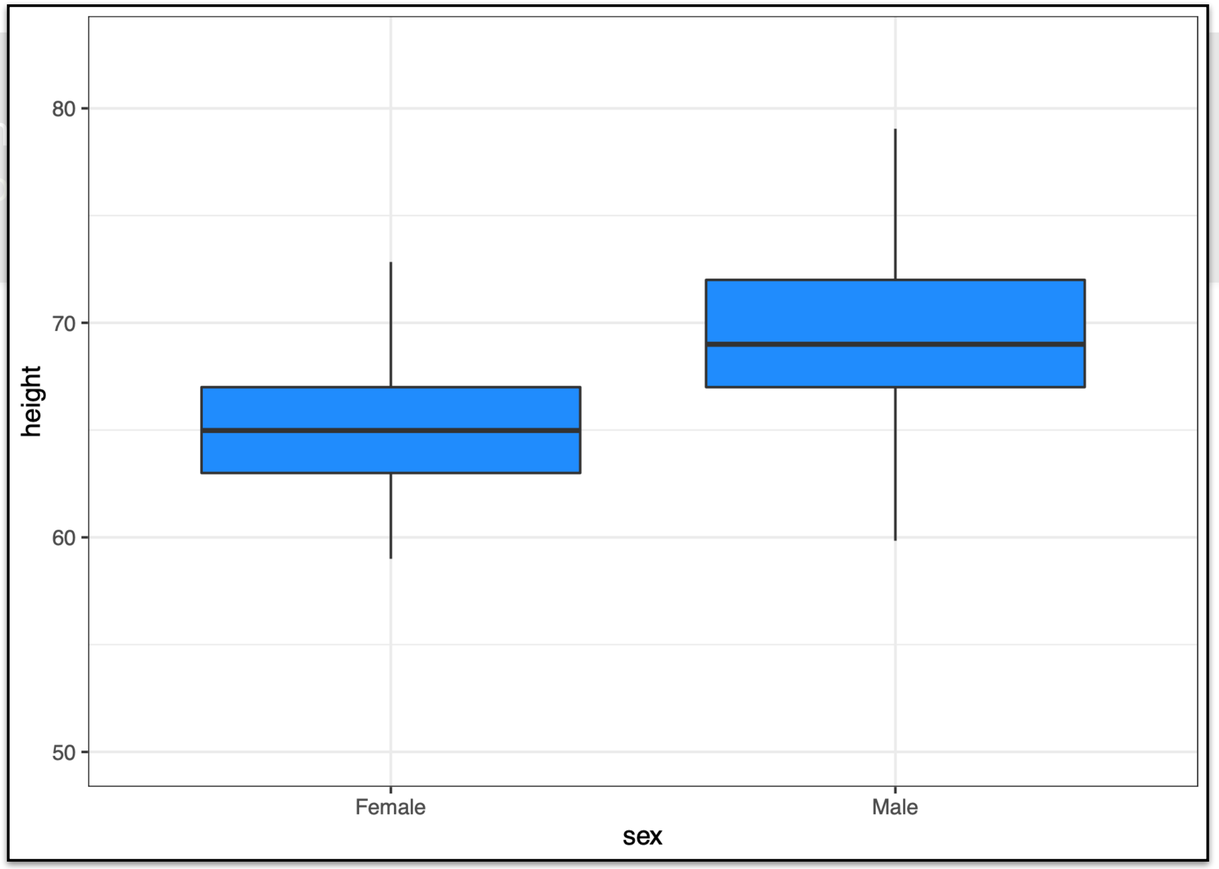
- A boxplot would also be informative here

```
heights %>%
  ggplot(aes(x=sex, y=height)) +
  geom_boxplot(fill="dodgerblue", outlier.alpha = 0) +
  theme_bw()
```

Use common axes

- A boxplot would also be informative here

```
heights %>%
  ggplot(aes(x=sex, y=h
  geom_boxplot(fill="dc
  theme_bw()
```



- Show the data!

Use common axes

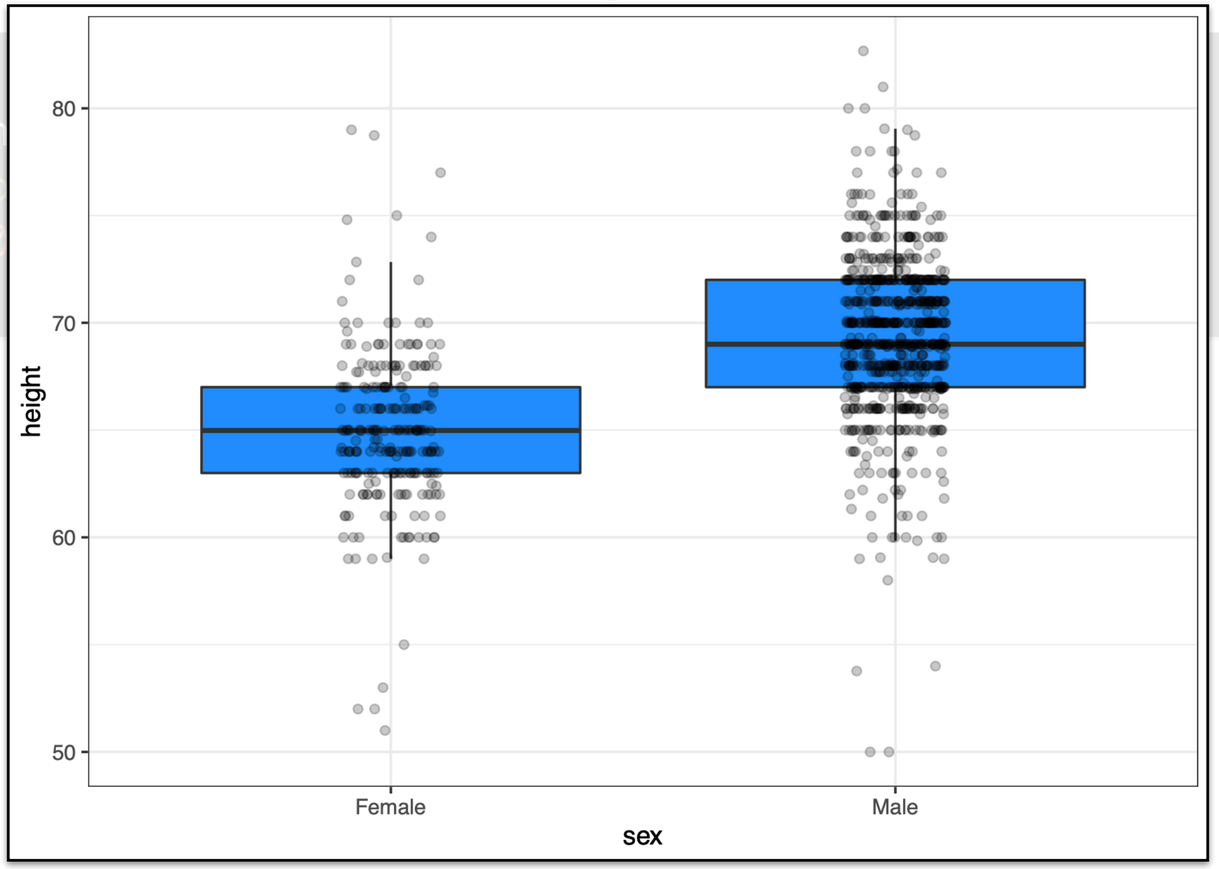
- We use `geom_jitter` to add the data points

```
heights %>%
  ggplot(aes(x=sex, y=height)) +
  geom_boxplot(fill="dodgerblue", outlier.alpha = 0) +
  geom_jitter(width = 0.1, alpha = 0.2) +
  theme_bw()
```

Use common axes

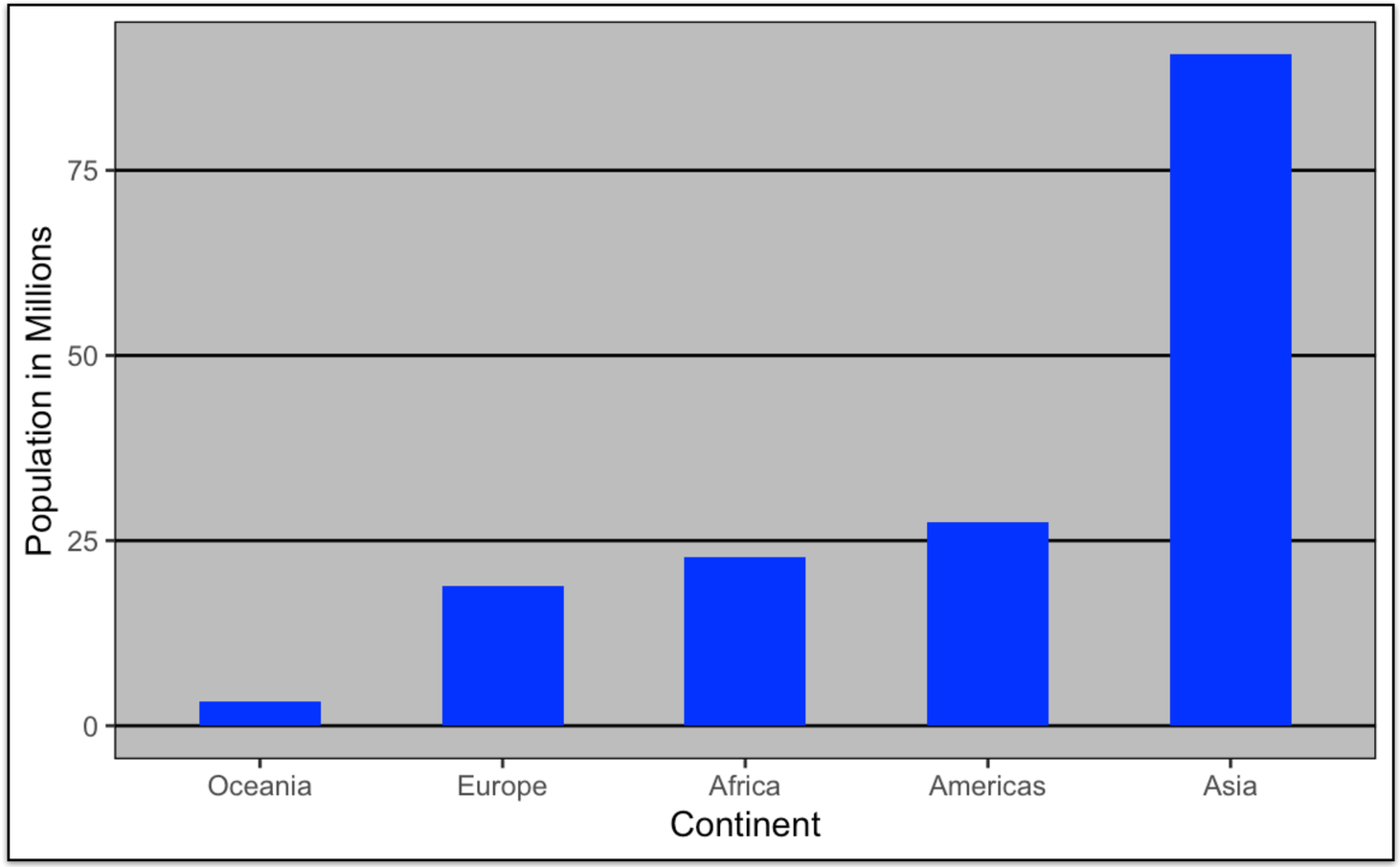
- We use `geom_jitter` to add the data points

```
heights %>%
  ggplot(aes(x=sex, y=h
  geom_boxplot(fill="do
  geom_jitter(width = 0
  theme_bw()
```



Consider transformations

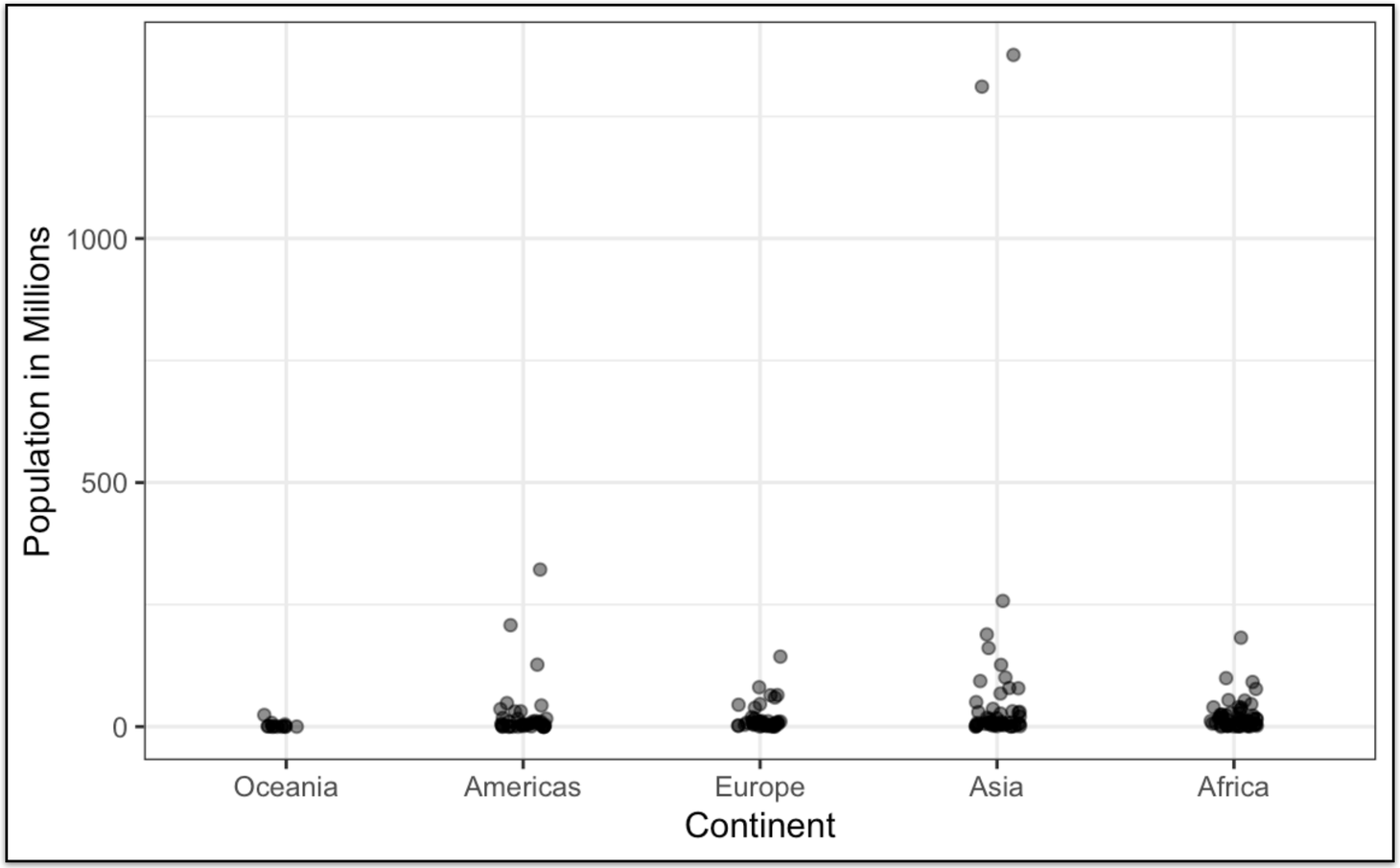
- Consider the following barplot of average population for each continent in 2015



- Any comments?

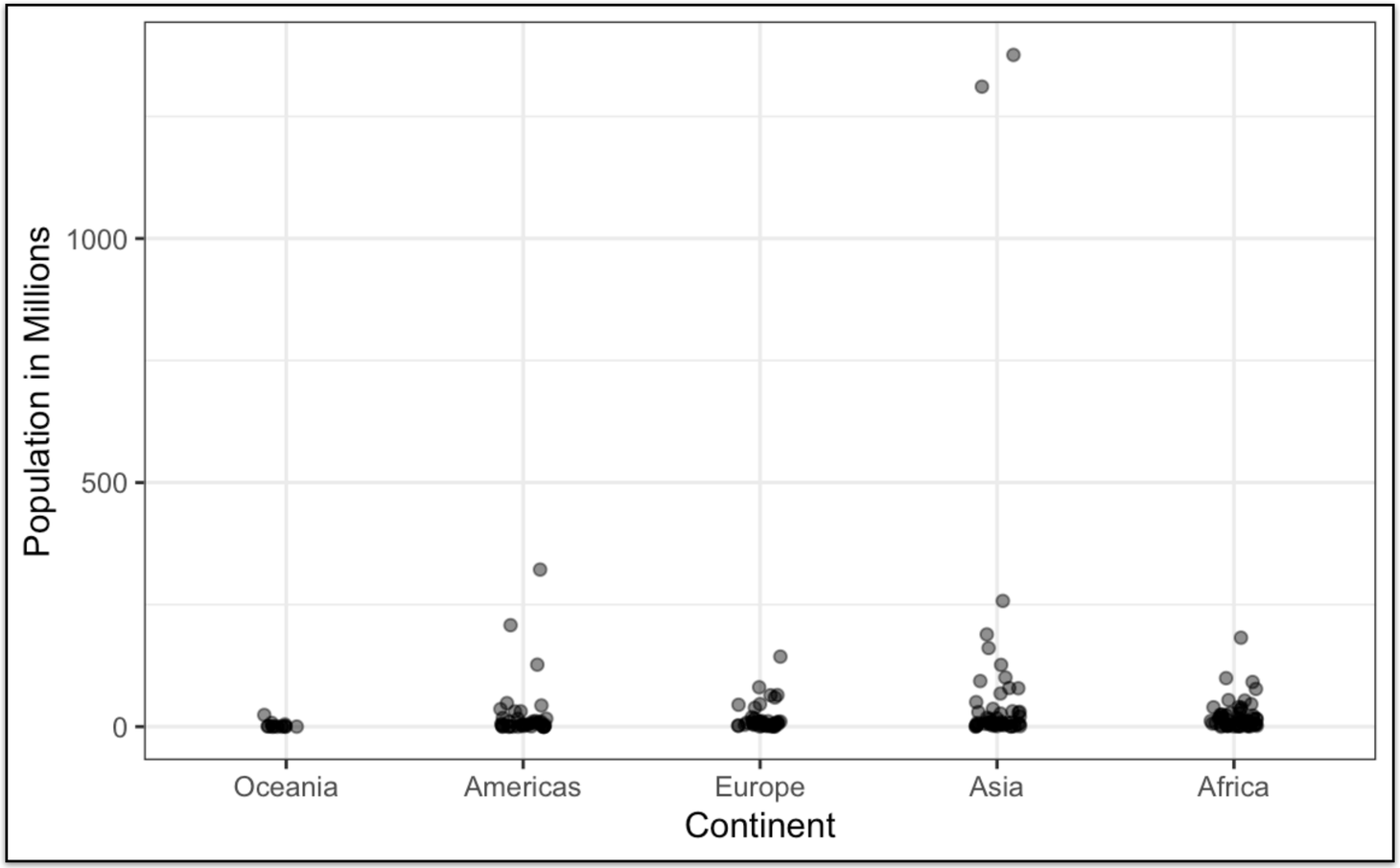
Consider transformations

- Consider the following barplot of average population for each continent in 2015



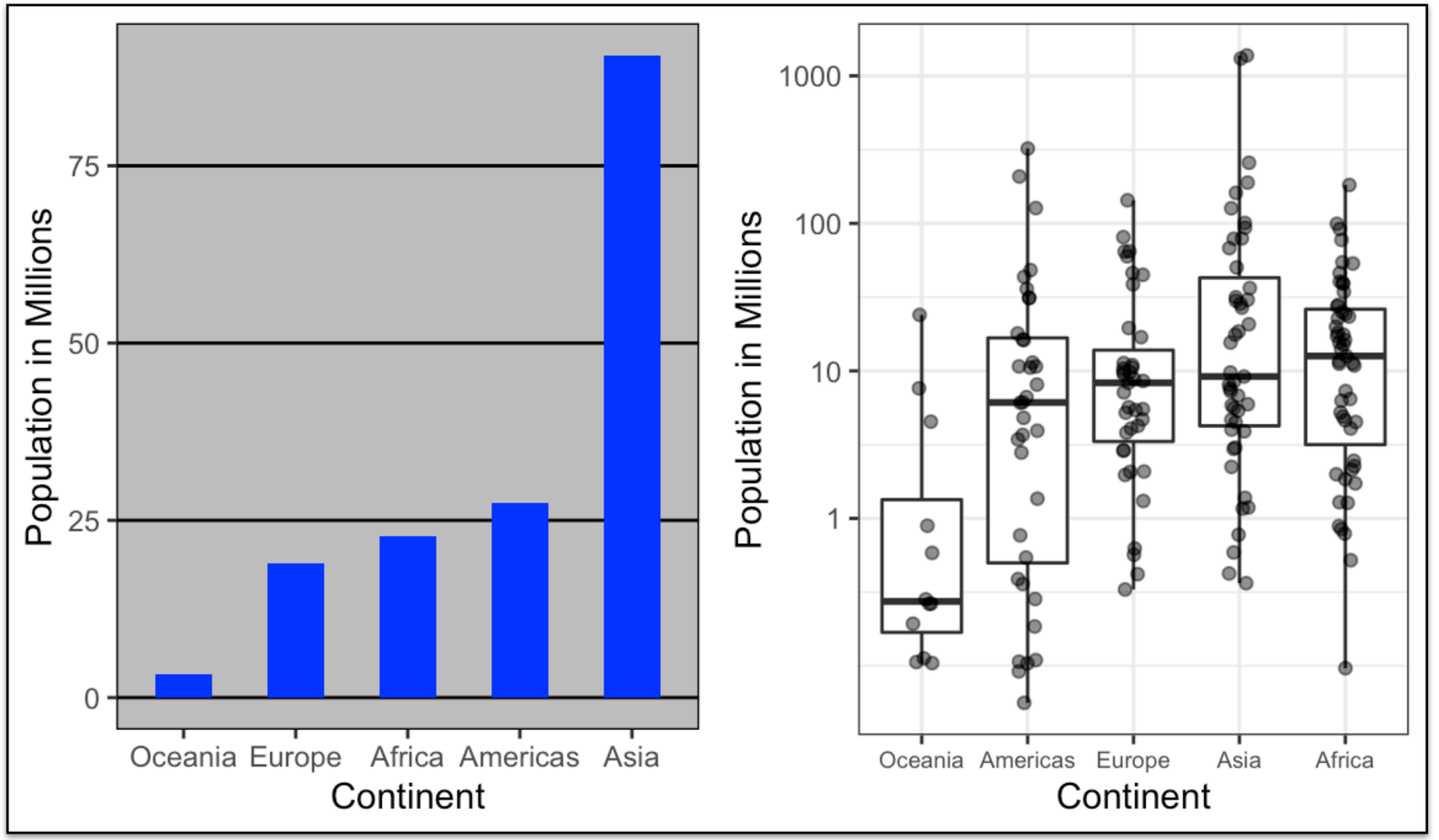
Consider transformations

- Consider the following barplot of average population for each continent in 2015



- Any ideas on what the two outliers are?

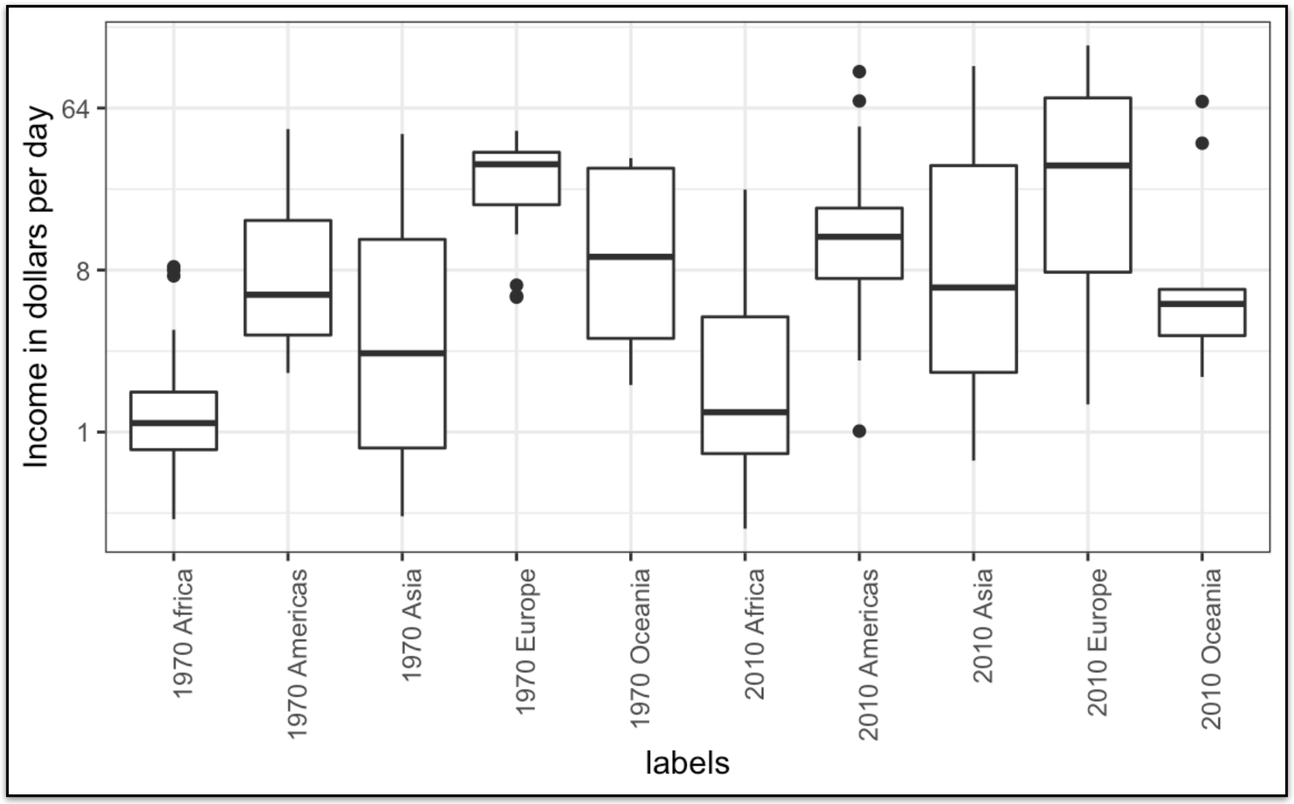
Consider transformations



- log 10 transformation of the *y-axis*
- It turns out that Africa has a higher median population than Asia

Use color to codify a third variable

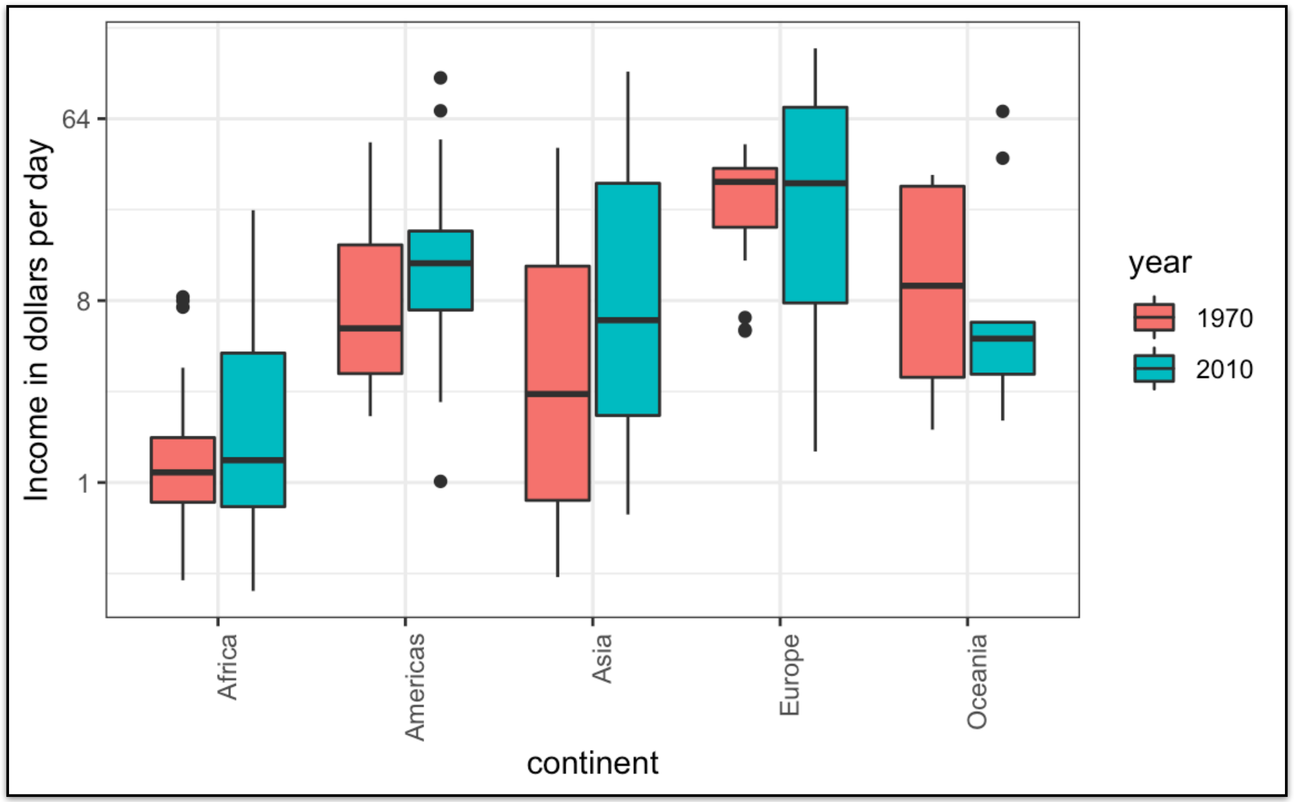
- This figures shows income per continent for 1970 and 2010:



- Its hard to compare, for example, Africa in 1970 to Africa in 2010 because the corresponding boxplots are visually far

Use color to codify a third variable

- By coding year with color, its easier to make the comparison

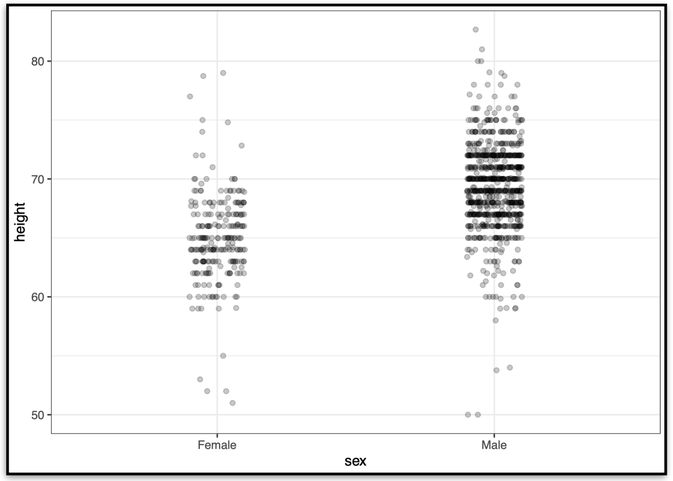


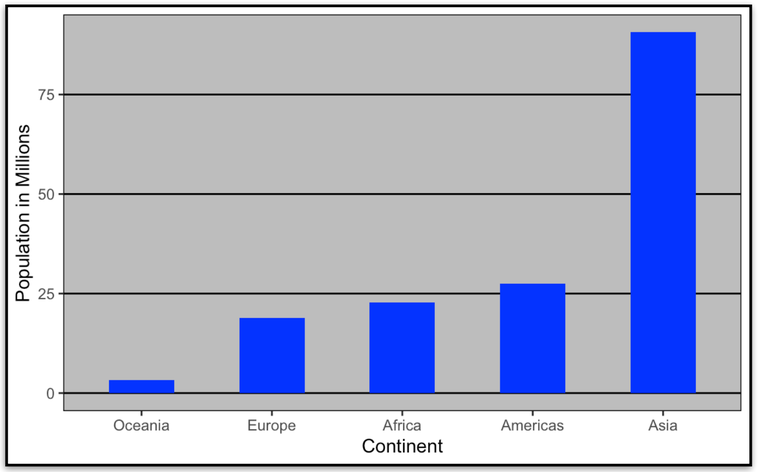
Think of the color blind

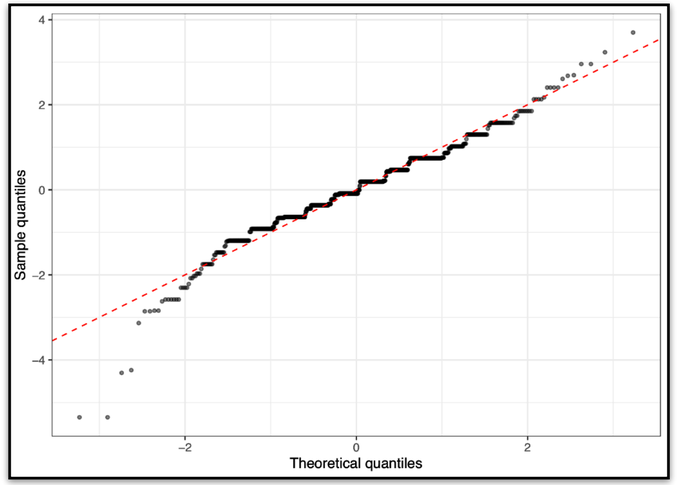
- About 10% of the population is color blind
- The default color scheme in `ggplot2` is not optimal for this population
- You can find a colorblind-friendly color palette here
- Here is one example:

Encoding more than two variables

- Most of the figures we have seen so far encode information on two variables:

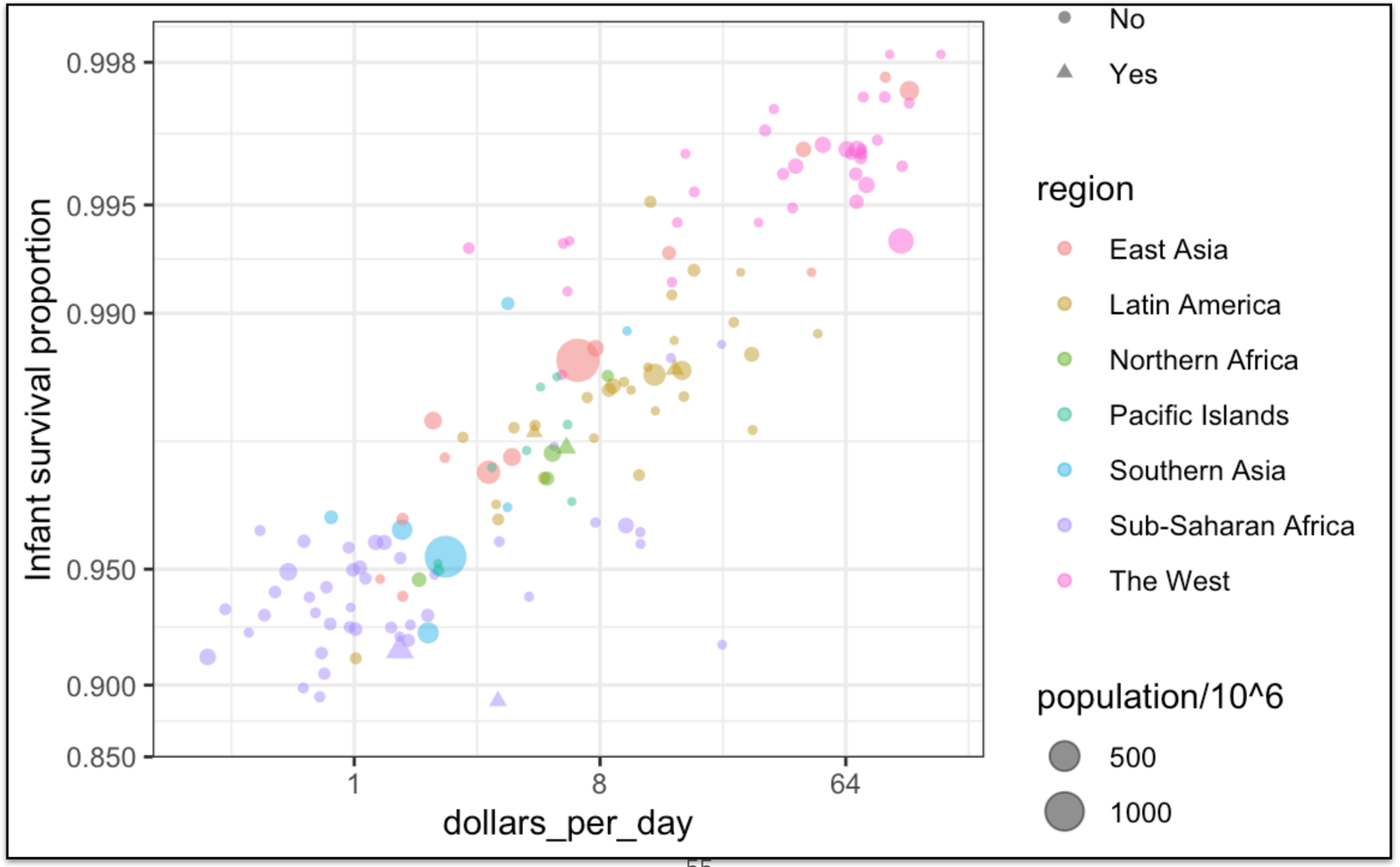






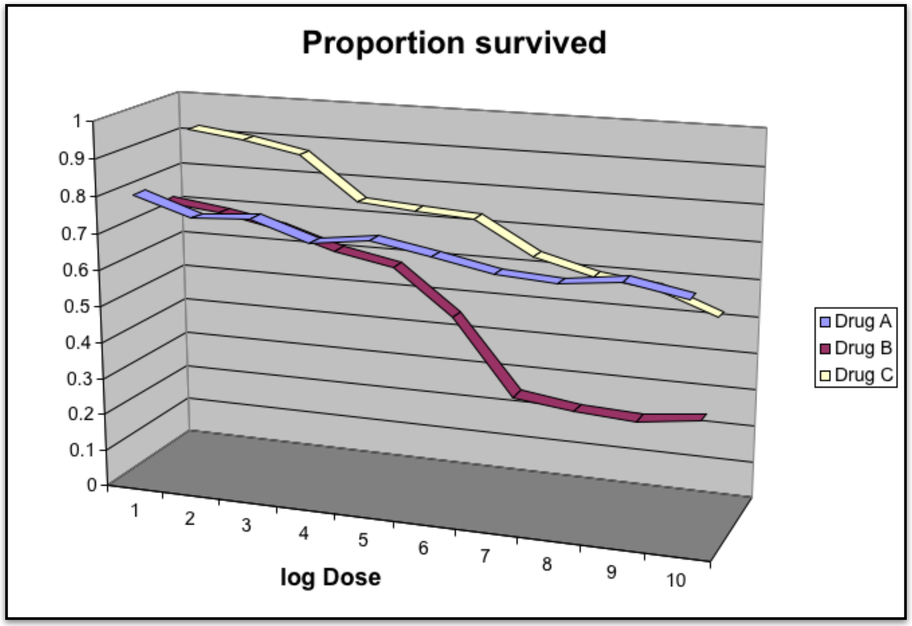
Encoding more than two variables

- In this example, we encode 3 variables: OPEC membership, region, and population



Avoid pseudo-three dimensional plots

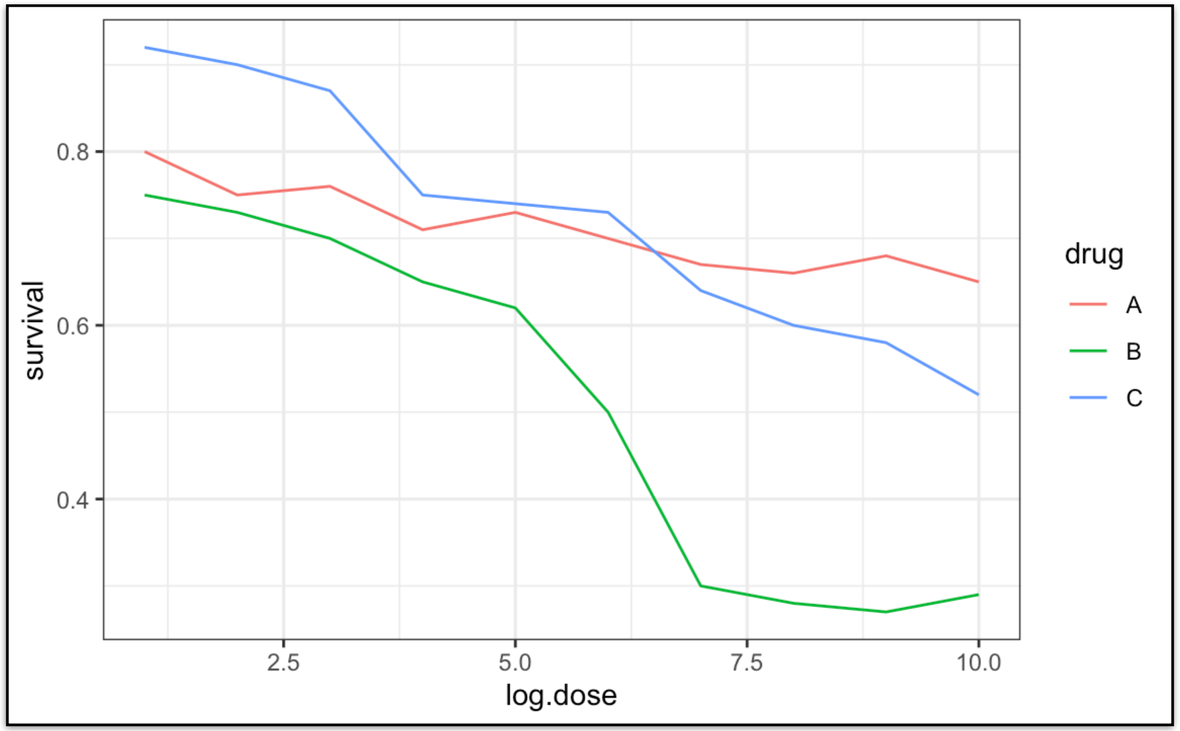
- Humans are not well-equipped to understand 3d figures
- Take the following example:



- Can you tell when the purple ribbon intersects the red one?

Avoid pseudo-three dimensional plots

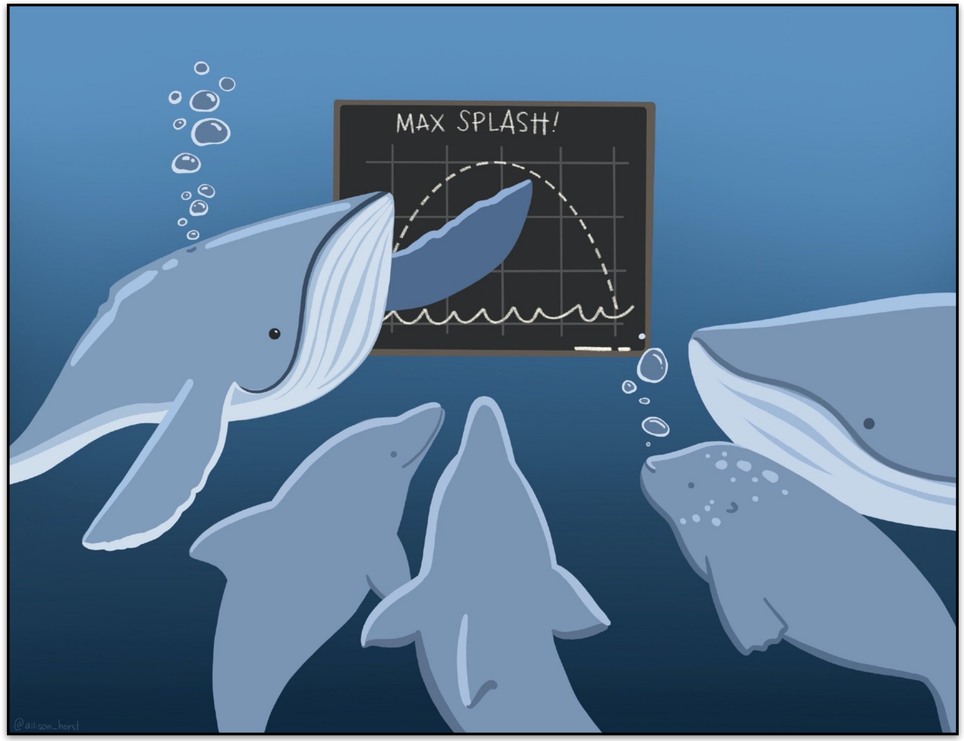
- Humans are not well-equipped to understand 3d figures
- Take the following example:



- They never do!

Know your audience

- Graphs can be used for:
    1. Our own exploratory data analysis
    2. To convey a message to experts
    3. To help tell a story to a general audience
- For example, we may use a log transform of the *y-axis* for our EDA but may advise against it when presenting to a general audience



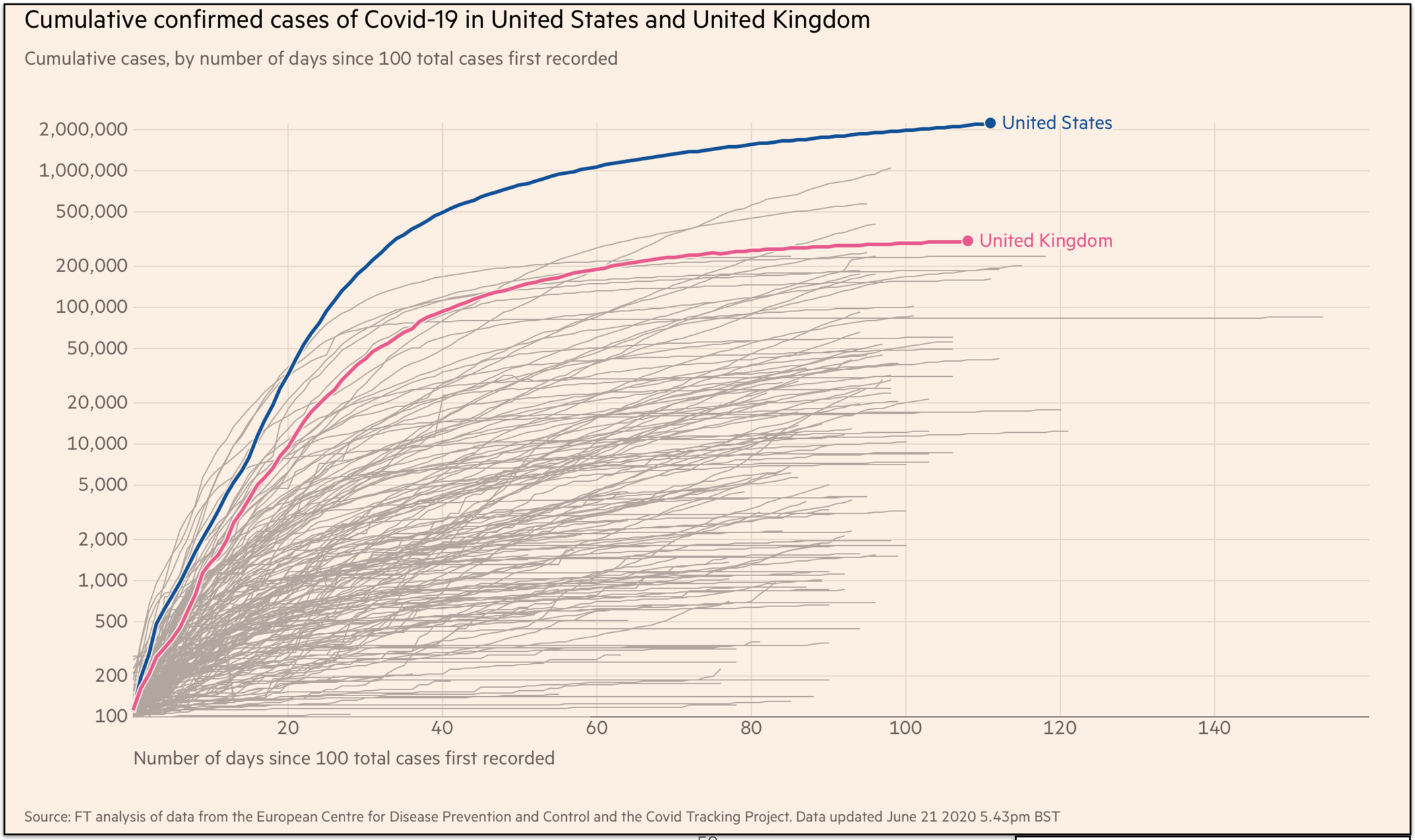


Figure from the Financial Times

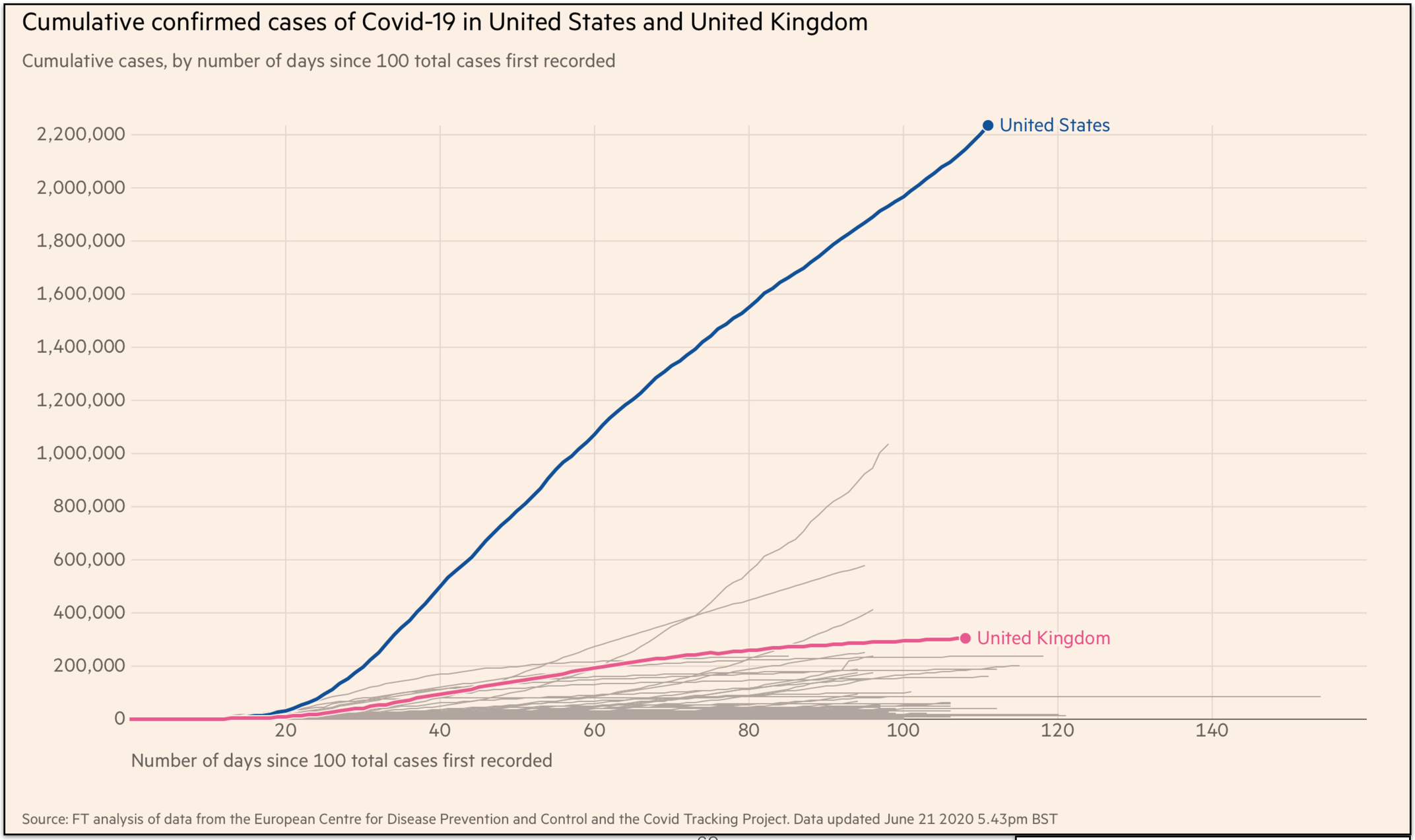
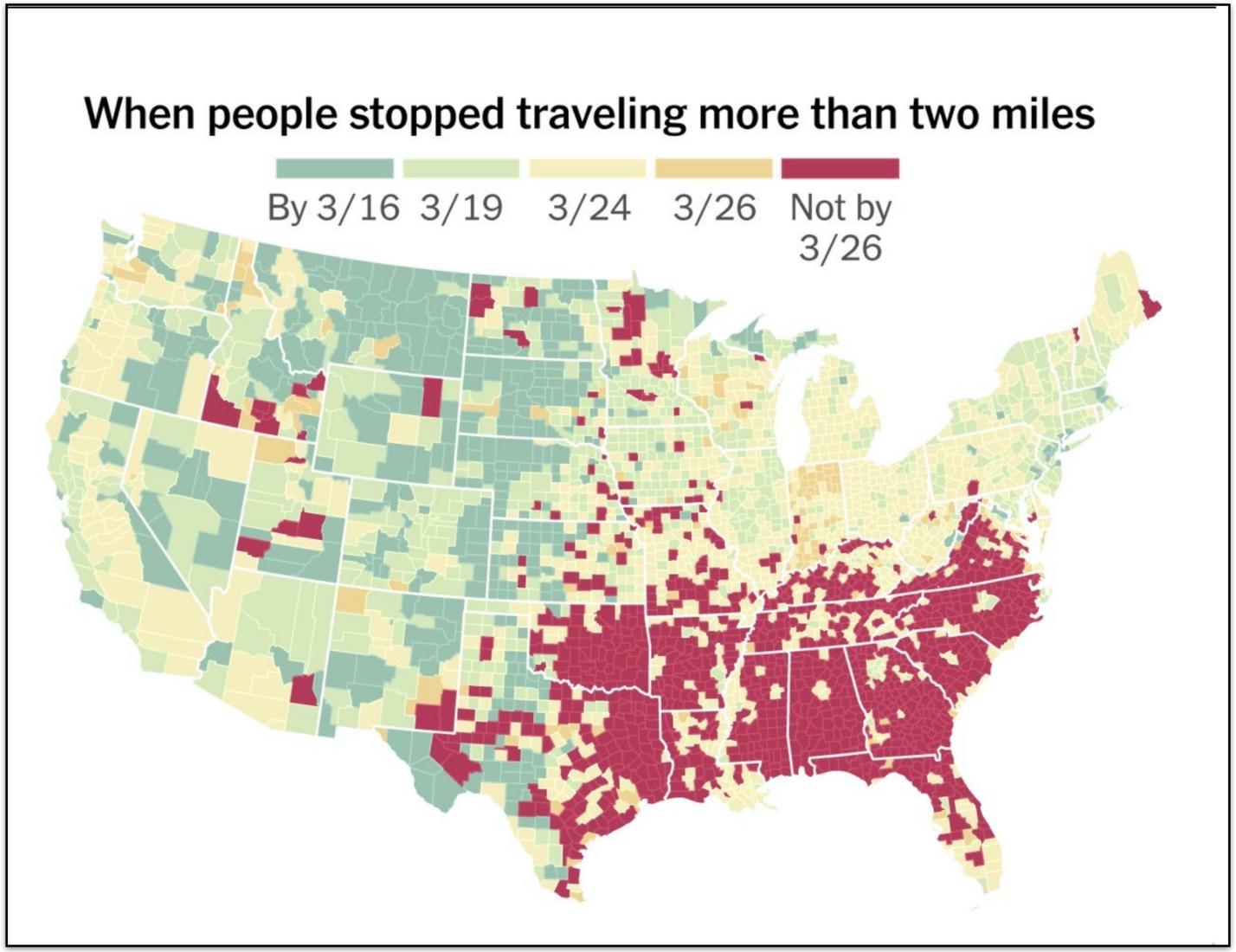


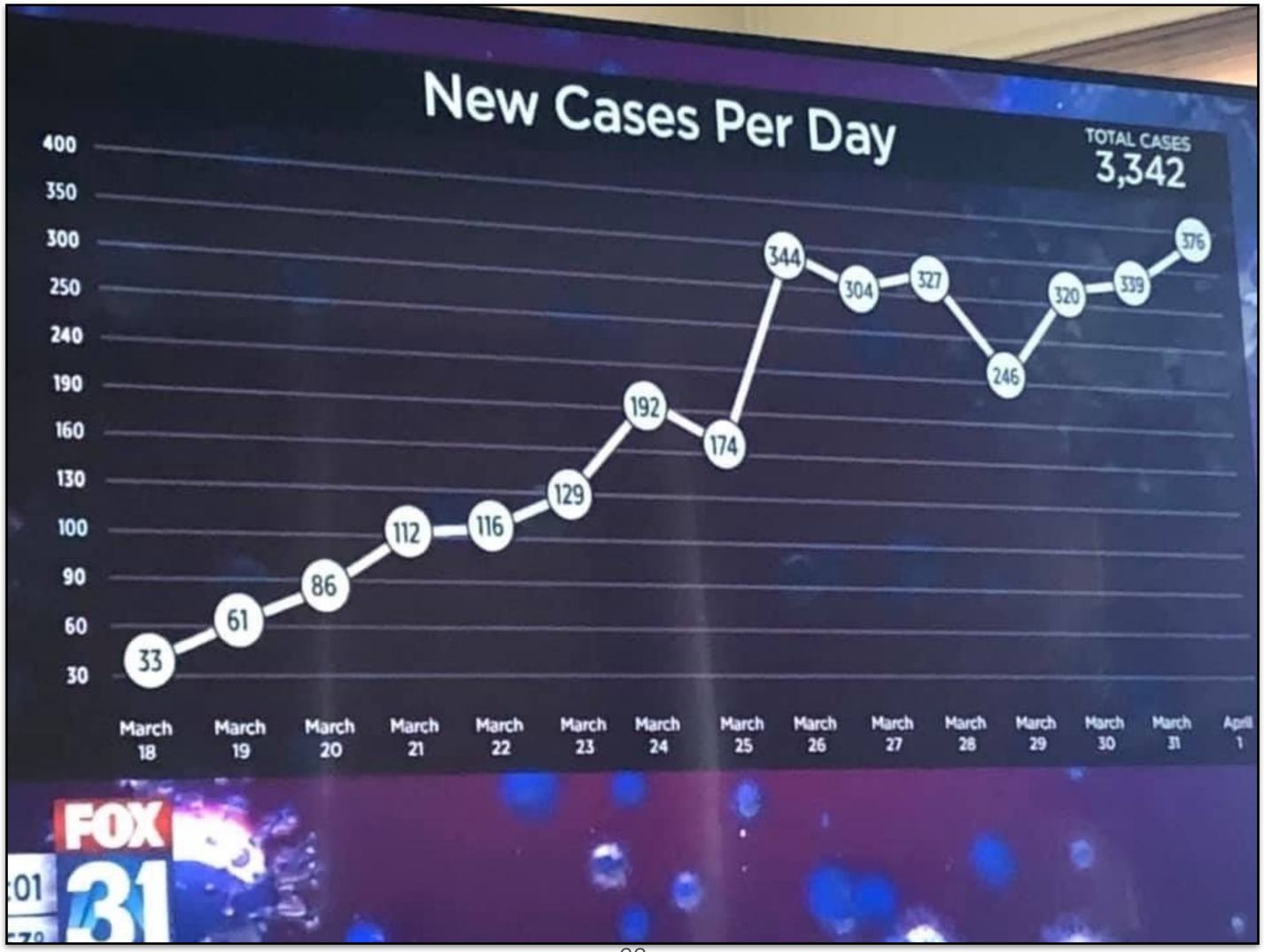
Figure from the Financial Times

Beware of biases when creating figures

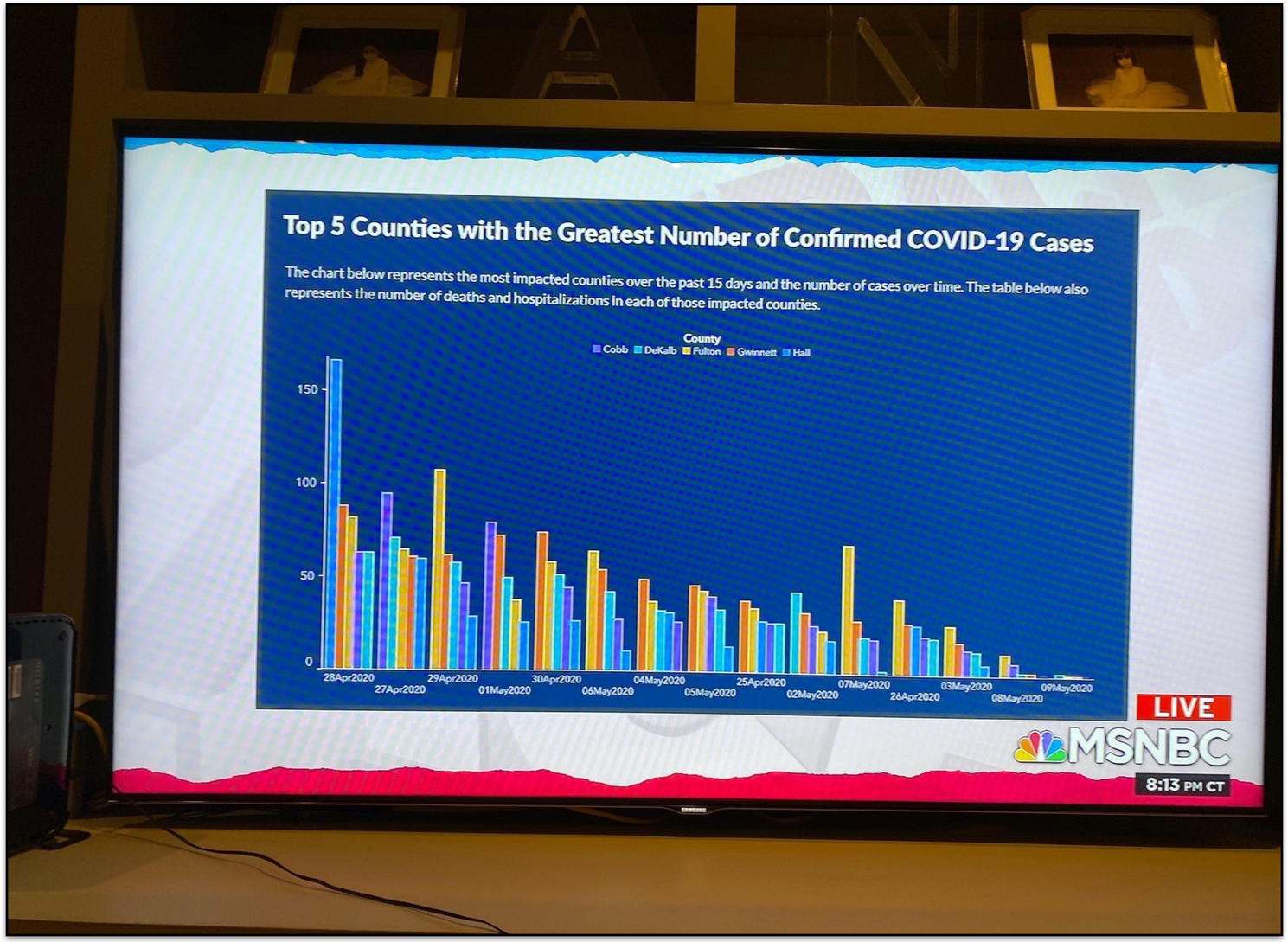


Beware of biases when creating figures

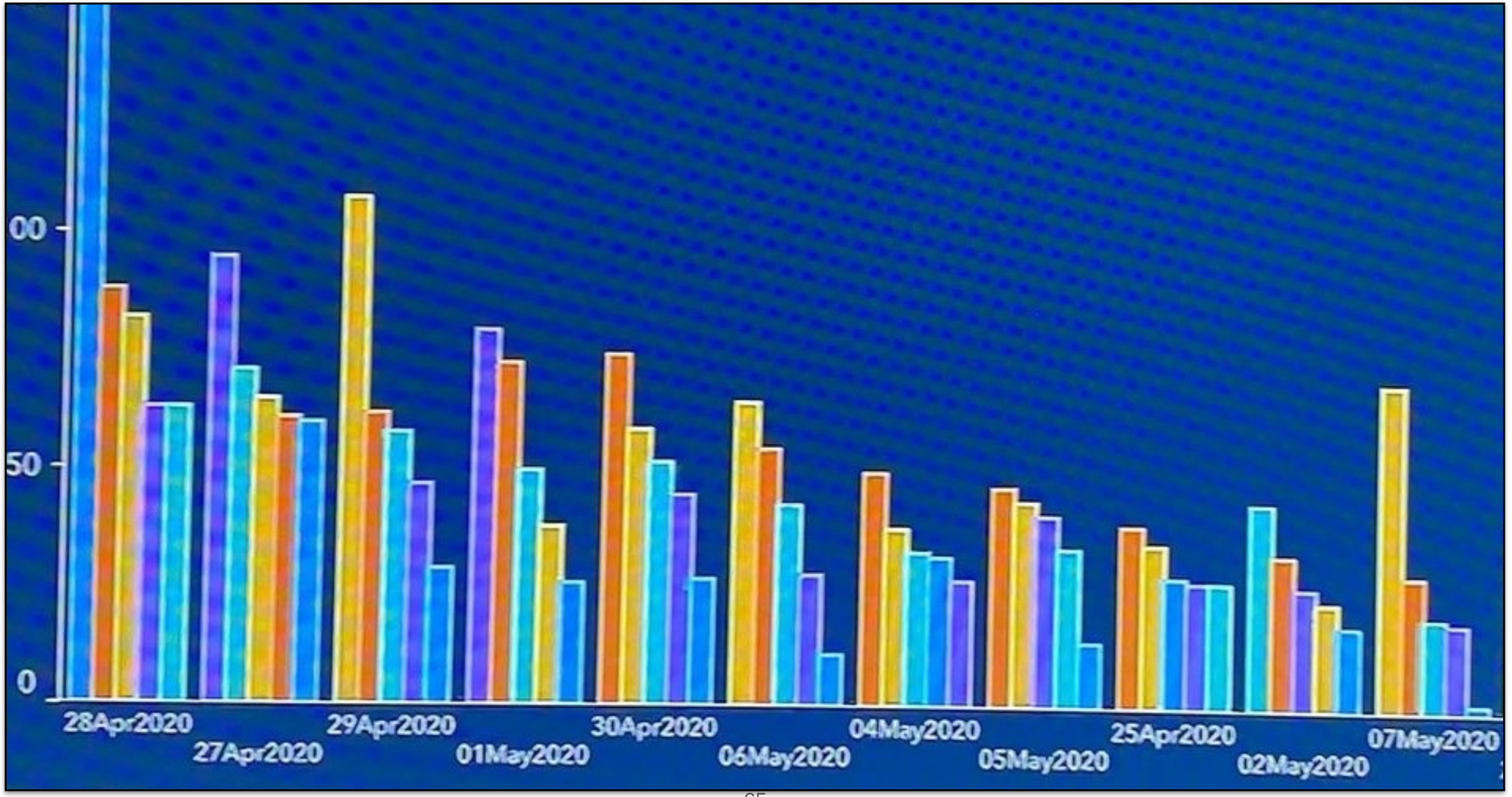
Beware of misleading practices



Beware of misleading practices



Beware of misleading practices



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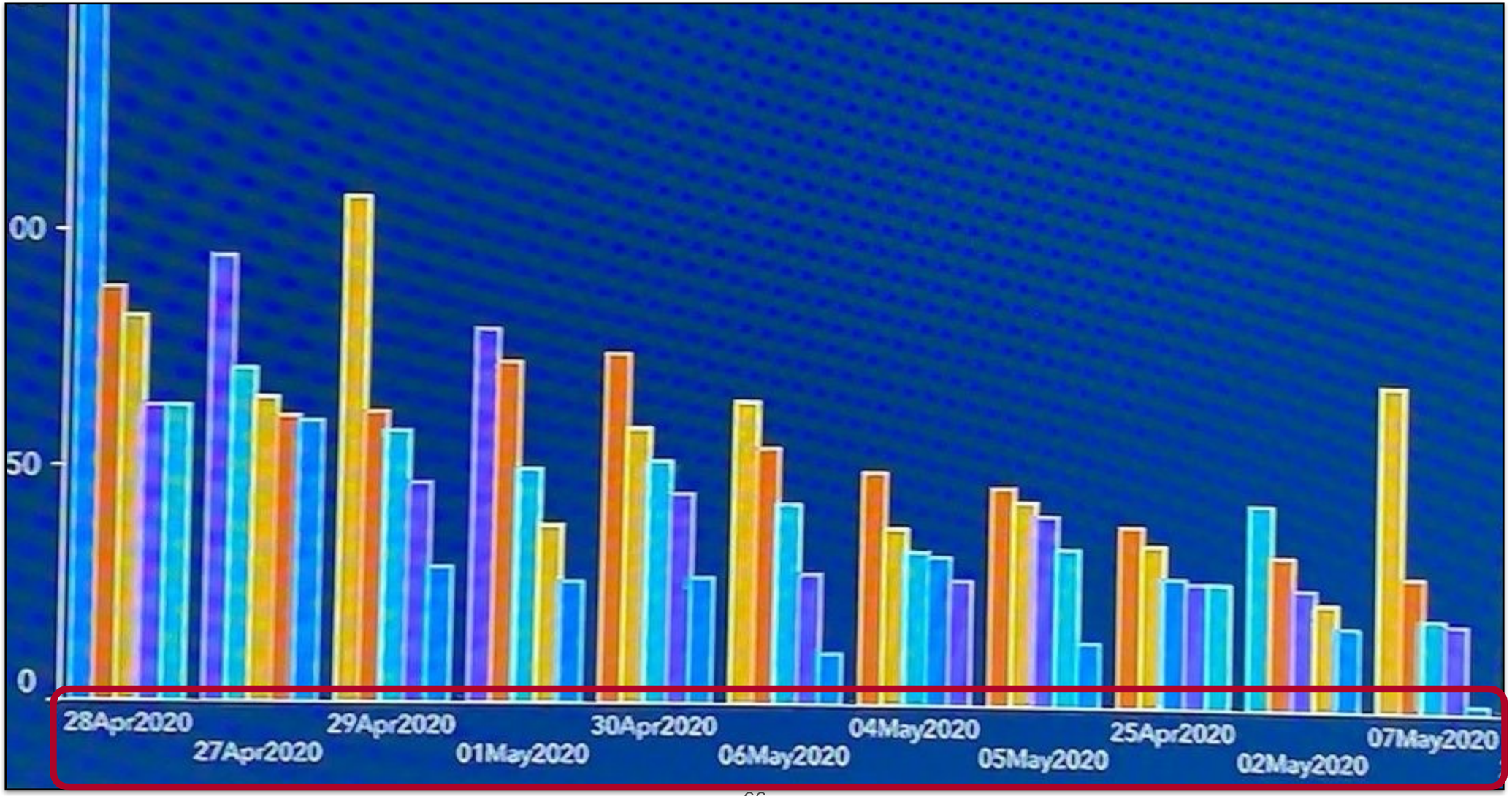

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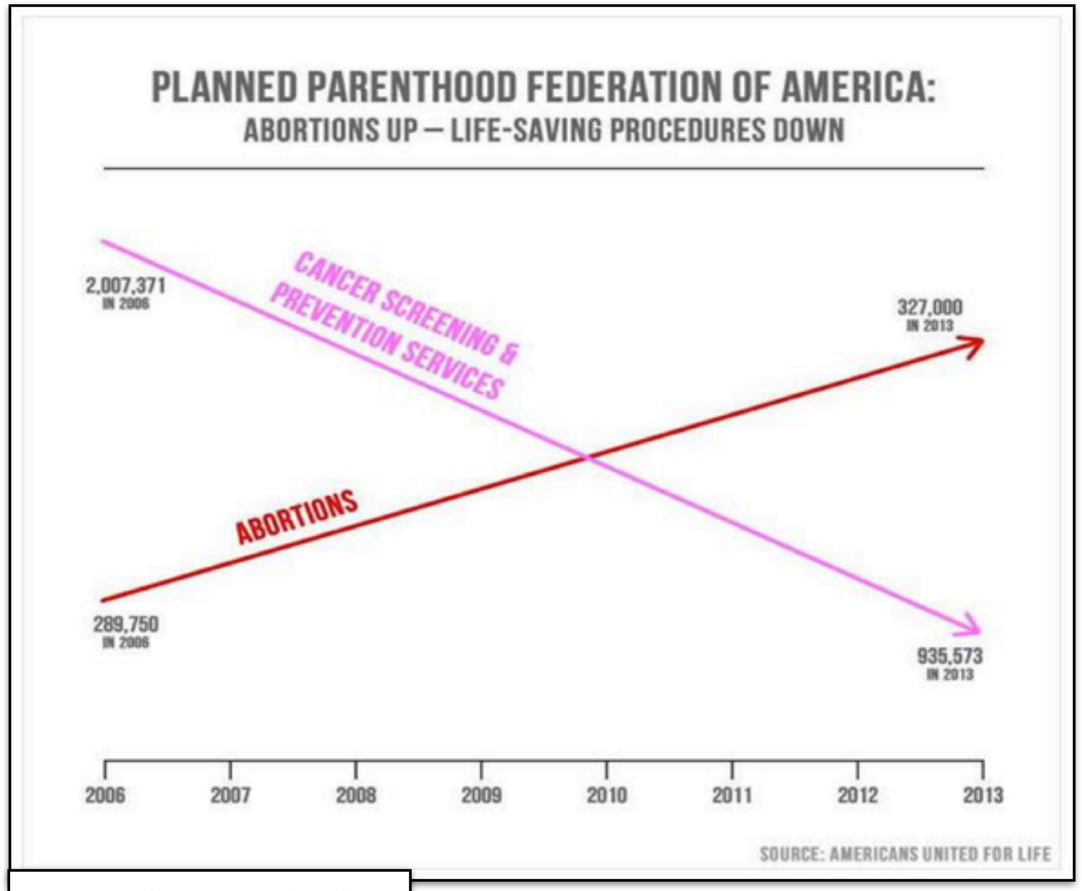

Taken from Politifact

Increase in abortions from 2006 to 2013

$$327{,}000 - 289{,}750 = 37{,}250$$

Decrease in other services from 2006 to 2013

$$2{,}007{,}371 - 935{,}573 = 1{,}071{,}798$$

References

1. Introduction to Data Science: Data analysis and prediction algorithms with R by Rafael A. Irizarry, Chapter 10. https://rafalab.github.io/dsbook/
2. Creating effective figures and tables by Karl W. Brown. https://www.biostat.wisc.edu/~kbroman/presentations/graphs2017.pdf

Referencias en español:

1. Introducción a la Ciencia de Datos: Análisis de datos y algoritmos de predicción con R por Rafael A. Irizarry, Capítulo 10. https://rafalab.github.io/dslibro/