Eltecon Data Science Course by Emarsys

Data Visualization

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September 25, 2019

About me - Tamás

- Spent the last 6+ years of working with data daily one way or another
- 1 year mark @ Emarsys as a Data Scientist
- CEU MSc in Business Analytics
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About me - Peti

- Spent 1 year in Academia
- 2.5 yrs @ Emarsys
- Economics MSc in Amsterdam
- email: peter.lukacs@emarsys.com

Section 1

Communication as a Data Scientist

Why should you care?

- Data Science is a very complex, technical field
- But at the end we usually want to have an impact on the business
- Business people tend not to be technical
- Our impact as a data scientist depends on the decisions (human-made or automated) that we can influence.
- Communication is the tool to transfer the right ideas, and build *trust*
- You'll most frequently communicate using charts and other visualization tools

Let's see an example about Hurricanes

LIVE DEMO

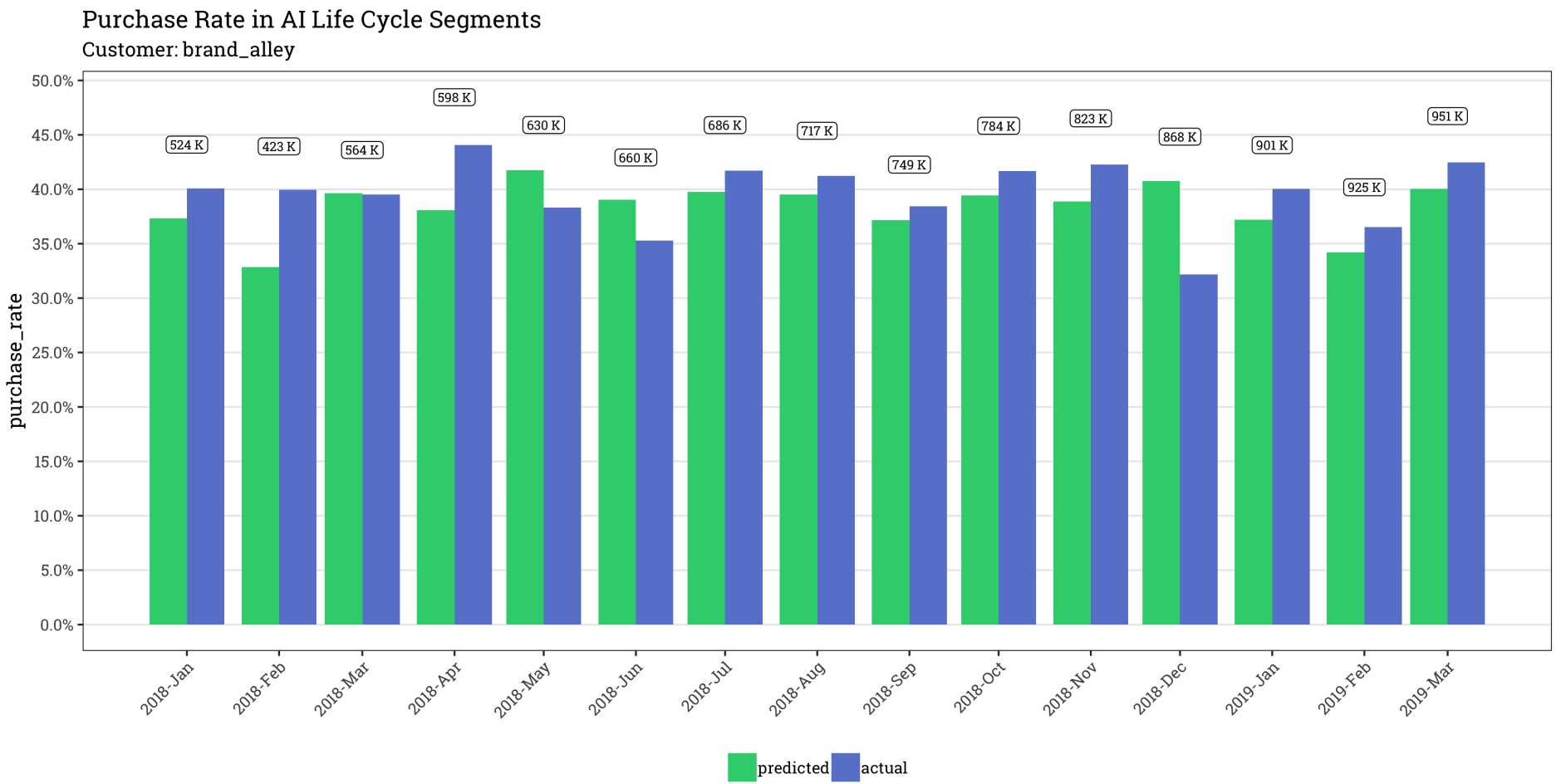
OR

use `hurricane_dorian_forecast_map.pdf`...

And a tweet by Mr. Trump...

For more "fun" click here.

An example from Emarsys



Notes:
- Excludes contacts aquired during the month
- Includes first time and repeat buyers
- # K numbers above bars represent number of contacts

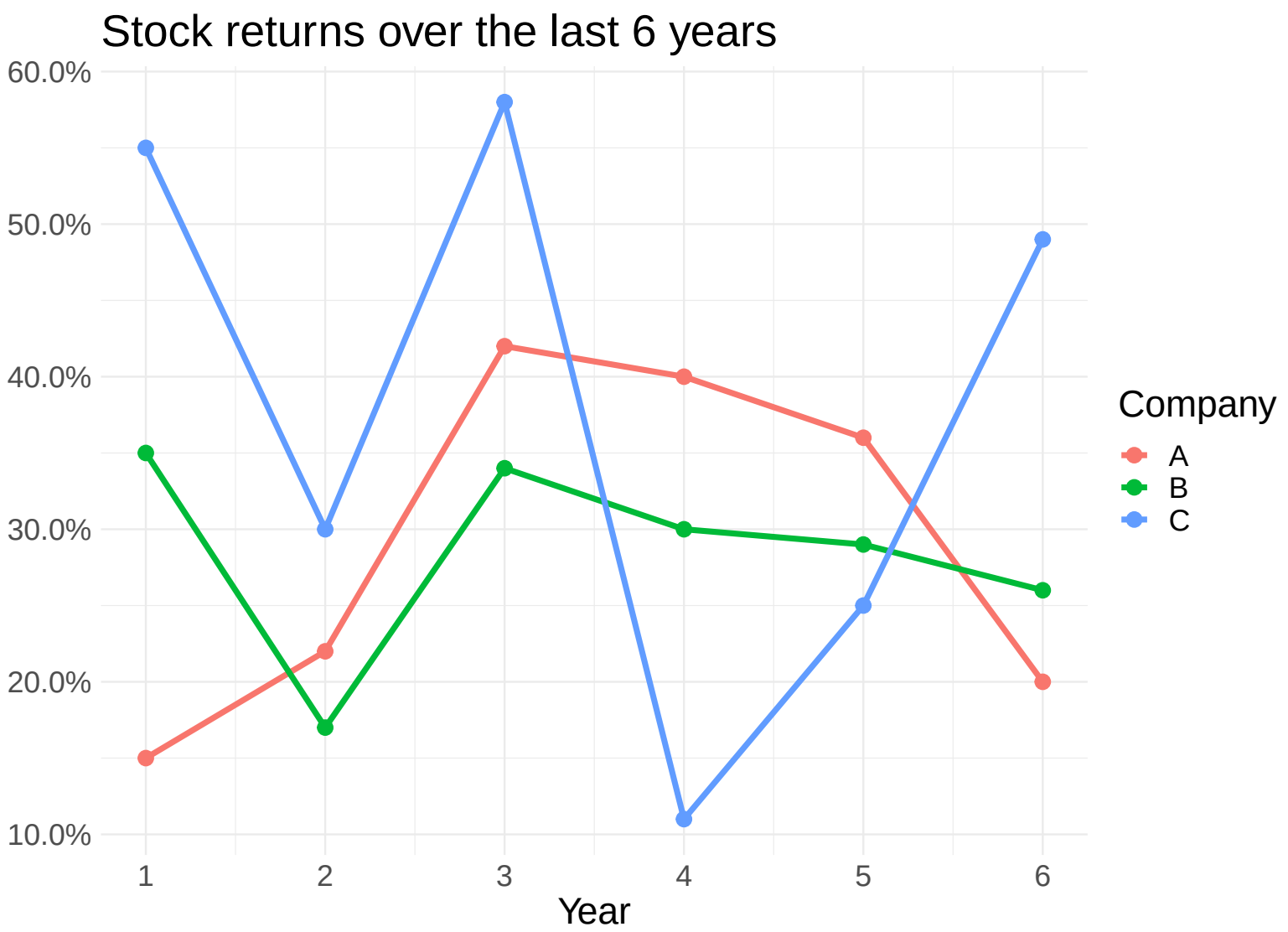
Section 2

Why does data visualization matter?

Tables vs charts

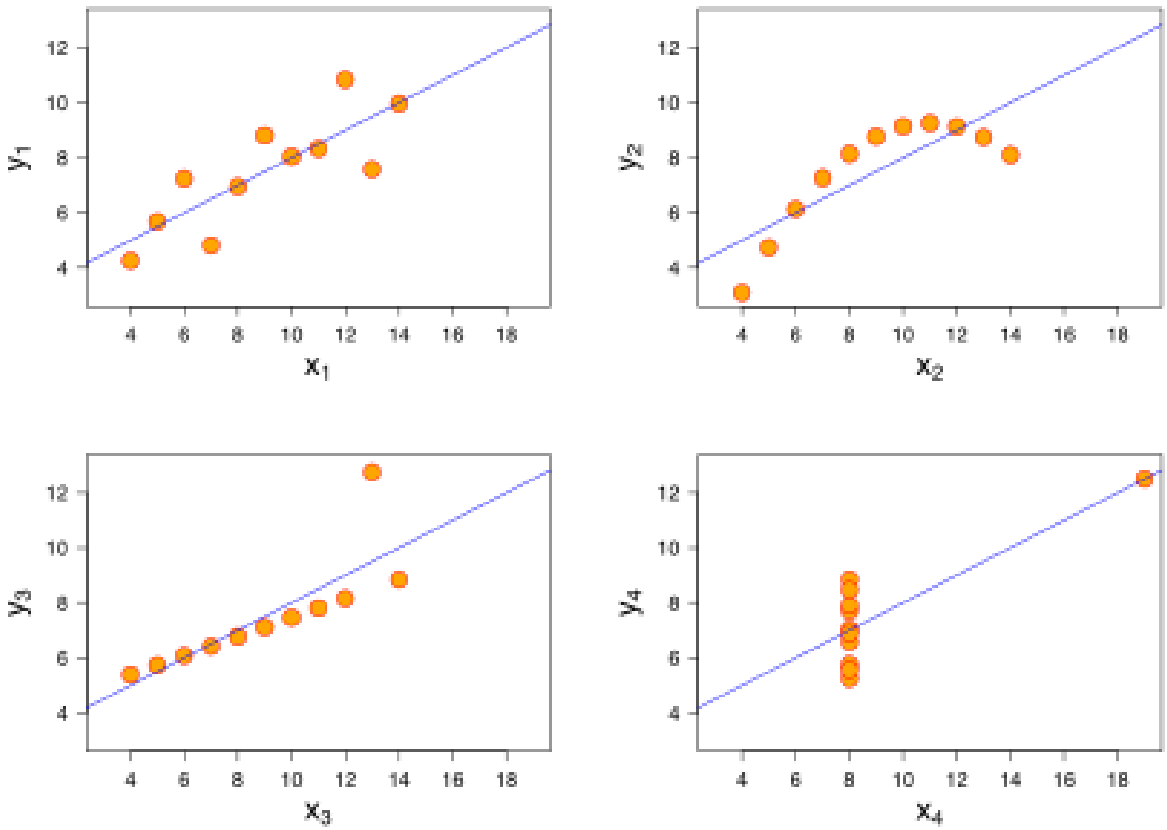
Year	A	B	C
1	0.15	0.35	0.55
2	0.22	0.17	0.30
3	0.42	0.34	0.58
4	0.40	0.30	0.11
5	0.36	0.29	0.25
6	0.20	0.26	0.49

Tables vs *charts*



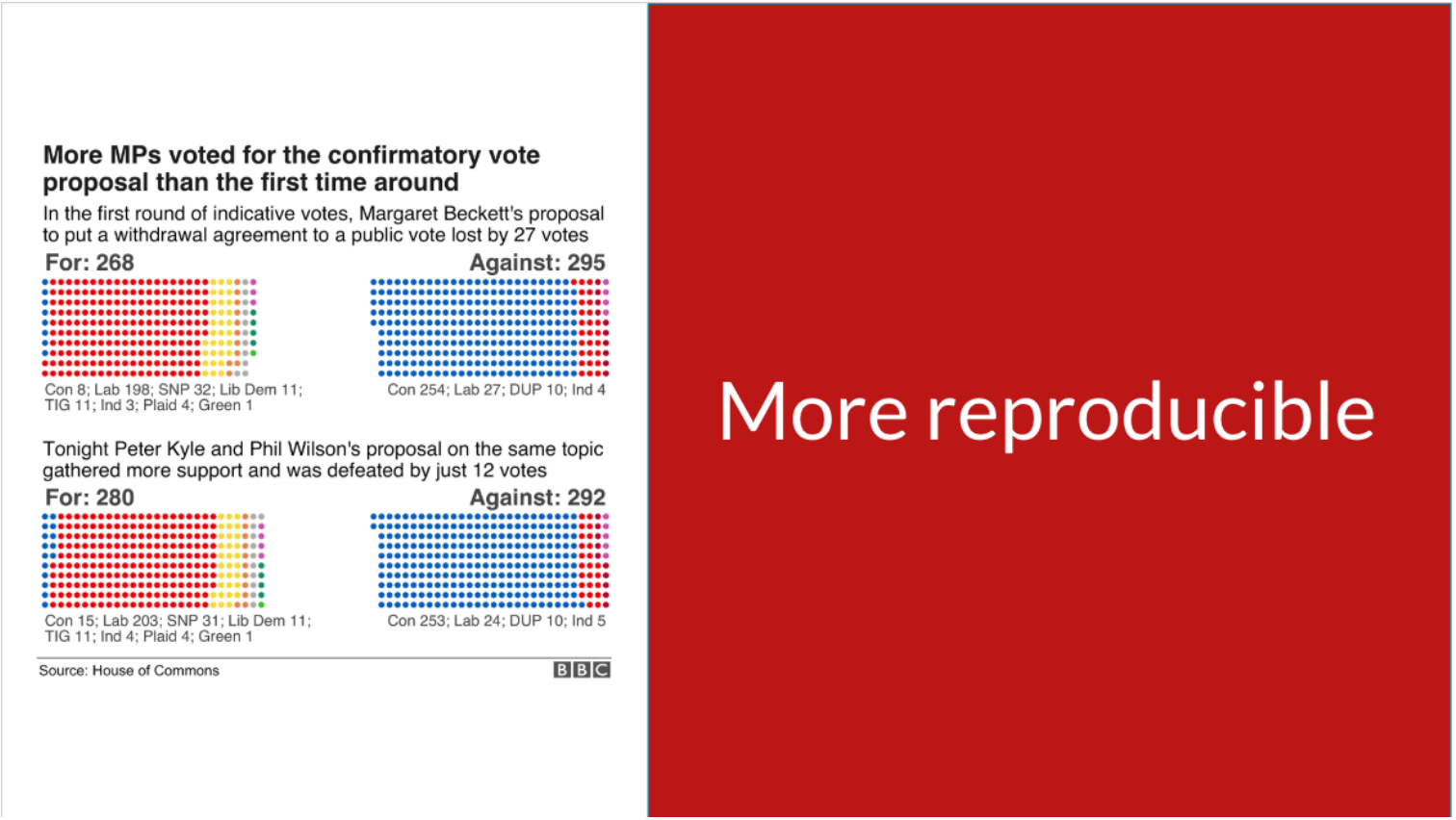
Anscombe's quartet

If it's about summarizing information, why are summary statistics insufficient? The below datasets have the same means, variances and correlations between X and Y.



Why R for data visualization?

- Reproducibility



Source: EARL London, 2019 - How the BBC uses R for data visualisation

Why R for data visualization?

- Reproducibility
  - BBC example
  - Data wrangling is an important step we have to do
    - If it's done e.g. in Excel, the steps might not be replicable, or they just take time to do
- Fast iteration
  - Above also means that it is easy to change something,
  - Or visualize new data in "old" ways

Explorative vs Descriptive Data Viz

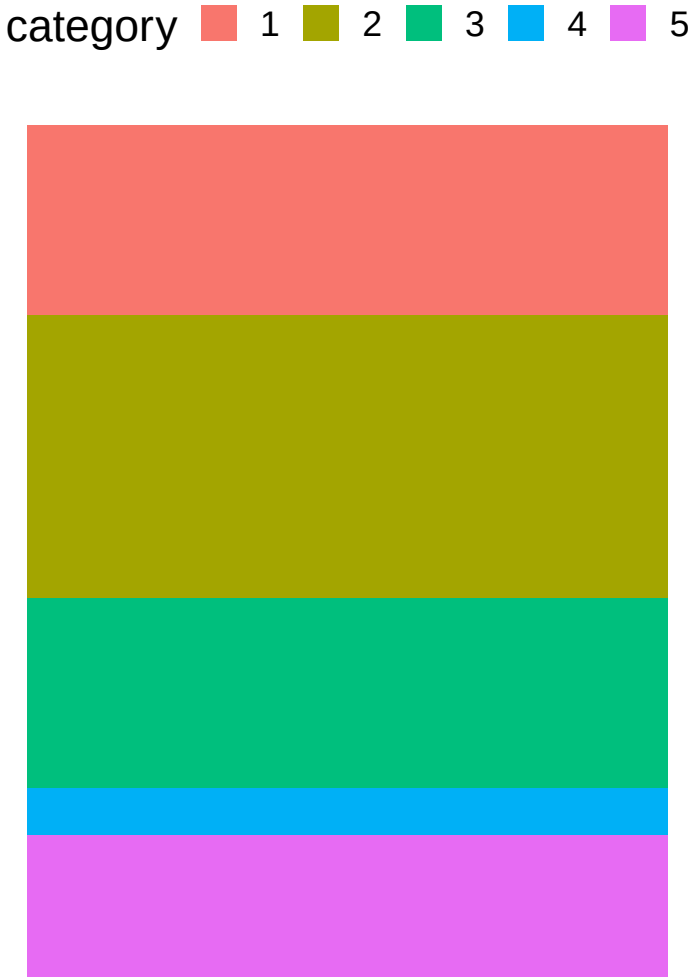
- Explorative: during research, getting to know the data
  - Interactivity! Specially when doing it for others
- Descriptive: summarizing findings, communication of results
  - Custom made
  - Know your audience: hard part. Others won't have the knowledge that you have. Right level of detail is also crucial.
  - Should show what we want it to show. Nothing more nothing less.
  - Usually 1 message / chart
  - Title, labels, etc. are all a MUST

Section 3

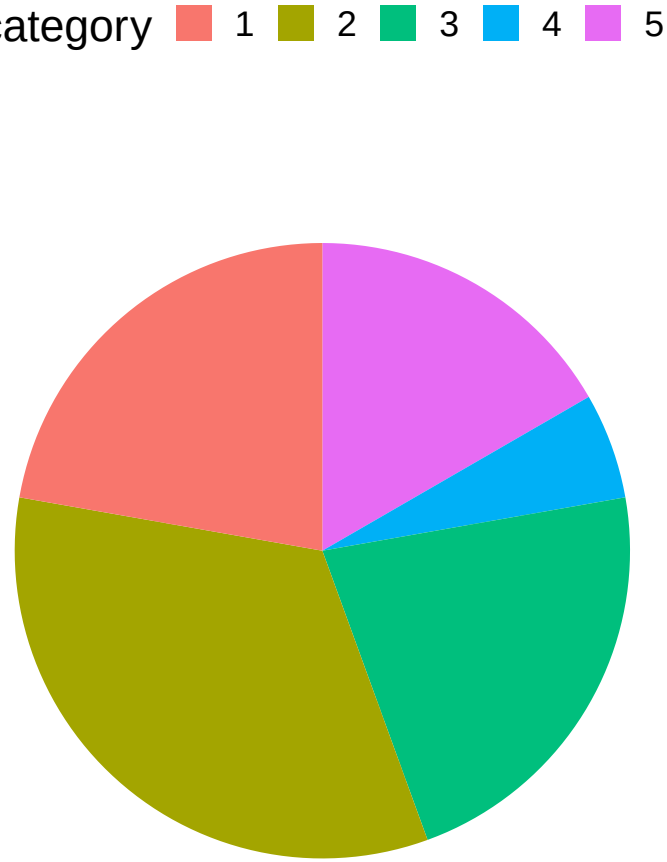
Visual Cues

Why we dislike pie charts?

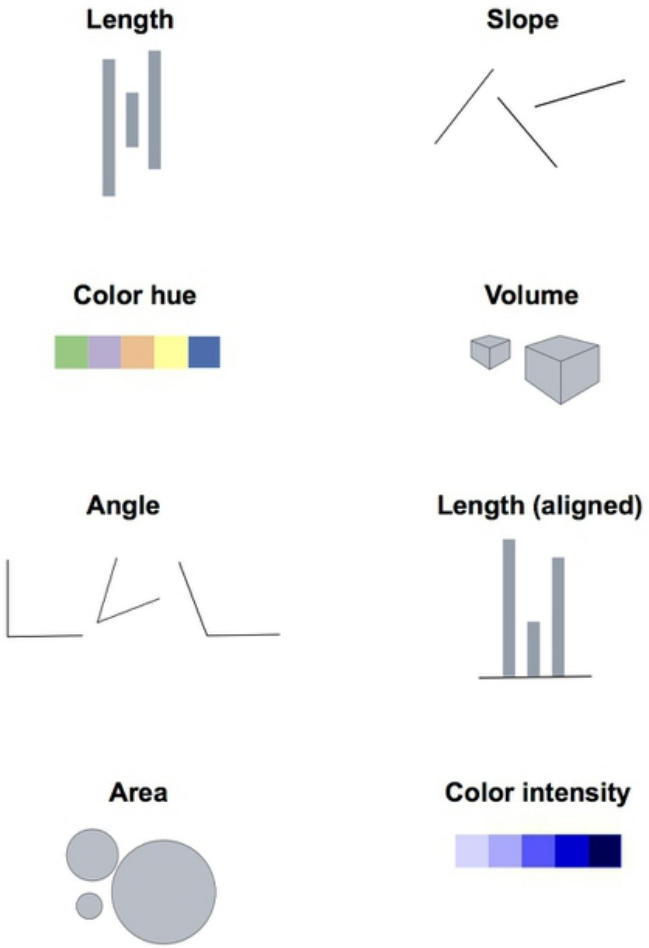
A stacked bar chart



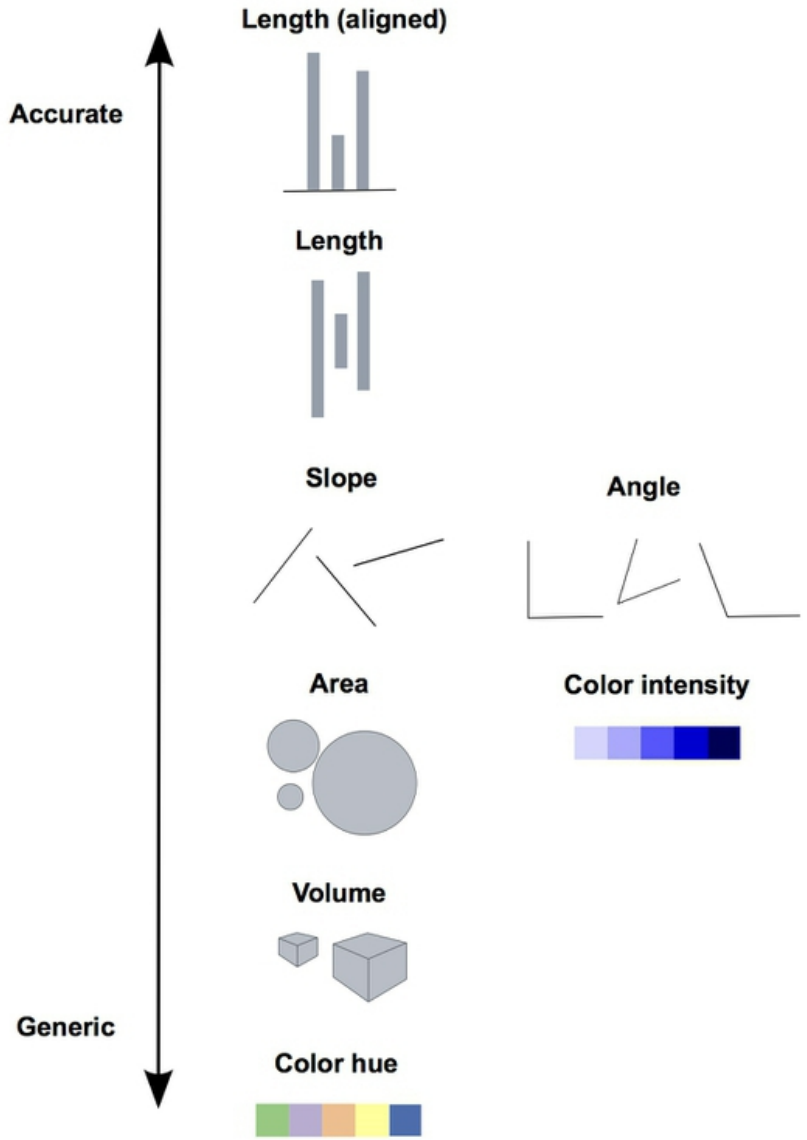
A pie chart



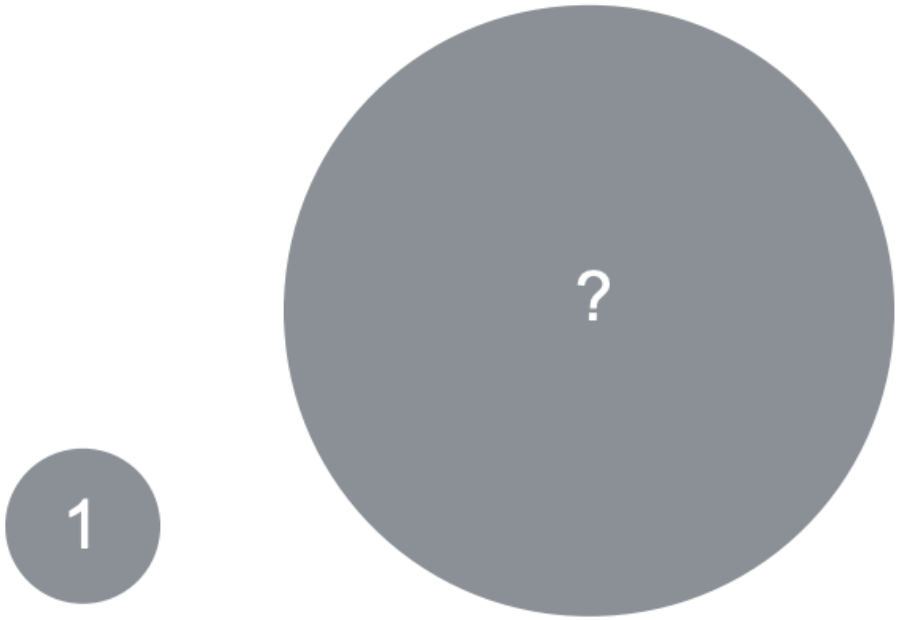
Perception of quantitative information



Perception of quantitative information

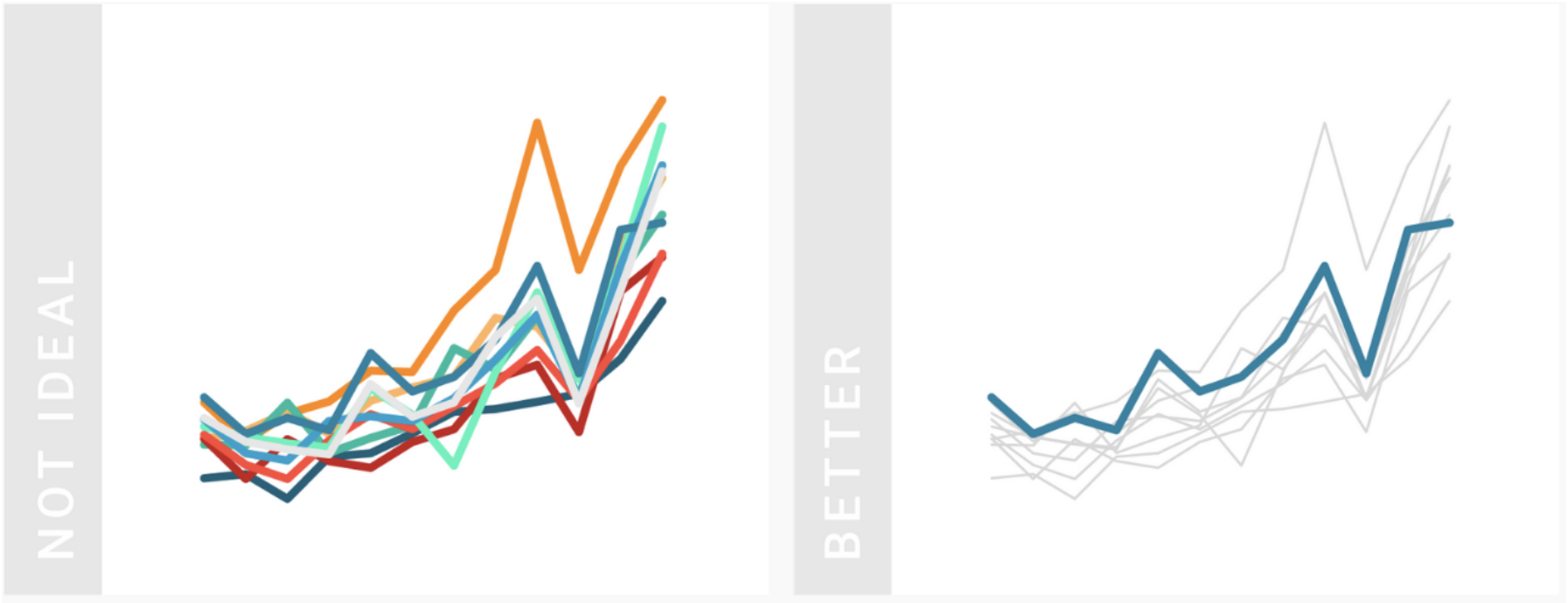


Test yourself



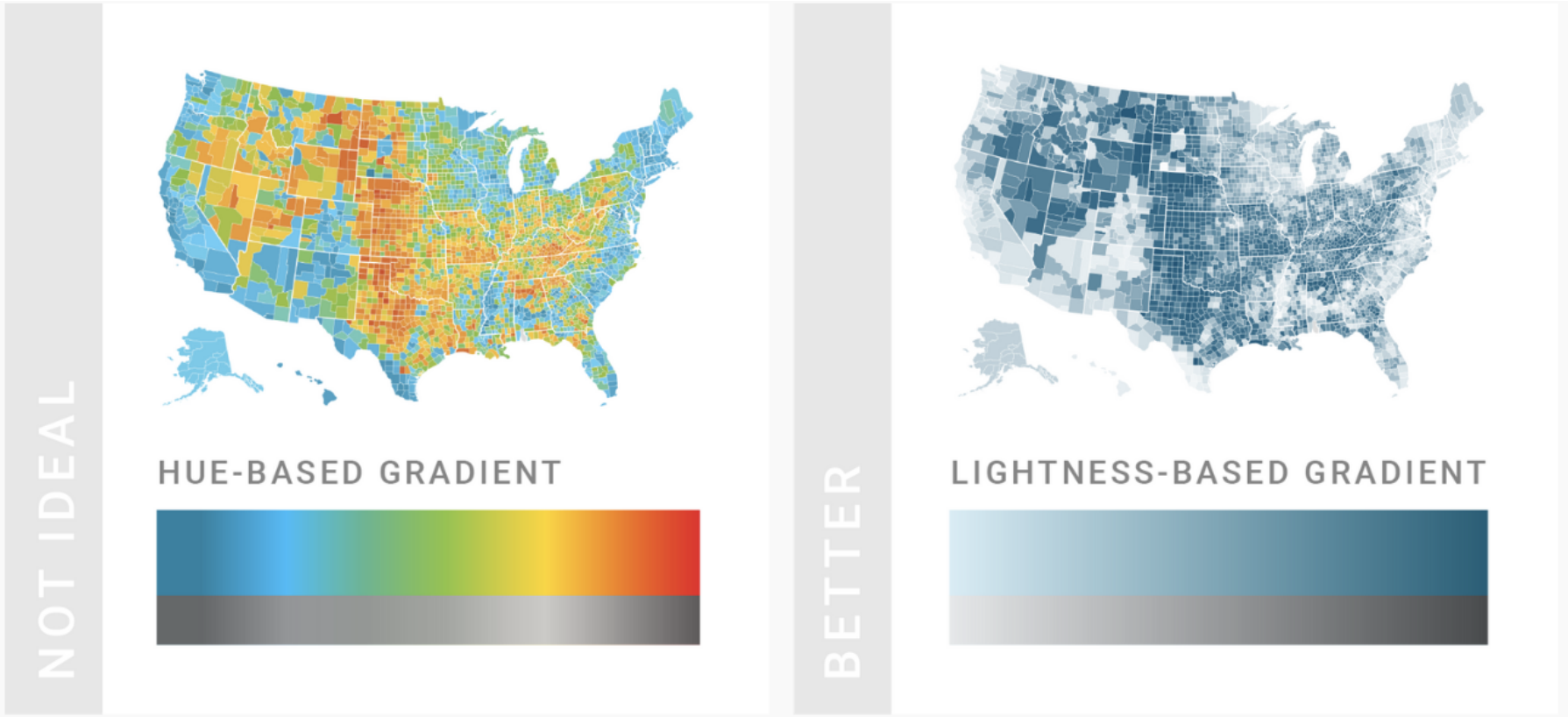
Source: Save the Pies for Dessert

About colors - highlighting



Source: What to consider when choosing colors for data visualization

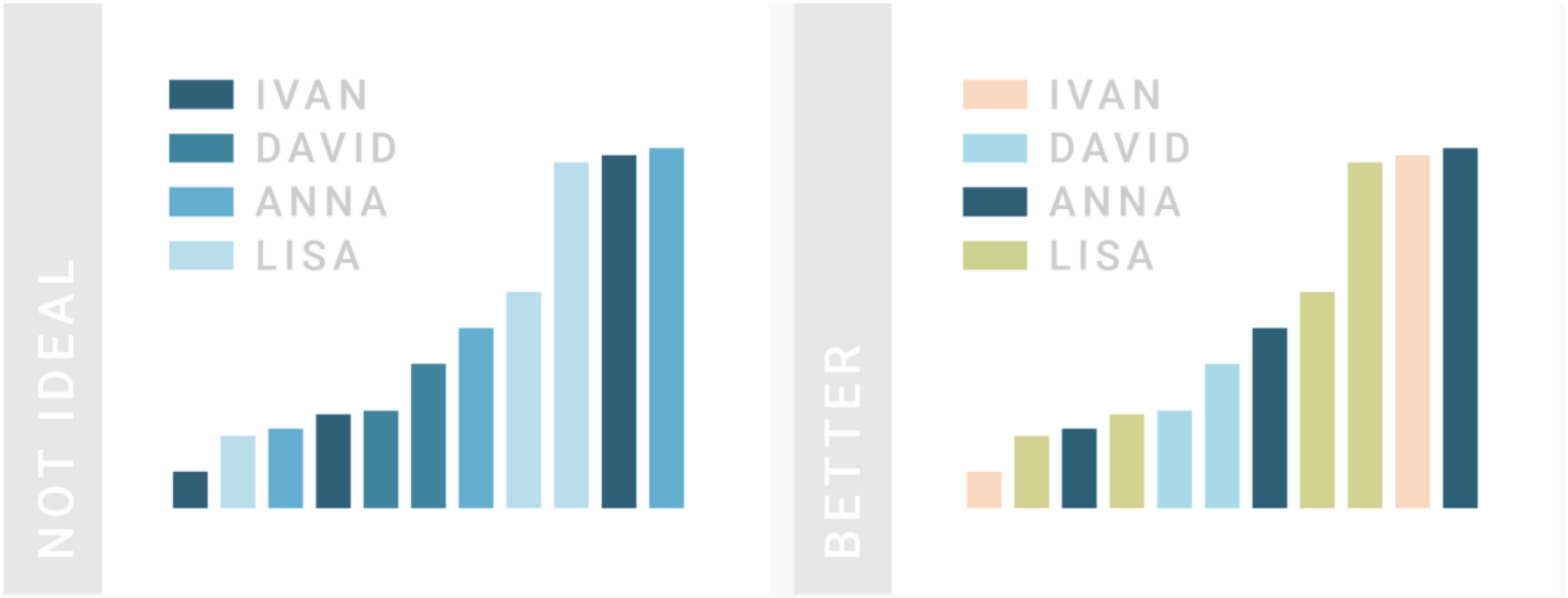
About colors - hue - 1



Source: What to consider when choosing colors for data visualization

About colors - hue - 1

About colors - hue - 2



Source: What to consider when choosing colors for data visualization

Another pitfall - the double Y-axis trap

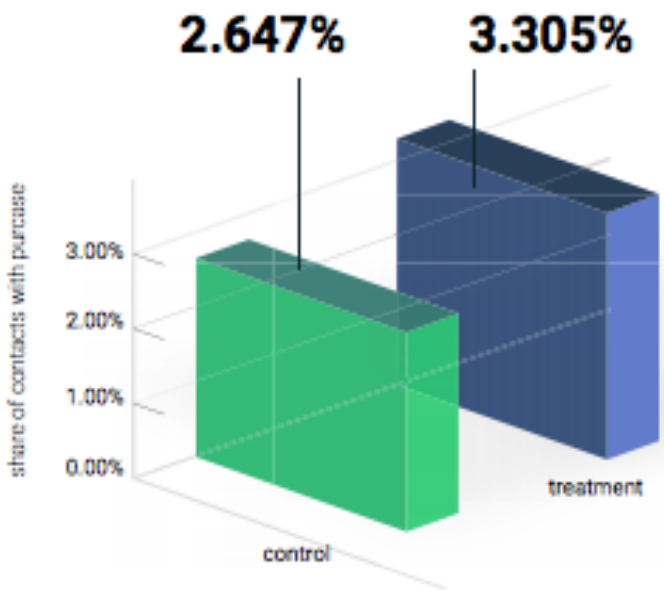
Source: Why you shouldn't use pie charts - Tips for better data visualization

Section 4

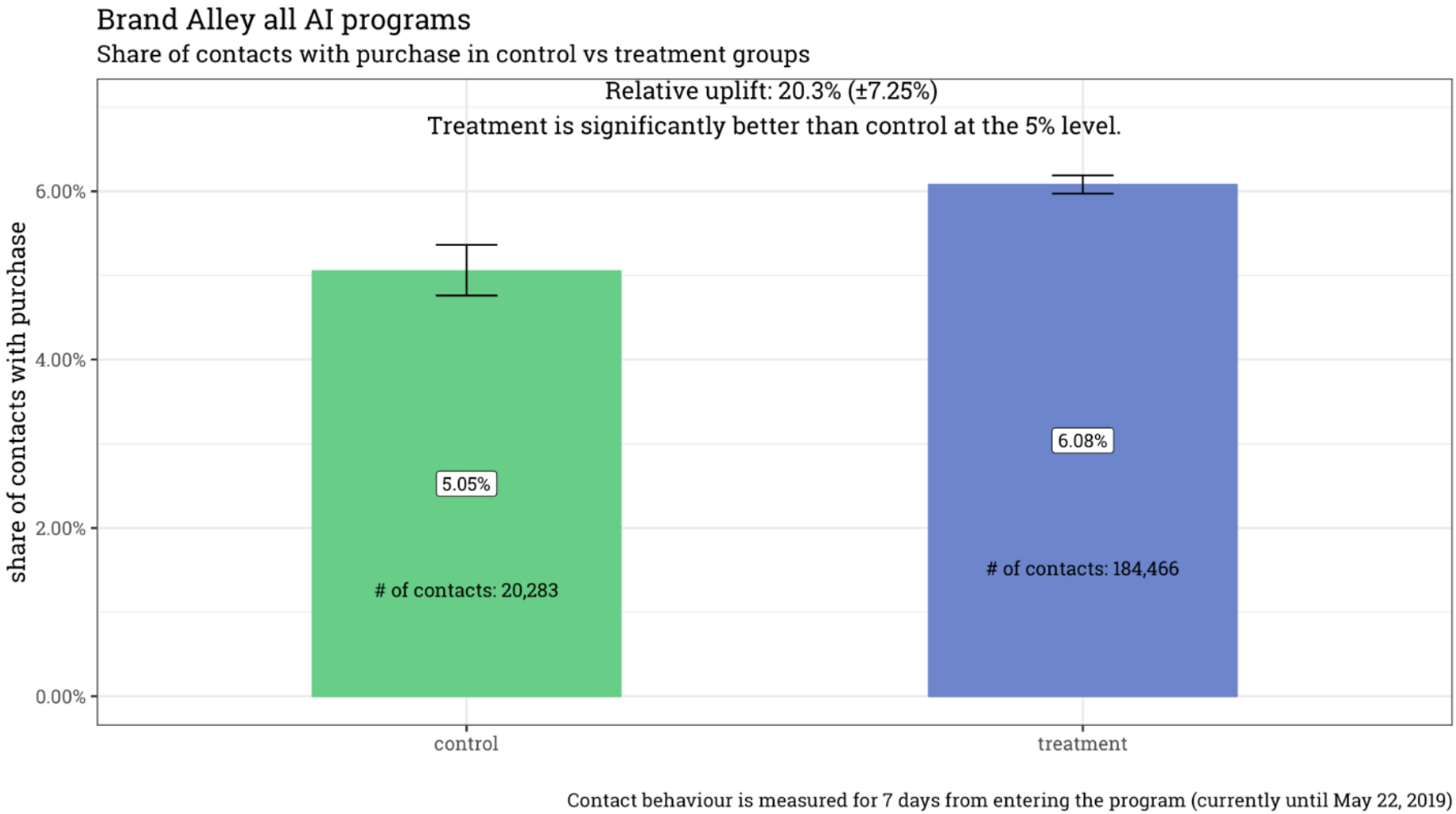
Visualizing uncertainty

A recent example at Emarsys

List the bad (and good) things about these charts!

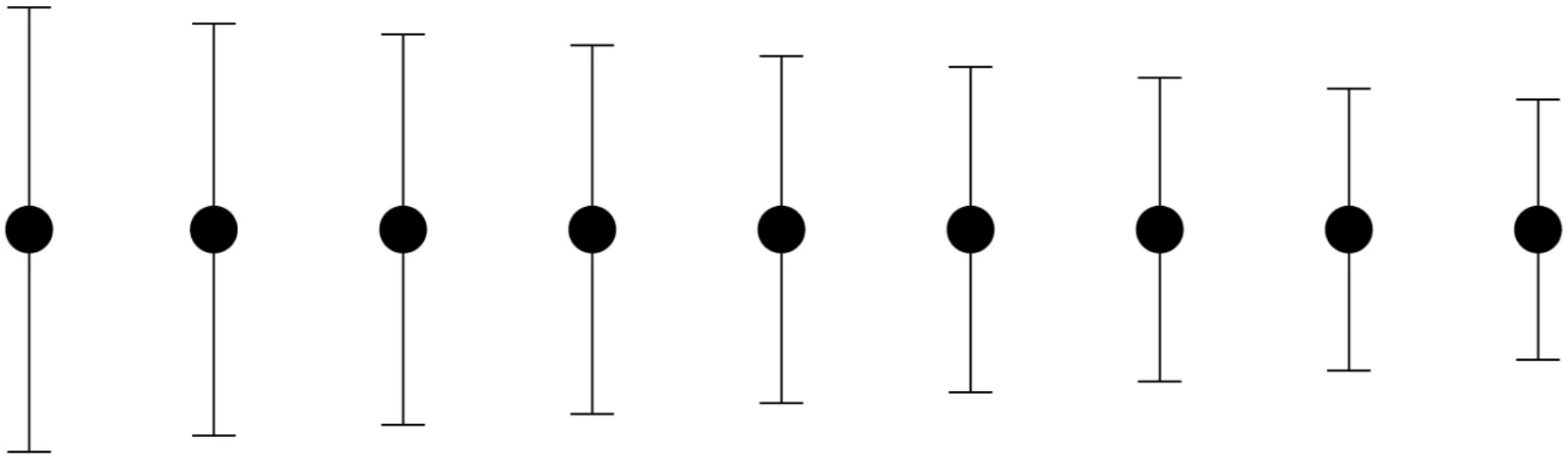


How we did it



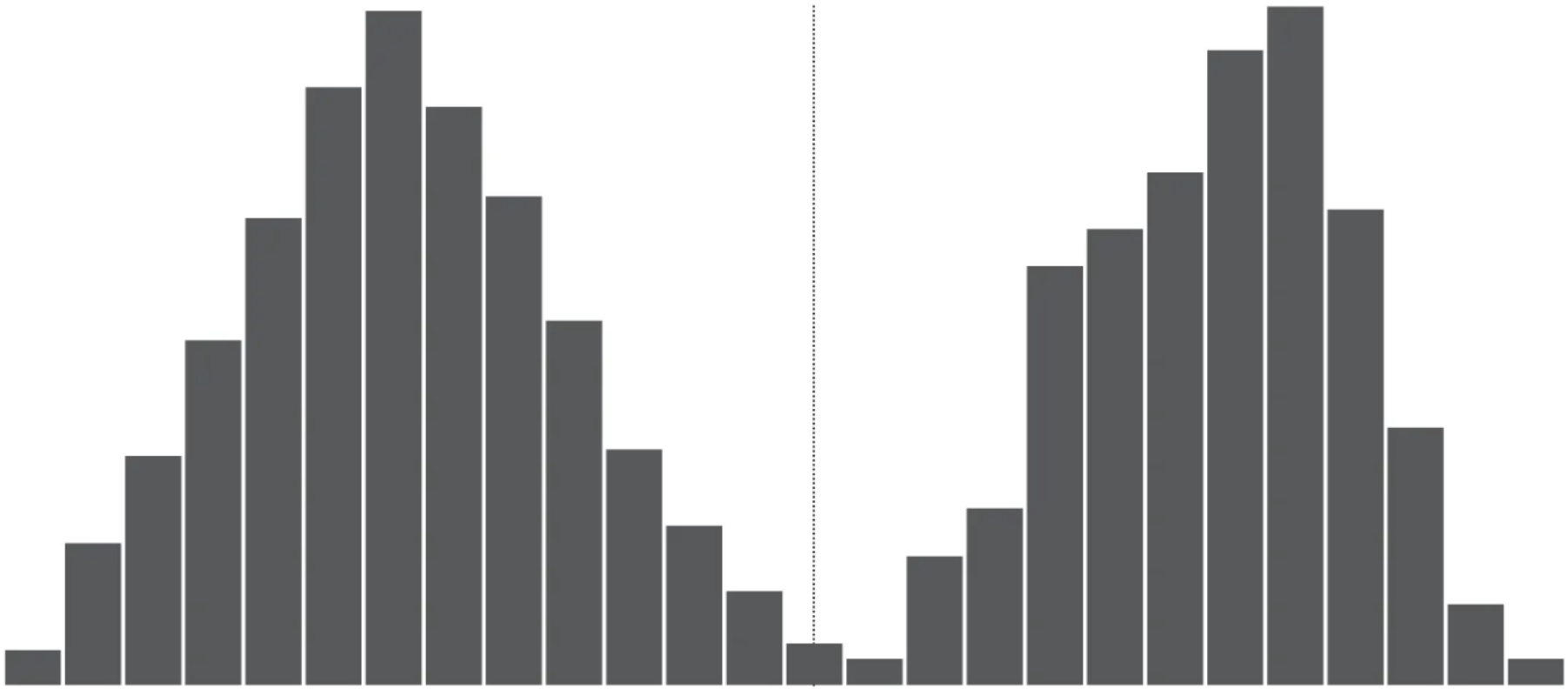
Contact behaviour is measured for 7 days from entering the program (currently until May 22, 2019)

Uncertainty - Ranges



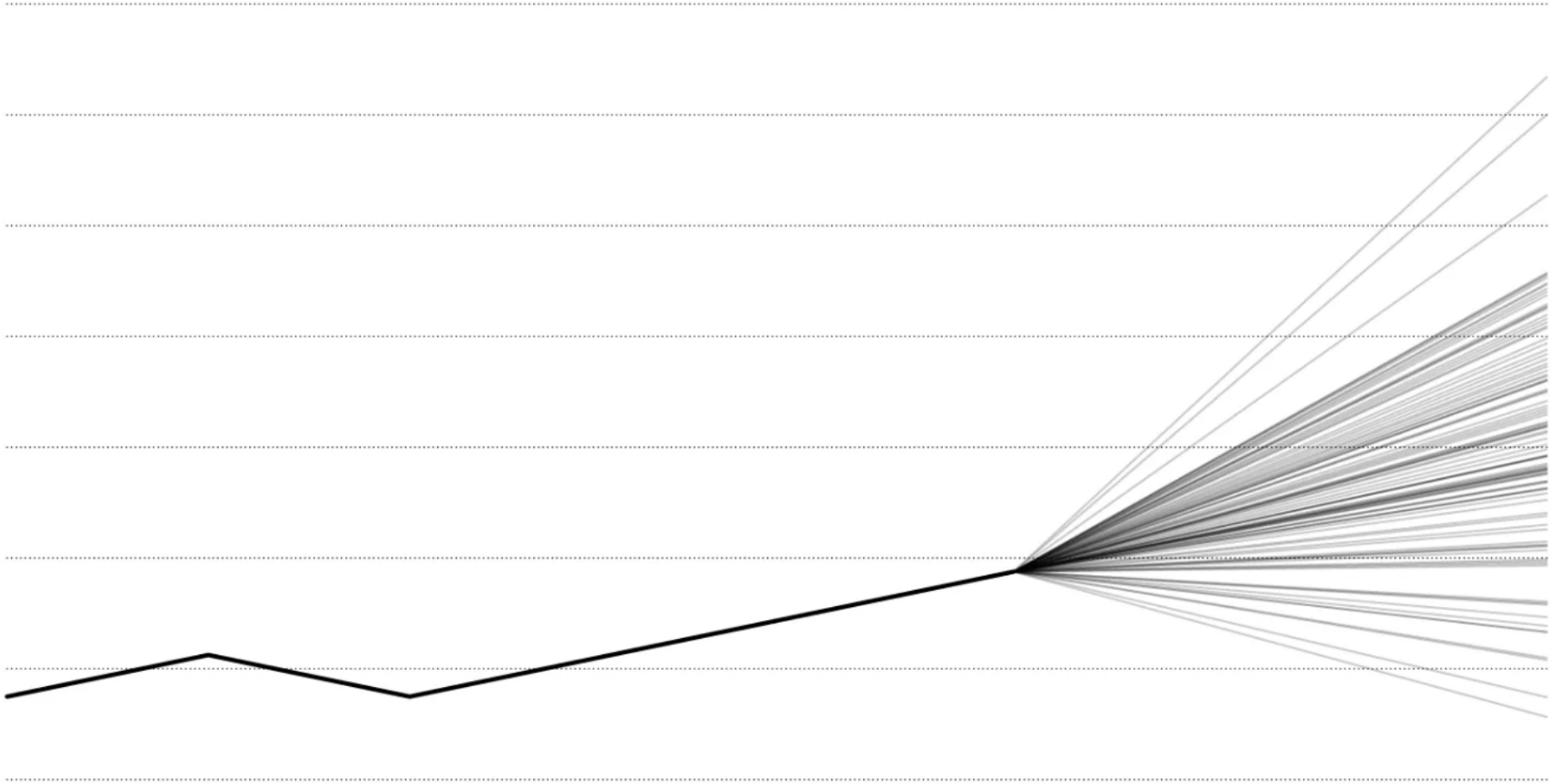
Source: Visualizing the Uncertainty in Data

Uncertainty - Distributions



Source: Visualizing the Uncertainty in Data

Uncertainty - Timeseries



Source: Visualizing the Uncertainty in Data

Section 5

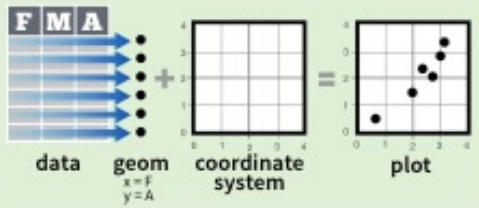
ggplot & the grammar of graphics

Why ggplot2?

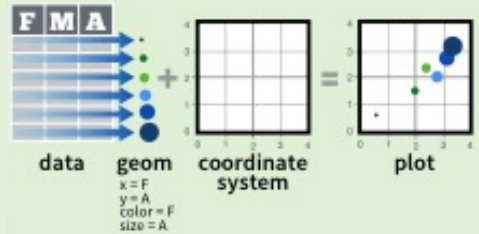
- Very mature, 10+ years in the making
- Enables fast in prototyping
- But also good enough in customization
- Great set of extensions
- Just get your data in the right format
- And then apply the "grammar of graphics"

Grammar of graphics

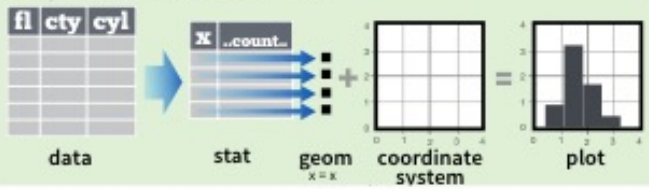
ggplot2 is based on the **grammar of graphics**, the idea that you can build every graph from the same few components: a **data** set, a set of **geoms**—visual marks that represent data points, and a **coordinate system.**



To display data values, map variables in the data set to aesthetic properties of the geom like **size**, **color**, and **x** and **y** locations.

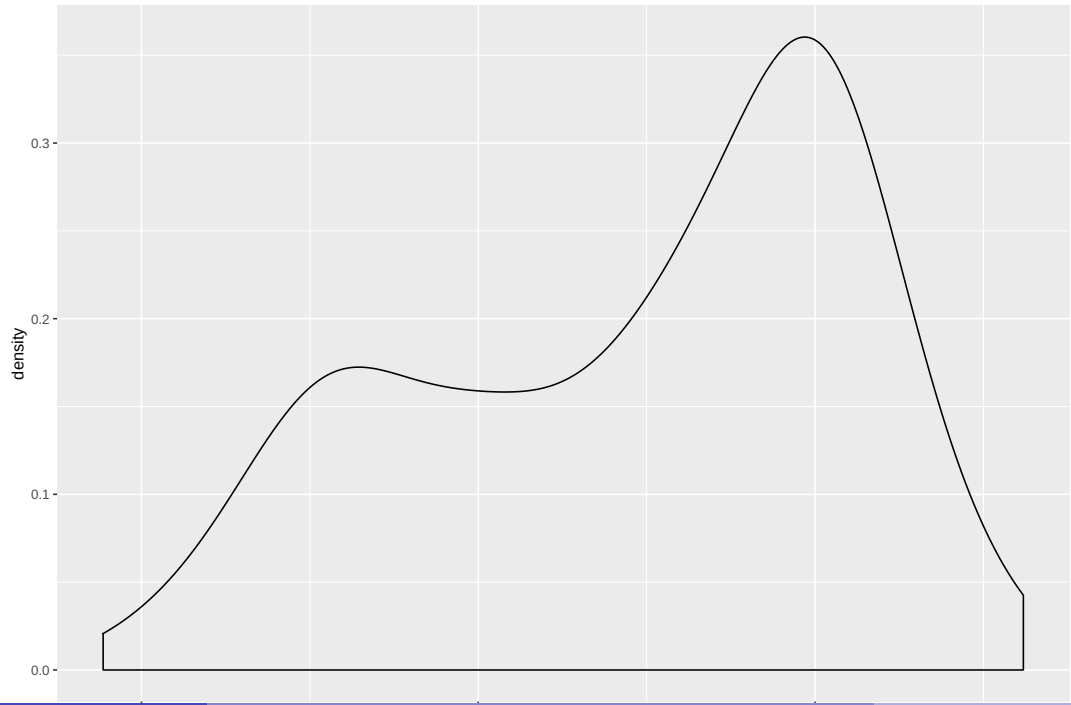


Some plots visualize a **transformation** of the original data set. Use a **stat** to choose a common transformation to visualize, e.g. a + geom_bar(stat = "bin")



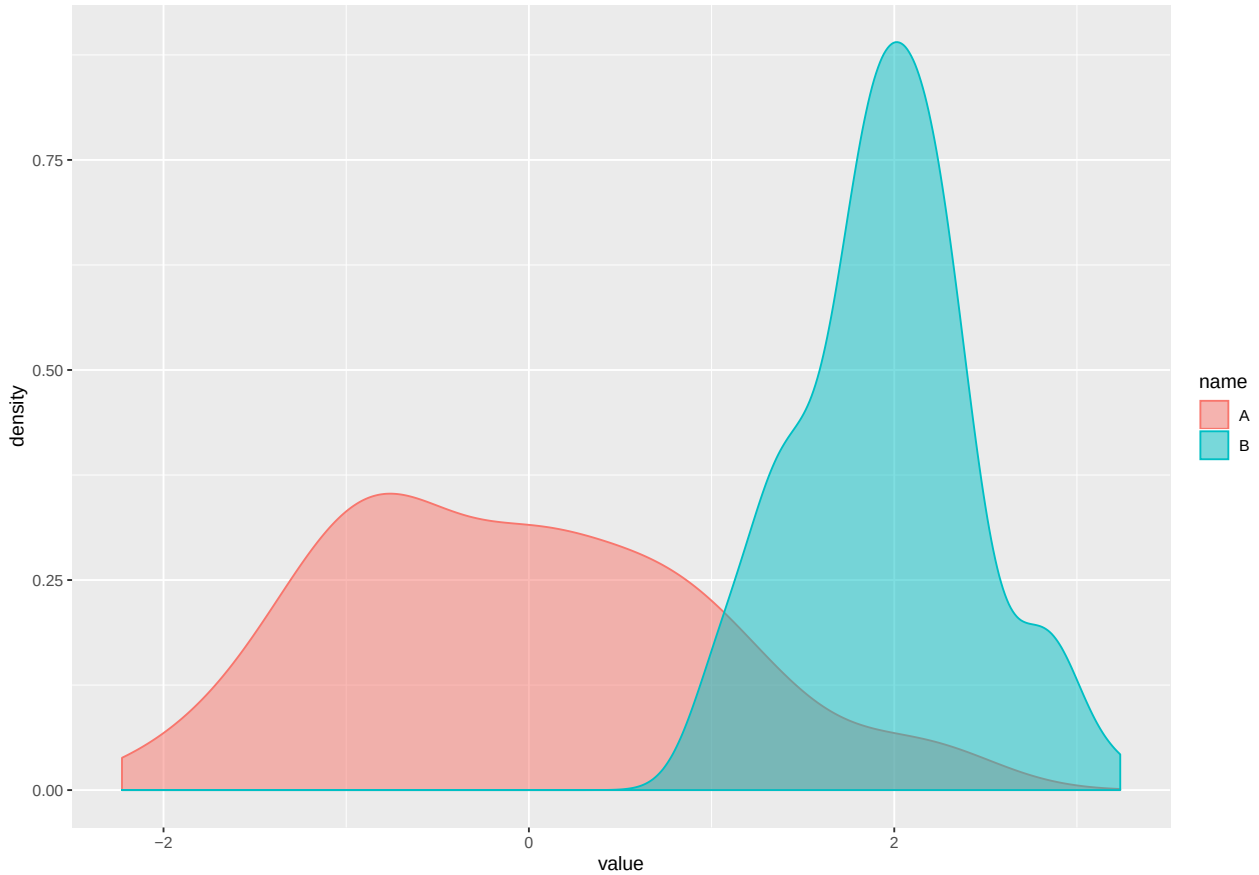
A minimal plot

```
set.seed(925)
dt <- data.table(
  name  = c(rep("A", 100),    rep("B", 100)),
  value = c(rnorm(100, 0, 1), rnorm(100, 2, 0.5))
)
ggplot(data = dt, mapping = aes(x = value)) +
  geom_density()
```



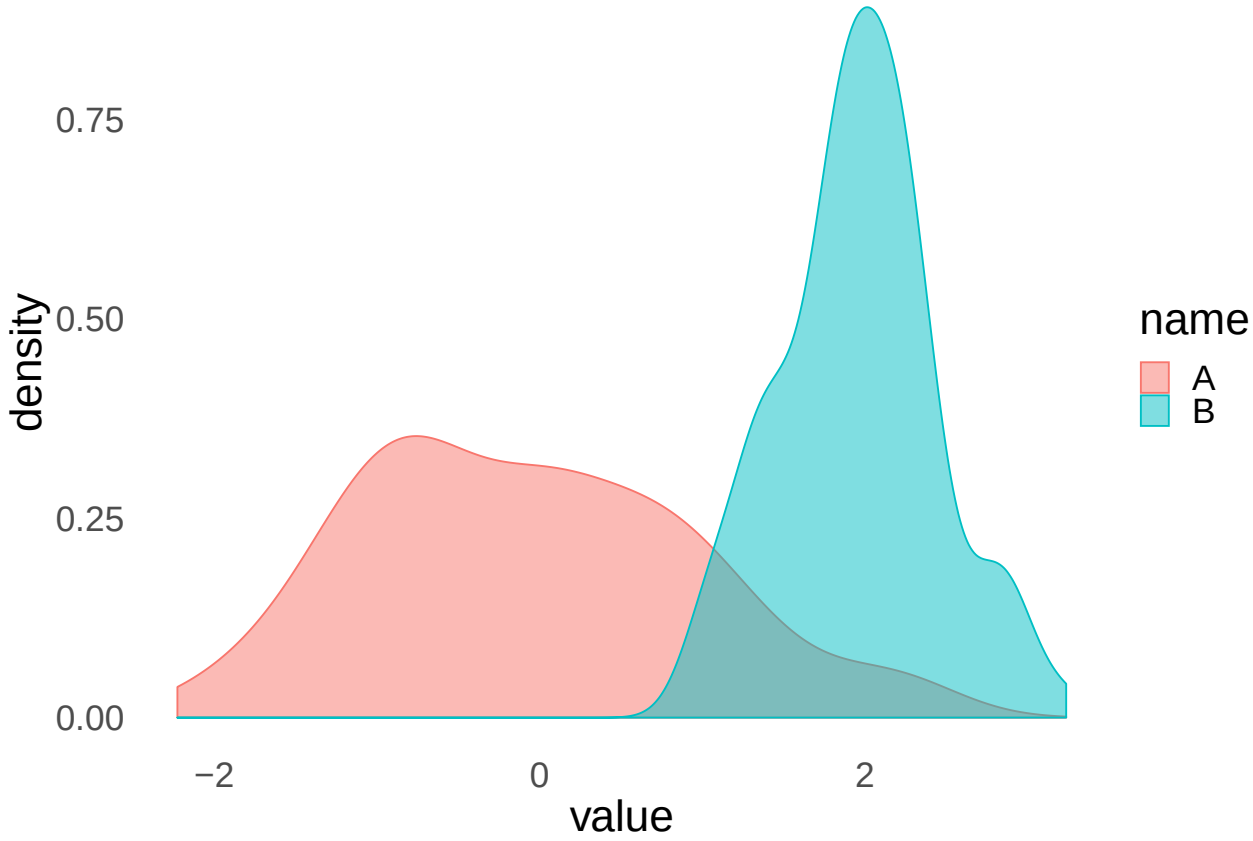
Let's add one more aesthetic

```
p <- ggplot(data = dt, mapping = aes(x = value)) +
  geom_density(aes(fill = name, color = name), alpha = 0.5)
p
```



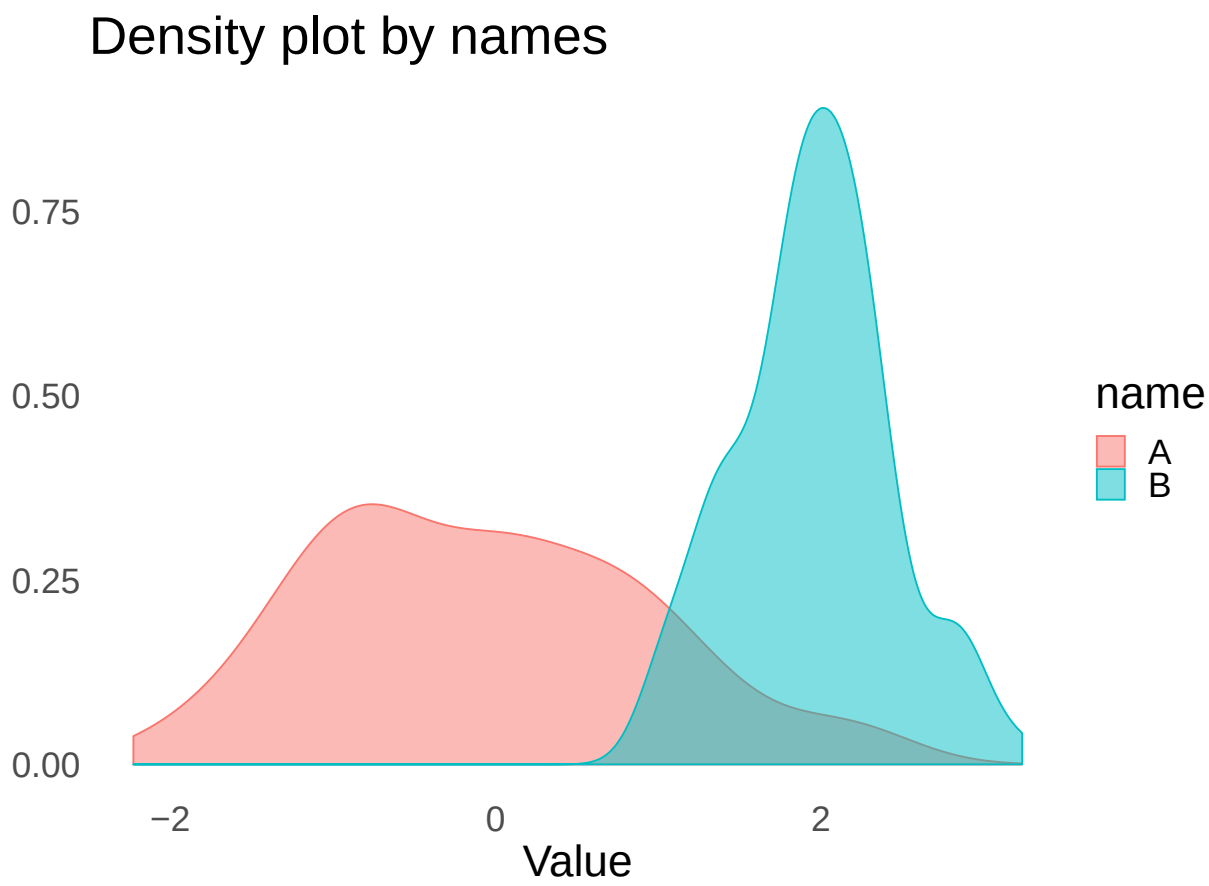
Apply some formatting

```
p <- p + theme_minimal() +
  theme(panel.grid = element_blank(), text = element_text(size = 25))
p
```



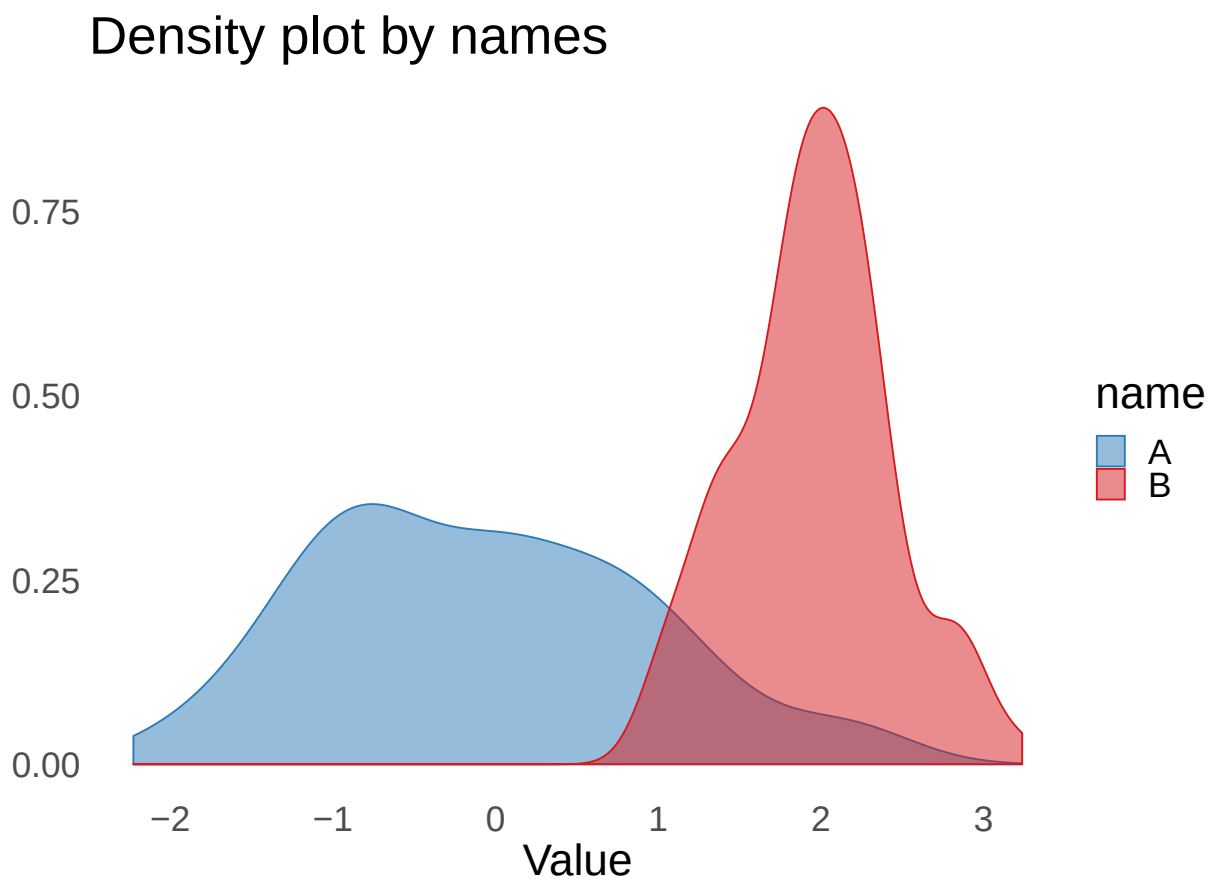
Add annotation

```
p <- p + labs(
  title = "Density plot by names", x = "Value", y = ""
)
p
```



Fix scales

```
p + scale_x_continuous(breaks = c(-2:3)) +
  scale_color_manual(values = c("A" = "#2c7bb6", "B" = "#d7191c")) +
  scale_fill_manual(values = c("A" = "#2c7bb6", "B" = "#d7191c"))
```



Some useful resources

- RStudio ggplot2 cheatsheet
- Hadley Wickham: ggplot2: Elegant Graphics for Data Analysis
- https://www.r-graph-gallery.com/
- https://coolors.co/app
- http://colorbrewer2.org/