Eltecon Data Science Course by Emarsys Data Visualization

Tamás Koncz

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
- reach me @ t.koncz@gmail.com
- Twitter, LinkedIn

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 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 DS 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 with charts and other visualization tools

Let's see an example about Hurricanes

LIVE DEMO

OR

use hurricane_dorian_forecast_map.pdf...

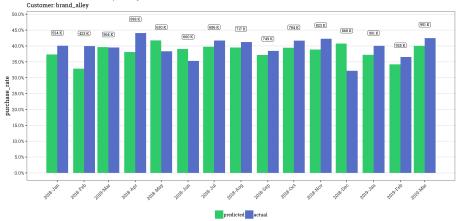
And a tweet by Mr. Trump...



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

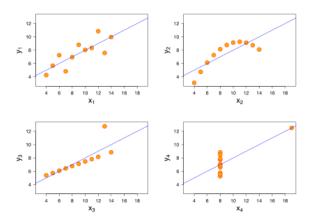
Year	Α	В	С
1	0.15	0.35	0.55
2	0.22	0.17	0.30
3	0.42	0.34	0.58
4	0.40	0.30	0.11
5	0.36	0.29	0.25
6	0.20	0.26	0.49

Tables vs charts



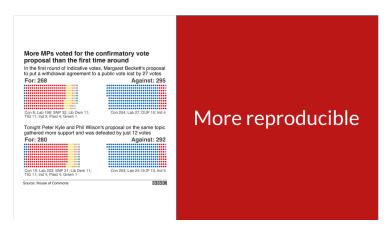
Anscombe's quartet

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

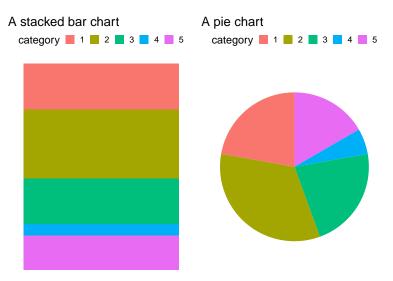
Explorative vs Descriptive Data Viz

- 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

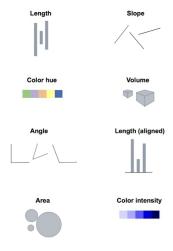
Section 3

Visual Cues

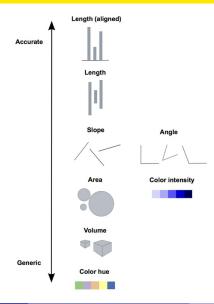
Why we dislike pie charts?



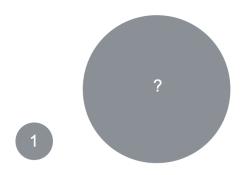
Perception of quantitative information



Perception of quantitative information

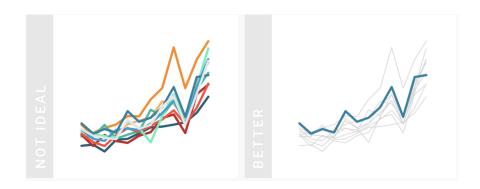


Test yourself



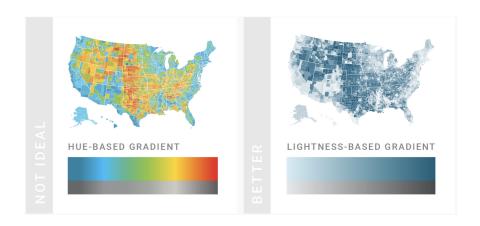
Source: Save the Pies for Dessert

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



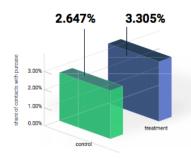
Source: Why you shouldn't use pie charts - Tips for better data visualization

Section 4

Visualizing uncertainty

A recent example at Emarsys

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

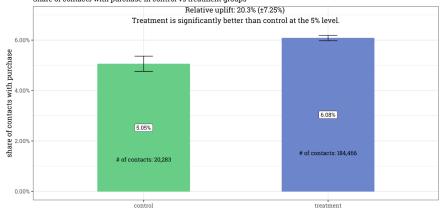




How we did it

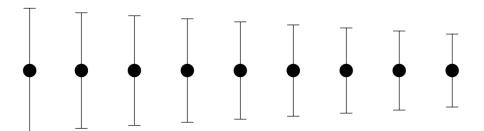
Brand Alley all AI programs

Share of contacts with purchase in control vs treatment groups



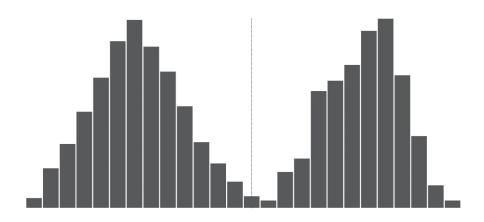
Contact behaviour is measured for 7 days from entering the program (currently until May 22, 2019)

Uncertainty - Ranges



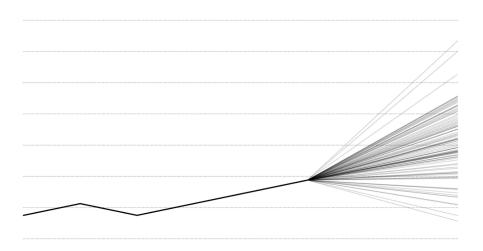
Source: Visualizing the Uncertainty in Data

Uncertainty - Distributions



Source: Visualizing the Uncertainty in Data

Uncertainty - Timeseries



Source: Visualizing the Uncertainty in Data

Section 5

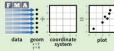
ggplot & the grammar of graphics

Why ggplot2?

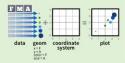
- Very mature, 10+ years in the making
- Enables fast in prototyping
- But also good enough in customization
- Great set of extensions
- Just get your data in the right format
- And then apply the "grammar of graphics"

Grammar of graphics

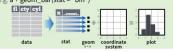
ggplot2 is based on the grammar of graphics, the idea that you can build every graph from the same few components: a data set, a set of geoms—visual marks that represent data points, and a coordinate system.



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

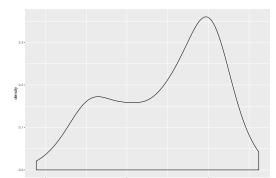


Some plots visualize a **transformation** of the original data set. Use a **stat** to choose a common transformation to visualize, e.g. a + geom_bar(stat = "bin")



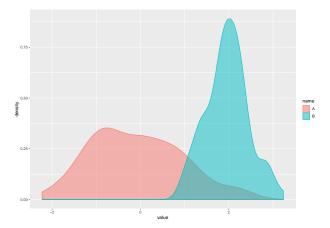
A minimal plot

```
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()</pre>
```



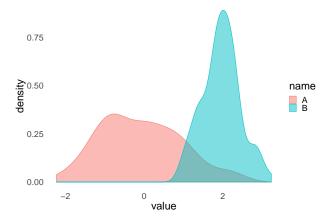
Let's add one more aesthetic

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



Apply some formatting

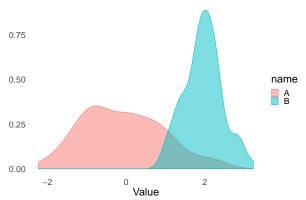
```
p <- p + theme_minimal() +
  theme(panel.grid = element_blank(), text = element_text(size = 25))
p</pre>
```



Add annotation

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

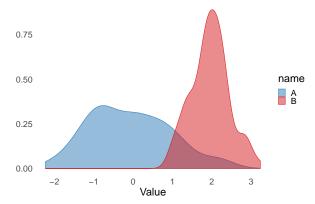
Density plot by names



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"))
```

Density plot by names



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/