

# Data Visualization. Exploratory Data Analysis

Seeing what's inside our data...  
and allowing others to see

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Technical Trainer

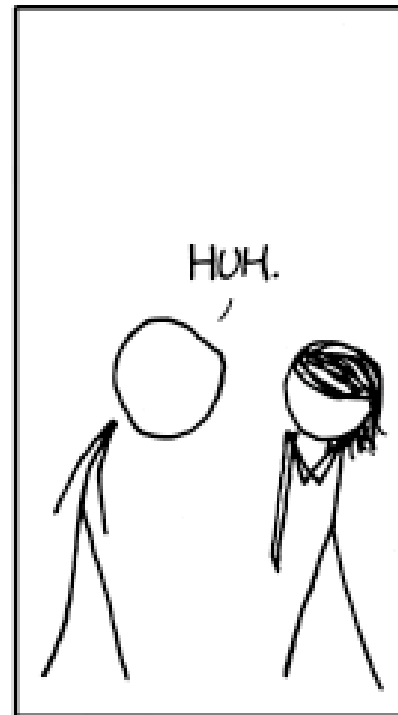
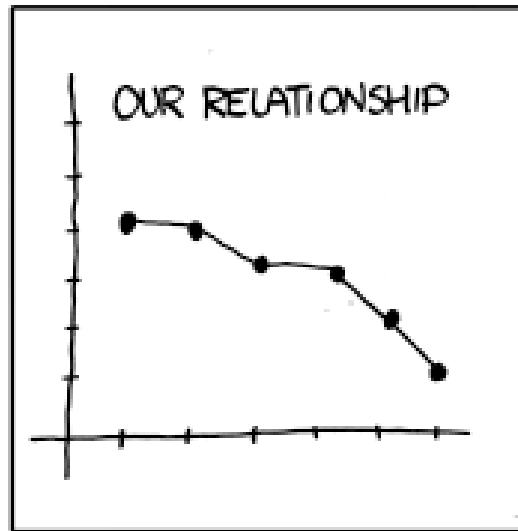
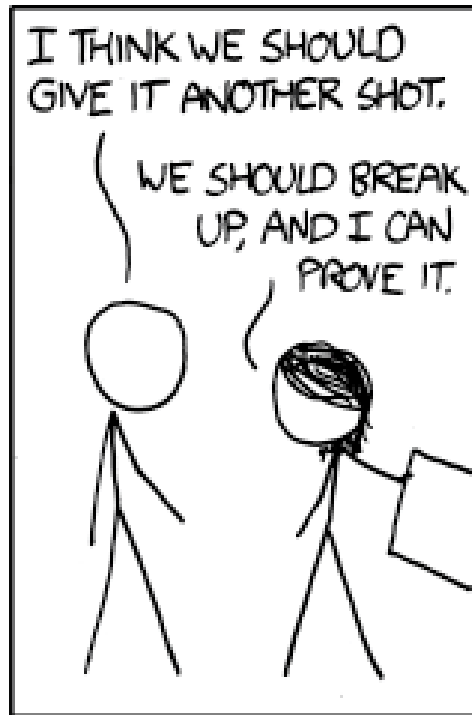
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- Main concepts and rules
- Creating simple plots
- Real-life examples: good and bad
- Customizing plots
- Exploratory data analysis
  - Basic guidelines
  - EDA as part of the data science process

# Be Careful...



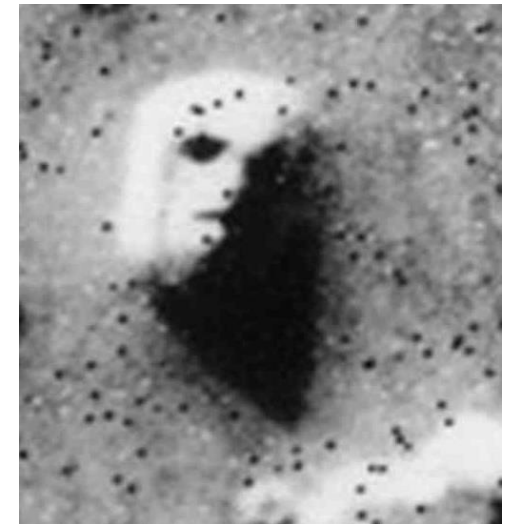
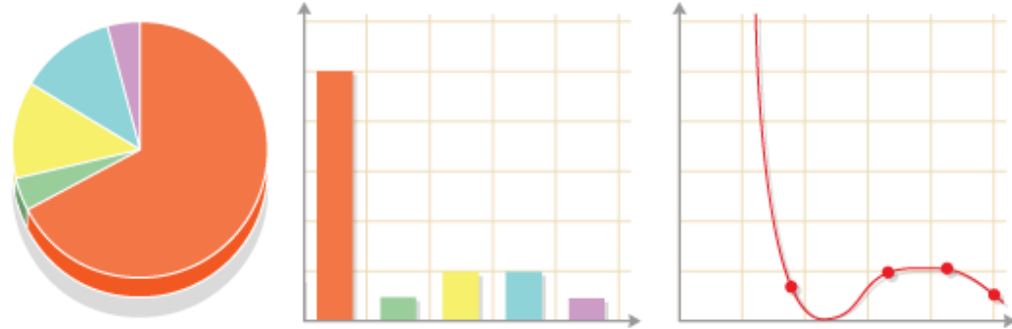


# Main Concepts in Data Visualization

How to tell the right story

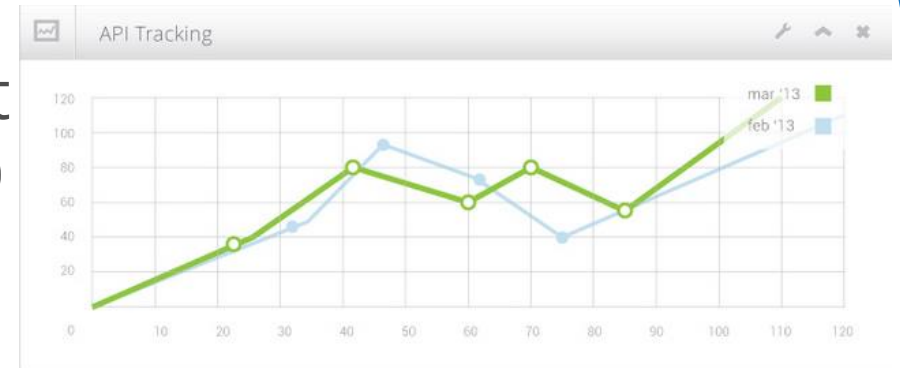
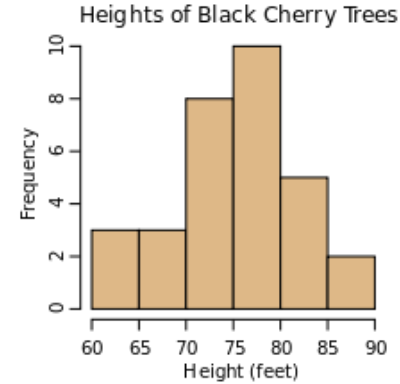
# Data Visualization

- We're amazingly good at spotting patterns
  - Trends over time, correlations, comparisons, ranges, etc.
- Visualizing data helps us understand the information better
- By plotting different views on the data we can
  - Help ourselves explore and understand the data
  - Convey the stories in data to others
- Note that we're too good at spotting patterns
  - We can find patterns where they don't exist



# Knowing What (and When) to Plot

- Many types of graphs, each with its own purpose
  - **Histograms** – show distributions
  - **Boxplots** – show the range and skewness of values
  - **Bar charts** – show how different categories compare
  - **Line plots** – show how one (dependent) variable varies with respect to an independent variable (e.g. over time)
  - **Pie charts** :( – show relative sizes between parts of a whole
  - Don't forget that we can also display **single numbers** when they provide sufficient information



Perceived Value for Money

43%



2%



# Knowing What (and When) to Plot (2)

- Many more types of graphics depending on the context
- Choosing the right plot is a matter of intuition
  - The goal is to present the message clearly
    - I.e. "tell the right story"
- Two main kinds of visualizations
  - For scientific analysis and work – stricter rules
    - For exploratory analysis / quick references
  - For presenting results to non-specialists – we can be creative but we have to keep our message in mind
  - The results may be printed or viewed as a dashboard
- How many dimensions?
  - Each plot has two spatial dimensions but we can add more using color, size, even animation

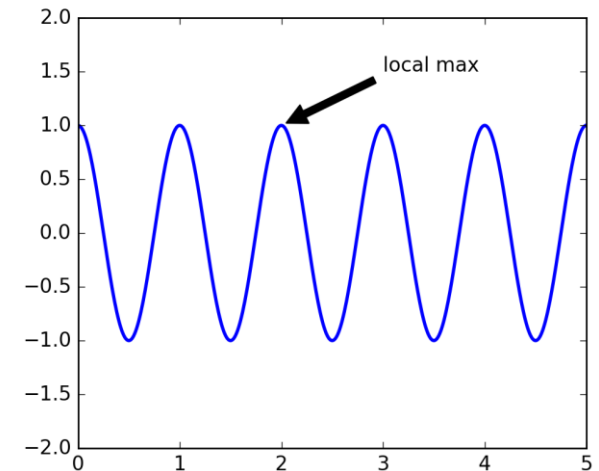
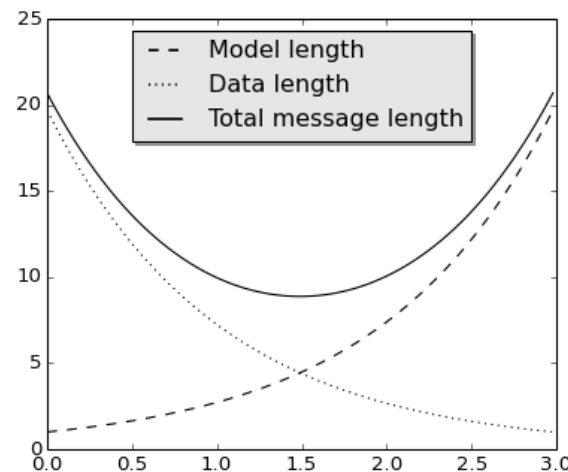
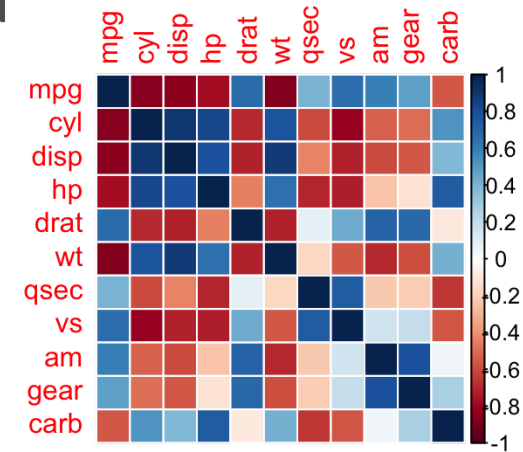
# Knowing What (and When) to Plot (3)

- To choose a plot type, think about
  - Numerical or categorical variables
  - Structure – spatial, temporal, etc.
  - Clustering
  - Relative size
- How can you know what all of these are?
  - Perform an **exploratory data analysis** first
  - "Play around" with the data
    - Check different measures (such as means, standard deviations, ranges, etc.), plot different charts
    - Explore the distributions and relations of variables
  - **Document** the **exploration process** and your **findings** to remember them later



# Basic Rules

- Choose the appropriate chart type
  - If you can (and want), compare different types of charts
- Make your plot big enough to fit the plotting area
- When it's not obvious, add a title and a legend
- **Label the axes!**
- Optionally, point at interesting data
- Use marker size and color to convey information
- Don't strain the reader!



# Plotting Basics

Starting out easy

# Plotting in matplotlib

- Quite easy to start plotting
- Very powerful
- There are many ways to do the same thing
- The documentation and examples are really good
  - We'll often end up consulting them, or the community
  - There are many options and it's difficult to remember them all
- Importing the library

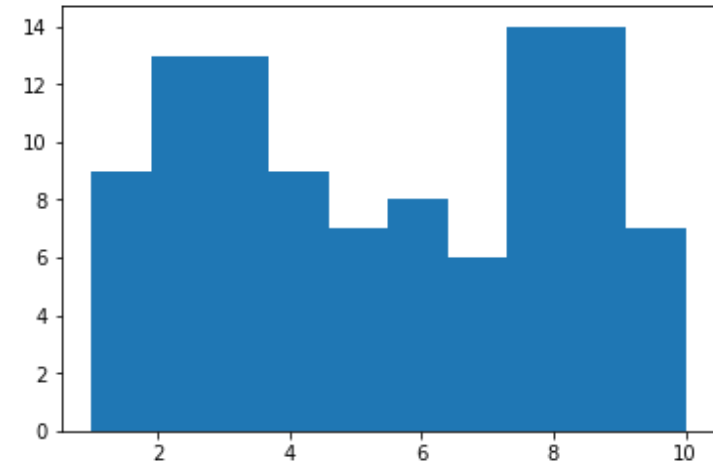
```
import matplotlib.pyplot as plt
```
- In Jupyter notebook, write the magic string `%matplotlib inline` in the first cell before importing
  - This will make plots appear as images in the notebook

# Creating Simple Plots

## ■ Histogram

- Shows the distribution of one variable

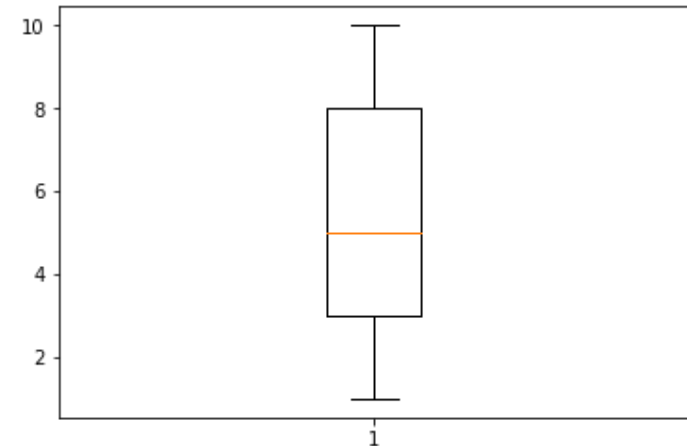
```
import numpy as np
values = np.random.randint(1, 11, 100)
plt.hist(values)
plt.show()
```



## ■ Boxplot

- Another way to show the distribution of one variable
- May also be used to compare many distributions
- [How to read](#) a boxplot

```
plt.boxplot(values)
plt.show()
```



# Creating Simple Plots (2)

## ■ Bar chart

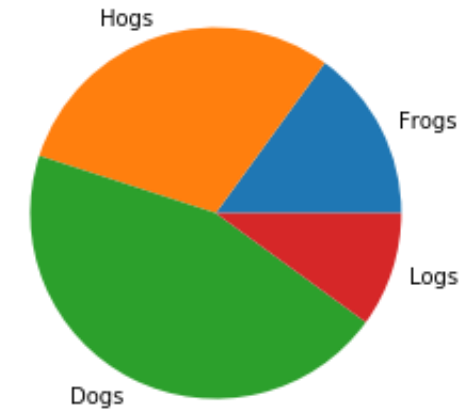
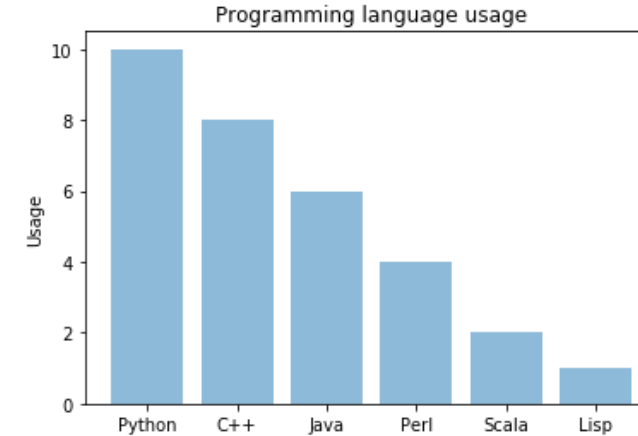
- Shows how one numeric value compares among different categories
- Two variables: one categorical, one numerical
- A little bit more difficult to plot
  - See a tutorial [here](#)

## ■ Although they look similar, histograms and bar charts are different!

## ■ Pie chart

- Shows the relation of each part to the whole

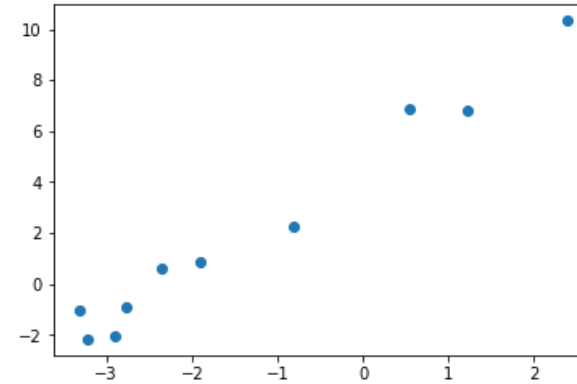
```
sizes = [15, 30, 45, 10]
plt.pie(sizes, labels = ["Frogs",
                        "Hogs", "Dogs", "Logs"])
# Make the plot look circular
plt.gca().set_aspect("equal")
```



# Creating Simple Plots (3)

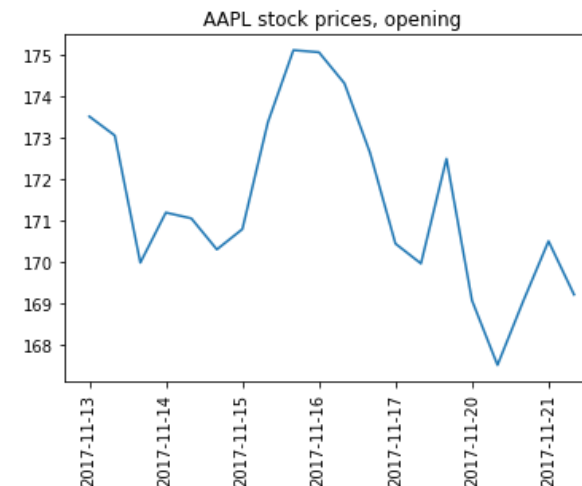
- Scatterplot (or scatter plot)
  - Shows how two variables compare
  - Can be used for displaying trends or correlations

```
x = [-2.35, 1.22, -3.32, 2.39, -2.77,  
      -3.21, 0.55, -0.81, -2.89, -1.9]  
y = [0.58, 6.79, -1.01, 10.32, -0.9,  
      -2.16, 6.87, 2.22, -2.05, 0.86]  
plt.scatter(x, y)  
plt.show()
```



- Line chart
  - Similar to scatterplot
  - Useful to show dependencies of two variables
    - If the horizontal axis is time – evolution

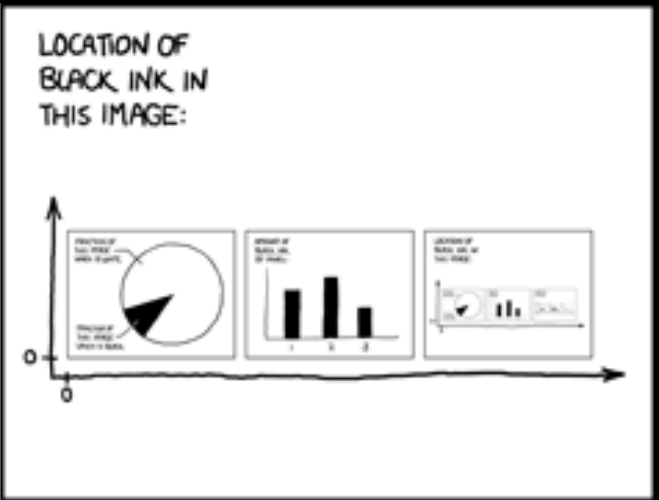
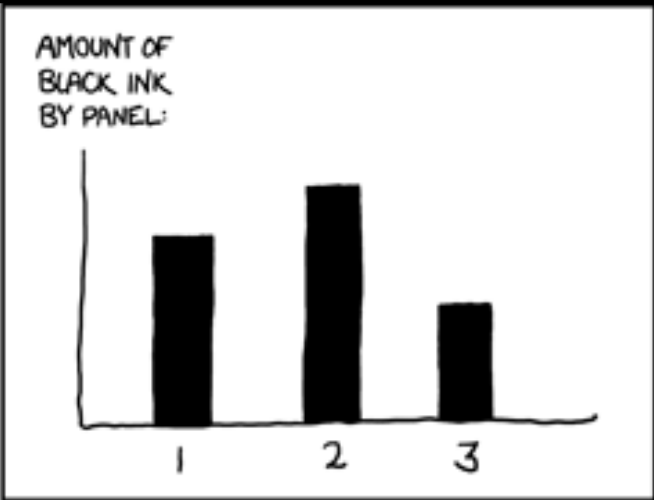
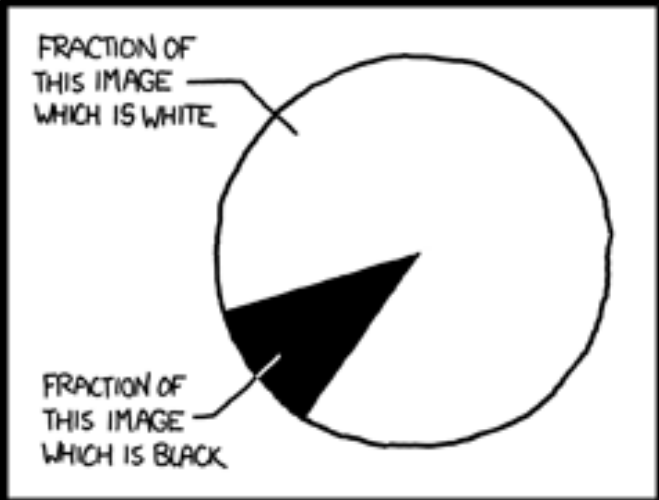
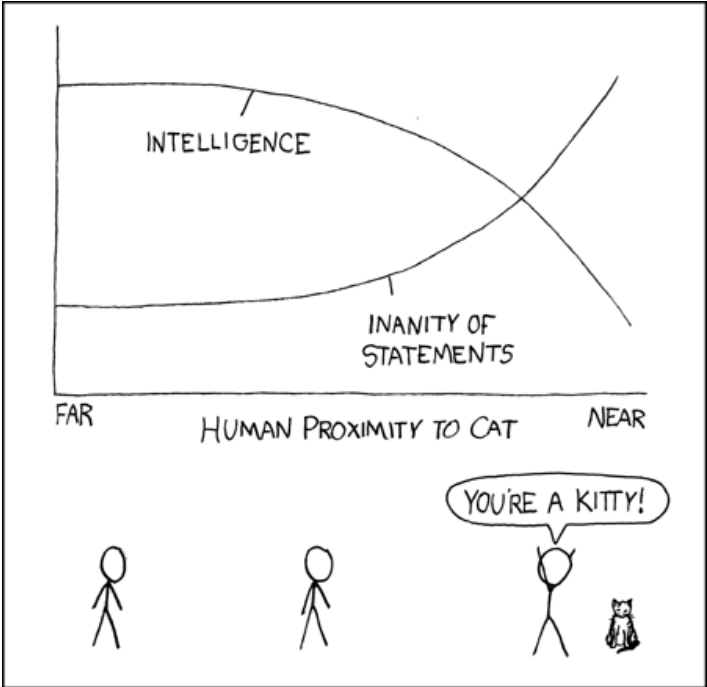
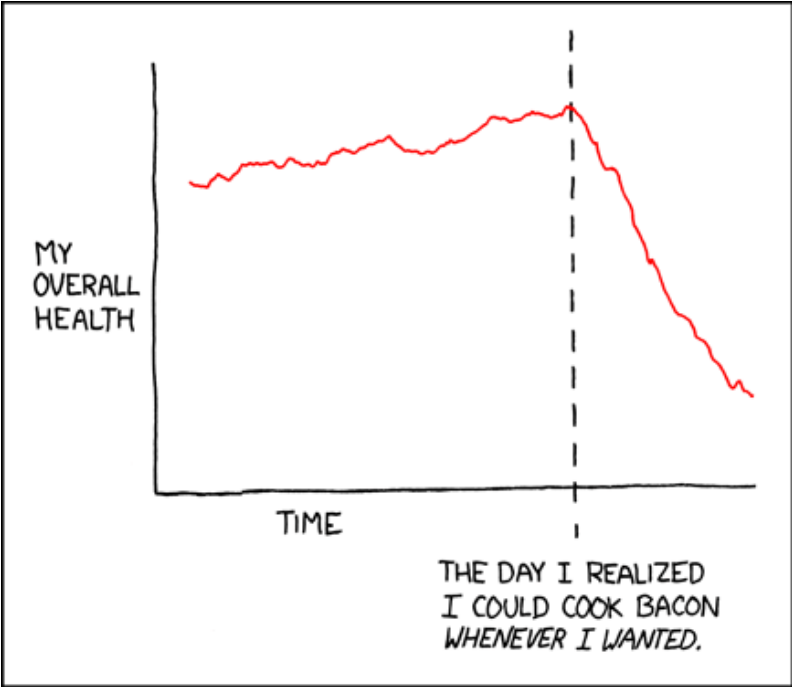
```
dates = ...  
open_prices = ...  
plt.plot(dates, open_prices)  
plt.xticks(dates[::3], rotation = "vertical")  
plt.title("AAPL stock prices, opening")  
plt.show()
```



# Data Visualization Examples

**The good, the bad, the ugly  
and the WTF**

# Some Examples

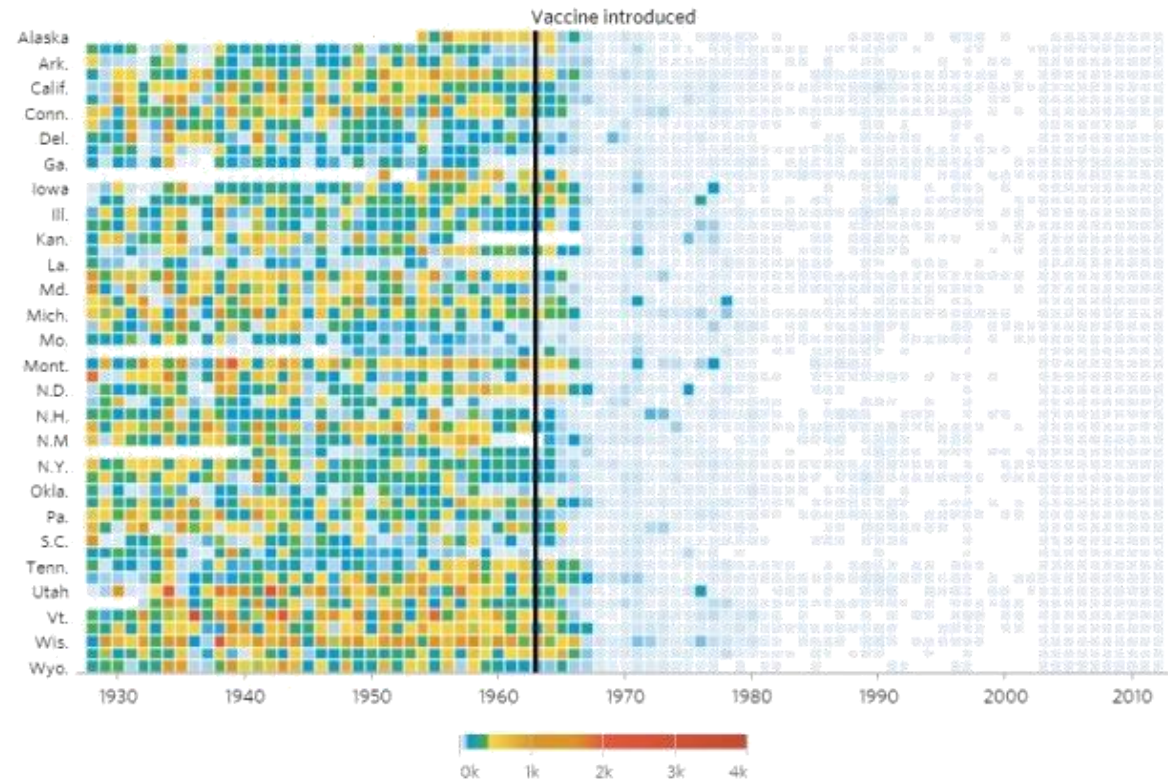




# Infectious Diseases and Vaccines ✓

- Once again, a heatmap is used to convey disease spread
  - The legend has numbers
  - The [full chart](#) is interactive (provides all numbers)
- Makes use of temporal data
- Labels an interesting point
  - Allows us to compare "before" / "after"
- Conveys a clear message
  - Vaccines almost eradicated diseases

Measles



Note: CDC data from 2003-2012 comes from its Summary of Notifiable Diseases, which publishes yearly rather than weekly and counts confirmed cases as opposed to provisional ones.

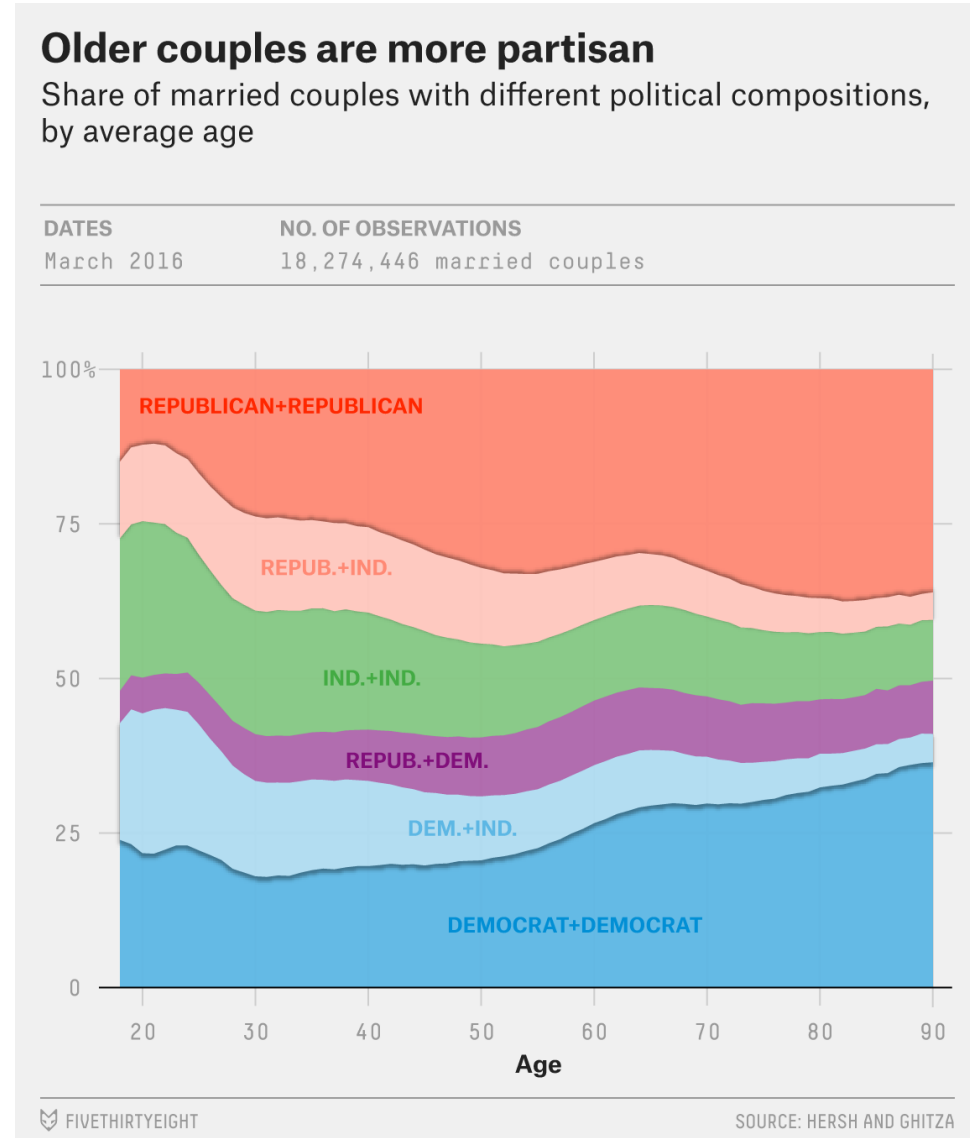
# Gay Marriage Acceptance ✓

- Good use of spatial structure (heatmaps)
- Overall message is clear
  - All states are in the "more" category
  - Some states are more accepting
- May additionally display numbers on the scale or on the map to give a quantitative view
  - This is an editorial, not a scientific plot so it's acceptable



# Political Views of Couples ✓

- Source: [FiveThirtyEight](#)
- Uses area plots to display relations
  - Allows comparison of different distributions for different ages
- Uses a clear color map
- Uses labels to make comparisons easier



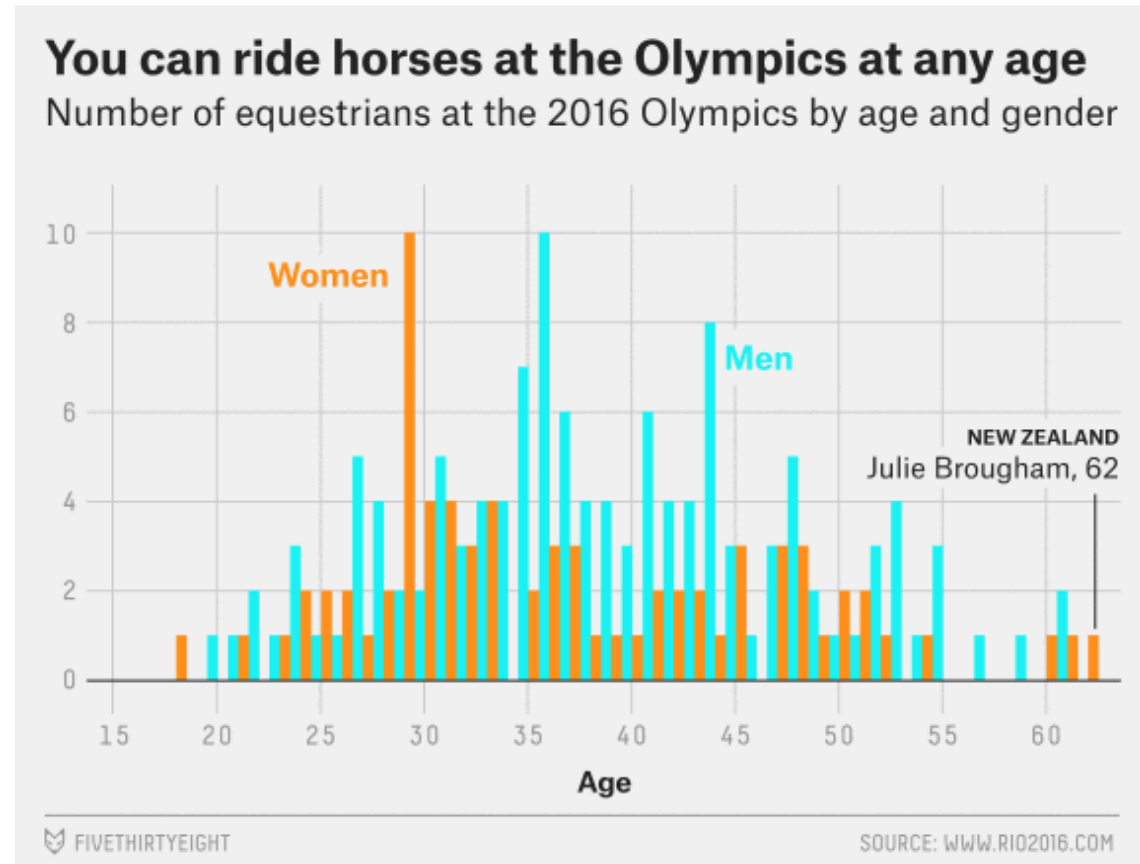
# On-Duty Officer Deaths in the US ✓

- Source: [FiveThirtyEight](#)
- Uses a stacked area chart
  - Total area – **overall** tendency
  - Colored parts – tendency **for different causes**
  - Allows to inspect both
- Labels an interesting point



# Horse Riders by Age and Gender ✓

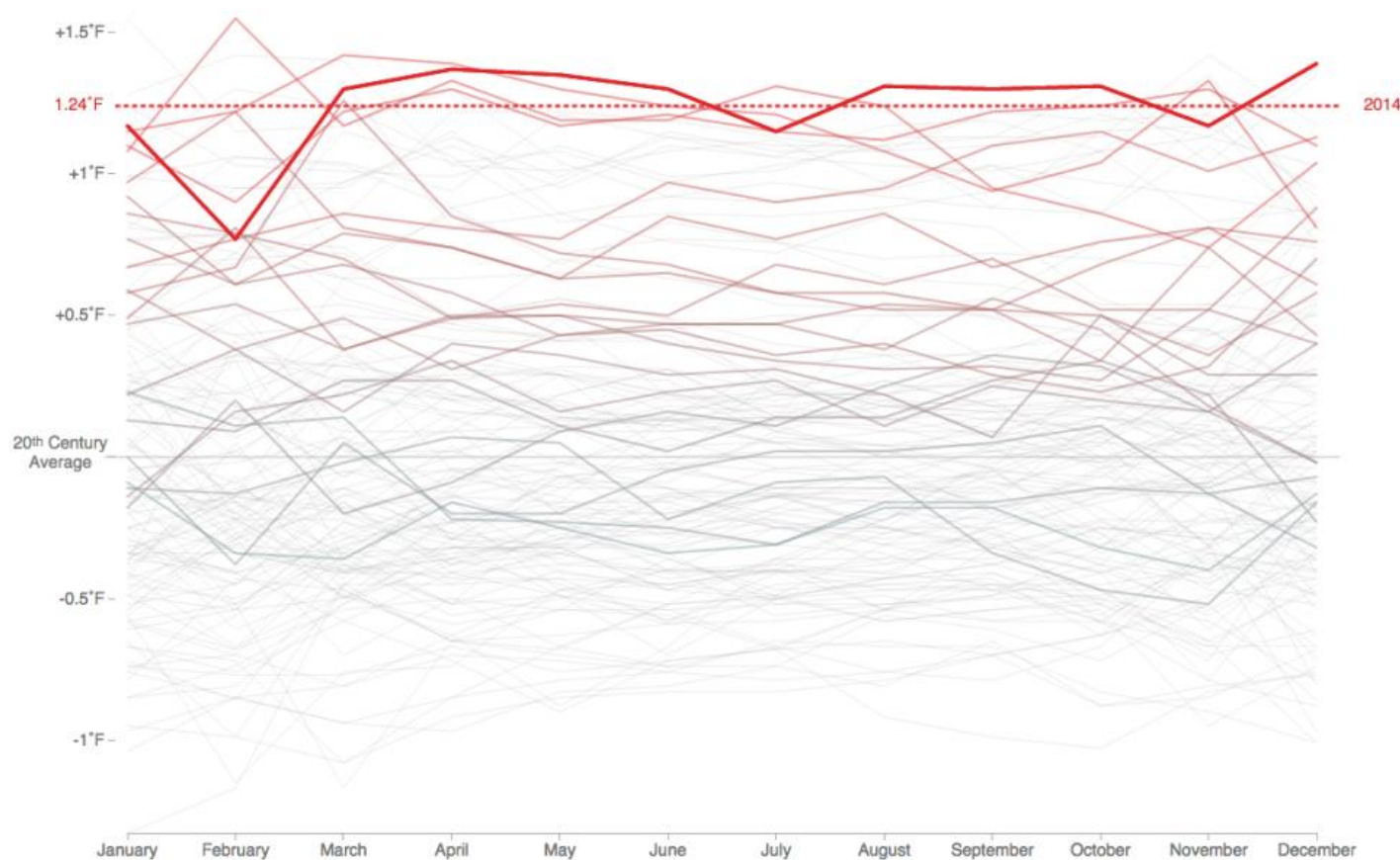
- Source: [FiveThirtyEight](#)
- Histograms are relatively rare in non-scientific visuals
- Shows the two distributions clearly
- Conveys the message
  - The distributions are nearly identical
- Uses labels for outliers





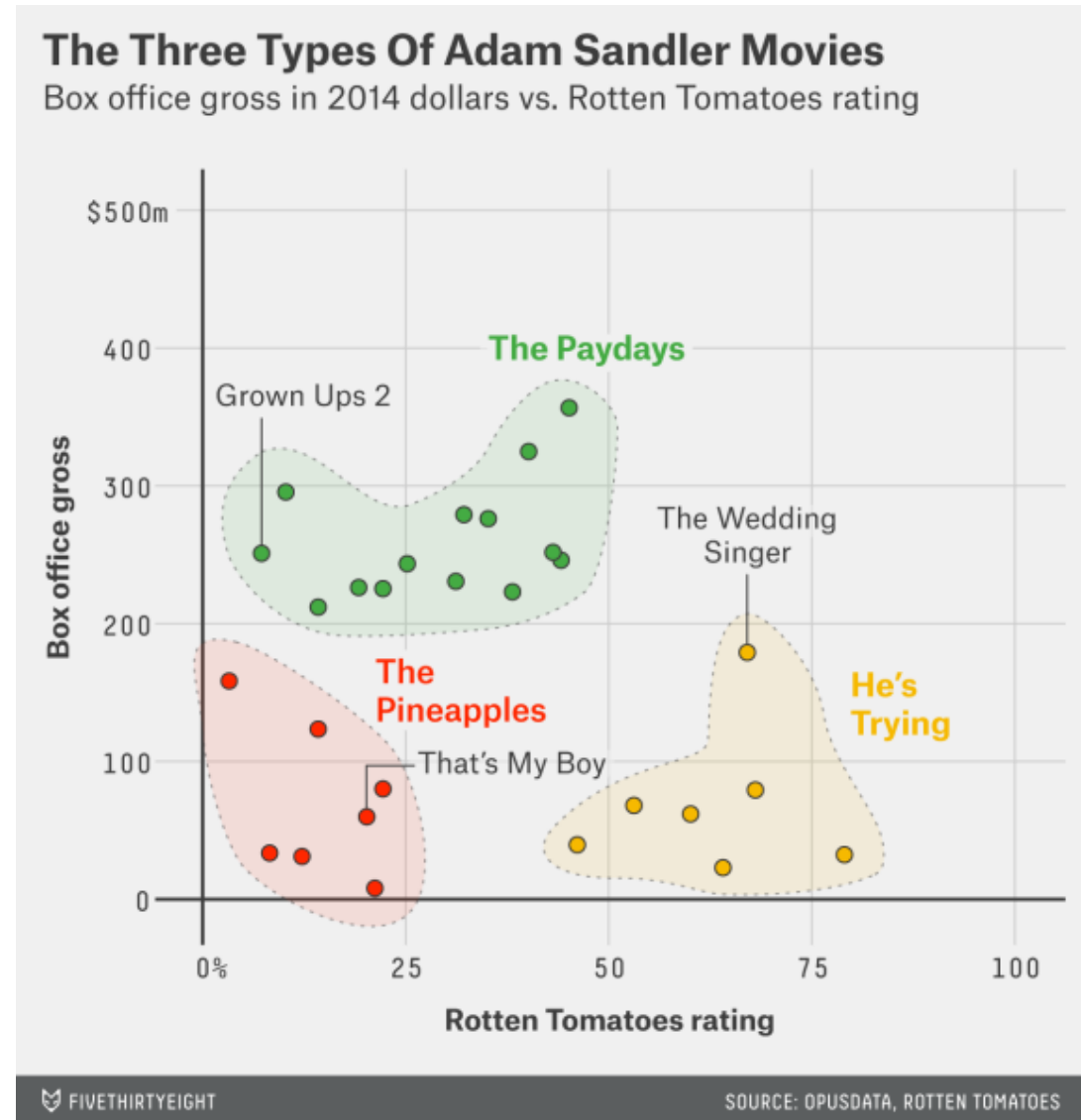
# 2014: The Hottest Year on Record ✓

- Source: [FlowingData](#)
- Presents temporal data in a classic way
- Uses color to show rising temperature
- Uses a thicker line to make it stand out in an otherwise very busy line plot



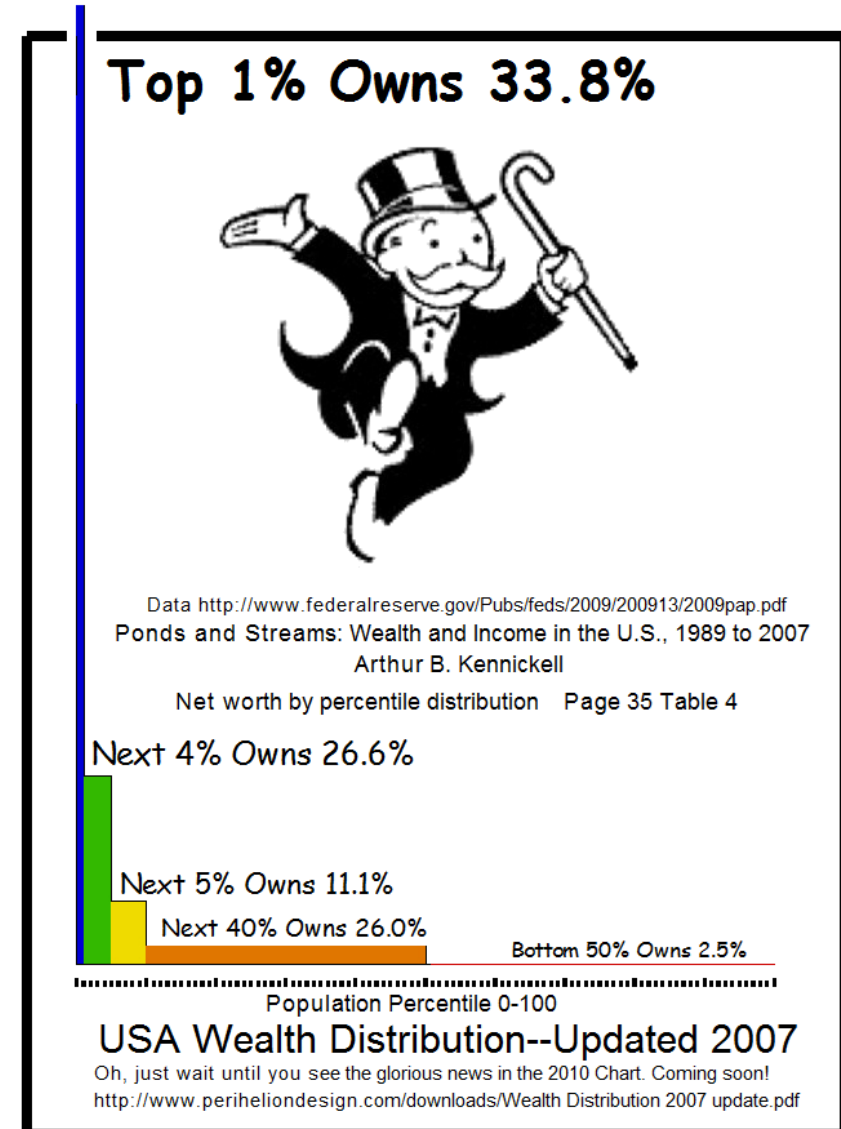
# Types of Adam Sandler Movies ✓

- Source: [FiveThirtyEight](#)
- Presents a scatterplot of rating and profits
- Shows and labels clusters clearly
  - Uses different colors
- Conveys a clear message



# USA Wealth Distribution X

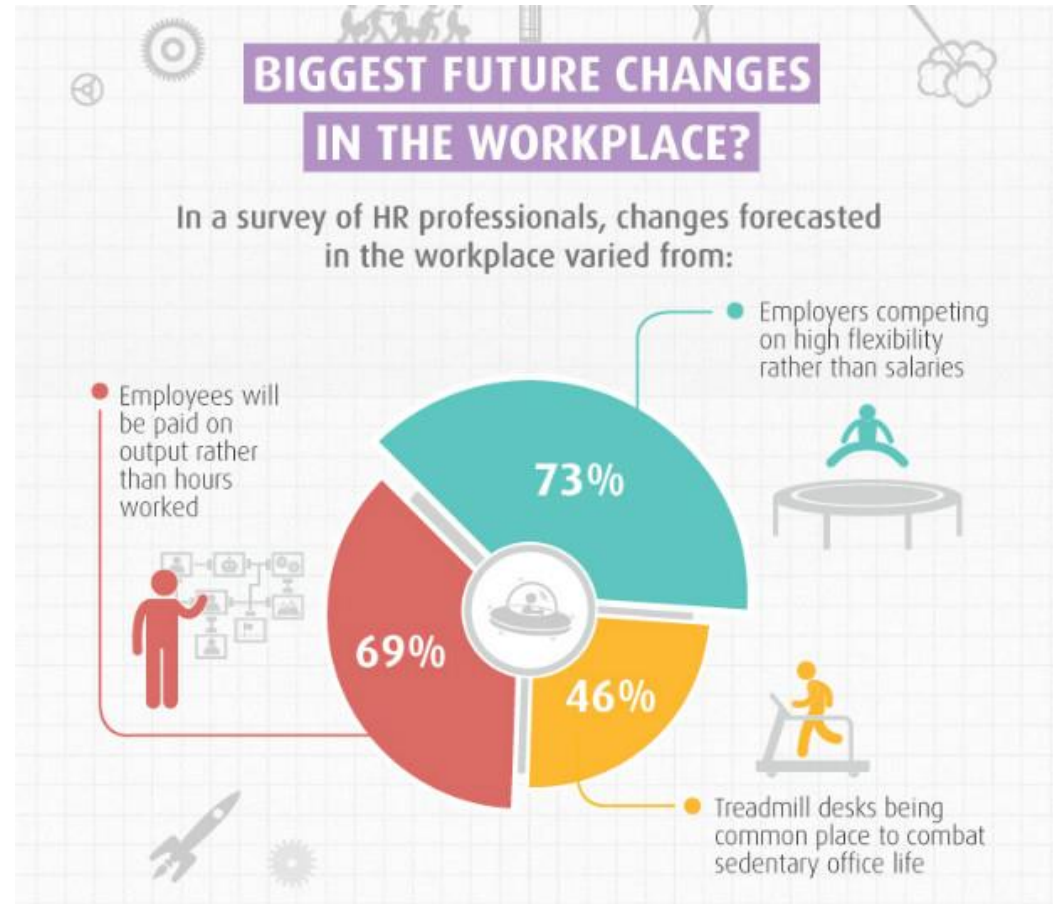
- Source: WTFViz via Gizmodo
- Highly skewed and disproportional elements
  - It wants to convey the message of disproportionality but there are better ways (e. g. "cutting" the y-axis and displaying y-axis labels)
- Comic Sans(?!), useless image and useless text right in the middle of the chart





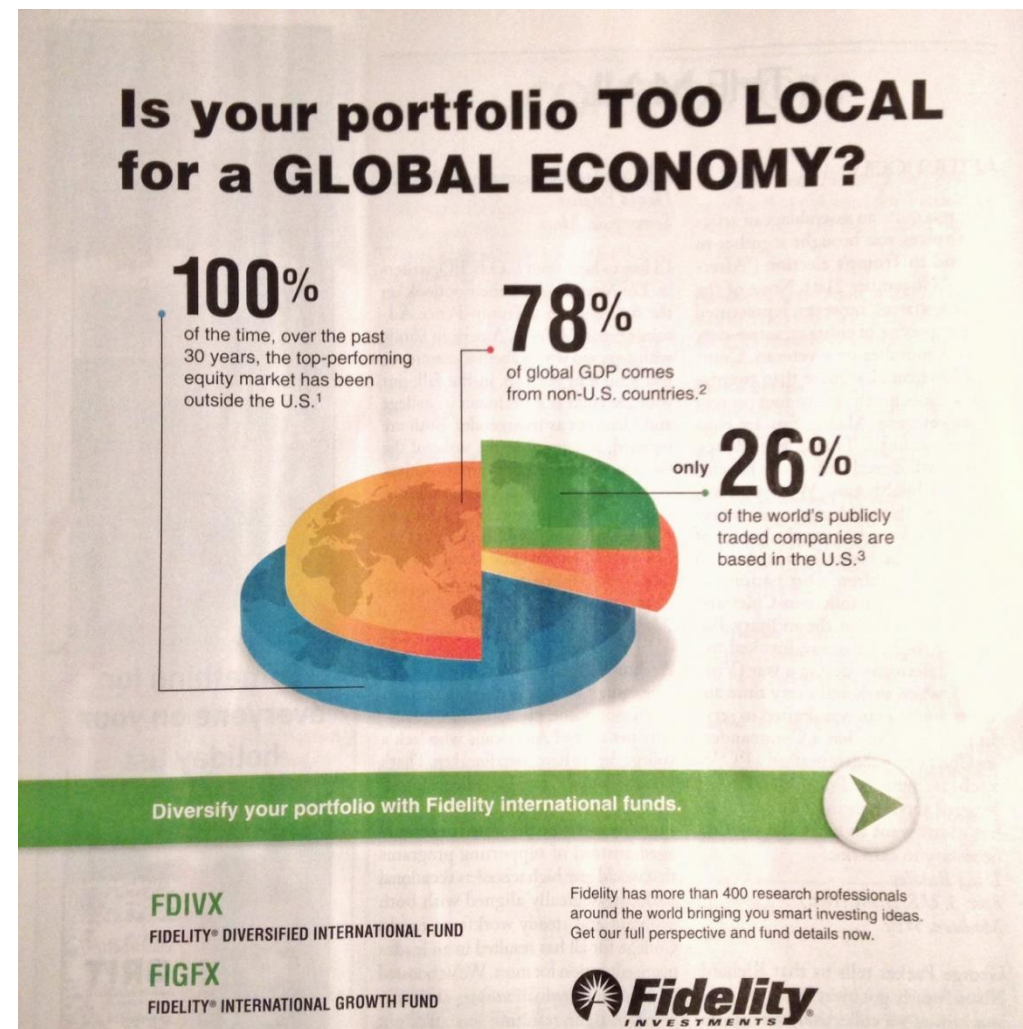
# Too Much Pie X

- Source: WTFViz via DesignRoast
- The parts of the pie add up to 188%
  - They're meant to be viewed on their own, e.g. there might be combinations of factors
- A pie chart is highly **not recommended** in this case
- Other than that, it shows good labels and a nice color scheme



# Too Much Pie, Part 2 X

- Source: WTFViz (New Yorker)
- Once again, the pie chart makes no sense
- The values aren't related at all
- Why is there a world map?



# Too Much Pie, Part 3 **X**

- Source: Email from GoDaddy, WTFViz
- The numbers aren't related to the color of the rings at all
- Maybe just a programming mistake
  - Still, be careful and check your work



of domain owners have put moderate to high consideration to how much their domains are worth



of respondents have bought and sold domain names for a profit

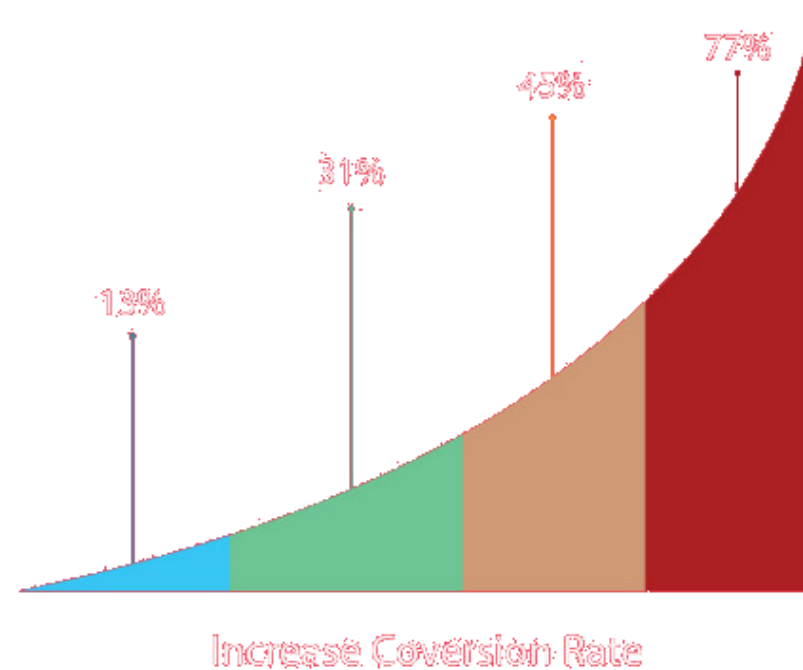


of small business owners want to make time to enhance or update their online presence

# No Axes X

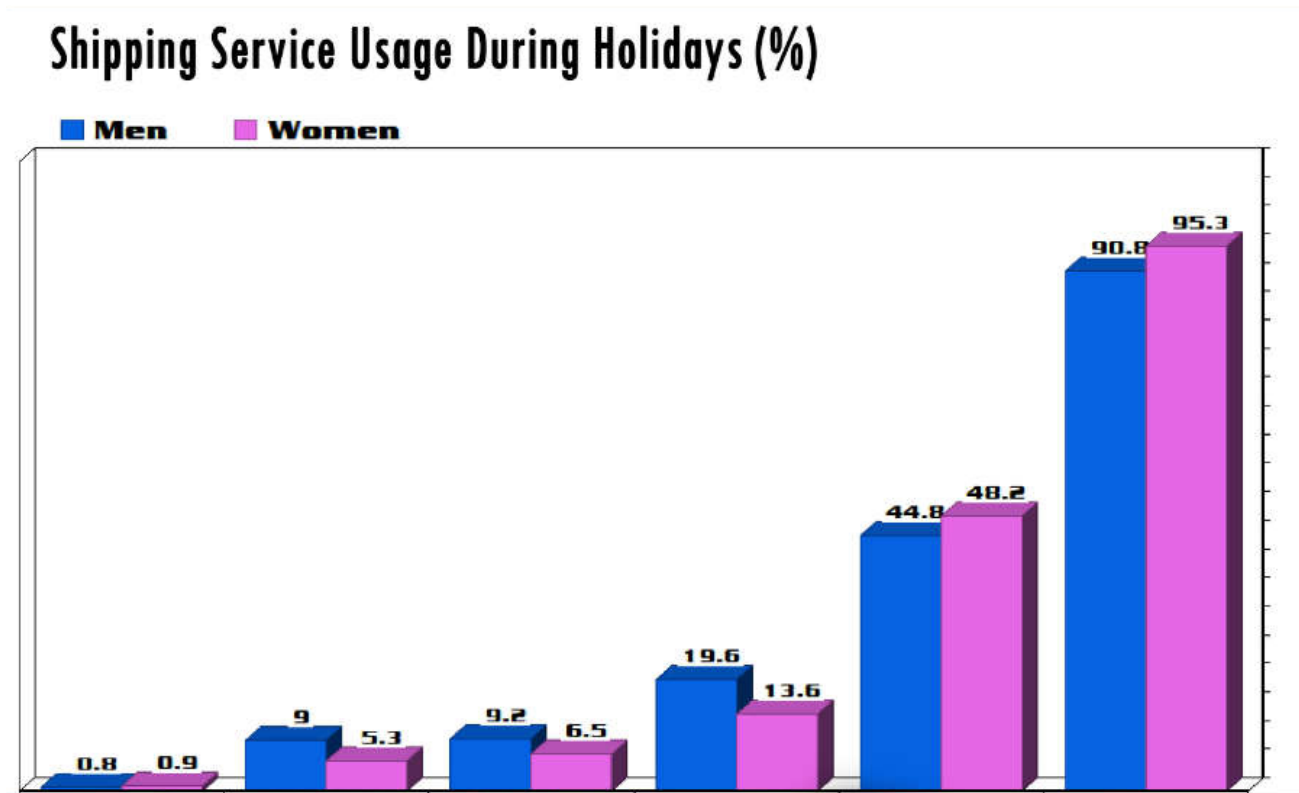
- Source: WTFViz via DesignRoast
- I don't know (and can't see) the real purpose
- No axis labels and no numbers (the bottom label is not the x-axis)
- Distracting background
  - Do you remember "Don't strain the reader"?

**Increase Conversion Rate:** Decrease your bounce rate by providing user a great experience and keep them on your site for longer time.



# No Axes, Part 2 X

- Source: WTFViz via DesignRoast
- The categories are gone
  - The image is not trimmed, this is the entire chart
  - Are those different days, different products or something else?
  - Also, 3D doesn't give additional information
- Also, the design is kind of lame



# Wrong Scales X

- Source: WTFViz via DesignRoast
- How come 71.9% is
  - Further than 77.1%
  - Close to full (looks like 95-98%)



1ST SERVE POINTS WON %



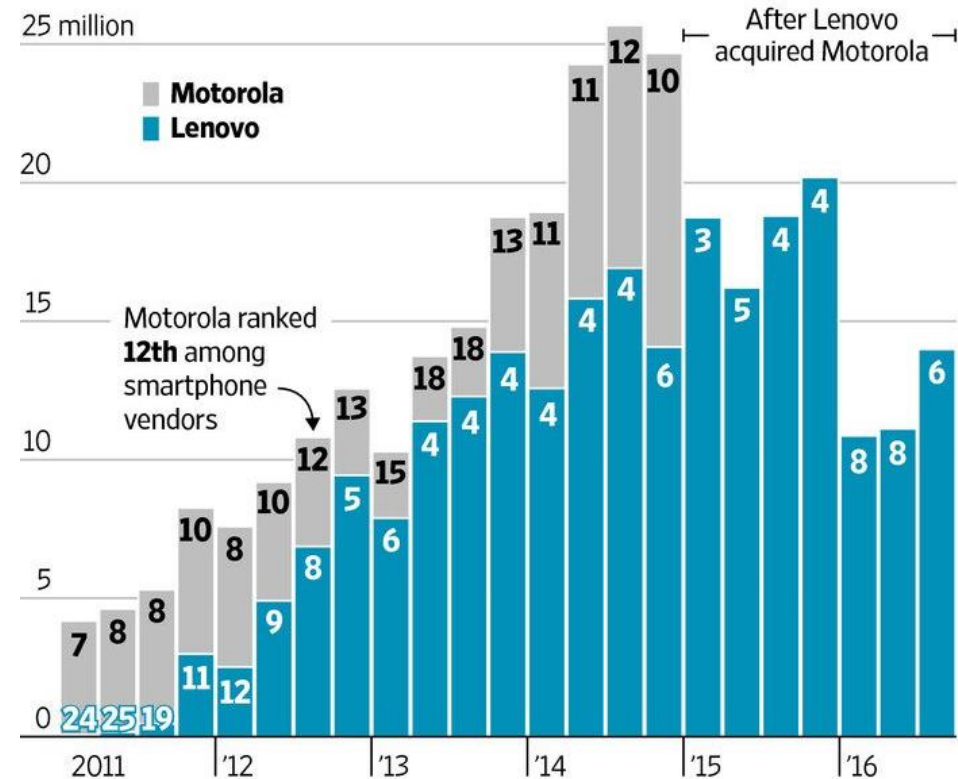
# Double Scales that Make No Sense X

- Source: WTFViz
- The y-axis scales and the numbers on the bars represent different things
  - They're also on different scales (blue 11 is less than gray 10 but blue 4 seems very close to gray 18)
- Impossible to read and understand without additional explanation

## Smartphone Hang-ups

China's Lenovo Group has struggled to integrate the smartphone business of Motorola, which it acquired in October 2014, part of a surge in Chinese acquisitions of foreign companies.

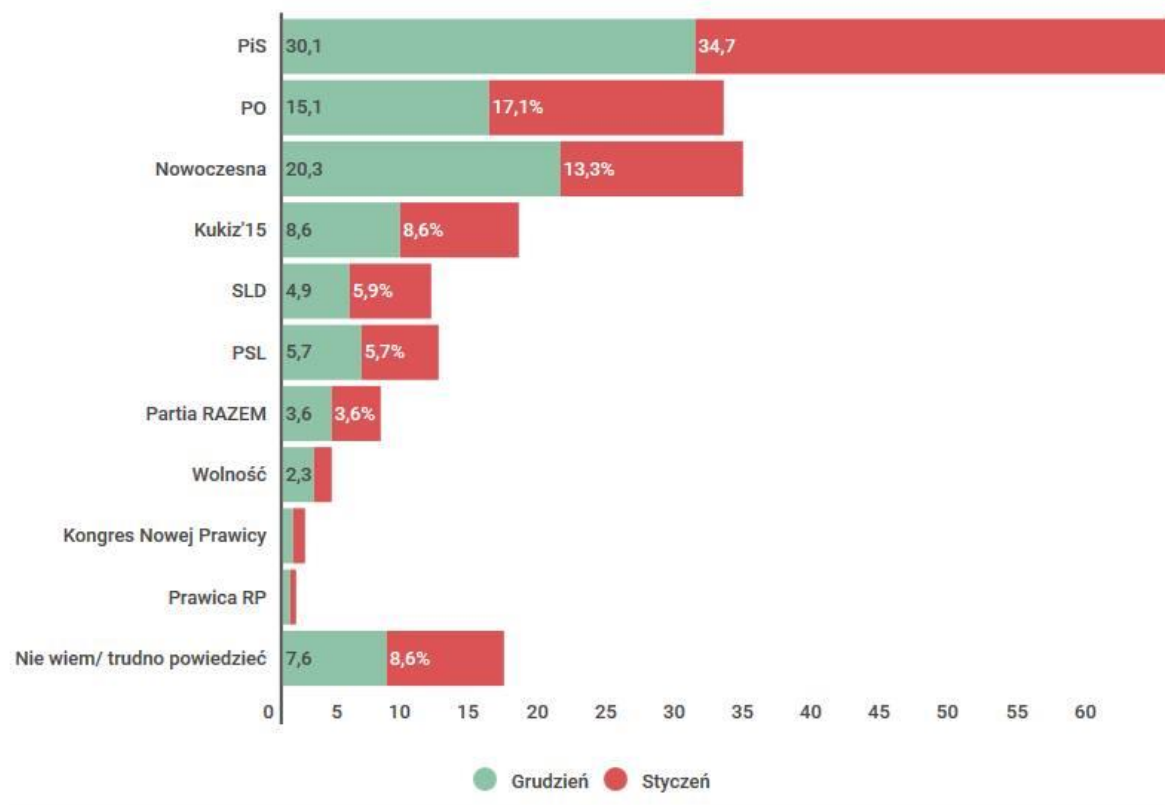
### World-wide smartphone shipments and vendor ranking



# Wrong Data X

- Source: WTFViz
- The chart looks OK
- Political party affirmation for December (blue) and January (red)
  - Why would one sum percentages like these? Makes no sense

Sondaż poparcia partii politycznych

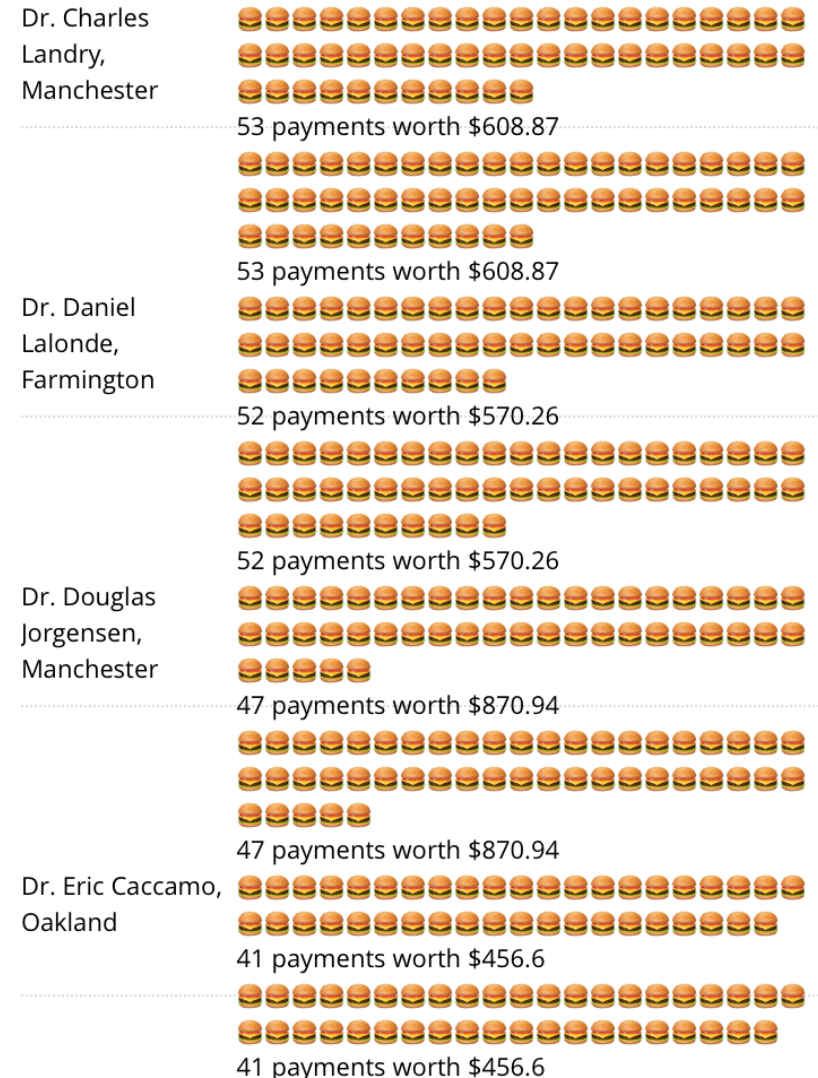




# Wrong Data X

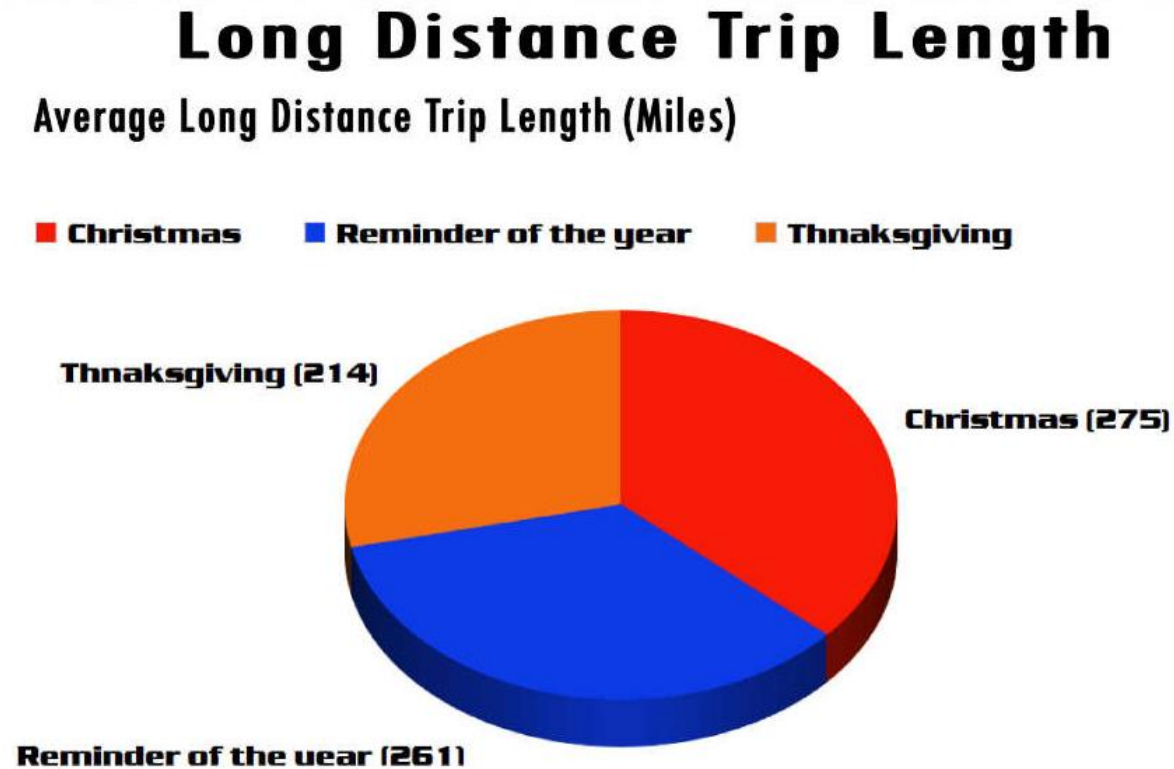
- Source: WTFViz
- Those burgers make data extremely difficult to compare
  - The numbers don't help very much

## Top 10 doctors with the most “food and beverage” payments from opioid manufacturers, Aug. 2013 – Dec. 2015:



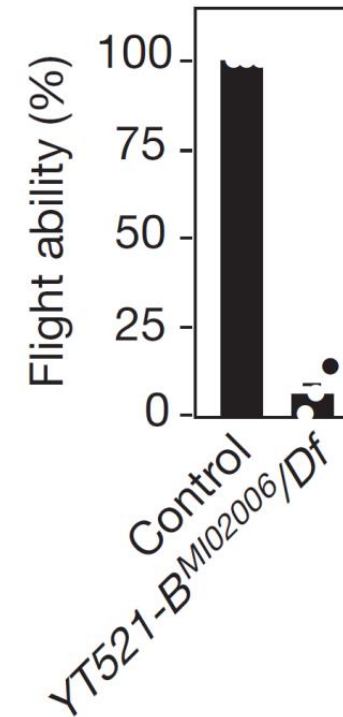
# Wrong Information and Mistakes X

- Source: WTFViz
- Spelling errors
  - Also, unreadable font
- The pie chart conveys no information at all
  - Better – use a bar chart



# Bar Chart Mistakes X

- Source: WTFViz
  - Original: Nature :(
- Bubbles make the values extremely difficult to compare
  - Where does the right bar end?
  - Where does even the left bar end?
- Below: Why are the bars warped?





# Customizing Plots

**Making things beautiful**

# Applying Styles

- Matplotlib has many default styles

```
print(plt.style.available)
```

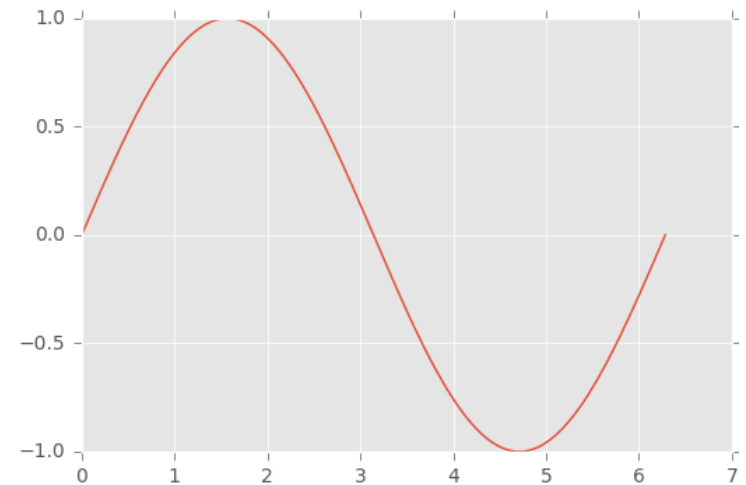
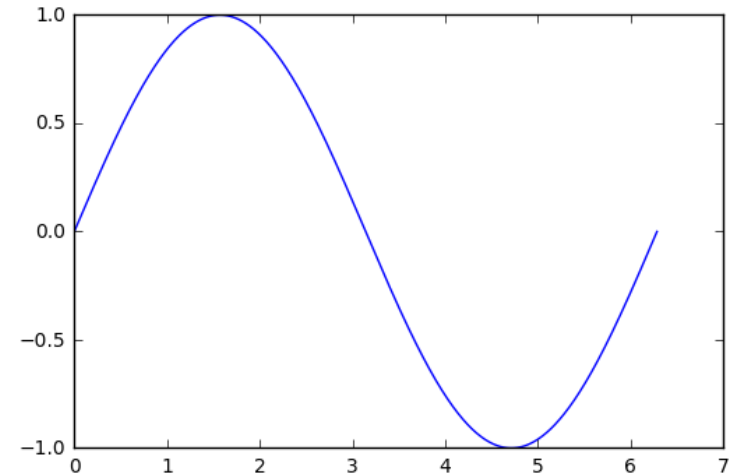
- Using a different style

```
plt.style.use("ggplot")
```

- Reverting to the default style

```
plt.style.use("default")
```

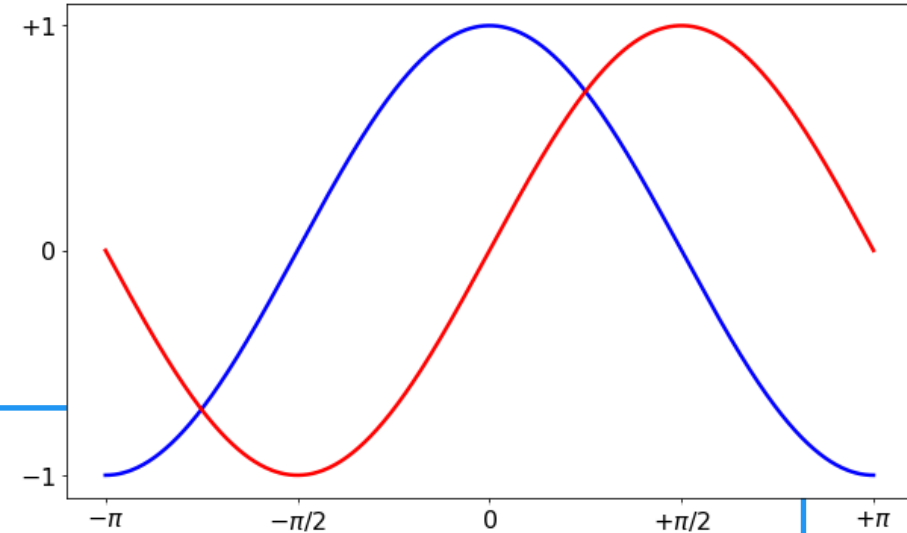
- In Jupyter notebook, `%matplotlib inline` uses its own styles
- Example: Draw a simple scatterplot, histogram and / or line chart in all different styles



# Customizing Plots

- Every call to `plt.hist()`, `plt.plot()`, `plt.boxplot()`, etc., accepts many arguments
  - Colors, markers (type, size)
  - Axis limits and locations, axis labels
  - Data labels and additional text
  - Legend location and appearance

```
cos_x = ... # [-pi; pi]
sin_x = ...
plt.figure(figsize = (10, 6))
plt.plot(x, cos_x, color = "blue", linewidth = 2.5, linestyle = "-")
plt.plot(x, sin_x, color = "red", linewidth = 2.5, linestyle = "-")
# Tick marks and labels
plt.xticks([-np.pi, -np.pi / 2, 0, np.pi / 2, np.pi],
           [r"$-\pi$", r"$-\pi/2$", r"$0$", r"$+\pi/2$", r"$+\pi$"])
plt.yticks([-1, 0, 1], [r"$-1$", r"$0$", r"$+1$"])
for label in ax.get_xticklabels() + ax.get_yticklabels():
    label.set_fontsize(16)
    label.set_bbox({facecolor: "white", edgecolor: "None", alpha: 0.65})
```

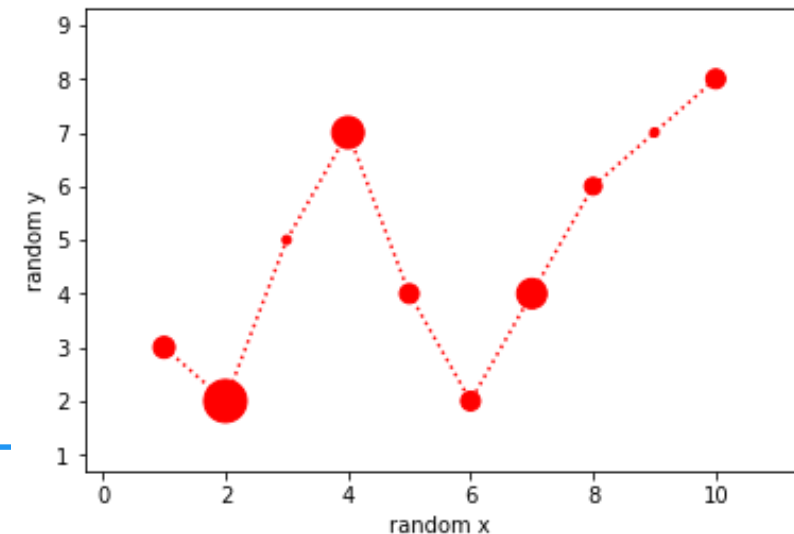


# Example: Create a Customized Plot

- Create a plot similar to the picture using the given data
  - This is to show that marker colors, sizes and types can be given as arrays – the elements are applied sequentially

```
x = [1, 2, 3, 4, 5, 6, 7, 8, 9, 10]  
y = [3, 2, 5, 7, 4, 2, 4, 6, 7, 8]  
y_radius = [10, 20, 4, 15, 9, 9, 14, 8, 4, 9]
```

```
# Note that s (for size) represents the area, not radius  
plt.scatter(x, y, s = np.array(y_radius) ** 2, color = "red")  
plt.plot(x, y, linestyle = "dotted", color = "red")  
  
plt.xlim(np.min(x) - 1.3, np.max(x) + 1.3)  
plt.ylim(np.min(y) - 1.3, np.max(y) + 1.3)  
plt.xlabel("random x")  
plt.ylabel("random y")  
  
plt.show()
```



## \* Lab: Playing with matplotlib

- A very good part of matplotlib are the examples
  - See them [here](#)
  - See a gallery [here](#)
- Many examples of common use cases
  - Creating multiple plots
  - Different types of plots: violin plot, residual plot, heatmap, etc.
  - Usages of color, shaded area, markers, labels, etc.
- Play with some of these examples to get a feel of what you can do with matplotlib
- Customize some of the examples
  - Read the docs to see all parameters



# Exploratory Data Analysis (EDA)

**Making sense of our data**

# Exploratory Data Analysis

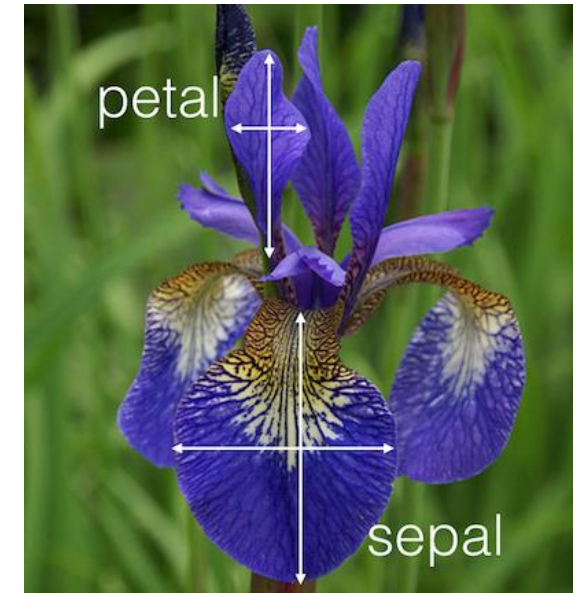
- A process to see what the data can tell us
  - Not tied to formal data modelling or hypothesis testing
- Many people have written about this
  - Most notably, John Tukey (1961)
- Like data cleaning, relies heavily on the scientist's intuition
- Objectives
  - Suggest hypotheses
  - Assess assumptions on which models will be based
  - Aid selection of features (feature engineering)
  - Provide a basis for further data collections

# Analytic Graphs

- Good for explaining the dataset visually
  - Show distributions, relations, comparisons and causality even in multivariate data
- Principles of analytic (scientific) graphs
  - Show **comparisons**
  - Show **causality**
    - **Correlation does not imply causation**
  - Show **multivariate data** (many variables)
  - Integrate evidence from **multiple sources**
  - Describe and **document** evidence
  - **"Content is king"**
    - We have to have something interesting to report
- These principles apply to EDA as well

# Exercise: Exploration of the Iris Dataset

- One of the most famous datasets in data science
  - Sizes of petals and sepals (see picture) for three classes of iris flowers
- Read, inspect and clean the dataset
  - Using the data cleaning approaches you already know
  - **Can we predict classes from sizes?**
- Inspect the distributions
  - Plot histograms and boxplots, print stats
    - Try different plot settings
  - Compare the quantities – scatterplots
    - In some cases, a "brute force" method might be useful – compare everything against everything else
  - Plot a correlation matrix



# Lab: Exploration of the Iris Dataset (2)

- Usually, we first perform univariate analysis, then go on to find correlations
  - Plot the entire distribution first
  - Start to break down by factors (in this case – the iris types)
  - Create additional columns if needed (data transforms)
  - Apply grouping, averaging and summing over groups to get an idea of possible "clusters" in the data
  - Inspect and plot certain data ranges (using filtering)
  - **Have fun with the data but don't forget the original question!**
- Next steps
  - After exploratory data analysis, we're usually able to form a hypothesis (a pair of hypotheses), model the data and check against the hypothesis
  - In other cases we can produce different visuals, graphics and dashboards to be used by others

## \* Lab: Exploration of the Iris Dataset (3)

- We can also plot beautiful graphics using other packages (not matplotlib)
- An example of one such package is seaborn
  - Contains utility functions for some commonly used plots
  - Based on matplotlib
  - Read the docs [here](#)
    - It shows how to plot different distributions on their own and together, and also includes a little tutorial on an algorithm called KDE (kernel density estimation)
  - It also has other [tutorials](#) (such as [plotting linear correlations](#))
  - It produces good-looking graphics but can lack customizability in some cases
- Other examples: [bokeh](#), [plot.ly](#), [ggplot](#)
  - And many more

# Summary

- Main concepts and rules
- Creating simple plots
- Real-life examples: good and bad
- Customizing plots
- Exploratory data analysis
  - Basic guidelines
  - EDA as part of the data science process

The image features a white background with two blue decorative bars. The top bar is a solid blue strip. The bottom bar is a gradient blue strip that transitions from a lighter blue on the left to a darker blue on the right. The word "Questions?" is centered in a blue, sans-serif font.

Questions?