Class Announcements

Due Friday:

- D3
- Project Proposal (Template in repo, turn in via repo)

Notes:

- Repo invites are out. Expire in 7 days so please login!

Data Visualization

- tools:
  - `seaborn` - generating plots
  - `pandas` - wrangling data
  - `matplotlib` - fine-tuning plots
- plotting
  - quantitative data
  - categorical data
- customizing visualizations

Open in Colab

For more information on this topic, check out: (1) Jake VanderPlas' Python Data Science Handbook and (2) Berkeley's Data 100 Textbook.

A good data visualization can help you:

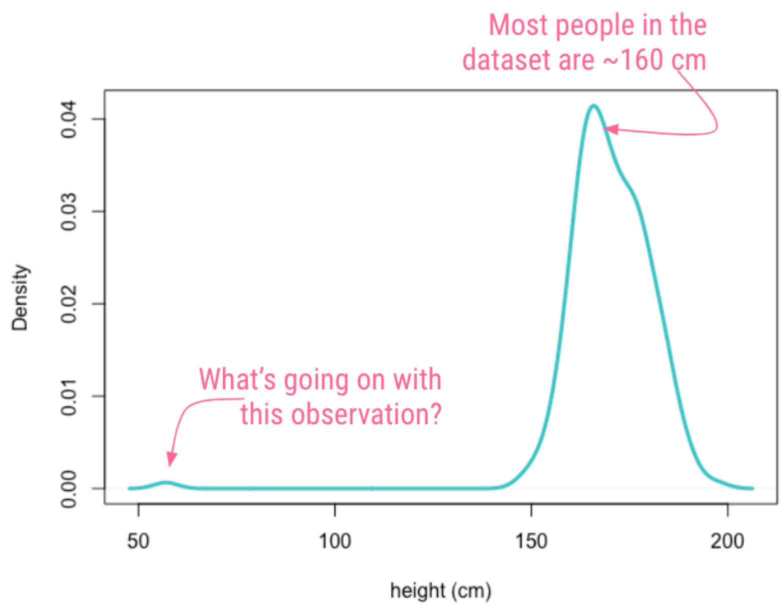
- identify anomalies in your data
- better understand your own data
- communicate your findings

Quick Introduction: Basic Visualizations

- histograms
- densityplots
- scatterplot
- barplot
    - grouped barplot
    - stacked barplot
- boxplot
- line plot

Densityplot

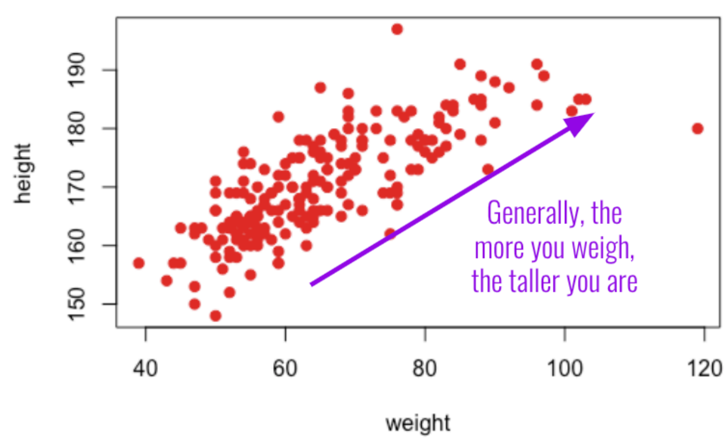
Information about a single quantitative variable



A smoothed version of a histogram - demonstrates the *distribution* of the data; helps to identify extreme values

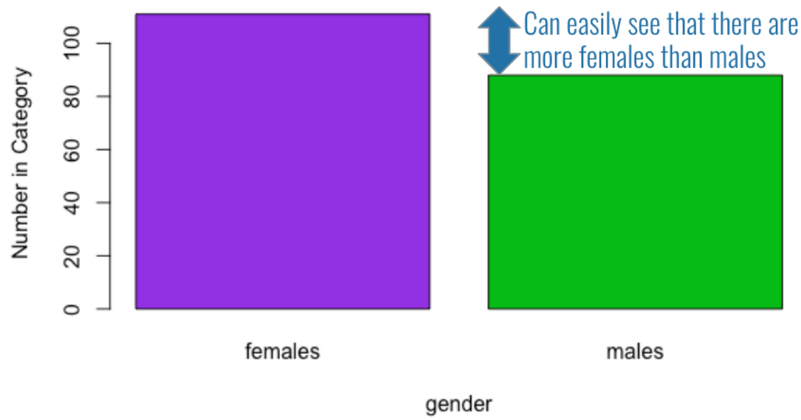
Scatterplot

Relationship between two quantitative variables



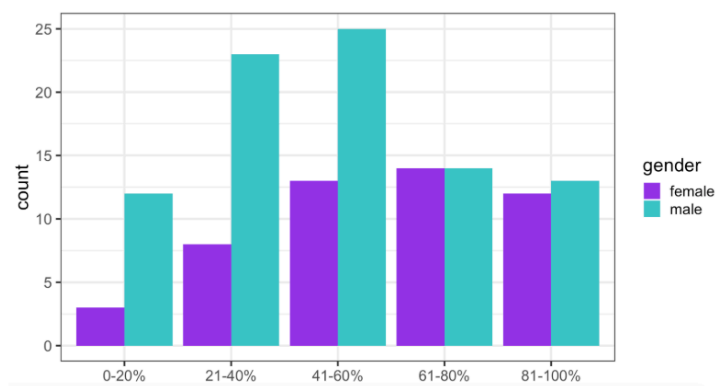
Barplot

Count of values within a single categorical variable



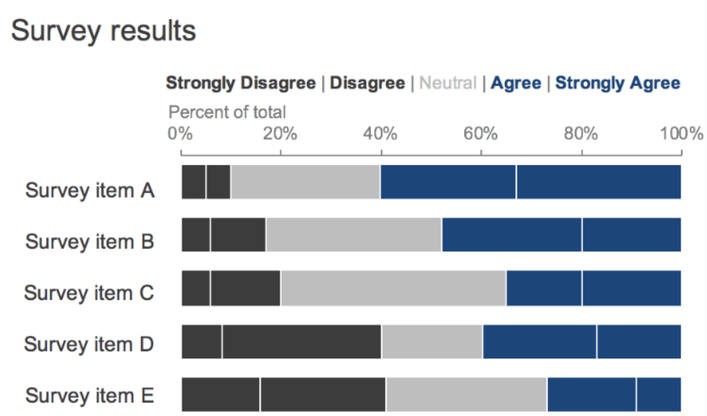
Grouped Barplot

Count of values broken down across two categorical variables



Stacked Barplot

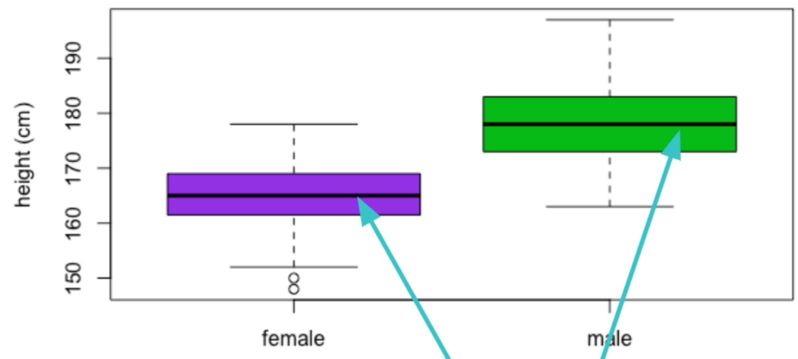
Count/proportion of values broken down across two categorical variables



Source: Storytelling with Data (Nussbaumer Knaflic)

Boxplot

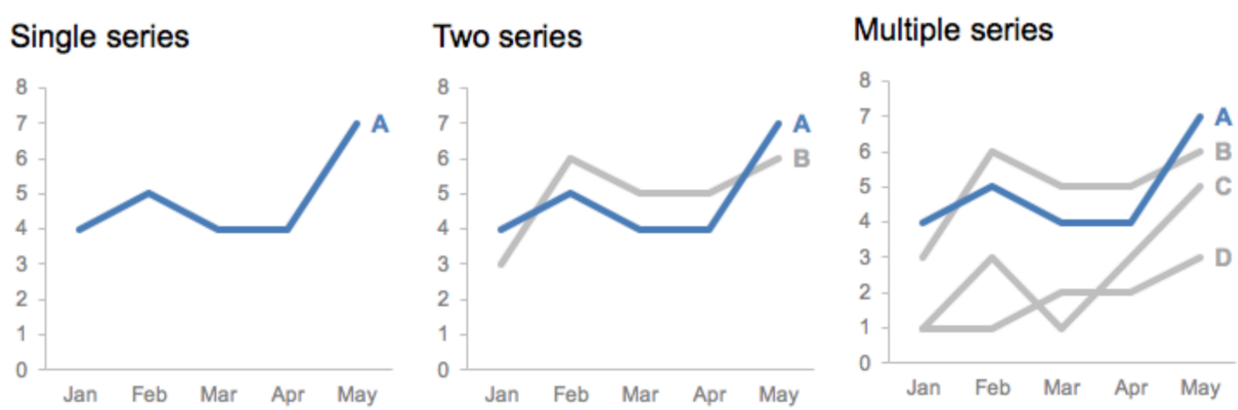
Summary of a quantitative variable broken down by a categorical variable



The middle line represents the median & tells you the typical height for females and males

Line plot

quantitative trend over time



Source: Storytelling with Data (Nussbaumer Knaflic)

https://forms.gle/Dn1k7uHoQSwoVoHS7

Clicker Question #1

You want to visualize how many people in your dataset prefer chocolate chip cookies and how many prefer oatmeal raisin cookies.

What type of visualization would be most appropriate?

- A) histogram
- B) scatterplot
- C) barplot
- D) boxplot
- E) line plot

Clicker Question #2

You're interested in visualizing how many servings of milk an individual drinks each day among those who prefer chocolate chip cookies and those who prefer oatmeal raisin cookies.

What type of visualization would be most appropriate?

- A) histogram
- B) scatterplot
- C) barplot
- D) boxplot
- E) line plot

Clicker Question #3

You're interested in visualizing how many servings of milk an individual drinks each year over the course of their life.

What type of visualization would be most appropriate?

- A) histogram
- B) scatterplot
- C) barplot
- D) boxplot
- E) line plot

Plotting in Python: Getting Started

First we'll import the libraries we'll use for plotting.

In [ ]:

```
# import working with data libraries
import pandas as pd
import numpy as np

# import seaborn
import seaborn as sns

# import matplotlib
import matplotlib.pyplot as plt # Typical way of import MPL
import matplotlib as mpl # This line is used less frequently

#improve resolution
#comment this line if erroring on your machine/screen
%config InlineBackend.figure_format ='retina'
```

In [ ]:

```
sns.__version__
```

seaborn

`seaborn` is a great place to get started when generating plots that don't look awful.

Class Data

With the libraries we need imported, the first dataset we'll use today is data from the COGS 108 class survey from the Spring of 2019.

In [ ]:

```
df = pd.read_csv('data/df_for_viz.csv')
```

In [96]:

```
df.shape
```

Out[96]:

```
(843, 11)
```

In [97]:

```
df.head()
```

Out[97]:

	gender	lecture_attendance	job	statistics	programming	Java	MATLAB	R	Python	C	SC
0	female	I prefer to attend lecture	No	5	8	1	0	0	0	0	
1	male	I prefer to attend lecture	No	8	4	0	1	0	1	0	
2	female	I prefer to attend lecture	No	6	7	1	0	0	0	0	
3	male	I prefer to attend lecture	No	2	10	1	0	0	0	1	
4	male	I prefer not to attend lecture (i.e. catch up ...	Yes	3	10	1	0	0	0	0	

Wrangling that's been done:

- removed lots of identifying information
- standardized gender & job
- separated out programming responses

In [98]:

```
df.describe()
```

Out[98]:

	statistics	programming	Java	MATLAB	R	Python	
count	843.000000	843.000000	843.000000	843.000000	843.000000	843.000000	843.0000
mean	5.575326	6.769870	0.809015	0.265718	0.153025	0.485172	0.198
std	1.985687	2.367976	0.393310	0.441977	0.360225	0.500077	0.3988
min	1.000000	1.000000	0.000000	0.000000	0.000000	0.000000	0.0000
25%	4.000000	5.000000	1.000000	0.000000	0.000000	0.000000	0.0000
50%	6.000000	7.000000	1.000000	0.000000	0.000000	0.000000	0.0000
75%	7.000000	9.000000	1.000000	1.000000	0.000000	1.000000	0.0000
max	10.000000	10.000000	1.000000	1.000000	1.000000	1.000000	1.0000

Quantitative Variables

- histograms
- densityplots
- scatterplots

Histograms and Densityplots

Histograms & **Densityplots** are helpful for visualizing information about a *single quantitative variable*.

We can use seaborn's `histplot` function. (`distplot` in older versions of `seaborn`)

In [99]:

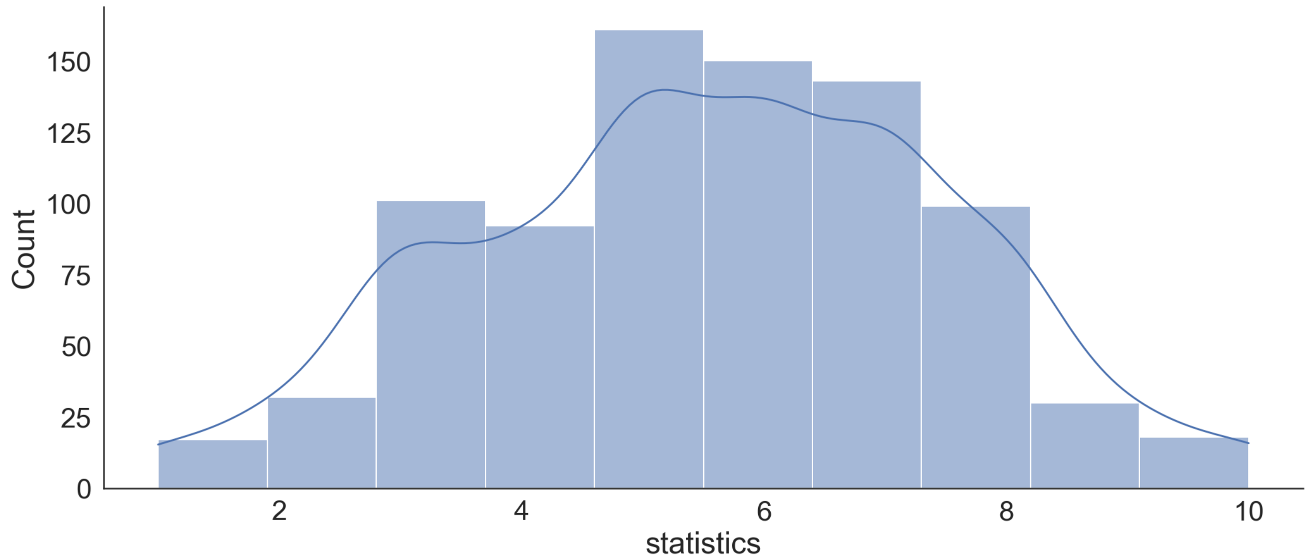
```
# set plotting size parameter
plt.rcParams['figure.figsize'] = (17, 7) #default plot size to output
```

In [111…

```
sns.set_theme(context='notebook',style='white',font_scale=2,rc={'axes.spines.
```

In [112…

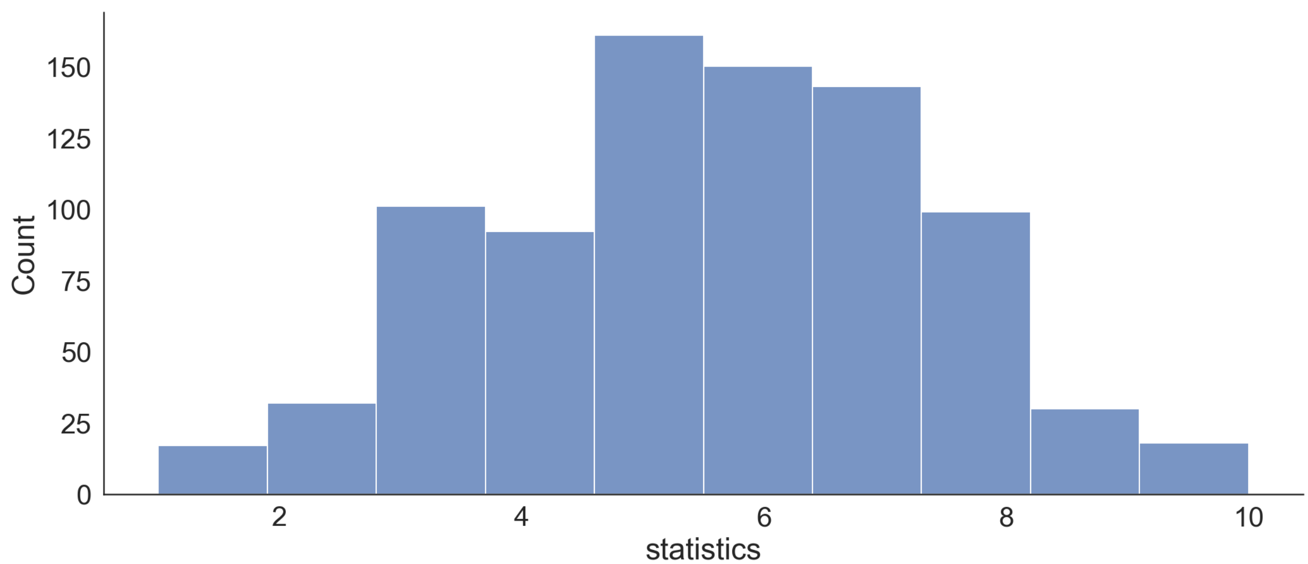
```
# histogram
#`distplot` in older versions of `seaborn`
sns.histplot(df['statistics'], bins=10, kde=True);
```



One thing to note about histograms is the fact that the number of bins displayed plays a large role what the viewer takes away from the visualization.

In [113…

```
# `distplot` in older versions of `seaborn`
# just histogram - set kde = False
sns.histplot(df['statistics'], bins=10);

# Alternative approach using pandas
# df['statistics'].hist(bins=10);
```

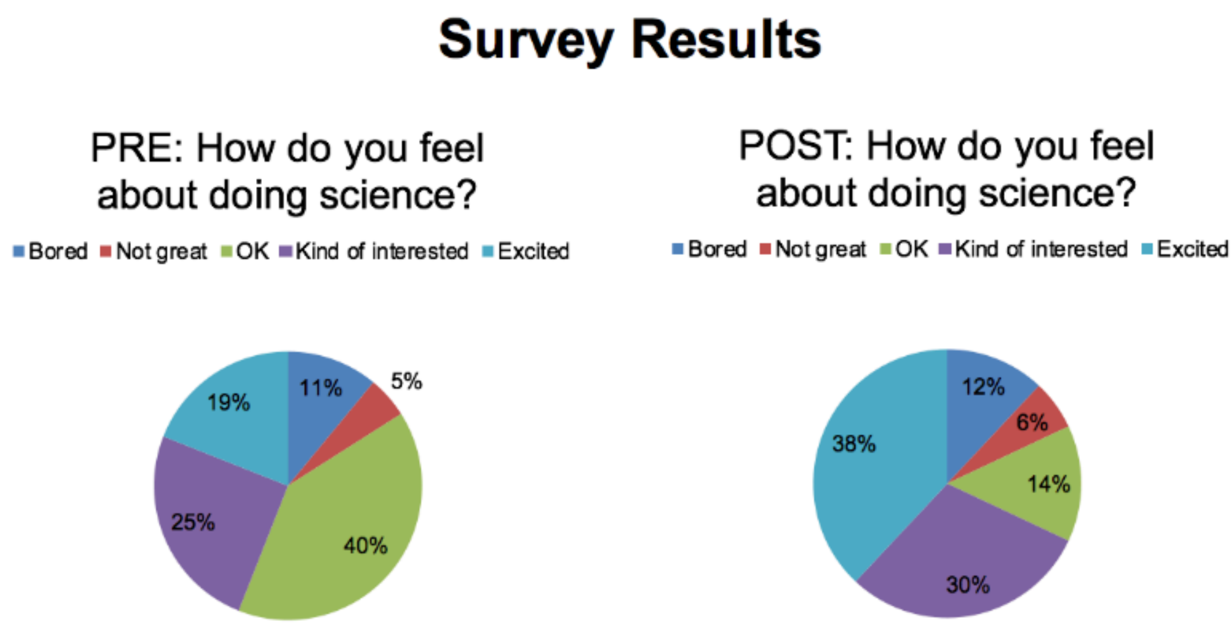


This doesn't follow "visualization best practices."

Visualization Best Practices

- Choose the right type of visualization
- Be mindful when choosing colors
- Label your axes
- Make text big enough
- Keep it simple
- Less is more:
    - Aim to improve your data:ink ratio
    - Everything on the page should serve a purpose. If it doesn't, remove it.

Best Practices: Example



Source: Storytelling with Data (Nussbaumer Knaflic)

Ideas:

- Pros:
  - consistent colors from left to right
  - values provided for each slice
  - overall picture
- Cons:
  - text size
  - legend not ideal
  - colors are not intuitive
  - pie chart not ideal b/c of # of categories

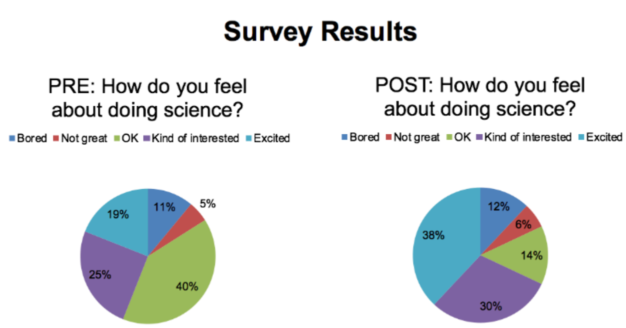
Suggestions:

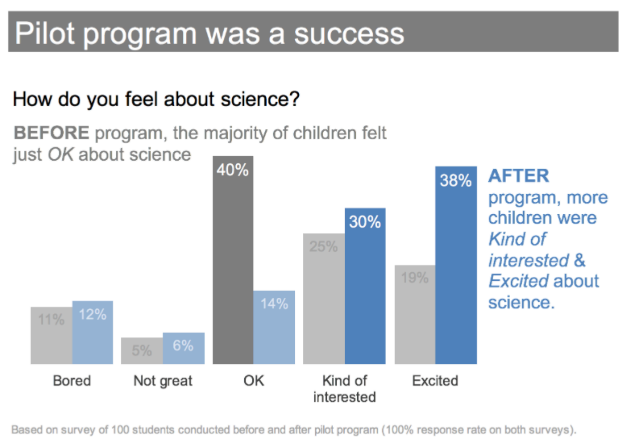
- different visualiztion - stacked barplot?

Clicker Question #4

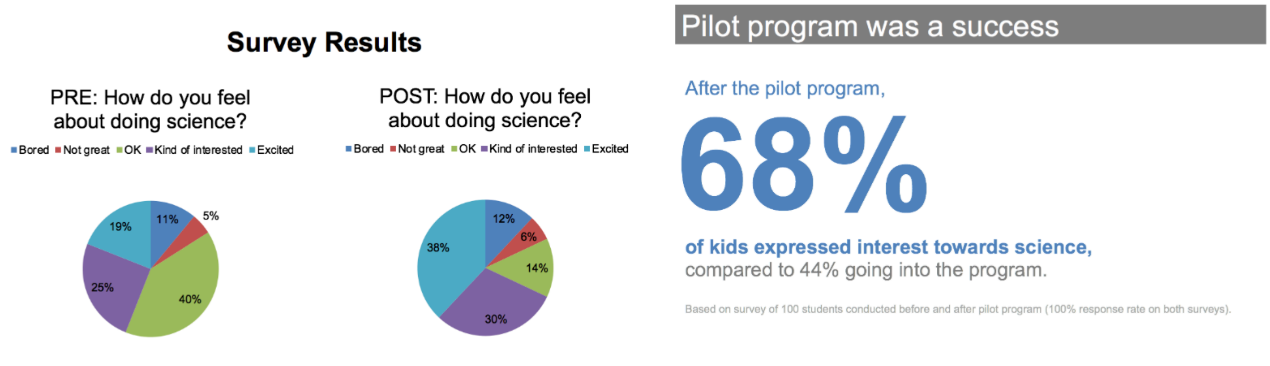
Consider what are some positive and some negative aspects of this visualization. Click in when you have finished thinking.

- A) I have some ideas!
- B) I've got no ideas.
- C) I'm not sure what I'm supposed to be thinking about.

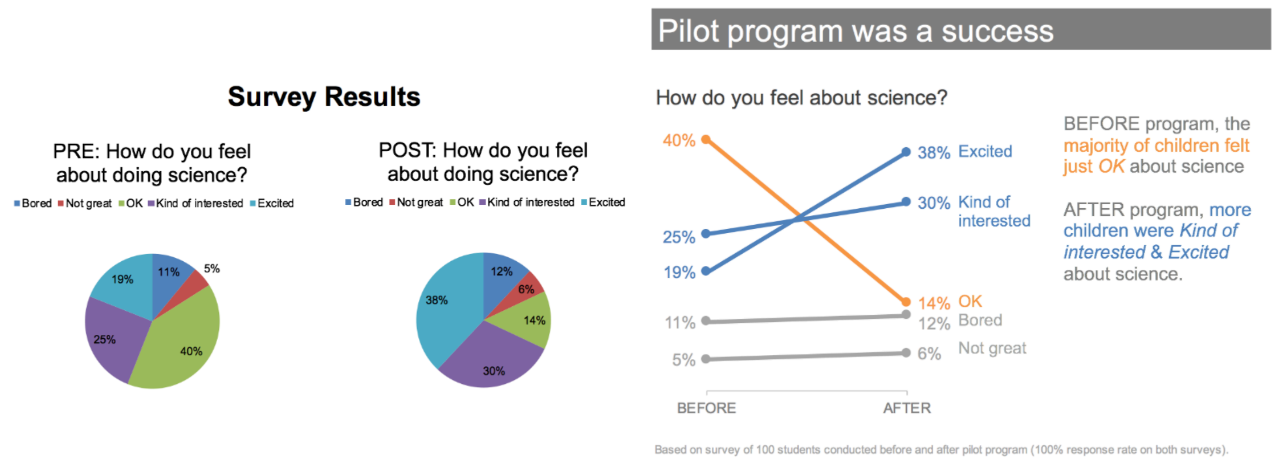




Source: Storytelling with Data (Nussbaumer Knaflic)



Source: [Storytelling with Data (Nussbaumer Knaflic)]



Source: [Storytelling with Data (Nussbaumer Knaflic)]

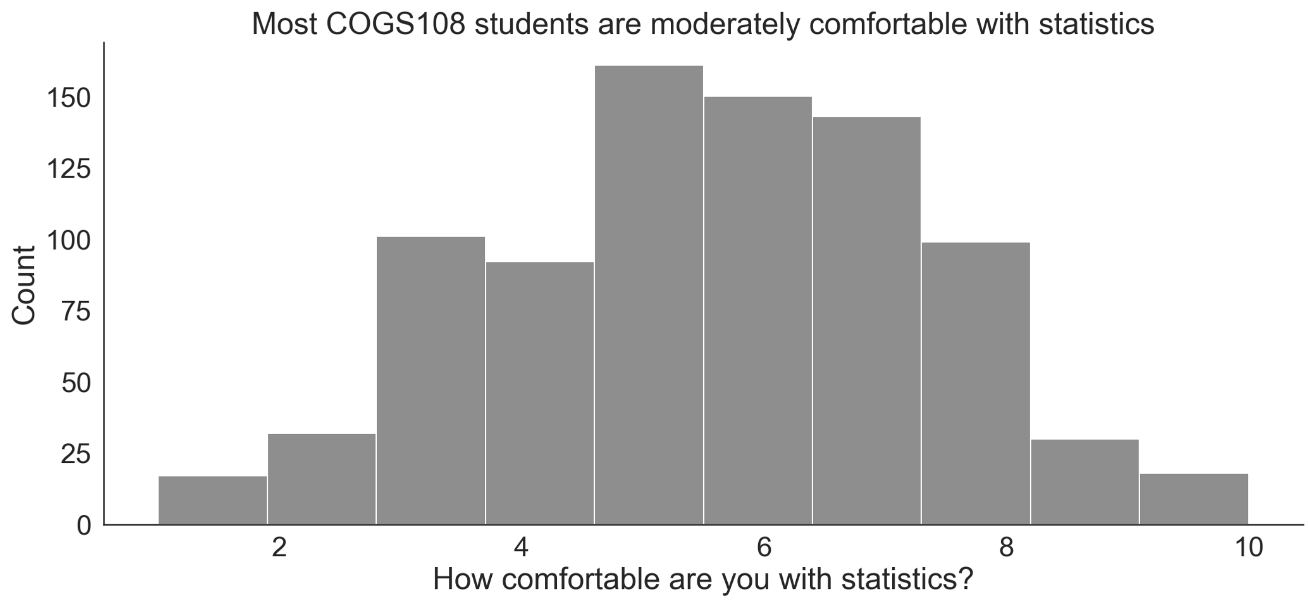
Less is more

The *less is more* approach suggests that we should probably get rid of this background color now and remove the gridlines. We'll use the *less is more* approach as we work through the other types of visualizations.

Let's improve that now for our original plot...

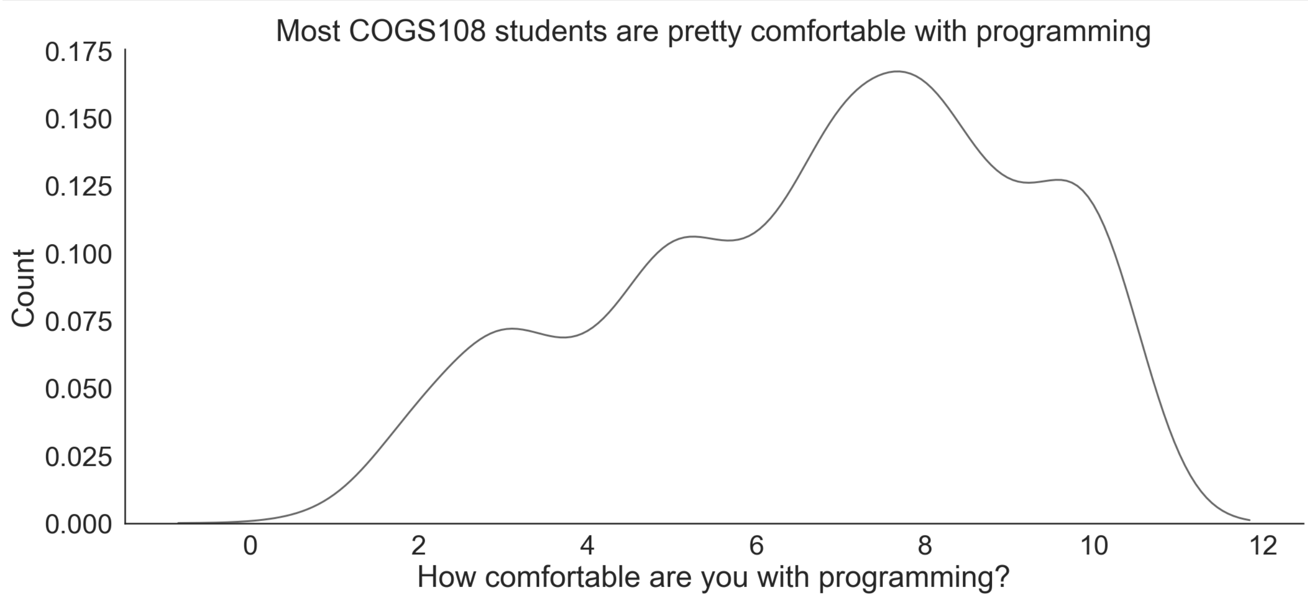
In [114…

```
# `distplot` in older versions of `seaborn`
# change color to dark grey
ax = sns.histplot(df['statistics'], kde=False,
                  bins=10, color='#686868')

# remove the top and right lines
sns.despine()

# add title and axis labels (modify x-axis label)
ax.set_title('Most COGS108 students are moderately comfortable with statistic
ax.set_ylabel('Count')
ax.set_xlabel('How comfortable are you with statistics?');
```



In [115…

```
# kdeplot to only display the densityplot
ax = sns.kdeplot(df['programming'], color='#686868')

# remove the top and right lines
sns.despine()

# add title and axis labels (modify x-axis label)
ax.set_title('Most COGS108 students are pretty comfortable with programming')
ax.set_ylabel('Count')
ax.set_xlabel('How comfortable are you with programming?');
```

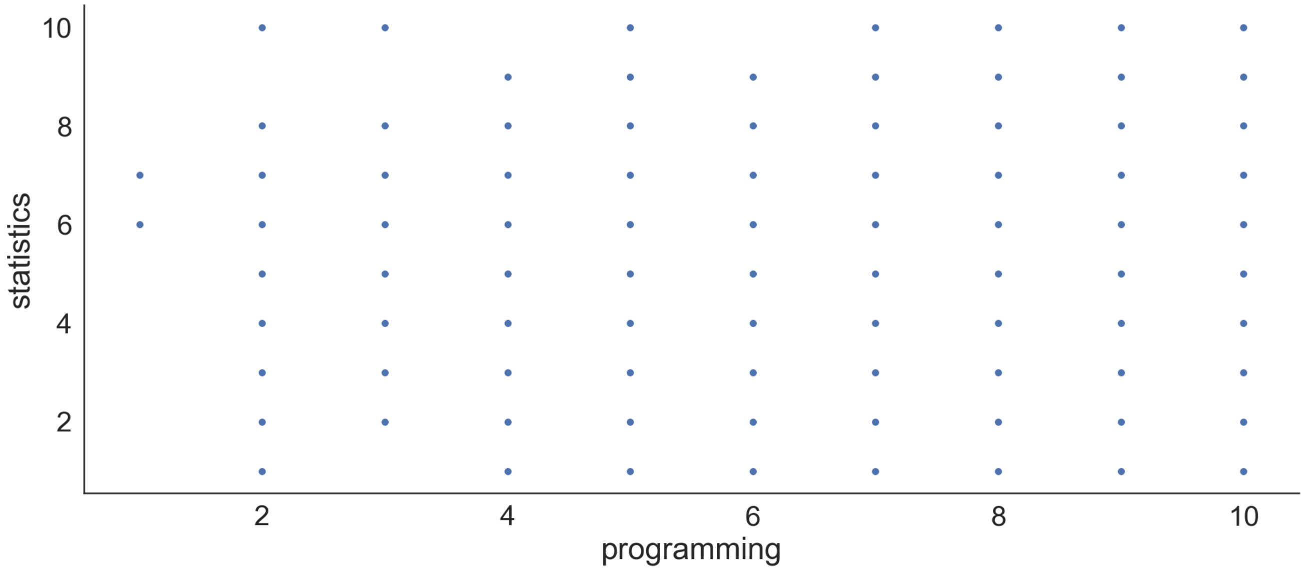


Scatterplots

Scatterplots can help visualize the relationship between **two quantitative variables**.

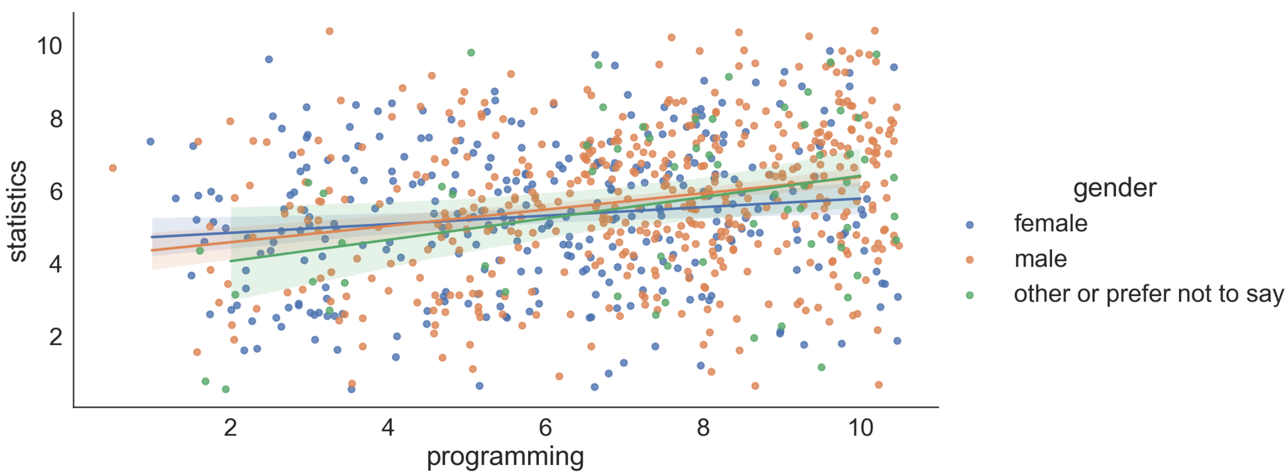
In [116…

```
sns.scatterplot(x='programming', y='statistics', data=df);

# alternative with pandas
# df.plot.scatter('programming', 'statistics');
```



In [119…

```
# jitter points to see relationship
sns.lmplot(x='programming', y='statistics', data=df, hue='gender',
           fit_reg=True, height=6, aspect=2,
           x_jitter=.5, y_jitter=.5);
```



Clicker Question #5

What can we say about the relationship between students' comfortability with programming and statistics?

- A) Students who are more comfortable programming are more comfortable with statistics
- B) Students sho are more comfortable programming are less comfortable with statistics
- C) There is little relationship between students' comfort level with programming and statistics

Scatterplots (by a categorical variable)

When you want to plot two numeric variables but want to get some insight about a *third* categorical variable, you can color the points on the plot by the categorical variable.

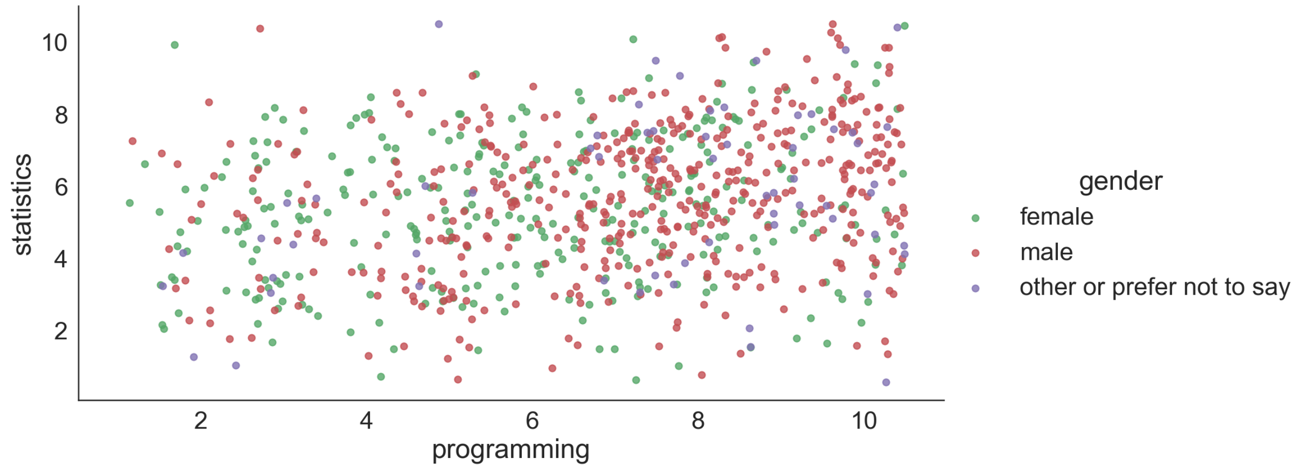
In [120…

```
# control color palette
unique = df["lecture_attendance"].append(df["gender"]).unique()
palette = dict(zip(unique, sns.color_palette()))
palette.update({"Total":"k"})
print(palette)
```

```
{'I prefer to attend lecture': (0.2980392156862745, 0.4470588235294118, 0.6901960784313725), 'I prefer not to attend lecture (i.e. catch up later, listen to podcast, etc.)': (0.8666666666666667, 0.5176470588235295, 0.3215686274509804), 'female': (0.3333333333333333, 0.6588235294117647, 0.40784313725490196), 'male': (0.7686274509803922, 0.3058823529411765, 0.3215686274509804), 'other or prefer not to say': (0.5058823529411764, 0.4470588235294118, 0.7019607843137254), 'Total': 'k'}
```

In [121…

```
# control color palette
unique = df["lecture_attendance"].append(df["gender"]).unique()
palette = dict(zip(unique, sns.color_palette()))
palette.update({"Total":"k"})

# color points by gender is
sns.lmplot(x='programming', y='statistics', data=df, hue='gender',
           fit_reg=False, height=6, aspect=2,
           x_jitter=.5, y_jitter=.5,
           palette=palette);
```



Clicker Question #6

What can we say about the relationship between students' comfortability with programming and statistics and gender? And, how easy is this to determine?

- A) Females and Other/Prefer not to say tend to be more comfortable with programming; easy to determine
- B) Females and Other/Prefer not to say tend to be more comfortable with programming; difficult to determine
- C) Males tend to be more comfortable with programming; easy to determine
- D) Males tend to be more comfortable with programming; difficult to determine
- E) I'm super lost.

We don't get a *ton* more information here, but what we may see a slight shift in programming comfortability to include more males relative to females. To better understand this, a boxplot would be helpful. (We'll look at this shortly.)

Categorical Variables

- barplots
- grouped barplots
- stacked barplots

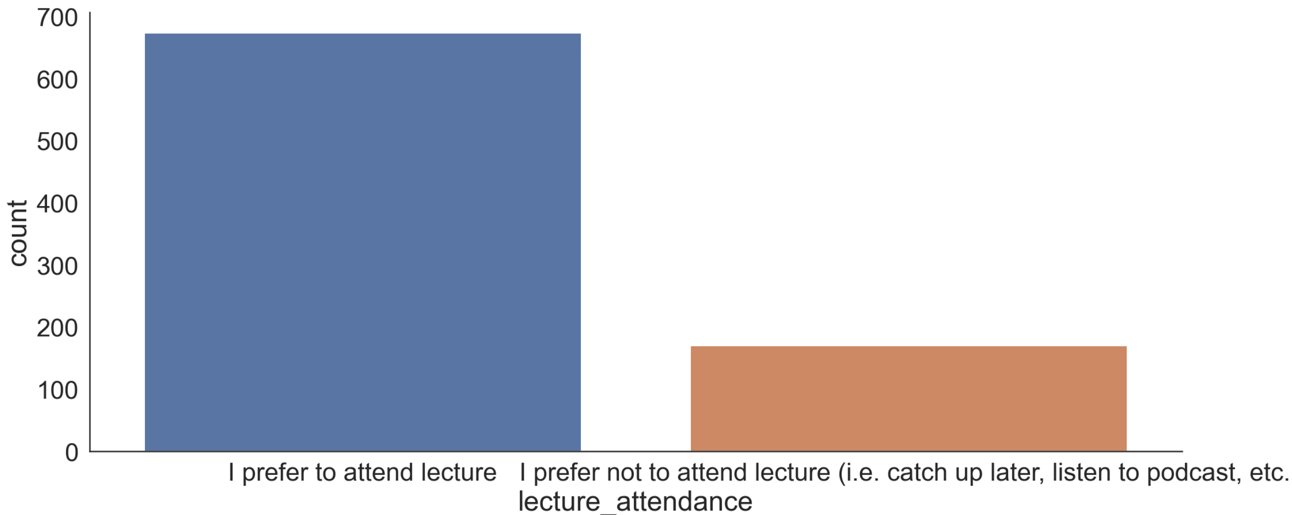
Barplots

In `seaborn` there are two types of bar charts:

1. `countplot` - counts the number of times each category appears in a column
2. `barplot` - groups dataframe by a categorical column and plots the height bars according to the average of a numerical column within each group (This is usually not the right way to visualize quantitative data, so we're not covering it in this class.)

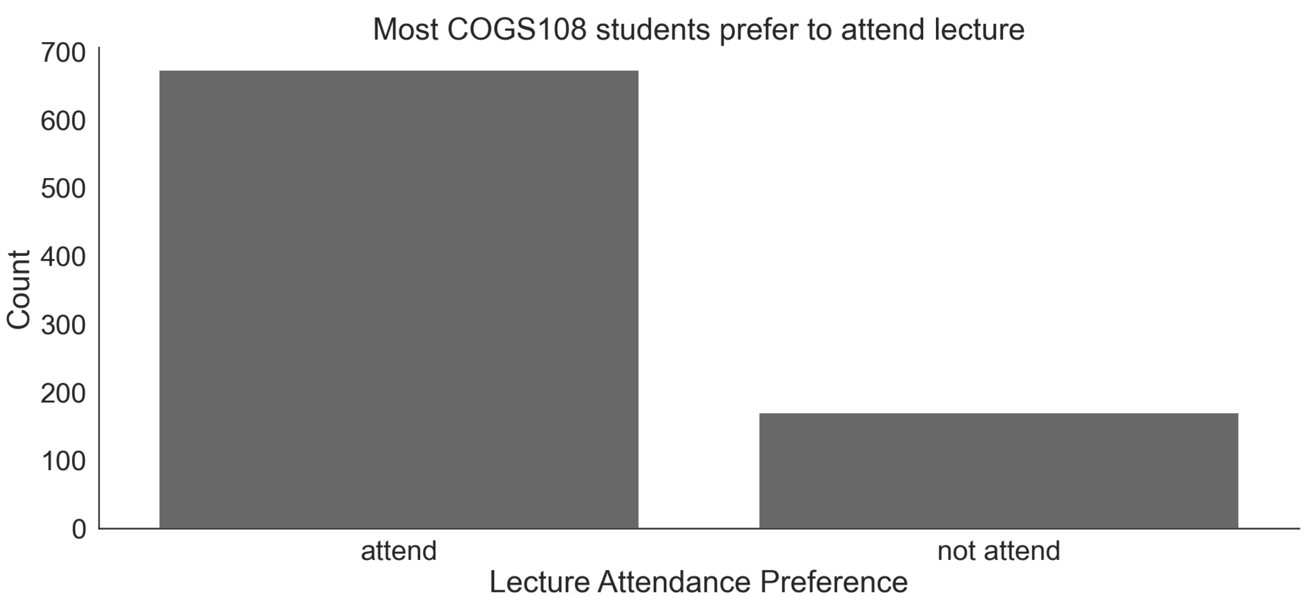
In [124…

```
# generate default barplot
sns.countplot(x='lecture_attendance',
              data=df);
```



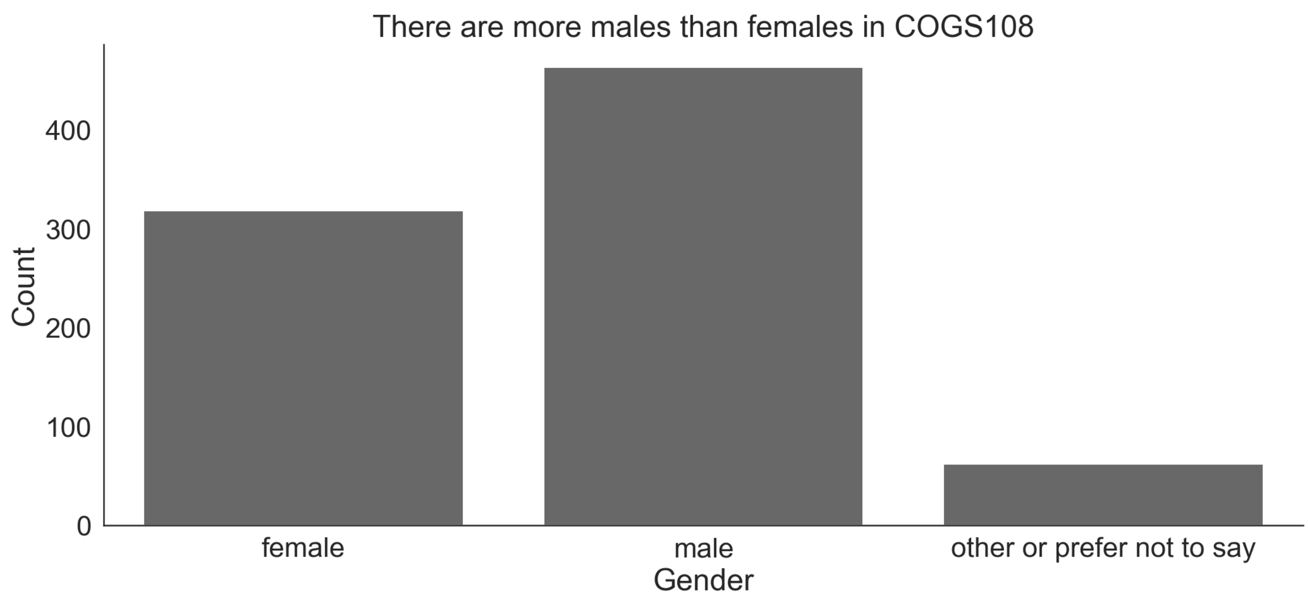
In [125…

```
ax = sns.countplot(x='lecture_attendance',
                   data=df, color = '#686868')

# add title and axis labels (modify x-axis label)
ax.set_title('Most COGS108 students prefer to attend lecture')
ax.set_ylabel('Count')
ax.set_xlabel('Lecture Attendance Preference')
# set tick labels
ax.set_xticklabels(("attend", "not attend"));
```



In [126…

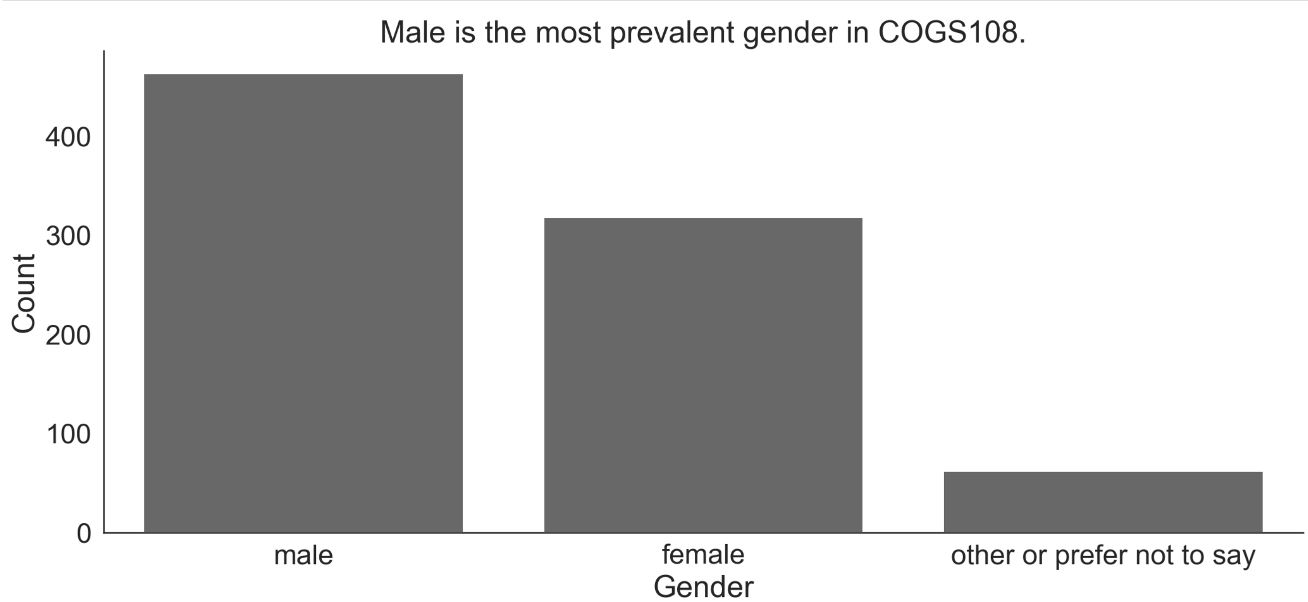
```
ax = sns.countplot(x='gender', data=df, color='#686868')

# add title and axis labels (modify x-axis label)
ax.set_title('There are more males than females in COGS108')
ax.set_ylabel('Count')
ax.set_xlabel('Gender');
```



It's often a good idea to order axes from largest to smallest for categorical data.

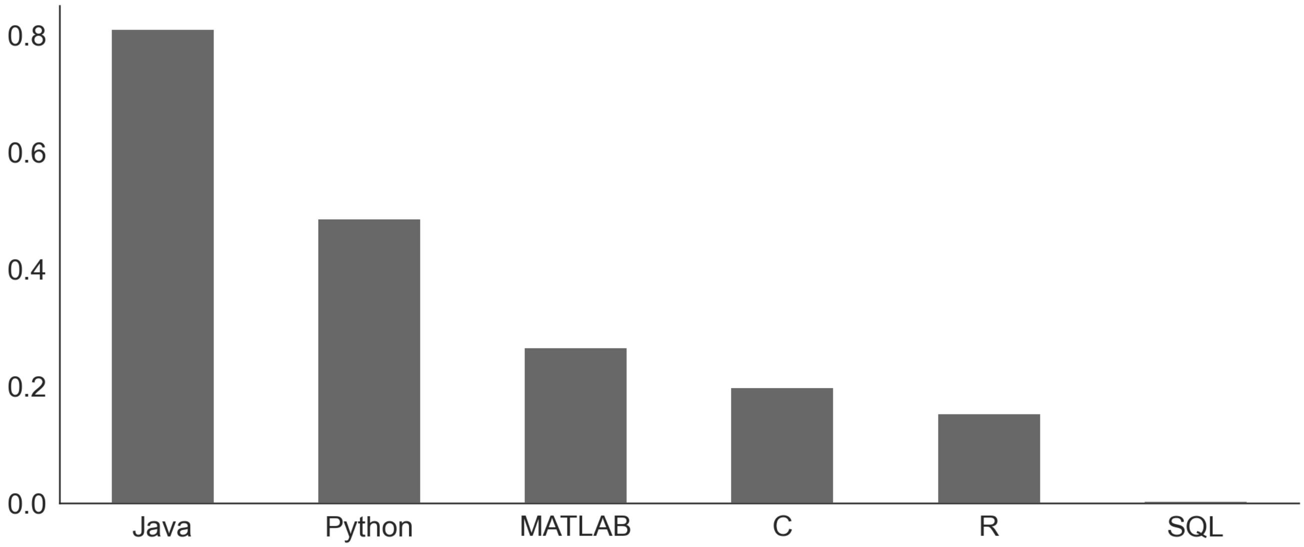
In [127…

```
ax = sns.countplot(x='gender', data=df, color = '#686868',
             order=['male', 'female', 'other or prefer not to say'])

# add title and axis labels (modify x-axis label)
ax.set_title('Male is the most prevalent gender in COGS108.')
ax.set_ylabel('Count')
ax.set_xlabel('Gender');
```



In [128…

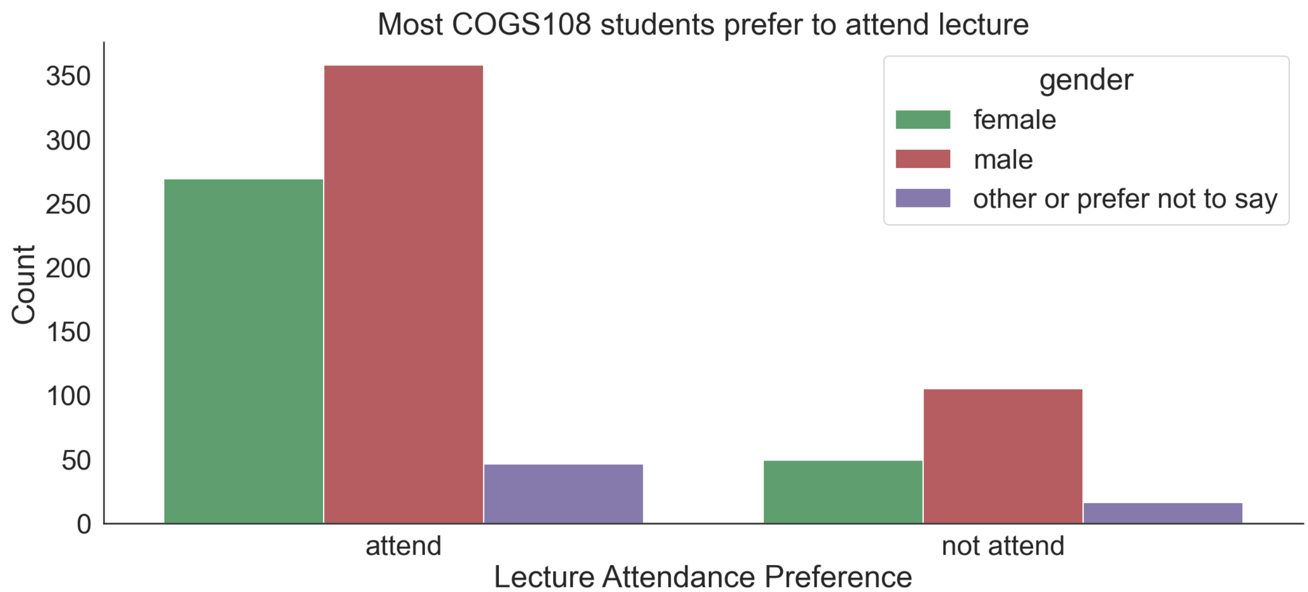
```
# warning: not seaborn
# pandas approach
# proportion of the class familiar with each programming language
a = df.iloc[:,5:11].sum()/len(df)
a = a.sort_values(axis=0, ascending=False)
a.plot.bar(color='#686868', rot=0);
```



Grouped Barplots

In [129…

```
# same color palette as defined earlier
# generate grouped barplot by specifying hue
ax = sns.countplot(x='lecture_attendance', hue='gender',
                   data=df, palette=palette)

# add title and axis labels (modify x-axis label)
ax.set_title('Most COGS108 students prefer to attend lecture')
ax.set_ylabel('Count')
ax.set_xlabel('Lecture Attendance Preference')
ax.set_xticklabels(('attend', 'not attend'));
```



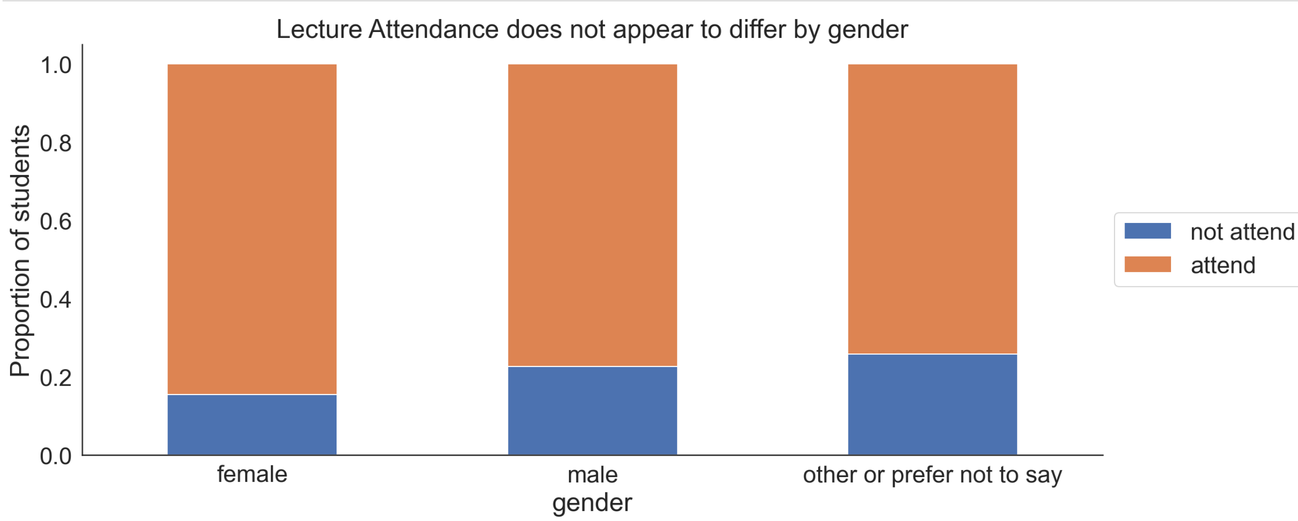
Because we have different numbers of males and females, comparing counts is not all that helpful...

We need proportions.

Stacked Barplots

In [130...

```
# warning: this is not seaborn
df2 = df.groupby([ 'lecture_attendance','gender'])['lecture_attendance'].coun
sub_df2 = np.transpose(df2.div(df2.sum()))

# generate plot
ax = sub_df2.plot(kind='bar', stacked=True, rot=0,
                  title='Lecture Attendance does not appear to differ by gend

# customize plot
ax.legend(('not attend','attend'), loc='center left', bbox_to_anchor=(1.0, 0.
ax.set_ylabel("Proportion of students");
```



More plots

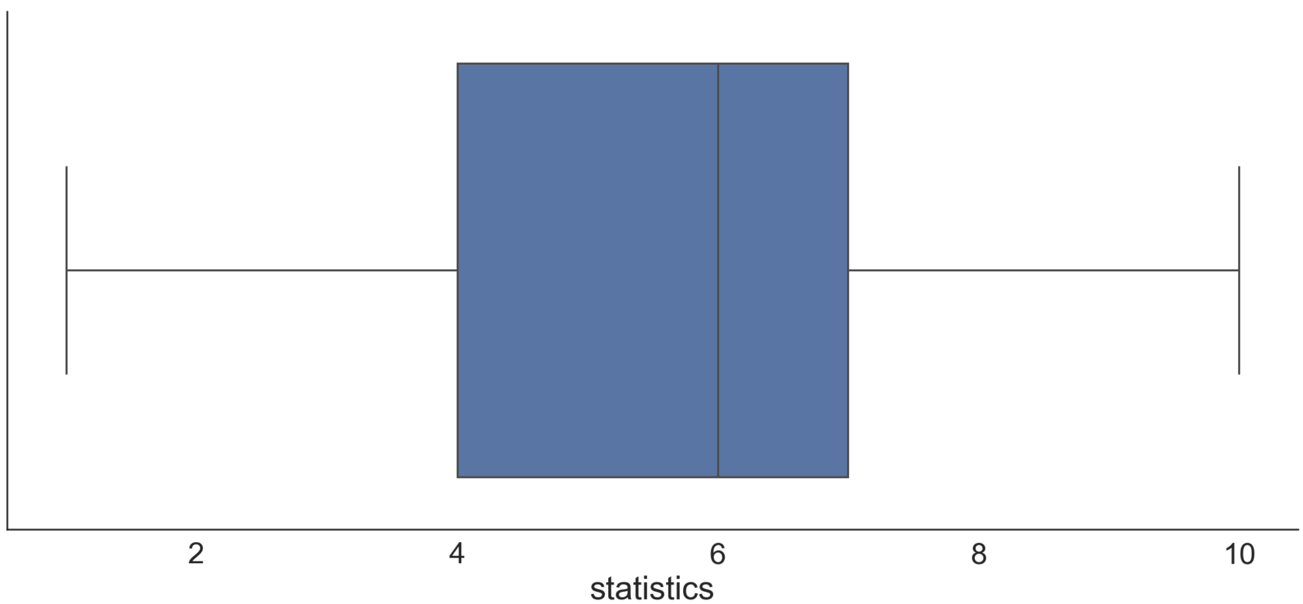
- boxplots (quantitative + categorical)
- lineplots (quantitative over time)

Boxplots

By default, the box delineates the 25th and 75th percentile. The line down the middle represents the median. "Whiskers" extend to show the range for the rest of the data, excluding outliers. Outliers are marked as individual points outside of the whiskers.

In [131…

```
# generate boxplots
sns.boxplot(x='statistics', data=df);
```



Outlier determination

Outliers show up as individual points on boxplots. But, we don't see any on this boxplot. Let's see why...

In [132…

```
# determine the 25th and 75th percentiles
lower, upper = np.percentile(df['statistics'], [25, 75])
lower, upper
```

Out[132…

```
(4.0, 7.0)
```

In [133…

```
# calculate IQR
iqr = upper - lower
iqr
```

Out[133… 3.0

Typically, the inter-quartile range (IQR) is used to determine which values get marked as outliers. The IQR is: 75th percentile - 25th percentile. Values greater than 1.5 x IQR above the 75th or below the 25th percentile are marked as outliers.

In [134…

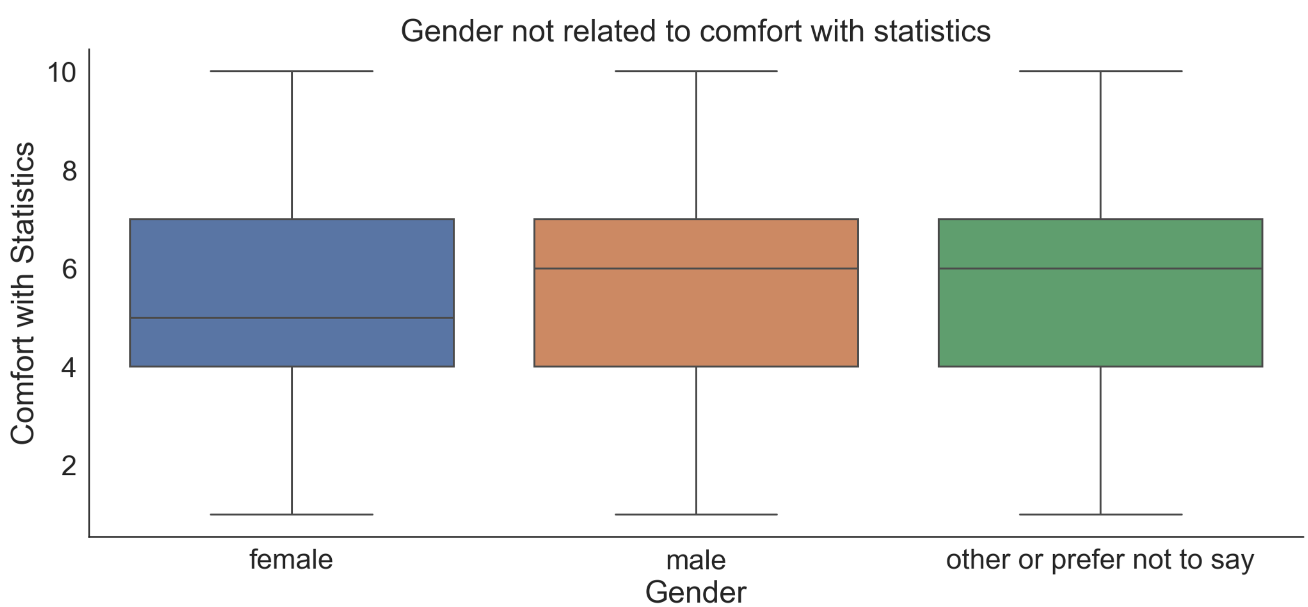
```
# calculate lower cutoff
# values below this are outliers
lower_cutoff = lower - 1.5 * iqr

# calculate upper cutoff
# values above this are outliers
upper_cutoff = upper + 1.5 * iqr

lower_cutoff, upper_cutoff
```

Out[134… (-0.5, 11.5)

Boxplots really shine when you want to look at the range of typical values for a quantitative variable, *broken down by a separate categorical variable*.

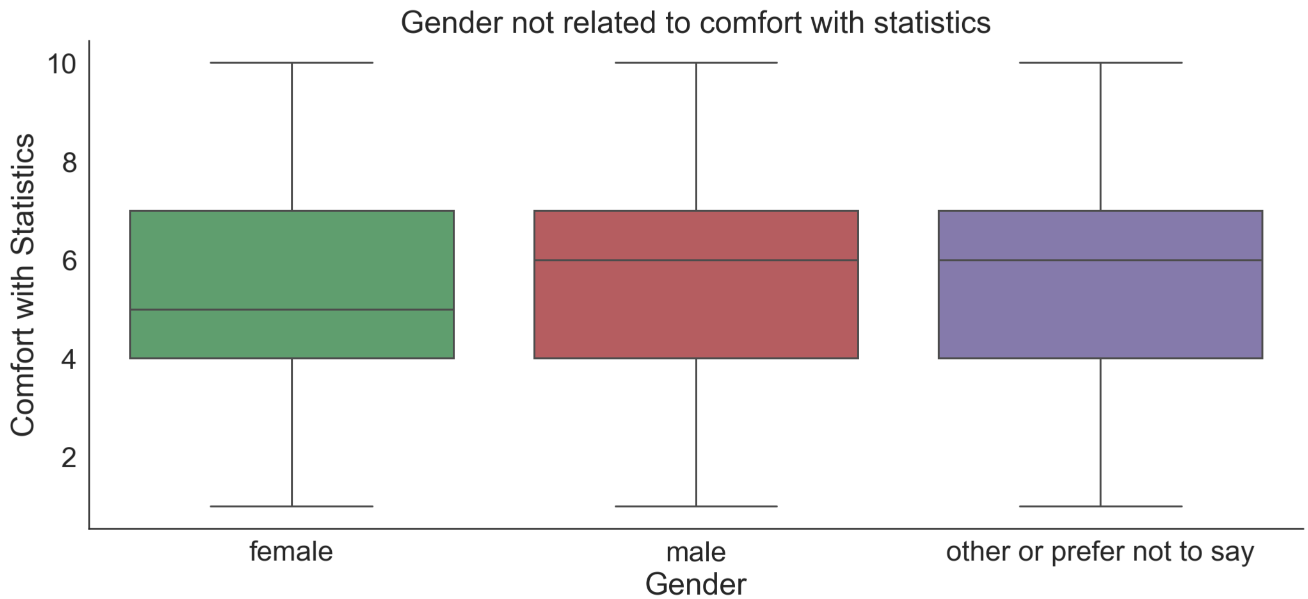
In [135…

```
# generate boxplots
# we can make sure the colors match what we used earlier for the same groups
ax = sns.boxplot(x='gender', y='statistics', data=df)

ax.set_title('Gender not related to comfort with statistics')
ax.set_ylabel('Comfort with Statistics')
ax.set_xlabel('Gender');
```



In [136…

```
# generate boxplots
# we can make sure the colors match what we used earlier for the same groups
ax = sns.boxplot(x='gender', y='statistics', data=df, palette=palette)

ax.set_title('Gender not related to comfort with statistics')
ax.set_ylabel('Comfort with Statistics')
ax.set_xlabel('Gender');
```



Much better!

Histograms (by a categorical variable)

The same data plotted as a histogram are not so easily interpretable.

In [ ]:

```
# `distplot` in older versions of `seaborn`
sns.histplot(df.loc[df['gender'] == 'female', 'statistics'], kde=True, color=
sns.histplot(df.loc[df['gender'] == 'male', 'statistics'], kde=True, color="p
sns.histplot(df.loc[df['gender'] == 'other or prefer not to say', 'statistics
```

Customization: `births` data

Now that we're getting the hang of this, let's see how complicated things can get. We'll return to using a line chart to look at birth patterns over time.

In [137…

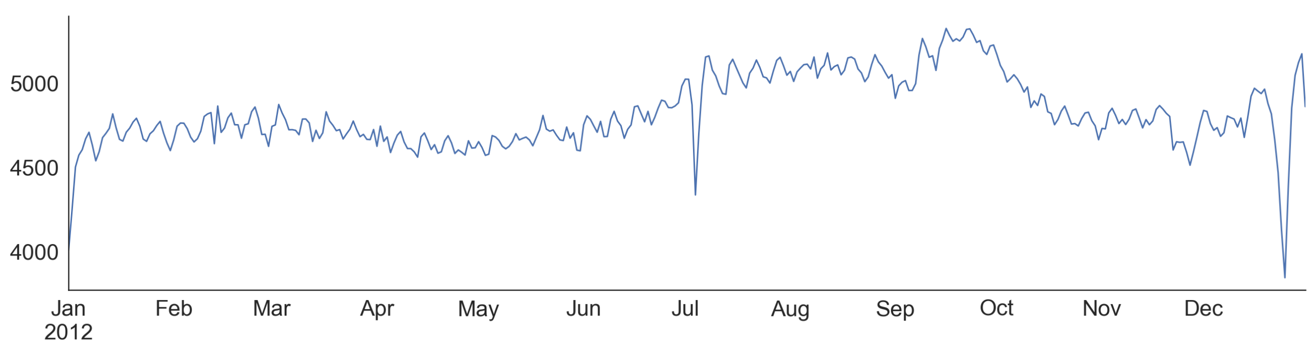
```
# get the data
births = pd.read_csv('data/births.csv')
births.head()
```

Out[137...

	year	month	day	gender	births
0	1969	1	1.0	F	4046
1	1969	1	1.0	M	4440
2	1969	1	2.0	F	4454
3	1969	1	2.0	M	4548
4	1969	1	3.0	F	4548

In [138...

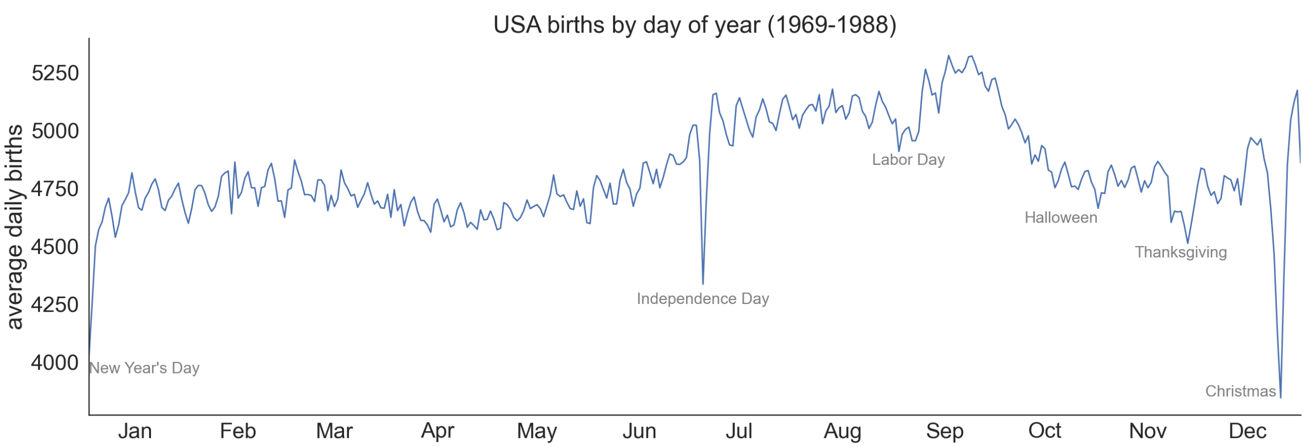
```
from datetime import datetime

# calculate values & wrangle
quartiles = np.percentile(births['births'], [25, 50, 75])
mu, sig = quartiles[1], 0.74 * (quartiles[2] - quartiles[0])
births = births.query('(births > @mu - 5 * @sig) & (births < @mu + 5 * @sig)'

births['day'] = births['day'].astype(int)

births.index = pd.to_datetime(10000 * births.year +
                              100 * births.month +
                              births.day, format='%Y%m%d')
births_by_date = births.pivot_table('births',
                                    [births.index.month, births.index.day])
births_by_date.index = [datetime(2012, month, day)
                        for (month, day) in births_by_date.index]


# plot the thing
fig, ax = plt.subplots(figsize=(22, 5))
births_by_date.plot(ax = ax)
ax.get_legend().remove()
```



What are all those dips? Well, let's annotate the plot to get a better sense of what's going on.

In [139…

```
# plot the thing
fig, ax = plt.subplots(figsize=(22, 7))
births_by_date.plot(ax=ax)
ax.get_legend().remove();

# define style
style = dict(size=16, color='gray')

# add annotation
ax.text('2012-1-1', 3950, "New Year's Day", **style)
ax.text('2012-7-4', 4250, "Independence Day", ha='center', **style)
ax.text('2012-9-4', 4850, "Labor Day", ha='center', **style)
ax.text('2012-10-31', 4600, "Halloween", ha='right', **style)
ax.text('2012-11-25', 4450, "Thanksgiving", ha='center', **style)
ax.text('2012-12-25', 3850, "Christmas ", ha='right', **style)

# label the axes
ax.set(title='USA births by day of year (1969-1988)',
       ylabel='average daily births')

# format the x axis with centered month labels
ax.xaxis.set_major_locator(mpl.dates.MonthLocator())
ax.xaxis.set_minor_locator(mpl.dates.MonthLocator(bymonthday=15))
ax.xaxis.set_major_formatter(plt.NullFormatter())
ax.xaxis.set_minor_formatter(mpl.dates.DateFormatter('%h'));
```



Annotation directly on plots can help explain the plot to viewers.

Saving Plots

While we're using a Jupyter notebook right now, you won't always be. So, you'll need to know how to save figures.

In [140…

```
# save fig to plots directory
# this will only work if you have
# a plots directory in your working directory
fig.savefig('images/my_figure.png')
```

Note that the file format is inferred from the extension you specify in the filename.

To see which file types are supported:

In [141…

```
fig.canvas.get_supported_filetypes()
```

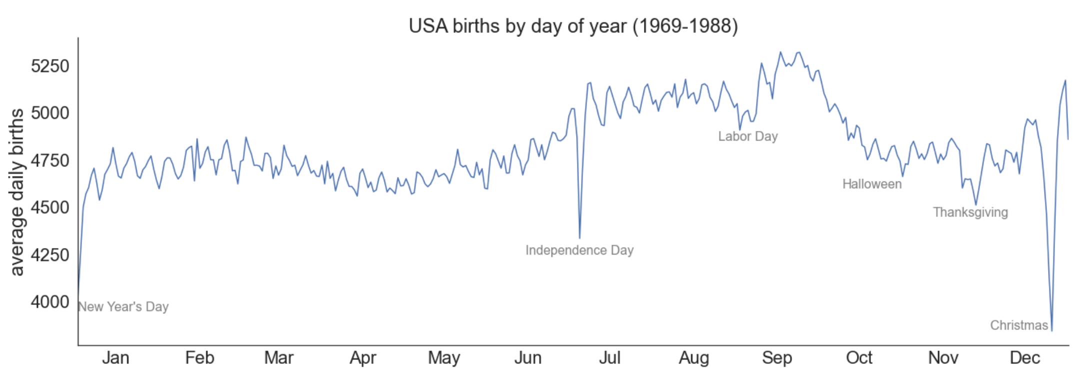
Out[141…

```
{'eps': 'Encapsulated Postscript',
 'jpg': 'Joint Photographic Experts Group',
 'jpeg': 'Joint Photographic Experts Group',
 'pdf': 'Portable Document Format',
 'pgf': 'PGF code for LaTeX',
 'png': 'Portable Network Graphics',
 'ps': 'Postscript',
 'raw': 'Raw RGBA bitmap',
 'rgba': 'Raw RGBA bitmap',
 'svg': 'Scalable Vector Graphics',
 'svgz': 'Scalable Vector Graphics',
 'tif': 'Tagged Image File Format',
 'tiff': 'Tagged Image File Format'}
```

Viewing Saved Plots

Once a plot is saved, it may be helpful to view it through IPython or your notebook. To do so, you'd use the following:

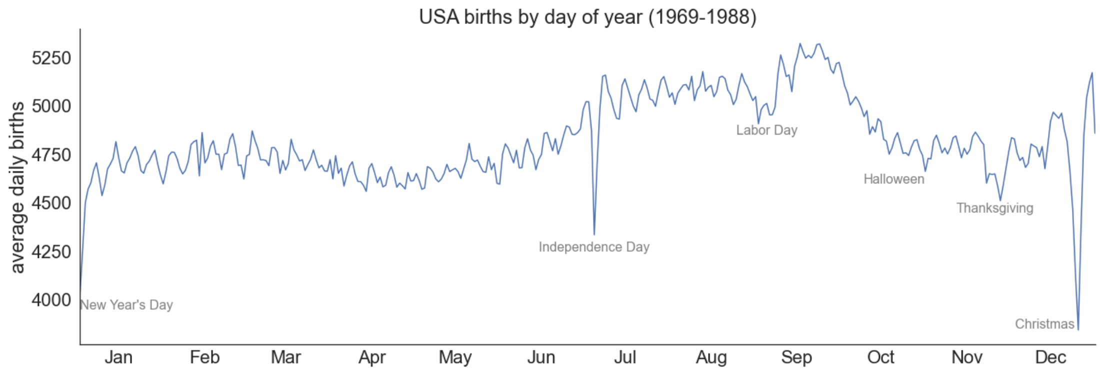
Can import with Markdown formatting... (or with HTML in a markdown cell)



In [142…

```
# to see contents of a saved image
from IPython.display import Image
Image('images/my_figure.png')
```

Out[142…


USA births by day of year (1969-1988)
average daily births
5250
5000
4750
4500
4250
4000
New Year's Day
Independence Day
Labor Day
Halloween
Thanksgiving
Christmas
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec

In [ ]: