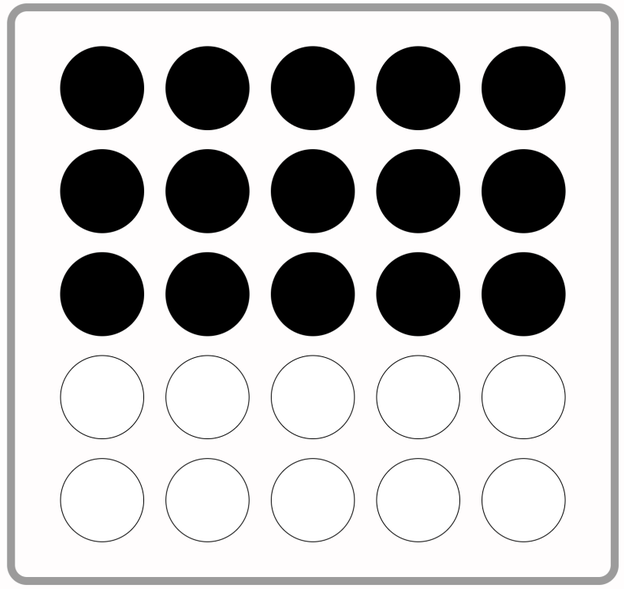
Point estimate intervals

IMPROVING YOUR DATA VISUALIZATIONS IN PYTHON

Nick Strayer
Instructor

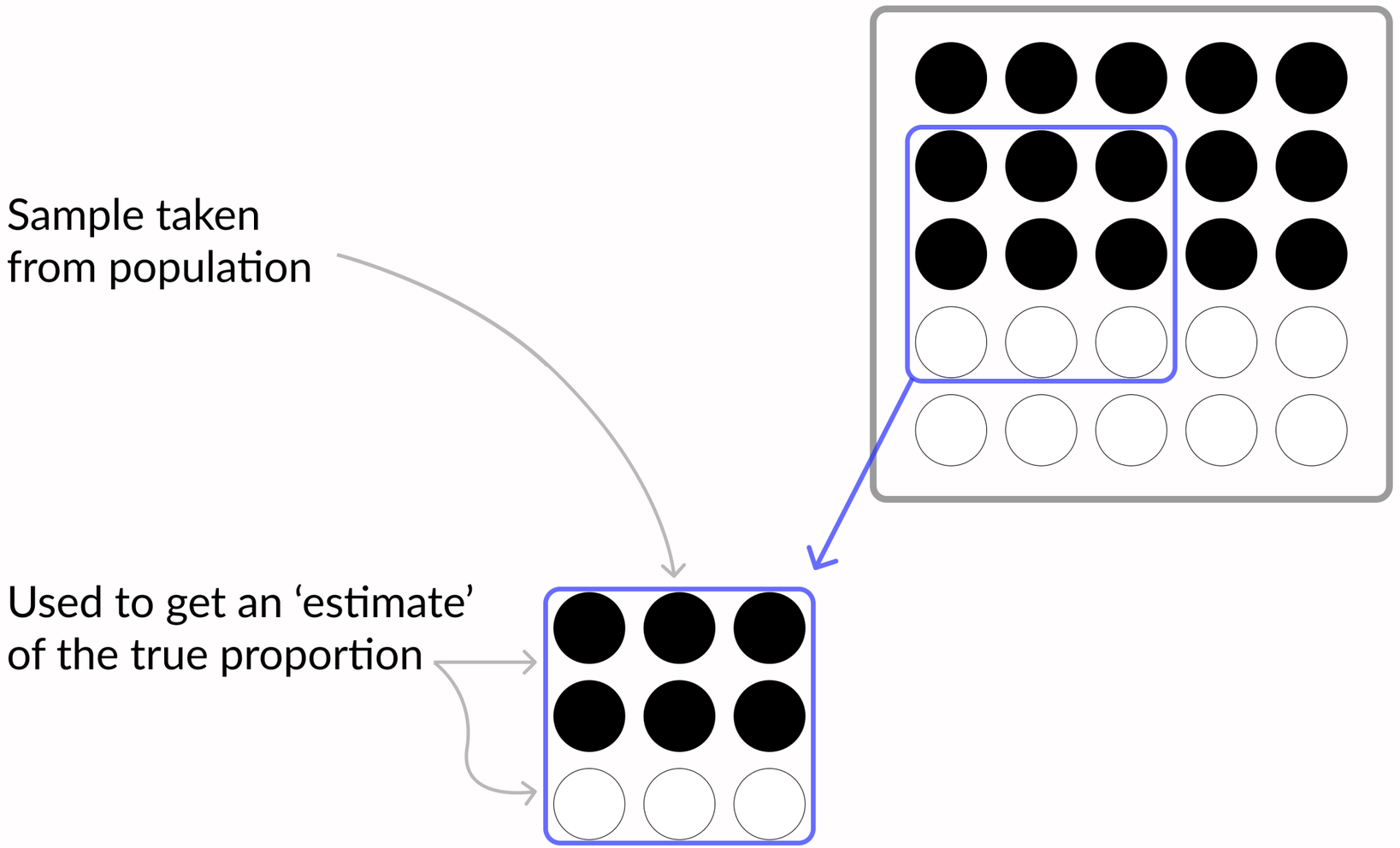
What is uncertainty?

Population of interest:
E.g. All sheep on farm

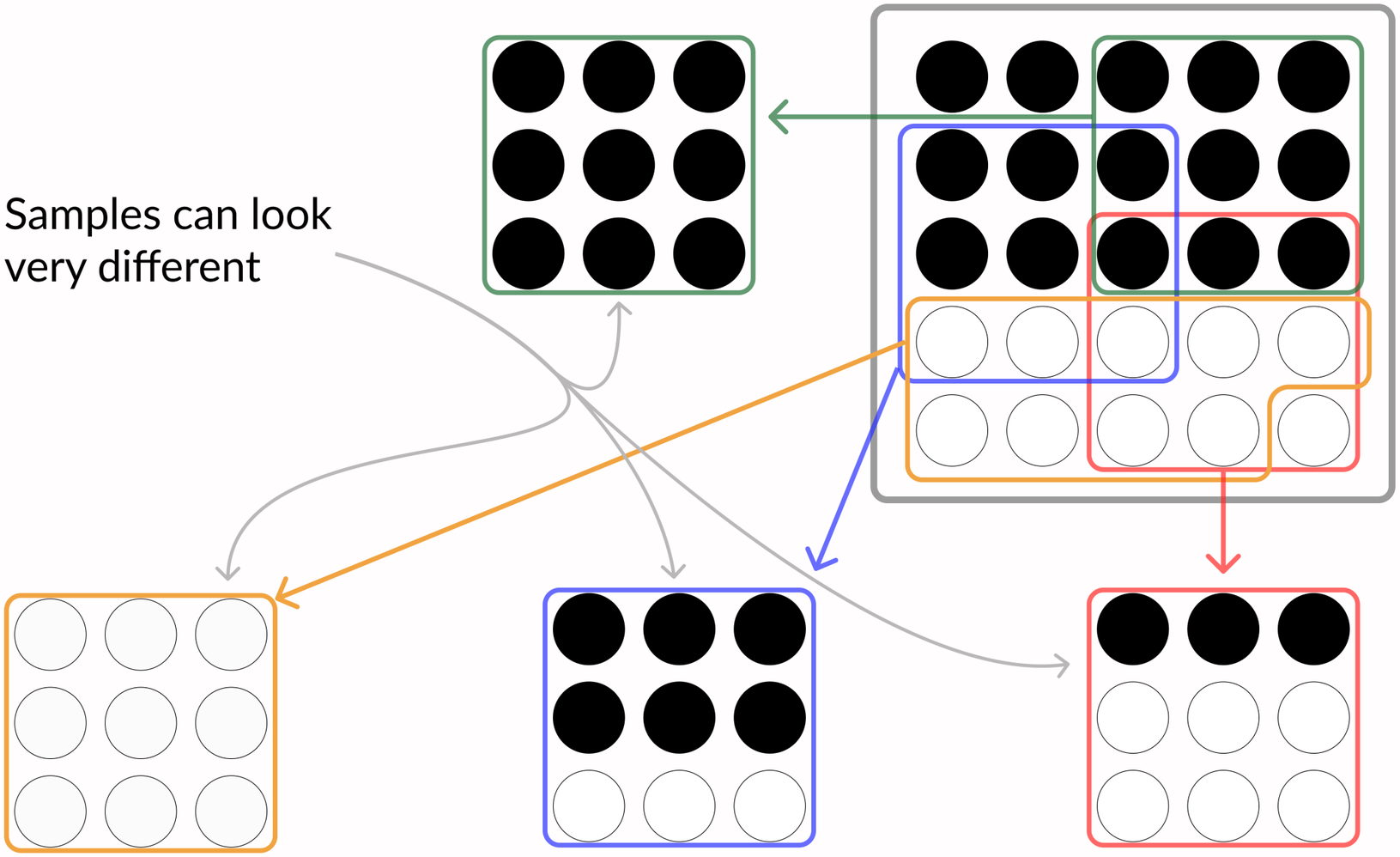


True proportion black to white sheep

What is uncertainty?



What is uncertainty?



When is uncertainty important?

Needs uncertainty

- *Estimates from sample*
  - Average of a subset
  - Linear model coefficients

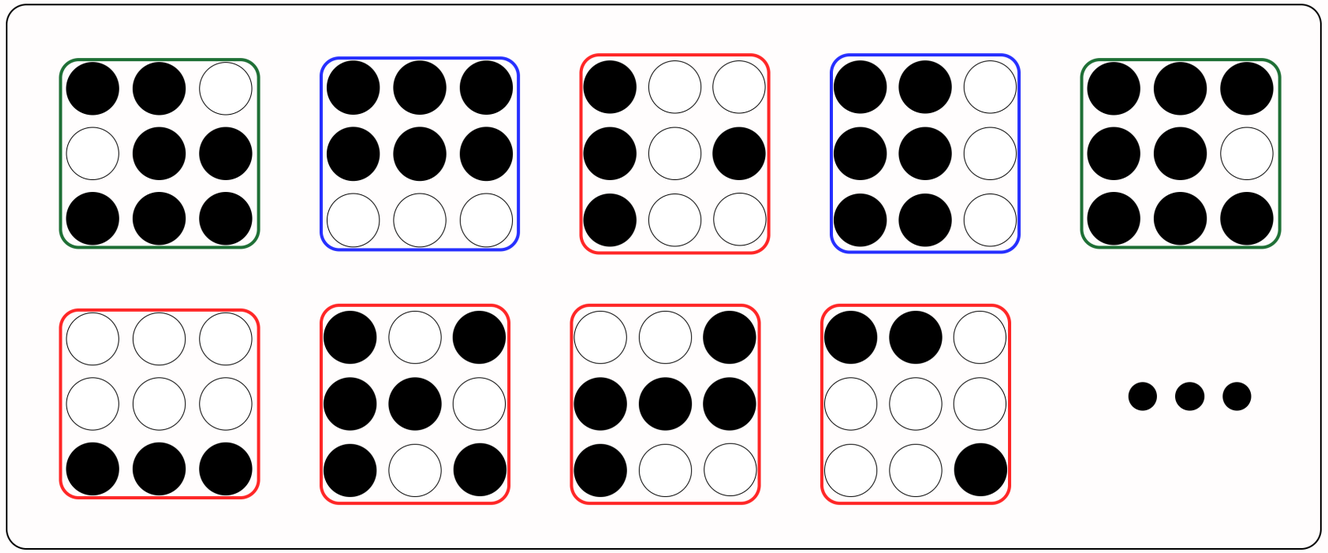
Doesn't need uncertainty

- *Facts*
  - Counts
  - Summaries of an entire population

Why is uncertainty important?

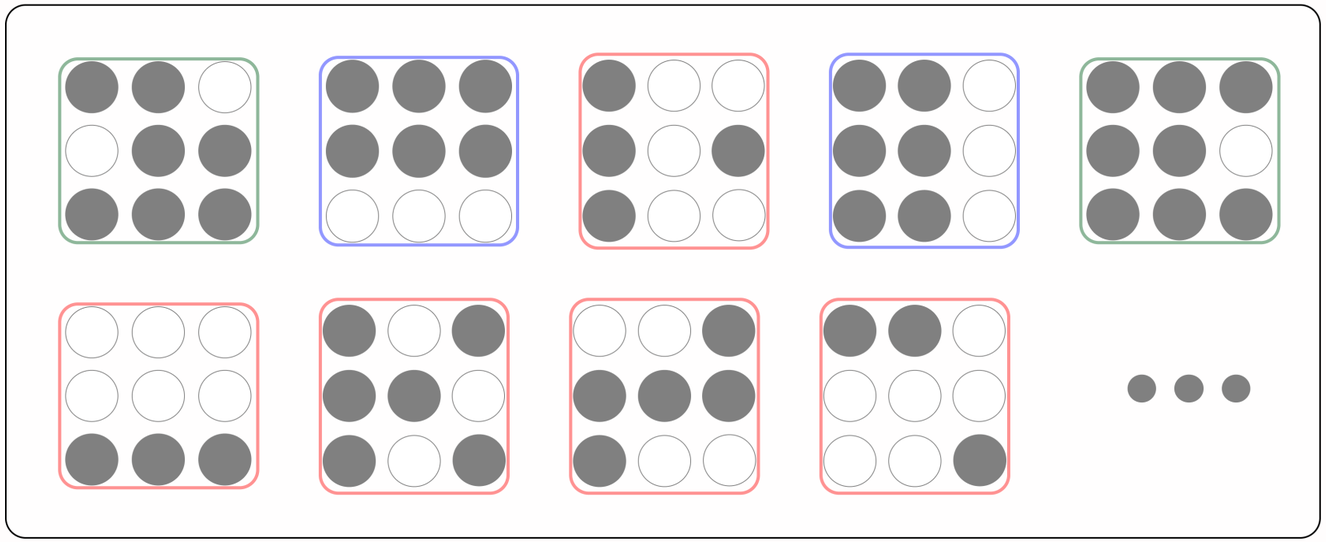
- Helps inform confidence in estimate
- Necessary for decision making
- Acknowledges limitations of data

The Confidence Interval

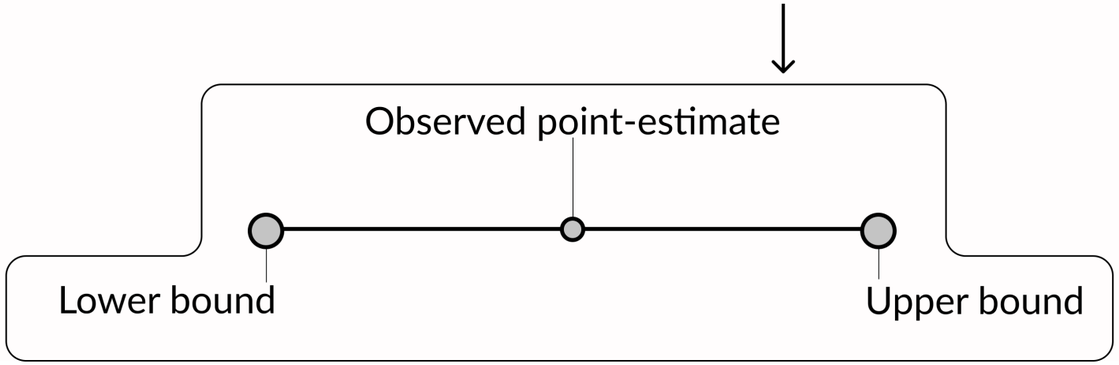


Pretend you could take infinite resamples of your data

The Confidence Interval

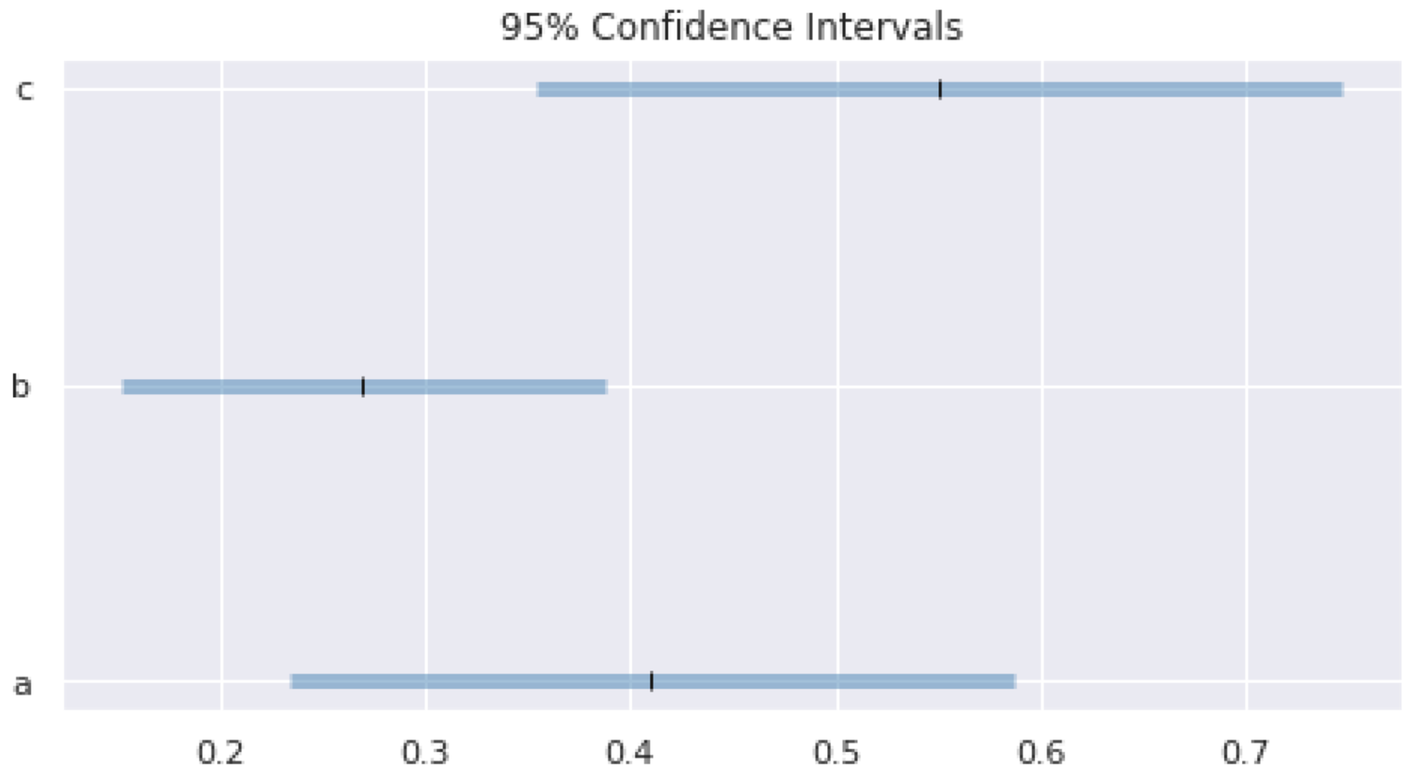


95% of estimates from the resamples will fall inside the **95%** confidence interval



```
plt.hlines(xmin='lower', xmax='upper', y='y', data=data,
           linewidth=5, color='steelblue', alpha=0.5)

# Point-estimate for reference
plt.plot('est', 'y', 'k|', data = data)
```



Let's show some uncertainty!

IMPROVING YOUR DATA VISUALIZATIONS IN PYTHON

Confidence bands

IMPROVING YOUR DATA VISUALIZATIONS IN PYTHON

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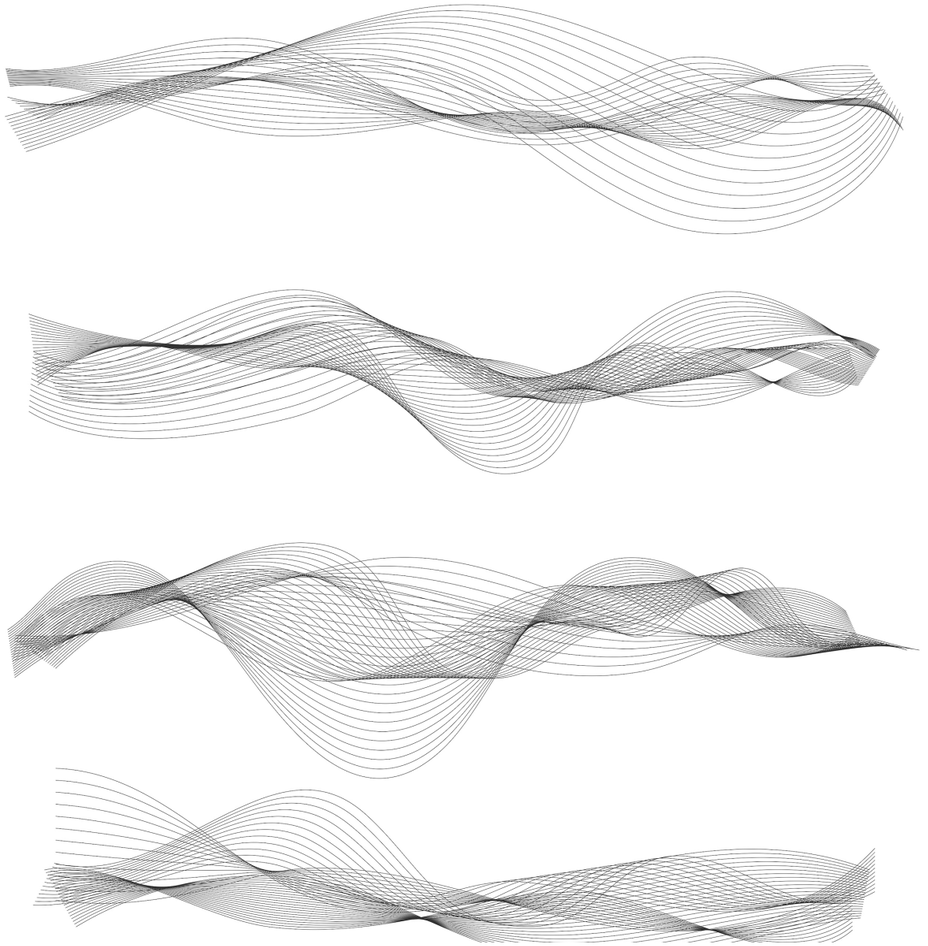
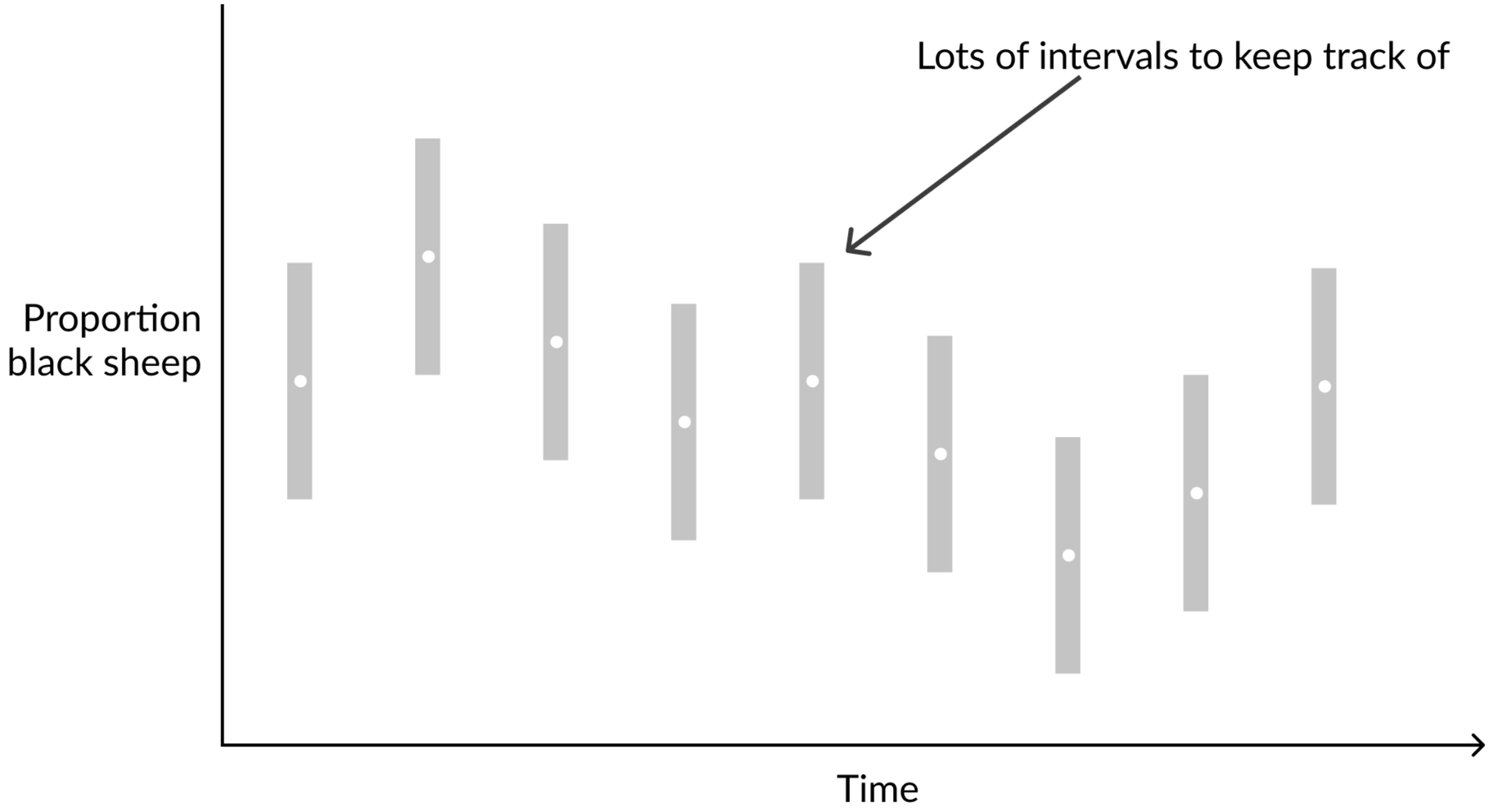
Continuous estimation functions

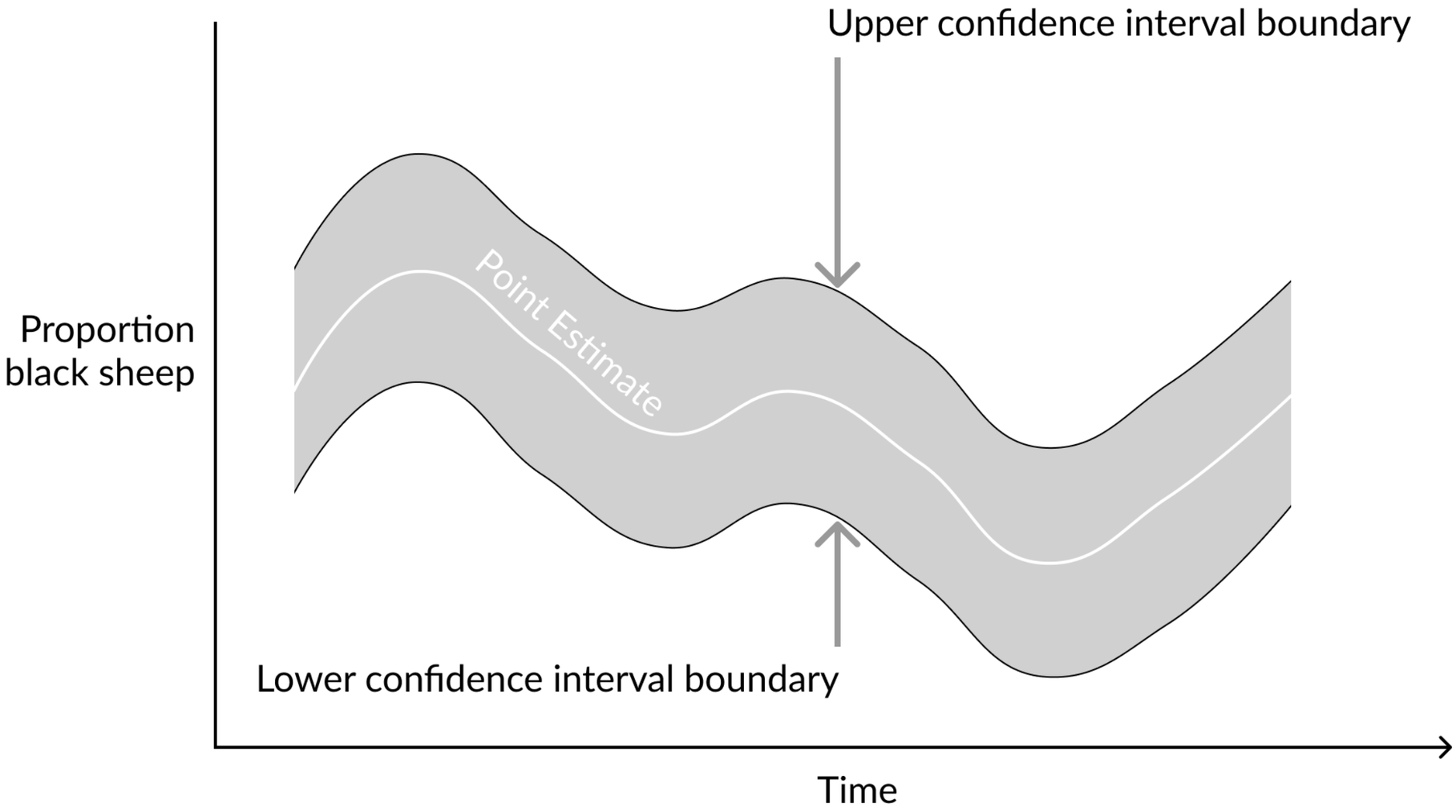
- Estimates over a continuous axis
- Often over time
- Have uncertainty and should be plotted as such.



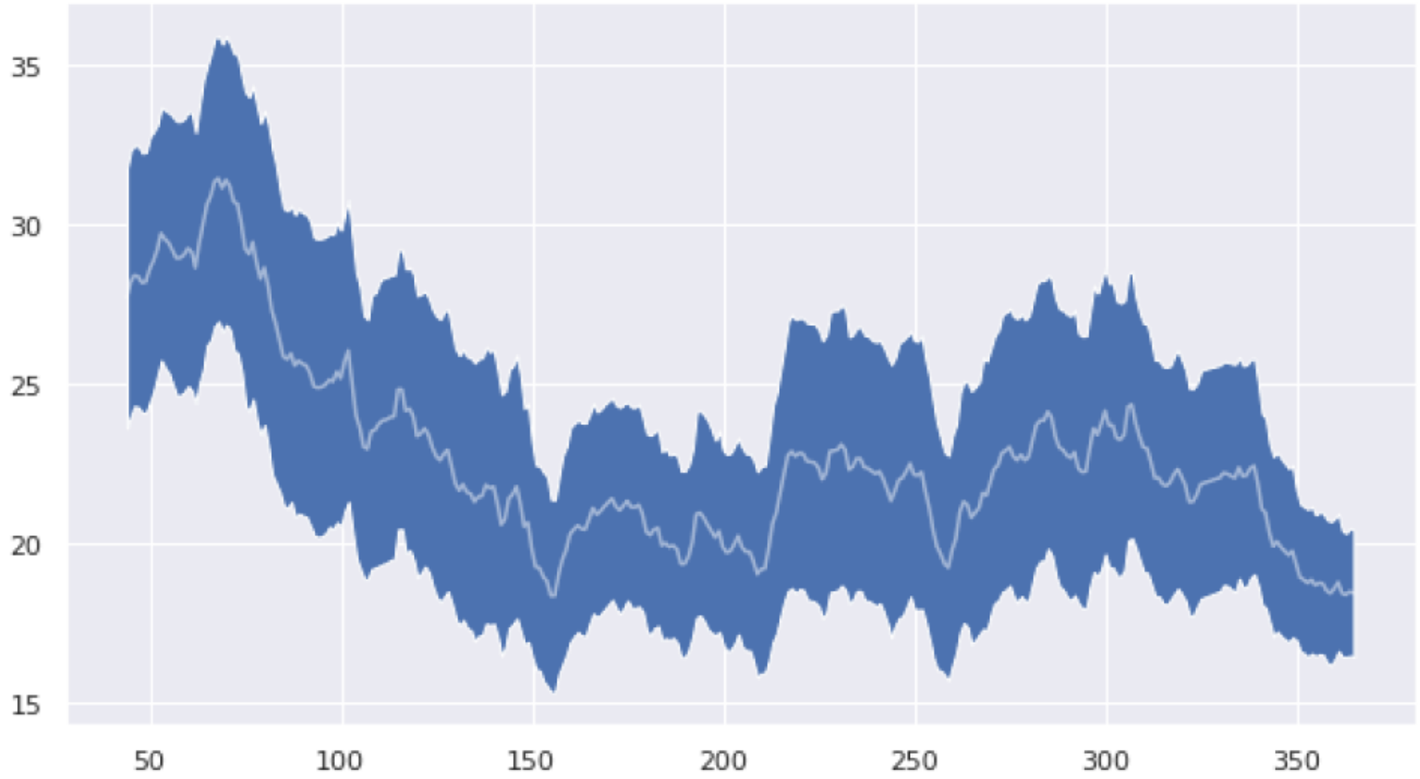
Lots of confidence intervals



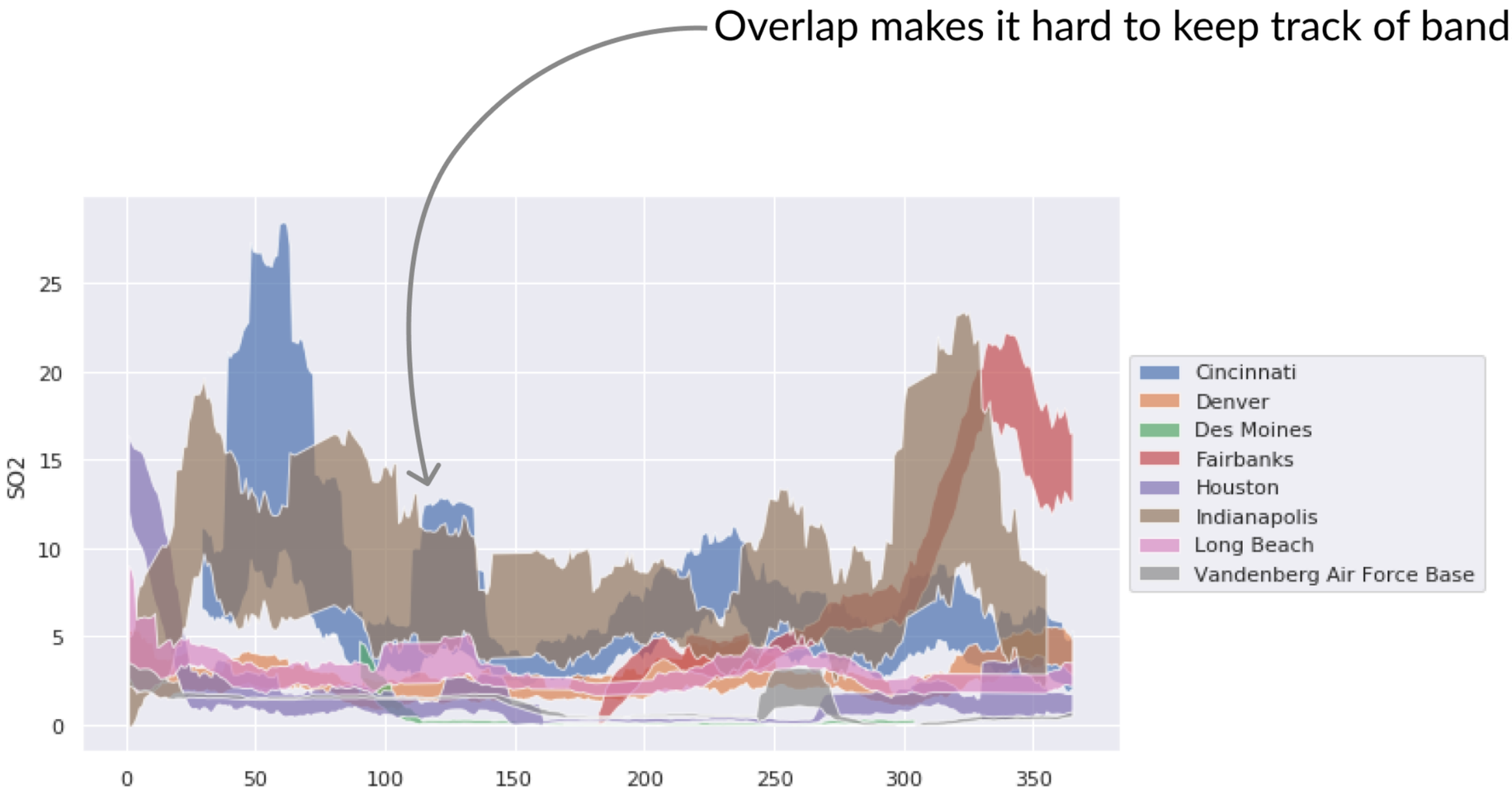
The confidence band



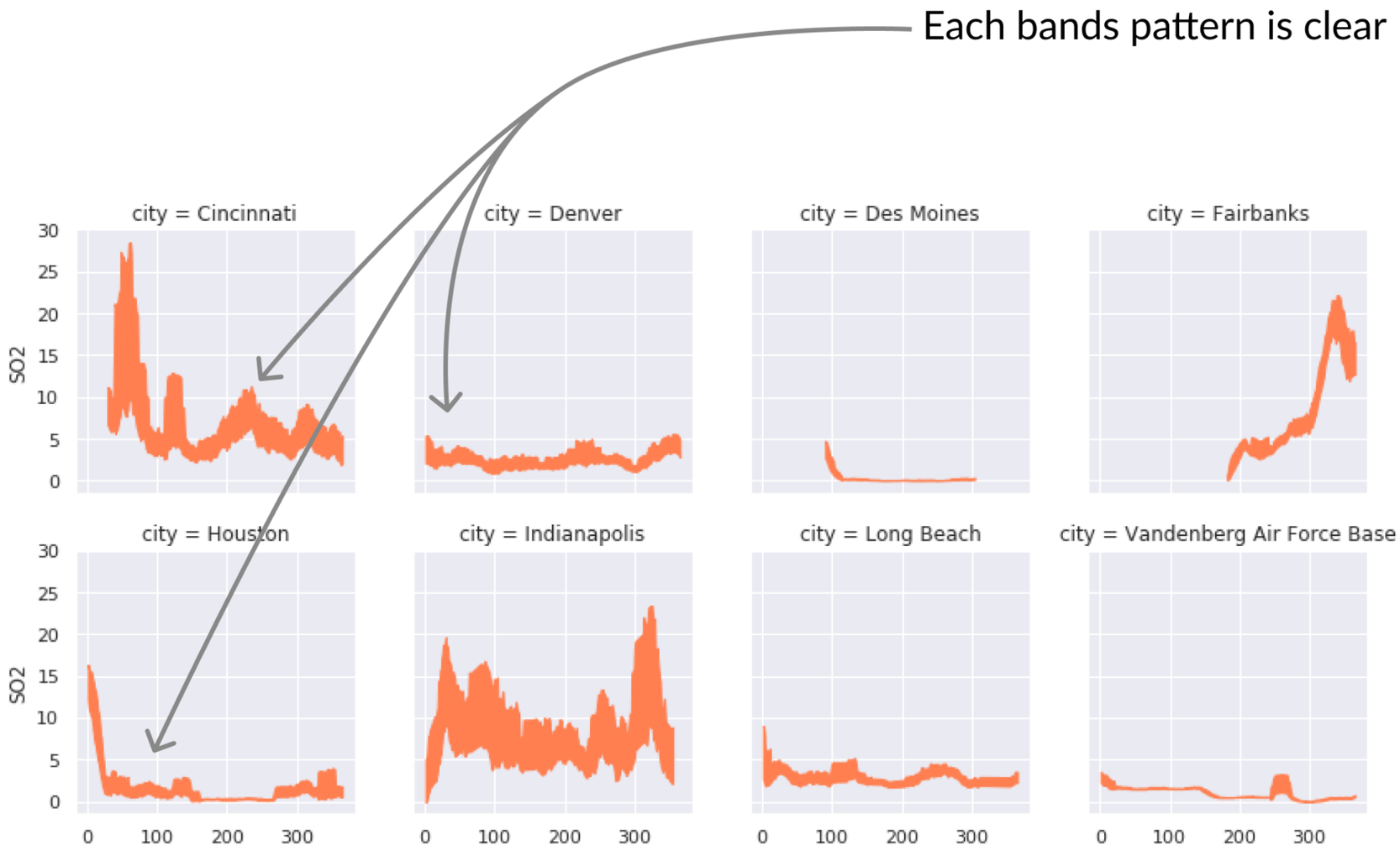
```
# Set lower and upper bounds of ribbon
plt.fill_between(x='day', y1='lower', y2='upper', data=cinci_so2)

# Add point-estimate reference line
plt.plot('day', 'mean', 'w-', alpha=0.5, data=data)
```



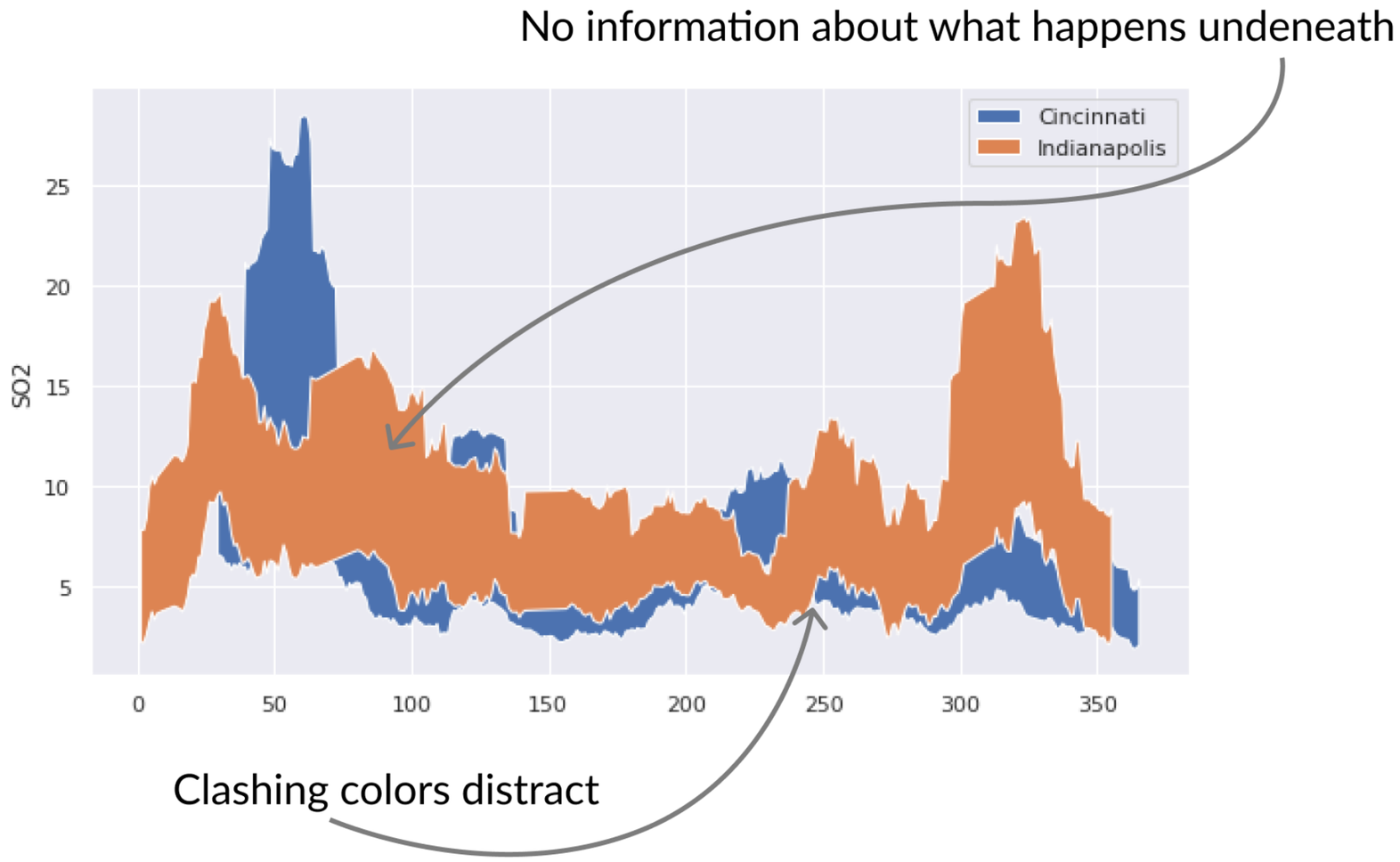
Separate your bands



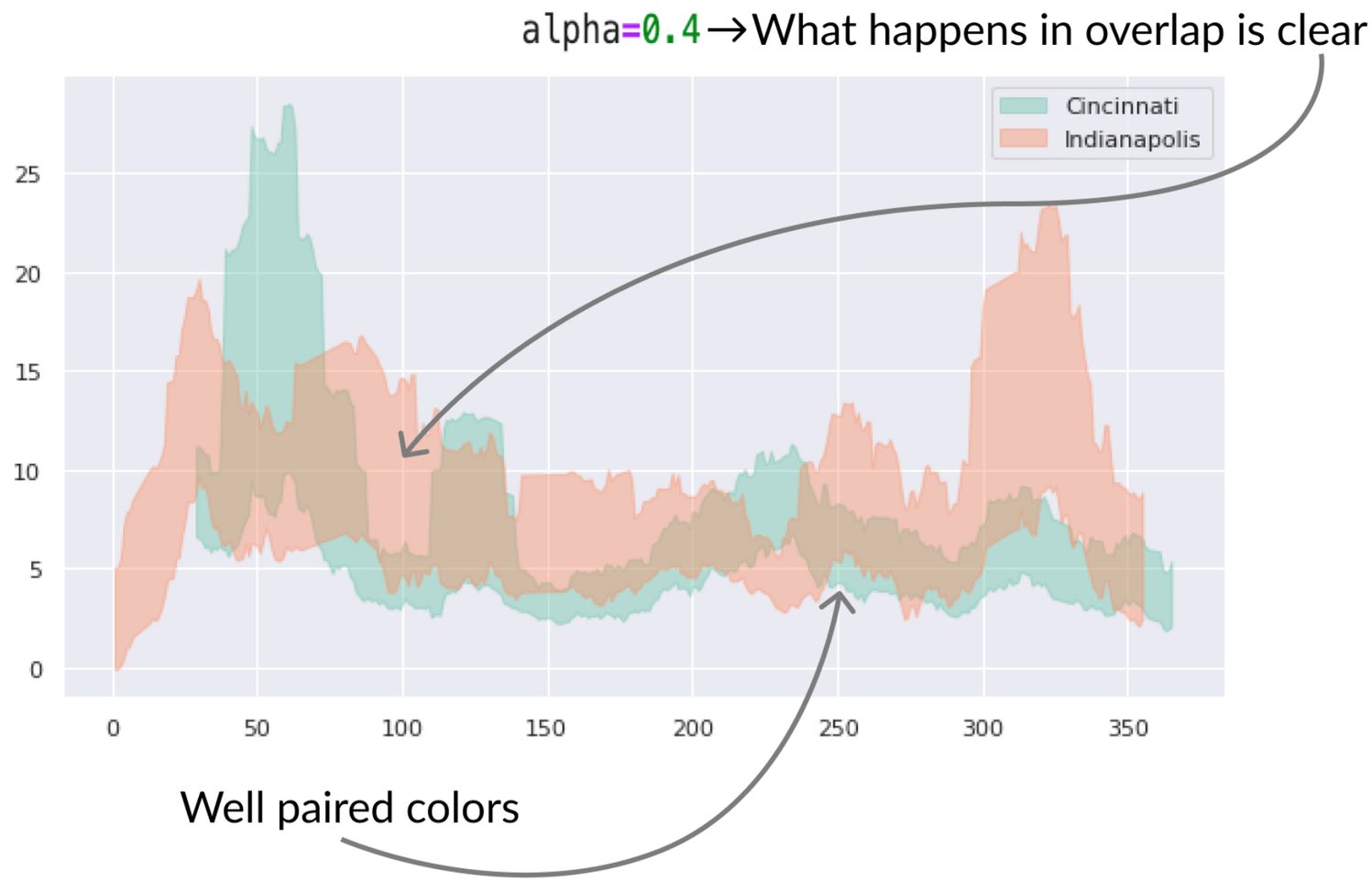
Separate your bands



Cleaning up confidence band comparisons



Cleaning up confidence band comparisons



Let's draw some bands!

IMPROVING YOUR DATA VISUALIZATIONS IN PYTHON

Beyond 95%

IMPROVING YOUR DATA VISUALIZATIONS IN PYTHON

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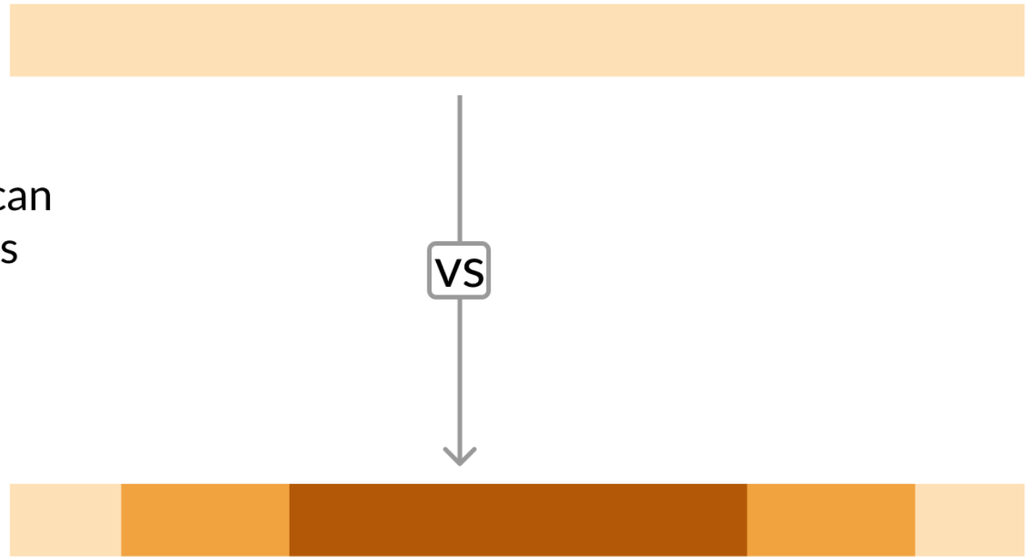
Instructor

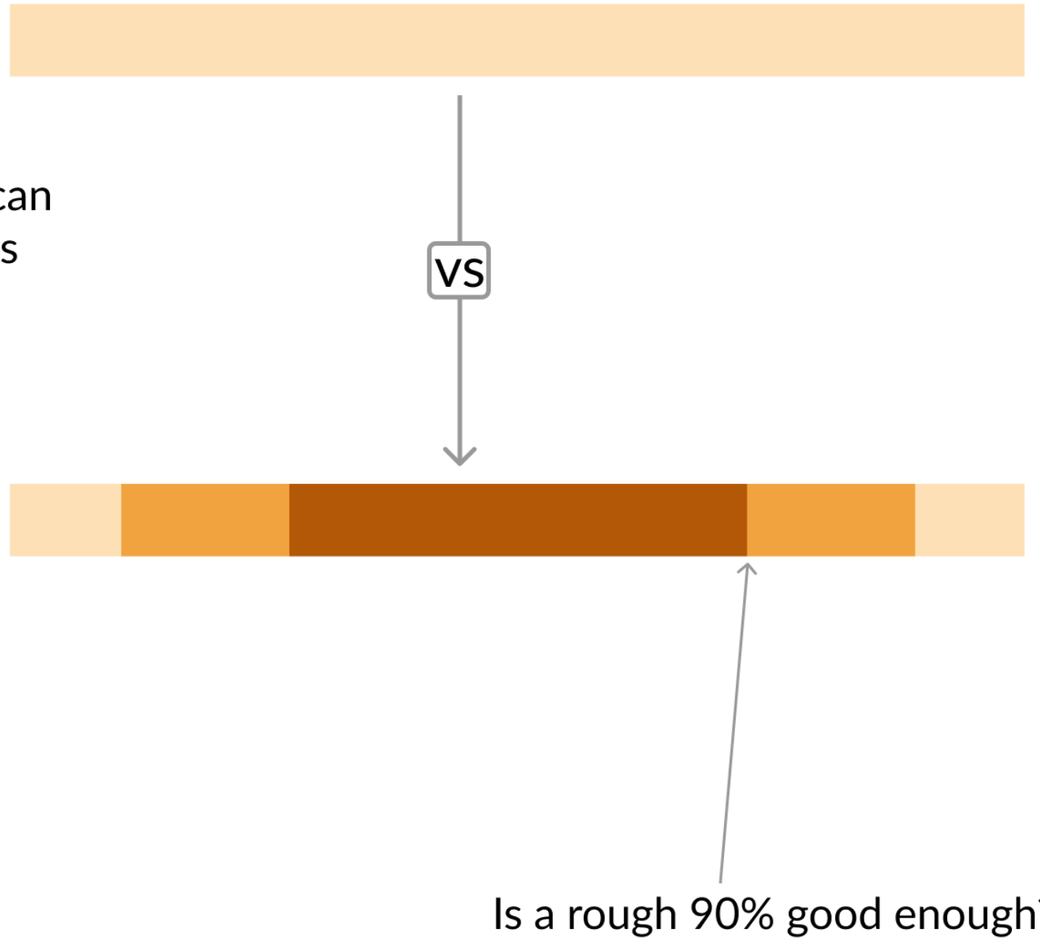
Why show more than one interval?

Different interval widths can answer different questions



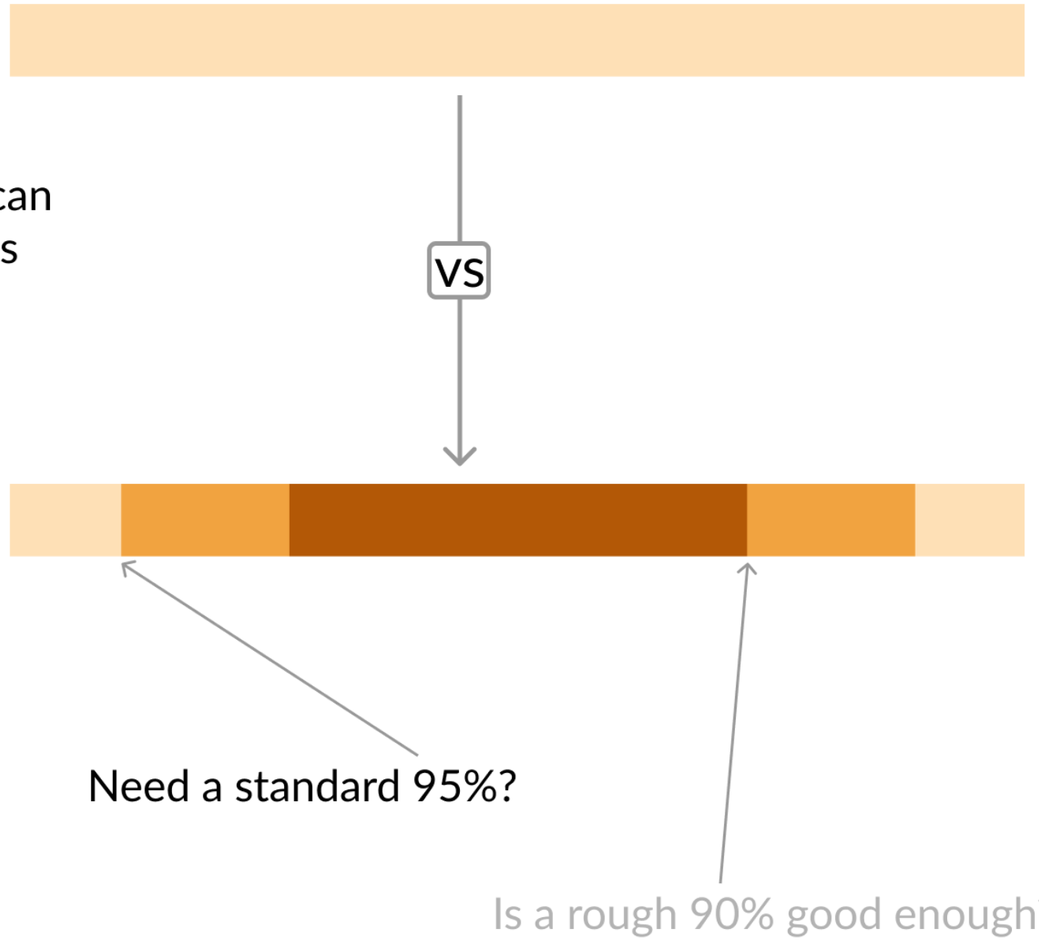
Why show more than one interval?

Different interval widths can answer different questions



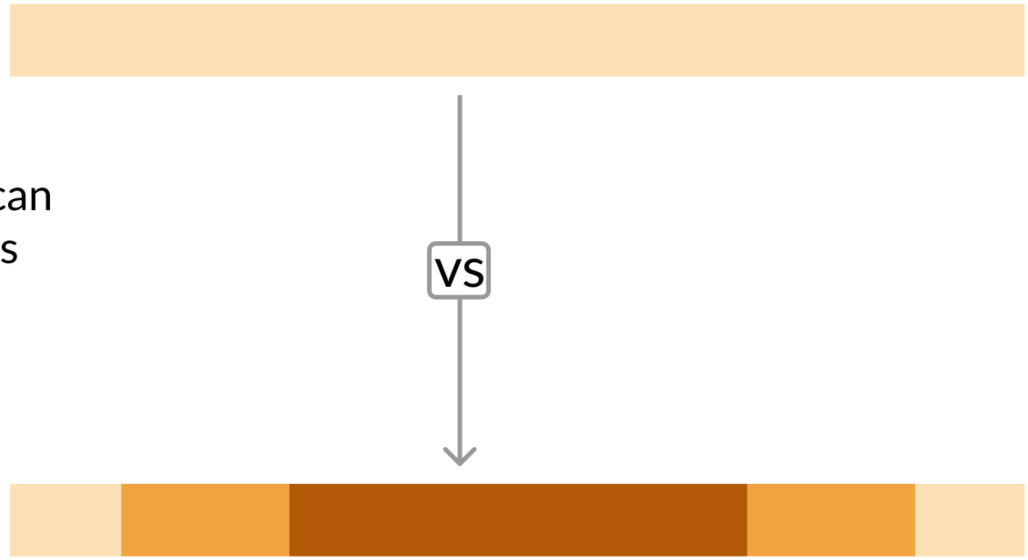
Why show more than one interval?

Different interval widths can answer different questions



Why show more than one interval?

Different interval widths can answer different questions

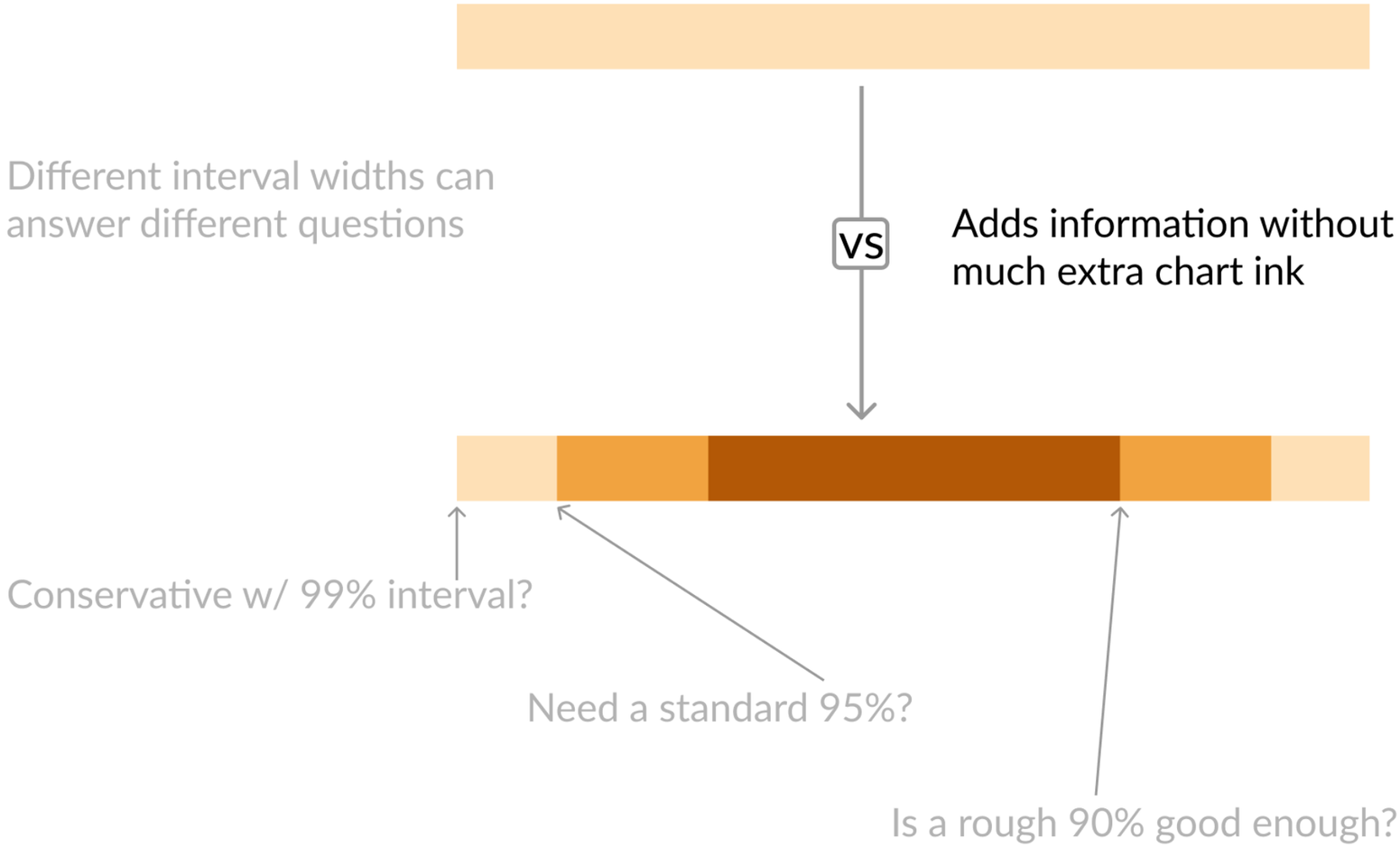


Conservative w/ 99% interval?

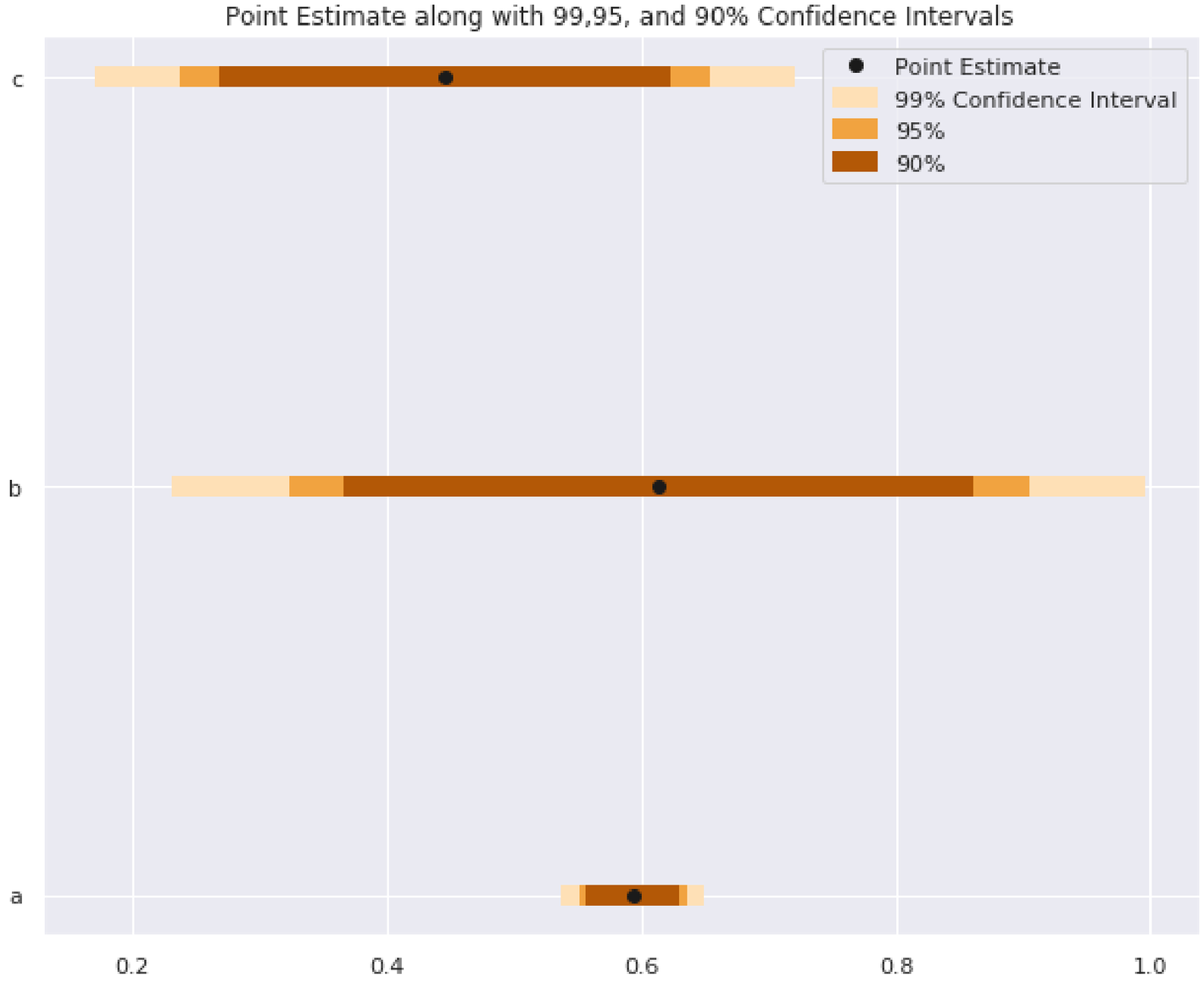
Need a standard 95%?

Is a rough 90% good enough?

Why show more than one interval?



```
# Interval size setup
sizes    = ['99%', '95%', '90%']
Z_scores = [2.58,   1.96,  1.67]
colors   = ['#fee0b6','#f1a340', '#b35806']

for size, z, color in zip(sizes, Z_scores, colors):

    plt.hlines(y = data.y,
               # Calculate lower and upper boundaries
               xmin = data['est'] - z*data['std_err'],
               xmax = data['est'] + z*data['std_err'],
               # Color by interval size
               color = color,
               # Make line thicker for visibility
               linewidth = 7,
               # Label line so legend text is clear
               label = size)
plt.plot('est', 'y', 'ko', data = data, label = 'Point Estimate')
plt.legend()
```


Point Estimate along with 99,95, and 90% Confidence Intervals
Point Estimate
99% Confidence Interval
95%
90%
c
b
a
0.2
0.4
0.6
0.8
1.0

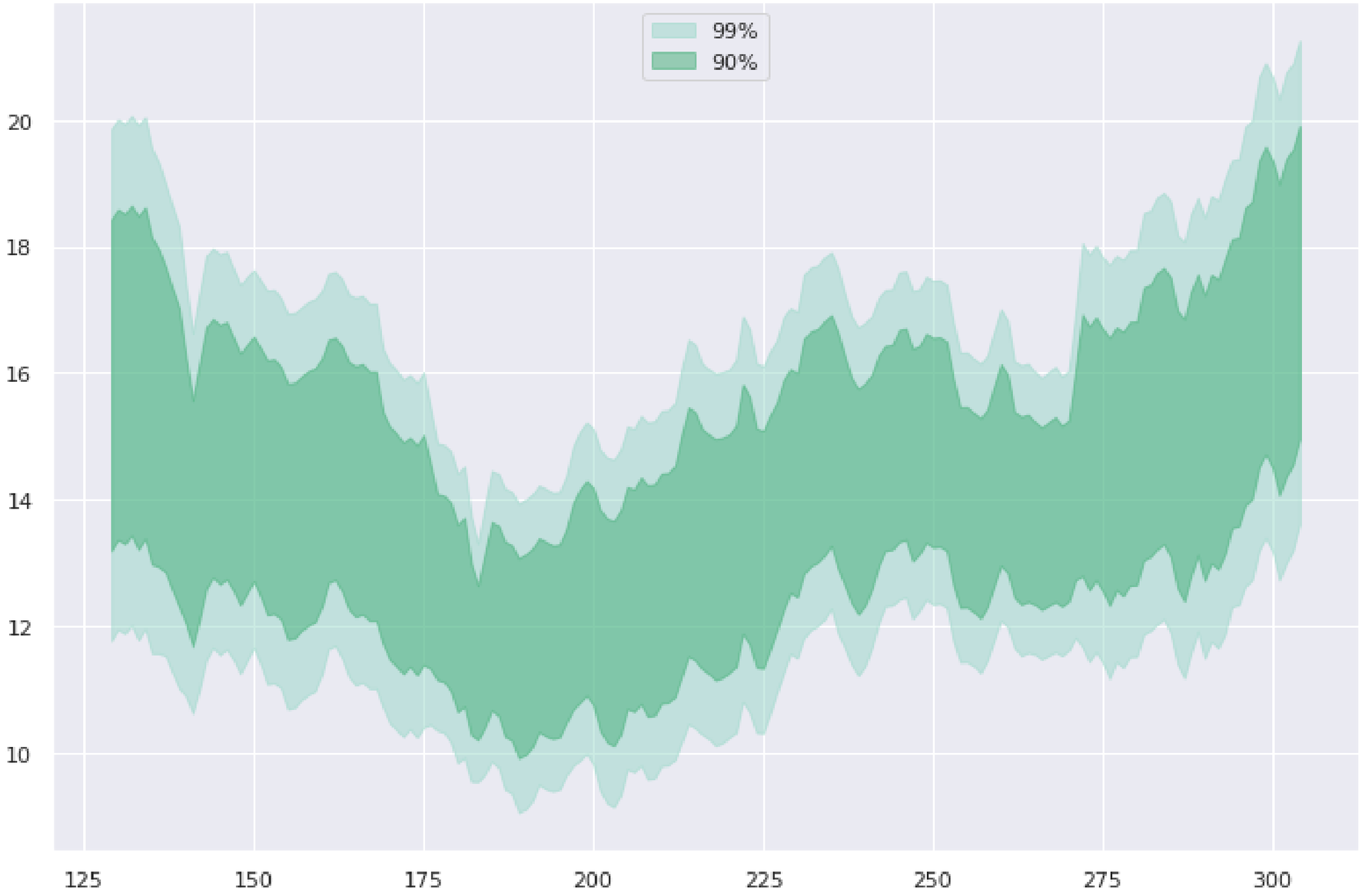
Coloring your intervals

Lighter colors on inside create illusion of two intervals

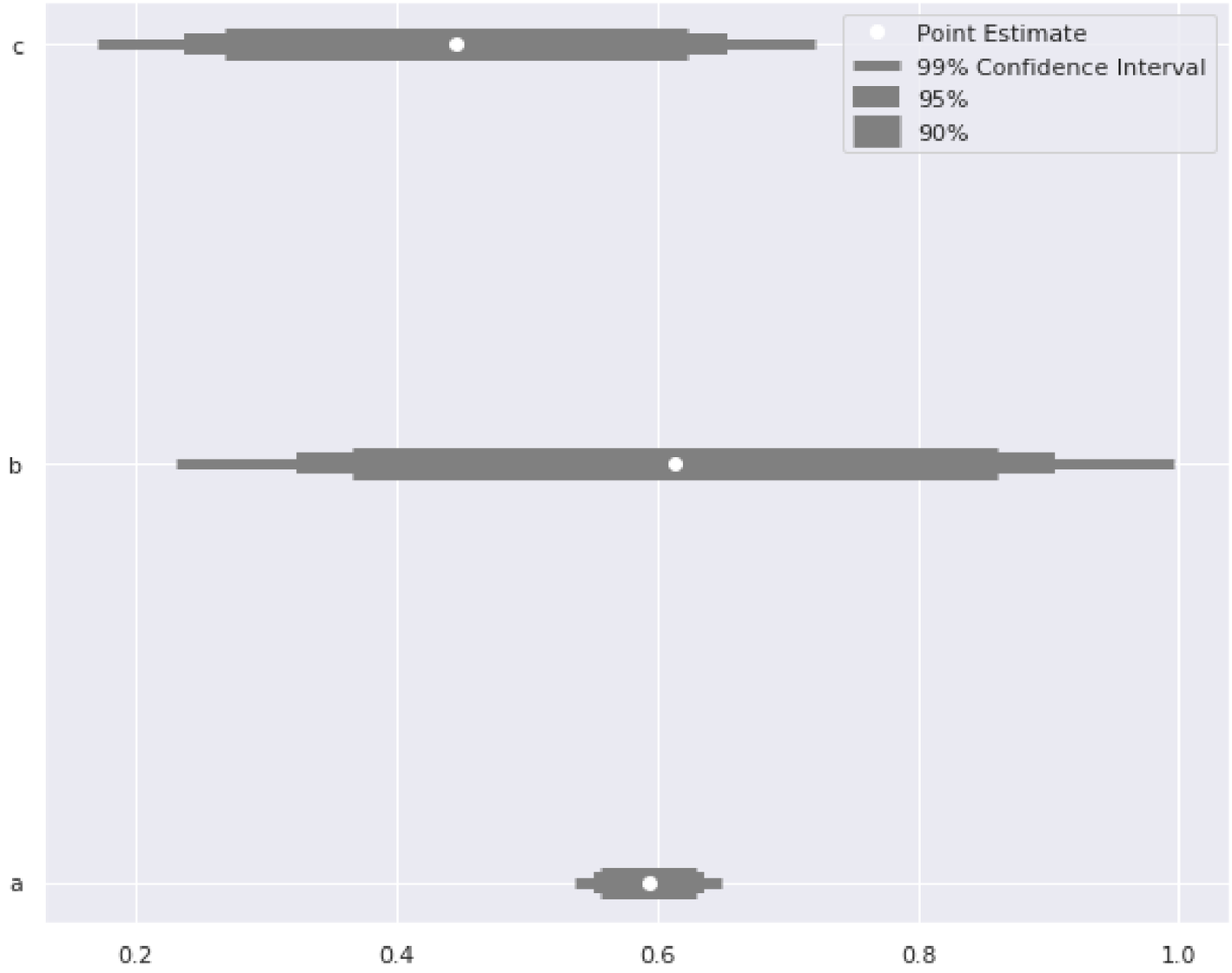
Colors too similar make reading difficult

Well separated ordinal palette with darker colors inside

```
widths   = [    '99%',     '90%']
z_scores = [     2.58,      1.67]
colors   = ['#99d8c9', '#41ae76']

for percent, Z, color in zip(widths, z_scores, colors):
    # Set color to distinquish bands
    plt.fill_between(
        x=data.day,
        y1=data['mean'] - Z*data['std_err'],
        y2=data['mean'] + Z*data['std_err']
        color=color,
        # Lower opacity so grid can show through
        alpha=0.5,
        # Give each band id for the legend
        label=percent)
```


99%
90%
20
18
16
14
12
10
125
150
175
200
225
250
275
300

```
sizes = ['99% Confidence Interval', '95%', '90%']

# Set up different line widths for intervals
widths   = [   5,     10,    15]
Z_scores = [2.58,   1.96,  1.67]

for size, z, width in zip(sizes, Z_scores, widths):
    plt.hlines(
        y = data.y, label = size,
        xmin = data['est'] - z*data['std_err'],
        xmax = data['est'] + z*data['std_err'],
        color = 'grey'
        # Adjust line thickness by interval
        linewidth = width)
plt.plot('est', 'y', 'wo', data = data, label = 'Point Estimate')
plt.legend()
```


Point Estimate
99% Confidence Interval
95%
90%
c
b
a
0.2
0.4
0.6
0.8
1.0

Let's expand our boundaries!

IMPROVING YOUR DATA VISUALIZATIONS IN PYTHON

Visualizing the bootstrap

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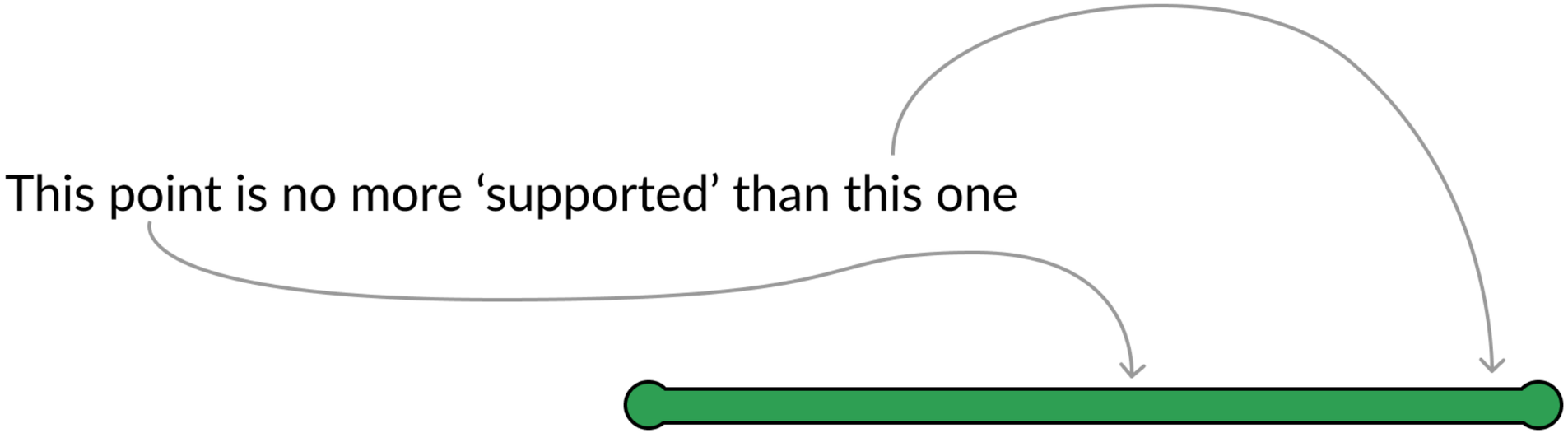
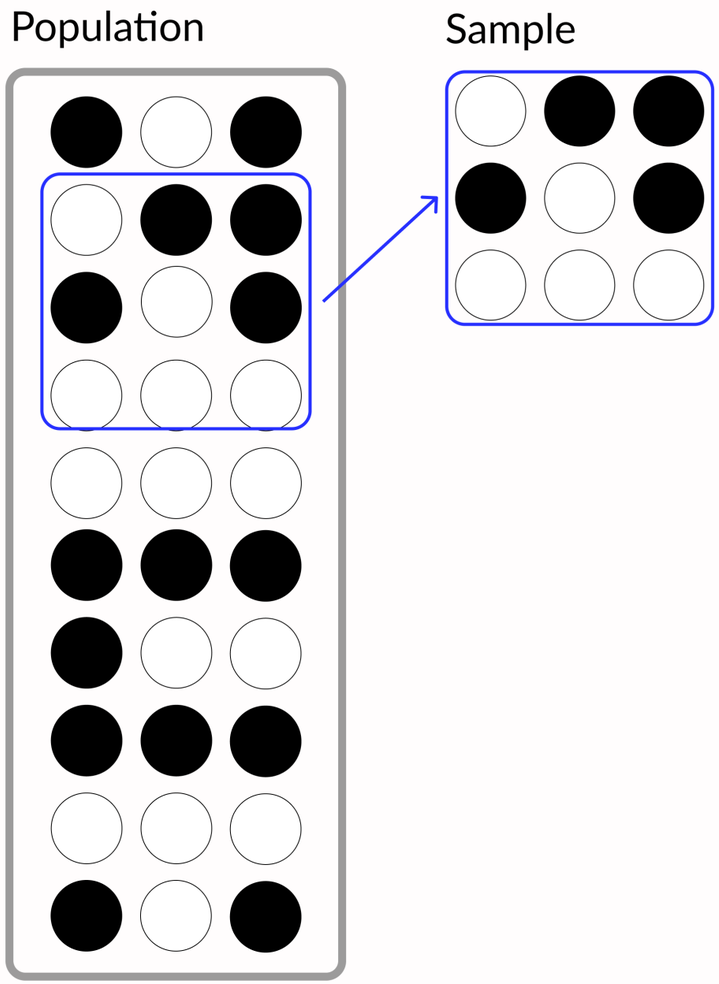
Confidence interval issues



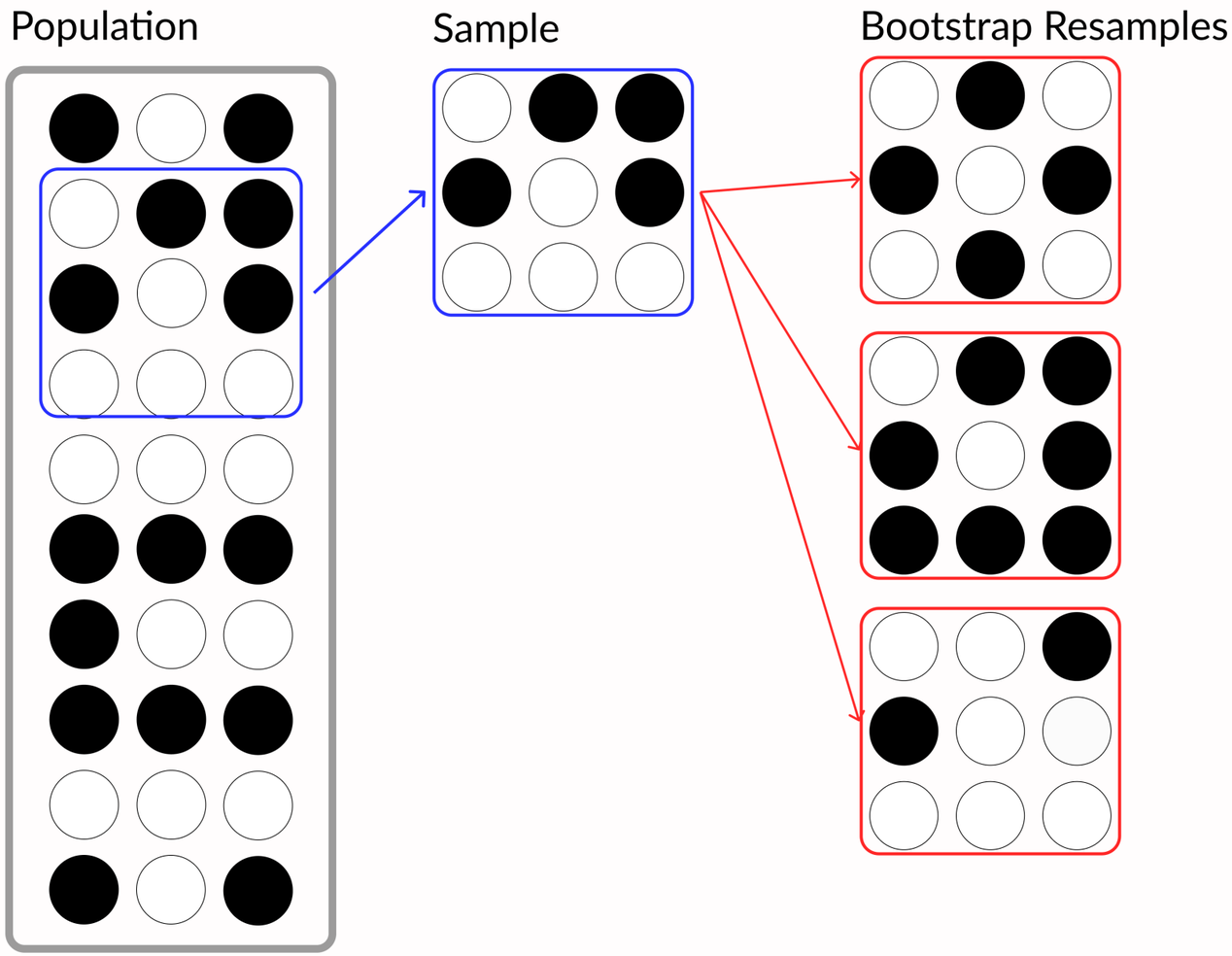
Confidence interval issues

It would be nice to have statements about support within our interval

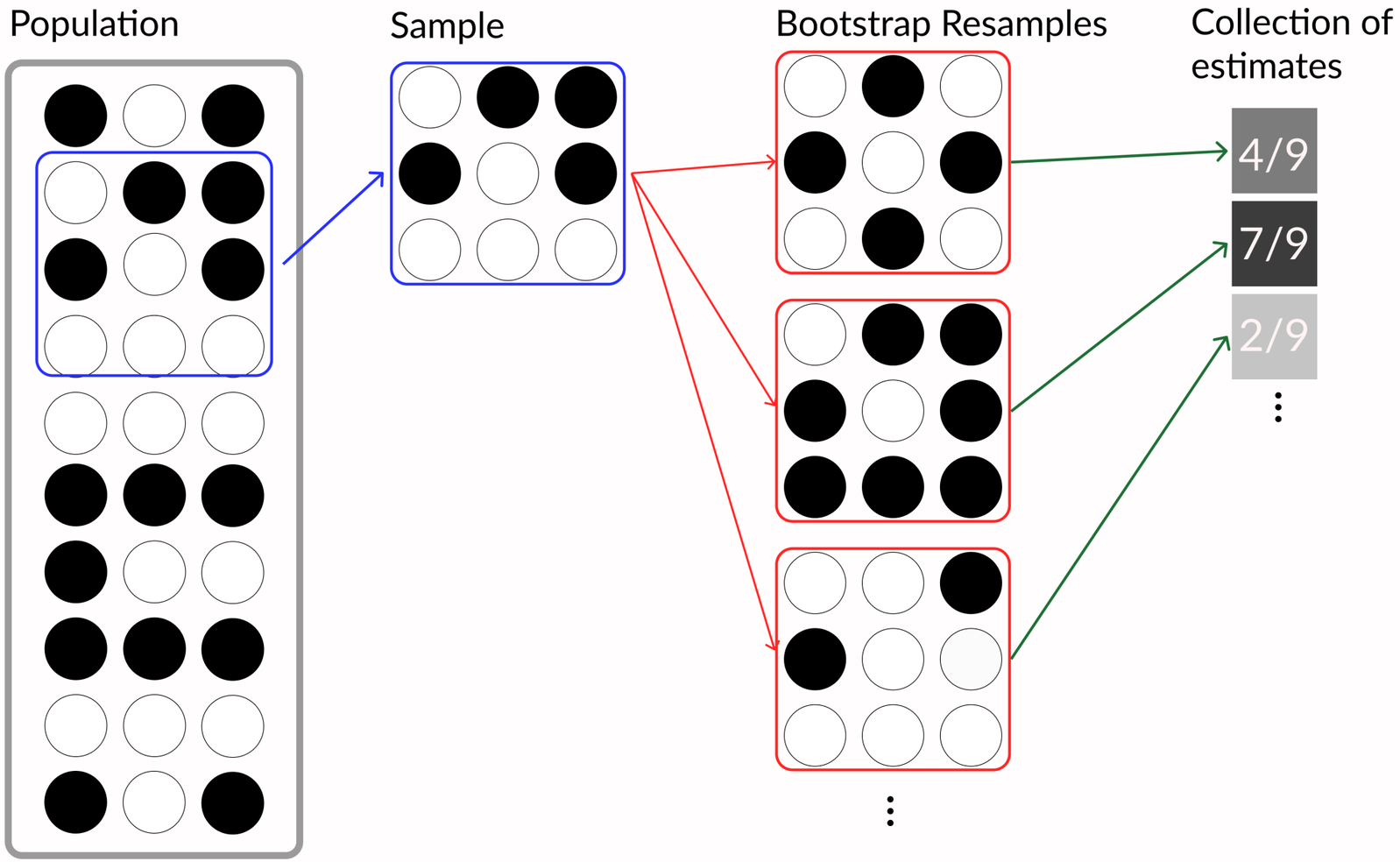
The “Bootstrap”



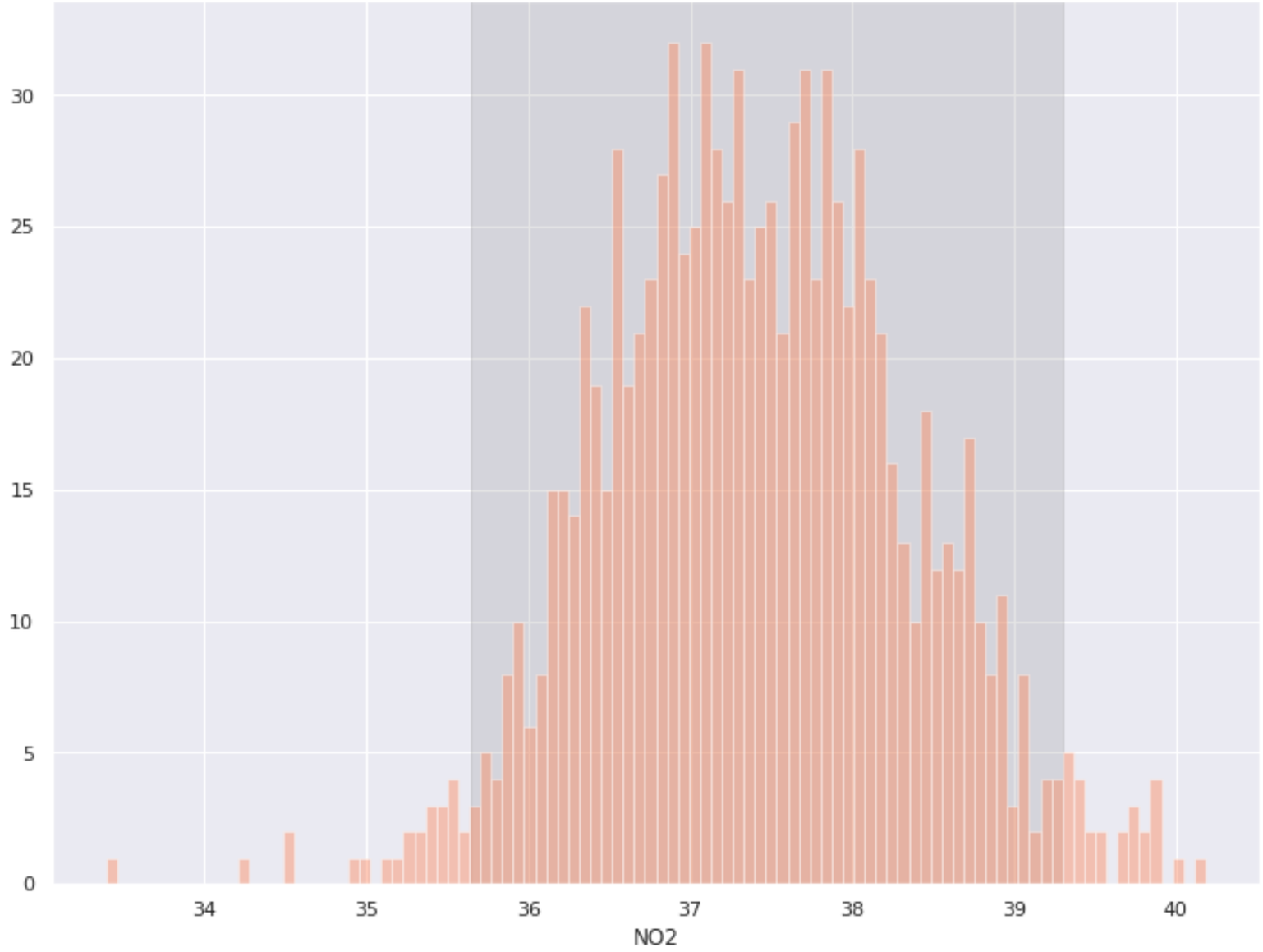
The “Bootstrap”



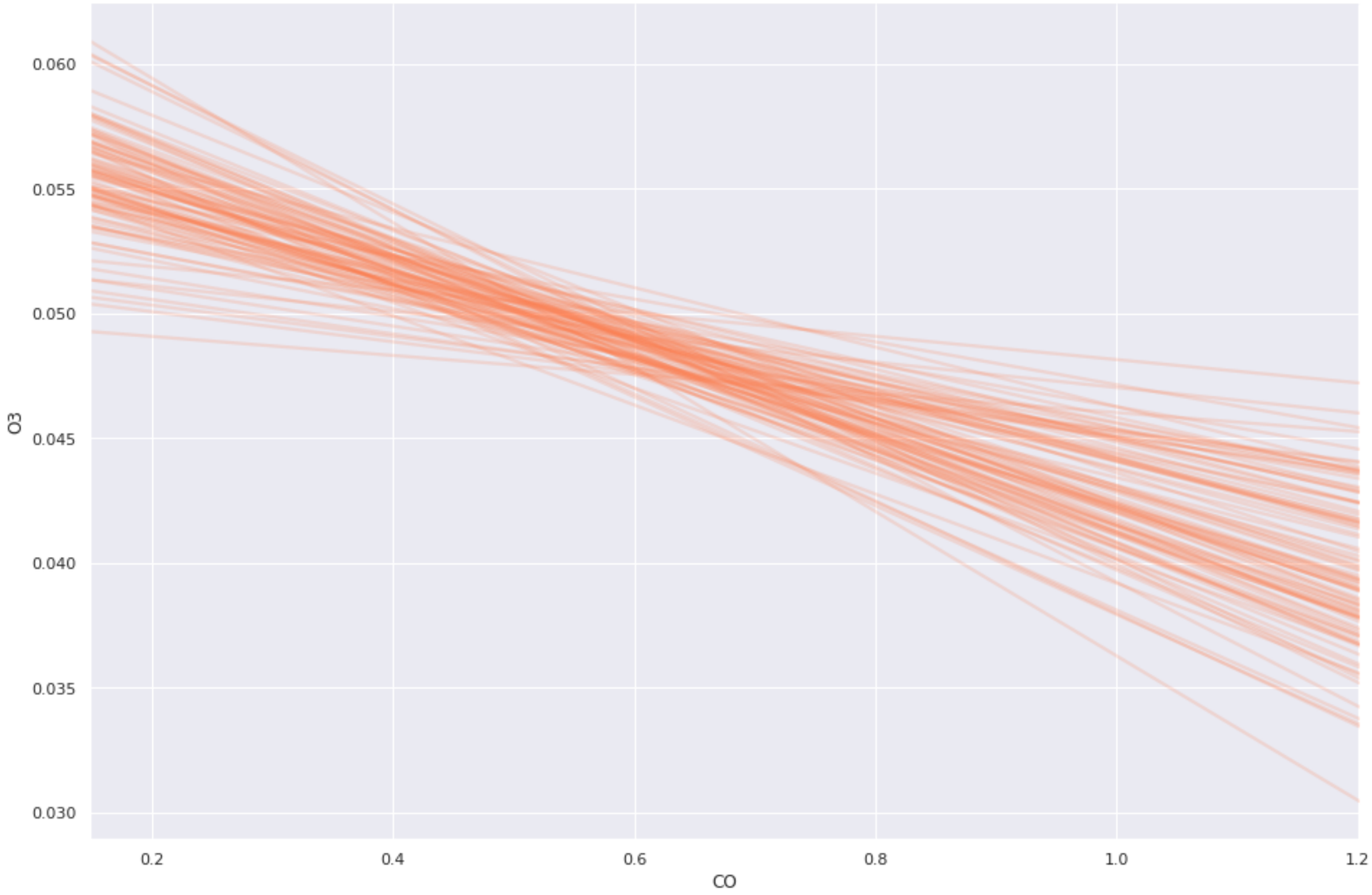
The “Bootstrap”



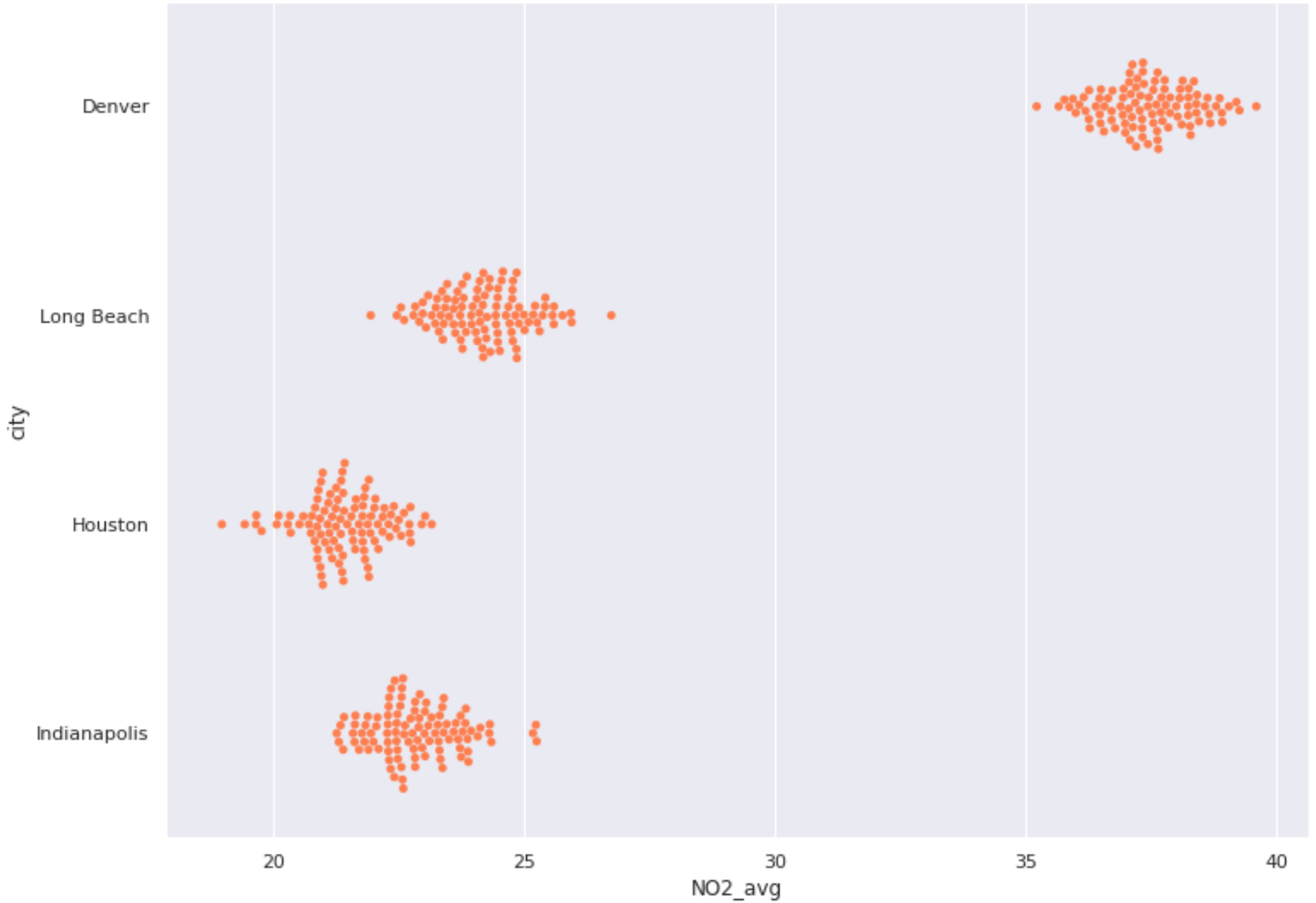
```
denver_may = pollution.query("city == 'Denver' & month == 8")

# Perform bootstrapped mean on a vector
def bootstrap(data, n_boots):
    return [np.mean(np.random.choice(data,len(data)))
            for _ in range(n_boots) ]

# Generate 1,000 bootstrap samples
boot_means = bootstrap(denver_may.NO2, 1000)

# Get lower and upper 95% interval bounds
lower, upper = np.percentile(boot_means, [2.5, 97.5])

# Shaded background of interval
plt.axvspan(lower, upper, color='grey', alpha=0.2)

# Plot histogram of samples
sns.distplot(boot_means, bins = 100, kde=False)
```


30
25
20
15
10
5
0
34
35
36
37
38
39
40
NO2

```
# Make dataframe of bootstraped data
denver_may_boot = pd.concat([
    denver_may.sample(n=len(denver_may), replace=True).assign(sample=i)
    for i in range(100)])

# Plot regressions for each sample
sns.lmplot('CO', 'O3', data=denver_may_boot, scatter=False,
           # Tell seaborn to draw a regression
           # line for each resample's data
           hue='sample',
           # Make lines orange and transparent
           line_kws = {'color': 'coral', 'alpha': 0.2},
           # No confidence intervals
           ci=None, legend = False)
```


0.060
0.055
0.050
0.045
0.040
0.035
0.030
O3
0.2
0.4
0.6
0.8
1.0
1.2
CO

```
aug_pol = pollution.query("month == 8")

# Holder DataFrame for bootstrap samples
city_boots = pd.DataFrame()

for city in ['Denver', 'Long Beach', 'Houston', 'Indianapolis']:
    # Filter to city's NO2
    city_NO2 = aug_pol[aug_pol.city == city].NO2
    # Perform 100 bootstrap samples of city's NO2 & put in DataFrame
    cur_boot = pd.DataFrame({ 'NO2_avg': bootstrap(city_NO2, 100),
                              'city': city })
    # Append to other city's bootstraps
    city_boots = pd.concat([city_boots,cur_boot])

# Use beeswarm plot to visualize bootstrap samples
sns.swarmplot(y="city", x="NO2_avg", data=city_boots,
              # Set all the colors to be the same
              color='coral')
```


Denver
Long Beach
Houston
Indianapolis
city
20
25
30
35
40
NO2_avg

Let's get (re)sampling

IMPROVING YOUR DATA VISUALIZATIONS IN PYTHON