STATISTICAL THINKING IN PYTHON II

Welcome to the course!

You will be able to...

- Estimate parameters
- Compute confidence intervals
- Perform linear regressions
- Test hypotheses

with *real* data!


Caltech

We use hacker statistics

- Literally simulate probability
- Broadly applicable with a few principles

Statistical analysis of the beak of the finch

Geospiza fortis

Geospiza scandens

Source: John Gould, public domain

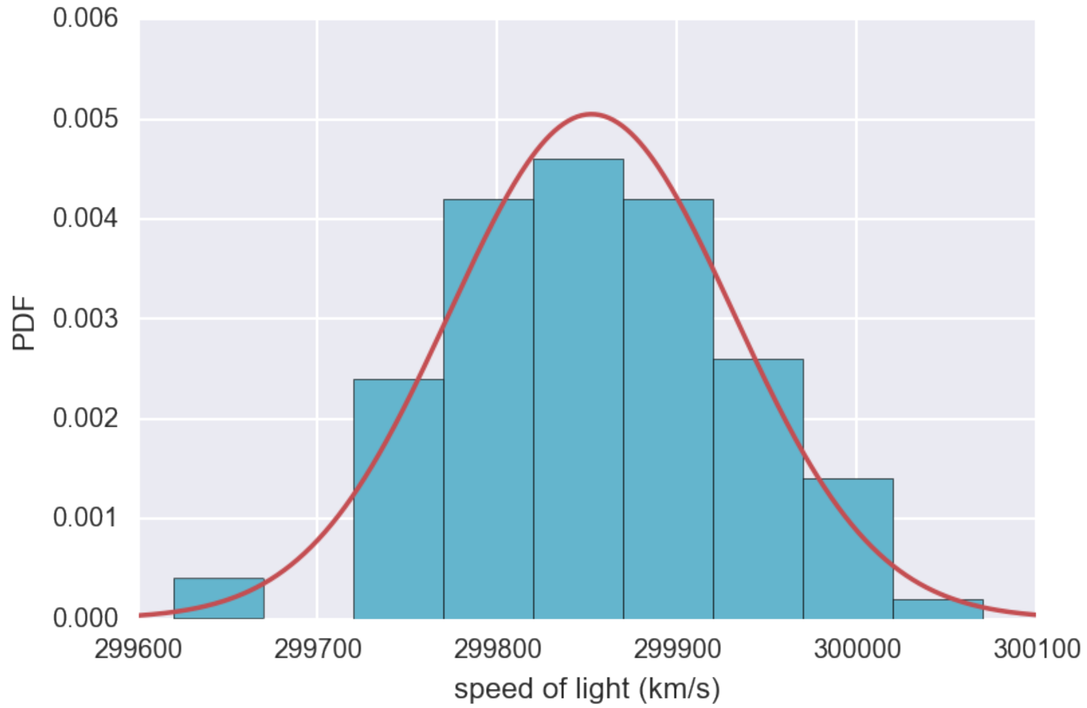
STATISTICAL THINKING IN PYTHON II

Let's start thinking statistically!

STATISTICAL THINKING IN PYTHON II

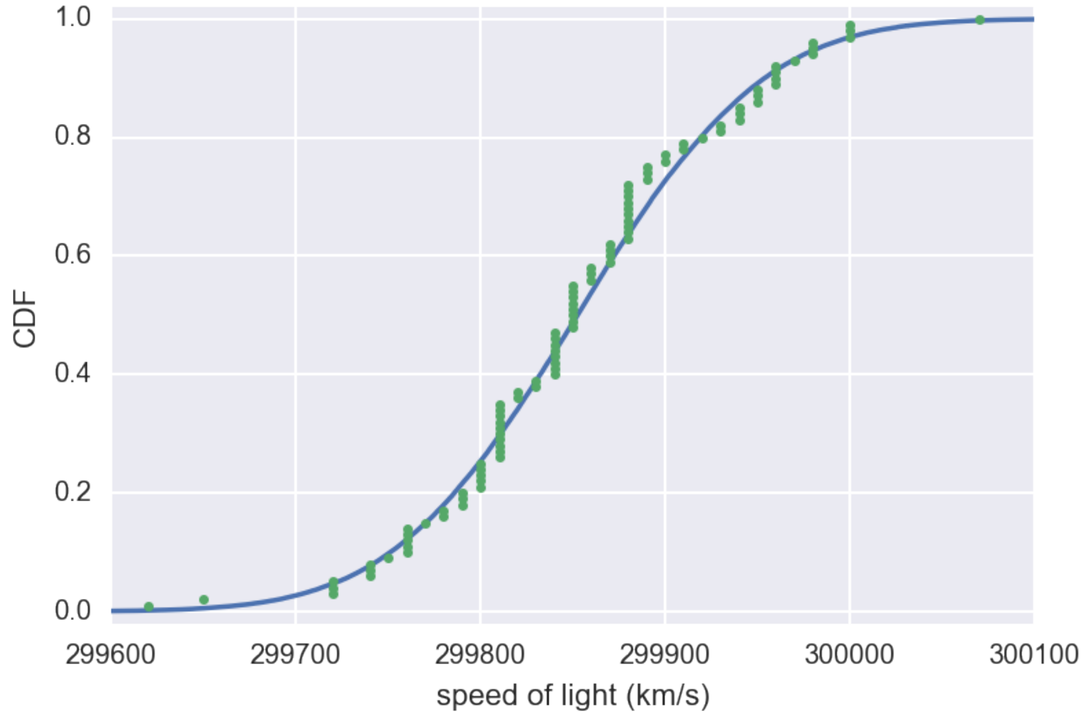
Optimal parameters

Histogram of Michelson's measurements



Data: Michelson, 1880

CDF of Michelson's measurements

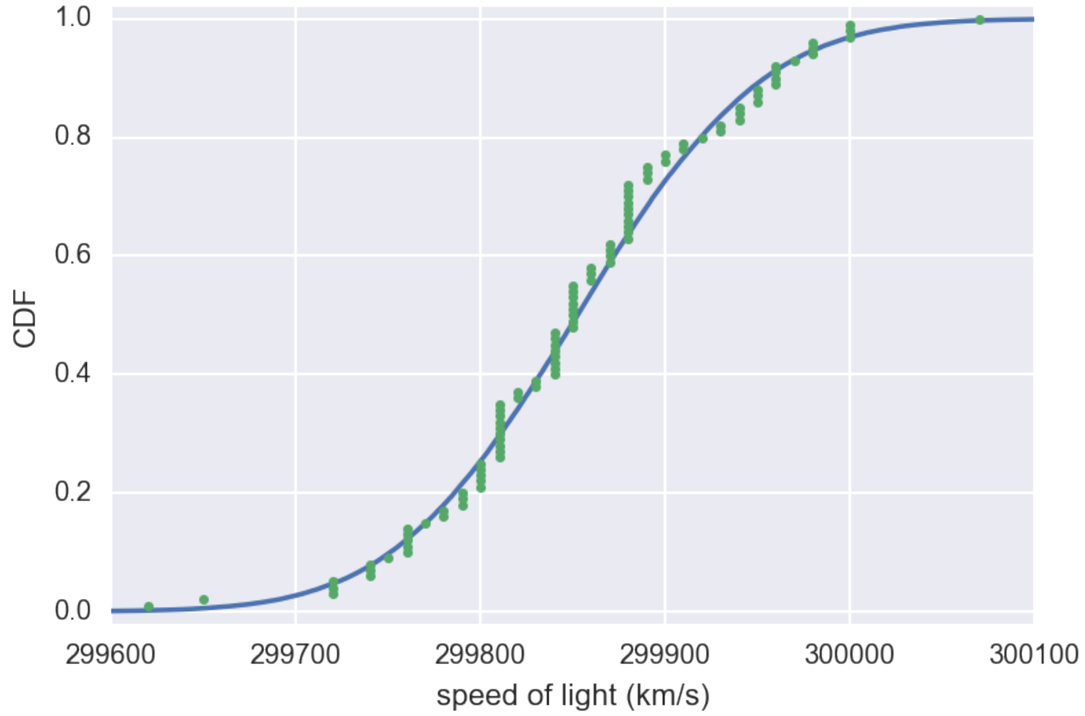


Data: Michelson, 1880

Checking Normality of Michelson data

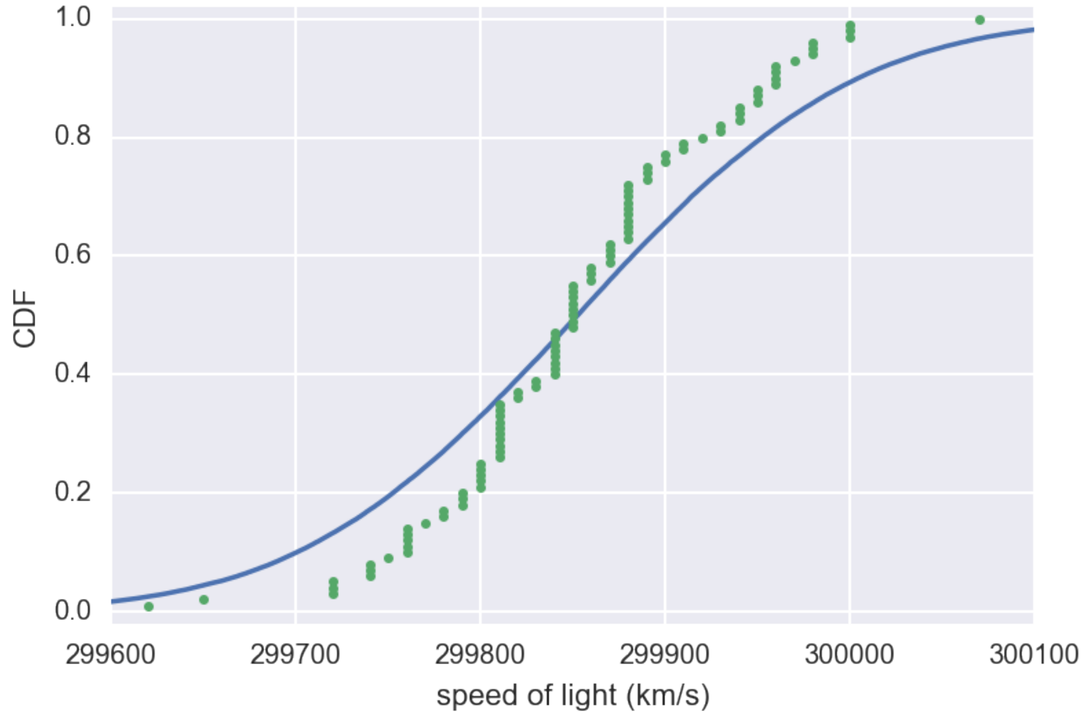
```
In [1]: import numpy as np

In [2]: import matplotlib.pyplot as plt

In [3]: mean = np.mean(michelson_speed_of_light)

In [4]: std = np.std(michelson_speed_of_light)

In [5]: samples = np.random.normal(mean, std, size=10000)
```

CDF of Michelson's measurements



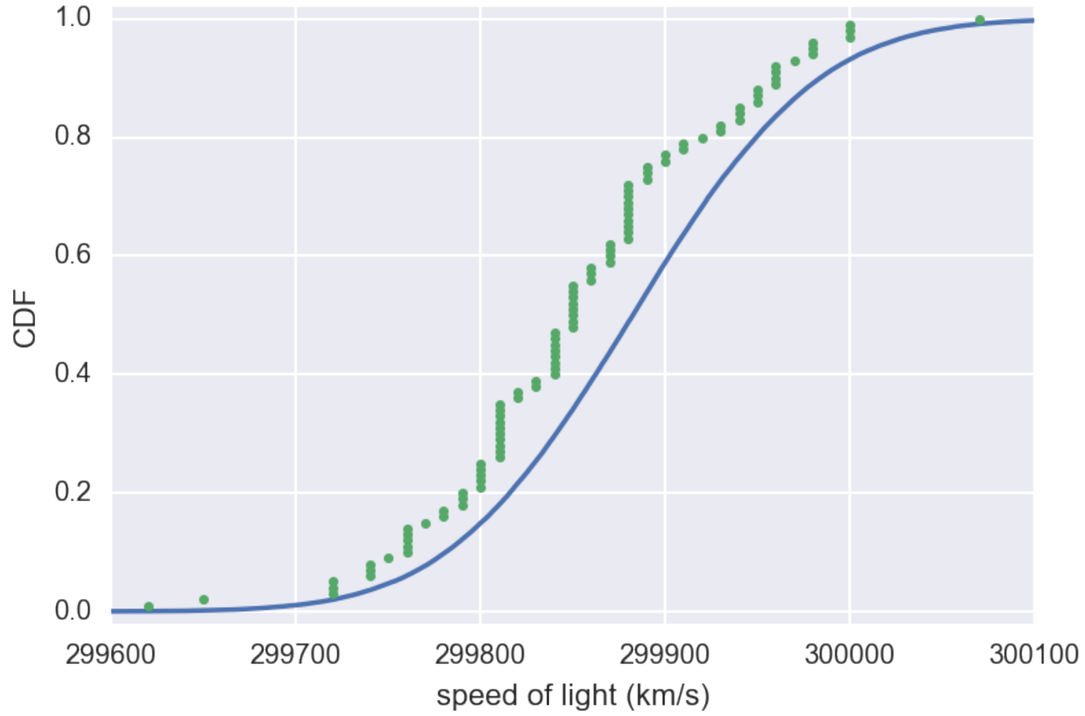
Data: Michelson, 1880

CDF with bad estimate of st. dev.



Data: Michelson, 1880

CDF with bad estimate of mean

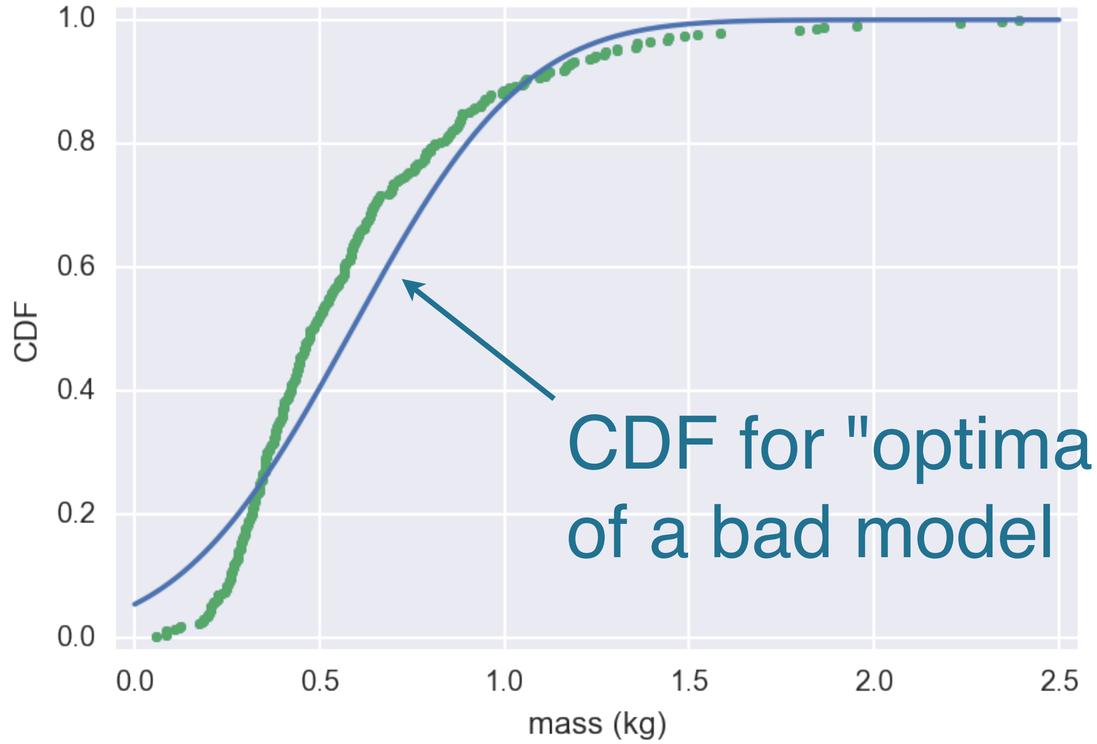


Data: Michelson, 1880

Optimal parameters

- Parameter values that bring the model in closest agreement with the data

Mass of MA large mouth bass



Source: Mass. Dept. of Environmental Protection

Packages to do statistical inference

`scipy.stats`

`statsmodels`

`hacker stats with numpy`

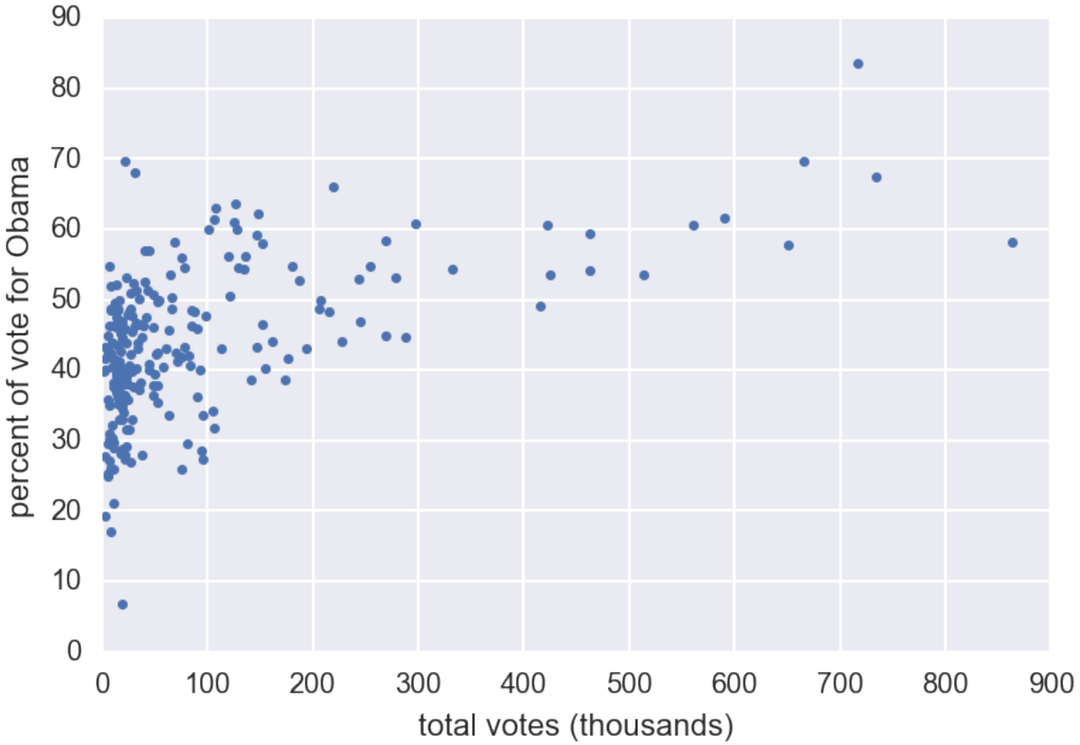
STATISTICAL THINKING IN PYTHON II

Let’s practice!

STATISTICAL THINKING IN PYTHON II

Linear regression by least squares

2008 US swing state election results

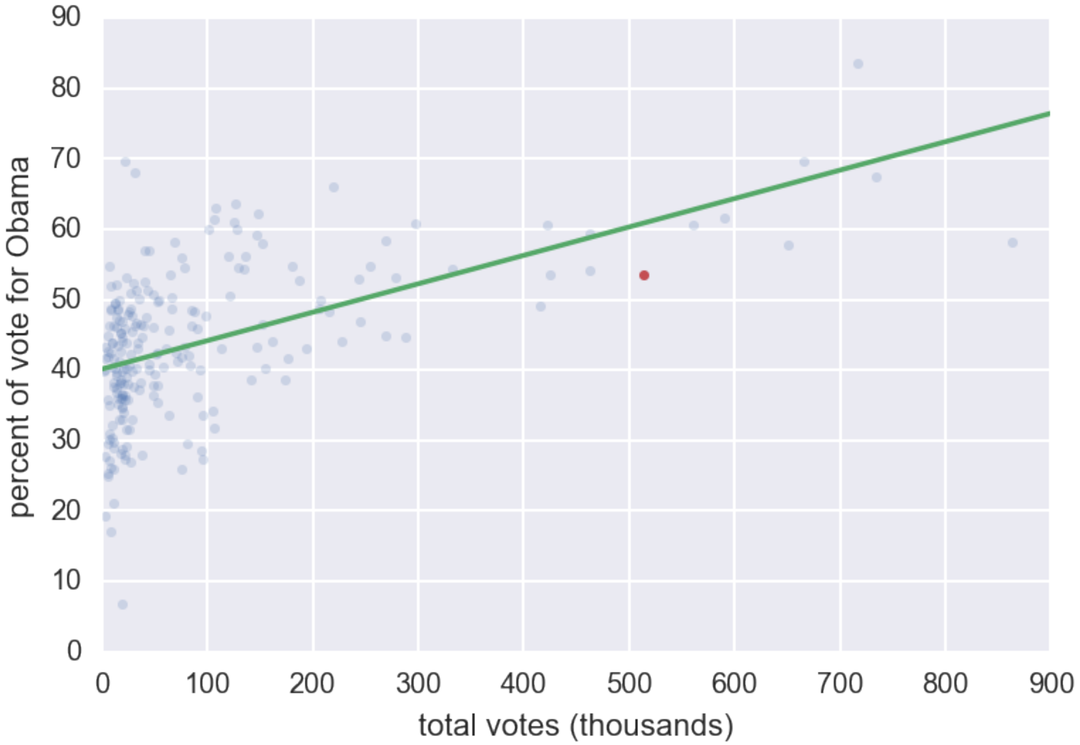


Data retrieved from Data.gov (https://www.data.gov/)

2008 US swing state election results

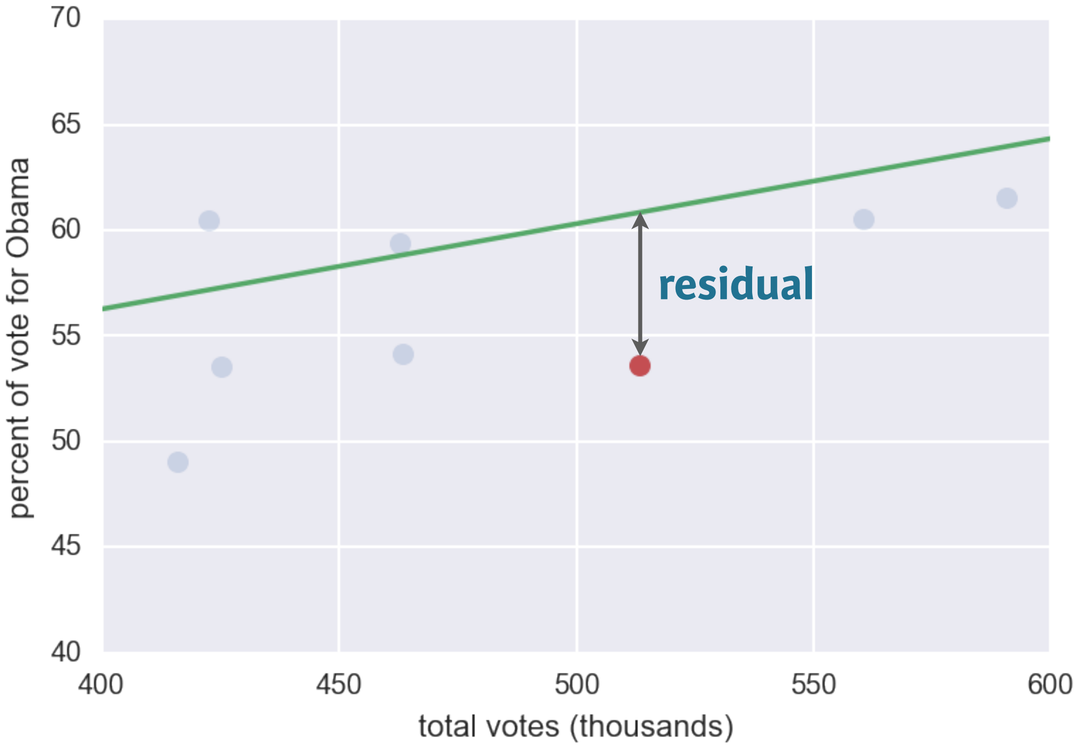
Data retrieved from Data.gov (https://www.data.gov/)

2008 US swing state election results



Data retrieved from Data.gov (https://www.data.gov/)

Residuals



Data retrieved from Data.gov (https://www.data.gov/)

Least squares

- The process of finding the parameters for which the sum of the squares of the residuals is minimal

Least squares with `np.polyfit()`

```
In [1]: slope, intercept = np.polyfit(total_votes,
   ...:                               dem_share, 1)

In [2]: slope
Out[2]: 4.037071700946555e-05

In [3]: intercept
Out[3]: 40.113911968641744
```

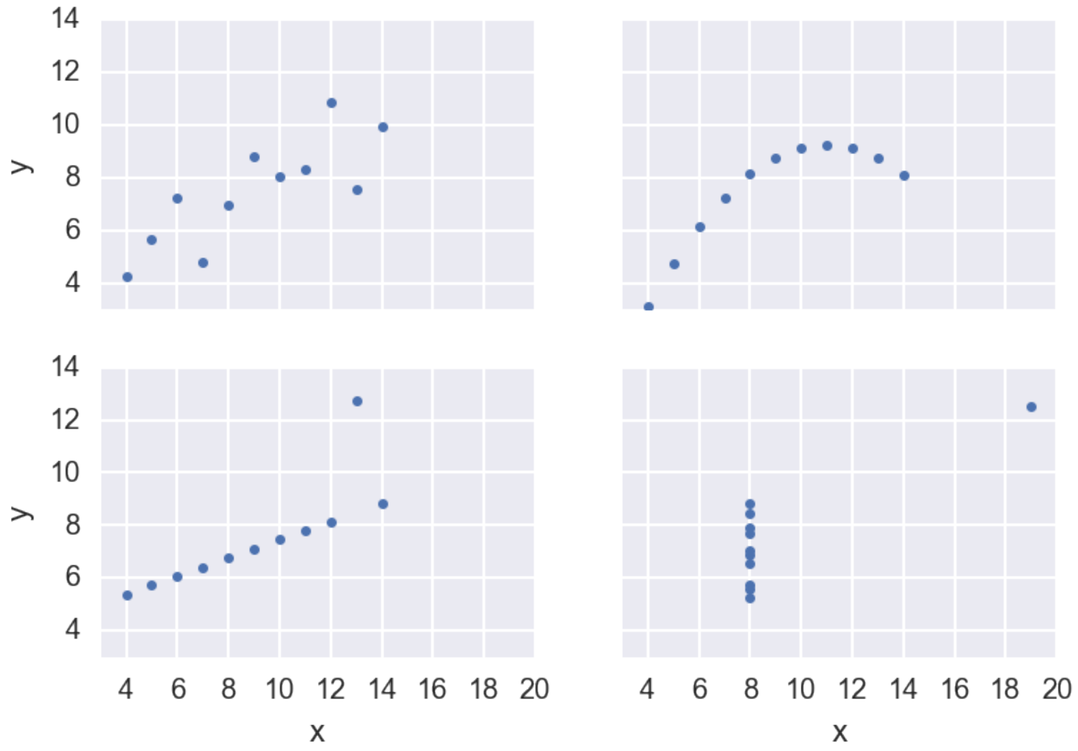
STATISTICAL THINKING IN PYTHON II

Let’s practice!

STATISTICAL THINKING IN PYTHON II

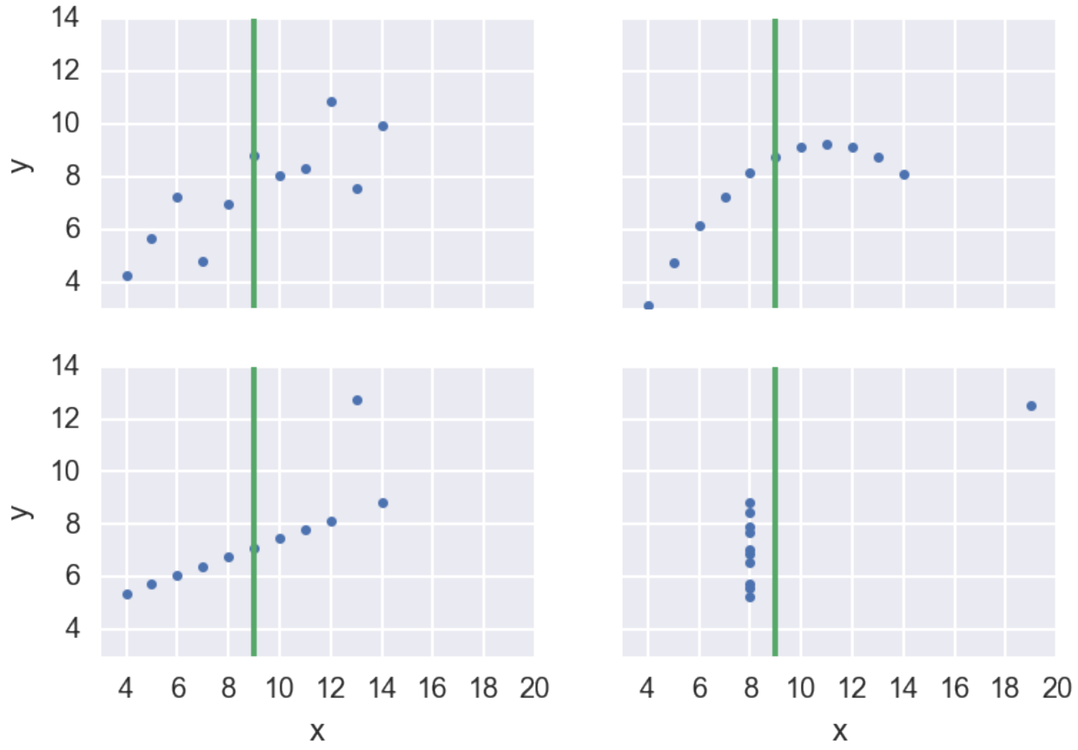
The importance of EDA: Anscombe's quartet

Anscombe's quartet



Data: Anscombe, The American Statistician, *1973*

Anscombe's quartet



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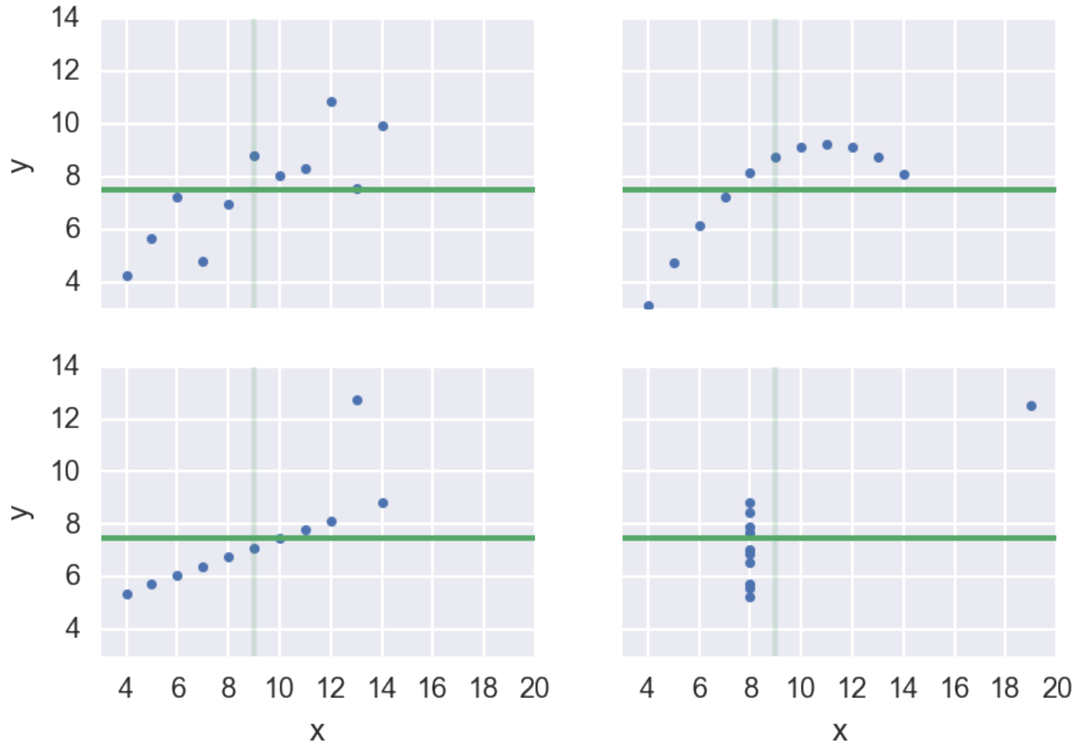
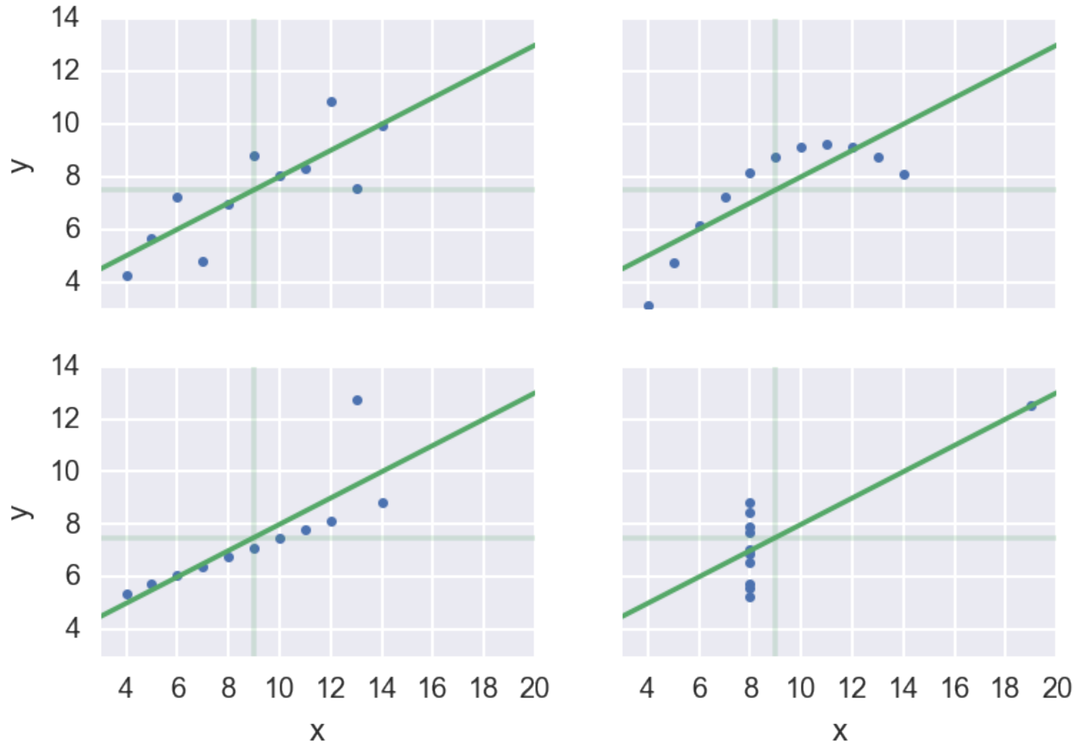
Anscombe's quartet



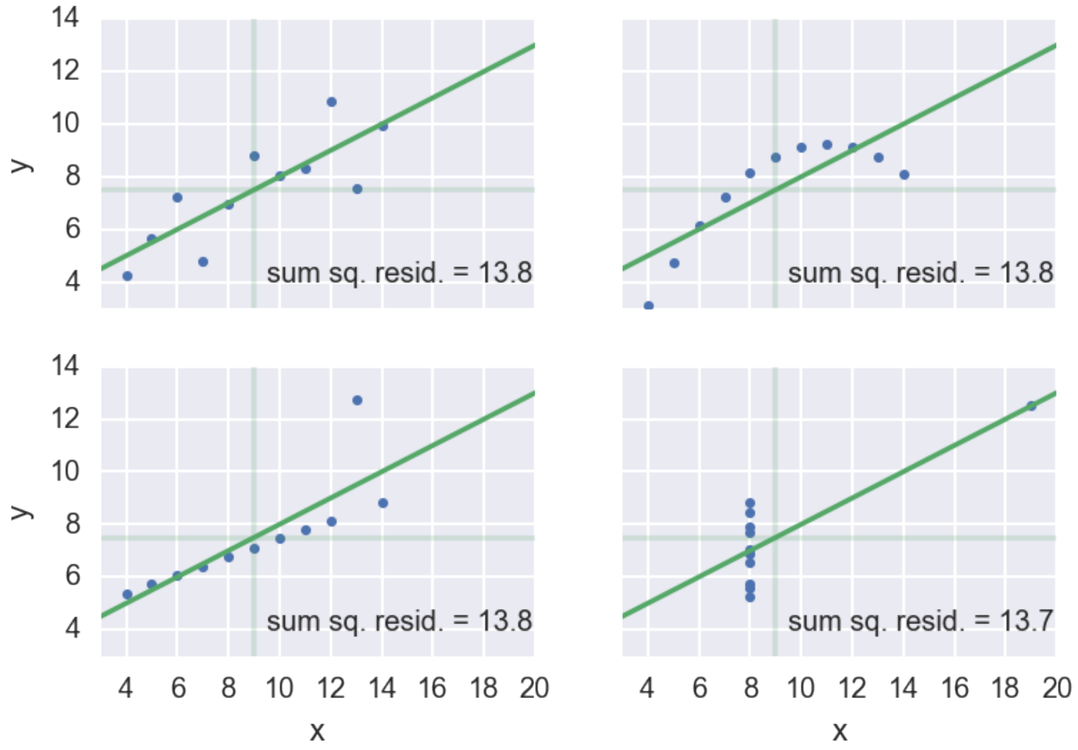
Data: Anscombe, The American Statistician, *1973*

Anscombe's quartet



Data: Anscombe, The American Statistician, *1973*

Anscombe's quartet

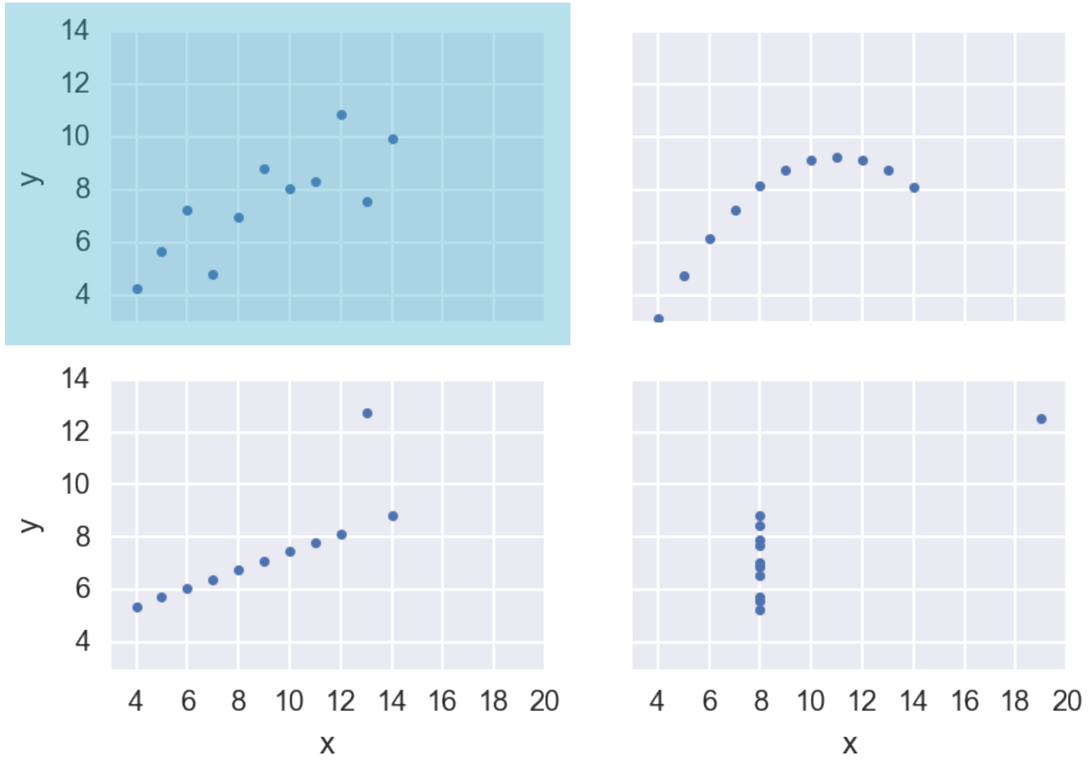


Data: Anscombe, The American Statistician, *1973*

Look before you leap!

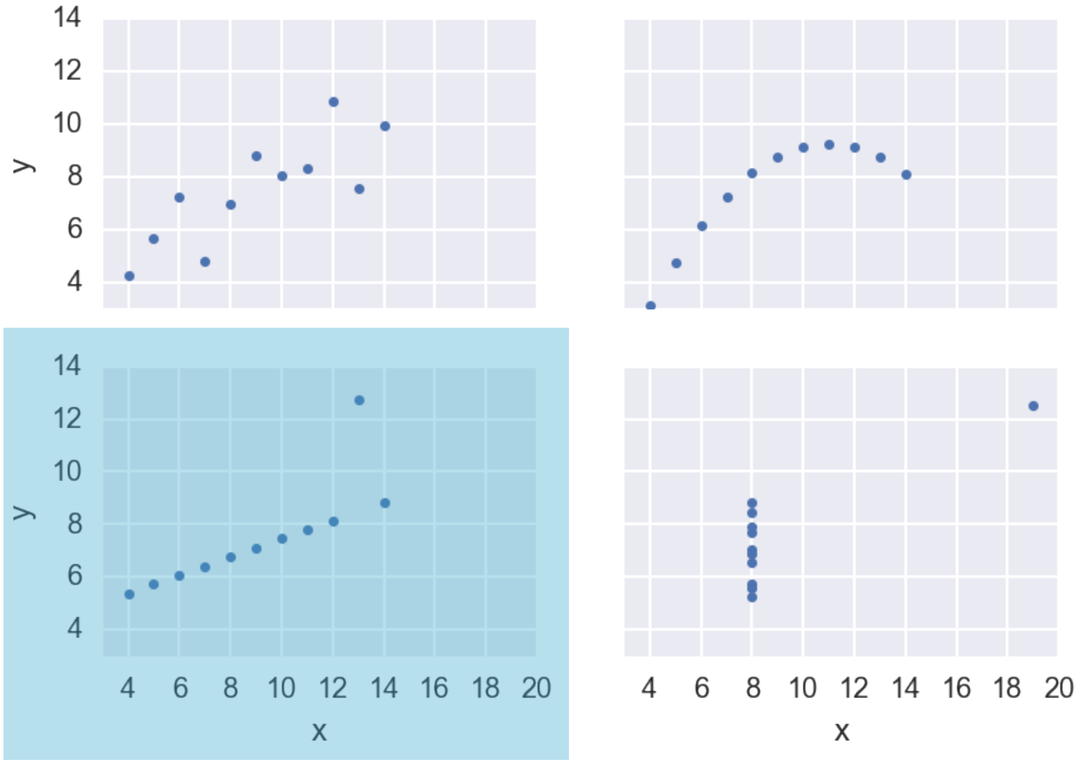
- Do graphical EDA first

Anscombe's quartet



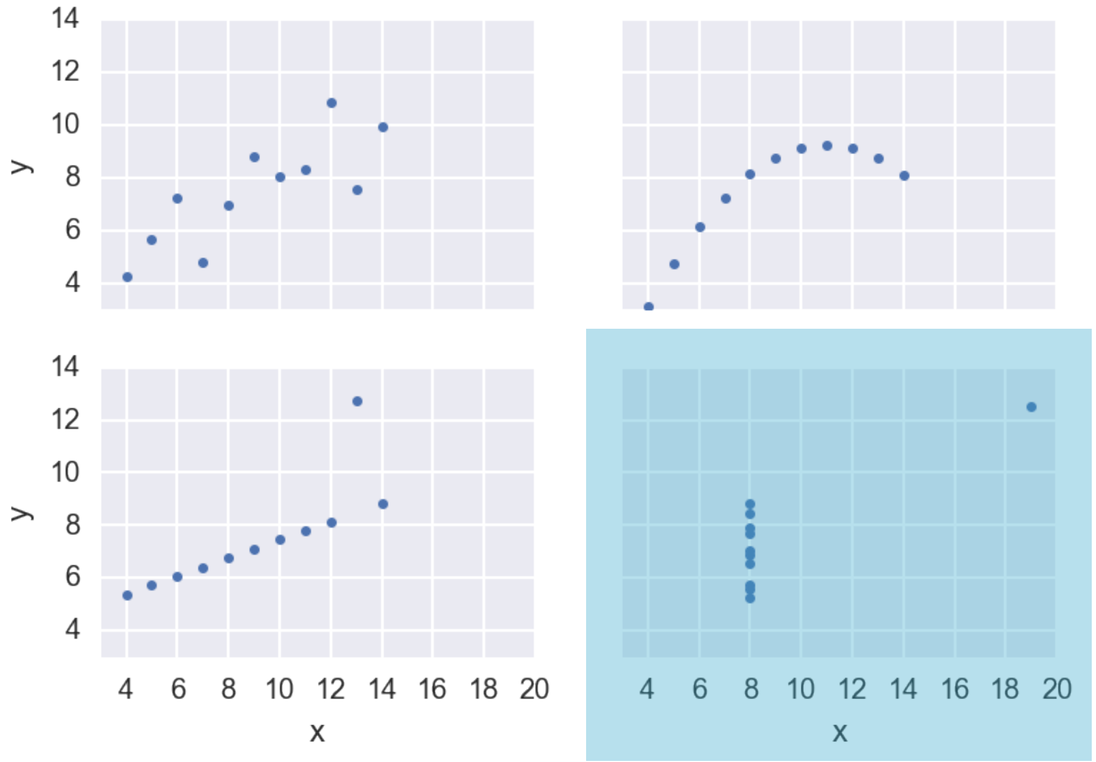
Data: Anscombe, The American Statistician, *1973*

Anscombe's quartet



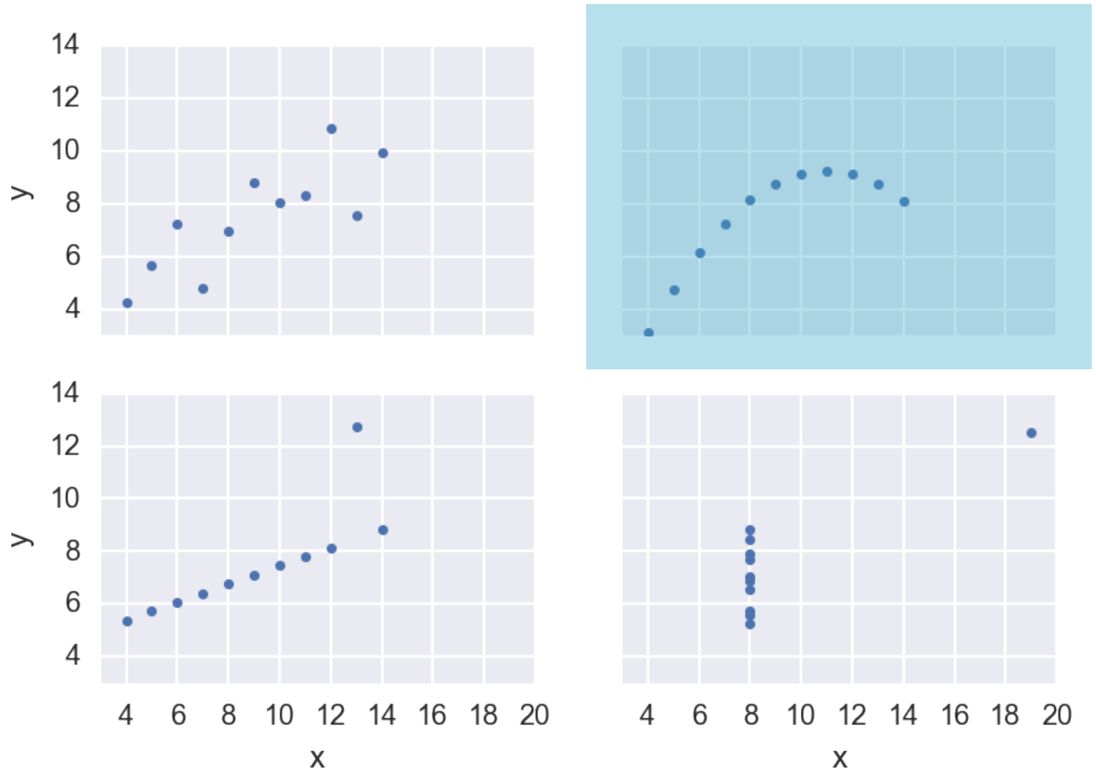
Data: Anscombe, The American Statistician, *1973*

Anscombe's quartet



Data: Anscombe, The American Statistician, *1973*

Anscombe's quartet



Data: Anscombe, The American Statistician, *1973*

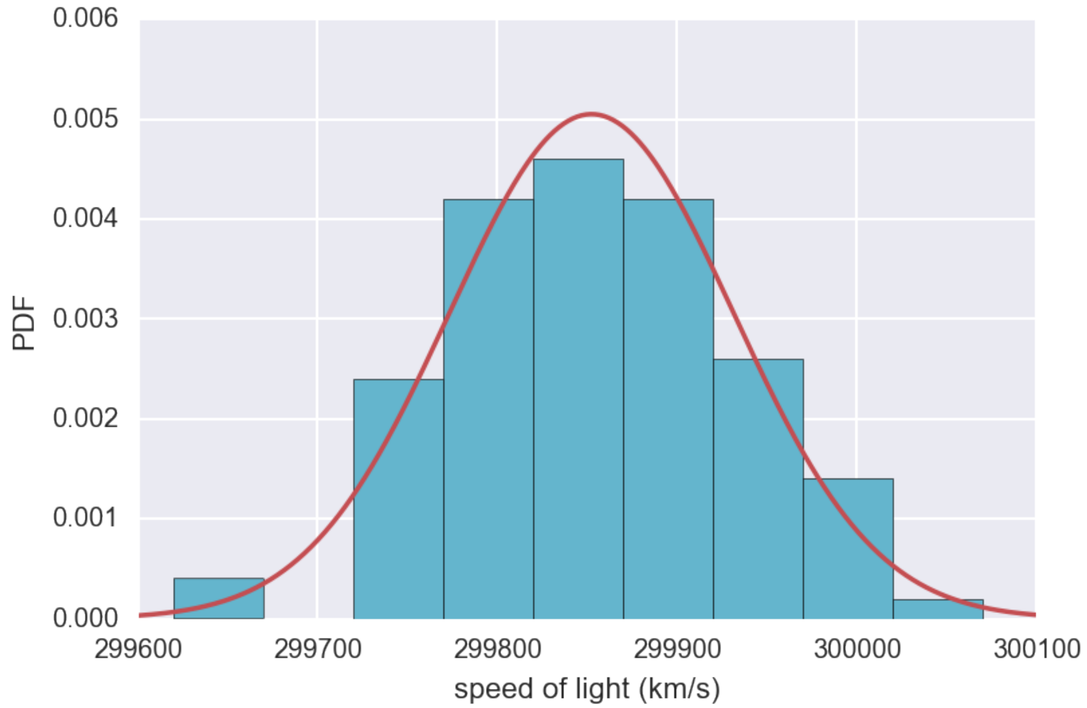
STATISTICAL THINKING IN PYTHON II

Let’s practice!

STATISTICAL THINKING IN PYTHON II

Generating bootstrap replicates

Michelson's speed of light measurements



Data: Michelson, 1880

Resampling an array

Data:

[23.3, 27.1, 24.3, 25.3, 26.0]

Mean = 25.2

Resampled data:

[, , , ,]

Resampling an array

Data:

[23.3, , 24.3, 25.3, 26.0]

Mean = 25.2

Resampled data:

[27.1, , , ,]

Resampling an array

Data:

```
[23.3, 27.1, 24.3, 25.3, 26.0]
```

Mean = 25.2

Resampled data:

```
[27.1,      ,      ,      ]
```

Resampling an array

Data:

```
[23.3, 27.1, 24.3, 25.3, 26.0]
```

Mean = 25.2

Resampled data:

```
[27.1, 26.0,     ,     ,     ]
```

Resampling an array

Data:

```
[23.3, 27.1, 24.3, 25.7, 26.0]
```

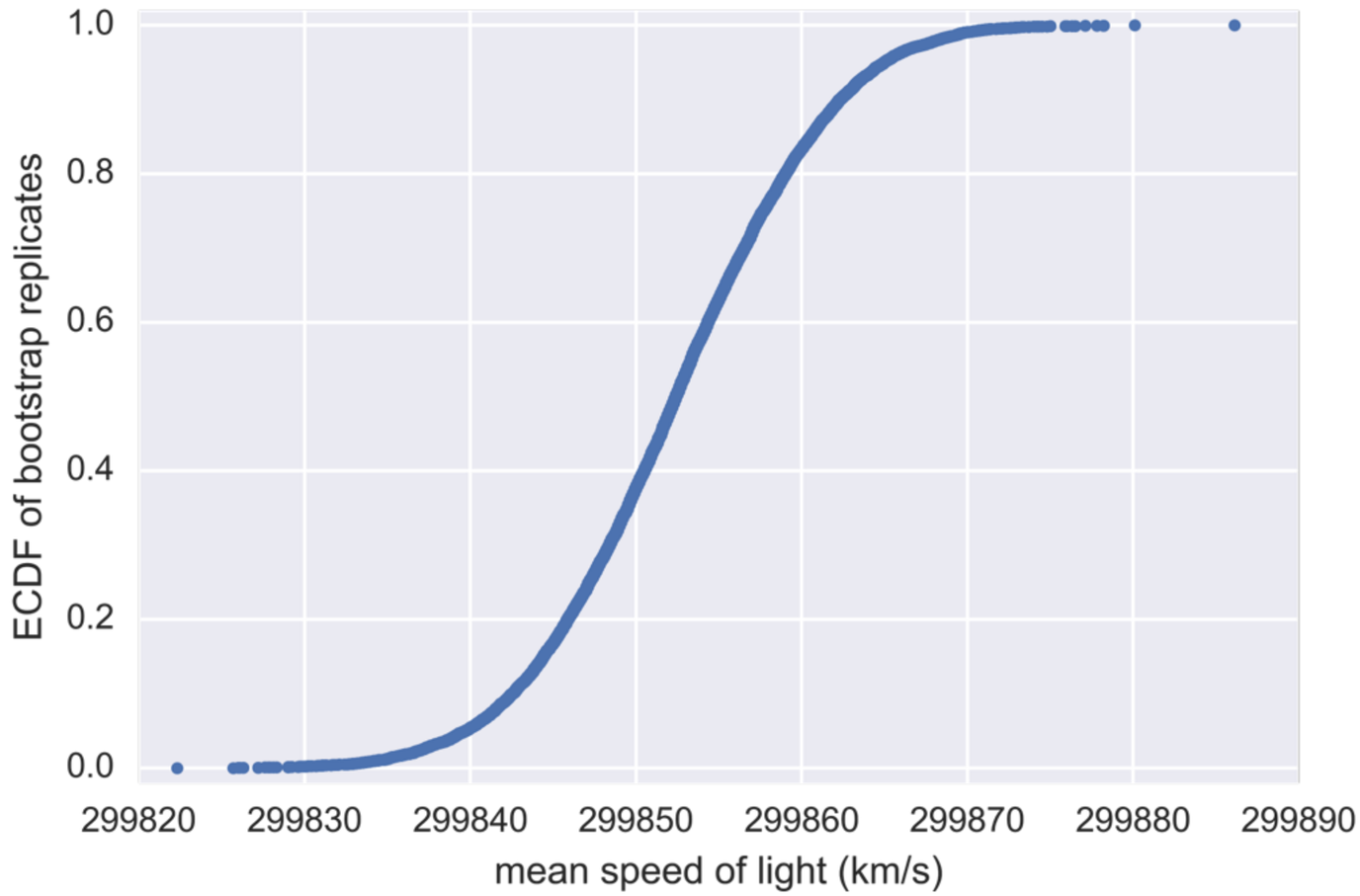
Mean = 25.2

Resampled data:

```
[27.1, 26.0, 23.3, 25.7, 23.3]
```

Mean = 25.08

Mean of resampled Michelson measurements



Bootstrapping

- The use of resampled data to perform statistical inference

Bootstrap sample

- A resampled array of the data

Bootstrap replicate

- A statistic computed from a resampled array

Resampling engine: `np.random.choice()`

```
In [1]: import numpy as np

In [2]: np.random.choice([1,2,3,4,5], size=5)
Out[2]: array([5, 3, 5, 5, 2])
```

Computing a bootstrap replicate

```
In [1]: bs_sample = np.random.choice(michelson_speed_of_light,
   ...:                              size=100)

In [2]: np.mean(bs_sample)
Out[2]: 299847.79999999999

In [3]: np.median(bs_sample)
Out[3]: 299845.0

In [4]: np.std(bs_sample)
Out[4]: 83.564286025729331
```

STATISTICAL THINKING IN PYTHON II

Let’s practice!

STATISTICAL THINKING WITH PYTHON II

Bootstrap confidence intervals

Bootstrap replicate function

```
In [1]: def bootstrap_replicate_1d(data, func):
   ...:     """Generate bootstrap replicate of 1D data."""
   ...:     bs_sample = np.random.choice(data, len(data))
   ...:     return func(bs_sample)
   ...:

In [2]: bootstrap_replicate_1d(michelson_speed_of_light, np.mean)
Out[2]: 299859.20000000001

In [3]: bootstrap_replicate_1d(michelson_speed_of_light, np.mean)
Out[3]: 299855.70000000001

In [4]: bootstrap_replicate_1d(michelson_speed_of_light, np.mean)
Out[4]: 299850.29999999999
```

Many bootstrap replicates

```
In [1]: bs_replicates = np.empty(10000)

In [2]: for i in range(10000):
    ...:     bs_replicates[i] = bootstrap_replicate_1d(
    ...:                        michelson_speed_of_light, np.mean)
    ...:
```

Plotting a histogram of bootstrap replicates

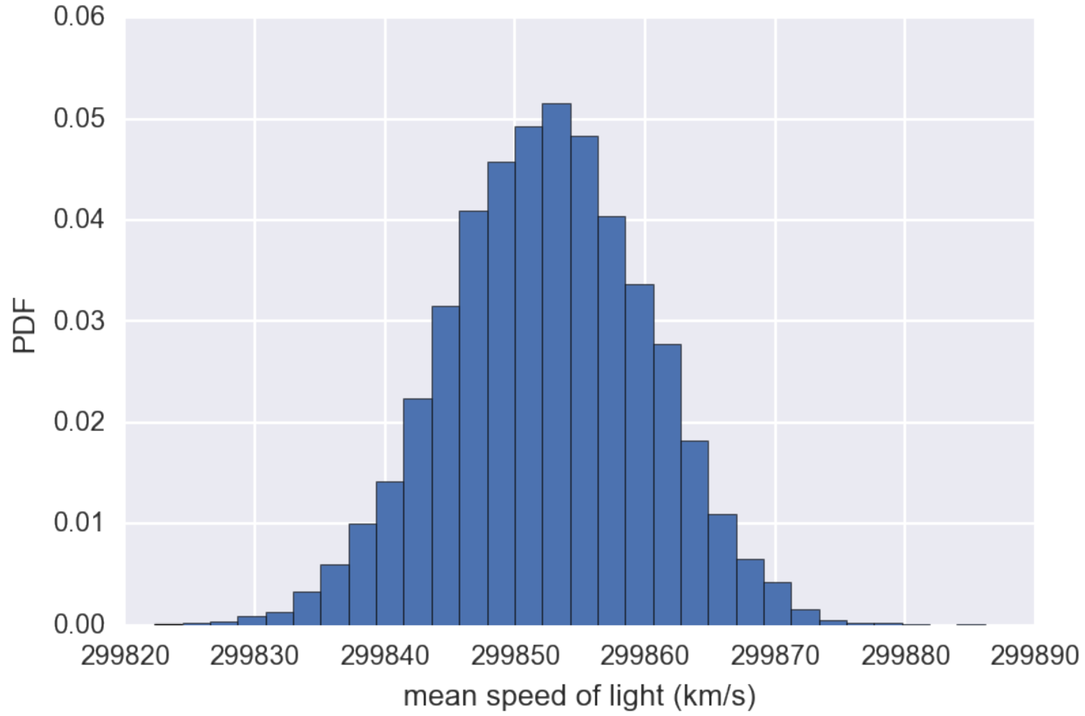
```
In [1]: _ = plt.hist(bs_replicates, bins=30, normed=True)

In [2]: _ = plt.xlabel('mean speed of light (km/s)')

In [3]: _ = plt.ylabel('PDF')

In [4]: plt.show()
```

Bootstrap estimate of the mean

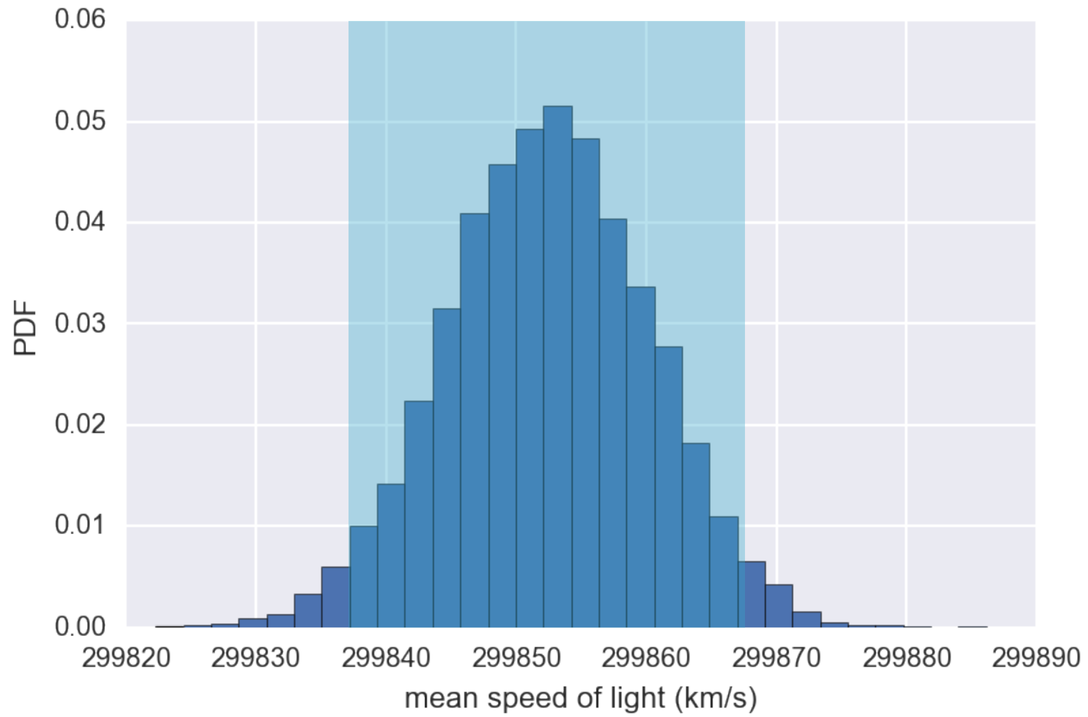


Confidence interval of a statistic

- If we repeated measurements over and over again, p% of the observed values would lie within the p% confidence interval.

Bootstrap confidence interval

```
In [1]: conf_int = np.percentile(bs_replicates, [2.5, 97.5])
Out[1]: array([ 299837.,  299868.])
```



STATISTICAL THINKING WITH PYTHON II

Let’s practice!

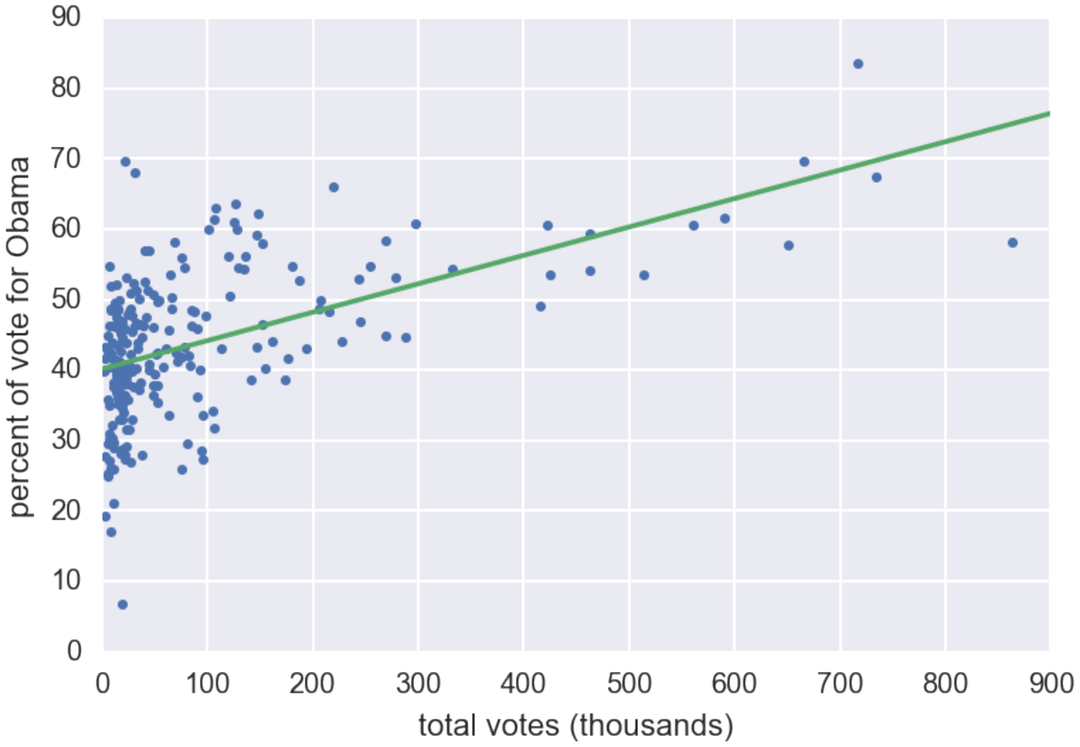
STATISTICAL THINKING IN PYTHON II

Pairs bootstrap

Nonparametric inference

- Make no assumptions about the model or probability distribution underlying the data

2008 US swing state election results



Data retrieved from Data.gov (https://www.data.gov/)

Pairs bootstrap for linear regression

- Resample data *in pairs*
- Compute slope and intercept from resampled data
- Each slope and intercept is a bootstrap replicate
- Compute confidence intervals from percentiles of bootstrap replicates

Generating a pairs bootstrap sample

```
In [1]: np.arange(7)
Out[1]: array([0, 1, 2, 3, 4, 5, 6])

In [1]: inds = np.arange(len(total_votes))

In [2]: bs_inds = np.random.choice(inds, len(inds))

In [3]: bs_total_votes = total_votes[bs_inds]

In [4]: bs_dem_share = dem_share[bs_inds]
```

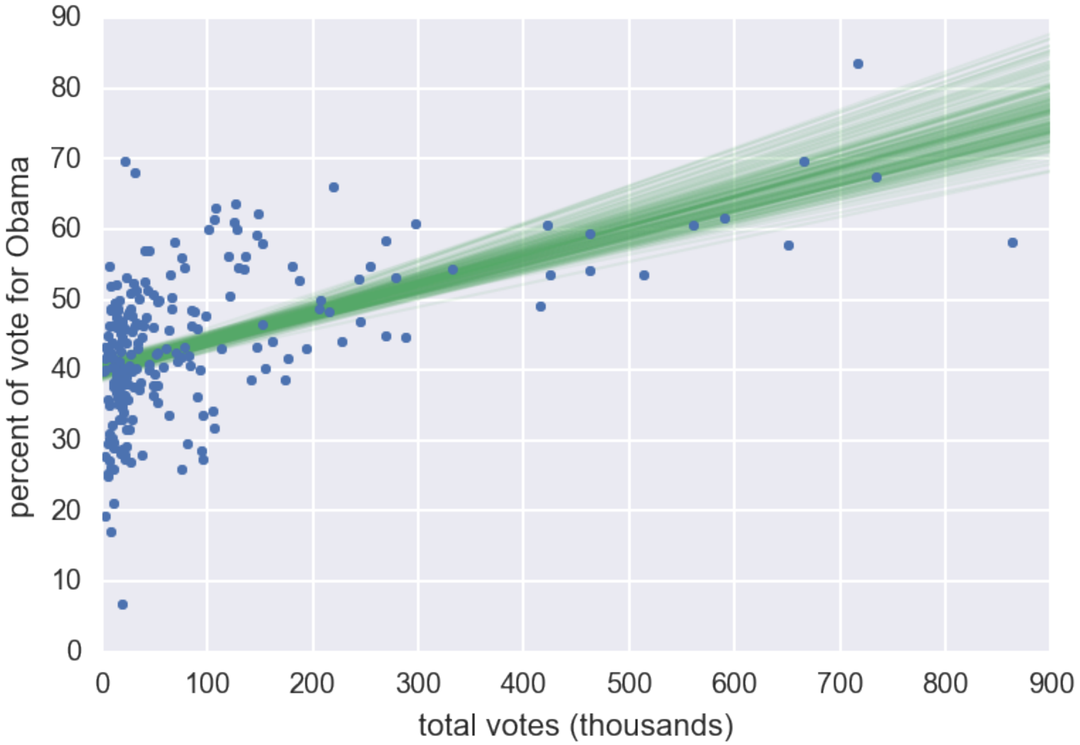
Computing a pairs bootstrap replicate

```
In [1]: bs_slope, bs_intercept = np.polyfit(bs_total_votes,
   ...:                                     bs_dem_share, 1)

In [2]: bs_slope, bs_intercept
Out[2]: (3.9053605692223672e-05, 40.387910131803025)

In [3]: np.polyfit(total_votes, dem_share, 1)  # fit of original
Out[3]: array([  4.03707170e-05,   4.01139120e+01])
```

2008 US swing state election results



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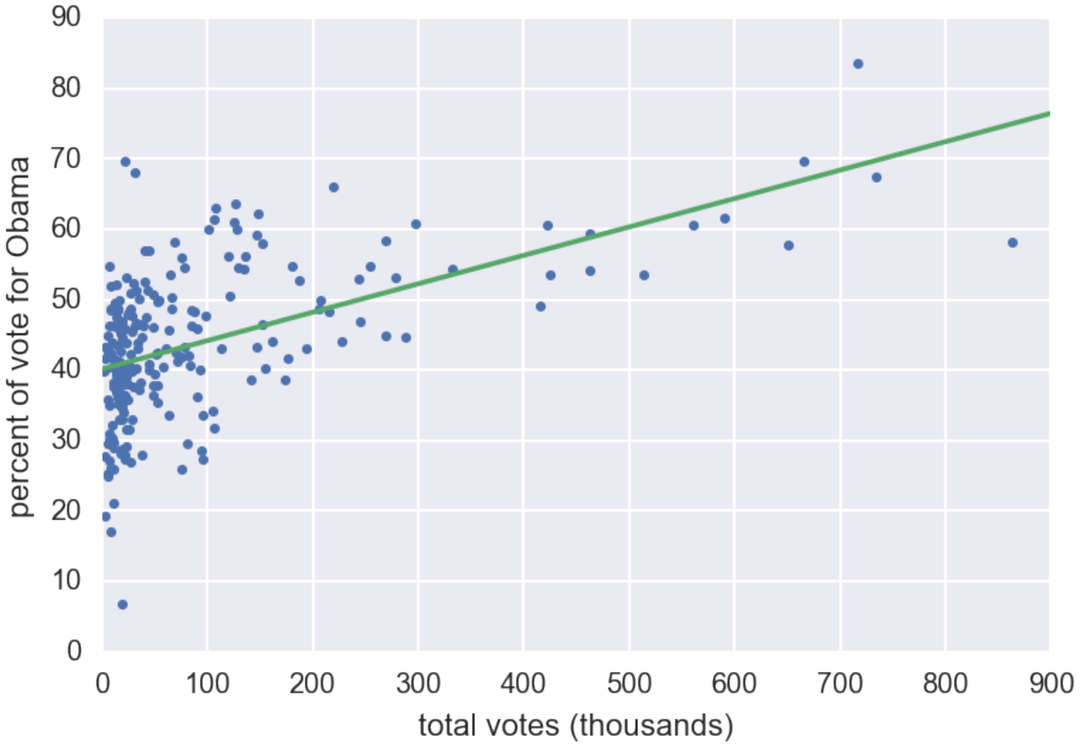
STATISTICAL THINKING IN PYTHON II

Let’s practice!

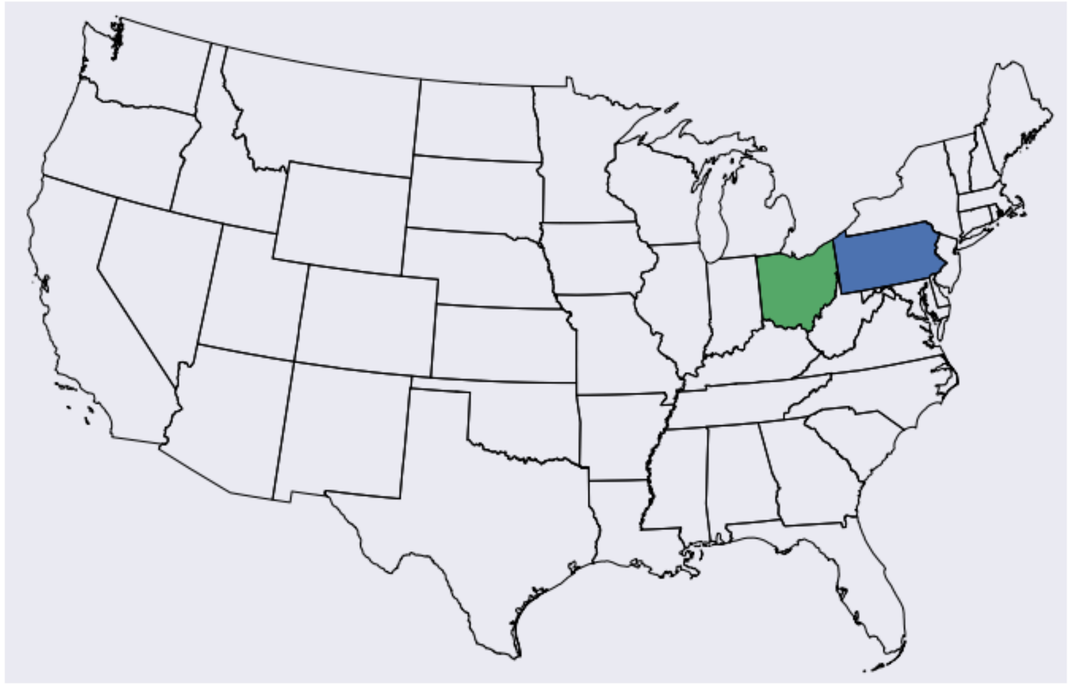
STATISTICAL THINKING IN PYTHON II

Formulating and simulating hypotheses

2008 US swing state election results



Data retrieved from Data.gov (https://www.data.gov/)



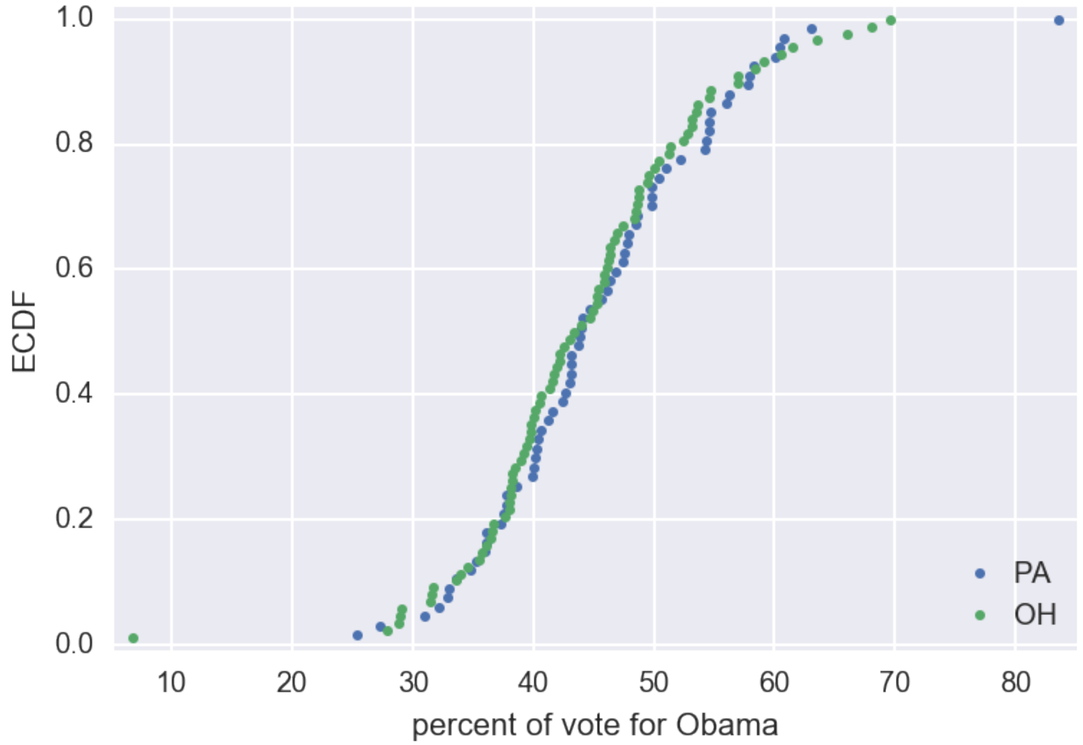
Hypothesis testing

- Assessment of how reasonable the observed data are assuming a hypothesis is true

Null hypothesis

- Another name for the hypothesis you are testing

ECDFs of swing state election results



Data retrieved from Data.gov (https://www.data.gov/)

Percent vote for Obama

	PA	OH	PA — OH difference
mean	45.5%	44.3%	1.2%
median	44.0%	43.7%	0.4%
standard deviation	9.8%	9.9%	—0.1%

Data retrieved from Data.gov (https://www.data.gov/)

Simulating the hypothesis

60.08,	40.64,	36.07,	41.21,	31.04,	43.78,	44.08,	46.85,
44.71,	46.15,	63.10,	52.20,	43.18,	40.24,	39.92,	47.87,
37.77,	40.11,	49.85,	48.61,	38.62,	54.25,	34.84,	47.75,
43.82,	55.97,	58.23,	42.97,	42.38,	36.11,	37.53,	42.65,
50.96,	47.43,	56.24,	45.60,	46.39,	35.22,	48.56,	32.97,
57.88,	36.05,	37.72,	50.36,	32.12,	41.55,	54.66,	57.81,
54.58,	32.88,	54.37,	40.45,	47.61,	60.49,	43.11,	27.32,
44.03,	33.56,	37.26,	54.64,	43.12,	25.34,	49.79,	83.56,
40.09,	60.81,	49.81,	56.94,	50.46,	65.99,	45.88,	42.23,
45.26,	57.01,	53.61,	59.10,	61.48,	43.43,	44.69,	54.59,
48.36,	45.89,	48.62,	43.92,	38.23,	28.79,	63.57,	38.07,
40.18,	43.05,	41.56,	42.49,	36.06,	52.76,	46.07,	39.43,
39.26,	47.47,	27.92,	38.01,	45.45,	29.07,	28.94,	51.28,
50.10,	39.84,	36.43,	35.71,	31.47,	47.01,	40.10,	48.76,
31.56,	39.86,	45.31,	35.47,	51.38,	46.33,	48.73,	41.77,
41.32,	48.46,	53.14,	34.01,	54.74,	40.67,	38.96,	46.29,
38.25,	6.80,	31.75,	46.33,	44.90,	33.57,	38.10,	39.67,
40.47,	49.44,	37.62,	36.71,	46.73,	42.20,	53.16,	52.40,
58.36,	68.02,	38.53,	34.58,	69.64,	60.50,	53.53,	36.54,
49.58,	41.97,	38.11					

Pennsylvania

Ohio

Data retrieved from Data.gov (https://www.data.gov/)

Simulating the hypothesis

```
60.08,  40.64,  36.07,  41.21,  31.04,  43.78,  44.08,  46.85,
44.71,  46.15,  63.10,  52.20,  43.18,  40.24,  39.92,  47.87,
37.77,  40.11,  49.85,  48.61,  38.62,  54.25,  34.84,  47.75,
43.82,  55.97,  58.23,  42.97,  42.38,  36.11,  37.53,  42.65,
50.96,  47.43,  56.24,  45.60,  46.39,  35.22,  48.56,  32.97,
57.88,  36.05,  37.72,  50.36,  32.12,  41.55,  54.66,  57.81,
54.58,  32.88,  54.37,  40.45,  47.61,  60.49,  43.11,  27.32,
44.03,  33.56,  37.26,  54.64,  43.12,  25.34,  49.79,  83.56,
40.09,  60.81,  49.81,  56.94,  50.46,  65.99,  45.88,  42.23,
45.26,  57.01,  53.61,  59.10,  61.48,  43.43,  44.69,  54.59,
48.36,  45.89,  48.62,  43.92,  38.23,  28.79,  63.57,  38.07,
40.18,  43.05,  41.56,  42.49,  36.06,  52.76,  46.07,  39.43,
39.26,  47.47,  27.92,  38.01,  45.45,  29.07,  28.94,  51.28,
50.10,  39.84,  36.43,  35.71,  31.47,  47.01,  40.10,  48.76,
31.56,  39.86,  45.31,  35.47,  51.38,  46.33,  48.73,  41.77,
41.32,  48.46,  53.14,  34.01,  54.74,  40.67,  38.96,  46.29,
38.25,   6.80,  31.75,  46.33,  44.90,  33.57,  38.10,  39.67,
40.47,  49.44,  37.62,  36.71,  46.73,  42.20,  53.16,  52.40,
58.36,  68.02,  38.53,  34.58,  69.64,  60.50,  53.53,  36.54,
49.58,  41.97,  38.11
```

Data retrieved from Data.gov (https://www.data.gov/)

Simulating the hypothesis

```
59.10,  38.62,  51.38,  60.49,   6.80,  41.97,  48.56,  37.77,
48.36,  54.59,  40.11,  57.81,  45.89,  83.56,  40.64,  46.07,
28.79,  55.97,  33.57,  42.23,  48.61,  44.69,  39.67,  57.88,
48.62,  54.66,  54.74,  48.46,  36.07,  43.92,  49.85,  53.53,
48.76,  41.77,  36.54,  47.01,  52.76,  49.44,  34.58,  40.24,
44.08,  46.29,  49.81,  69.64,  60.50,  27.32,  45.60,  63.10,
35.71,  39.86,  40.67,  65.99,  50.46,  37.72,  50.96,  42.49,
31.56,  38.23,  37.26,  41.21,  37.53,  46.85,  44.03,  41.32,
45.88,  40.45,  32.12,  35.22,  49.79,  43.12,  43.18,  45.45,
25.34,  46.73,  44.90,  56.94,  58.23,  39.84,  36.05,  43.05,
38.25,  40.47,  31.04,  54.25,  46.15,  57.01,  52.20,  47.75,
36.06,  47.61,  51.28,  43.43,  42.97,  38.01,  54.64,  45.26,
47.47,  34.84,  49.58,  48.73,  29.07,  54.58,  27.92,  34.01,
38.07,  31.47,  36.11,  39.26,  41.56,  52.40,  40.18,  47.87,
46.33,  46.39,  43.11,  38.53,  33.56,  42.65,  68.02,  35.47,
40.09,  36.43,  36.71,  60.08,  50.36,  39.43,  28.94,  58.36,
42.20,  47.43,  44.71,  43.78,  39.92,  37.62,  63.57,  53.61,
40.10,  46.33,  53.16,  32.88,  38.96,  41.55,  56.24,  38.11,
42.38,  38.10,  43.82,  45.31,  60.81,  54.37,  53.14,  32.97,
61.48,  50.10,  31.75
```

Data retrieved from Data.gov (https://www.data.gov/)

Simulating the hypothesis

59.10,	38.62,	51.38,	60.49,	6.80,	41.97,	48.56,	37.77,
48.36,	54.59,	40.11,	57.81,	45.89,	83.56,	40.64,	46.07,
28.79,	55.97,	33.57,	42.23,	48.61,	44.69,	39.67,	57.88,
48.62,	54.66,	54.74,	48.46,	36.07,	43.92,	49.85,	53.53,
48.76,	41.77,	36.54,	47.01,	52.76,	49.44,	34.58,	40.24,
44.08,	46.29,	49.81,	69.64,	60.50,	27.32,	45.60,	63.10,
35.71,	39.86,	40.67,	65.99,	50.46,	37.72,	50.96,	42.49,
31.56,	38.23,	37.26,	41.21,	37.53,	46.85,	44.03,	41.32,
45.88,	40.45,	32.12,	35.22,	49.79,	43.12,	43.18,	45.45,
25.34,	46.73,	44.90,	56.94,	58.23,	39.84,	36.05,	43.05,
38.25,	40.47,	31.04,	54.25,	46.15,	57.01,	52.20,	47.75,
36.06,	47.61,	51.28,	43.43,	42.97,	38.01,	54.64,	45.26,
47.47,	34.84,	49.58,	48.73,	29.07,	54.58,	27.92,	34.01,
38.07,	31.47,	36.11,	39.26,	41.56,	52.40,	40.18,	47.87,
46.33,	46.39,	43.11,	38.53,	33.56,	42.65,	68.02,	35.47,
40.09,	36.43,	36.71,	60.08,	50.36,	39.43,	28.94,	58.36,
42.20,	47.43,	44.71,	43.78,	39.92,	37.62,	63.57,	53.61,
40.10,	46.33,	53.16,	32.88,	38.96,	41.55,	56.24,	38.11,
42.38,	38.10,	43.82,	45.31,	60.81,	54.37,	53.14,	32.97,
61.48,	50.10,	31.75					

"Pennsylvania"

"Ohio"

Data retrieved from Data.gov (https://www.data.gov/)

Permutation

- Random reordering of entries in an array

Generating a permutation sample

```
In [1]: import numpy as np

In [2]: dem_share_both = np.concatenate(
   ...:                          (dem_share_PA, dem_share_OH))

In [3]: dem_share_perm = np.random.permutation(dem_share_both)

In [4]: perm_sample_PA = dem_share_perm[:len(dem_share_PA)]

In [5]: perm_sample_OH = dem_share_perm[len(dem_share_PA):]
```

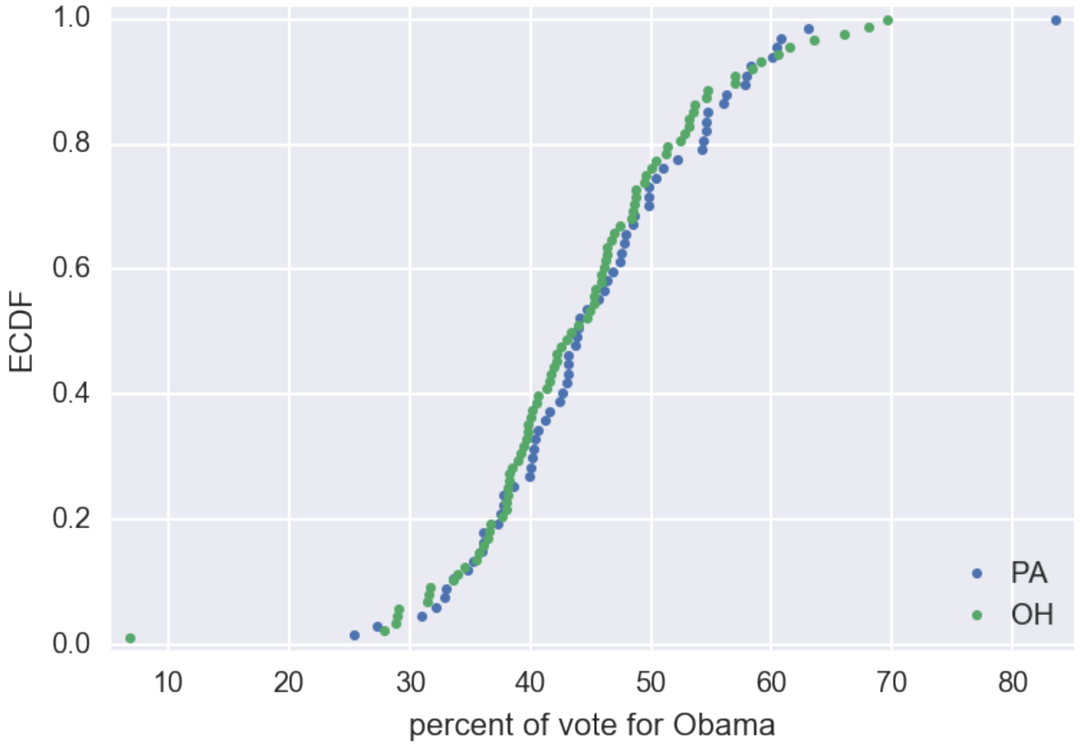
STATISTICAL THINKING IN PYTHON II

Let’s practice!

STATISTICAL THINKING IN PYTHON II

Test statistics and p-values

Are OH and PA different?



Data retrieved from Data.gov (https://www.data.gov/)

Hypothesis testing

- Assessment of how reasonable the observed data are assuming a hypothesis is true

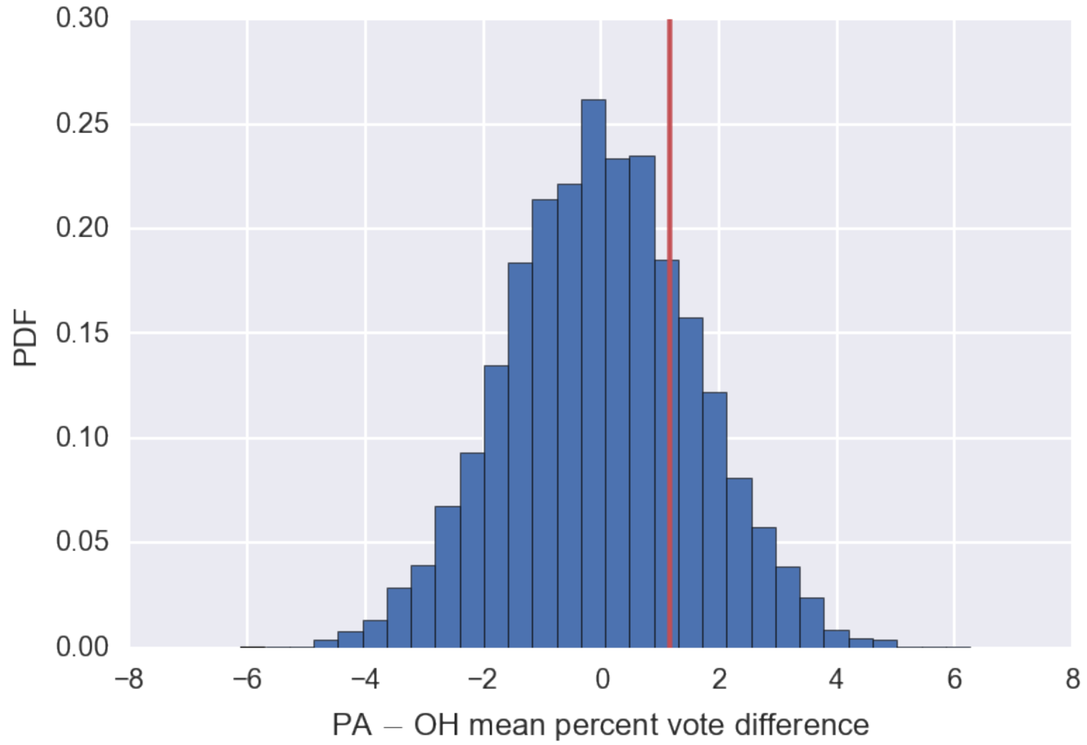
Test statistic

- A single number that can be computed from observed data and from data you simulate under the null hypothesis
- It serves as a basis of comparison between the two

Permutation replicate

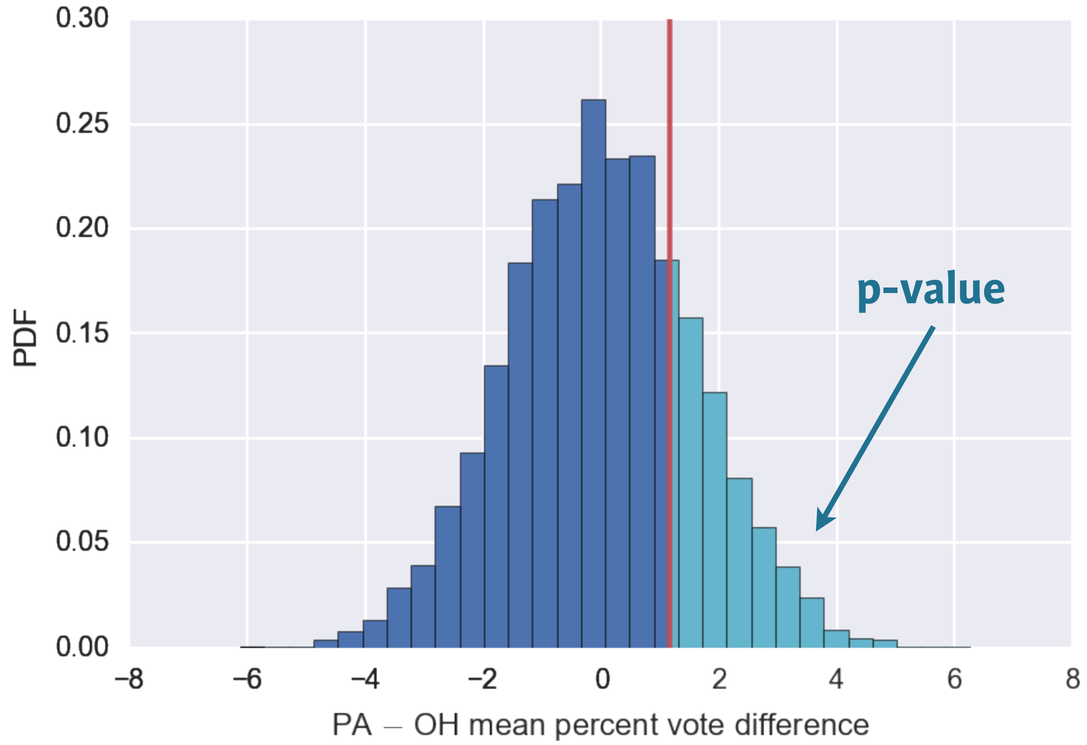
```
In [1]: np.mean(perm_sample_PA) - np.mean(perm_sample_OH)
Out[1]: 1.122220149253728

In [2]: np.mean(dem_share_PA) - np.mean(dem_share_OH) # orig. data
Out[2]: 1.1582360922659518
```

Mean vote difference under null hypothesis



Data retrieved from Data.gov (https://www.data.gov/)

Mean vote difference under null hypothesis



Data retrieved from Data.gov (https://www.data.gov/)

p-value

- The probability of obtaining a value of your test statistic that is at least as extreme as what was observed, under the assumption the null hypothesis is true
- **NOT** the probability that the null hypothesis is true

Statistical significance

- Determined by the smallness of a p-value

Null hypothesis significance testing (NHST)

- Another name for what we are doing in this chapter

statistical significance ≠ practical significance

STATISTICAL THINKING IN PYTHON II

Let’s practice!

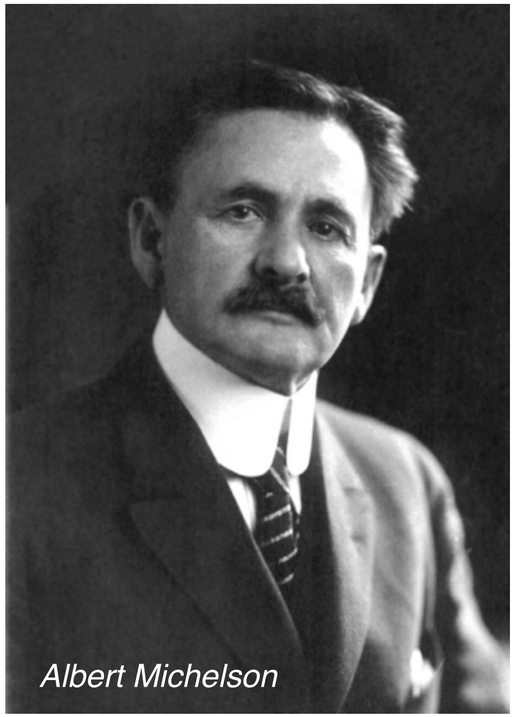
STATISTICAL THINKING IN PYTHON II

Bootstrap hypothesis tests

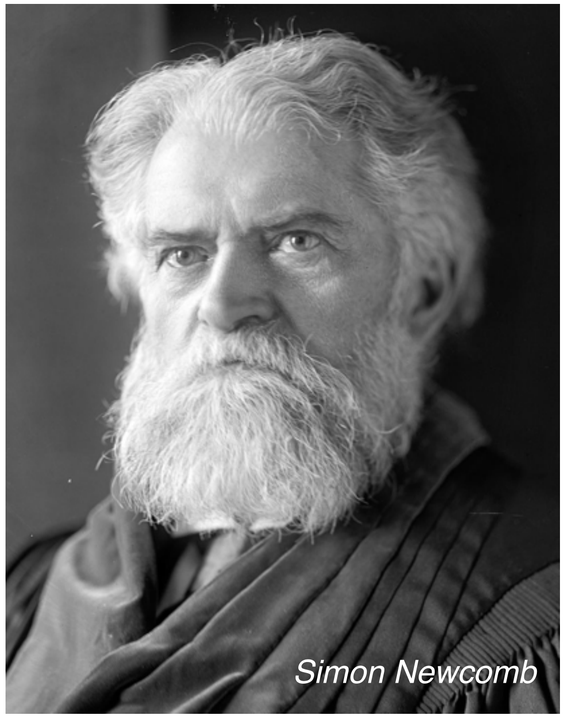
Pipeline for hypothesis testing

- Clearly state the null hypothesis
- Define your test statistic
- Generate many sets of simulated data assuming the null hypothesis is true
- Compute the test statistic for each simulated data set
- The p-value is the fraction of your simulated data sets for which the test statistic is at least as extreme as for the real data

Michelson and Newcomb: speed of light pioneers



299,852 km/s



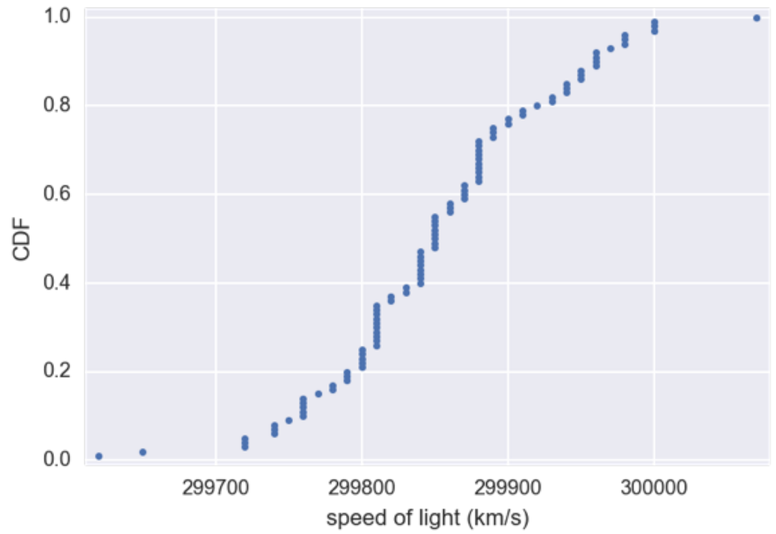
299,860 km/s

Michelson image: public domain, Smithsonian

Newcomb image: US Library of Congress

The data we have

Michelson:



Newcomb:

mean = 299,860 km/s

Data: Michelson, 1880

Null hypothesis

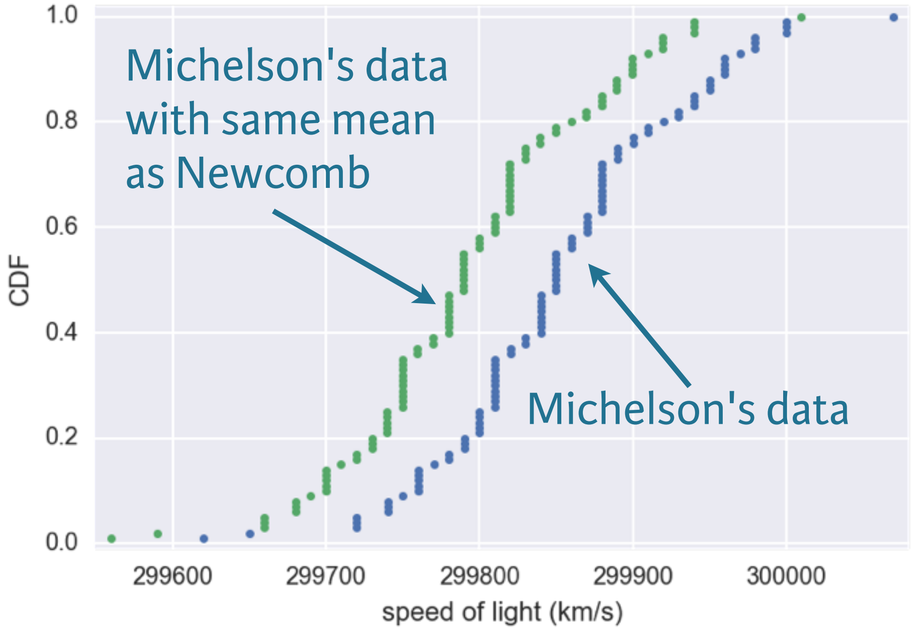
- The true mean speed of light in Michelson’s experiments was actually Newcomb's reported value

Shifting the Michelson data

```
In [1]: newcomb_value = 299860  # km/s

In [2]: michelson_shifted = michelson_speed_of_light \
   ...:         - np.mean(michelson_speed_of_light) + newcomb_value
```

Shifting the Michelson data

```
In [1]: newcomb_value = 299860  # km/s

In [2]: michelson_shifted = michelson_speed_of_light \
   ...:         - np.mean(michelson_speed_of_light) + newcomb_value
```



Calculating the test statistic

```
In [1]: def diff_from_newcomb(data, newcomb_value=299860):
  ...:     return np.mean(data) - newcomb_value
  ...:

In [2]: diff_obs = diff_from_newcomb(michelson_speed_of_light)

In [3]: diff_obs
Out[3]: -7.599999999767169
```

Computing the p-value

```
In [1]: bs_replicates = draw_bs_reps(michelson_shifted,
   ...:                              diff_from_newcomb, 10000)

In [2]: p_value = np.sum(bs_replicates <= diff_observed) / 10000

In [3]: p_value
Out[3]: 0.1603999999999999
```

One sample test

- Compare one set of data to a single number

Two sample test

- Compare two sets of data

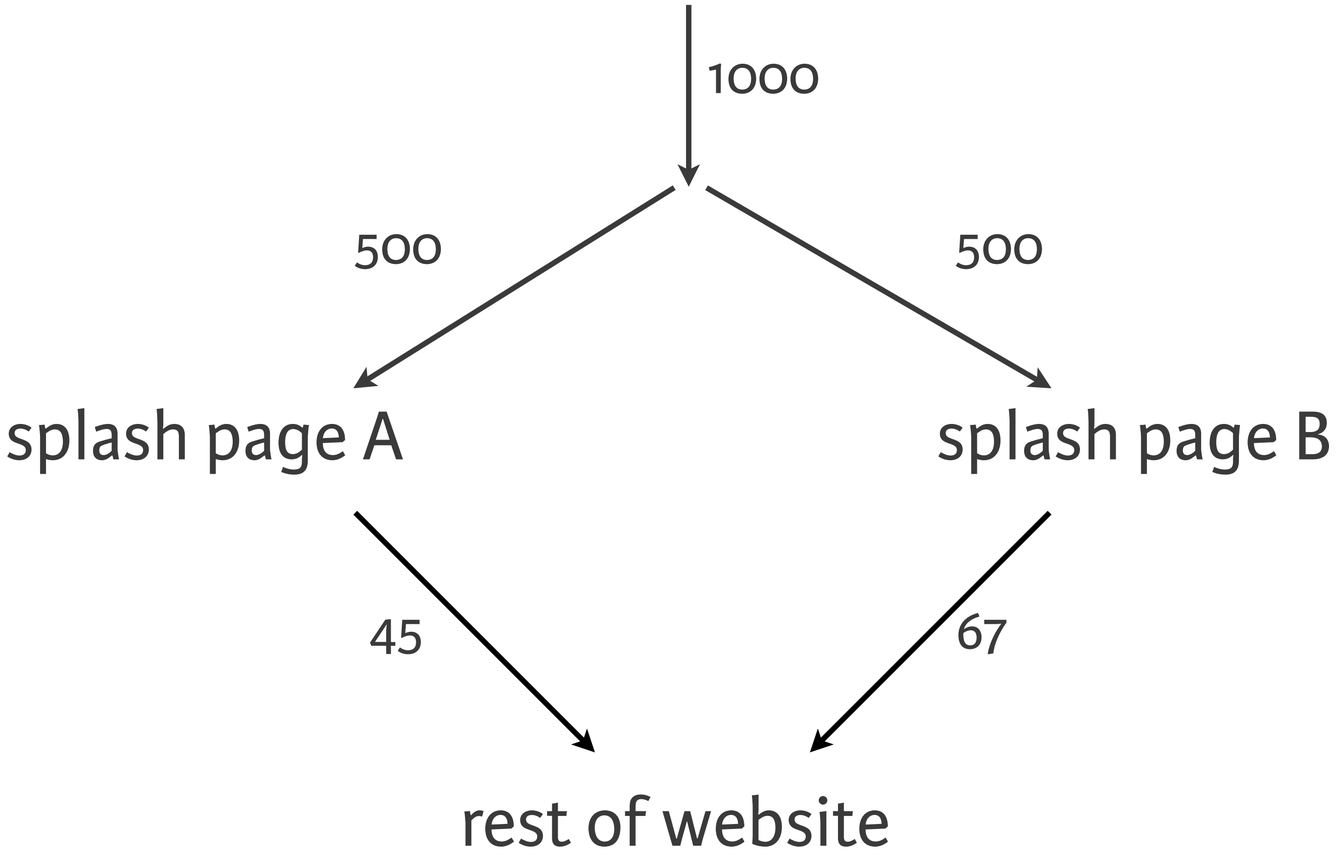
STATISTICAL THINKING IN PYTHON II

Let’s practice!

STATISTICAL THINKING IN PYTHON II

A/B testing

Is your redesign effective?



Null hypothesis

- The click-through rate is not affected by the redesign

Permutation test of clicks through

```
In [1]: import numpy as np

In [2]: # clickthrough_A, clickthrough_B: arr. of 1s and 0s

In [3]: def diff_frac(data_A, data_B):
   ...:     frac_A = np.sum(data_A) / len(data_A)
   ...:     frac_B = np.sum(data_B) / len(data_B)
   ...:     return frac_B - frac_A
   ...:

In [4]: diff_frac_obs = diff_frac(clickthrough_A,
   ...:                           clickthrough_B)
```

Permutation test of clicks through

```
In [1]: perm_replicates = np.empty(10000)

In [2]: for i in range(10000):
    ...:     perm_replicates[i] = permutation_replicate(
    ...:                 clickthrough_A, clickthrough_B, diff_frac)
    ...:

In [3]: p_value = np.sum(perm_replicates >= diff_frac_obs) / 10000

In [4]: p_value
Out[4]: 0.016
```

A/B test

- Used by organizations to see if a strategy change gives a better result

Null hypothesis of an A/B test

- The test statistic is impervious to the change

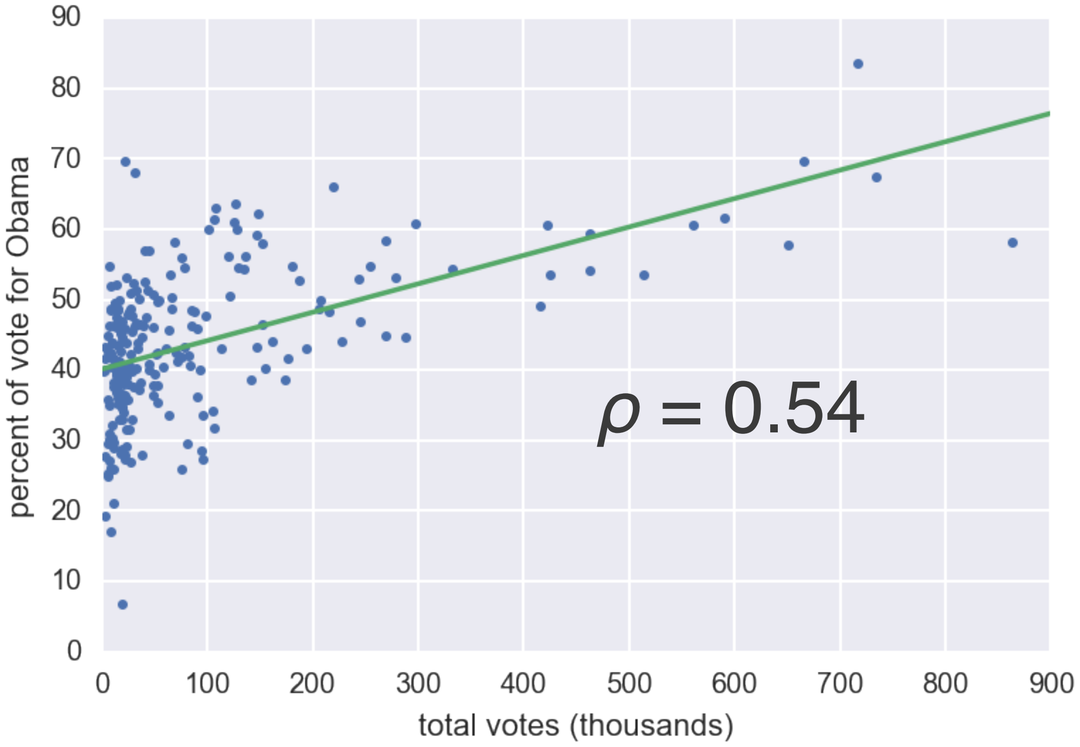
STATISTICAL THINKING IN PYTHON II

Let’s practice!

STATISTICAL THINKING IN PYTHON II

Test of correlation

2008 US swing state election results

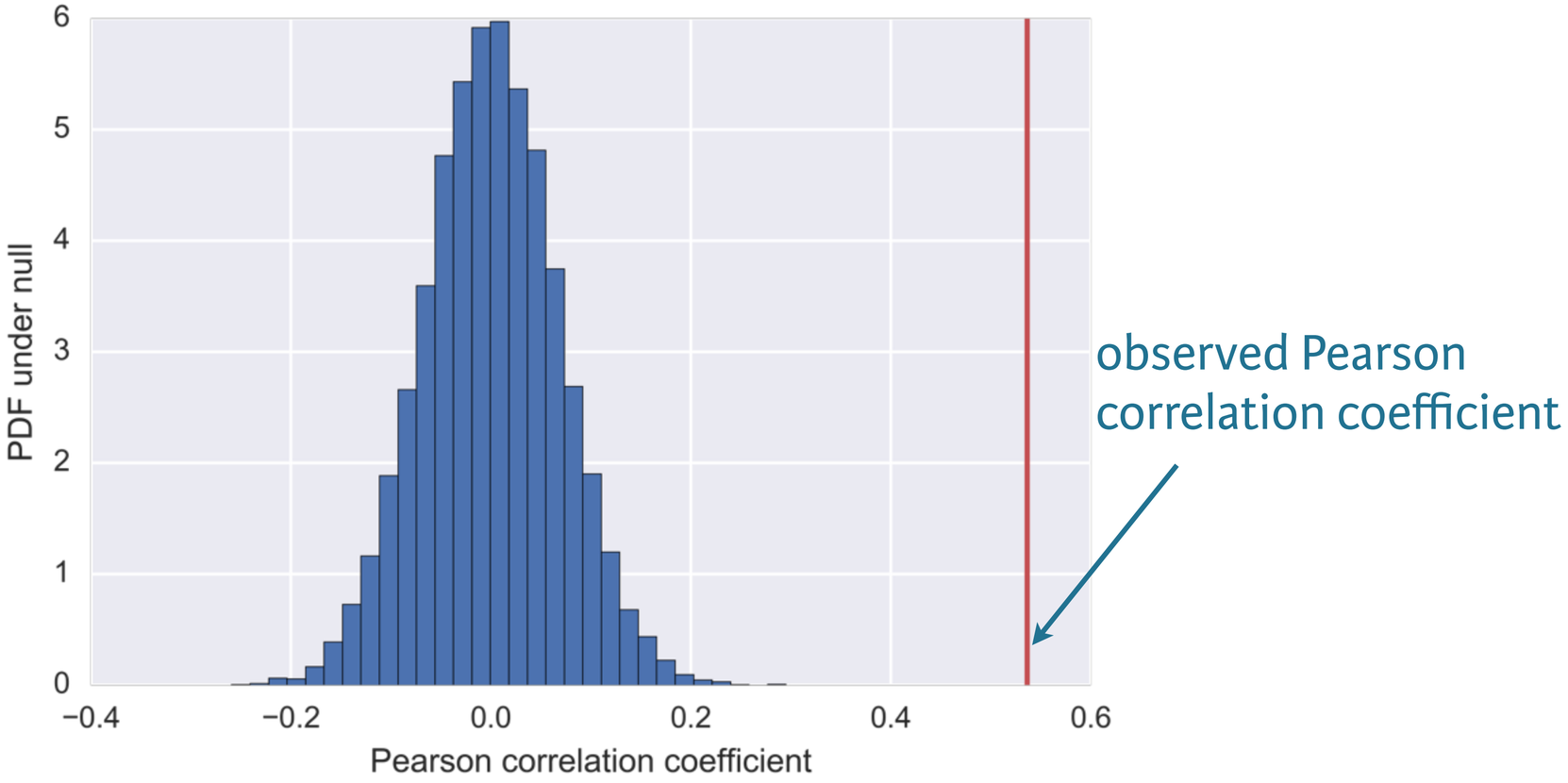


Data retrieved from Data.gov (https://www.data.gov/)

Hypothesis test of correlation

- Posit null hypothesis: the two variables are completely uncorrelated
- Simulate data assuming null hypothesis is true
- Use Pearson correlation, ρ, as test statistic
- Compute p-value as fraction of replicates that have ρ at least as large as observed.

More populous counties voted for Obama



p-value is very very small

STATISTICAL THINKING IN PYTHON II

Let’s practice!

STATISTICAL THINKING IN PYTHON II

Darwin's finches: A full-blown statistical analysis

Your well-equipped toolbox

- Graphical and quantitative EDA
- Parameter estimation
- Confidence interval calculation
- Hypothesis testing

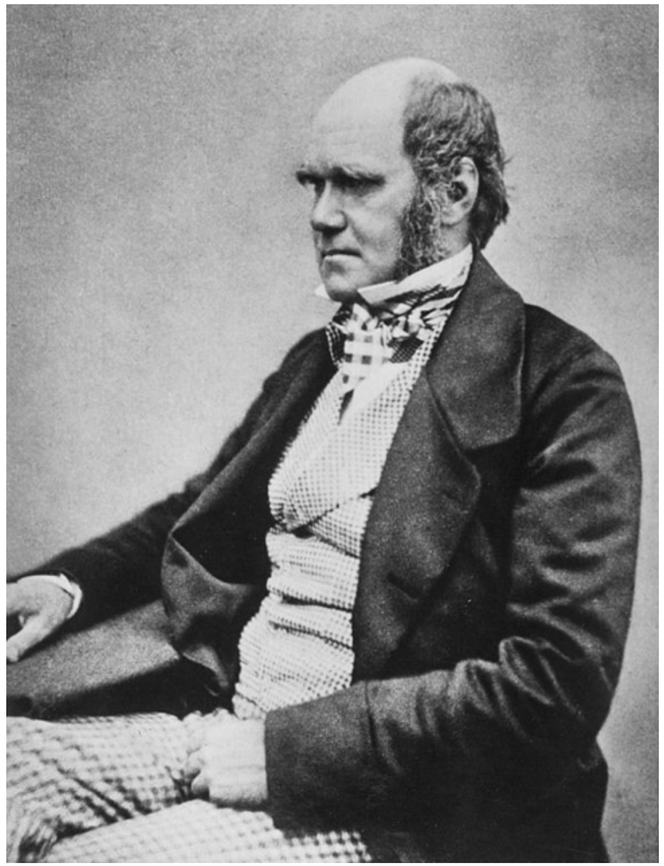


Image: Public domain, US

Image: NASA

The island of Daphne Major

Image: Grant and Grant, 2014

The finches of Daphne Major

Geospiza fortis

Geospiza scandens

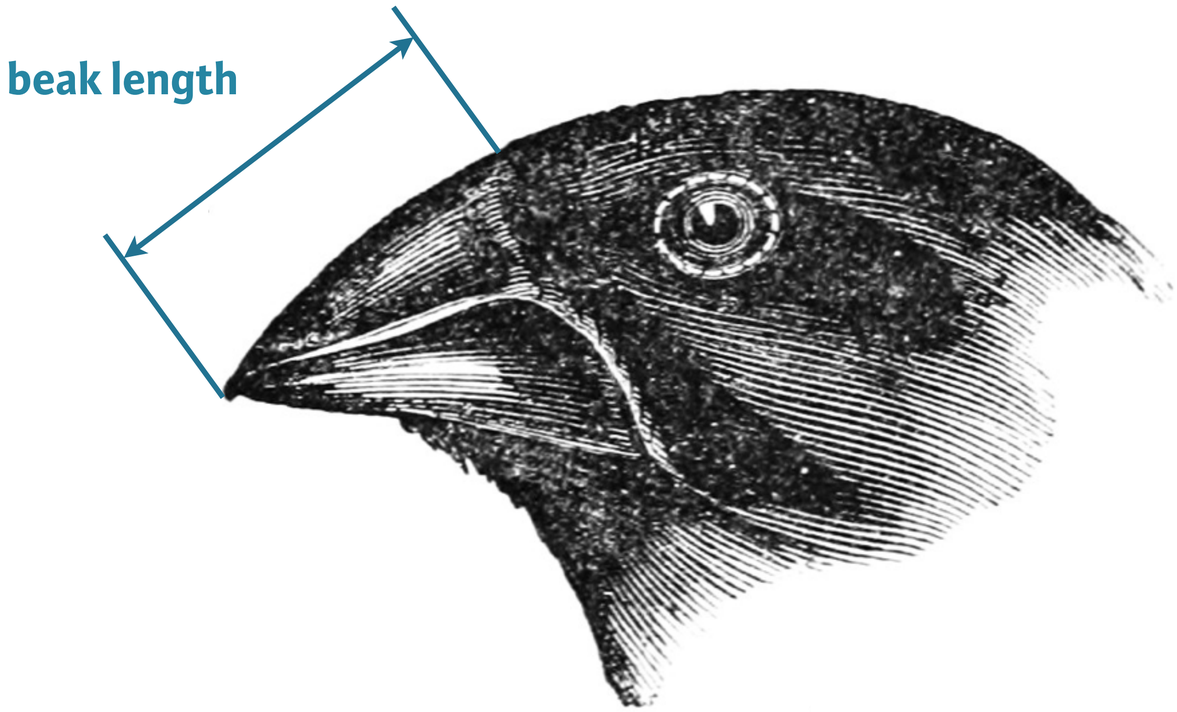
Source: John Gould, public domain

Our data source

- Peter and Rosemary Grant
  40 Years of Evolution: Darwin's Finches on Daphne Major Island
  Princeton University Press, 2014

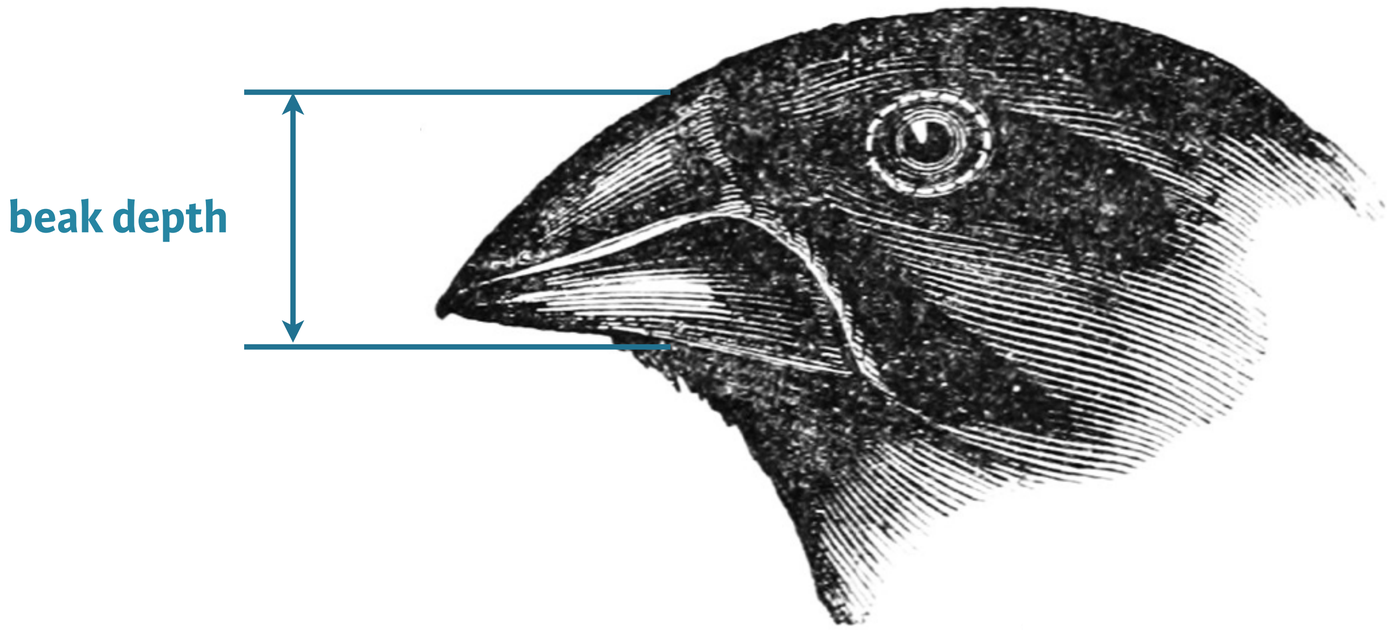
- Data acquired from Dryad Digital Repository
  http://dx.doi.org/10.5061/dryad.g6g3h

The dimensions of the finch beak



Source: John Gould, public domain

The dimensions of the finch beak



Source: John Gould, public domain

Investigation of *G. scandens* beak depth

- EDA of beak depths in 1975 and 2012
- Parameter estimates of mean beak depth
- Hypothesis test: did the beaks get deeper?

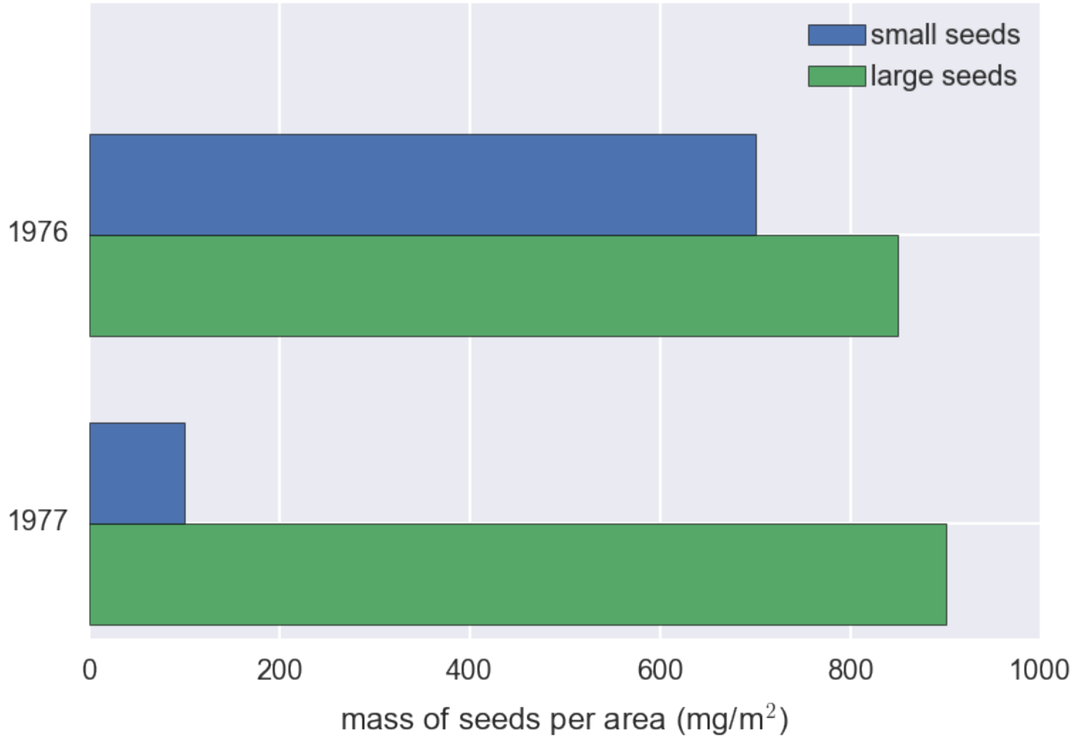
STATISTICAL THINKING IN PYTHON II

Let’s do it!

STATISTICAL THINKING IN PYTHON II

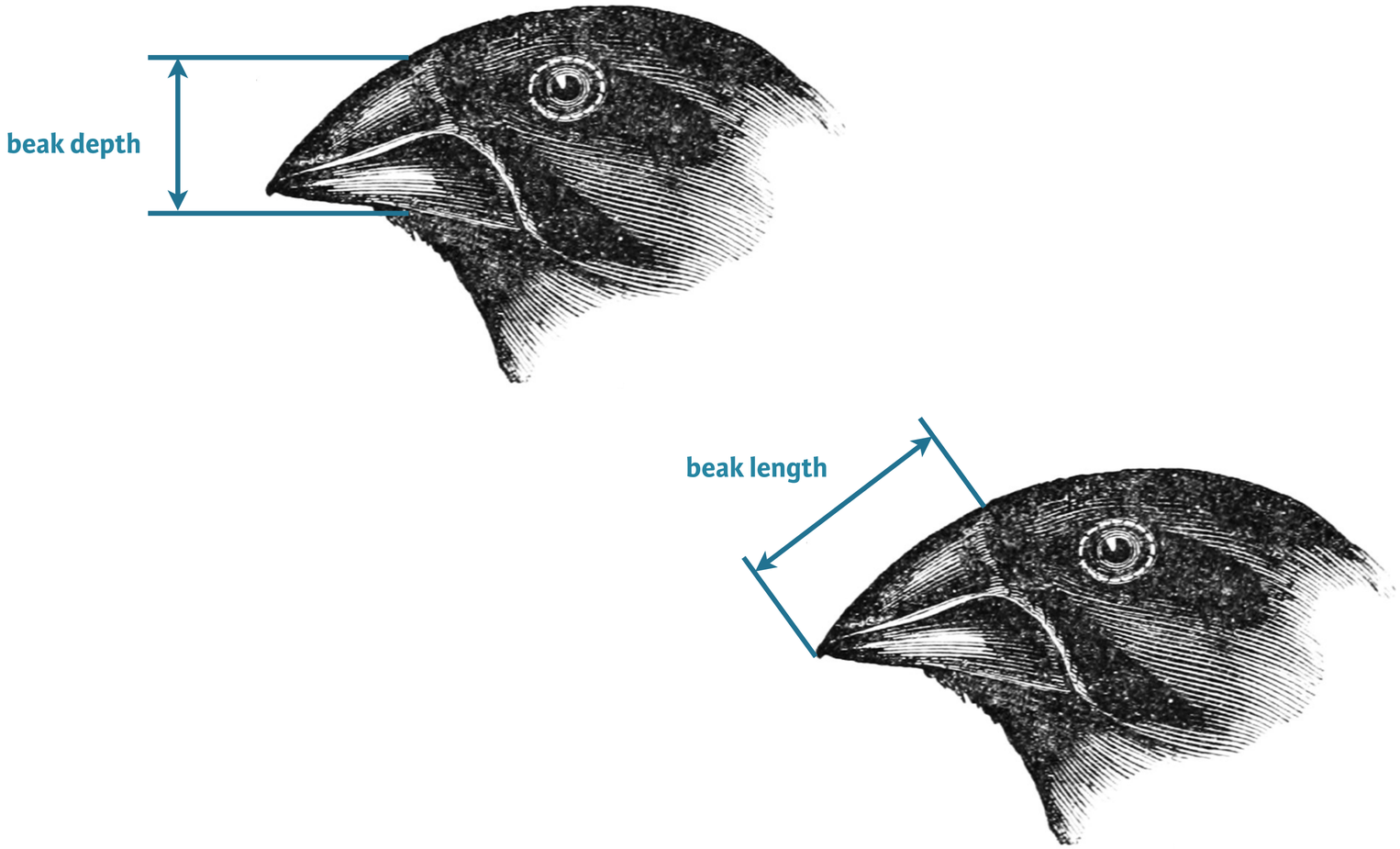
Variation in beak shapes

The drought of winter 1976/1977



Source: Grant and Grant, 2014

Beak geometry



Source: John Gould, public domain

Hint

- `draw_bs_pairs_linreg()` will come in handy

STATISTICAL THINKING IN PYTHON II

Let’s do it!

STATISTICAL THINKING IN PYTHON II

Calculation of heredity

The finches of Daphne Major

Geospiza fortis

Geospiza scandens

Source: John Gould, public domain

Heredity

- The tendency for parental traits to be inherited by offspring

STATISTICAL THINKING IN PYTHON II

Let’s do it!

STATISTICAL THINKING IN PYTHON II

Final thoughts

Your statistical thinking skills

- Perform EDA
  - Generate effective plots like ECDFs
  - Compute summary statistics
- Estimate parameters
  - By optimization, including linear regression
  - Determine confidence intervals
- Formulate and test hypotheses

STATISTICAL THINKING IN PYTHON II

Bon voyage!