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video instruction from technology experts

Lesson 8: Making Inferences: Statistical Estimation and Evaluation

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Process

DOMAIN KNOWLEDGE		DATA MANIPULATION AND TRANSFORMATION		MATHEMATICS, STATISTICS, AND DATA MINING		COMMUNICATION	
Define Problem	Acquisition	Integration	Exploration	**Analysis**	Evaluation	Presentation	Dissemination

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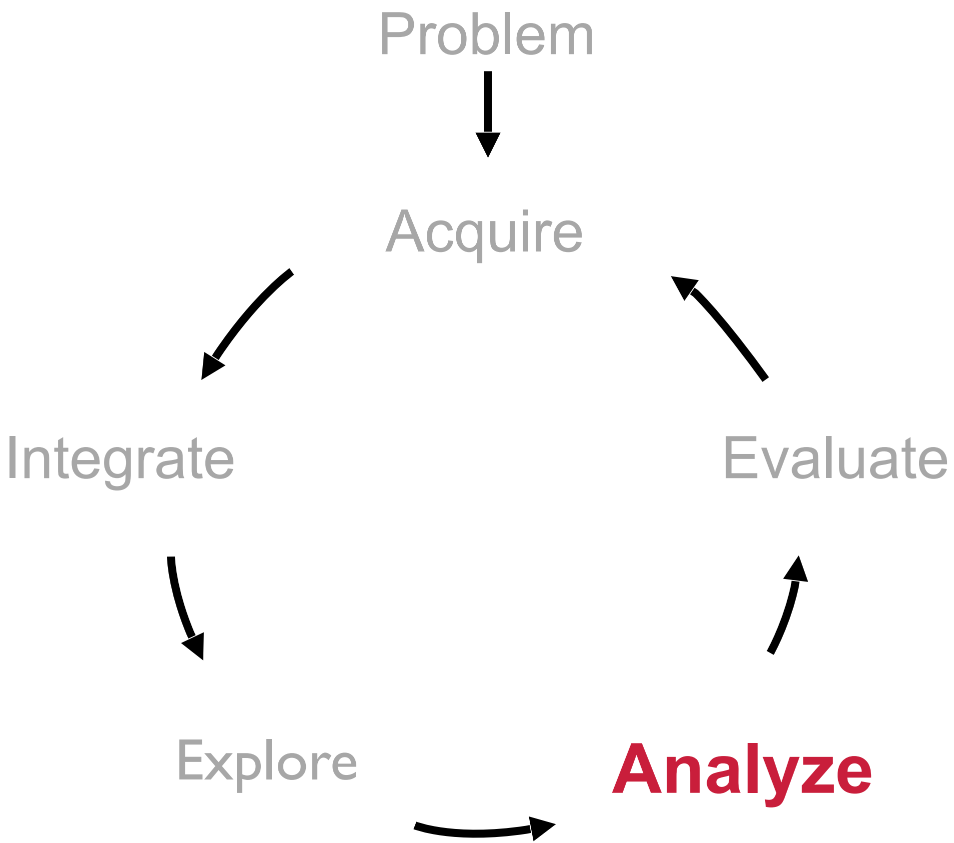
Process + Iteration



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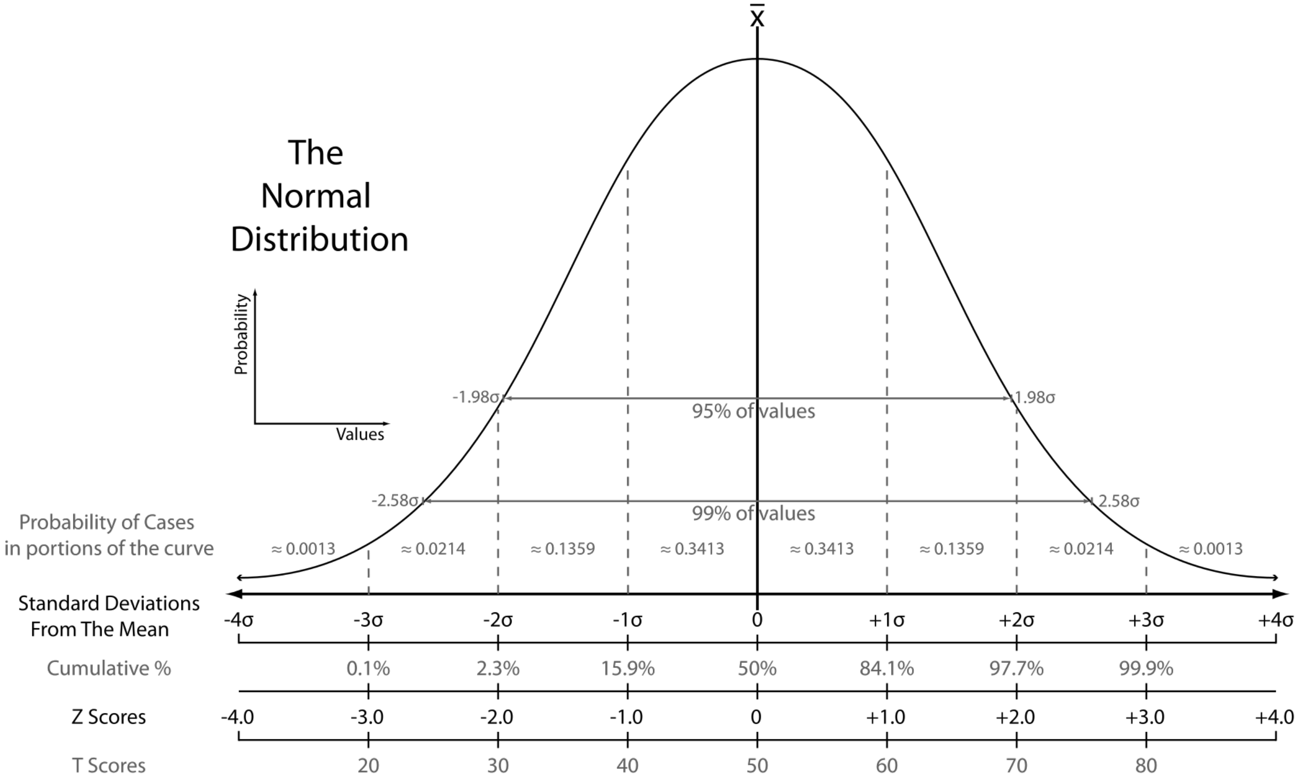
What is Statistics?



source: Wikipedia

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What is Statistics?

Statistics is the study of the collection, analysis, interpretation, presentation, and organization of data.

- Wikipedia

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What is Statistics?

> *Statistics is the activity of inferring results about a population given a sample.*

- Dennis Shasha & Manda Wilson, *Statistics is Easy!*

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> *Statistics is the activity of **inferring** results about a **population** given a **sample**.*

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The Problem

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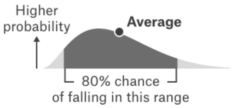
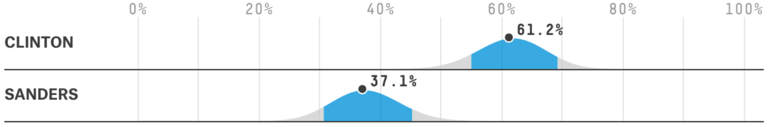
projects.fivethirtyeight.com/election-2016/primary-forecast/california-democratic/

Polls-plus forecast

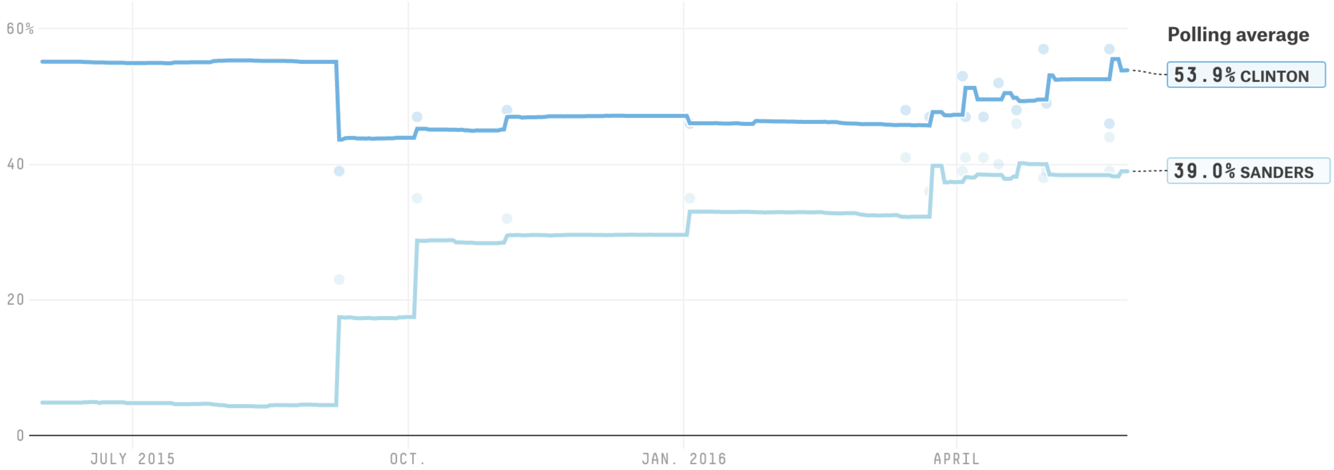
Polls-only forecast



Projected results



Not all **polls** are created equal, so our forecasts are calculated based on weighted **polling averages**.



Polls-plus forecast

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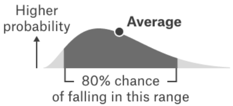
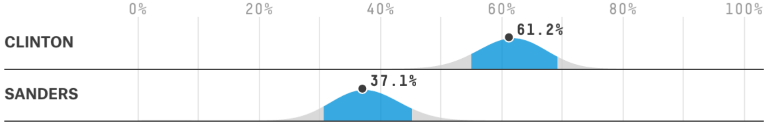


Projected results



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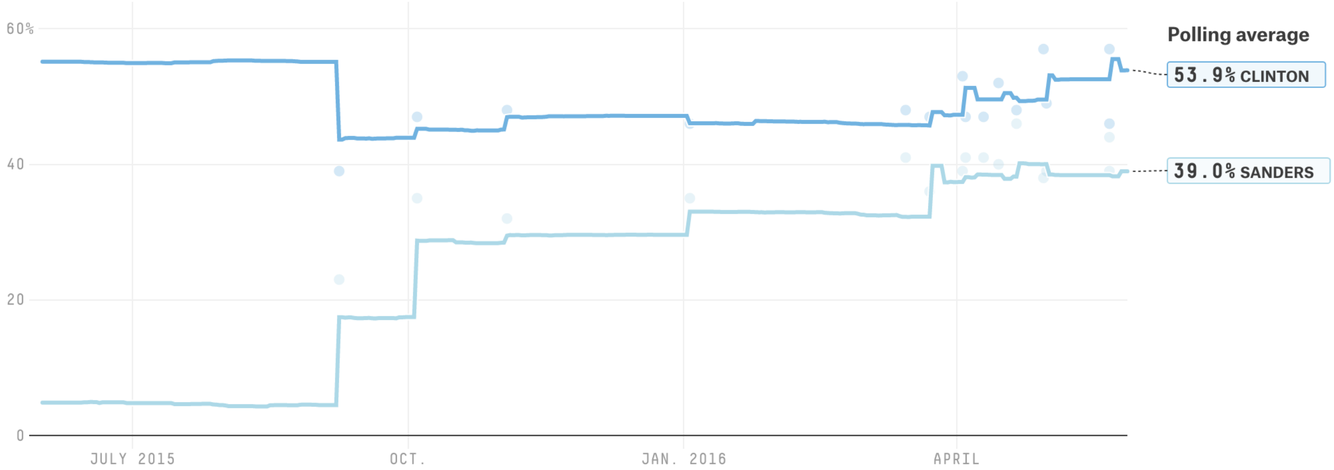

projects.fivethirtyeight.com/election-2016/primary-forecast/california-democratic/

● = NEW A = ALL ADULTS RV = REGISTERED VOTERS LV = LIKELY VOTERS

	POLLSTER	SAMPLE	WEIGHT	LEADER	CLINTON	SANDERS
● MAY 19-22	SurveyUSA	803 LV	1.48	Clinton +18	57%	39%
● MAY 13-22	PPIC	552 LV	0.34	Clinton +2	46%	44%
APR. 27-30	SurveyUSA	826 LV	0.05	Clinton +19	57%	38%
APR. 28-MAY 1	Sextant Strategies	1,617 RV	0.04	Clinton +10	49%	39%
APR. 18-21	Fox News	623 LV	0.01	Clinton +2	48%	46%
APR. 13-15	YouGov	1,123 LV	0.01	Clinton +12	52%	40%
APR. 7-10	Gravis Marketing	846 LV	0.00	Clinton +6	47%	41%
MAR. 24-APR. 4	Field Poll	584 LV	0.00	Clinton +6	47%	41%
MAR. 30-APR. 3	SurveyUSA	767 LV	0.00	Clinton +14	53%	39%
MAR. 16-23	USC Dornsife	363 LV	0.00	Clinton +11	47%	36%

Show more polls ▾

*Leader or runner-up is not in the race.

If you can't find a contest in the dropdown menu above, it's because there hasn't been enough polling in that state yet. We'll add new polling averages and forecasts as soon as the data is available. Notice any bugs or missing polls? Send us an email.

By Jay Boice, Aaron Bycoffe, Harry Enten, Ritchie King, Dhrumil Mehta, Andrei Scheinkman and Nate Silver.

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Reasoning in an Uncertain World

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Questions

- Do US eligible voters favor Hillary Clinton over Bernie Sanders?
- Is drug **A** effective at treating a medical condition?
- Has the Facebook News Feed significantly increased the amount of time users spend on the platform?
- Is Uber making NYC rush hour traffic worse?
- Has an unregulated AirBnB marketplace led to an increasing rate of evictions in San Francisco?

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At the end of the day we want to reason in an informed way to make decisions

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(hypothetical) Decisions

- Hillary Clinton should be the presumptive Democratic nominee
- Approve drug **A** for consumer use
- Roll out the Facebook News Feed interface to all users permanently
- Cap the number of Uber vehicles (and other services) in NYC
- Restrict private short term housing rentals in San Francisco to 75 nights per year

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In Pictures

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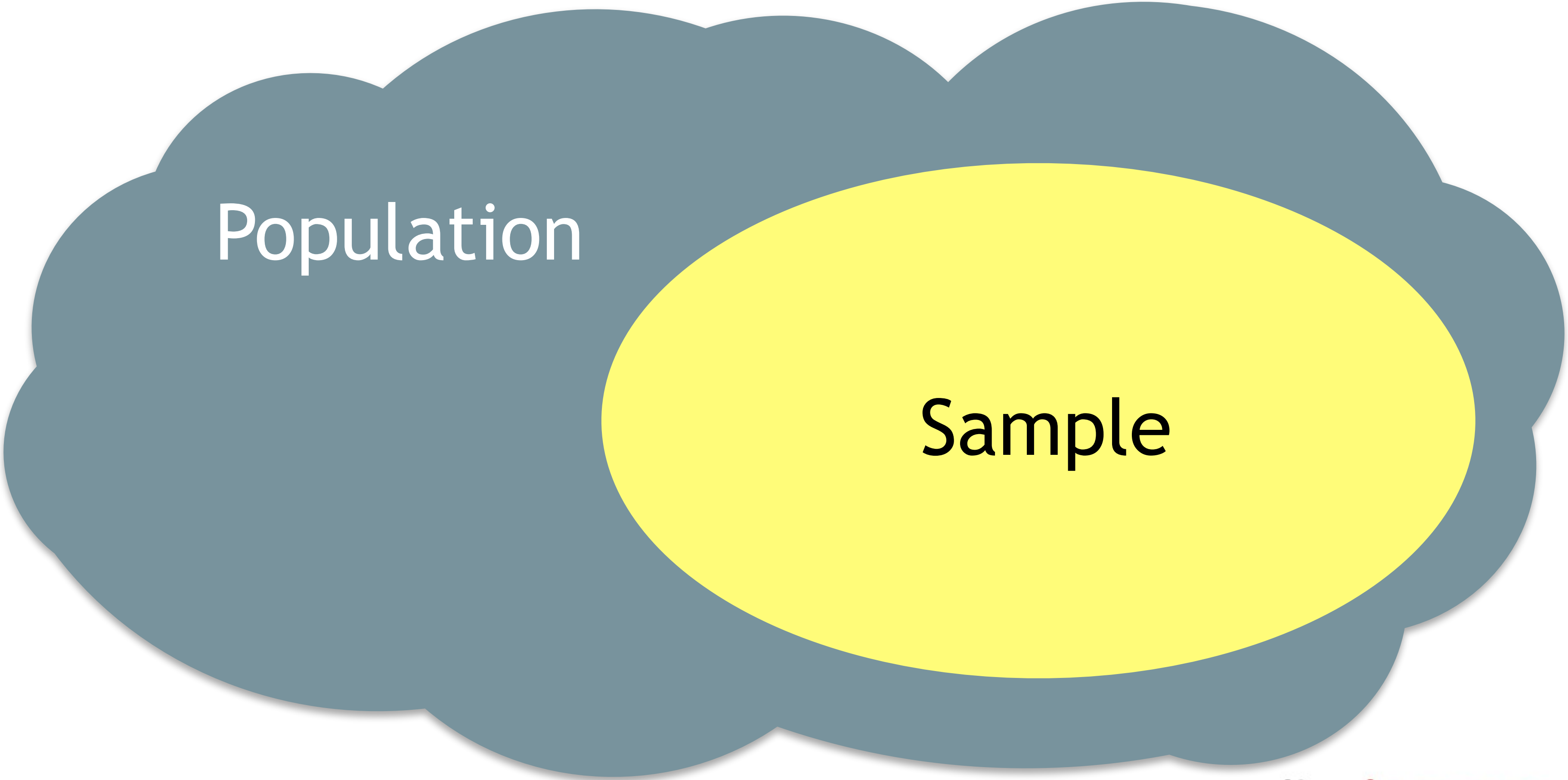

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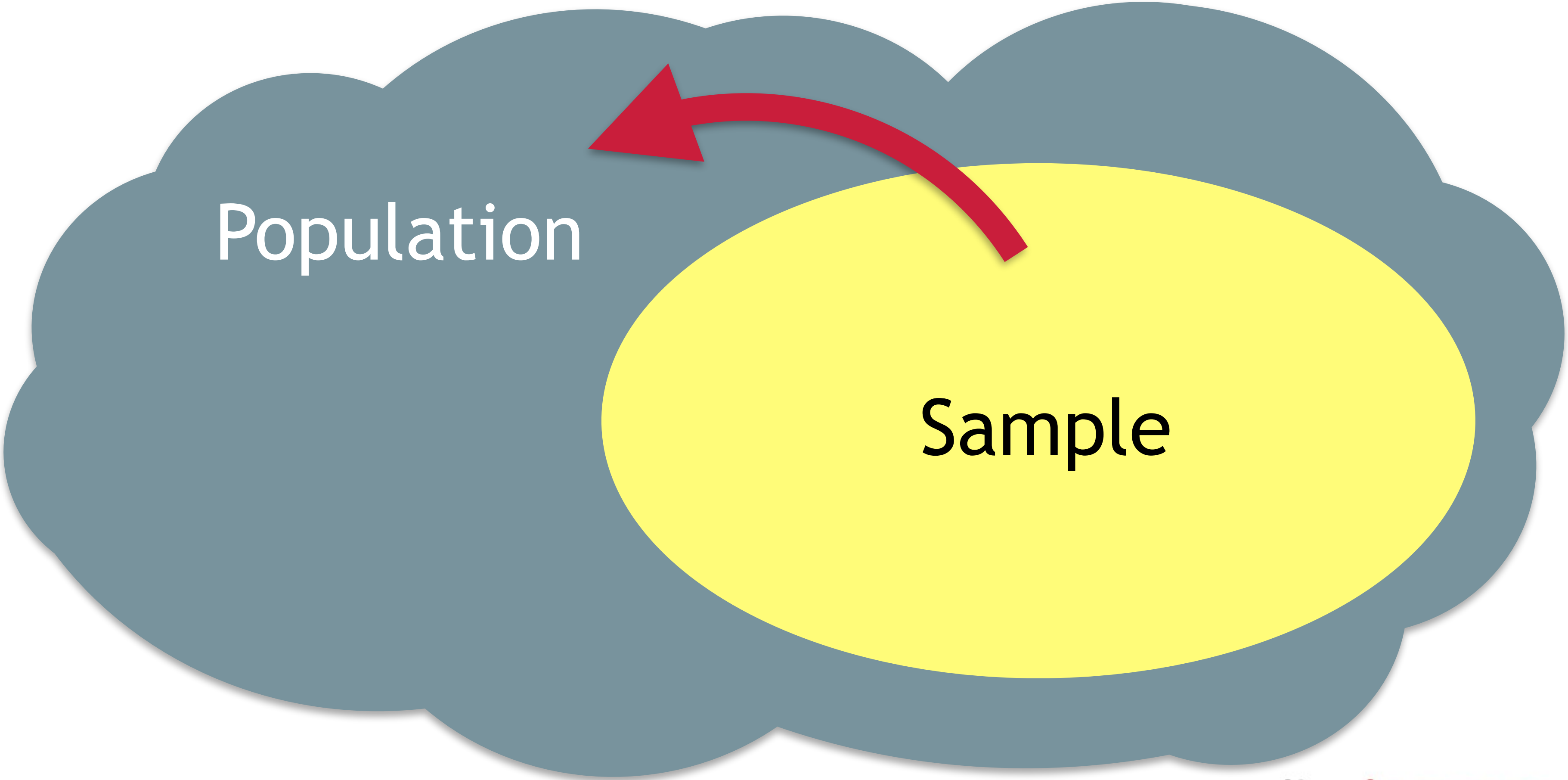

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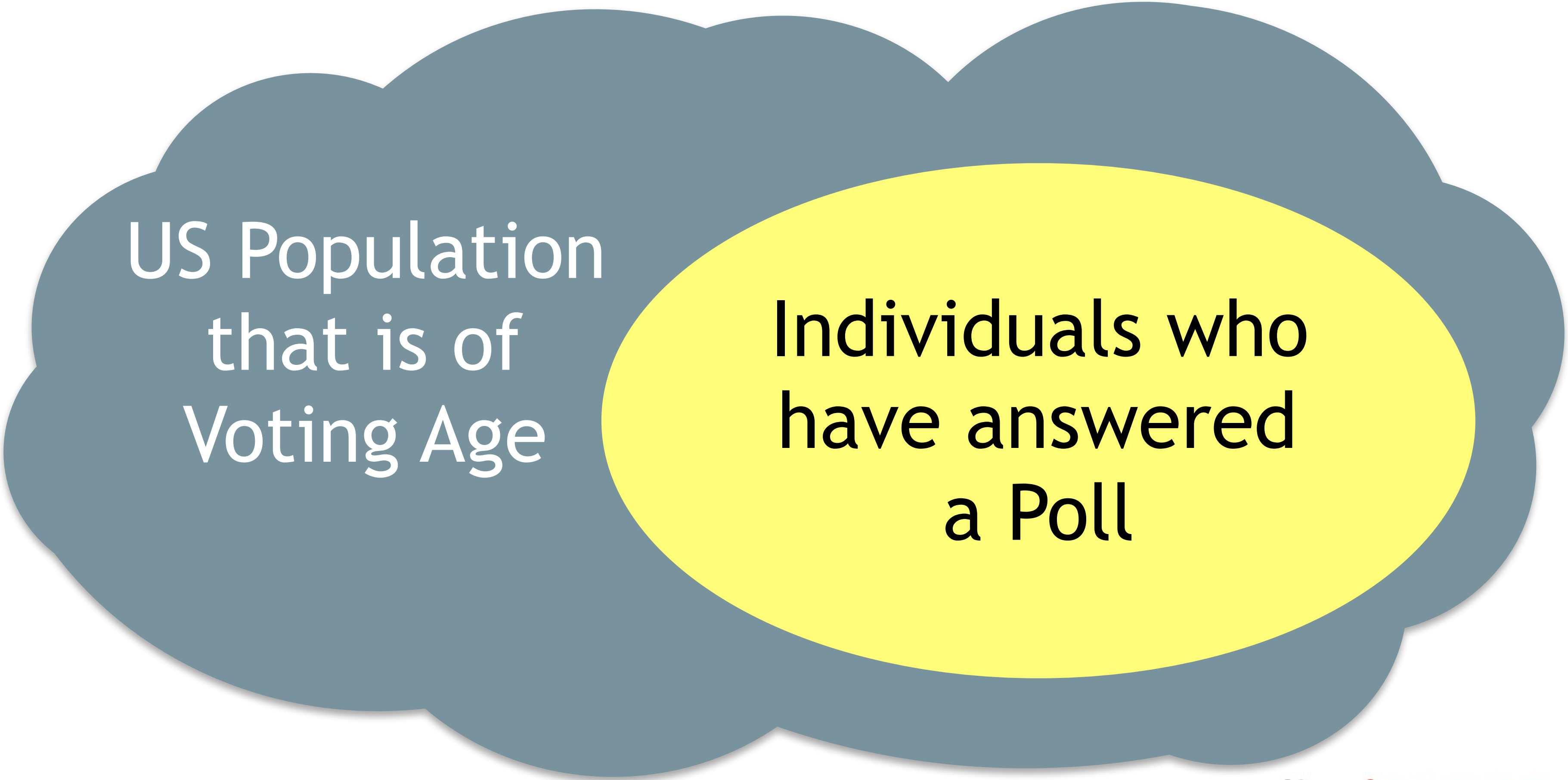

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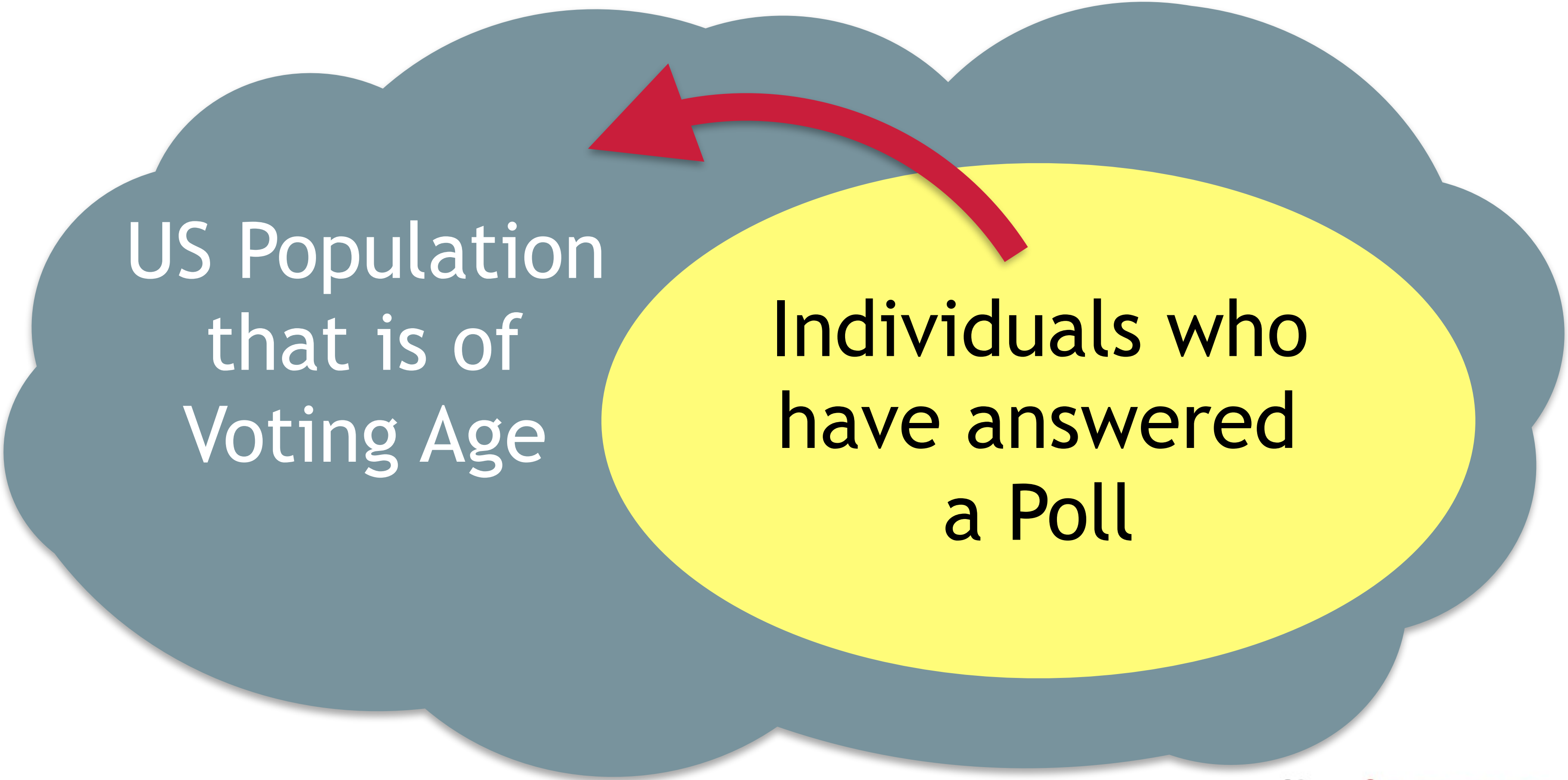

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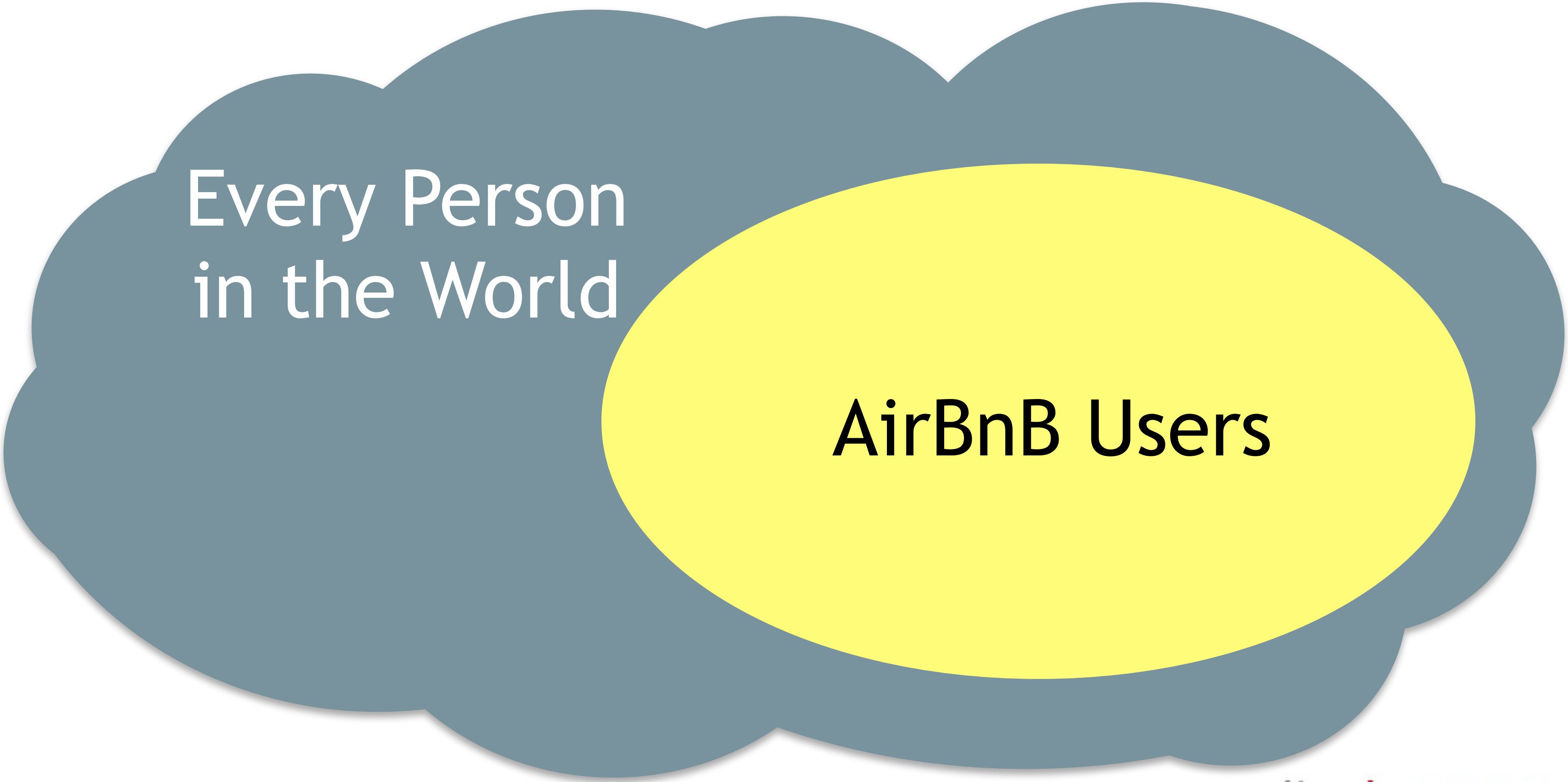

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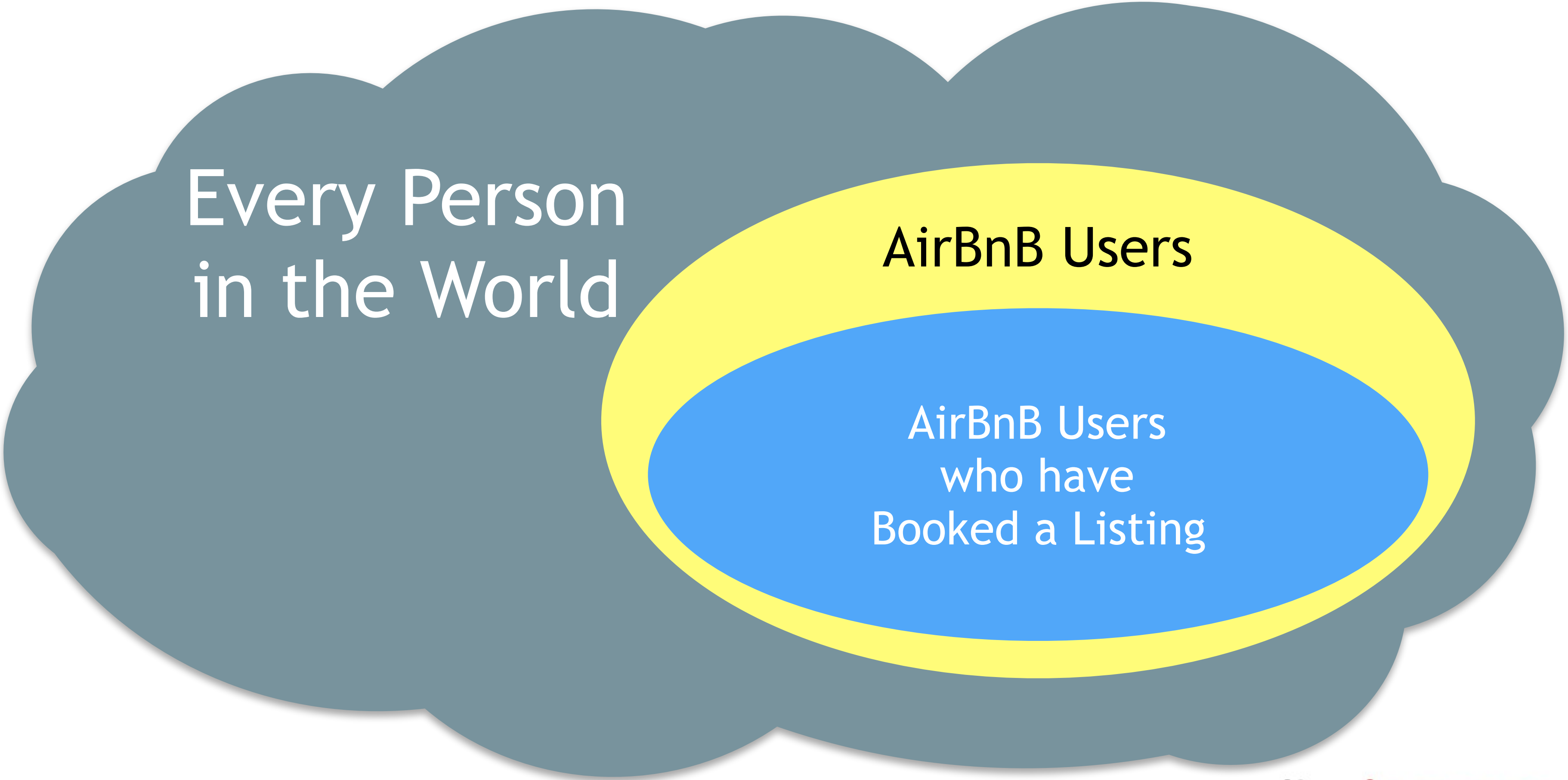

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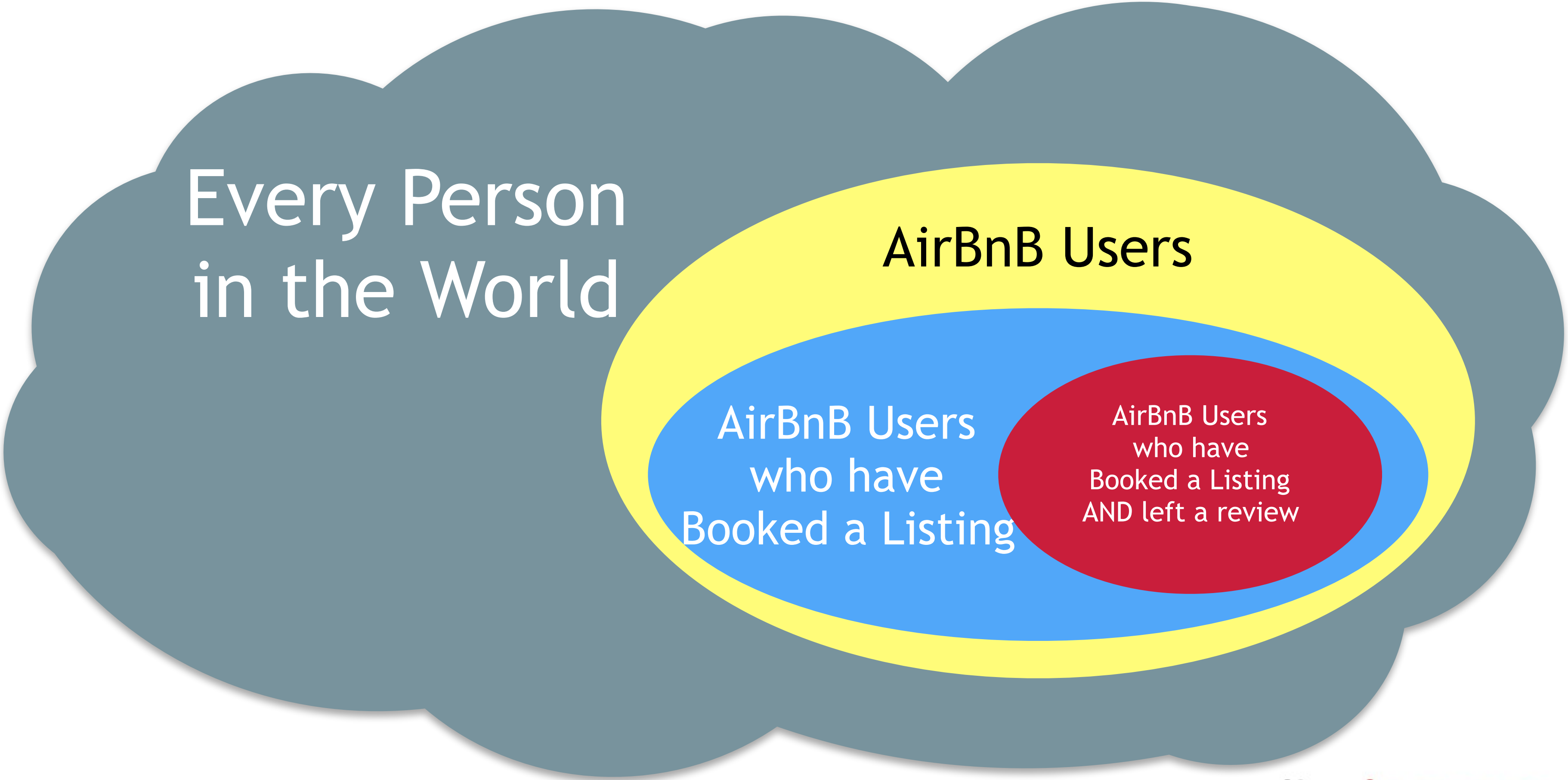

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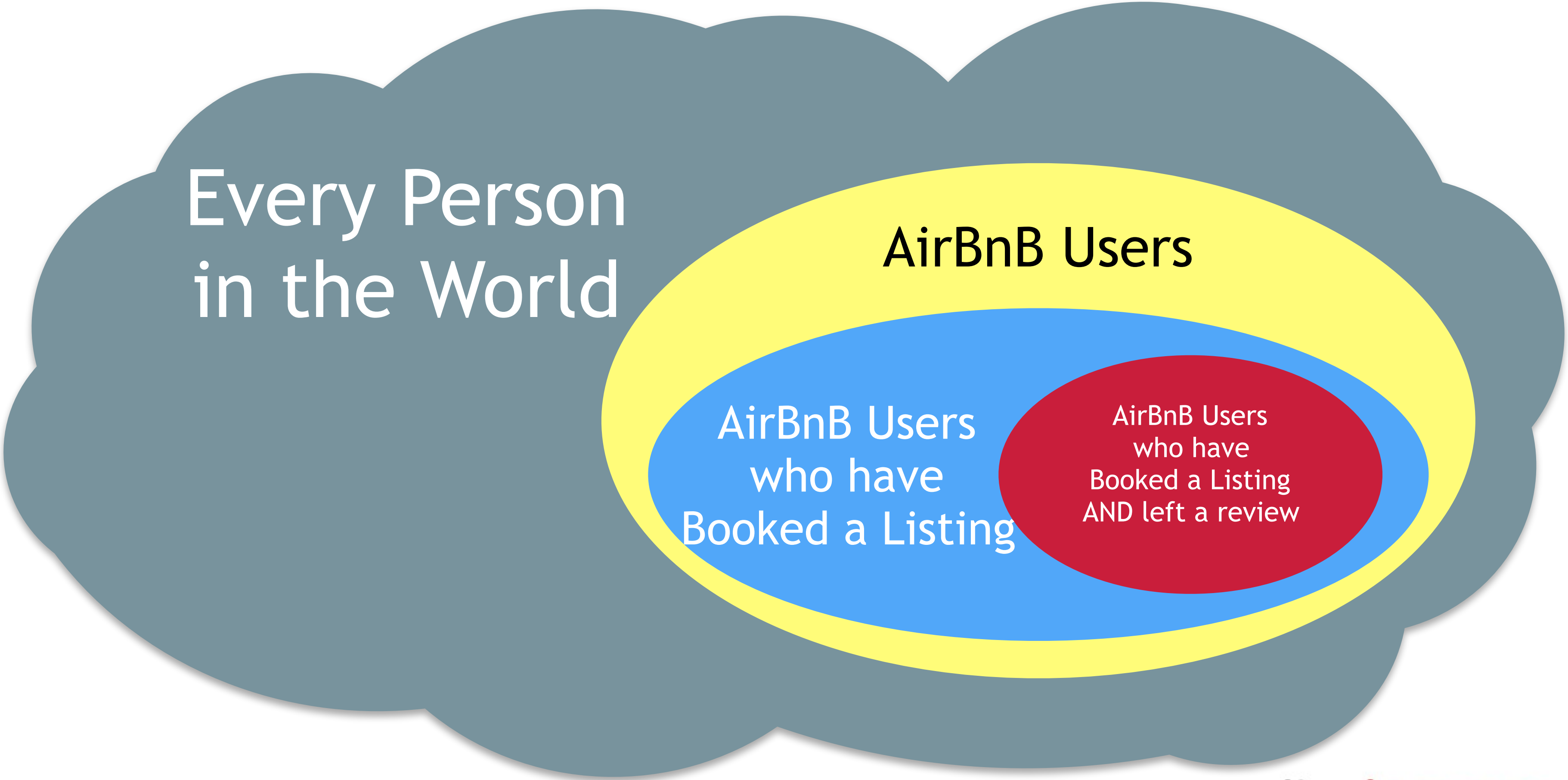

* Not to Scale

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We Want This

Every Person
in the World

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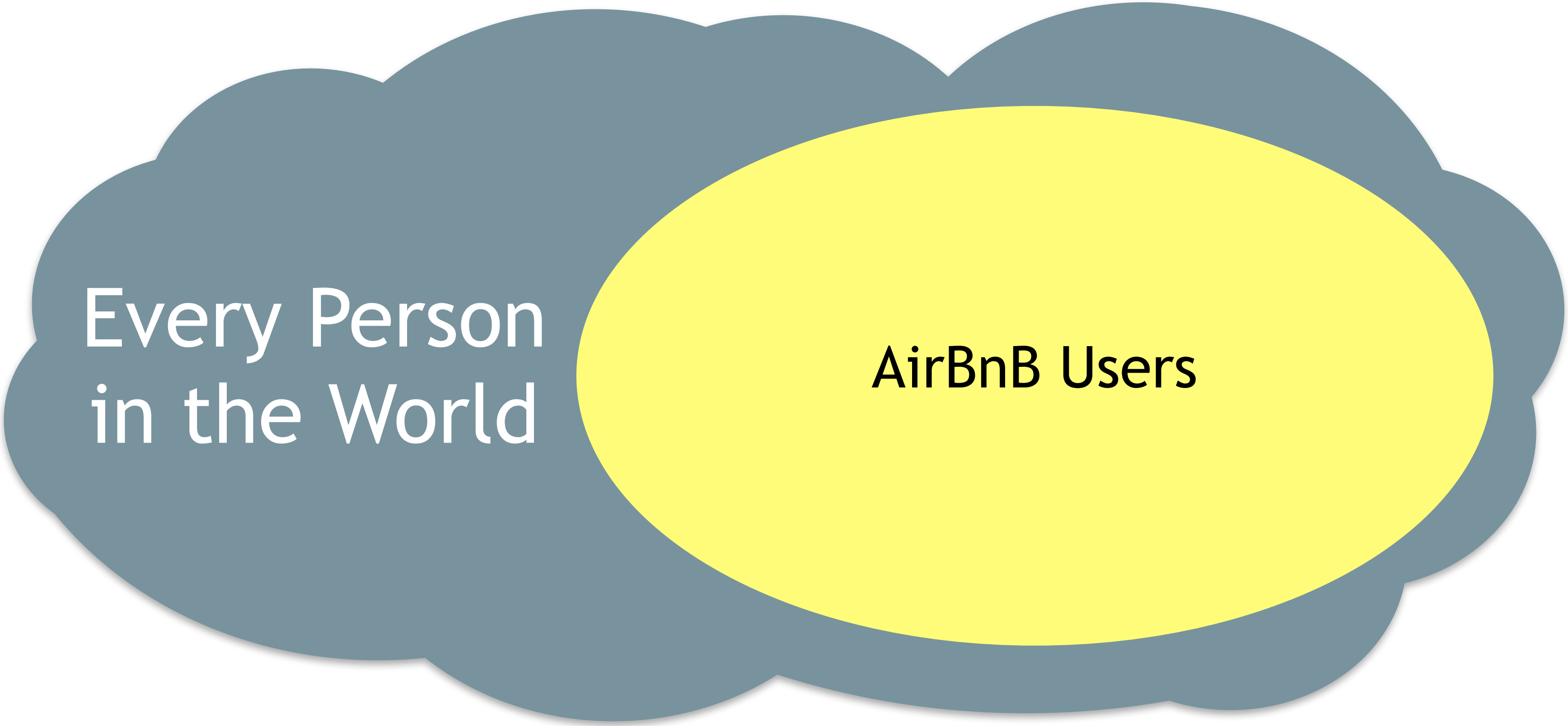
Or Even This...



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But Only Have This...

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Uncertainty

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Goals

- Estimate Quantities of Interest (i.e. statistics/parameters)
- Quantify Uncertainty (i.e. confidence intervals)

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Statistics

Descriptive

- Central Tendency (mean, median, mode, etc.)
- Dispersion (variance and standard deviation)
- Quantiles (min/max, median)
- Bivariate (correlation and covariance)

Inferential

- Estimation (MoM, MLE, MAP)
- Confidence Intervals
- Hypothesis Testing
- Bootstrap Methods
- Regression

Predictive

- Modeling (generative distributions)
- Machine Learning
  - Linear Regression
  - Logistic Regression
  - K Nearest Neighbors

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Moments (mean, median, etc.)

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Average

$$A = \frac{1}{n}\sum_{i=1}^{n} a_i$$

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Expected Value

$$\mu = \sum xP(x)$$

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Statistics

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Helpful… but not enough to answer our questions

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Statistics

Understand

- Central Tendency (mean, median, mode, etc.)
- Dispersion (variance and standard deviation)
- Quantiles (min/max, median)
- Bivariate (correlation and covariance)

Decide

- Estimation (MoM, MLE, MAP)
- Confidence Intervals
- Hypothesis Testing
- Bootstrap Methods
- Regression

Forecast

- Modeling (generative distributions)
- Machine Learning
    - Linear Regression
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    - K Nearest Neighbors

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Statistics

Past

- Central Tendency (mean, median, mode, etc.)
- Dispersion (variance and standard deviation)
- Quantiles (min/max, median)
- Bivariate (correlation and covariance)

Present

- Estimation (MoM, MLE, MAP)
- Confidence Intervals
- Hypothesis Testing
- Bootstrap Methods
- Regression

Future

- Modeling (generative distributions)
- Machine Learning
  - Linear Regression
  - Logistic Regression
  - K Nearest Neighbors

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Statistics

Lesson 7 & 8

- Central Tendency (mean, median, mode, etc.)
- Dispersion (variance and standard deviation)
- Quantiles (min/max, median)
- Bivariate (correlation and covariance)

Lesson 8 & 9

- Estimation (MoM, MLE, MAP)
- Confidence Intervals
- Hypothesis Testing
- Bootstrap Methods
- Regression

Lesson 9+

- Modeling (generative distributions)
- Machine Learning
  - Linear Regression
  - Logistic Regression
  - K Nearest Neighbors

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Statistics

Lesson 7 & 8

- Central Tendency (mean, median, mode, etc.)
- Dispersion (variance and standard deviation)
- Quantiles (min/max, median)
- Bivariate (correlation and covariance)

Lesson 8 & 9

- Estimation (MoM, MLE, MAP)
- Confidence Intervals
- Hypothesis Testing
- Bootstrap Methods
- Regression

Lesson 9+

- Modeling (generative distributions)
- Machine Learning
  - Linear Regression
  - Logistic Regression
  - K Nearest Neighbors

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Questions

AirBnB

- Does recommending listings increase the number of reservations that users make on the AirBnB platform?
- Do listings in neighborhoods with more restaurants and shops attract more visitors?

The Public

- Does the presence of AirBnB in a city cause rents to increase more than they would have otherwise?
- Has AirBnB contributed to falling hotel rates in NYC?

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Let's try to first solve a simpler problem

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That doesn’t involve a comparison

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The simple, humble, mean

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Questions

AirBnB

- Does recommending listings increase the number of reservations that users make on the AirBnB platform?
- What are the “best” restaurants in each neighborhood?

Simplify!

The Public

- Does the presence of AirBnB in a city cause rents to increase more than they would have otherwise?
- Has AirBnB contributed to falling hotel rates in NYC?

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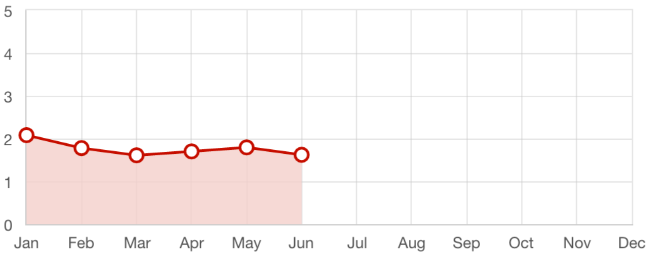
Rating Details

Monthly Trend

2016 2015 2014 2013 2012



Understand how a business' rating changes month-to-month. Learn more.

Overall Rating

Yelping since 2004 with 8381 reviews

5 stars	2007
4 stars	639
3 stars	527
2 stars	705
1 star	4507

We calculate the overall star rating using only reviews that our automated software currently recommends. Learn more.

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Closed
Sun Closed

"Locally, I enjoy bei
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"Reviews galore, ta
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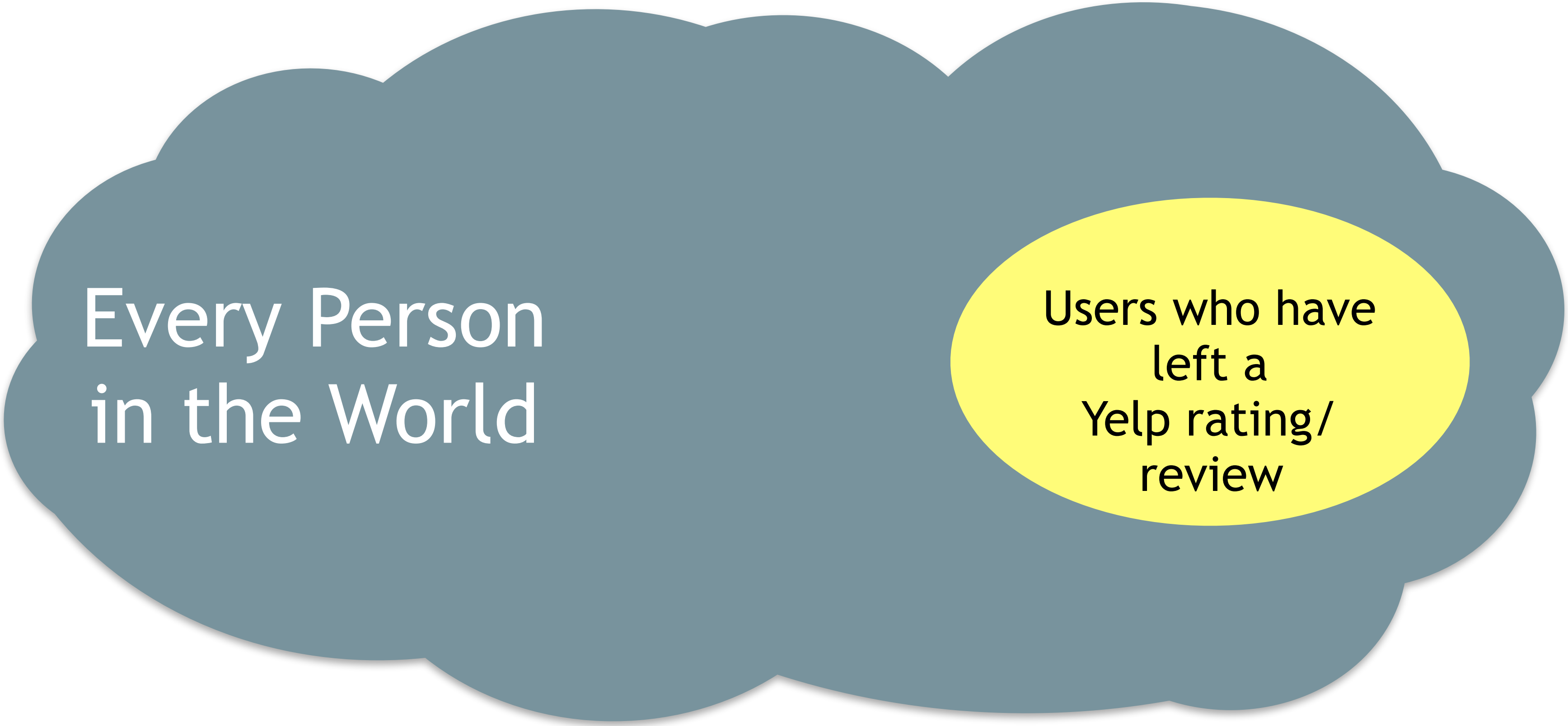
General Inference



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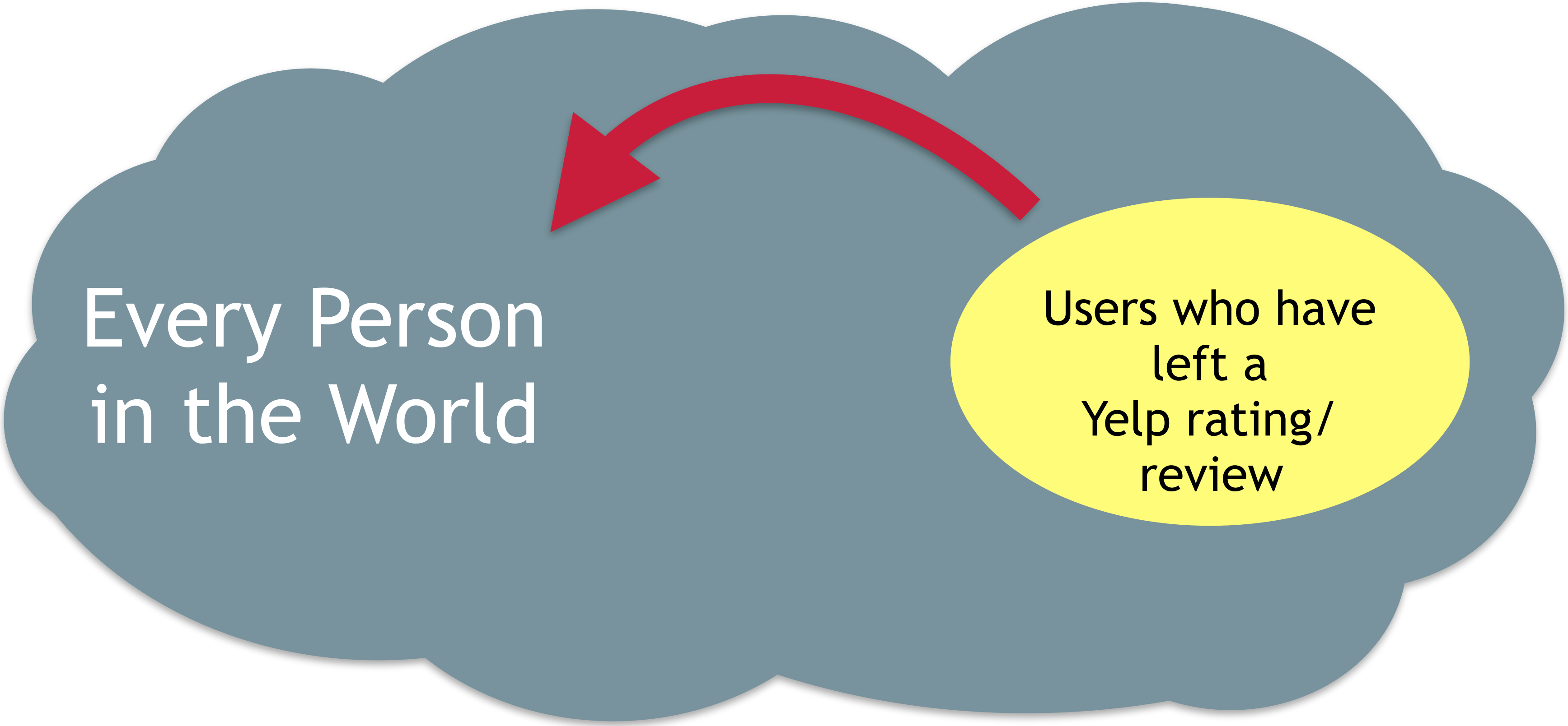
General Inference



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Represent your Population by Your Sample

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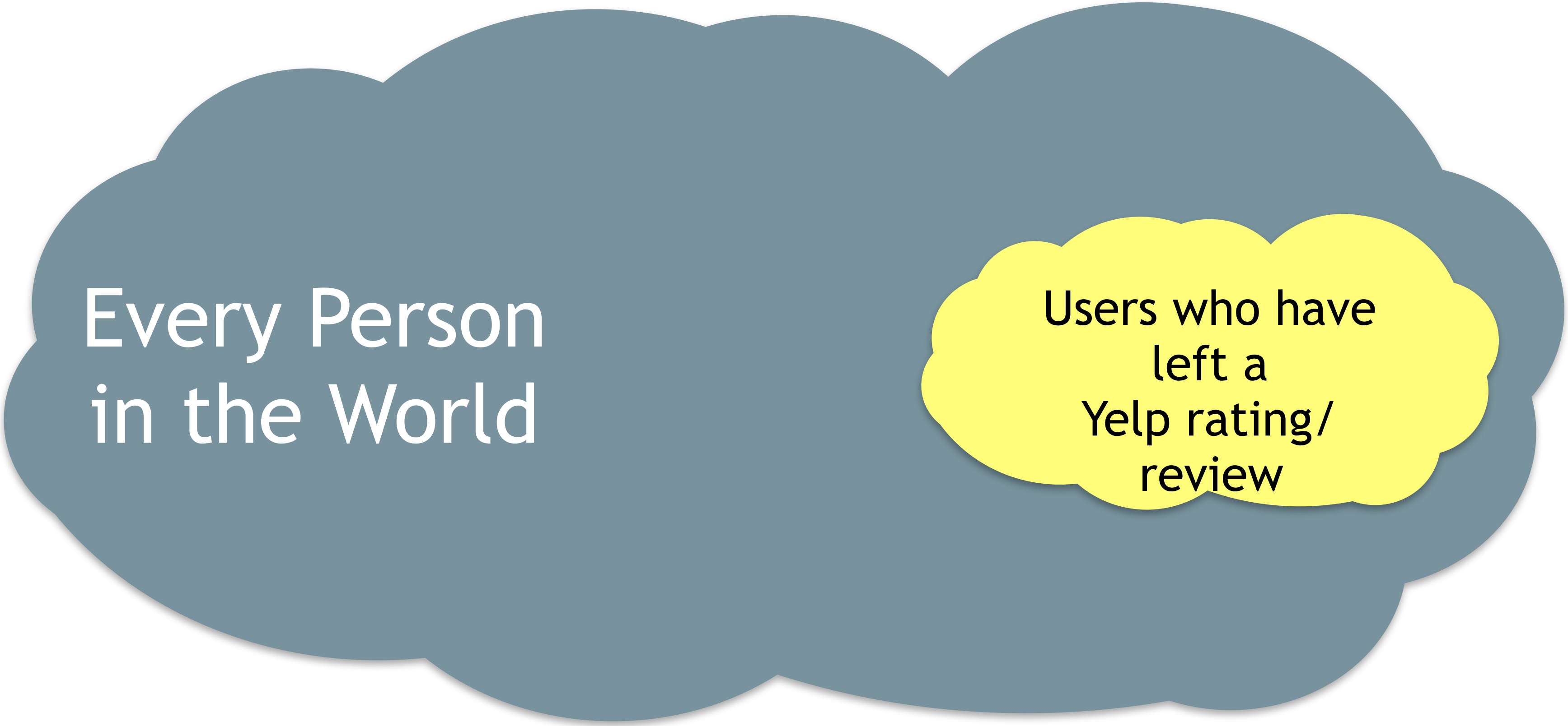
General Inference



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Sample your Sample

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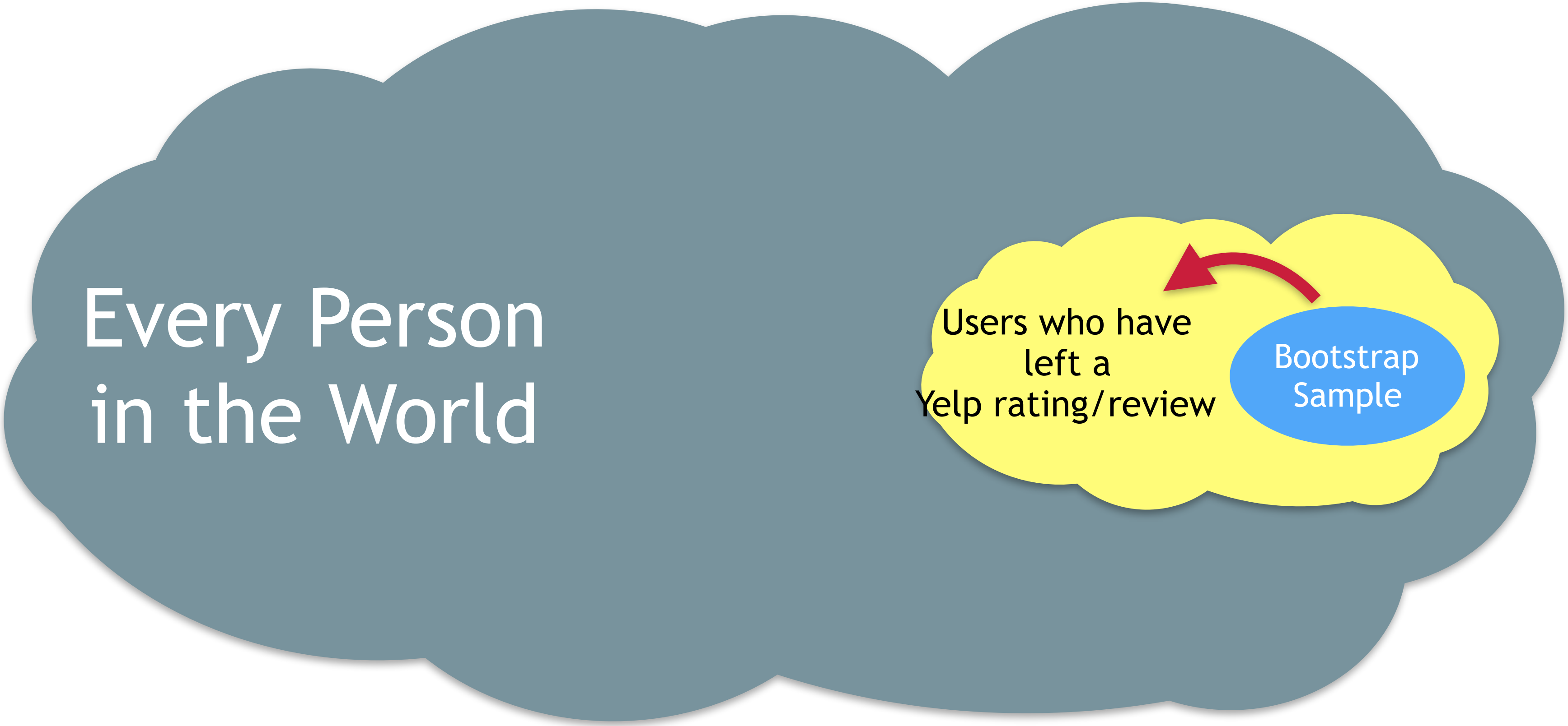
The Bootstrap



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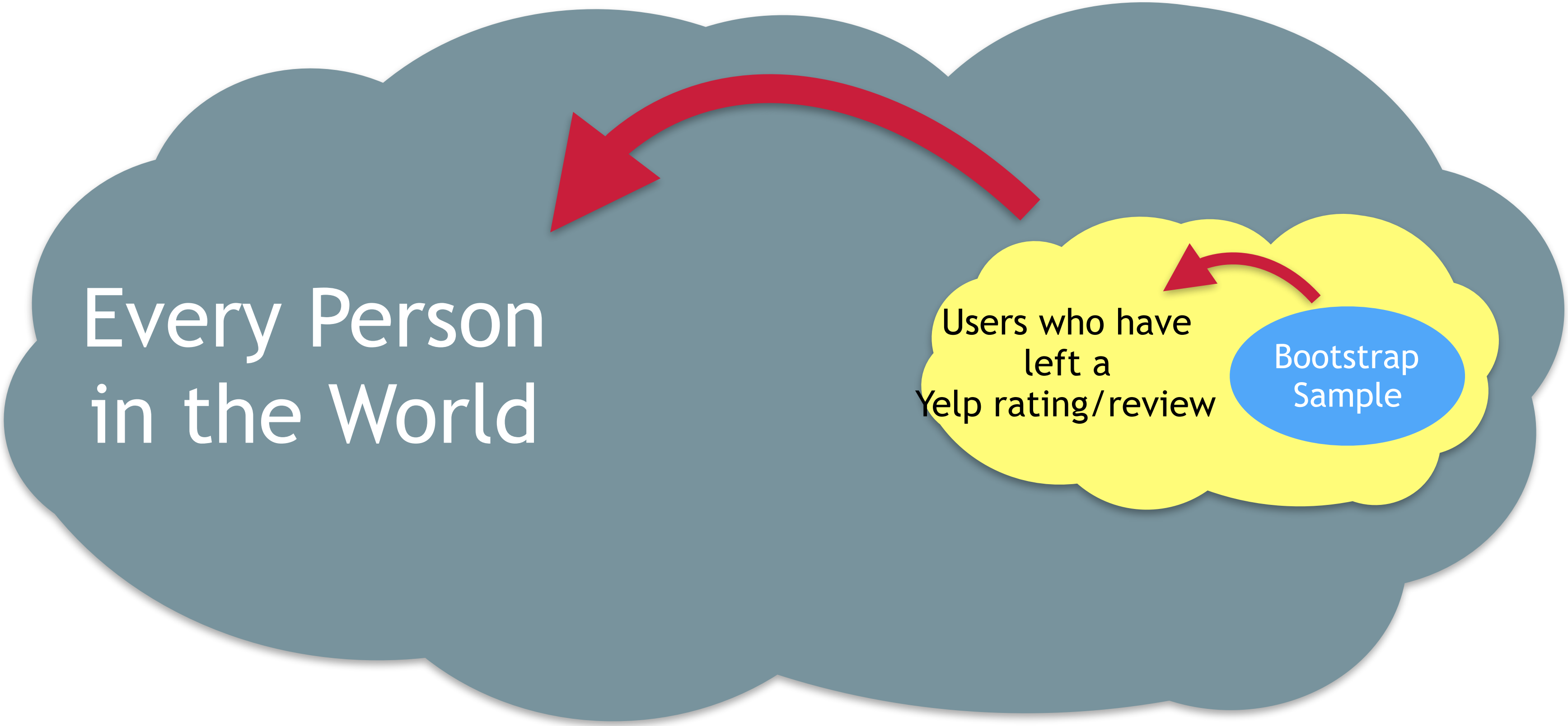
Sample -> Population

Bootstrap sample -> Sample

Bootstrap sample -> Sample -> Population

* Works as long as the sample is somewhat representative of the population

The Bootstrap



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```python
df = pd.read_csv('yelp_stars/' + filename)
num_samples = len(df)
boots = []

for i in range(2000):
    bootstrap = df.sample(num_samples, replace = True)
    boots.append(bootstrap.rating.mean())
```

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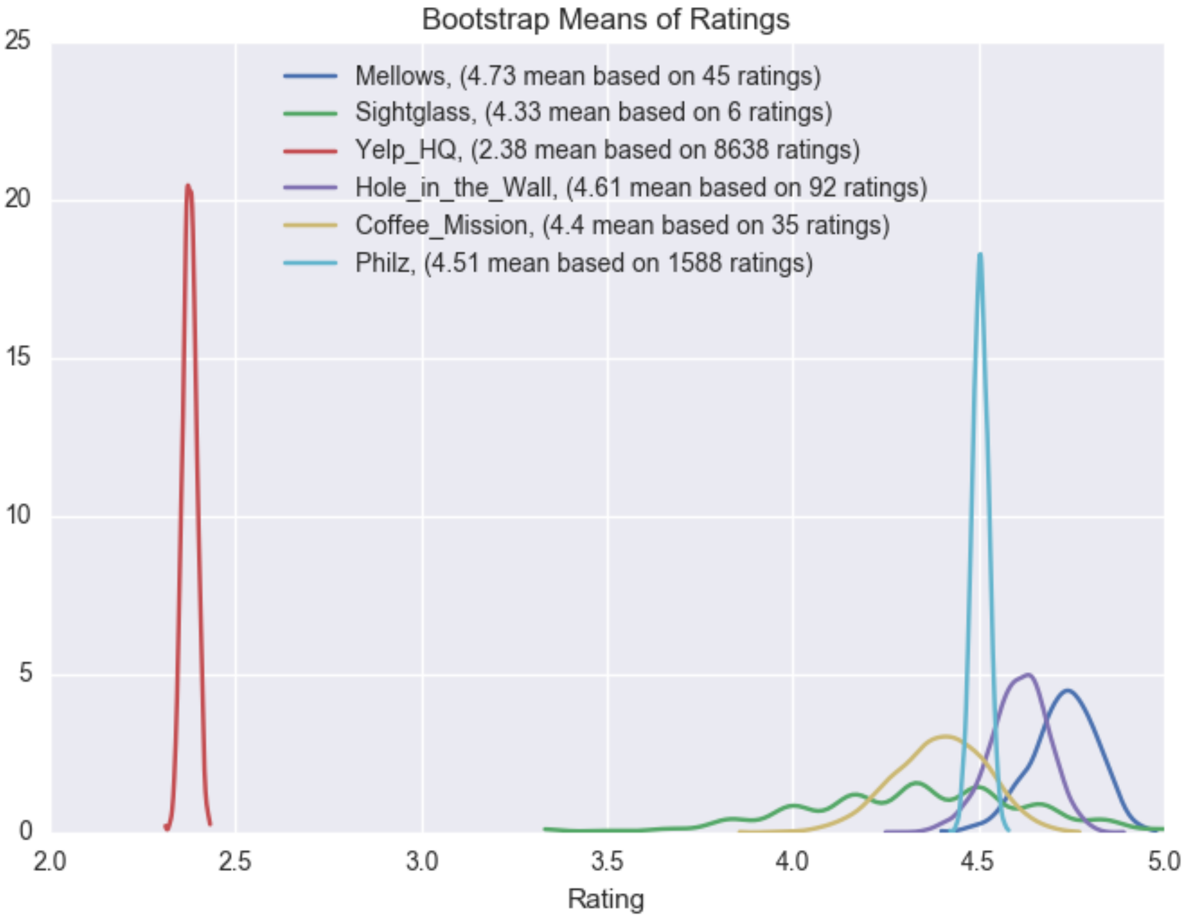

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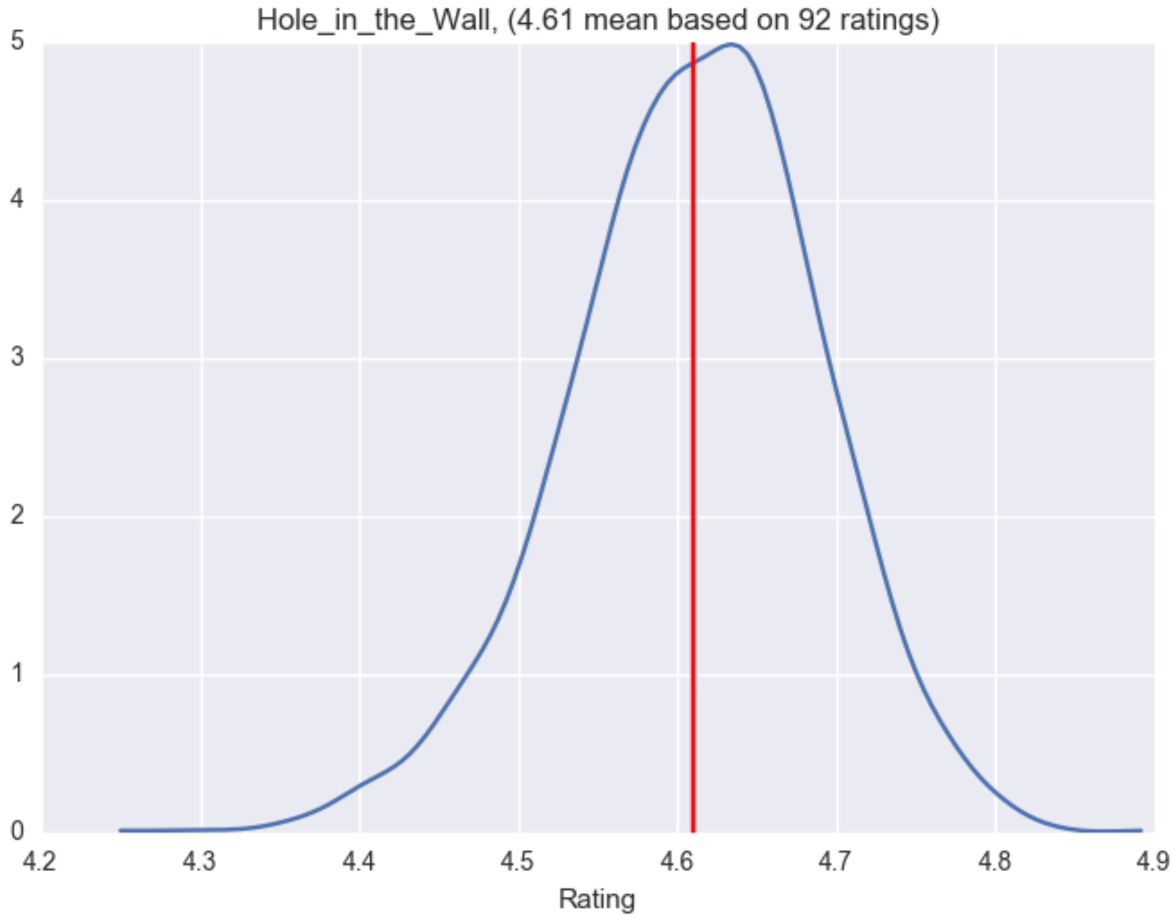

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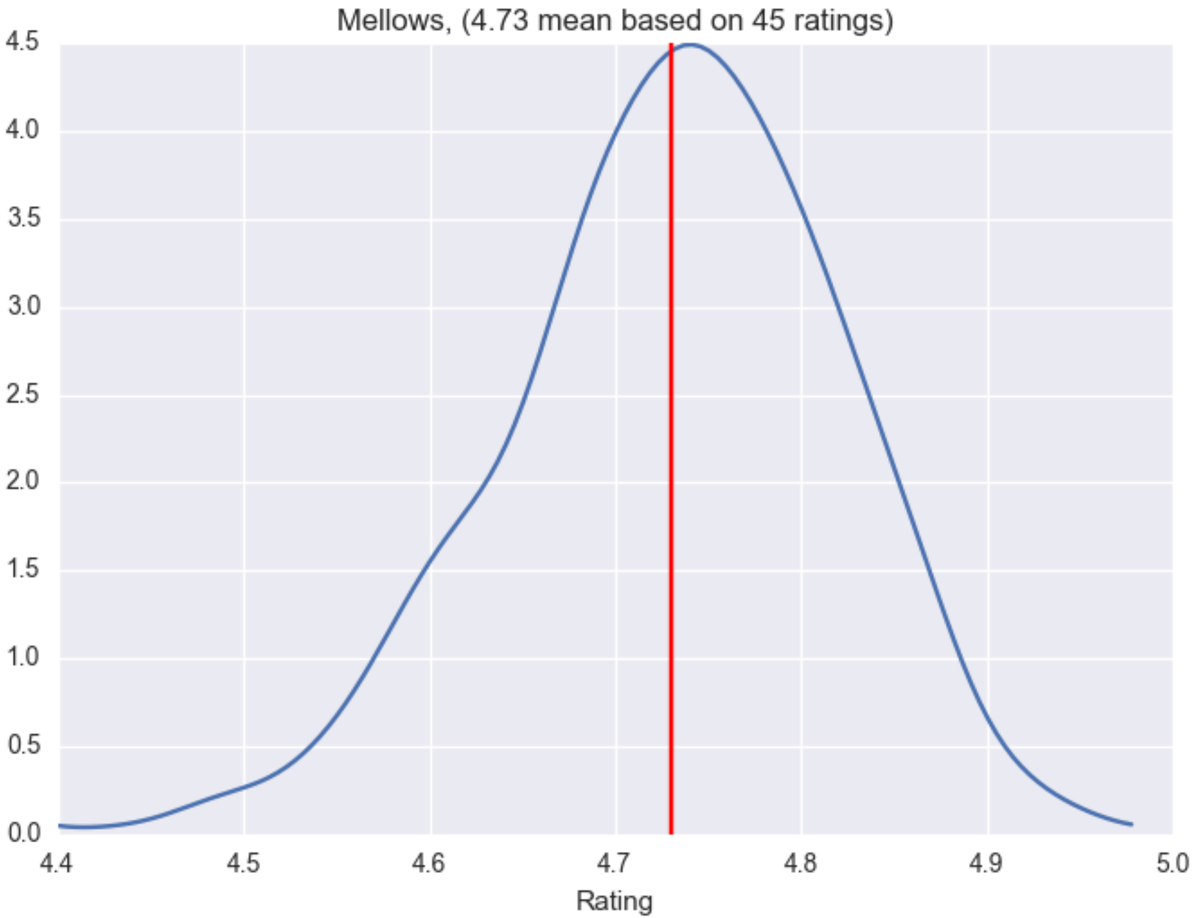

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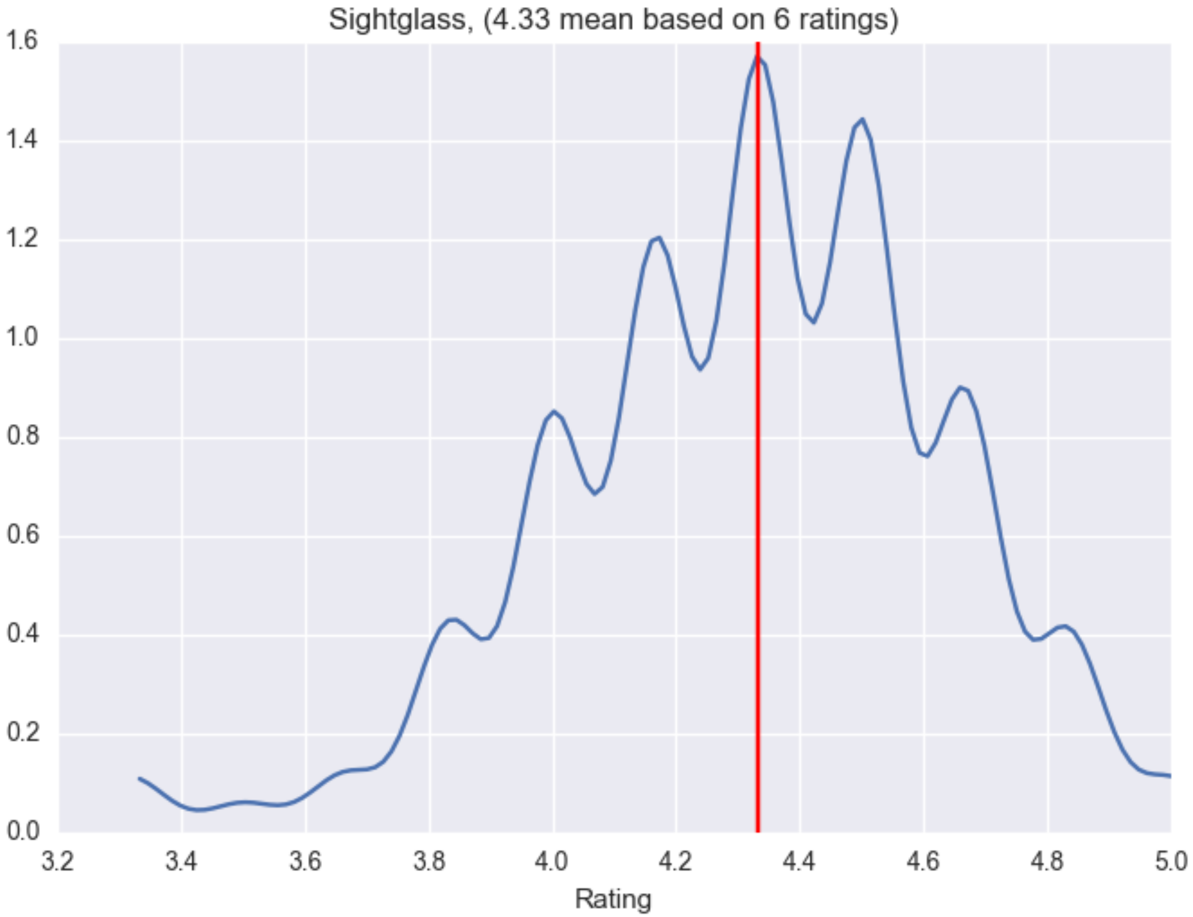

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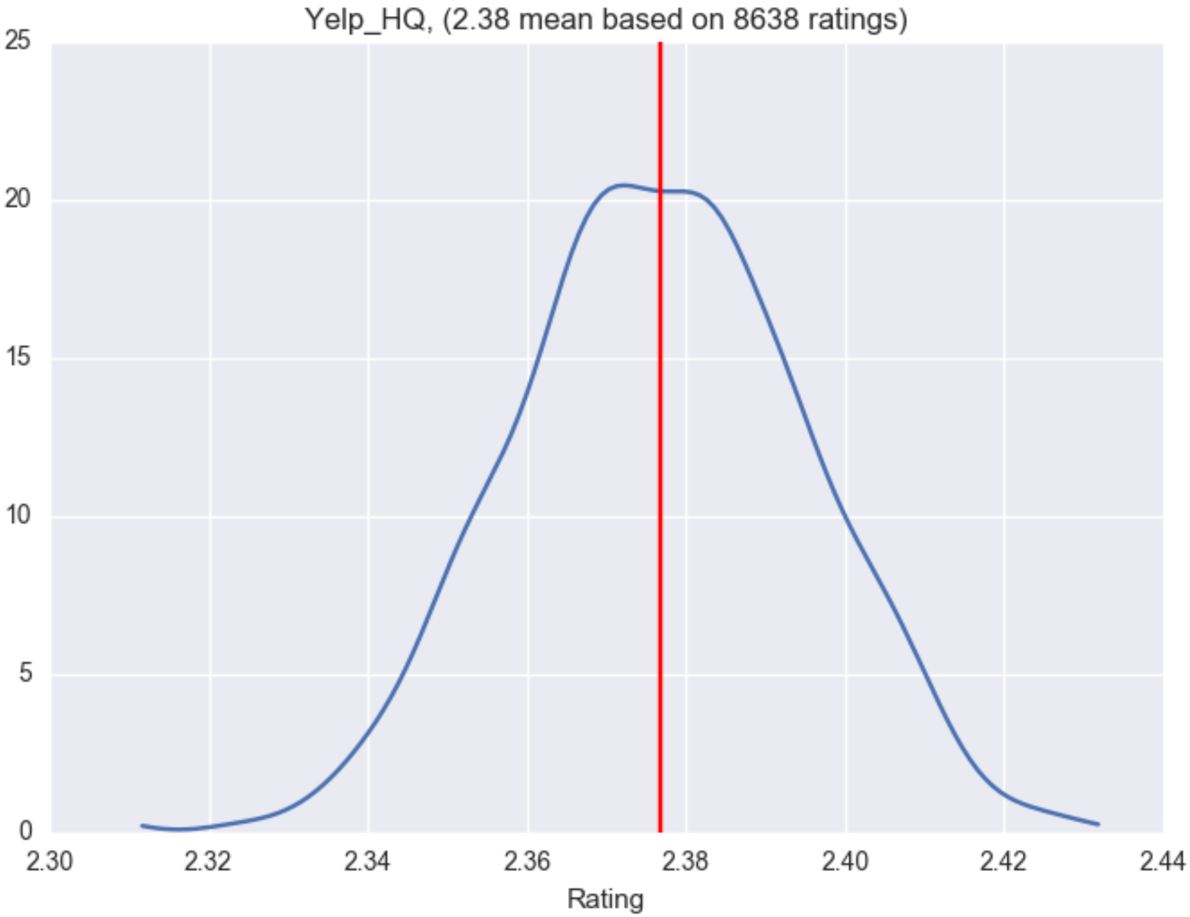

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Given the ratings I have, there is a 95% chance that the "real" fraction of positive ratings is at least what?

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Back to Non Parametrics

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Just like non-parametric methods make no assumptions, I will make no assumptions of background or prerequisite knowledge either

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But now we can use these ideas to understand uncertainty…

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Goals

- Estimate Quantities of Interest (i.e. statistics/parameters)
- Quantify Uncertainty (i.e. confidence intervals)

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Classic (frequentist) approach

Population Standard Deviation

$$\bar{x} \pm 1.96 \frac{\sigma}{\sqrt{n}}$$

Size of Sample

for a 95% CI

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Why Bootstrap?

- Estimate arbitrary statistics (mean, percentiles, etc.)
- Distribution Agnostic (non-parametric)
- Natural Confidence Intervals

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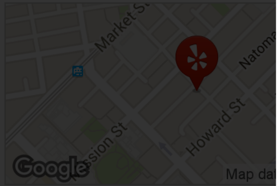
Local Flavor, Mass Media



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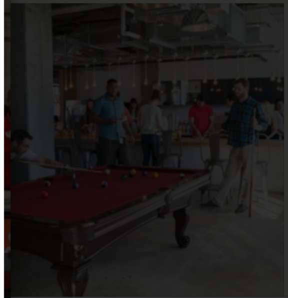
"Locally, I enjoy bei
way I do about writ

"Reviews galore, ta
know, love, hate or

"Of course, all thos
forward to attend m

Photo Share Bookmark



See all 1240

8:00 am - 6:00 pm Open now

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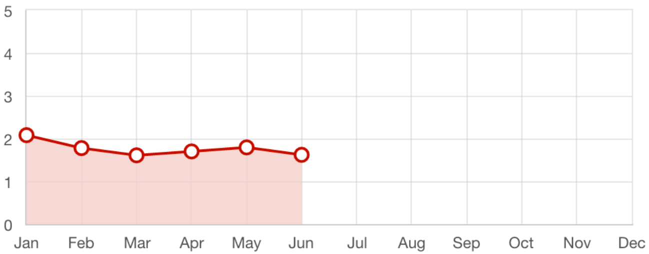
:00 am - 6:00 pm
:00 am - 6:00 pm
:00 am - 6:00 pm Open now
:00 am - 6:00 pm
Closed
Sun Closed

Rating Details

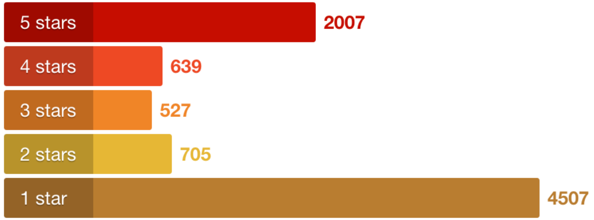
Monthly Trend 2016 2015 2014 2013 2012



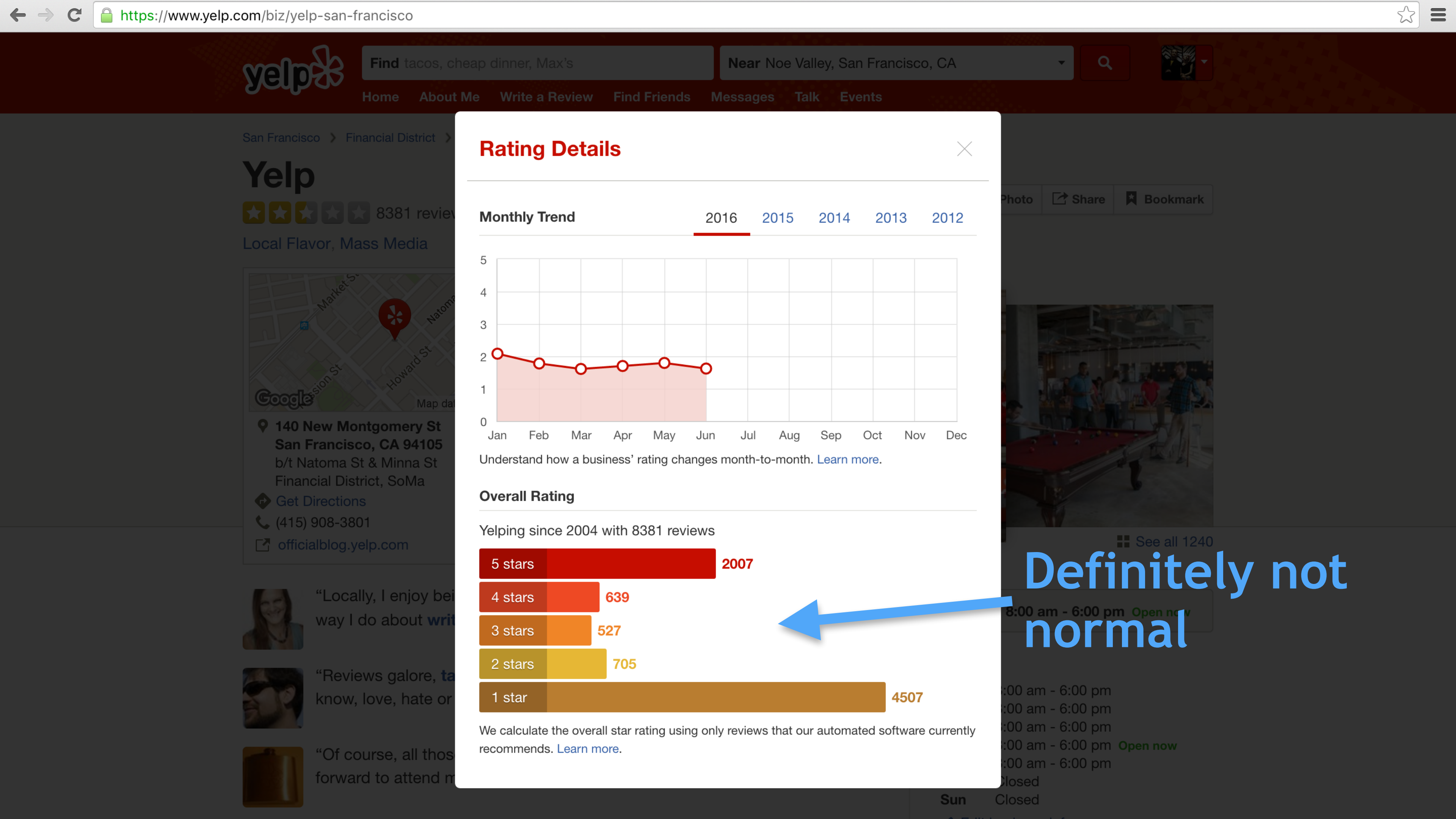
Understand how a business' rating changes month-to-month. Learn more.

Overall Rating

Yelping since 2004 with 8381 reviews



We calculate the overall star rating using only reviews that our automated software currently recommends. Learn more.


https://www.yelp.com/biz/yelp-san-francisco
Find tacos, cheap dinner, Max's
Near Noe Valley, San Francisco, CA
Home About Me Write a Review Find Friends Messages Talk Events
San Francisco > Financial District >
Yelp
8381 revie
Local Flavor, Mass Media
140 New Montgomery St
San Francisco, CA 94105
b/t Natoma St & Minna St
Financial District, SoMa
Get Directions
(415) 908-3801
officialblog.yelp.com
Rating Details
Monthly Trend
2016 2015 2014 2013 2012
5
4
3
2
1
0
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Understand how a business' rating changes month-to-month. Learn more.
Overall Rating
Yelping since 2004 with 8381 reviews
5 stars 2007
4 stars 639
3 stars 527
2 stars 705
1 star 4507
We calculate the overall star rating using only reviews that our automated software currently recommends. Learn more.
Photo
Share
Bookmark
See all 1240
Definitely not normal
Sun Closed

The Bootstrap Formalized

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The Bootstrap

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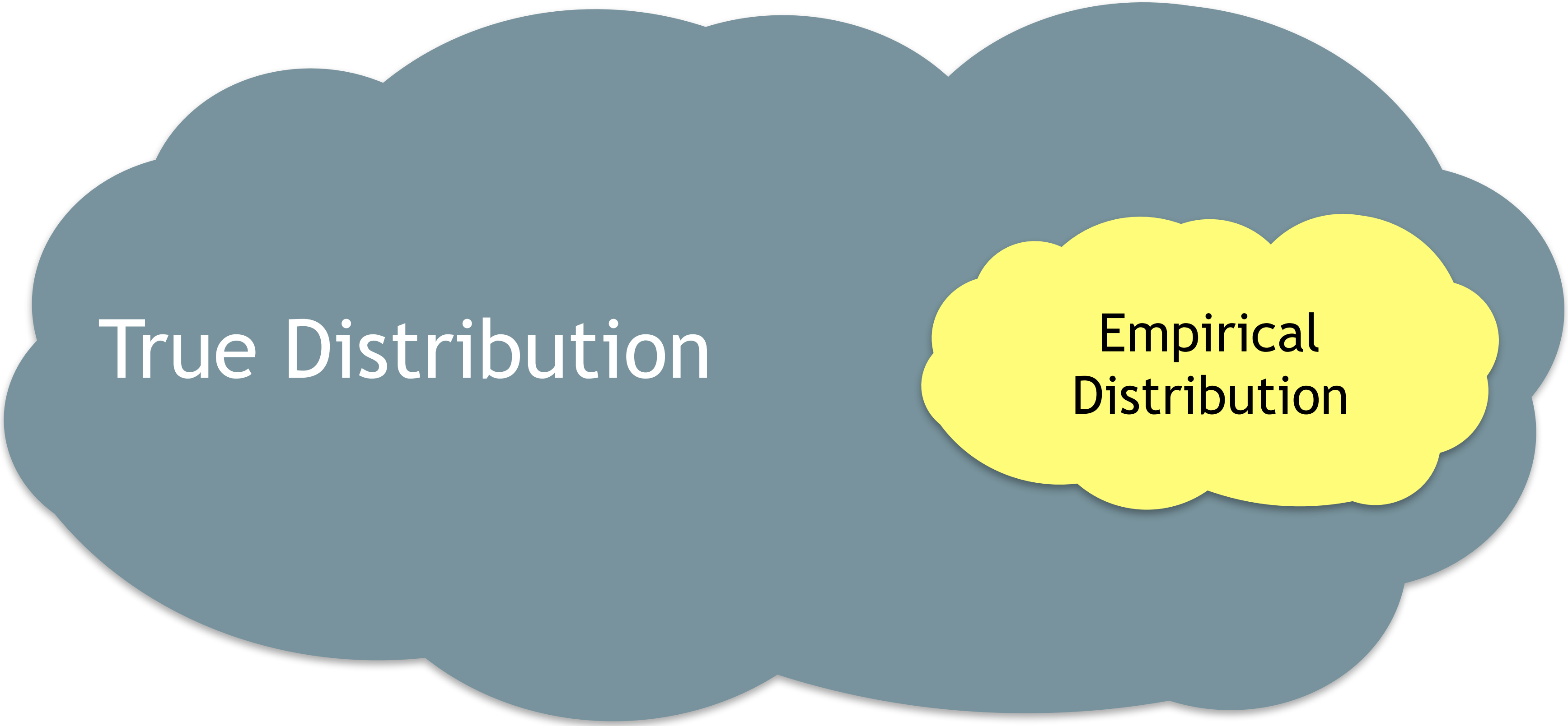
The Bootstrap



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The Bootstrap

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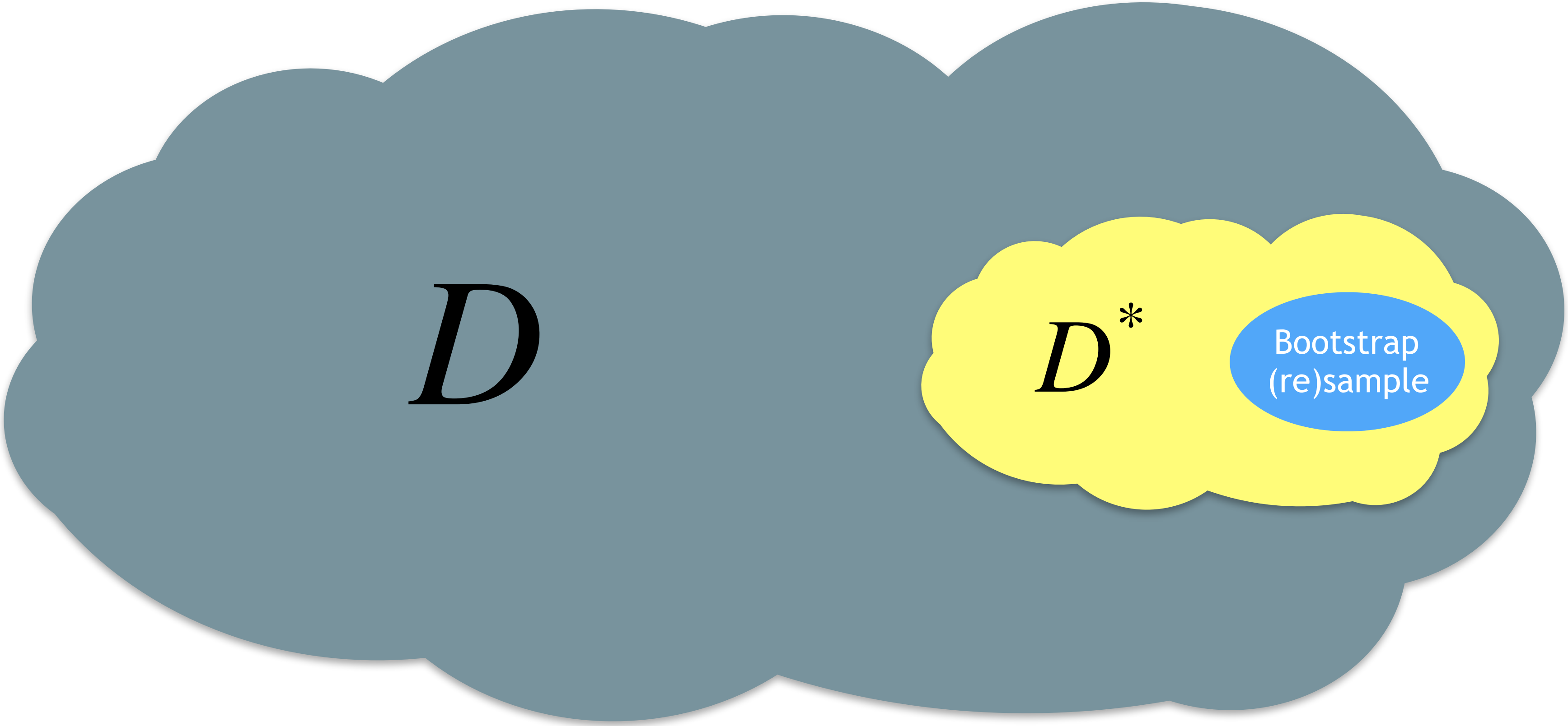
The Bootstrap



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Why Bootstrap?

- Estimate arbitrary statistics (mean, percentiles, etc.)
- Distribution Agnostic (non-parametric)
- Natural Confidence Intervals

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The Bootstrap Principle

Distribution Approximation

$$D^* \approx D$$

Statistic Approximation

For any statistic ***s***, the (resampled) distribution of ***s**** approximates ***s***

$$s^* \rightarrow s$$

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Just treat the confidence interval as our statistic of interest

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Statistic of Interest

Sample mean

True mean

Difference in means
for one sample

$$\theta = \bar{x} - \mu$$

*For confidence intervals we are interested in the ***distribution*** of the difference in means

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Bootstrap Approximation

For any statistic ***s***, the (resampled) distribution of ***s**** approximates ***s***

$$\theta^* = \overline{x}^* - \overline{x}$$

$$\theta^* \rightarrow \theta$$

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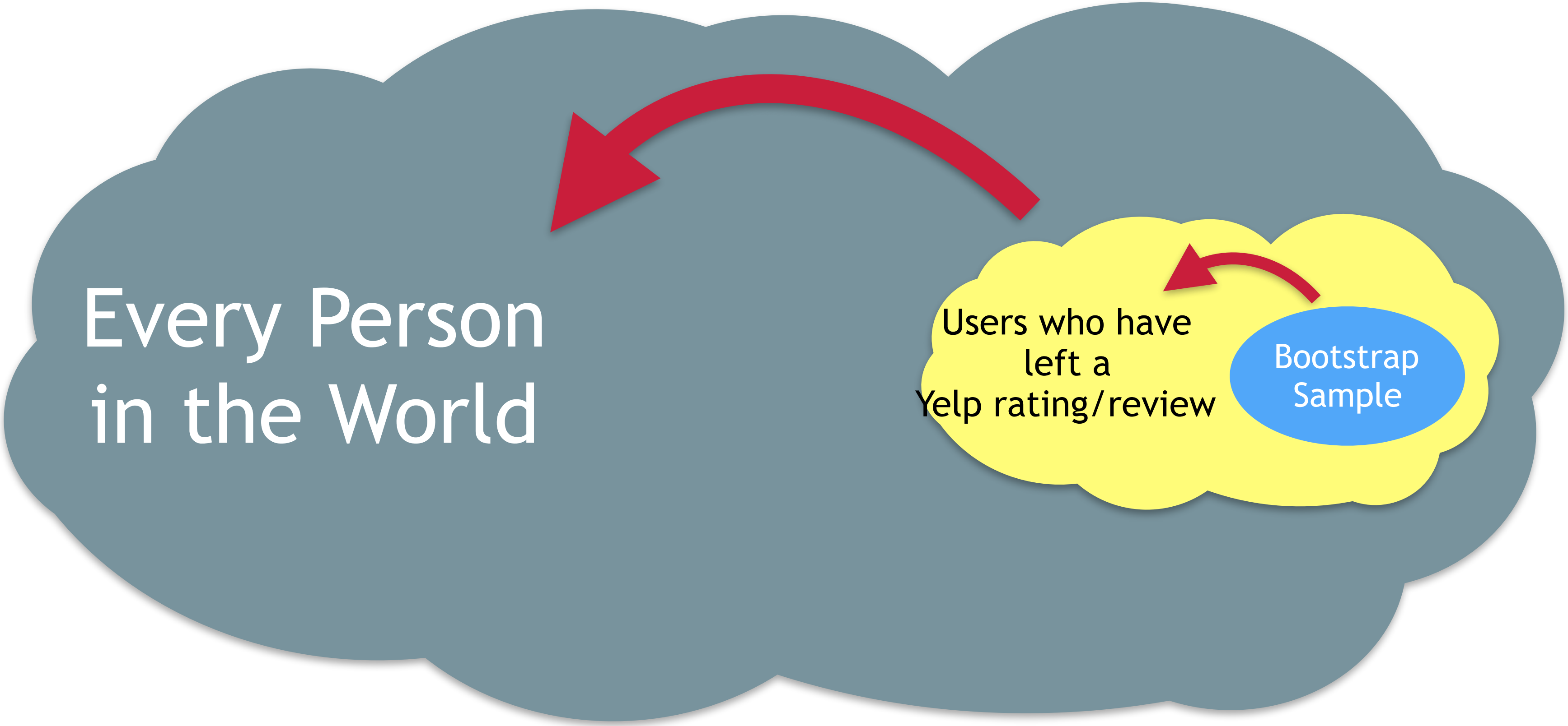
The Bootstrap



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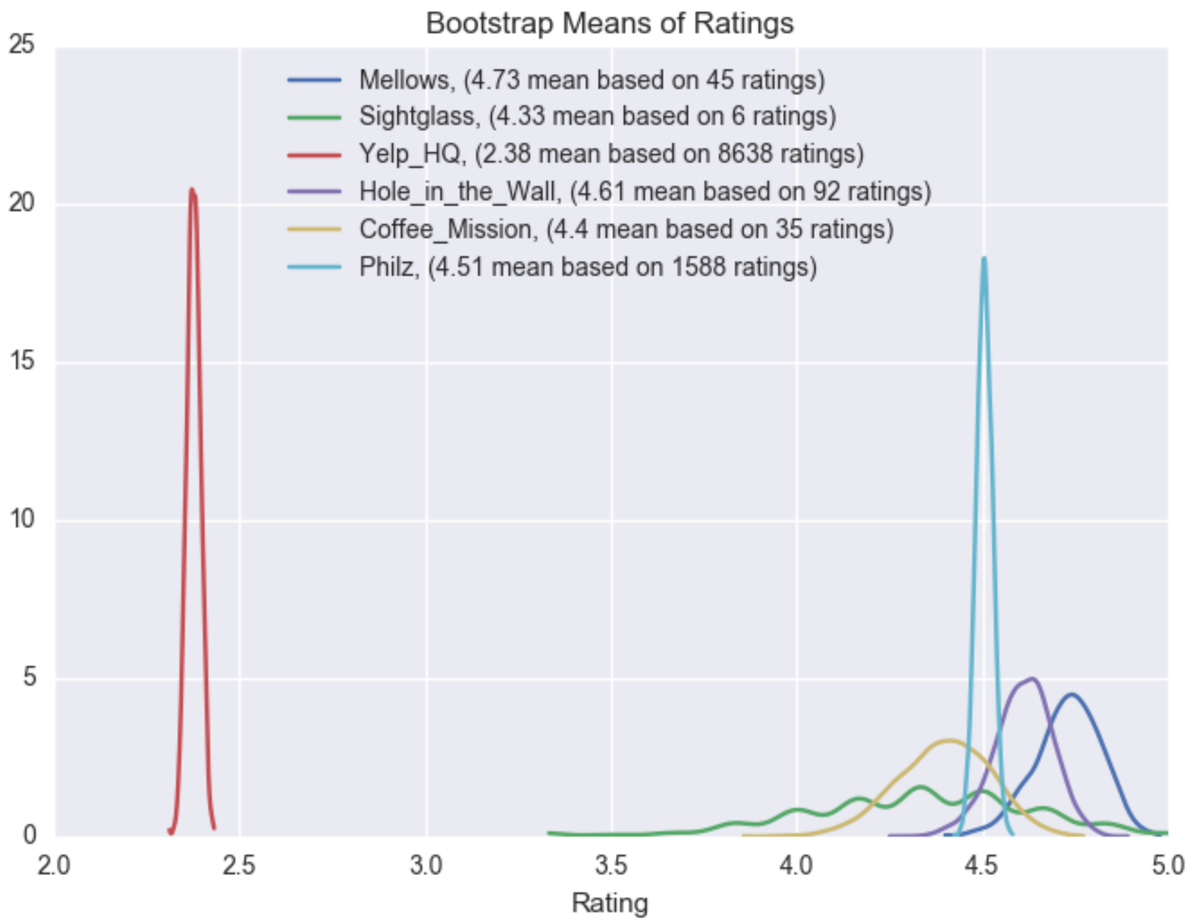

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```
df = pd.read_csv('yelp_stars/' + filename)
num_samples = len(df)
boots = []

for i in range(2000):
    bootstrap = df.sample(num_samples, replace = True)
    boots.append(bootstrap.rating.mean())
```

Statistic of interest

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```
df = pd.read_csv('yelp_stars/' + filename)
num_samples = len(df)
boots = []
x_bar = df.rating.mean()

for i in range(2000):
    bootstrap = df.sample(num_samples, replace = True)
    boots.append(bootstrap.rating.mean() - x_bar)
```

Statistic of interest

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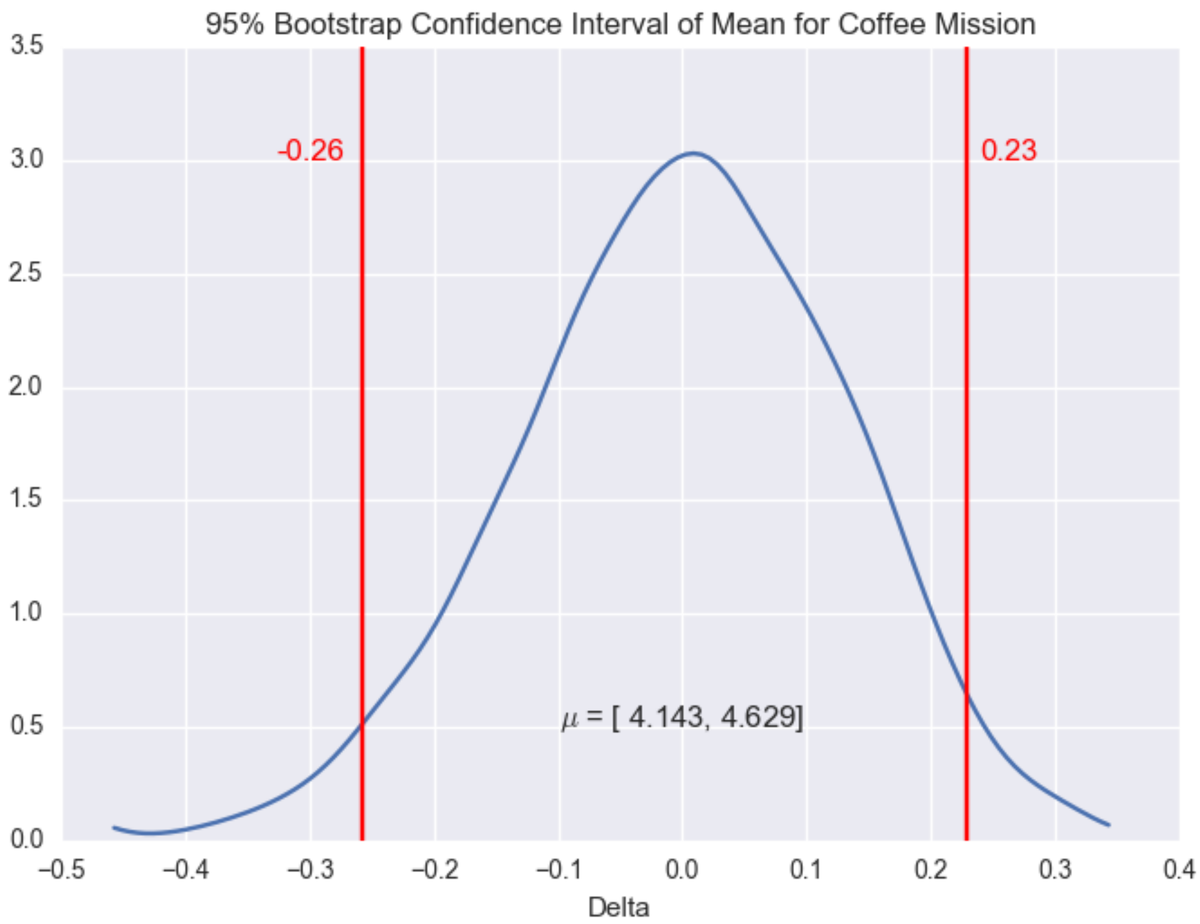

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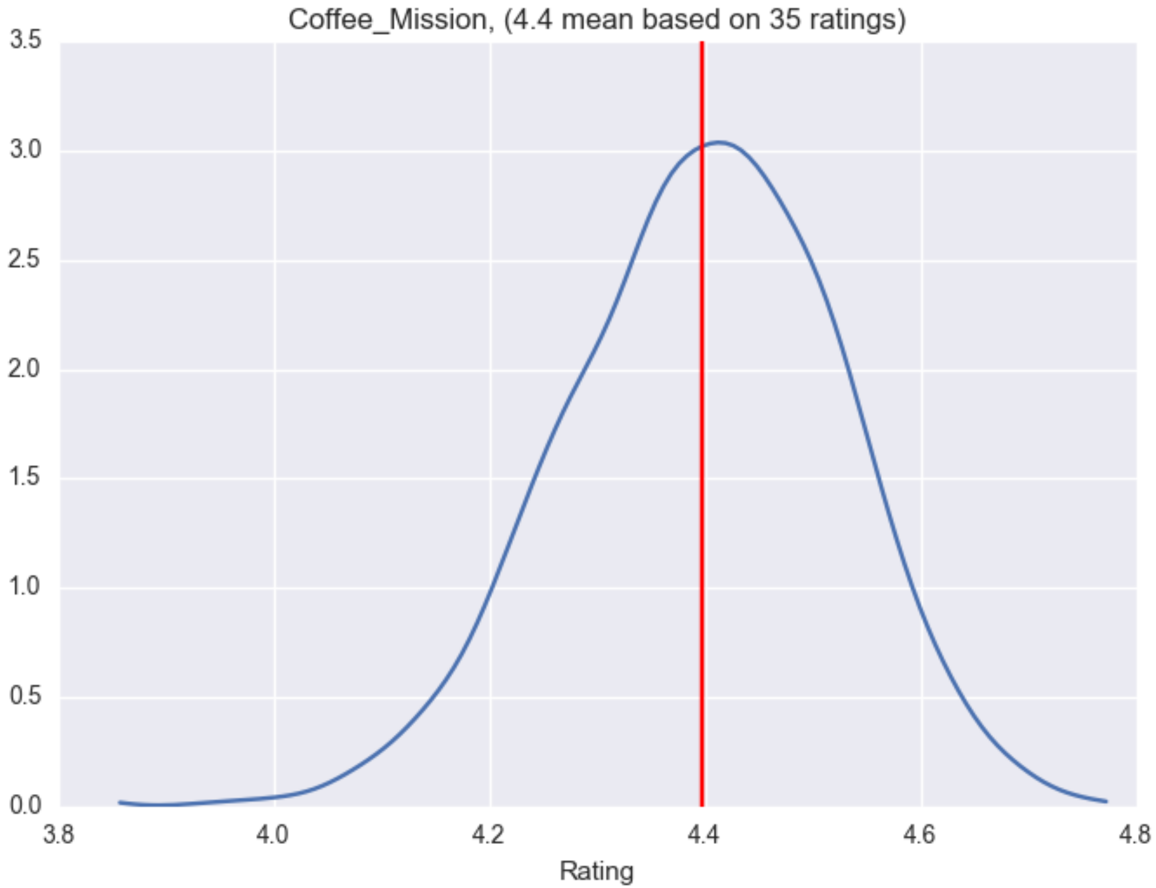

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```
df = pd.read_csv('yelp_stars/Coffee_Mission.csv')
num_samples = len(df)
boots = []

for i in range(2000):
    bootstrap = df.sample(num_samples, replace = True)
    boots.append(bootstrap.rating.mean())

data_arr = np.array(boots)

>>>print("The 2.5th percentile is {0:.4f}".format(np.percentile(data_arr, 2.5)))
The 2.5th percentile is 4.1429

>>>print("The 97.5th percentile is {0:.4f}".format(np.percentile(data_arr, 97.5)))
The 97.5th percentile is 4.6286
```

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rpsychologist.com/d3/CI/

Interpreting Confidence Intervals

an interactive visualization

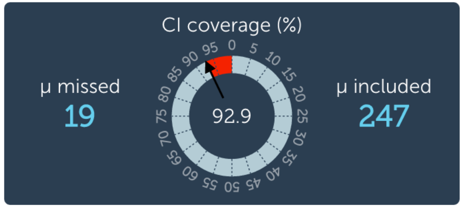
Created by Kristoffer Magnusson

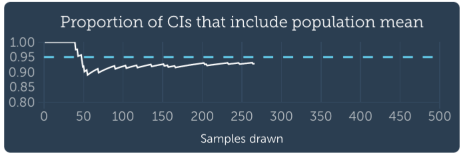
Follow @krstoffr | 1,298 follower | Kristoffer's LinkedIn profile

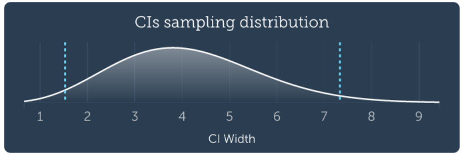
Tweet | Gilla | Dela | 225

Slide me

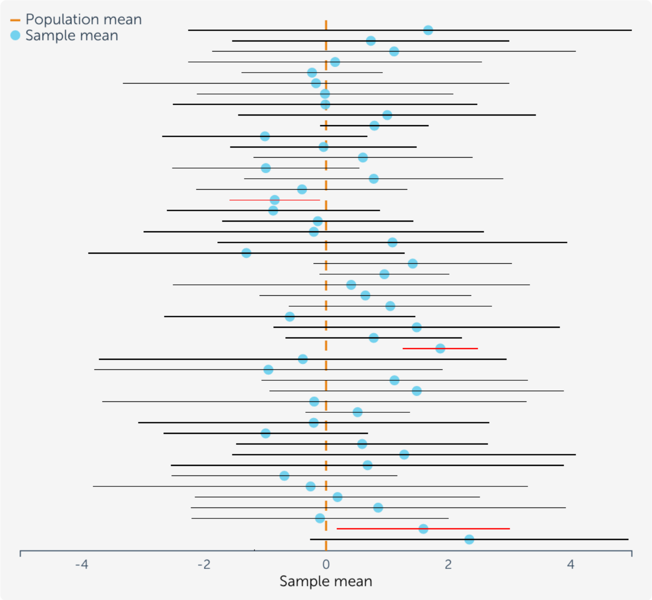
Simulation statistics







93% confidence intervals



Cheaper Beds, **Better** Breakfasts

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Exploratory Question

What variables affect the price of a listing?

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Hypothesis Statement

“Superhosts” have more expensive listings

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Hypothesis Statement

“Superhosts” have more expensive listings

(implicit assumption: since they can attract more guests)

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Confounding Variables

- Do they have the same volume of guests?
- Is it an equivalent price per # of guests or sq. footage?
- Or do they just happen to have bigger places?
- What else is correlated with price?

(correlation can be useful in determining causation)

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Hypothesis Statement

More on this later…

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Question for Inference

What variables are correlated with the price of a listing?

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Correlation

Determining relationship between two variables

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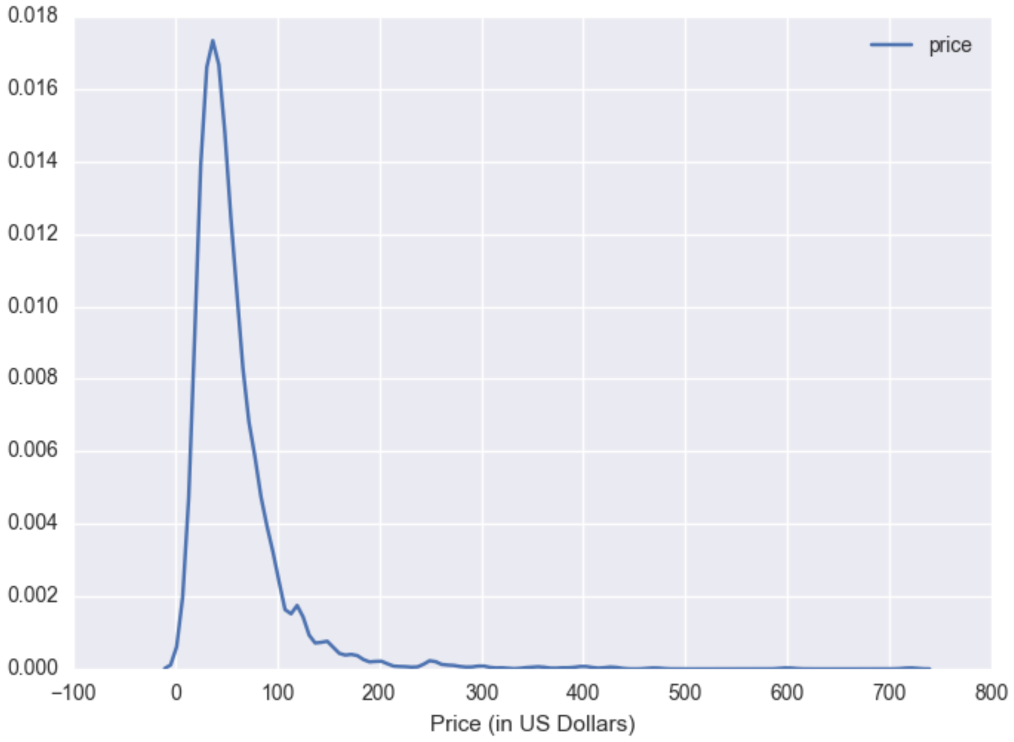
Price Distribution for Athens



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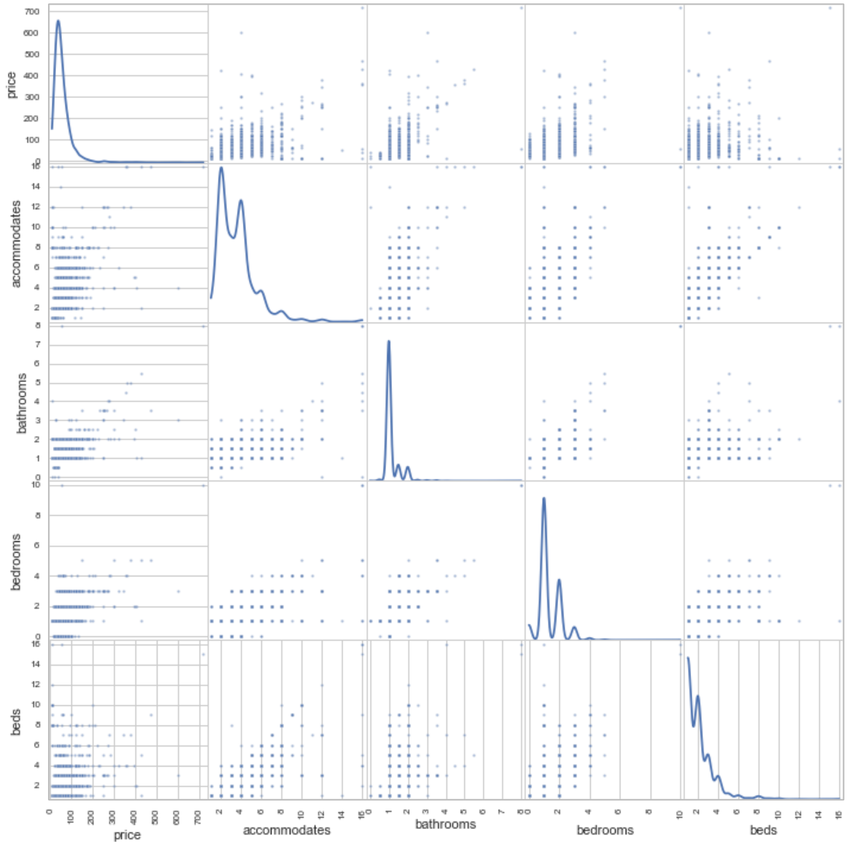
Correlation: Visually



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(Pearson's) Correlation Analytically

Covariance*

Standard Deviation* of x

Standard Deviation* of y

$$r = \frac{\boxed{\sum_{i}^{n}(x_i - \bar{x})(y_i - \bar{y})}}{\sqrt{\sum_{i}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i}^{n}(y_i - \bar{y})^2}}$$

*without normalizing 1/N factors

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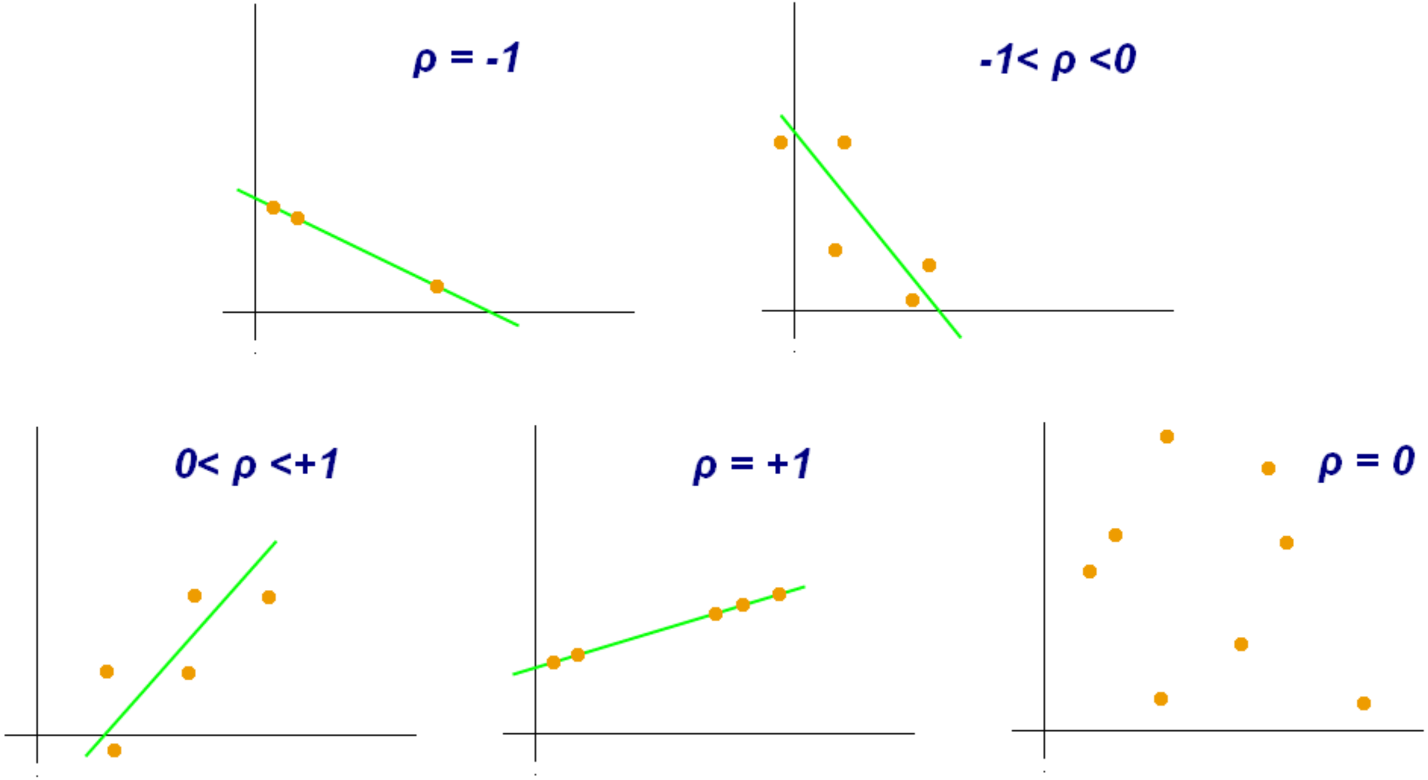
Correlation: Visually



source: Wikipedia

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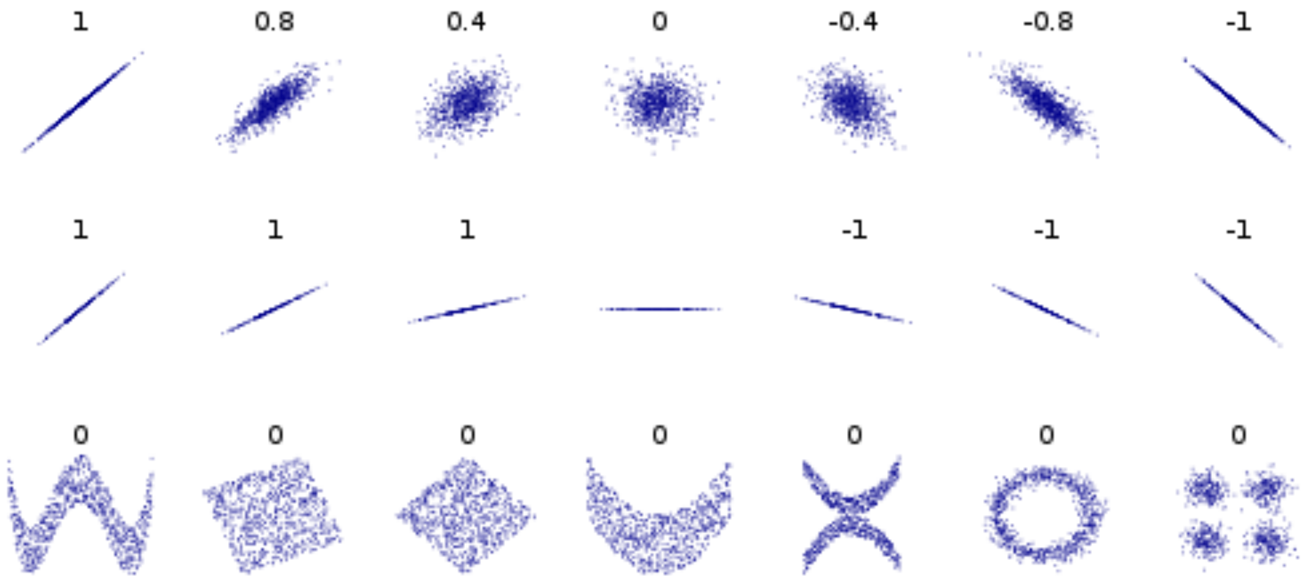
Correlation: Visually



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Correlation Confidence Intervals

Live Code

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Correlation Confidence Intervals

Problematic to calculate analytically…

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Correlation Confidence Intervals

Sampling distribution is not normally distributed…

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Correlation Confidence Intervals

To the bootstrap!

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Correlation Confidence Intervals

Live Code

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Hypothesis Testing

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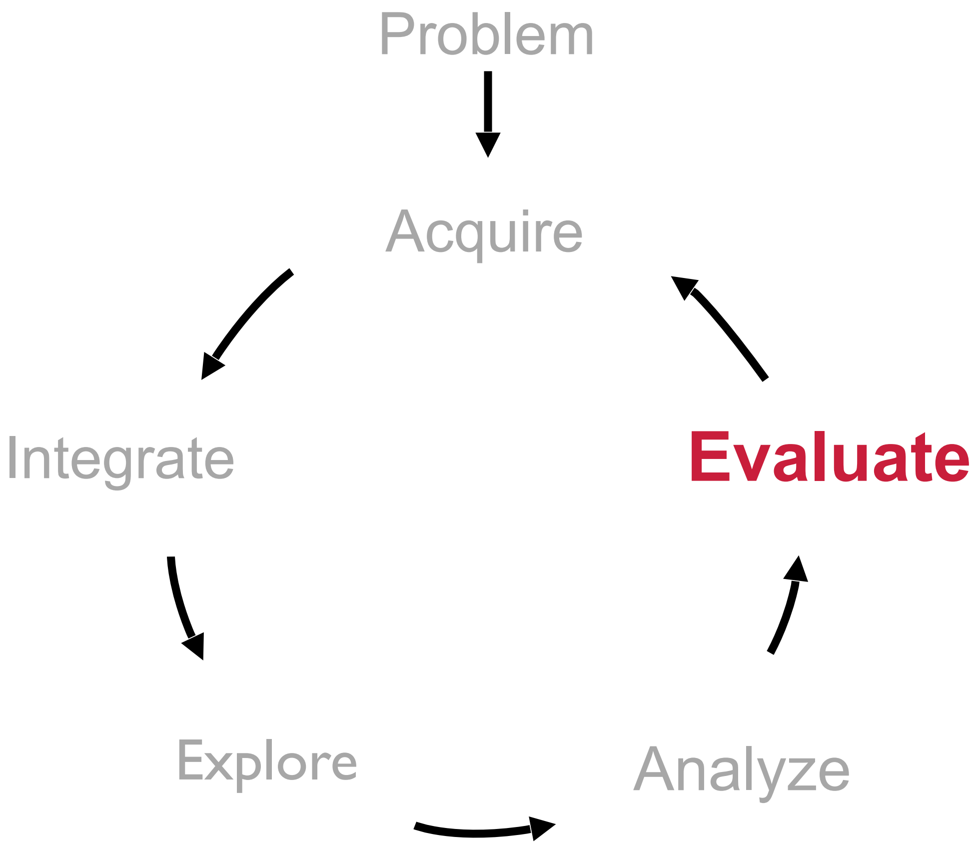
Process + Iteration



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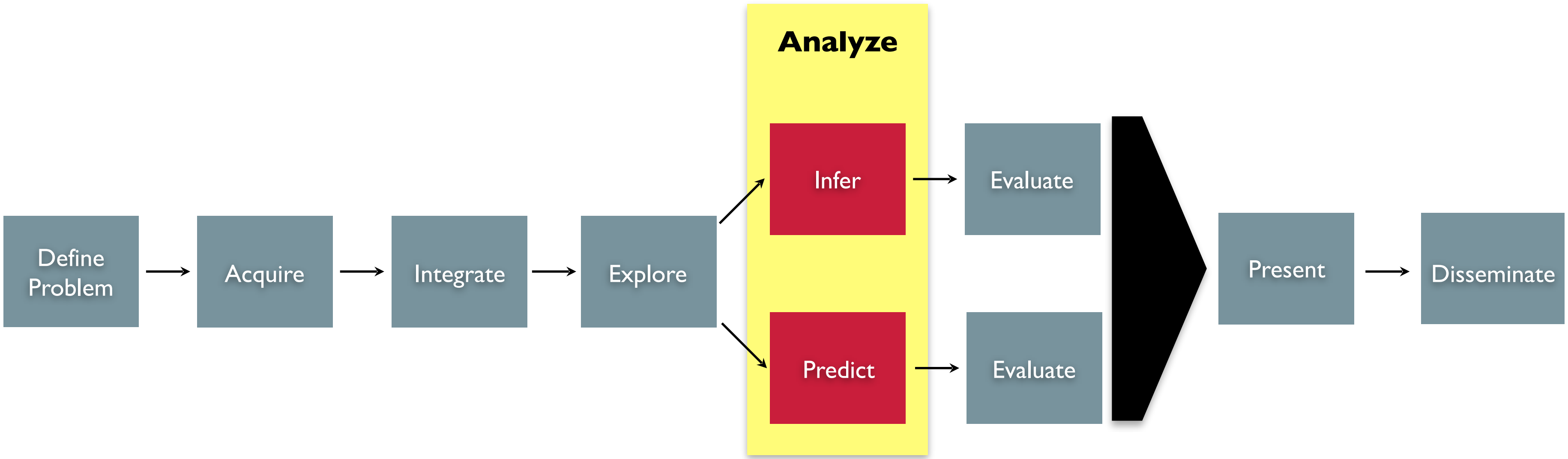
Process + Statistics



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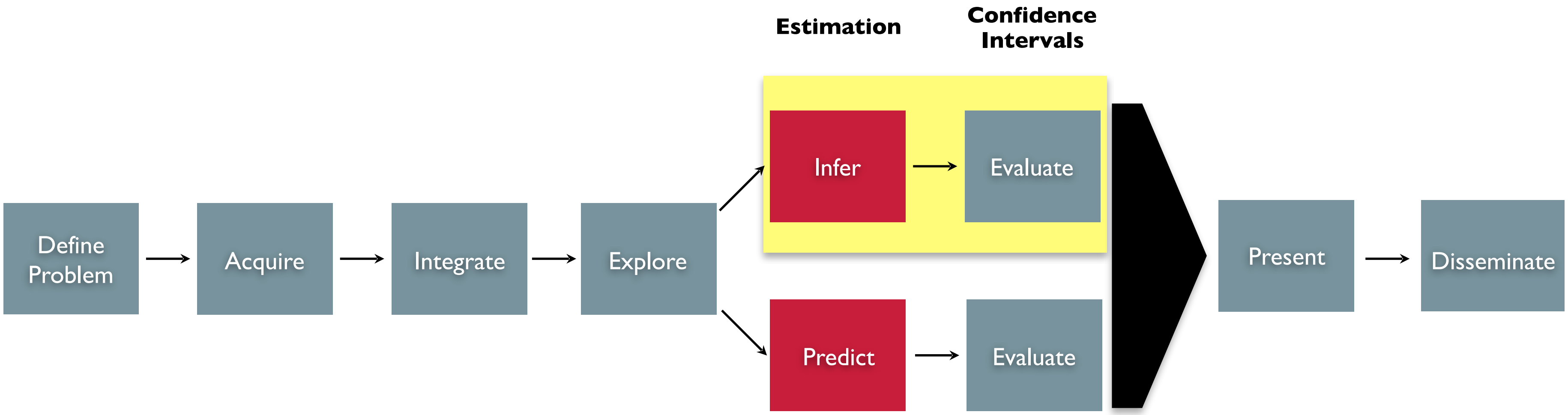
Process + Statistics



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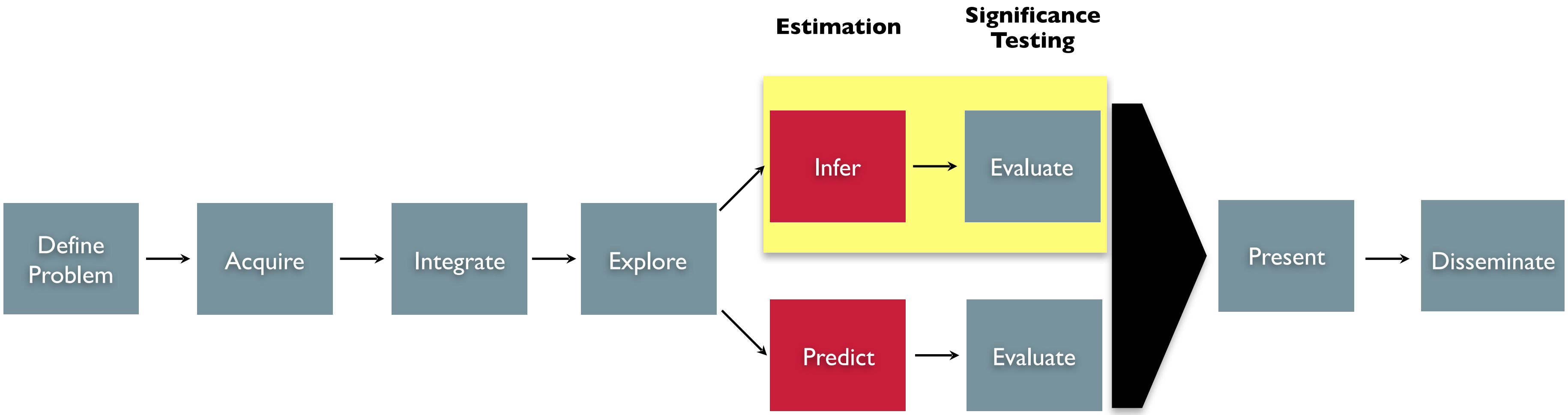
Process + Statistics



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Hypothesis Testing

Experimental Study

- Design experiment a priori
- Manipulate explanatory variable (control versus treatment)
- More robust to confounding factors
- Can demonstrate causal effects (double blind randomized trial)

Observational Study

- Leverage existing data
- No manipulation of subjects
- Used when experiment would be infeasible or unethical
- Analysis post hoc
- Only possible to show correlation

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Hypothesis Testing

Experimental Study

- Ex: Showing photos above the fold results in higher rates of requests for a listing

Observational Study

- Ex: Hosts who make less than $30,000 a year accept a higher proportion of requests

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Observational Study Setup

Null Hypothesis (H_0)

Instantly bookable listings do not have a higher rate (# reviews per month) of guests.

Alternative

Instantly bookable listings have a higher rate (# reviews per month) of guests.

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Observational Study Setup

Explanatory Variable (used to segment groups)

Whether or not a given listing can be booked instantly as determined by the `instant_bookable` variable.

Response Variable (property of interest)

Throughput of a listing as determined by `reviews_per_month` variable.

Statistic

Mean of `reviews_per_month`

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Hypothesis Testing: Outcomes

Reject the null, accept the alternative

— OR —

Fail to reject the null, conclude there is not enough evidence

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Hypothesis Testing: Outcomes

Instant booking increases the amount of guests a listing receives

— OR —

“Not Guilty”

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Hypothesis Testing: Mechanics

Confidence interval of the difference of means (or your test statistic)

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Hypothesis Testing: Mechanics

But this time two different samples…

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Hypothesis Testing: Mechanics

Live Code

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	Fail to Reject	Reject
TRUE	Correct Inference (True Negative)	Type I Error (False Positive)
FALSE	Type II Error (False Negative)	Correct Inference (True Positive)

True Condition (H_0)

Predicted Condition (H_0)

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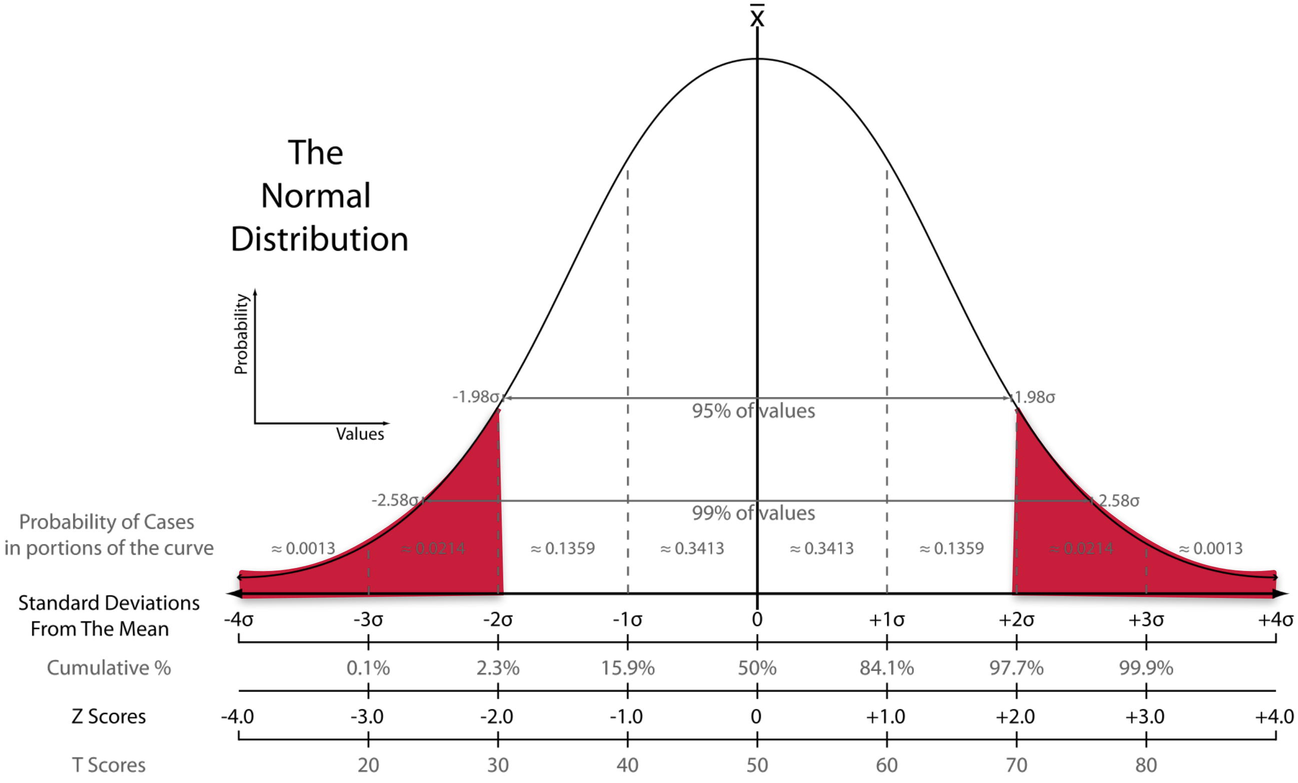
Our Familiar Friend



source: Wikipedia

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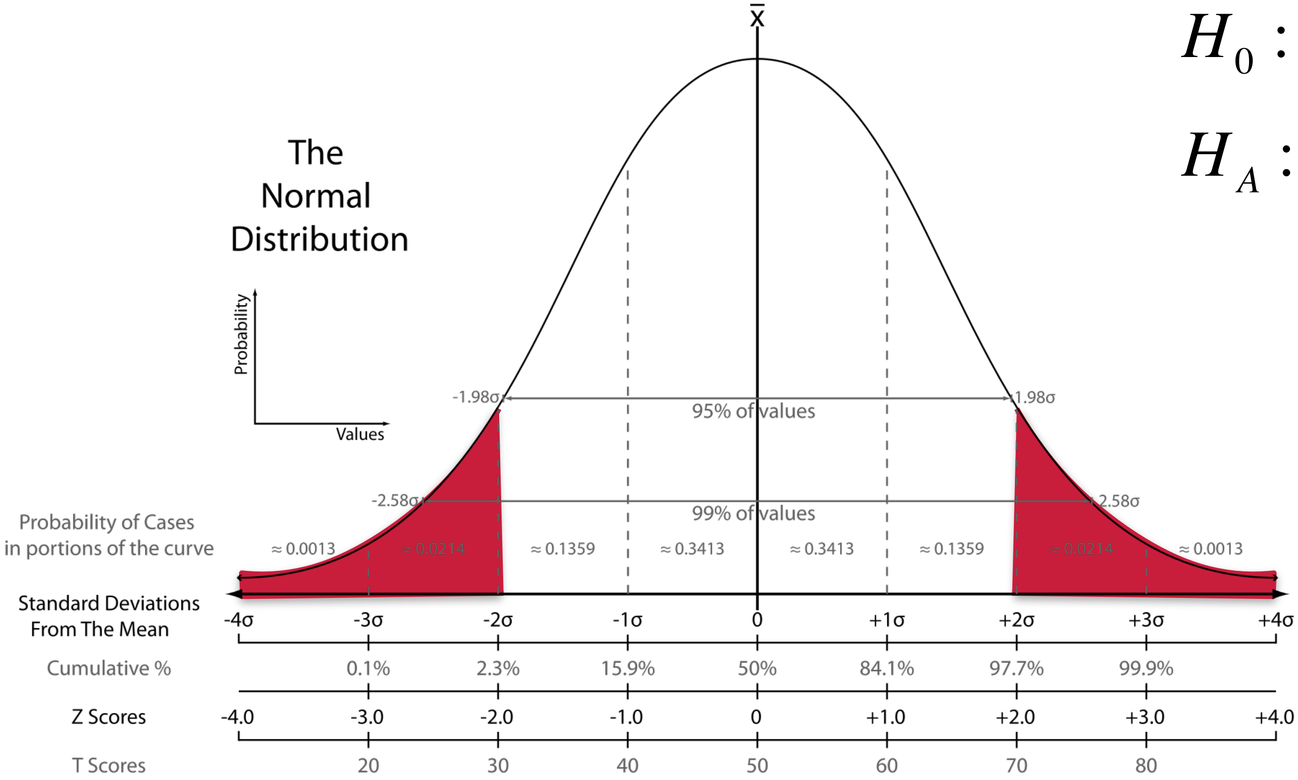
Two Sided

$$H_0 : \delta = 0$$

$$H_A : \delta \neq 0$$



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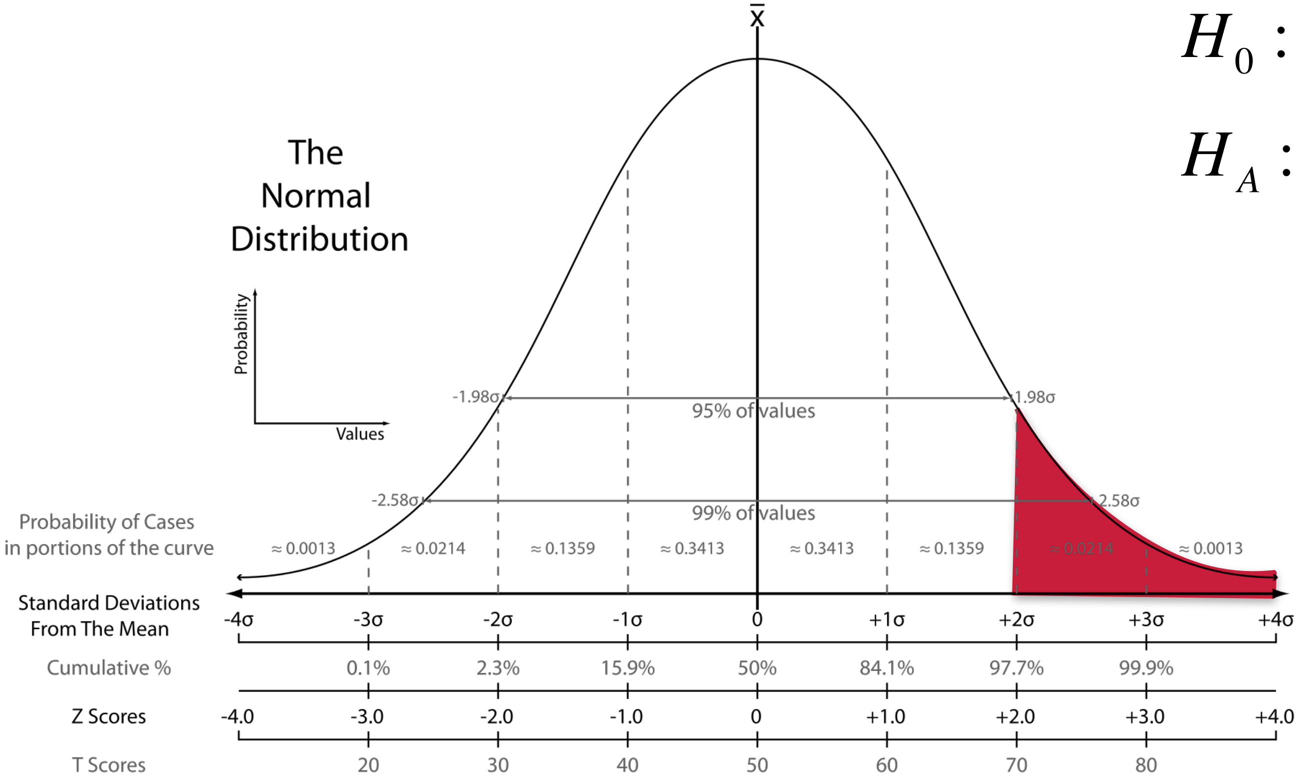
One Sided

$$H_0 : \delta \leq 0$$

$$H_A : \delta > 0$$



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Hypothesis Testing Terminology

Null Hypothesis

A default position that there is **no relationship** between two measured phenomena (or no association among groups)

Z-score

Number of standard deviations away from the mean of the **sampling distribution**

p-value

The probability of obtaining a result equal to or "more extreme" than what was actually observed, when the null hypothesis is true

source: Wikipedia

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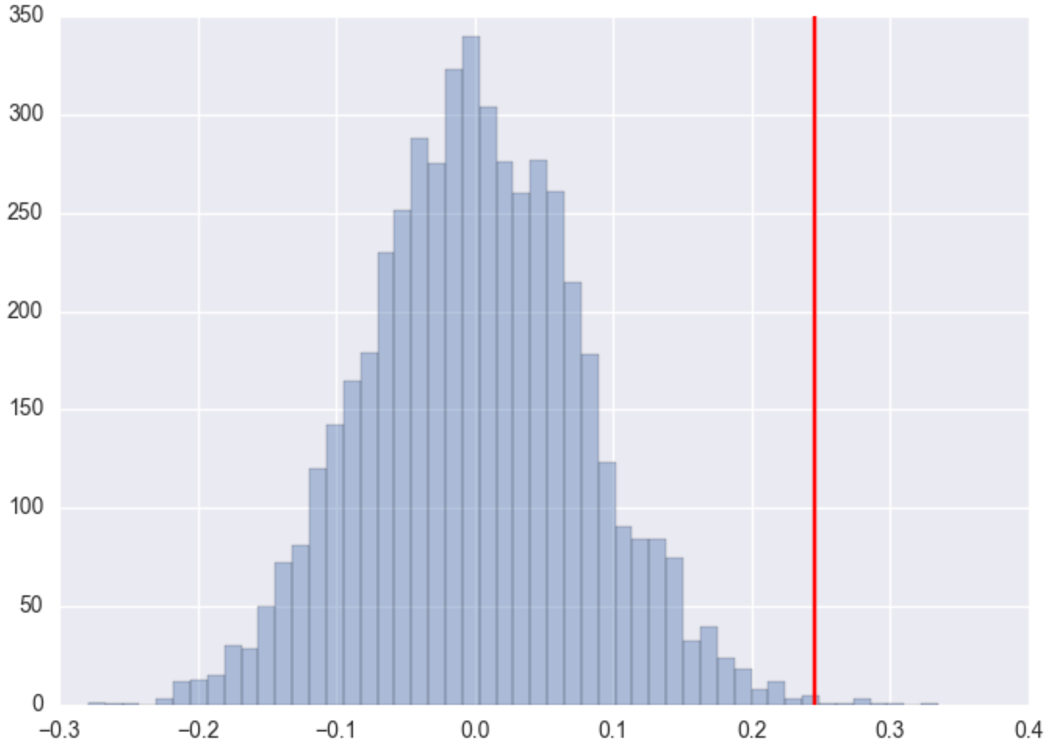
Sampling Distribution of Instant Bookable



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Hypothesis Testing Terminology

Power of the Test

The probability that the test correctly rejects the null hypothesis (H0) when the alternative hypothesis (H1) is true.

Effect Size

They estimate the strength (magnitude) of, for example, an apparent relationship, rather than assigning a significance level reflecting whether the magnitude of the relationship observed could be due to chance.

source: Wikipedia

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rpsychologist.com/d3/NHST/

Settings

Solve for? ◉ Power ○ Alpha ○ n ○ d

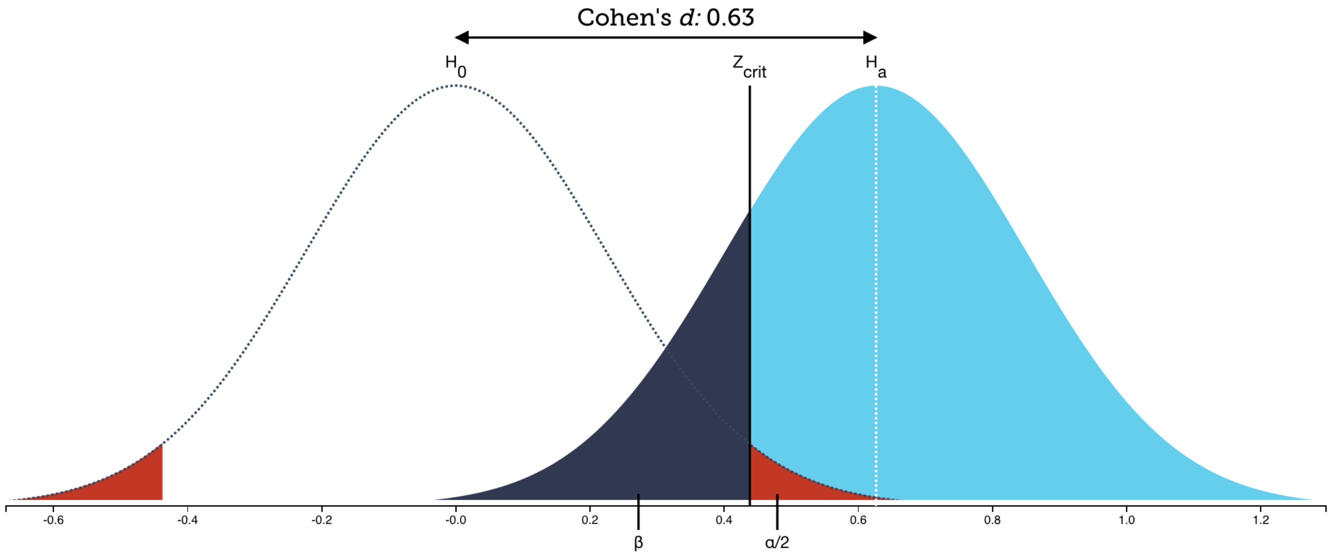
Significance level (α = 0.05)

Sample size (n = 20)

Effect size (d = 0.63)

One-tailed | Two-tailed

Reset zoom



5 %	20 %	80 %	20
Type I error	**Type II error**	**Power**	**Sample size**

Hypothesis Testing Errors

- **Multiple Testing:** Bonferroni correction (or similar corrections)
- **Stopping Early:** Use a calculated sample size or Bayesian methods
- **Large N:** Use an appropriate effect size

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Observational Study Setup

Null Hypothesis (H_0)

Instantly bookable listings do not have a higher rate (# reviews per month) of guests.

Alternative

Instantly bookable listings have a higher rate (# reviews per month) of guests.

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Hypothesis Testing: Outcomes

Instant booking increases the amount of guests a listing receives

— OR —

“Not Guilty”

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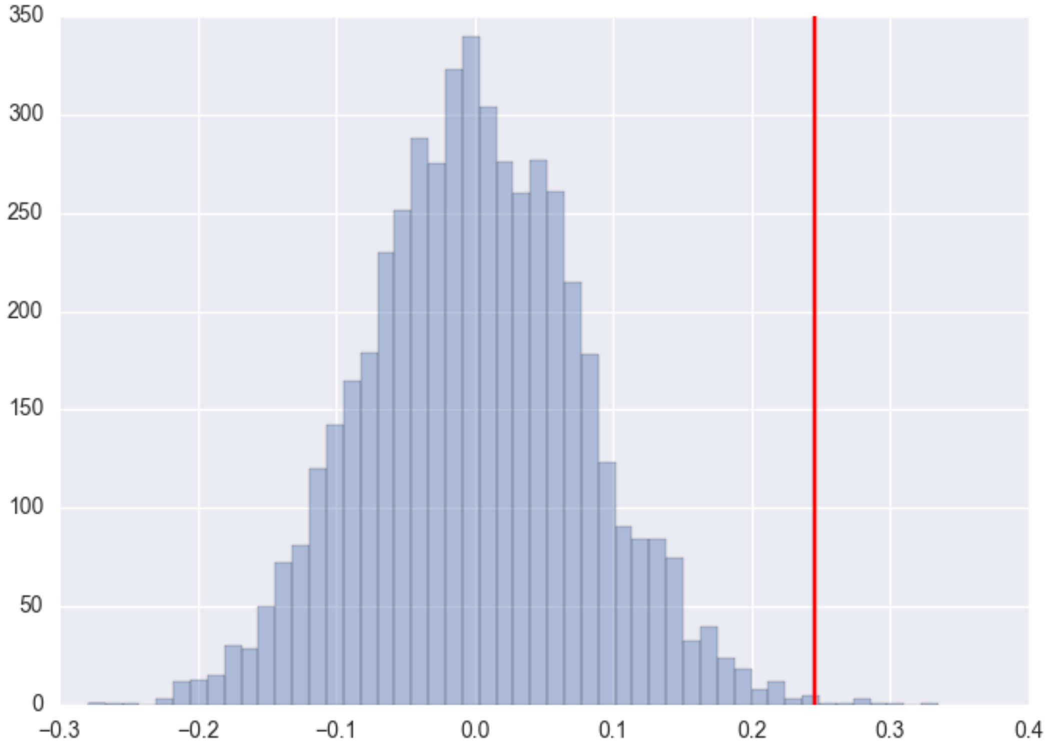
Sampling Distribution of Instant Bookable



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Hypothesis Testing: Outcomes

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— OR —

“Not Guilty”

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Business Decisions and Actions

What **action** to take and **when** to take it

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Business Decisions and Actions

- Provide this **insight/statistic** when new users are **creating their listing**
- Suggest changing their listing to **enable instant-bookable** for hosts who are **struggling to attract guests**.
- Suggest changing their listing to **disable instant-bookable** for hosts who are **receiving too many guests**.

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Business Decisions and Actions

Context and goal dependent….

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Flavors of Statistics

Parametric

- Assume underlying generating distribution
- More accurate and precise (when they work)
- More informative (though can be harder to interpret)
- Simpler & easier to compute (can be done by hand)
- Generative (i.e. can *create* data)

Non-Parametric

- Makes little to no assumptions about data (distribution free)
- Requires no *a priori* decisions (i.e. probability distributions)
- More general and robust
- Needs larger sample sizes
- Often requires simulation/ computation

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Flavors of Statistics

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- More general and robust
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Examples

Parametric

- **Descriptive:** Mean & Standard Deviation
- **Inferential:** Hypothesis Tests & MLE
- **Predictive:** Linear Regression (OLS)

Non-Parametric

- **Descriptive:** Histograms & KDE
- **Inferential:** Bootstrap Methods
- **Predictive:** K Nearest Neighbors

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Spectrum of Statistics

Non-parametric Parametric Bayesian

Less Assumptions ⟷ More (statistical) Power & Specificity

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Spectrum of Statistics

Non-parametric Parametric Bayesian

More Objective ⟷ More Subjective

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Spectrum of Statistics

Non-parametric | Parametric | Bayesian

Easier to Learn?
(and apply)

More Subjective

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Spectrum of Statistics

Non-parametric

Parametric

Bayesian

Less Assumptions

More (statistical) Power & Specificity

Middle Ground

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Spectrum of Statistics

Non-parametric | Parametric | Bayesian

Less Assumptions ⟷ More (statistical) Power & Specificity

Tends to be most popular/common

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Spectrum of Statistics

Non-parametric Parametric Bayesian

Less Assumptions ← → More (statistical) Power & Specificity

But at the End of the Day…

Tends to be most popular/common

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Spectrum of Statistics

Non-parametric

Parametric

Bayesian

Less Assumptions

More
(statistical) Power

Most Differences are cosmetic and philosophical

Tends to be most
popular/common

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Next Up: Modeling and Machine Learning

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