# Using Bootstrapping to Evaluate Your Experiment

## Introduction to Bootstrapping

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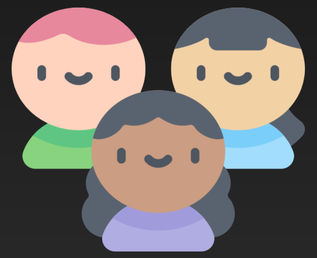
# Agenda

- Imagine you are doing an experiment
- Hypothesis testing
- Introduction to bootstrapping
- Apply bootstrapping to evaluate your experiment
- Code sample

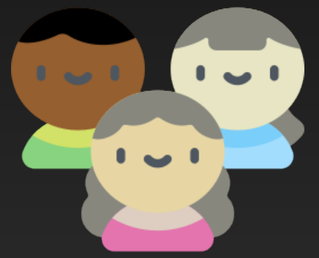
# Imagine You're Doing Experiment for the Company...

**Test**



**Converted 20 people out of total 1000**
**Conversion: 2%**

**Control**



**Converted 15 people out of total 1000**
**conversion: 1.5%**

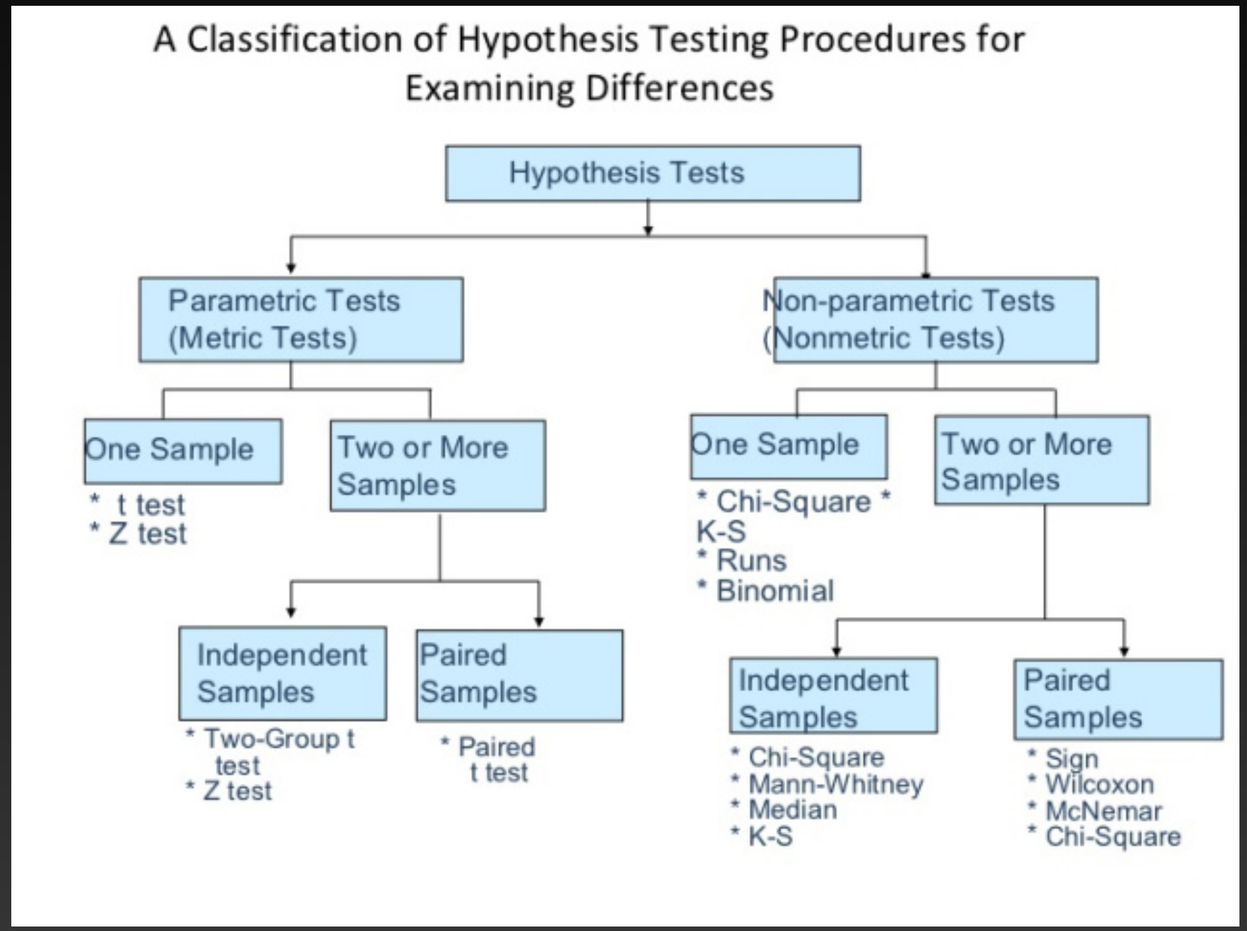
# Hypothesis Testing

**Test group looks better than control group - but does it really better?**

- You want to test whether test group works better, a.k.a. two groups are statistically different.
- Parametric test - make assumptions about the parameters of the population distribution from which the sample is drawn. This is often the assumption that the population data are normally distributed.
- Non-parametric tests are “distribution-free” and, as such, can be used for non-Normal variables.

# Hypothesis Testing II

## Statistical Tests




https://mkhernandez.wordpress.com/2017/04/29/quant-parametric-and-non-parametric-stats/

# Bootstrapping Method

“Bootstrapping is any test or metric that uses random sampling with replacement, and falls under the broader class of resampling methods. It assigns measures of accuracy (bias, variance, confidence intervals, prediction error, etc.) to sample estimates. “ - Wikipedia.

- This resampling method is widely used in statistics and machine learning.
- For instance, Bagging (bootstrap aggregating) will create bootstrapped subsamples from the population and calculate the average.
- Random Forest tweaks Bagging a bit to reduce the variance by learning from only handful of features while growing trees.

# Apply Bootstrapping to the Evaluation

- Central Limit Theorem:

  if you have a population with mean μ and standard deviation σ and take sufficiently large random samples from the population with replacement , then the distribution of the sample means will be approximately normally distributed

- Non-parametric: no assumption about the population distribution
- Tackle small sample problems
- Can easily get p-value and confidence intervals
- Code is reused for different experiments
- Can also be applied to design the experiment & conduct power analysis; however, I will only focus on the evaluation today.
- Disadvantage: bootstrapping can be time-consuming if there are too many iterations (at least 30 to fulfill the Central Limit Theorem)

# Apply Bootstrapping to the Evaluation II

## Process

1. Resample your data
2. Calculate the metric that you are interested
3. Repeat 1 & 2 for multiple times (you can decide the iteration)
4. Compare your test and control group: calculate p-value and confidence interval

# Apply Bootstrapping to the Evaluation III

## Example

- If we are interested in knowing whether the test group convert more than control group, we test whether the mean difference in conversion rate is statistically significant.
- Outcome variable: 0 for non-converted, 1 for converted  (the mean of all conversion data is the group conversion rate)

1. Resample the data
2. Get conversion rates in both groups
3. Calculate the difference in conversion rate
4. Repeat 1 - 3 for x times (normally I will do 2000+)
5. Calculate p-value and confidence interval from the bootstrapped data

| | test | cntrl |
|---|---|---|
| 0 | 0 | 0 |
| 1 | 0 | 0 |
| 2 | 0 | 0 |
| 3 | 0 | 0 |
| 4 | 1 | 0 |

# Code Sample

## Resampling

```
def resampling(dataframe, i):

    '''
    This function is used for resampling.

    data: your dataset
    i: the number of iternation

    '''

    # 1.resample your data, replace will be True because boostrapping allows replacement

    df = dataframe.sample(frac = 1, replace = True)

    # 2. get the difference in conversion rate and the number of iteration
    df1 = df.mean().reset_index()
    df1.columns = ['group','value']
    df1 = df1.pivot_table(columns = ['group'])
    df1['diff'] = df1['test'] - df1['cntrl']
    df1['delta'] = df1['diff'] > 0

    return df1
```

## Build bootstrapped data with 5000 iterations

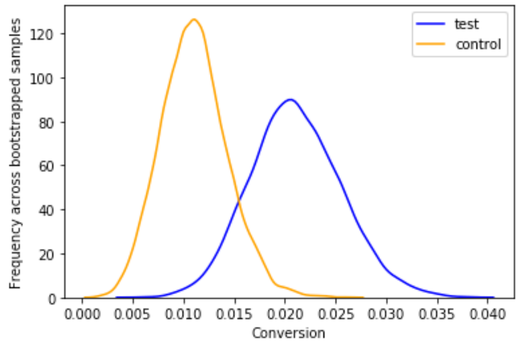
```
# get all bootstrapped data

bootstrapped = pd.concat([resampling(dataframe = data, i = i) for i in range(0,5000)])
bootstrapped.index = np.arange(0, bootstrapped.shape[0])

bootstrapped.head()
```

| group | cntrl | test | diff | delta |
|---|---|---|---|---|
| 0 | 0.014 | 0.020 | 0.006 | True |
| 1 | 0.019 | 0.019 | 0.000 | False |
| 2 | 0.013 | 0.022 | 0.009 | True |
| 3 | 0.016 | 0.029 | 0.013 | True |
| 4 | 0.012 | 0.028 | 0.016 | True |

# Code Sample

## Plotting the distribution

```
plt.figure()
ax = sns.distplot(bootstrapped['test'], label = 'test', hist = False, color = 'blue')
ax = sns.distplot(bootstrapped['cntrl'], label = 'control', hist = False, color = 'orange')
ax.set_ylabel('Frequency across bootstrapped samples')
ax.set_xlabel('Conversion')
plt.legend()
plt.show()
```




## Calculate p-value & confidence interval

```
# calculate p-value and confidence interval

p_value = 1 - bootstrapped['delta'].mean()

print('p-value: ', '{:0.5f}'.format(p_value))
if p_value < 0.05:
    print('Mean difference in conversion is significant at 0.05 level')
else: print('Mean difference in conversion is NOT significant at 0.05 level')

lower, upper = sm.stats.DescrStatsW(bootstrapped['delta']).tconfint_mean()
print('95% confidence interval', '[{:0.5f}, {:0.5f}]'.format(lower, upper))
```

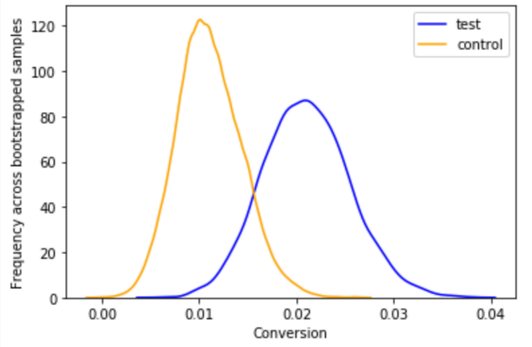
```
p-value:  0.03760
Mean difference in conversion is significant at 0.05 level
95% confidence interval [0.95713, 0.96767]
```

# Code Sample

## Full Code

```python
class bootstrapping:

    def resampling(self, dataframe, i):

        '''
        This function is used for resampling.

        dataframe: your dataset
        i: the number of iternation
        '''

        # 1.resample your data, replace will be True because boostrapping allows replacement

        df = dataframe.sample(frac = 1, replace = True)

        # 2. get the difference in conversion rate and the number of iteration
        df1 = df.mean().reset_index()
        df1.columns = ['group','value']
        df1 = df1.pivot_table(columns = ['group'])
        df1['diff'] = df1['test'] - df1['cntrl']
        df1['delta'] = df1['diff'] > 0

        return df1

    def measuring(self, data, iteration):

        # 3. get all bootstrapped data

        bootstrapped = pd.concat([self.resampling(dataframe = data, i = i) for i in range(0, iteration)])
        bootstrapped.index = np.arange(0, bootstrapped.shape[0])


        plt.figure()
        ax = sns.distplot(bootstrapped['test'], label = 'test', hist = False, color = 'blue')
        ax = sns.distplot(bootstrapped['cntrl'], label = 'control', hist = False, color = 'orange')
        ax.set_ylabel('Frequency across bootstrapped samples')
        ax.set_xlabel('Conversion')
        plt.legend()
        plt.show()

        # 4. calculate p-value and confidence interval

        p_value = 1 - bootstrapped['delta'].mean()

        print('p-value: ', '{:0.5f}'.format(p_value))
        if p_value < 0.05:
            print('Mean difference in conversion is significant at 0.05 level')
        else: print('Mean difference in conversion is NOT significant at 0.05 level')

        lower, upper = sm.stats.DescrStatsW(bootstrapped['delta']).tconfint_mean()
        print('95% confidence interval', '[{:0.5f}, {:0.5f}]'.format(lower, upper))
```

```python
b = bootstrapping()
b.measuring(data, 7000)
```




```
p-value:  0.04343
Mean difference in conversion is significant at 0.05 level
95% confidence interval [0.95180, 0.96135]
```

# Thank You!

Questions/Comments?

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We are looking for volunteers!