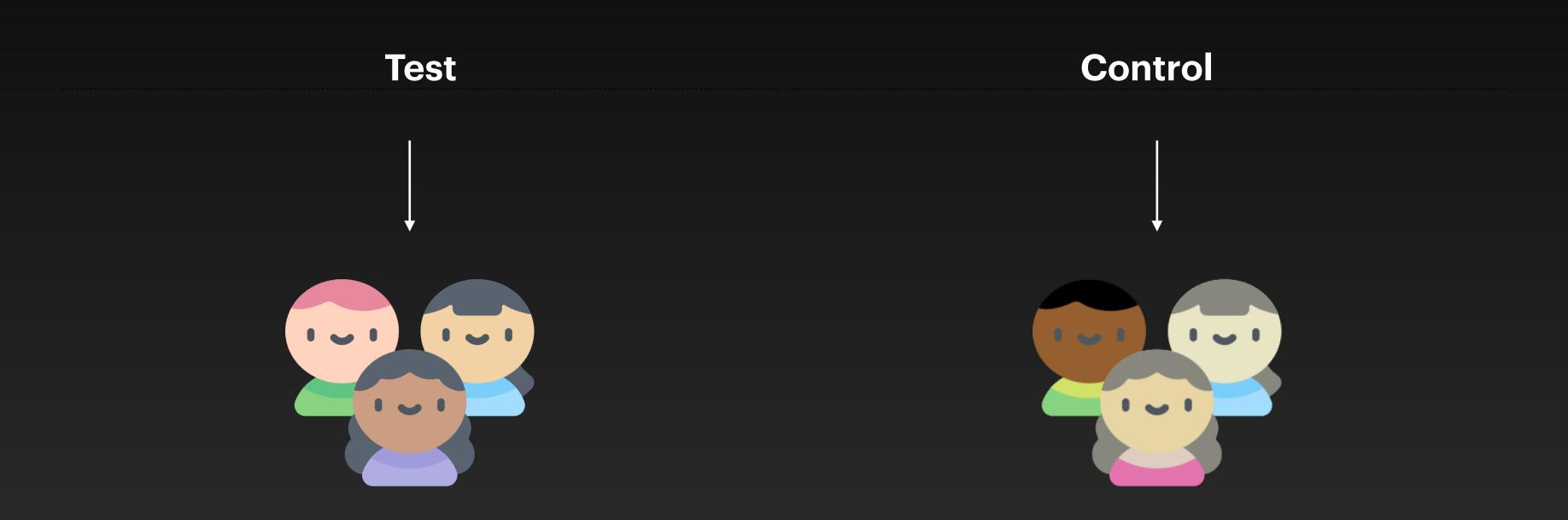
Using Bootstrapping to Evaluate Your Experiment

Introduction to Bootstrapping

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...



Converted 20 people out of total 1000 Conversion: 2%

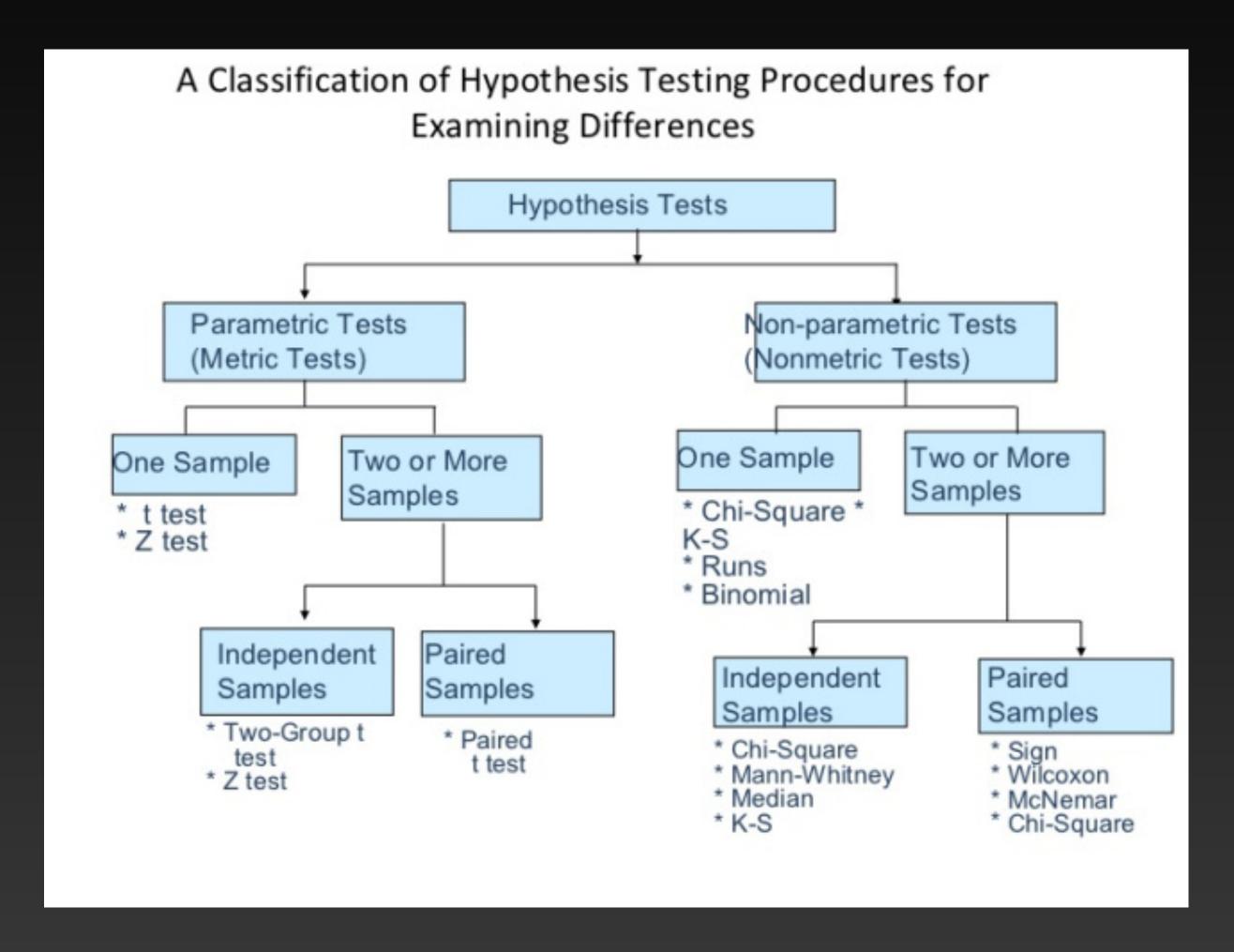
Converted 15 people out of total 1000 conversion: 1.5%

Hypothesis Testing

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

- You want to test whether test group works better, a.k.a. the difference between two groups are statistically significant.
- 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



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 a 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

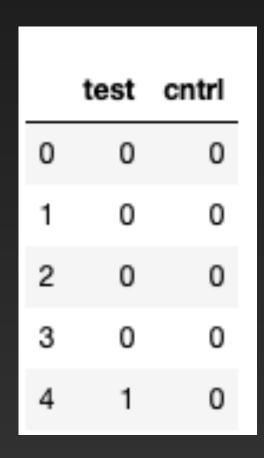
- Non-parametric: no assumption about the population distribution
- Tackle small sample problems
- Can easily get p-value and confidence intervals
- Code is reused for different experiments
- Can also be applied to design the experiment & conduct power analysis;
 however, I will only focus on the evaluation 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



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

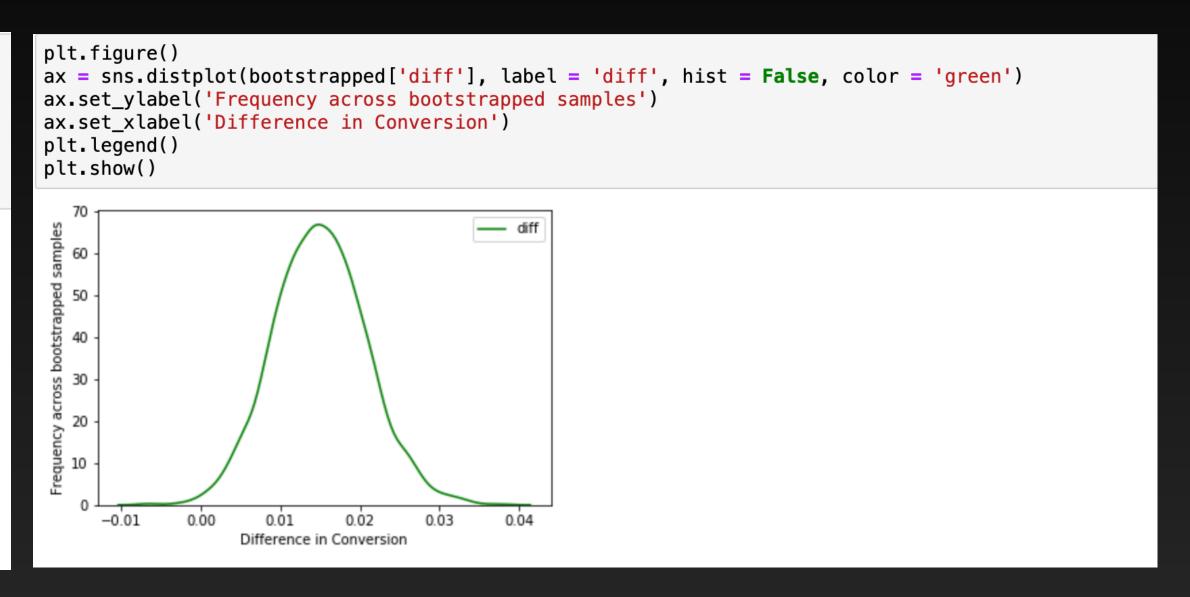
4 0.012 0.028 0.016 True
```

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()

significant for the st or the st orange in the state of the state of
```



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['diff']).tconfint_mean()
print('95% confidence interval', '[{:0.5f}, {:0.5f}]'.format(lower, upper))

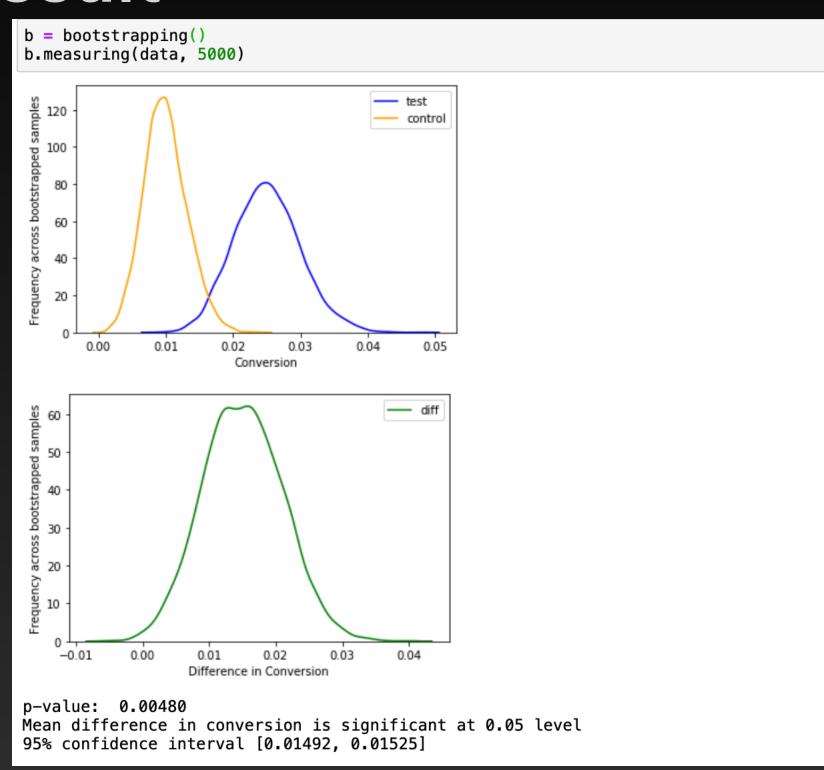
p-value: 0.00500
Mean difference in conversion is significant at 0.05 level
95% confidence interval [0.01482, 0.01515]</pre>
```

Code Sample

Full Code

```
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])
       # plot test v. control
       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()
       # plot the difference in conversion
       ax = sns.distplot(bootstrapped['diff'], label = 'diff', hist = False, color = 'green')
       ax.set_ylabel('Frequency across bootstrapped samples')
       ax.set_xlabel('Difference in 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['diff']).tconfint_mean()
       print('95% confidence interval', '[{:0.5f}, {:0.5f}]'.format(lower, upper))
```

Result



Thank You!

Questions/Comments?

- Code on GitHub: szuminyu/bootstrapping_TDP_monthly_2021
- Connect me on LinkedIn: szuminyu
- Follow TDP on Facebook & join slack channel
- https://www.facebook.com/twdatany
- We are looking for volunteers!