Analyzing difference in means A/B tests

A/B TESTING IN PYTHON

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Framework for difference in means

- Calculate required sample size
- Run experiment and perform sanity checks

$$H_0 : \mu_B - \mu_A = 0$$

$$H_1 : \mu_B - \mu_A \neq 0$$

- Calculate the metrics per variant
- Analyze the difference using t-test

- If p-value < α
  - Reject Null hypothesis
- If p-value > α
  - Fail to reject Null hypothesis

```
checkout.groupby('checkout_page')['time_on_page'].mean()
```

```
checkout_page
A    44.668527
B    42.723772
C    42.223772
```

Pingouin t-test

```
checkout.groupby('checkout_page')['time_on_page'].mean()
```

```
checkout_page
A     44.668527
B     42.723772
C     42.223772
```

```
ttest = pingouin.ttest(x=checkout[checkout['checkout_page']=='C']['time_on_page'],
                       y=checkout[checkout['checkout_page']=='B']['time_on_page'],
                       paired=False,
                       alternative="two-sided")
print(ttest)
```

```
            T          dof      alternative     p-val      CI95%                cohen-d     BF10     power
T-test    -1.995423    5998     two-sided     0.046042     [-0.99, -0.01]     0.051522     0.212     0.514054
```

Pingouin pairwise

```
pairwise = pingouin.pairwise_tests(data = checkout,
                                   dv = "time_on_page",
                                   between = "checkout_page",
                                   padjust = "bonf")
print(pairwise)
```

```
        Contrast  A  B  Paired  Parametric         T     dof alternative  \
0  checkout_page  A  B   False        True  7.026673  5998.0   two-sided
1  checkout_page  A  C   False        True  8.833244  5998.0   two-sided
2  checkout_page  B  C   False        True  1.995423  5998.0   two-sided

          p-unc        p-corr p-adjust       BF10    hedges
0  2.349604e-12  7.048812e-12     bonf  1.305e+09  0.181405
1  1.316118e-18  3.948354e-18     bonf  1.811e+15  0.228045
2  4.604195e-02  1.381258e-01     bonf      0.212  0.051515
```

Let's practice!

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Non-parametric statistical tests

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Parametric tests assumptions

1. **Random sampling**
   - Data is randomly sampled from the population.
   - Investigate the data collection/sampling process.
2. **Independence**
   - Each observation/data point is independent.
   - Not accounting for dependencies inflates error rates.
3. **Normality**
   - Normally distributed data.
   - Large "enough" sample size.
     - Two sample t-test n >= 30 in each group.
     - Two sample proportions test: >=10 successes and >=10 failures in each group.

Mann-Whitney U test

- Non-parametric test for statistical significance
- Determines if two independent samples have the same parent distribution
- Rank sum test
- Unpaired data

Mann-Whitney U test in python

```
# Calculate the mean and count of time on page by variant
print(checkout.groupby('checkout_page')['time_on_page'].agg({'mean', 'count'}))
```

```
                    mean  count
checkout_page
A              44.668527   3000
B              42.723772   3000
C              42.223772   3000
```

```
# Set random seed for repeatability
np.random.seed(40)
# Take a random sample of size 25 from each variant
ToP_samp_A = checkout[checkout['checkout_page'] == 'A'].sample(25)['time_on_page']
ToP_samp_B = checkout[checkout['checkout_page'] == 'B'].sample(25)['time_on_page']
```

Mann-Whitney U test in python

```python
# Run a Mann-Whitney U test
mwu_test = pingouin.mwu(x=ToP_samp_A,
                        y=ToP_samp_B,
                        alternative='two-sided')
# Print the test results
print(mwu_test)
```

```
     U-val alternative     p-val     RBC    CLES
MWU  441.0   two-sided  0.013007 -0.4112  0.7056
```

Chi-square test of independence

- Free from parametric test assumptions
- Tests whether two or more categorical variables are independent
  - **Null hypothesis:** The variables are independent.
  - **Alternative hypothesis:** The variables are not independent.

Chi-square test in python

Homepage signup rates A/B test

Null: There is no significant difference in signup rates between landing page designs C and D

Alternative: There is no significant difference in signup rates between them

```
# Calculate the number of users in groups C and D
n_C = homepage[homepage['landing_page'] == 'C']['user_id'].nunique()
n_D = homepage[homepage['landing_page'] == 'D']['user_id'].nunique()
```

```
# Compute unique signups in each group
signup_C = homepage[homepage['landing_page'] == 'C'].groupby('user_id')['signup'].max().sum()
no_signup_C = n_C - signup_C
signup_D = homepage[homepage['landing_page'] == 'D'].groupby('user_id')['signup'].max().sum()
no_signup_D = n_D - signup_D
```

Chi-square test in python

```python
# Create the signups table
table = [[signup_C, no_signup_C], [signup_D, no_signup_D]]
print('Group C signup rate:',round(signup_C/n_C,3))
print('Group D signup rate:',round(signup_D/n_D,3))

# Calculate p-value
print('p-value=',stats.chi2_contingency(table,correction=False)[1])
```

```
Group C signup rate: 0.064
Group D signup rate: 0.048
p-value= 0.009165
```

Let's practice!

A/B TESTING IN PYTHON

Ratio metrics and the delta method

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Ratio metrics A/B testing

- **Mean metrics**

$$\text{Mean order value} = \frac{\text{Total orders value}}{\text{\# users}} \qquad \text{Mean Time-on-page} = \frac{\text{Total time on page}}{\text{\# users}}$$

- **Unit of analysis:**
  - The entity being analyzed in an A/B test
  - Denominator in ratio metrics
- **Randomization unit:**
  - The subject randomly allocated to each variant

Ratio metrics A/B testing

- **Per-user Ratio metrics**

$$\text{CTR} = \frac{\text{clicks}}{\text{page views}} = \frac{\dfrac{\text{clicks}}{\text{users}}}{\dfrac{\text{page views}}{\text{users}}}$$

$$\begin{matrix}\text{Revenue} \\ \text{per session}\end{matrix} = \frac{\text{revenue}}{\text{sessions}} = \frac{\dfrac{\text{revenue}}{\text{users}}}{\dfrac{\text{sessions}}{\text{users}}}$$

Delta method motivation

```
print(checkout.groupby('checkout_page')[['order_value','purchased']].agg({'sum','count','mean'}))
```

```
              order_value                        purchased
                     mean           sum  count        mean     sum  count
checkout_page
A               24.956437  61417.791564   2461    0.820333  2461.0   3000
B               29.876202  75915.430125   2541    0.847000  2541.0   3000
C               34.917589  90890.484142   2603    0.867667  2603.0   3000
```

```
checkout.groupby('checkout_page')['order_value'].sum()/
checkout.groupby('checkout_page')['purchased'].count()
```

```
checkout_page
A    20.472597
B    25.305143
C    30.296828
dtype: float64
```

Delta method variance

- **Delta method ratio metrics variance estimation:**[1]

$$\operatorname{Var}\frac{X}{Y} \approx \frac{1}{\mathrm{E}[Y]^2}\operatorname{Var}X + \frac{\mathrm{E}[X]^2}{\mathrm{E}[Y]^4}\operatorname{Var}Y - 2\frac{\mathrm{E}[X]}{\mathrm{E}[Y]^3}\operatorname{cov}(X,Y)$$

```python
# Delta method variance of ratio metric
def var_delta(x,y):
    x_bar = np.mean(x)
    y_bar = np.mean(y)
    x_var = np.var(x,ddof=1)
    y_var = np.var(y,ddof=1)
    cov_xy = np.cov(x,y,ddof=1)[0][1]
    # Note that we divide by len(x) here because the denominator of the test statistic is standard error (=sqrt(var/n))
    var_ratio = (x_var/y_bar**2 + y_var*(x_bar**2/y_bar**4) - 2*cov_xy*(x_bar/y_bar**3))/len(x)
    return var_ratio
```

[1] Budylin, Roman & Drutsa, Alexey & Katsev, Ilya & Tsoy, Valeriya. (2018). Consistent Transformation of Ratio Metrics for Efficient Online Controlled Experiments. 55-63. 10.1145/3159652.3159699.

Delta method z-test

```
# Delta method ztest calculation
ztest_delta(x_control,y_control,x_treatment,y_treatment, alpha = 0.05)
```

Input arguments:

- `x_control` : control variant user-level ratio numerator column
- `y_control` : control variant user-level ratio denominator column
- `x_treatment` : treatment variant user-level ratio numerator column
- `y_treatment` : treatment variant user-level ratio denominator column

Output:

- `mean_control` : control group ratio metric mean
- `mean_treatment` : treatment group ratio metric mean
- `difference` : difference between treatment and control means
- `diff_CI` : confidence interval of the difference in means
- `p-value` : the two-tailed z-test p-value

[1] https://medium.com/@ahmadnuraziz3/applying-delta-method-for-a-b-tests-analysis-8b1d13411c22

Python example

```python
# Create DataFrames for per user metrics for variants A and B
A_per_user = pd.DataFrame({'order_value':checkout[checkout['checkout_page']=='A'].groupby('user_id')['order_value'].sum()
                           ,'page_view':checkout[checkout['checkout_page']=='A'].groupby('user_id')['user_id'].count()})
B_per_user = pd.DataFrame({'order_value':checkout[checkout['checkout_page']=='B'].groupby('user_id')['order_value'].sum()
                          ,'page_view':checkout[checkout['checkout_page']=='B'].groupby('user_id')['user_id'].count()})

# Assign the control and treatment ratio columns
x_control = A_per_user['order_value']
y_control = A_per_user['page_view']
x_treatment = B_per_user['order_value']
y_treatment = B_per_user['page_view']

# Run a z-test for ratio metrics
ztest_delta(x_control,y_control,x_treatment,y_treatment)
```

```
{'mean_control': 20.472597188012,
 'mean_treatment': 25.30514337484097,
 'difference': 4.833,
 'diff_CI': '[4.257, 5.408]',
 'p-value': 5.954978880467735e-61}
```

Let's practice!

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A/B Testing best practices and advanced topics intro

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Best practices

Avoid peeking

- Avoid making decisions by peeking at the results before reaching the designed sample size, as this inflates error rates similar to multiple comparisons.

Account for day-of-the-week effects

- Users may behave differently on weekends versus weekdays, so we should include overall behavior.

Best practices

- **Simplicity/feasibility:**
  - Do we need to build the full feature?
  - Painted door tests
- **Isolation**
  - Change one variable at a time to attribute impact.

Advanced topics

- **Multifactorial design and interaction effects**
  - Measures the isolated effect of each variable
  - Uncovers interaction/synergistic effects
- **Bayesian A/B testing**
  - Incorporates prior data into current experiment
  - Views population parameters as distributions
  - More intuitive understanding of test results
- **SUTVA violation and network effects**
  - One user's assignment in a test impacts others
  - Common in social networks A/B tests
  - One solution: clusters assignment

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A/B TESTING IN PYTHON

Wrap-up: A/B testing in python

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A/B testing summary

Chapter 1

- A/B testing steps and use-cases
- Metrics definition and estimation
- `.sample()` , `.corr()` , `pairplot` , `heatmap`

Chapter 2

- Formulating A/B testing hypotheses
- Error rates, power, effect size
- Power analysis: sample size estimation
- Multiple comparisons corrections

Chapter 3

- Data cleaning and EDA
- Sanity checks for validation
- Analyzing difference in proportions
- `proportions_ztest` , `proportion_confint`

Chapter 4

- Analyzing differences in means
- Non-parametric tests
- Delta method for ratio metrics
- Best practices and advanced topics

Congratulations!

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