A/B Testing Project

Dataset - https://www.kaggle.com/datasets/zhangluyuan/ab-testing/code?select=ab_data.csv

Reference Course - https://www.udacity.com/course/ab-testing--ud257

Disclaimer - This is just to showcase some skill, the dataset needs more features to make better explainable conclusions.

1. Experiment Introduction and Hypothesis Testing

The aim is to formulate and test the hypothesis for comparing the conversion rate between Old web page vs New web page.

Two Tailed test:

$H_0 : p = p_0$

$H_\alpha : p \neq p_0$

At confidence interval of 95% - $\alpha = 0.05$

2. Data and Preprocessing

```
import pandas as pd
import numpy as np
```

Import Data

```
df = pd.read_csv('ab_data.csv')
```

Independent Variables: -

Control Group is shown Old web page.

Treatment Group is shown New web page.

Dependent Variable: -

Converted (0 or 1) represents a buy or click.

```
df.head()

   user_id                   timestamp      group landing_page
converted
0   851104  2017-01-21 22:11:48.556739    control     old_page
0
1   804228  2017-01-12 08:01:45.159739    control     old_page
```

```
0
2   661590  2017-01-11 16:55:06.154213  treatment     new_page
0
3   853541  2017-01-08 18:28:03.143765  treatment     new_page
0
4   864975  2017-01-21 01:52:26.210827    control     old_page
1
```

```
df.shape
```

```
(294478, 5)
```

Check for null values and data type

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 294478 entries, 0 to 294477
Data columns (total 5 columns):
 #   Column        Non-Null Count   Dtype
---  ------        --------------   -----
 0   user_id       294478 non-null  int64
 1   timestamp     294478 non-null  object
 2   group         294478 non-null  object
 3   landing_page  294478 non-null  object
 4   converted     294478 non-null  int64
dtypes: int64(2), object(3)
memory usage: 11.2+ MB
```

Data Description

```
df.describe()
```

```
             user_id      converted
count  294478.000000  294478.000000
mean   787974.124733       0.119659
std     91210.823776       0.324563
min    630000.000000       0.000000
25%    709032.250000       0.000000
50%    787933.500000       0.000000
75%    866911.750000       0.000000
max    945999.000000       1.000000
```

```
pd.crosstab(df['group'], df['landing_page'])
```

```
landing_page  new_page  old_page
group
control           1928    145274
treatment       145311      1965
```

```
df.converted.mean()
```

```
0.11965919355605512
```

Check for duplicate user_id

```
session_counts = df['user_id'].value_counts(ascending=False)
multi_users = session_counts[session_counts > 1].count()

print(f'There are {multi_users} users that appear multiple times in
the dataset')
```

```
There are 3894 users that appear multiple times in the dataset
```

Remove duplicate user_id

```
users_to_drop = session_counts[session_counts > 1].index

df = df[~df['user_id'].isin(users_to_drop)]
print(f'The updated dataset now has {df.shape[0]} entries')
```

```
The updated dataset now has 286690 entries
```

Re-check for duplicate user_id

```
df[df.user_id.duplicated(keep=False)]
```

```
Empty DataFrame
Columns: [user_id, timestamp, group, landing_page, converted]
Index: []
```

Assumptions to calculate sample size: -

Lets Assume the baseline conversion rate is 11% based on the past data and through the experiment the organization is aiming for 14% conversation rate.

The function sms.proportion_effectsize(0.11, 0.14) is calculating the effect size based on a proportion for two independent samples, in this case with proportions of 0.11 and 0.14.

The function sms.NormalIndPower().solve_power(effect_size, power=0.8, alpha=0.05, ratio=1) is used to calculate the sample size required for the study. Here power=0.8 and alpha=0.05 are the statistical power and significance level used for the calculation, respectively, and ratio=1 indicates that the sample sizes for the two groups are equal.

In the context of hypothesis testing in statistics, power is the probability that a test correctly rejects the null hypothesis when the alternative hypothesis is true. The power of a statistical test is generally defined as 1 - β, where β is the probability of Type II error.

Type II error occurs when the null hypothesis is false, but we fail to reject it. So, the power of a test is essentially the test's ability to detect an effect if there is one.

Finally, required_n = ceil(required_n) rounds up the number to ensure it is a whole number, since we can't have a fraction of a sample.

```
import statsmodels.stats.api as sms
from math import ceil

effect_size = sms.proportion_effectsize(0.11, 0.14)    # Calculating 
effect size based on our expected rates

required_n = sms.NormalIndPower().solve_power(
    effect_size, 
    power=0.8, 
    alpha=0.05, 
    ratio=1
    )                                                  # Calculating 
sample size needed

required_n = ceil(required_n)                          # Rounding up 
to next whole number

print(required_n)
```

```
1902
```

Sample Collection from both Control Group and Treatment Group

```
control_sample = df[df['group'] == 'control'].sample(n=required_n,
random_state=22)
treatment_sample = df[df['group'] == 'treatment'].sample(n=required_n,
random_state=22)

ab_test = pd.concat([control_sample, treatment_sample], axis=0)
ab_test.reset_index(drop=True, inplace=True)

ab_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3804 entries, 0 to 3803
Data columns (total 5 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   user_id       3804 non-null   int64 
 1   timestamp     3804 non-null   object
 2   group         3804 non-null   object
 3   landing_page  3804 non-null   object
 4   converted     3804 non-null   int64 
dtypes: int64(2), object(3)
memory usage: 148.7+ KB
```

```
ab_test['group'].value_counts()
```

```
control      1902
treatment    1902
Name: group, dtype: int64
```

Mean and Standard Deviation of Control Group and Treatment Group

```
import scipy.stats as stats

conversion_rates = ab_test.groupby('group')['converted']

std_p = lambda x: np.std(x, ddof=0)              # Std. deviation of
the proportion
se_p = lambda x: stats.sem(x, ddof=0)            # Std. error of the
proportion (std / sqrt(n))

conversion_rates = conversion_rates.agg([np.mean, std_p, se_p])
conversion_rates.columns = ['conversion_rate', 'std_deviation',
'std_error']


conversion_rates.style.format('{:.3f}')
```

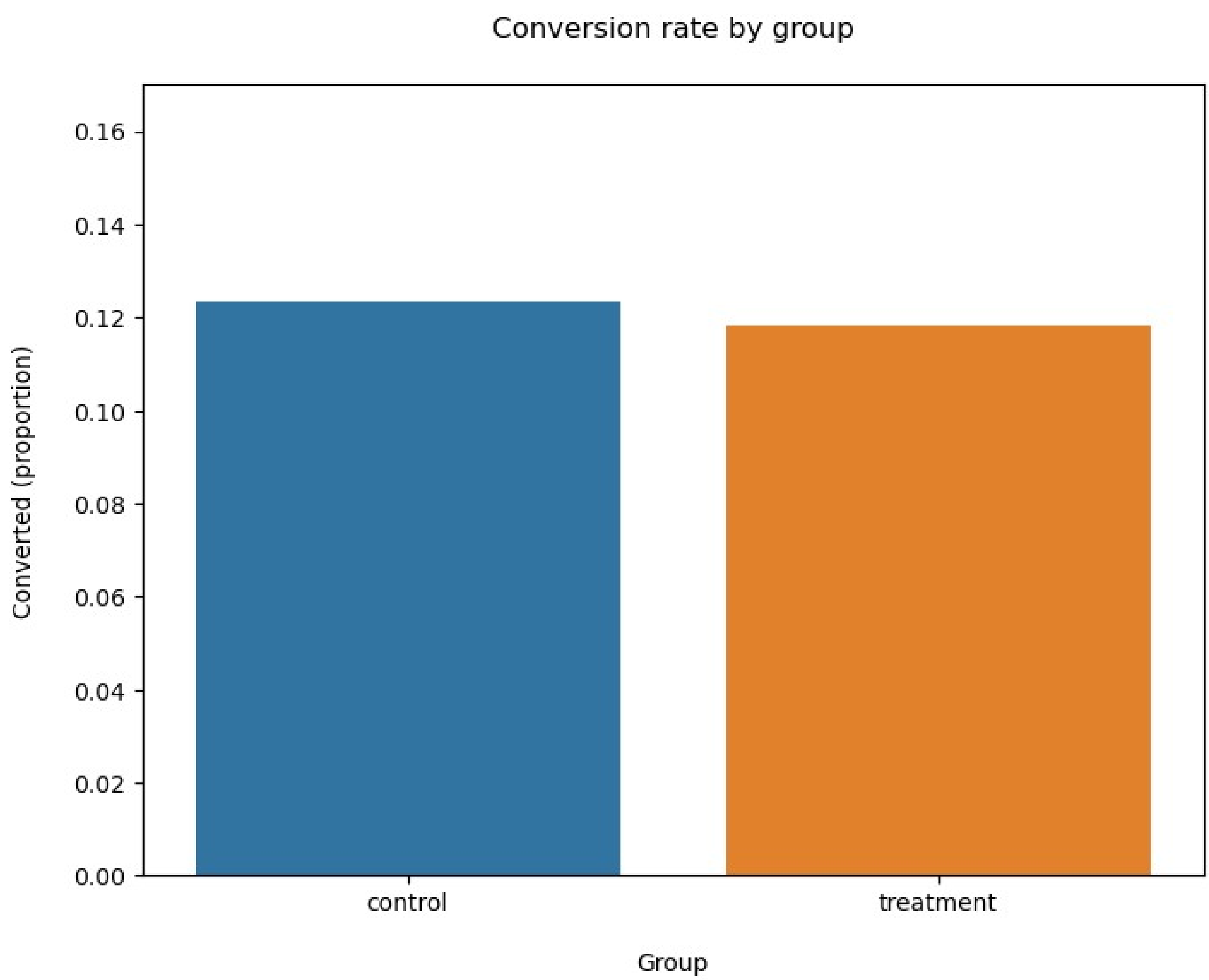
```
<pandas.io.formats.style.Styler at 0x25c4c2005b0>
```

The Mean and Standard Deviation of Control Group and Treatment Group are fairly close indicating not much of significance difference between groups even before test.

3. Plot of Connversion for Control Group and Treatment Group

```
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(8,6))

sns.barplot(x=ab_test['group'], y=ab_test['converted'], ci=False)

plt.ylim(0, 0.17)
plt.title('Conversion rate by group', pad=20)
plt.xlabel('Group', labelpad=15)
plt.ylabel('Converted (proportion)', labelpad=15);
```

```
C:\Users\achal\AppData\Local\Temp\ipykernel_10568\3362076549.py:6:
FutureWarning:

The `ci` parameter is deprecated. Use `errorbar=('ci', False)` for the
same effect.

  sns.barplot(x=ab_test['group'], y=ab_test['converted'], ci=False)
```



4. Testing the Hypothesis: -

The goal is to determine if the proportion of successes (conversions) is significantly different between the two groups. The test statistic is a Z-score (Z-stat).

The two-proportion Z-test is used when you have two samples and you want to see if the success rates are significantly different from each other.

At other times, a binomial test may be used when you have one sample and you want to compare the observed success rate to a hypothesized success rate.

```
from statsmodels.stats.proportion import proportions_ztest,
proportion_confint

control_results = ab_test[ab_test['group'] == 'control']['converted']
treatment_results = ab_test[ab_test['group'] == 'treatment']
['converted']

n_con = control_results.count()
```

```python
n_treat = treatment_results.count()
successes = [control_results.sum(), treatment_results.sum()]
nobs = [n_con, n_treat]

z_stat, pval = proportions_ztest(successes, nobs=nobs)
(lower_con, lower_treat), (upper_con, upper_treat) =
proportion_confint(successes, nobs=nobs, alpha=0.05)

print(f'z statistic: {z_stat:.2f}')
print(f'p-value: {pval:.3f}')
print(f'ci 95% for control group: [{lower_con:.3f}, {upper_con:.3f}]')
print(f'ci 95% for treatment group: [{lower_treat:.3f},
{upper_treat:.3f}]')
```

```
z statistic: 0.50
p-value: 0.619
ci 95% for control group: [0.109, 0.138]
ci 95% for treatment group: [0.104, 0.133]
```

5. Conclusions: -

For a two-tailed test at a 95% confidence level (significance level of α = 0.05), the critical Z values are approximately -1.96 and +1.96. suggesting that the result is not statistically significant at the 95% confidence level and fails to reject the null hypothesis.

The p-value of 0.619 > 0.05 and thus, insignificant to reject null hypothesis H_0.

The confidence values of treatment group are not approaching to 14% aim expectation.

The confidence values of treatment group does not show increment compared to control group instead has only slightly decreased.

Thank you