Report on A/B Testing

Introduction

A/B tests are very commonly performed by data analysts and data scientists. In this project, we will be working to understand the results of an A/B test run by an e-commerce website. Our goal in this project is to help the company understand if they should implement the new page, keep the old page, or perhaps run the experiment longer to make their decision.

The Data

This dataset is provided by Udacity under the Udacity-Data-Analysis-Nanodegree program. It is named ab_test.csv. It contains 294478 rows and 5 columns namely,

- user_id : User Id of the person who accessed the web page.
- timestamp : Time at which the user accessed the web page.
- group : The group of users (‘control’ and ‘treatment’).
- landing_page : The landing page the user gets (‘new_page’ and ‘old_page’)
- converted : Whether the users want to convert or not.

Analysis

In this project, I have preprocessed the data and tested the data using **‘A/B Testing’** procedure to draw the conclusions whether the company has to change their web page to the new page or can keep the same, using the difference in **‘conversion rate’** of **‘new_page’** and **‘old_page’** as a metric. I have calculated the **‘p-value’** of the **‘observed difference’** under the null hypothesis assumption that ‘old_page’ is better than ‘new_page’. Then concluded the test based on the statistical significance of the result.

Code

Performing A/B Test for the dataset ab_data.csv

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Introduction

A/B tests are very commonly performed by data analysts and data scientists. In this project, we will be working to understand the results of an A/B test run by an e-commerce website. Our goal is to work through this notebook to help the company understand if they should implement the new page, keep the old page, or perhaps run the experiment longer to make their decision.

Importing essential libraries

[1]
```
import numpy as np
import pandas as pd
import random
import matplotlib.pyplot as plt
import seaborn as sns
random.seed(42) # to give the same results everytime
```

Reading the Dataset

[2]
```
# reading the csv file using pandas
df = pd.read_csv('/content/ab_data.csv')
```

Information about the dataset

[3]
```
# top 5 rows of the dataframe
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

[4]
```
# column names of the dataframe
df.columns.to_list()
```

```
['user_id', 'timestamp', 'group', 'landing_page', 'converted']
```

[5]
```
# shape of the dataframe
df.shape
```

```
(294478, 5)
```

Data Preprocessing

Checking for missing values

[6]
```
# checking for any null values
df.isnull().sum()
```

```
user_id         0
timestamp       0
group           0
landing_page    0
converted       0
dtype: int64
```

Data types of the columns

[7]
```
df.dtypes
```

```
user_id          int64
timestamp       object
group           object
landing_page    object
converted        int64
dtype: object
```

Number of times the **new_page** and **treatment** is not lined up

```
[8] # no. of times the new_page and treatment is not lined up is equal to
    not_linedup_1 = df.query("group == 'treatment' and landing_page == 'old_page'").count()
    not_linedup_2 = df.query("group == 'control' and landing_page == 'new_page'").count()
    print(not_linedup_1 + not_linedup_2)
```

```
user_id         3893
timestamp       3893
group           3893
landing_page    3893
converted       3893
dtype: int64
```

Eliminating those rows where the **group** is not lined up with the **landing_page** as we only want to give **new_page** to the **control** group.

```
# storing the aligned data in another dataframe
df2 = df.query("(group=='treatment' and landing_page=='new_page') or (group=='control' and landing_page=='old_page')")
```

```
[10] # top 5 rows of the new dataframe
     df2.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

```
[11] # shape
     df2.shape
```

```
(290585, 5)
```

```
[12] # how many number of 0's and 1's
     df2.converted.value_counts()
```

```
0    255832
1     34753
Name: converted, dtype: int64
```

Number of unique users

```
[13] df['user_id'].nunique()
```

```
290584
```

Number of duplicated users

```
[14] df2['user_id'].duplicated().sum()
```

```
1
```

Eliminating the duplicated row

```
[15] # displaying the duplicated rows
     df2[df2['user_id'].duplicated(keep=False)]
```

	user_id	timestamp	group	landing_page	converted
1899	773192	2017-01-09 05:37:58.781806	treatment	new_page	0
2893	773192	2017-01-14 02:55:59.590927	treatment	new_page	0

```
[16] # removing the second row
     df2.drop_duplicates(subset=['user_id'], inplace = True)
     df2['user_id'].duplicated().sum()
```

```
/usr/local/lib/python3.7/dist-packages/pandas/util/_decorators.py:311: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  return func(*args, **kwargs)
0
```

A/B Test

Background Information to help you better understand the results :

In this case, we will take the difference of conversion rates of the pages as the metric of our A/B Testing.

We will calculate p-value, if p-value is really small, less likely to observe the statistic in the null , more likely from the alternative. p-value is large you will end up staying with the null hypothesis as your choice.

Type 1 error threshold is alpha

- If p < alpha , reject the null , choose H1
- If p > alpha , fail to reject the null, choose H0

1. If you want to assume that the old page is better unless the new page proves to be definitely better at a Type I error rate of 5%, the null and alternative hypotheses be

- H0 : p(new)-p(old) <= 0 old has better conversion
- H1 : p(new)-p(old) > 0 new has better conversion

where **p(new)** and **p(old)** are the conversion rates.

2. Assume under the null hypothesis, and both have "true" success rates equal to the converted success rate regardless of page - that is and are equal. Furthermore, assume they are equal to the converted rate in ab_data.csv regardless of the page.

Use a sample size for each page equal to the ones in ab_data.csv.

Perform the sampling distribution for the difference in converted between the two pages over 10,000 iterations of calculating an estimate from the null.

Steps:

1. Compute the observed difference between the metric, p_new for treatment group and p_old for control group.
2. Simulate the sampling distribution for the difference of the conversion rate.
3. Use this sampling distribution to simulate the distribution under null hypothesis, by creating a random normal distribution centered at 0 with the same size and spread.
4. Compute the p-value by finding the difference of the conversion rates from the null distribution that are greater than our observed difference.
5. Use this p-value to determine the statistical significance of our observed difference.

Step-1: Observed statistic

Observed Difference is equal to the difference between new conversion rate and old conversion rate.

[17]
```
# number of unique users accessing old page
N_old = df2.query("landing_page =='old_page'")['user_id'].nunique()
N_old
```

```
145274
```

[18]
```
# number of unique users accessing new page
N_new = df2.query("landing_page =='new_page'")['user_id'].nunique()
N_new
```

```
145310
```

[19]
```
# compute actual conversion rate
# number of landing new page and converted  / number of landing new page
converted_new = df2.query('converted == 1 and landing_page== "new_page"')['user_id'].nunique()
actual_new = float(converted_new) / float(N_new)

# number of landing old page and converted  / number of landing old page
converted_old = df2.query('converted == 1 and landing_page== "old_page"')['user_id'].nunique()
actual_old = float(converted_old) / float(N_old)

#observed difference in converted rate
obs_diff = actual_new - actual_old
obs_diff
```

```
-0.0015782389853555567
```

But does this result statistically significant? We check it by calculating the p-value.

Step-2: Simulating sampling distribution

[20]
```
# top 5 rows of the dataframe
df2.head()
```

	user_id	timestamp	group	landing_page	converted
0	851104	2017-01-21 22:11:48.556739	control	old_page	0
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4	864975	2017-01-21 01:52:26.210827	control	old_page	1

Under null hypothesis, both the conversion rates of new_page and old_page are the same. They are equal to the converted rate regardless of the page.

[21]
```
p_new = p_old = round(float(df2.query('converted==1').user_id.nunique()) / float(df2.shape[0]), 4)
print(p_new,' ',p_old)
```

```
0.1196   0.1196
```

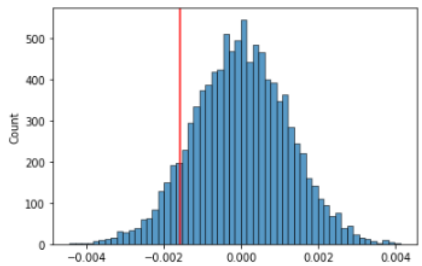
[22]
```
p_diffs = []
size = df2.shape[0]
for _ in range(10000):
  sample = df2.sample(size, replace = True)
  old_conversion = np.random.choice(sample['converted'], N_old, (p_old,1-p_old))
  new_conversion = np.random.choice(sample['converted'], N_new, (p_new,1-p_new))
  p_diffs.append(new_conversion.mean() - old_conversion.mean())

p_diffs = np.array(p_diffs)
```

Step-3: Simulating the random normal distribution

Generating normal distribution under null hypothesis using numpy library with zero mean and size and spread same as the samples.

```
[23] null_values = np.random.normal(0, p_diffs.std(), p_diffs.size)
```

```
[24] sns.histplot(null_values)
     plt.axvline(x=obs_diff,color ='red')
     plt.show()
```



Step-4 : Calculating p-value

```
[25] # as the test is a right tailed test
     p_value = (null_values > obs_diff).mean()
     p_value
```

```
0.8977
```

Step-5: Determining the statistical significance

The p-value we got from the A/B testing is greater than the significance level (>0.05) which concludes that there is no enough evidence to reject the null hypothesis.

We fail to reject the null. Therefore, the data show, with a Type I error rate of 0.05, that the old page has higher probablity of conversion rate than new page.

Conclusion

From the statistical result we got by performing A/B Test on the dataset we have, we can conclude that the company should keep their old page.

+ Code + Text

Data Source

➔ https://github.com/ozlerhakan/ab-test/blob/master/ab_data.csv

References

➔ https://github.com/CICIFLY/Data-Analytics-Projects/tree/d413f4e4539f09be53d4533107ae9cc4b07468e4/AB%20Testing%20Result%20Analyze

➔ https://github.com/ozlerhakan/ab-test/blob/master/Analyze_ab_test_results_notebook.ipynb