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Website of the Grocery Store Chain

Experimental Design and A/B Testing

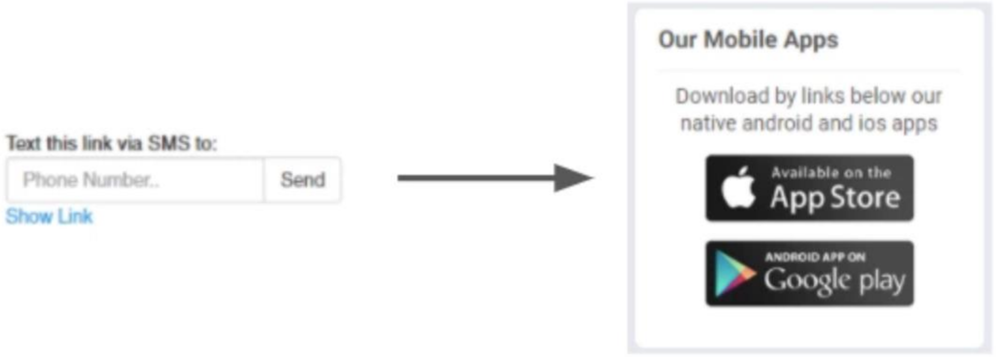
Outline

- Introduction/Background
- Setting Up Problem
- Designing Experiments
- Analyzing and Interpreting the Data
- Conclusion and Recommendation
- References

Introduction/Background

Introduction

- There is a large grocery chain. The company’s goal is to drive more customers to download the mobile app and register for the loyalty program. The manager is curious if changing the link to a button of the app store will improve the user’s ability to download the app. Here is the existing link button of the app store.



Text this link via SMS to:

Our Mobile Apps

Download by links below our native android and ios apps

- The manager asked to create an A/B testing plan for changing the link to a button of the app store with the expectation it will the user’s interest to download the app.

Setting Up Problem

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Setting Up Problem

1. Experiment Goal
   To see if changes to the link to a button of the app store can increase user interest in downloading the mobile application.

2. Choosing Metrics
   - Goal Metrics : User Counts
     - Represents the company's purpose or core business.
       Objective : Drive more customers to download our mobile app and register for the loyalty program.
       Reason : User counts can measure how many interested customers have downloaded the mobile app on their devices.
     - Simple to communicate with stakeholders.
       Stakeholder : Internal team, manager, executives.
       Reason : When using this metric, stakeholders can understand how far the mission/goal has been achieved.

Setting Up Problem

- Driver Metrics : Click-Through-Rate (CTR)
  - Reason : This metric measures how many customers download the mobile application and sign up for the loyalty program on the link.

$$\frac{\textit{people who click to download mobile app from website}}{\textit{total number of website visitor}} \times 100$$

- Guardrail Metrics : Mobile app loading time
  - Reason : If mobile app loading time increases a few ms -> decreased satisfaction -> abandon/uninstall mobile app -> lose users -> potential loss.

Setting Up Problem

3. Define Variants
   - Control : Existing link.
   - Treatment : New link, such as in picture not text.

4. Define Hypothesis
   - H_0 (Null Hypothesis) : CTR New link such as in the picture, not text equal to or less than the existing link.
   - H_1 (Alternative Hypothesis) : CTR New link such as in the picture, not text more than the existing link.

Designing Experiments

Designing Experiments

1. Randomization Unit : User

2. Target of Randomization Unit : All users who visit the web pages of the grocery store chain that contain links

3. Sample Size :

   a. Significance level (α) = 5% or 0.05
   b. Power level (1-β) = 80% or 0.8
   c. Standard deviation of population (σ) = 0.5
   d. Difference between control and treatment (δ) = 2%

   Then the number of Sample Size : $n \approx \dfrac{16\sigma^2}{\delta^2}$ $\quad n \approx \dfrac{16(0.5)^2}{0.02^2} = 10.000$

   Sample size 10.000 for 1 variant, so total for 2 variants : 10.000 x 2 = 20.000

Designing Experiments

e. Since this experiment requires a very large sample size, the length of time to run the experiment depends on the number of visitors to the website.

If the experiment is run for 6 full weeks with the frequency of users visiting the website at least 500 times per day, then the total number of users involved in the experiment is 42 days x 500 = 21,000.

From this, the time sufficient to collect data is at least 6-8 weeks, the length of this experiment is done to avoid primacy and novelty effects.

Analyzing and Interpreting the Data

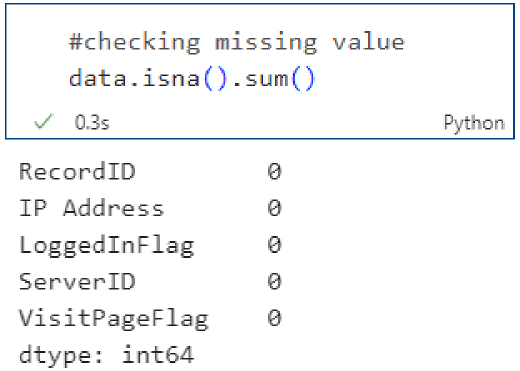
Analyzing and Interpreting the Data

- The dataset used in this project comes from Grocery website data for AB test. The dataset has 184.588 records with 5 variables. Here is information from the data variables used:
  - RecordID : identifier of the row of data.
  - IP Address : address of the user, who is visiting website.
  - LoggedInFlag : 1 - when user has an account and logged in.
  - ServerID : one of the servers user was routed through.
  - VisitPageFlag : 1 - when user clicked on the loyalty program page.

- From the sample size calculation, 10,000 users are obtained for each variant. Therefore, Simple Random Sampling is carried out to get a sample. To analyze and interpret data, the following steps were taken :

Analyzing and Interpreting the Data

1. Ensure the trustworthiness
   a. Check the data quality (missing value, duplicate data, distribution of data).

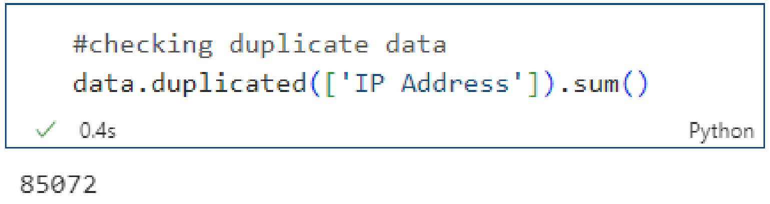


```
#checking missing value
data.isna().sum()
```

✓ 0.3s Python

```
RecordID         0
IP Address       0
LoggedInFlag     0
ServerID         0
VisitPageFlag    0
dtype: int64
```

There is no missing value. Next, check for duplicate data.



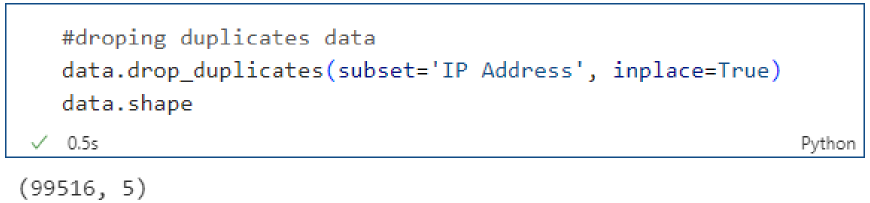
```
#checking duplicate data
data.duplicated(['IP Address']).sum()
```

✓ 0.4s Python

```
85072
```

Analyzing and Interpreting the Data

There are 85,072 duplicate data, so delete the duplicate data.

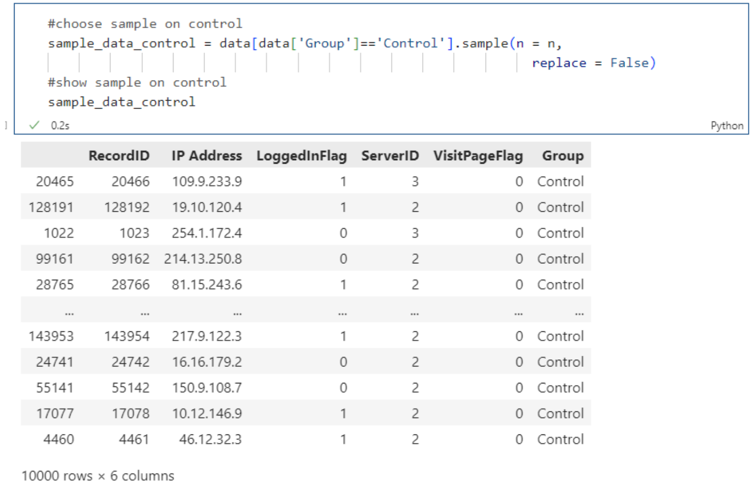


```python
#droping duplicates data
data.drop_duplicates(subset='IP Address', inplace=True)
data.shape
```

```
(99516, 5)
```

Now, there are 99.516 total records without duplicates and the data is ready for analysis.

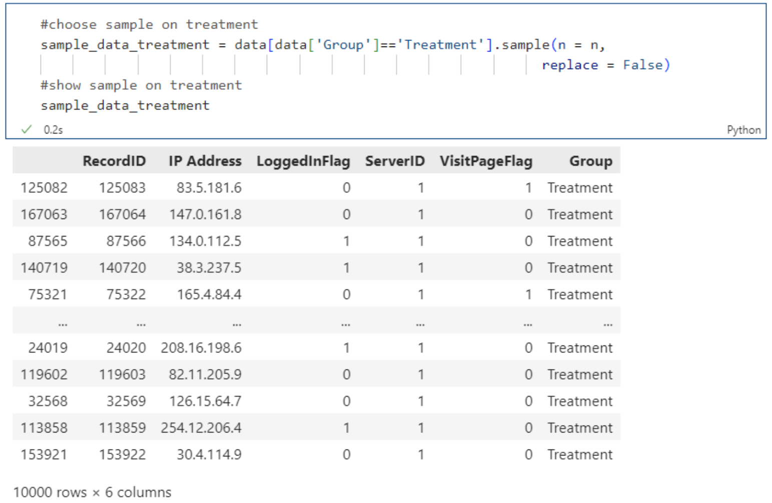
b. Data exploration (how many users in each group, and other insight from dataset)



```python
#choose sample on control
sample_data_control = data[data['Group']=='Control'].sample(n = n,
                                                          replace = False)
#show sample on control
sample_data_control
```

	RecordID	IP Address	LoggedInFlag	ServerID	VisitPageFlag	Group
20465	20466	109.9.233.9	1	3	0	Control
128191	128192	19.10.120.4	1	2	0	Control
1022	1023	254.1.172.4	0	3	0	Control
99161	99162	214.13.250.8	0	2	0	Control
28765	28766	81.15.243.6	1	2	0	Control
...	...	...	...	...	...	...
143953	143954	217.9.122.3	1	2	0	Control
24741	24742	16.16.179.2	0	2	0	Control
55141	55142	150.9.108.7	0	2	0	Control
17077	17078	10.12.146.9	1	2	0	Control
4460	4461	46.12.32.3	1	2	0	Control

10000 rows × 6 columns



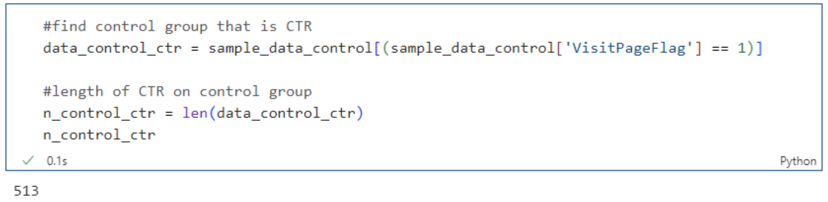
```python
#choose sample on treatment
sample_data_treatment = data[data['Group']=='Treatment'].sample(n = n,
                                                              replace = False)
#show sample on treatment
sample_data_treatment
```

	RecordID	IP Address	LoggedInFlag	ServerID	VisitPageFlag	Group
125082	125083	83.5.181.6	0	1	1	Treatment
167063	167064	147.0.161.8	0	1	0	Treatment
87565	87566	134.0.112.5	1	1	0	Treatment
140719	140720	38.3.237.5	1	1	0	Treatment
75321	75322	165.4.84.4	0	1	1	Treatment
...	...	...	...	...	...	...
24019	24020	208.16.198.6	1	1	0	Treatment
119602	119603	82.11.205.9	0	1	0	Treatment
32568	32569	126.15.64.7	0	1	0	Treatment
113858	113859	254.12.206.4	1	1	0	Treatment
153921	153922	30.4.114.9	0	1	0	Treatment

10000 rows × 6 columns

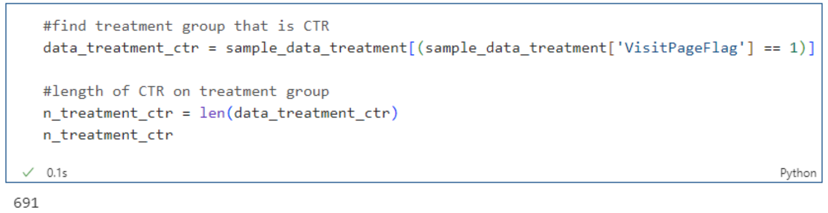
Analyzing and Interpreting the Data

Then calculate the CTR, for both groups as follows.



```python
#find control group that is CTR
data_control_ctr = sample_data_control[(sample_data_control['VisitPageFlag'] == 1)]

#length of CTR on control group
n_control_ctr = len(data_control_ctr)
n_control_ctr
```

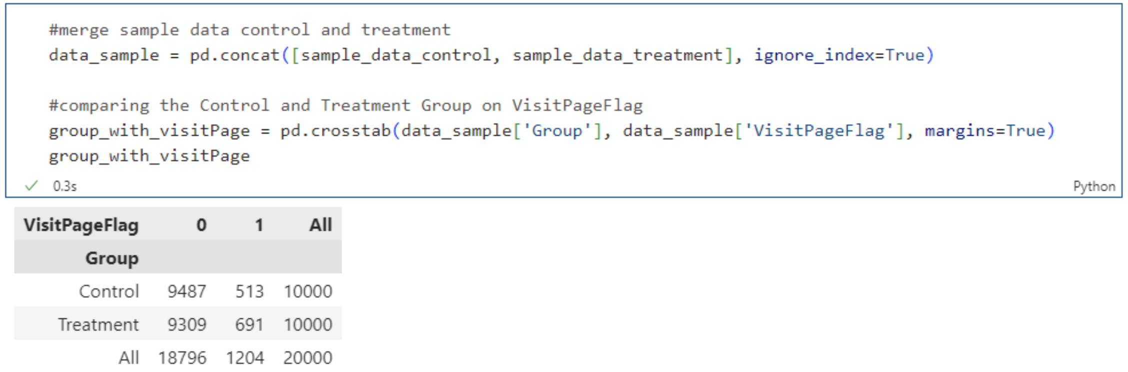
```
513
```



```python
#find treatment group that is CTR
data_treatment_ctr = sample_data_treatment[(sample_data_treatment['VisitPageFlag'] == 1)]

#length of CTR on treatment group
n_treatment_ctr = len(data_treatment_ctr)
n_treatment_ctr
```

```
691
```

To see more clearly, compare the control group and the treatment group. Create the following code.

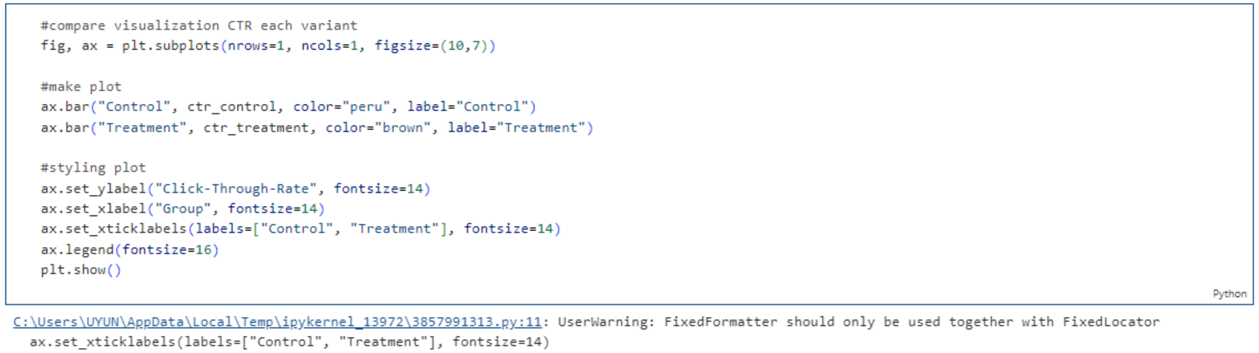


```python
#merge sample data control and treatment
data_sample = pd.concat([sample_data_control, sample_data_treatment], ignore_index=True)

#comparing the Control and Treatment Group on VisitPageFlag
group_with_visitPage = pd.crosstab(data_sample['Group'], data_sample['VisitPageFlag'], margins=True)
group_with_visitPage
```

VisitPageFlag	0	1	All
Group			
Control	9487	513	10000
Treatment	9309	691	10000
All	18796	1204	20000

Analyzing and Interpreting the Data

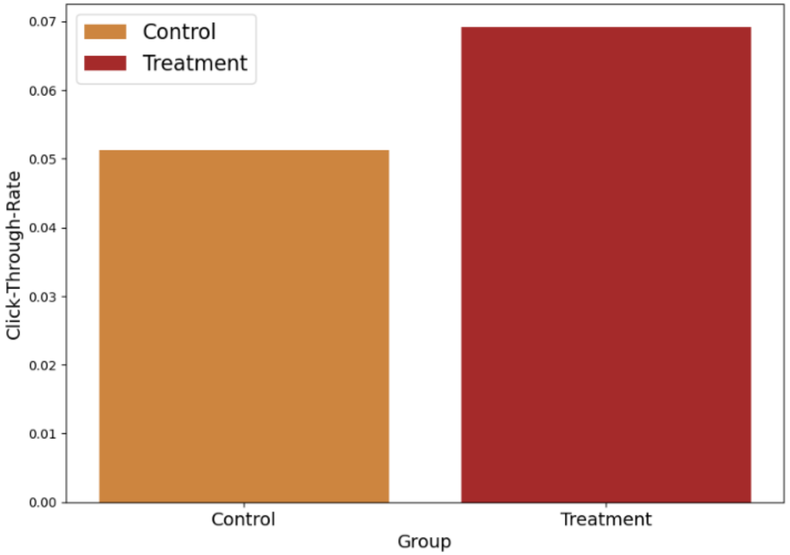
Next make a visualization, to see the comparison of CTR on each variant.



```python
#compare visualization CTR each variant
fig, ax = plt.subplots(nrows=1, ncols=1, figsize=(10,7))

#make plot
ax.bar("Control", ctr_control, color="peru", label="Control")
ax.bar("Treatment", ctr_treatment, color="brown", label="Treatment")

#styling plot
ax.set_ylabel("Click-Through-Rate", fontsize=14)
ax.set_xlabel("Group", fontsize=14)
ax.set_xticklabels(labels=["Control", "Treatment"], fontsize=14)
ax.legend(fontsize=16)
plt.show()
```

Python

```
C:\Users\UYUN\AppData\Local\Temp\ipykernel_13972\3857991313.py:11: UserWarning: FixedFormatter should only be used together with FixedLocator
  ax.set_xticklabels(labels=["Control", "Treatment"], fontsize=14)
```



Analyzing and Interpreting the Data

Perform SRM test with chi-square test

- Define the null and alternative hypothesis (H_0 and H_1)

  H_0 : No SRM detected

  H_1 : SRM detected

- Calculate chi-square statistic

$$\chi^2 = \sum \frac{(\text{observed - expected})^2}{\text{expected}}$$

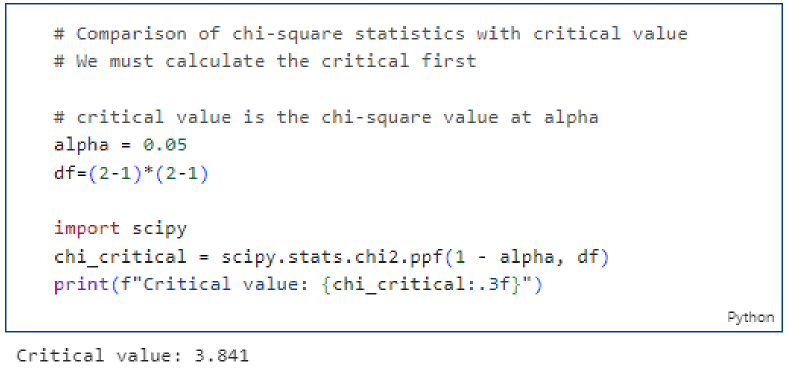
- Define decision rules

  In making statical test decision, use :

  - Comparison of chi-square statistics with critical value $\chi^2 > \chi^2_{\alpha,df} \rightarrow \text{reject } H_0$
  - Comparion of p-value with alpha $\text{pvalue} < \alpha \rightarrow \text{reject } H_0$
  - Degree of freedom (df) is calculated as : $df = (rows - 1) \times (columns - 1)$

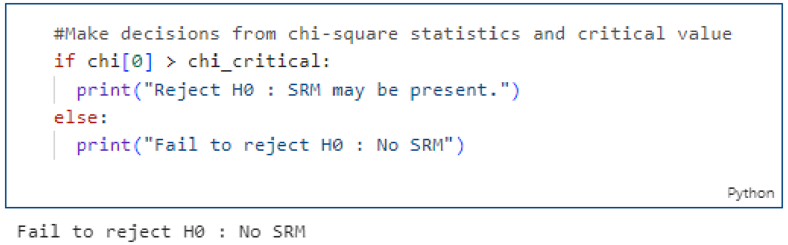
Analyzing and Interpreting the Data

- Based on the detection of SRM, SRM was not detected.



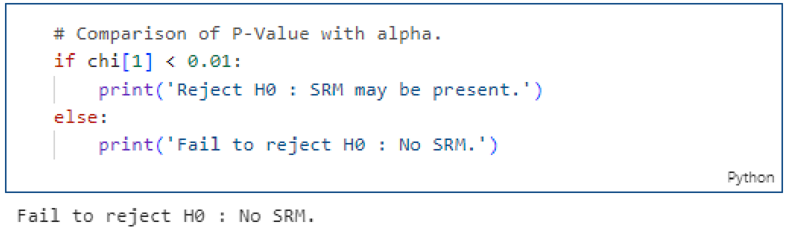
```
# Comparison of chi-square statistics with critical value
# We must calculate the critical first

# critical value is the chi-square value at alpha
alpha = 0.05
df=(2-1)*(2-1)

import scipy
chi_critical = scipy.stats.chi2.ppf(1 - alpha, df)
print(f"Critical value: {chi_critical:.3f}")
```

```
Critical value: 3.841
```



```
#Make decisions from chi-square statistics and critical value
if chi[0] > chi_critical:
  print("Reject H0 : SRM may be present.")
else:
  print("Fail to reject H0 : No SRM")
```

```
Fail to reject H0 : No SRM
```



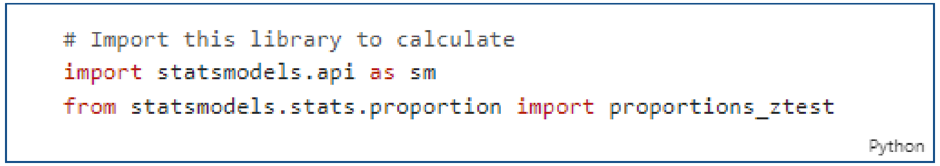
```
# Comparison of P-Value with alpha.
if chi[1] < 0.01:
    print('Reject H0 : SRM may be present.')
else:
    print('Fail to reject H0 : No SRM.')
```

```
Fail to reject H0 : No SRM.
```

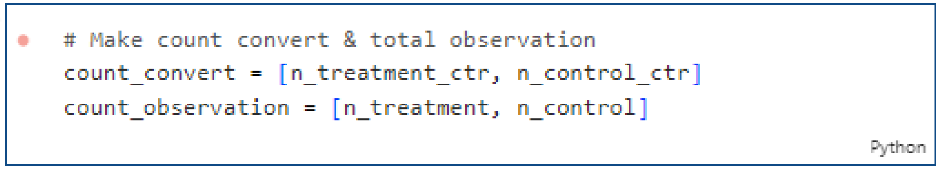
Analyzing and Interpreting the Data

2. Conduct hypothesis testing and analyze the result
   - Define null hypothesis H_0 and alternative hypothesis H_1
     H_0 (Null Hypothesis) : CTR New link, such as in picture not text ≤ existing link
     H_1 (Alternative Hypothesis) : CTR New link, such as in picture not text > existing link

First, define Zcrit, Zstatistic, and p-value. To calculate Zstatistic and p-value use this function.



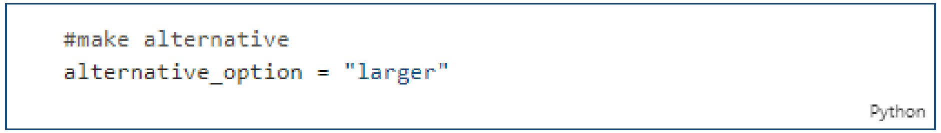
```python
# Import this library to calculate
import statsmodels.api as sm
from statsmodels.stats.proportion import proportions_ztest
```



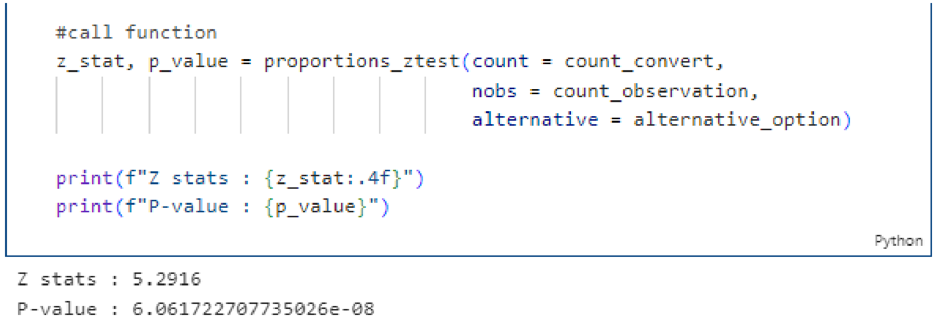
```python
# Make count convert & total observation
count_convert = [n_treatment_ctr, n_control_ctr]
count_observation = [n_treatment, n_control]
```

Analyzing and Interpreting the Data

Create an alternative for this hypothesis test case, in this case use ‘larger’ because want to prove CR_{new} is greater than CR_{old}.

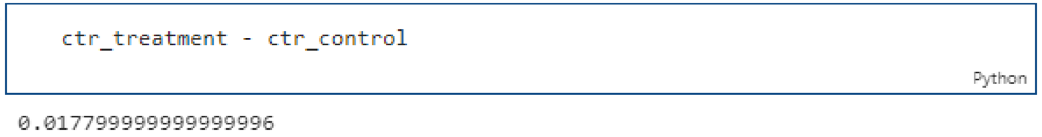


```
#make alternative
alternative_option = "larger"
```



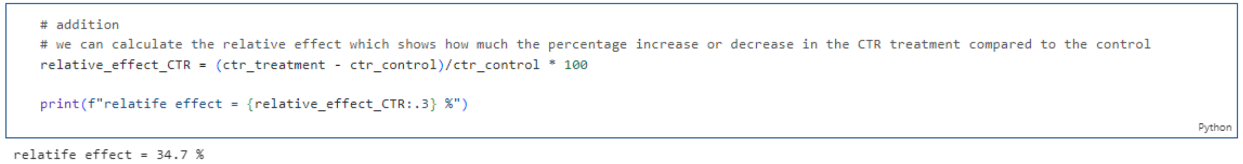
```
#call function
z_stat, p_value = proportions_ztest(count = count_convert,
                                    nobs = count_observation,
                                    alternative = alternative_option)

print(f"Z stats : {z_stat:.4f}")
print(f"P-value : {p_value}")
```

```
Z stats : 5.2916
P-value : 6.061722707735026e-08
```



```
ctr_treatment - ctr_control
```

```
0.017799999999999996
```

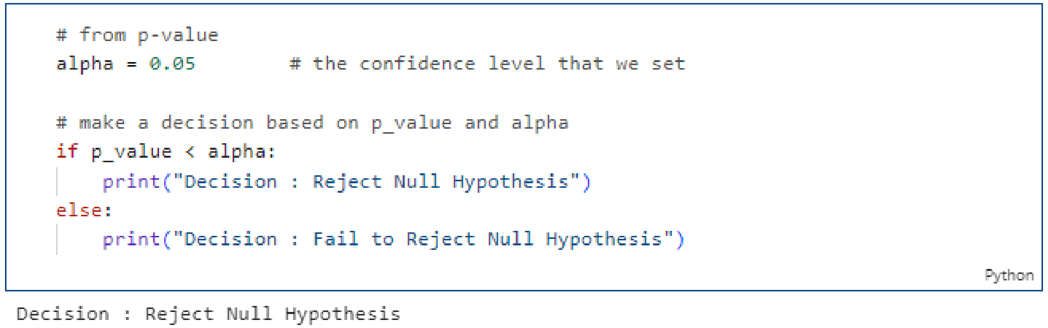


```
# addition
# we can calculate the relative effect which shows how much the percentage increase or decrease in the CTR treatment compared to the control
relative_effect_CTR = (ctr_treatment - ctr_control)/ctr_control * 100

print(f"relatife effect = {relative_effect_CTR:.3} %")
```

```
relatife effect = 34.7 %
```

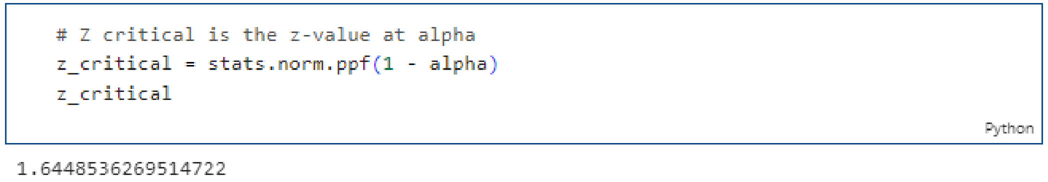
Analyzing and Interpreting the Data

There is a relative increase of 34.7%. Next, summarize the statistical test results.



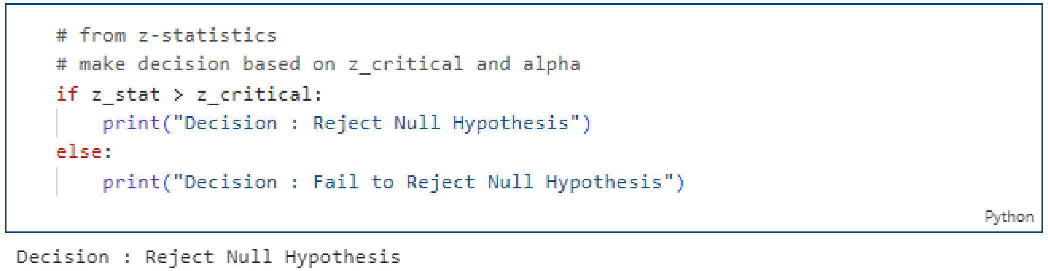
```python
# from p-value
alpha = 0.05        # the confidence level that we set

# make a decision based on p_value and alpha
if p_value < alpha:
    print("Decision : Reject Null Hypothesis")
else:
    print("Decision : Fail to Reject Null Hypothesis")
```

```
Decision : Reject Null Hypothesis
```



```python
# Z critical is the z-value at alpha
z_critical = stats.norm.ppf(1 - alpha)
z_critical
```

```
1.6448536269514722
```

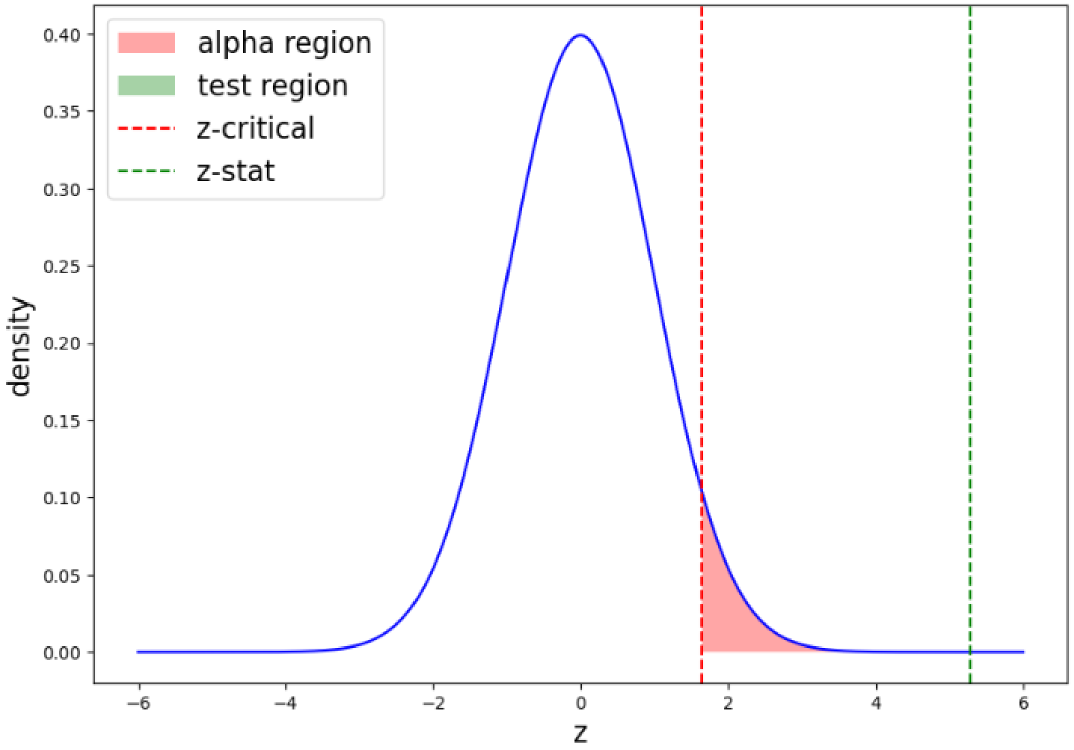


```python
# from z-statistics
# make decision based on z_critical and alpha
if z_stat > z_critical:
    print("Decision : Reject Null Hypothesis")
else:
    print("Decision : Fail to Reject Null Hypothesis")
```

```
Decision : Reject Null Hypothesis
```

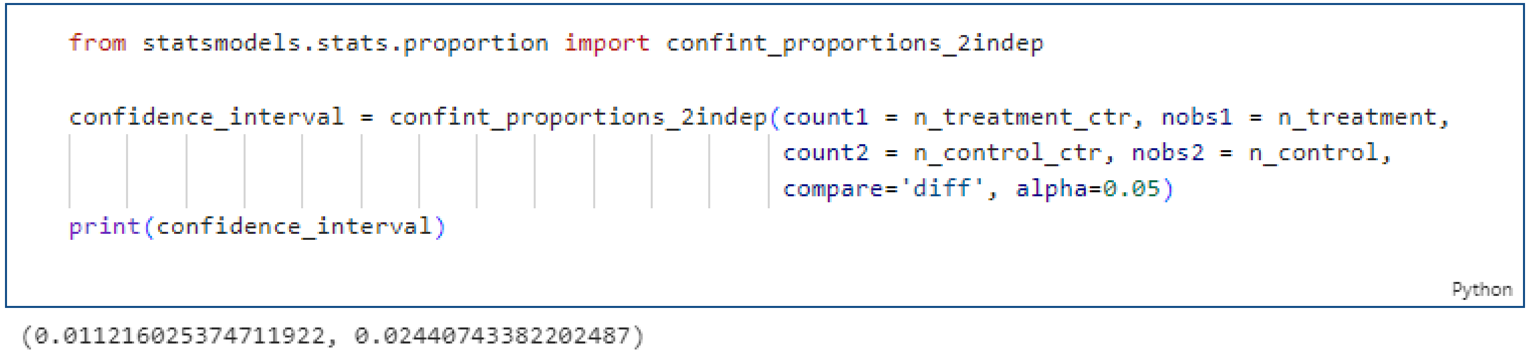
Analyzing and Interpreting the Data

Next, visualize the statistical test results above. The visualization is made in a z value distribution graph. Therefore, find the z value when alpha = 0.05. The results of the visualization obtained will be seen in the following figure.



Analyzing and Interpreting the Data

3. Calculate confidence interval of difference between treatment and control



```python
from statsmodels.stats.proportion import confint_proportions_2indep

confidence_interval = confint_proportions_2indep(count1 = n_treatment_ctr, nobs1 = n_treatment,
                                                 count2 = n_control_ctr, nobs2 = n_control,
                                                 compare='diff', alpha=0.05)
print(confidence_interval)
```

```
(0.011216025374711922, 0.024407433822202487)
```

Conclusion and Recommendation

Conclusion

- P-value (6.061722707735026e-08) < α (0.05) -> Reject H0
- Z Statistic (5.2916) > Z Critical (1.644) -> Reject H0
- With significance level 5%, there is sufficient evidence that CTR New link such as in picture not text (treatment) more than existing link (control). In other words, CTR New link, such as in picture not text will increase user interest in downloading the application.
- Recommendations for website of the grocery store chain :
  - Based on the statistical test results, the results are statistically significant. P-value = 0.05 indicates that there is a 5% probability that the observed difference is due to chance or other factors unrelated to the variable being observed.

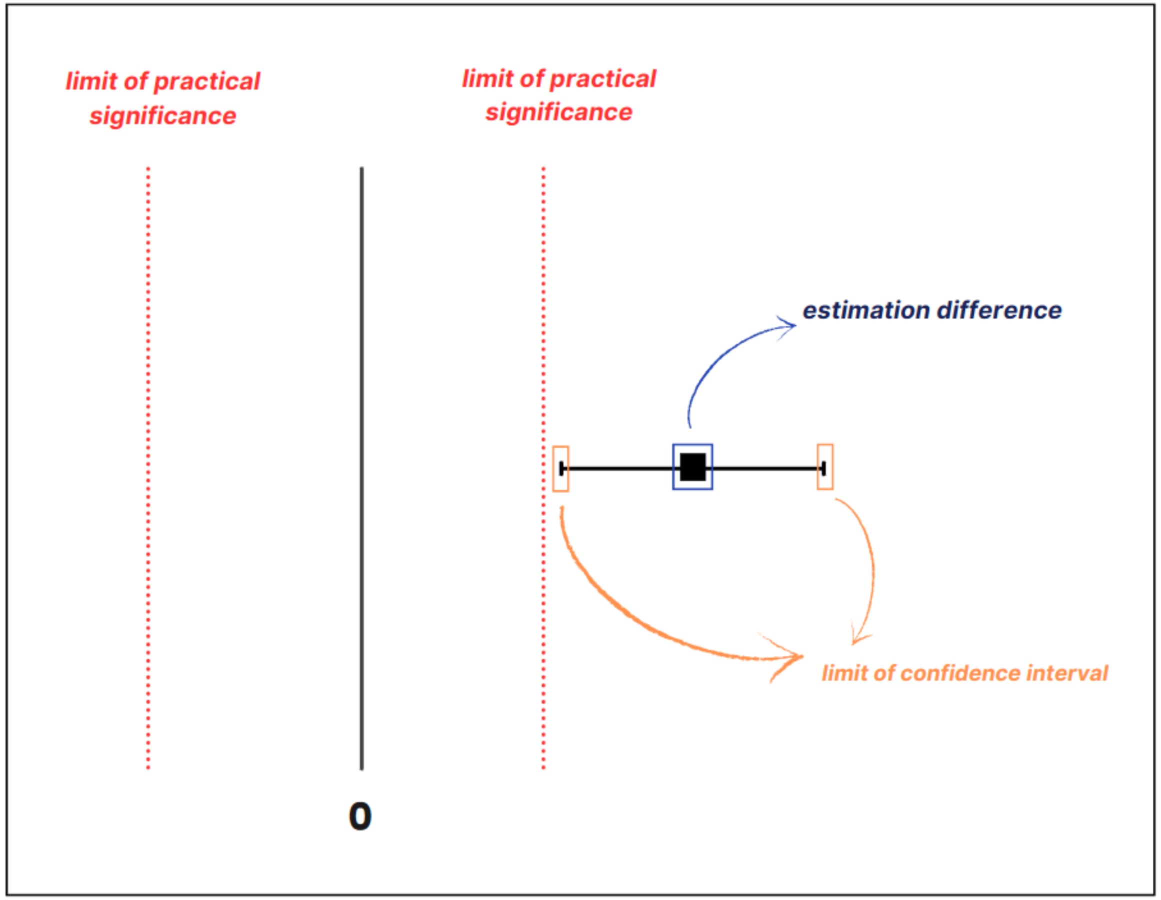
Conclusion

- But to make a decision whether to change the link to a button of the app store or not, must be practically significant such as :
  1. Resources and costs required to implement the change. If the cost required for the change to the link to a button of the app store on the website is very high and not proportional to the impact on mobile app downloads, then the change may not be considered practically significant.
  2. It is also necessary to consider the difference between performance before and after the change. If the change to the link to a button of the app store on the website can increase mobile app downloads by 1% or more, then the change may be considered practically significant. However, if the change only increases mobile app downloads by 0.1% or less, then the change may not be considered practically significant.

Based on the above considerations, the change is considered practically significant.

Conclusion

Launch Feature :


limit of practical significance
limit of practical significance
estimation difference
limit of confidence interval
0

Recommendation

- Download page variants: change the layout or content of the mobile app download page, such as adding images or positive reviews from other users.

- App description: Change the app description on the website, such as highlighting the benefits or advantages of the app.

- Changes to the overall appearance and content of the website: Changing the overall layout, design, and content of the website can affect the way users interact with the website.

- Target audience: There may be certain groups of users who are more likely to download apps than others, so changing the look and content of the website to appeal more to certain target groups could be a recommendation for future experiments.

Reference

- mobileappdaily.com, Top 8 App Engagement Metrics For Mobile Apps To Track in 2023. March 14, 2023. [Accessed on April 1, 2023]. https://www.mobileappdaily.com/top-metrics-to-measure-user-engagement.
- Damaševiˇcius Robertas, Zailskaite-Jakšte Ligita. Usability and Security Testing of Online Links: A Framework for Click-Through Rate Prediction Using Deep Learning, 2022.
- storyly.io, App Loading. [Accessed on April 1, 2023]. https://www.storyly.io/glossary/app-loading.
- Festing Michael FW. On determining sample size in experiments involving laboratory animals, 2017.
- Khanacademy.org, Population standard deviation. [Accessed on April 1, 2023]. https://www.khanacademy.org/math/statistics-probability/summarizing-quantitative-data/variance-standard-deviation-population/v/population-standard-deviation#:~:text=The%20population%20standard%20deviation%20is,data%20is%20from%20its%20mean.
- dimewiki.worldbank.org, Minimum Detectable Effect. [Accessed on April 9, 2023]. https://dimewiki.worldbank.org/Minimum_Detectable_Effect#:~:text=The%20minimum%20detectable%20effect%20is,and%20survey%20and%20project%20budgets.

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Thank You