MARKETING A/B TESTING

Marketing companies want to run successful campaigns, but the market is complex and several options can work. So normally they tun A/B tests, that is a randomized experimentation process wherein two versions of a treatment (web page, wordingd of headlines, price of products, design of button, web interface design, banner, etc.) are randomly applied to different segments of people at the same time to determine which version leaves the maximum impact and drive business metrics. in conducting A/B tests, companies are interested in answering two questions:

- Would the campaign be successful?
- If the campaign was successful, how much of that success could be attributed to the treatment being examined? With the second question in mind, we normally do an A/B test.

Dataset

The dataset for this project was generated from A/B testing designed to ads perform better than public service announcement (PSA). Here, more people were exposed to the treatment (ads) while fewer people were exposed to the control (PSA). The majority of the people will be exposed to ads (the experimental group). As rule of thumb, the sample size of over 500k is considered sufficient to detect small effect sizes. The dataset was downloaded from https://www.kaggle.com/datasets/faviovaz/marketing-ab-testing. The idea of the dataset is to analyze the groups, find if the ads were successful, how much more money is the company expected to make from the ads.

- Data dictionary:
 - Index: Row index
 - user id: User ID (unique)
 - test group: If "ad" the person saw the advertisement, if "psa" they only saw the public service announcement
 - converted: If a person bought the product then True, else is False
 - total ads: Amount of ads seen by person
 - most ads day: Day that the person saw the biggest amount of ads
 - most ads hour: Hour of day that the person saw the biggest amount of ads Only the test group and converted columns will be used in this test to determine if there is interaction between ad and psa

```
import pandas as pd
import matplotlib.pyplot as pt
import seaborn as sns
import scipy.stats as st
import seaborn as sns
df = pd.read_csv('marketing_AB.csv')
```

In [50]: df.head()

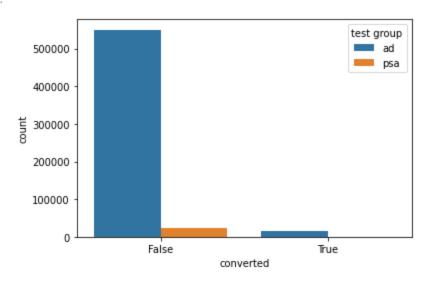
Out[50]:		Unnamed: 0	user id	test group	converted	total ads	most ads day	most ads hour
	0	0	1069124	ad	False	130	Monday	20
	1	1	1119715	ad	False	93	Tuesday	22
	2	2	1144181	ad	False	21	Tuesday	18

3	3 1435133	ad	False	355	Tuesday	10
4	4 1015700	ad	False	276	Fridav	14

The Null Hypothesis of no association between test grooup and converted (that is, ads or psa have no impact on conversion rate) will be rejected is the p - value for the test is less that alph value of 0.05. alpha is a pre-determined probability of the difference in conversion rate being attributed to random chance while p - value is alpha value calculated from available sample.

```
In [51]: #count plot for conversion rate across the 2 treatments
sns.countplot(x = 'converted', hue = 'test group', data = df)
```

Out[51]: <AxesSubplot: xlabel='converted', ylabel='count'>



```
In [52]: #I amend the column name to enable crosstabulation
df = df[['test group','converted']]
df.columns = ['test_group','converted']
```

In [53]: df

Out[53]:

	test_group	converted
0	ad	False
1	ad	False
2	ad	False
3	ad	False
4	ad	False
•••		
588096	ad	False
588097	ad	False
588098	ad	False
588099	ad	False
588100	ad	False

588101 rows × 2 columns

```
ad 550154 14423
psa 23104 420

In [55]: ab_contingency = pd.crosstab(df.test_group,df.converted)

In [56]: chi2, pval, dof, expected = st.chi2_contingency(ab_contingency)
print(pval)
```

1.9989623063390075e-13

converted test group

False True

p-value of 0.00000000000013 < alpha hence we reject the null hypothesis of no interaction and conclude that the ads generated much more conversions than the public service announcement. Conversion rate for ads is 2.55 while conversion rate for public service announcement is 1.79 hence the difference in conversion rate which is 0.76% is significant