Customer Analytics¶

What is A/B test

- test two or more variants agianst each other
- to evaluate which one performs best
- in the context of randomized experiment

A/B testing Process

1. develop a hypothesis about your product or business
2. randomly assign users to two different groups
    - group 1 to current product rules
    - group 2 to a product that test hypothesis
3. pick according to KPI

Key performance indicators (KPIs)

**How to identity KPIs:

- experience+Domain knowledge + exploratory data analysis
- stability over time
- the importance with other factors

Question: which paywall has a higher conversion rate

- Current paywall:" I hoped that you enjoyed your free-trail, please consider subscribing"(control)
- Proposed paywall:" Your free-trail has ended, do not miss out, subscribe today"(experiment)

Process

- Randomly subset the users and show one set the contrl and one the treatment
- Monitor the conversion rates of each group to see which is better

The importance of randomness

- isolate the impact of the change made
- reduce the potential impact of confounding variabels
- use a assigment criteria may introduce confounders

Pros and Cons

- Pros: users are impacted individually; testing changes that directly impact hteir behavior
- Cons: challenging to segment the users inot groups; difficult to untangle the impact of the test

Initial A/B test design

Responsabe variable

- The quantity used to measure the impact of your change
- Should either be a KPI or directly related to a KPI
- The easier to measure, the better

Factors & variants

- Factors: the type of variable you are changing
  - The paywall color
- Variants: Particular changes you are testing
  - A red vs a blue paywall

Experimental unit of our test

- The smallest unit you are measuring the change over
- Individual users make a convenient experimental unit

Preparing to run an A/B test

test sensitivity

- First question: what size of impact is meaningful to test
- Smaller changes=more difficult to dect
- Sensitivity: the minimum level of change we want to be able to detect in our test
  - Evaluate different sensitivity values

Data variability

- Standard Error
  - the variance and standard deviation of the estimate
- Hypothesis
  - Null Hypothesise: The launch of feature does not statistical significant change the KPI
  - Reject Null Hypothesise: The launch of feature does statistical significant change the KPI

Parameters

- Statistical Power
  - Probability of finding a statistically significant result when the Null Hypothesis is false
- Estimate sample size
  - needed level of sensitivity
  - our desired test power & confidence level
- Effect size

Significance or Not?

- P-value
  - probability if the Null Hypothesis is true...

  - Low p-values: the observation is unlikely to have happened due to randomness
- Test
  - how significant the differences between groups are
  - One-sample:same population
  - Two-sample: different population

Our data set

We are looking at data from an app. The app is very simple and has just 4 pages:

- The first page is the home page. When you come to the site for the first time, you can only land on the home page as a first page.
- From the home page, the user can perform a search and land on the search page.
- From the search page, if the user clicks on a product, she will get to the payment page (paywall), where she is asked to provide payment information in order to subscribe.
- If she does decide to buy, she ends up on the confirmation page

Data set overview We have 5 files, 4 of them contains page_visit information and 1 of them contains user information.

- page_visit_information
  - home_page_table.csv
  - search_page_table.csv
  - payment_page_table.csv
  - payment_confirmation_table.csv
- user_information page
  - user_table.csv

Import

In [1]:

```
import warnings
warnings.filterwarnings('ignore')
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from functools import reduce
from sklearn import preprocessing
from scipy import stats
```

In [2]:

```
user_table = pd.read_csv('user_table.csv')
```

In [3]:

```
user_table
```

Out[3]:

	user_id	date	device	sex
0	450007	2015-02-28	Desktop	Female
1	756838	2015-01-13	Desktop	Male
2	568983	2015-04-09	Desktop	Male
3	190794	2015-02-18	Desktop	Female
4	537909	2015-01-15	Desktop	Male
...	...	...	...	...
90395	307667	2015-03-30	Desktop	Female
90396	642989	2015-02-08	Desktop	Female
90397	659645	2015-04-13	Desktop	Male
90398	359779	2015-03-23	Desktop	Male

Create control and test groups

randomized two groups

In [4]:

```
length=len(user_table['user_id'])
```

In [5]:

```
k=np.random.binomial(1,0.495,length)
```

In [6]:

```
user_table['group']=k
user_table.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 90400 entries, 0 to 90399
Data columns (total 5 columns):
 #   Column   Non-Null Count  Dtype 
---  ------   --------------  ----- 
 0   user_id  90400 non-null  int64 
 1   date     90400 non-null  object
 2   device   90400 non-null  object
 3   sex      90400 non-null  object
 4   group    90400 non-null  int64 
dtypes: int64(2), object(3)
memory usage: 3.4+ MB
```

In [7]:

```
user_table['group']=user_table['group'].replace(1,'test')
user_table['group']=user_table['group'].replace(0,'control')
```

import datasets

In [8]:

```
home_page = pd.read_csv('home_page_table.csv')
payment_confirmation= pd.read_csv('payment_confirmation_table.csv')
payment_page= pd.read_csv('payment_page_table.csv')
search_page= pd.read_csv('search_page_table.csv')
```

In [9]:

```
home_page.columns
payment_confirmation.columns
```

Out[9]:

```
Index(['user_id', 'page'], dtype='object')
```

In [171]:

```
# Compile the list of dataframes you want to merge
data_frames = [user_table, home_page, search_page, payment_page, payment_confirm
df_merged = reduce(lambda  left,right: pd.merge(left,right,on=['user_id'], how='
df_merged.columns = ['user_id', 'date', 'device', 'sex', 'group', 'home_page', '
                     'payment_page', 'payment_confirm']
df_merged.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 90400 entries, 0 to 90399
Data columns (total 9 columns):
 #   Column           Non-Null Count  Dtype 
---  ------           --------------  ----- 
 0   user_id          90400 non-null  int64 
 1   date             90400 non-null  object
 2   device           90400 non-null  object
 3   sex              90400 non-null  object
 4   group            90400 non-null  object
 5   home_page        90400 non-null  object
 6   search_page      45200 non-null  object
 7   payment_page     6030 non-null   object
 8   payment_confirm  452 non-null    object
dtypes: int64(1), object(8)
memory usage: 6.9+ MB
```

In [10]:

```
df=user_table.merge(home_page,on=['user_id'],how='left')
```

In [11]:

```
df=df.merge(search_page,on=['user_id'],how='left')
```

In [12]:

```
df=df.merge(payment_page,on=['user_id'],how='left')
```

In [13]:

```
df=df.merge(payment_confirmation,on=['user_id'],how='left')
```

In [14]:

```
df
```

Out[14]:

	user_id	date	device	sex	group	page_x	page_y	page_x	page_y
0	450007	2015-02-28	Desktop	Female	control	home_page	NaN	NaN	NaN
1	756838	2015-01-13	Desktop	Male	control	home_page	NaN	NaN	NaN
2	568983	2015-04-09	Desktop	Male	test	home_page	search_page	NaN	NaN
3	190794	2015-02-18	Desktop	Female	test	home_page	search_page	NaN	NaN
4	537909	2015-01-15	Desktop	Male	control	home_page	NaN	NaN	NaN
...	...	...	...	...	...	...	...	...	...
90395	307667	2015-03-30	Desktop	Female	test	home_page	NaN	NaN	NaN
90396	642989	2015-02-08	Desktop	Female	test	home_page	search_page	NaN	NaN
90397	659645	2015-04-13	Desktop	Male	test	home_page	search_page	NaN	NaN
90398	359779	2015-03-23	Desktop	Male	test	home_page	NaN	NaN	NaN
90399	438929	2015-03-26	Mobile	Female	control	home_page	NaN	NaN	NaN

90400 rows × 9 columns

In [15]:

```
df.columns=['user_id','date','device','sex','group','home_page','search_page',
            'payment_page','payment_confirmation']
```

In [16]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 90400 entries, 0 to 90399
Data columns (total 9 columns):
 #   Column                Non-Null Count  Dtype 
---  ------                --------------  ----- 
 0   user_id               90400 non-null  int64 
 1   date                  90400 non-null  object
 2   device                90400 non-null  object
 3   sex                   90400 non-null  object
 4   group                 90400 non-null  object
 5   home_page             90400 non-null  object
 6   search_page           45200 non-null  object
 7   payment_page          6030 non-null   object
 8   payment_confirmation  452 non-null    object
dtypes: int64(1), object(8)
memory usage: 6.9+ MB
```

In [17]:

```
df['date']=pd.to_datetime(df['date'],utc=True)
```

In [18]:

```
df['home_page']=df['home_page'].fillna(0)
df['search_page']=df['search_page'].fillna(0)
df['payment_page']=df['payment_page'].fillna(0)
df['payment_confirmation']=df['payment_confirmation'].fillna(0)
```

In [19]:

```
df['home_page']=df['home_page'].replace('home_page',1)
df['search_page']=df['search_page'].replace('search_page',1)
df['payment_page']=df['payment_page'].replace('payment_page',1)
df['payment_confirmation']=df['payment_confirmation'].replace('payment_confirmat
```

In [20]:

```
df['search_page'].value_counts()
```

Out[20]:

```
0    45200
1    45200
Name: search_page, dtype: int64
```

In [21]:

```
df['payment_page'].value_counts()
```

Out[21]:

```
0    84370
1     6030
Name: payment_page, dtype: int64
```

In [23]:

```
df['payment_confirmation'].value_counts()
```

Out[23]:

```
0    89948
1      452
Name: payment_confirmation, dtype: int64
```

EAD

- overall Conversion rate
- group by gender
- group by device

In [24]:

```
df_purchase=df.groupby(by=['date'],as_index=False)
```

In [25]:

```
df_purchase=df_purchase.agg({'payment_confirmation':['sum','count']})
```

In [26]:

```
df_purchase.columns=df_purchase.columns.droplevel(level=0)
```

In [27]:

```
df_purchase.columns=['date','sum','count']
```

In [28]:

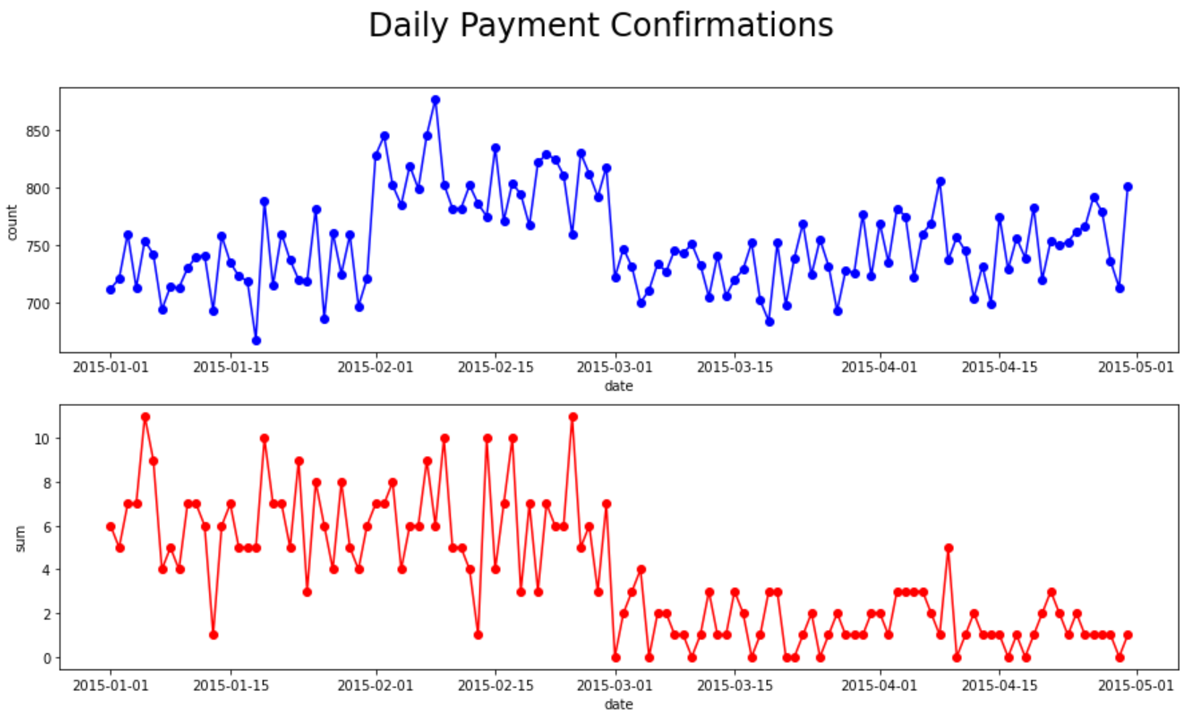
```
df_purchase
```

Out[28]:

	date	sum	count
0	2015-01-01 00:00:00+00:00	6	712
1	2015-01-02 00:00:00+00:00	5	721
2	2015-01-03 00:00:00+00:00	7	760
3	2015-01-04 00:00:00+00:00	7	713
4	2015-01-05 00:00:00+00:00	11	754
...	...	...	...
115	2015-04-26 00:00:00+00:00	1	792
116	2015-04-27 00:00:00+00:00	1	779
117	2015-04-28 00:00:00+00:00	1	736
118	2015-04-29 00:00:00+00:00	0	713

In [29]:

```
fig,ax=plt.subplots(2,1,figsize=(15,8))
ax[0].plot(df_purchase['date'],df_purchase['count'],color='b',linestyle='-',mark
ax[0].set_ylabel('count')
ax[0].set_xlabel('date')
ax[1].plot(df_purchase['date'],df_purchase['sum'],color='r',linestyle='-',marker
ax[1].set_ylabel('sum')
ax[1].set_xlabel('date')
fig.suptitle(f'Daily Payment Confirmations', fontsize=24)
plt.show()
```



Sex

In [56]:

```
### group by sex
sex_purchases = df.groupby(by=['date','sex']).agg({'payment_confirmation':['sum'
sex_purchases.columns = sex_purchases.columns.droplevel(level=1)
sex_purchases.reset_index(inplace=True)
sex_purchases.columns=['date','sex','sum','count']
```

In [57]:

```
sex_pivot = pd.pivot_table(sex_purchases, values=['sum'], columns=['sex'], index
```

In [58]:

```
sex_pivot.columns=sex_pivot.columns.droplevel(level=0)
```

In [59]:

```
sex_pivot=sex_pivot.reset_index()
```

In [60]:

```
sex_pivot
```

Out[60]:

sex	date	Female	Male
0	2015-01-01 00:00:00+00:00	3	3
1	2015-01-02 00:00:00+00:00	2	3
2	2015-01-03 00:00:00+00:00	3	4
3	2015-01-04 00:00:00+00:00	2	5
4	2015-01-05 00:00:00+00:00	6	5
...	...	...	...
115	2015-04-26 00:00:00+00:00	1	0
116	2015-04-27 00:00:00+00:00	1	0
117	2015-04-28 00:00:00+00:00	1	0
118	2015-04-29 00:00:00+00:00	0	0
119	2015-04-30 00:00:00+00:00	0	1

120 rows × 3 columns

Devices

In [35]:

```
### group by sex
device_purchases = df.groupby(by=['date','device']).agg({'payment_confirmation':
device_purchases
```

Out[35]:

		payment_confirmation	
		sum	**count**
date	**device**		
2015-01-01 00:00:00+00:00	**Desktop**	1	493
	Mobile	5	219
2015-01-02 00:00:00+00:00	**Desktop**	1	484
	Mobile	4	237
2015-01-03 00:00:00+00:00	**Desktop**	3	507
...	**...**	...	...
2015-04-28 00:00:00+00:00	**Mobile**	1	260
2015-04-29 00:00:00+00:00	**Desktop**	0	453
	Mobile	0	260
2015-04-30 00:00:00+00:00	**Desktop**	0	538
	Mobile	1	263

240 rows × 2 columns

In [36]:

```
device_purchases.reset_index(inplace=True)
```

In [37]:

```
device_purchases.columns=device_purchases.columns.droplevel(level=0)
```

In [38]:

```
device_purchases.columns=['date','device','sum','count']
```

In [39]:

```
device_pivot = pd.pivot_table(device_purchases, values=['count'], columns=['devi
```

In [40]:

```
device_pivot.reset_index()
```

Out[40]:

	date	count	
device		**Desktop**	**Mobile**
0	2015-01-01 00:00:00+00:00	493	219
1	2015-01-02 00:00:00+00:00	484	237
2	2015-01-03 00:00:00+00:00	507	253
3	2015-01-04 00:00:00+00:00	474	239
4	2015-01-05 00:00:00+00:00	483	271
...	...	...	...
115	2015-04-26 00:00:00+00:00	529	263
116	2015-04-27 00:00:00+00:00	509	270
117	2015-04-28 00:00:00+00:00	476	260

In [41]:

```
device_pivot.columns=device_pivot.columns.droplevel(level=0)
```

In [42]:

```
device_pivot=device_pivot.reset_index()
```

In [69]:

```
sex_pivot
```

Out[69]:

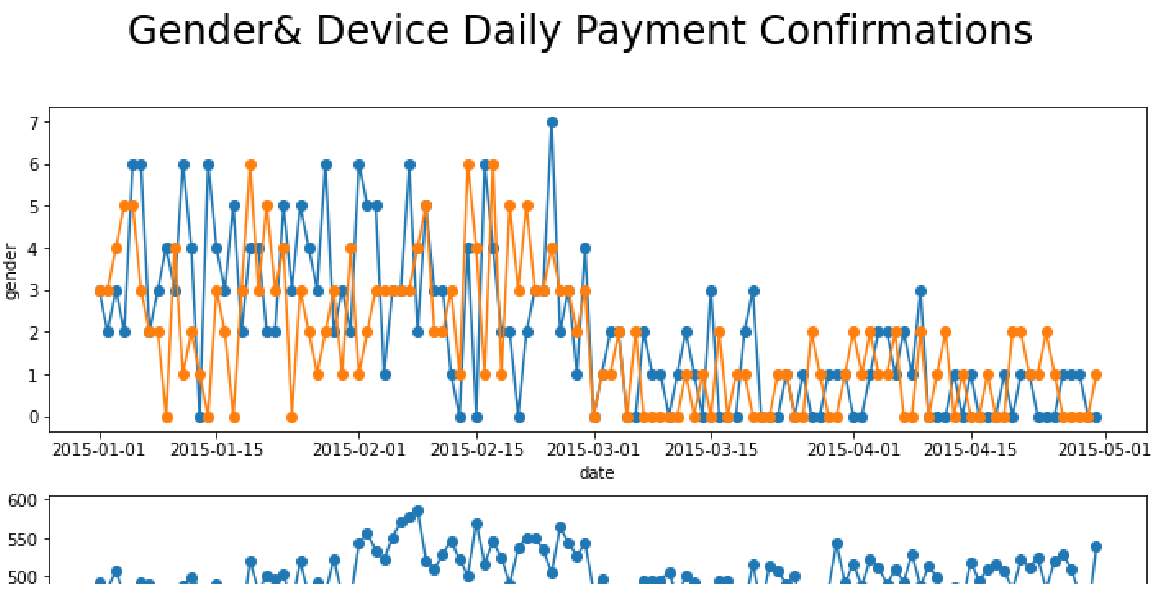
sex	date	Female	Male
0	2015-01-01 00:00:00+00:00	3	3
1	2015-01-02 00:00:00+00:00	2	3
2	2015-01-03 00:00:00+00:00	3	4
3	2015-01-04 00:00:00+00:00	2	5
4	2015-01-05 00:00:00+00:00	6	5
...	...	...	...
115	2015-04-26 00:00:00+00:00	1	0
116	2015-04-27 00:00:00+00:00	1	0
117	2015-04-28 00:00:00+00:00	1	0
118	2015-04-29 00:00:00+00:00	0	0
119	2015-04-30 00:00:00+00:00	0	1

120 rows × 3 columns

In [72]:

```
plt.set_cmap('jet')
fig,ax=plt.subplots(2,1,figsize=(12,8))
ax[0].plot(sex_pivot['date'],sex_pivot[['Female','Male']],marker='o')
ax[0].set_ylabel('gender')
ax[0].set_xlabel('date')
ax[1].plot(device_pivot['date'],device_pivot[['Desktop','Mobile']],linestyle='-'
ax[1].set_ylabel('device')
ax[1].set_xlabel('date')
fig.suptitle(f'Gender& Device Daily Payment Confirmations', fontsize=24)
plt.show()
```

```
<Figure size 432x288 with 0 Axes>
```



Initial A/B testing

Resonse variable

- Conversion rate
  - time frame: one day
  - Definition: #of payment confirmation/ # of home page
  - importance: strong measure of growth

In [73]:

```
df_purchases=round(df_purchase['sum'].mean()*1000,2)
df_views=round(df_purchase['count'].mean()*1000,2)
print('daily purchases=', df_purchases)
print('daily views=', df_views)
```

```
daily purchases= 3766.67
daily views= 753333.33
```

In [74]:

```
df_purchase
```

Out[74]:

	date	sum	count
0	2015-01-01 00:00:00+00:00	6	712
1	2015-01-02 00:00:00+00:00	5	721
2	2015-01-03 00:00:00+00:00	7	760
3	2015-01-04 00:00:00+00:00	7	713
4	2015-01-05 00:00:00+00:00	11	754
...	...	...	...
115	2015-04-26 00:00:00+00:00	1	792
116	2015-04-27 00:00:00+00:00	1	779
117	2015-04-28 00:00:00+00:00	1	736
118	2015-04-29 00:00:00+00:00	0	713
119	2015-04-30 00:00:00+00:00	1	801

120 rows × 3 columns

Test sensitivity

In [206]:

```
df
```

Out[206]:

	user_id	date	device	sex	group	home_page	search_page	payment_page	payment_conf
0	450007	2015-02-28 00:00:00+00:00	Desktop	Female	test	1	0	0	
1	756838	2015-01-13 00:00:00+00:00	Desktop	Male	control	1	0	0	
2	568983	2015-04-09 00:00:00+00:00	Desktop	Male	test	1	1	0	
3	190794	2015-02-18 00:00:00+00:00	Desktop	Female	test	1	1	0	
4	537909	2015-01-15 00:00:00+00:00	Desktop	Male	test	1	0	0	
...	...	...	...	...	...	...	...	...	
90395	307667	2015-03-30 00:00:00+00:00	Desktop	Female	test	1	0	0	

In [76]:

```
df['payment_confirmation'].value_counts()
```

Out[76]:

```
0    89948
1      452
Name: payment_confirmation, dtype: int64
```

In [77]:

```
total_subs_count=np.sum(df['payment_confirmation'])
total_subs_count
```

Out[77]:

```
452
```

In [78]:

```
users_count=len(df['user_id'].unique())
users_count
```

Out[78]:

```
90400
```

In [89]:

```
conversion_rate=round(total_subs_count/users_count*100,2)
std=round(df['payment_confirmation'].std(),2)
print('conversion_rate:%s%%'%(conversion_rate))
print('std:',std)
```

```
conversion_rate:0.5%
std: 0.07
```

In [100]:

```
##small_sensitivity
small_sensitivity=0.1
small_conversion_rate=(conversion_rate/100)*(1+small_sensitivity)
small_purchases=df_views*small_conversion_rate
purchase_lift=small_purchases-df_purchases

print('small_conversion_rate: %s%%' %(small_conversion_rate*100))
print('small_purchases: %s' %(round(small_purchases,2)))
print('purchase_lift: %s' %(round(purchase_lift,2)))
```

```
small_conversion_rate: 0.55%
small_purchases: 4143.33
purchase_lift: 376.66
```

In [99]:

```
##medium_sensitivity
medium_sensitivity=0.2
medium_conversion_rate=(conversion_rate/100)*(1+medium_sensitivity)
medium_purchases=df_views*medium_conversion_rate
purchase_lift=medium_purchases-df_purchases

print('medium_conversion_rate: %s%%' %(medium_conversion_rate*100))
print('medium_purchases: %s' %(round(medium_purchases,2)))
print('purchase_lift: %s' %(round(purchase_lift,2)))
```

```
medium_conversion_rate: 0.6%
medium_purchases: 4520.0
purchase_lift: 753.33
```

In [98]:

```
##large_sensitivity
large_sensitivity=0.5
large_conversion_rate=(conversion_rate/100)*(1+large_sensitivity)
large_purchases=df_views*large_conversion_rate
purchase_lift=large_purchases-df_purchases

print('medium_conversion_rate: %s%%' %(large_conversion_rate*100))
print('medium_purchases: %s' %(round(large_purchases,2)))
print('purchase_lift: %s' %(round(purchase_lift,2)))
```

```
medium_conversion_rate: 0.75%
medium_purchases: 5650.0
purchase_lift: 1883.33
```

```
We choose the sensitivity to 0.6%
```

Sample Size

In [101]:

```
purchase_mean=df['payment_confirmation'].mean()
purchase_std=df['payment_confirmation'].std()
```

Out[101]:

```
0.005
```

In [105]:

```
test_n=len(df[df['group']=='test'])
control_n=len(df[df['group']=='control'])
print(test_n,control_n)
sizes=[test_n,control_n]
ratio=max(sizes)/min(sizes)
print(ratio)
```

```
44810 45590
1.0174068288328497
```

In [106]:

```
## Sensitivity 0.6%, power=0.8, significance level 0.05
effect_size=(0.006-purchase_mean)/purchase_std
power=0.8
alpha=0.05
```

In [118]:

```
from statsmodels.stats import power as pwr
analysis=pwr.TTestIndPower()
ssresult=analysis.solve_power(effect_size=effect_size,
                              power=power,
                              nobs1=None,
                              alpha=alpha,
                              ratio=ratio)
print('Sample Size:',round(ssresult))
```

```
Sample Size: 77430
```

Effect Size

In [119]:

```
sample_size=round(ssresult)
analysis=pwr.TTestIndPower()
esresult=analysis.solve_power(effect_size=None,
                              power=power,
                              nobs1=sample_size,
                              alpha=alpha,
                              ratio=ratio)
print('effect Size:',round(esresult,2))
```

```
effect Size: 0.01
```

Statistical Power

In [122]:

```
effect_size=esresult
analysis=pwr.TTestIndPower()
pwresult=analysis.solve_power(effect_size=effect_size,
                              power=None,
                              nobs1=sample_size,
                              alpha=alpha,
                              ratio=ratio)
print('Power:',round(pwresult,3))
```

```
Power: 0.8
```

Analyzing the A/B testing

In [137]:

```
results=df.groupby(by=['group']).agg({'user_id':pd.Series.nunique})
print(results)
```

```
         user_id
group
control    45590
test       44810
```

In [138]:

```
results=pd.DataFrame(results)
```

In [139]:

```
results['unique_users']=len(df.user_id.unique())
```

In [146]:

```
results['percentage']=round(results['user_id']/results['unique_users']*100,2)
```

In [147]:

```
results
```

Out[147]:

	user_id	unique_users	percentage
group			
control	45590	90400	50.43
test	44810	90400	49.57

In [149]:

```
results2=df.groupby(by=['group','device','sex']).agg({'user_id':pd.Series.nuniqu
results2=pd.DataFrame(results2)
results2['unique_users']=len(df.user_id.unique())
results2['percentage']=round(results2['user_id']/results2['unique_users']*100,2)
print(results2)
```

```
                        user_id  unique_users  percentage
group   device  sex
control Desktop Female    15227         90400       16.84
                Male      15146         90400       16.75
        Mobile  Female     7515         90400        8.31
                Male       7702         90400        8.52
test    Desktop Female    14770         90400       16.34
                Male      15057         90400       16.66
        Mobile  Female     7563         90400        8.37
                Male       7420         90400        8.21
```

In [163]:

```
test=df[df.group=='test']
control=df[df.group=='control']
```

In [164]:

```
print('test_size:',len(test))
print('con_size:',len(control))
```

```
test_size: 44810
con_size: 45590
```

In [165]:

```
test_mean=test['payment_confirmation'].mean()
cntrol_mean=control['payment_confirmation'].mean()
test_std=test['payment_confirmation'].std()
cntrol_std=control['payment_confirmation'].std()
```

In [168]:

```
print('test_conversion_rate:%s%%' %round(test_mean*100,2))
print('control_conversion_rate:%s%%' %round(cntrol_mean*100,2))
print('test_std:',round(test_std,2))
print('control_std:',round(cntrol_std,2))
```

```
test_conversion_rate:0.49%
control_conversion_rate:0.51%
test_std: 0.07
control_std: 0.07
```

In [169]:

```
test_result=df[df.group=='test']['payment_confirmation']
control_result=df[df.group=='control']['payment_confirmation']
ttest=stats.ttest_ind(test_result,control_result)
statistic=ttest[0]
p_value=ttest[1]
print('statistic',statistic)
print('p_value',p_value)
if p_value>=0.05:
    print('Not significant')
else:
    print('Significant!')
```

```
statistic -0.38195831967542987
p_value 0.7024931787844451
Not significant
```

In [ ]:

```

```