Double-click (or enter) to edit

Author：Zhi Gui（Katy）

```
import pandas as pd
import numpy as np
import random
import matplotlib.pyplot as plt
import scipy
from scipy import stats

%matplotlib inline
#We are setting the seed to assure you get the same answers on quizzes as we set up
random.seed(42)
```

1. Now, read in the `ab_data.csv` data. Store it in `df`.

a. Read in the dataset and take a look at the top few rows here:

```
from google.colab import drive

# 连接到Google Drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
import pandas as pd

# 定义文件路径
file_path = '/content/drive/My Drive/of-ds/项目/abtest/ab_data.csv'

# 使用pandas读取数据
df = pd.read_csv(file_path)

# 打印数据的前几行
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
4	864975	2017-01-21 01:52:26.210827	control	old_page	1

b. Use the below cell to find the number of rows in the dataset.

```
#show the total number of rows
df.shape[0]
```

```
294478
```

c. The number of unique users in the dataset.

```
#calculare the number of unique user_id
len(df['user_id'].unique())
```

```
290584
```

d. The proportion of users converted.

```
#calculate the converted users
df['converted'].mean()
```

```
0.11965919355605512
```

e. The number of times the `new_page` and `treatment` don't line up.

```
#treatment in group will be called A and new_page in landing_page will
#be called B

df_A_not_B = df.query('group == "treatment" & landing_page != "new_page"') # query是

df_B_not_A = df.query('group != "treatment" & landing_page == "new_page"')

#calculate thenumber of time new_page and treatment don't line up
len(df_A_not_B) + len(df_B_not_A)
```

```
3893
```

f. Do any of the rows have missing values?

```
#view if there is any missing value
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
```

2. For the rows where **treatment** is not aligned with **new_page** or **control** is not aligned with **old_page**, we cannot be sure if this row truly received the new or old page.

```
# remove the mismatch rows df2
df2 = df.drop(df[(df.group =="treatment") & (df.landing_page != "new_page")].index)
df2 = df2.drop(df2[(df2.group =="control") & (df2.landing_page != "old_page")].index)
```

```
# Double Check all of the correct rows were removed - this should be 0
df2[((df2['group'] == 'treatment') == (df2['landing_page'] == 'new_page')) == False].shape[0]
```

```
0
```

3. Use **df2** to answer questions below.

a. How many unique **user_id**s are in **df2**?

```
#calculare the number of unique user_id
len(df2['user_id'].unique())
```

```
290584
```

b. There is one **user_id** repeated in **df2**. What is it?

```
#find out the duplicate user_id
df2[df2.duplicated(['user_id'], 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

c. What is the row information for the repeat **user_id**?

```
#information found above, rows 1899 and 2893
```

d. Remove **one** of the rows with a duplicate **user_id**, but keep your dataframe as **df2**.

```
#remove one of the duplicated rows
df2.drop(labels=2893, inplace=True)
```

```
#verify if number of rows have been drop by one
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 290584 entries, 0 to 294477
Data columns (total 5 columns):
 #   Column        Non-Null Count   Dtype 
---  ------        --------------   ----- 
 0   user_id       290584 non-null  int64 
 1   timestamp     290584 non-null  object
 2   group         290584 non-null  object
 3   landing_page  290584 non-null  object
 4   converted     290584 non-null  int64 
dtypes: int64(2), object(3)
memory usage: 13.3+ MB
```

4. Use **df2** to answer the questions below

a. What is the probability of an individual converting regardless of the page they receive?

```
#calculate the averga of the converted column
df2['converted'].mean()
```

```
0.11959708724499628
```

b. Given that an individual was in the `control` group, what is the probability they converted?

```
#view the probability of the converted rate for both control and treatment by applying method
conversion_rates = df2.groupby(['group'], as_index=False)['converted'].mean()
print(conversion_rates)
```

```
       group  converted
0    control   0.120386
1  treatment   0.118807
```

c. Given that an individual was in the `treatment` group, what is the probability they converted?

```
conversion_rates = df2.groupby(['group'], as_index=False)['converted'].mean(numeric_only=True)
print(conversion_rates)
```

```
       group  converted
0    control   0.120386
1  treatment   0.118807
```

d. What is the probability that an individual received the new page?

```
#retrieve the new_page values and compared with the total number of landing_page
#in order to obtain the probability that an individual that received the
#new_page was converted

len(df2.query('landing_page == "new_page"'))/len(df2.landing_page)
```

```
0.5000619442226688
```

e. Consider your results from a. through d. above, and explain below whether you think there is sufficient evidence to say that the new treatment page leads to more conversions.

No, there is not sufficient evidence to say that the new treatment page leads to more conversions.

The test seems to be well designed. Half of the population received the old_page and half of the population received the new_page. The population is considerable in size (290584 users).

11.98% that received the old_page were converted. 11.88% that received the new_page were converted. In conclusion, the new_page did not increase the conversion rate.

Part II - A/B Test

Notice that because of the time stamp associated with each event, you could technically run a hypothesis test continuously as each observation was observed.

However, then the hard question is do you stop as soon as one page is considered significantly better than another or does it need to happen consistently for a certain amount of time? How long do you run to render a decision that neither page is better than another?

These questions are the difficult parts associated with A/B tests in general.

1. For now, consider you need to make the decision just based on all the data provided. 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%, what should your null and alternative hypotheses be? You can state your hypothesis in terms of words or in terms of p_{old} and p_{new}, which are the converted rates for the old and new pages.

- Null hypothesis: the conversion rate of the old_page is greater or the same than the conversion rate of the new_page.p_{old} >= p_{new}
- Alternative hypothesis: the conversion rate of the old_page is less than the conversion rate of the new_page. p_{old} < p_{new}

2. Assume under the null hypothesis, p_{new} and p_{old} both have "true" success rates equal to the **converted** success rate regardless of page - that is p_{new} and p_{old} 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.

Use the cells below to provide the necessary parts of this simulation. If this doesn't make complete sense right now, don't worry - you are going to work through the problems below to complete this problem.

a. What is the **convert rate** for p_{new} under the null?

```
#the Null hypothesis states there is not difference between the
#conversion rates of old and new page. Thus, the whole dataset is used to
#calculate the convertion rate for the new page (pnew).
p_new = df2['converted'].mean()
p_new
```

```
0.11959708724499628
```

b. What is the **convert rate** for p_{old} under the null?

```
#the Null hypothesis states there is not difference between the
#conversion rates of old and new page. Thus, the whole dataset is used to
#calculate the convertion rate for the old_page (pold).
p_old = df2['converted'].mean()
p_old
```

```
0.11959708724499628
```

c. What is n_{new}?

```
#calculate the number of users landed and new_page
n_new = len(df2.query('landing_page == "new_page"'))

n_new
```

```
145310
```

d. What is n_{old}?

```
#calculate the number of users landed and new_page
n_old = len(df2.query('landing_page != "new_page"'))
n_old
```

```
145274
```

e. Simulate n_{new} transactions with a convert rate of p_{new} under the null. Store these n_{new} 1's and 0's in **new_page_converted**.

```
new_page_converted = np.random.binomial(1,p_new,n_new)

#new_page_converted = np.random.choice([1, 0], size=n_new, p=[p_new, (1-p_new)])
new_page_converted.mean()
```

```
0.11986786869451517
```

f. Simulate n_{old} transactions with a convert rate of p_{old} under the null. Store these n_{old} 1's and 0's in **old_page_converted**.

```
old_page_converted = np.random.binomial(1,p_old,n_old)

#old_page_converted = np.random.choice([1, 0], size=n_old, p=[p_old, (1-p_old)])
old_page_converted.mean()
```

```
0.1183005906080923
```

g. Find p_{new} - p_{old} for your simulated values from part (e) and (f).

```
#since new_page_converted and old_page_converted have different sizes,
#I use the mean to get the difference
new_page_converted.mean() - old_page_converted.mean()
```

```
0.0015672780864228741
```

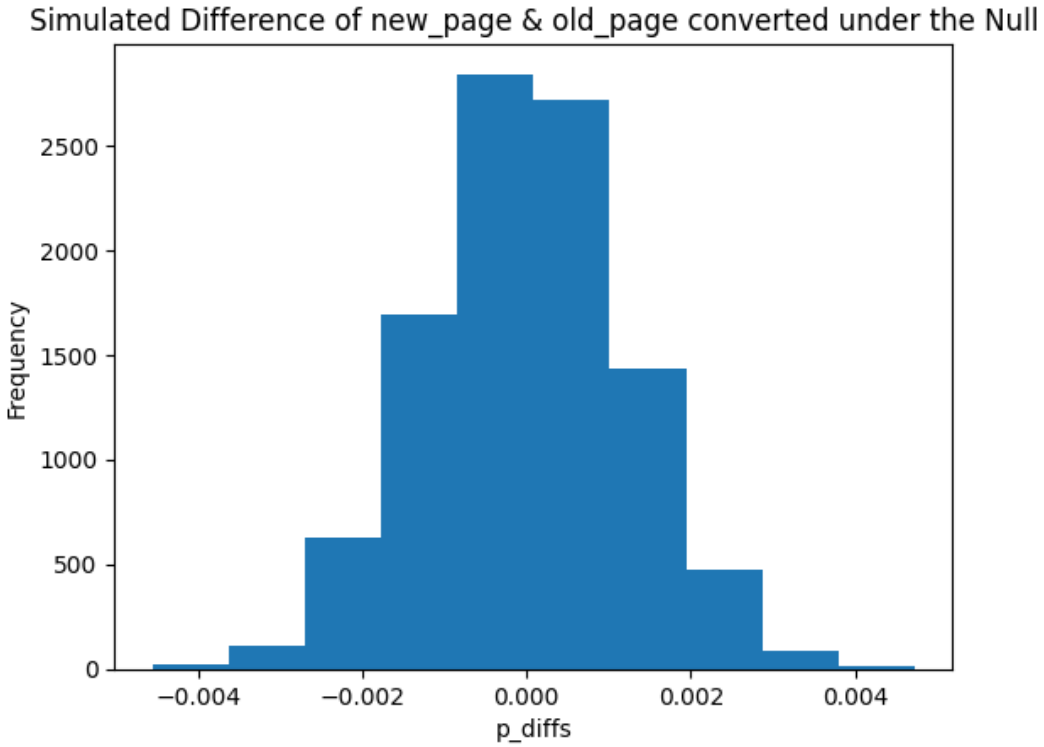
h. Simulate 10,000 p_{new} - p_{old} values using this same process similarly to the one you calculated in parts **a. through g.** above. Store all 10,000 values in a numpy array called **p_diffs**.

```
# run simulation 10000 times
p_diffs = []

for _ in range(10000):
    new_page_converted = np.random.binomial(1,p_new,n_new).mean()
    old_page_converted = np.random.binomial(1,p_old,n_old).mean()
```

```
    p_diffs.append(new_page_converted - old_page_converted)
```

i. Plot a histogram of the **p_diffs**. Does this plot look like what you expected? Use the matching problem in the classroom to assure you fully understand what was computed here.

```
# convert to numpy array
p_diffs = np.array(p_diffs)

# plot sampling distribution
plt.hist(p_diffs)
plt.xlabel('p_diffs')
plt.ylabel('Frequency')
plt.title('Simulated Difference of new_page & old_page converted under the Null');
```

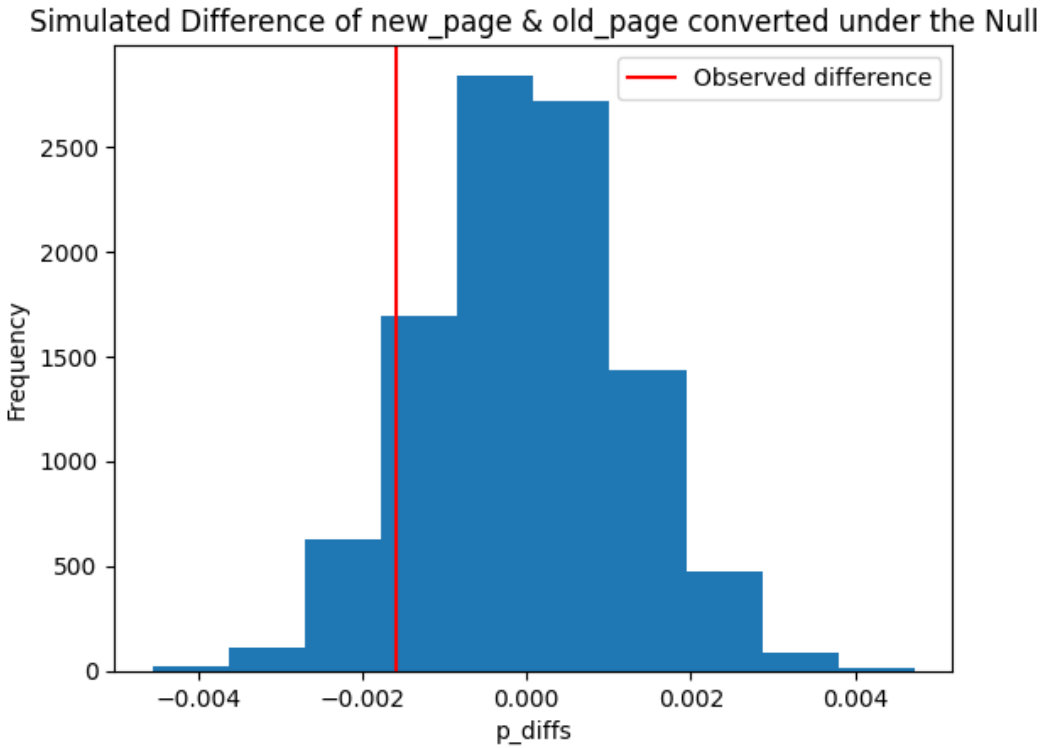


j. What proportion of the **p_diffs** are greater than the actual difference observed in **ab_data.csv**?

```
df_control = df2.query('group == "control"')
df_treatment = df2.query('group == "treatment"')

# display observed difference
obs_diff = df_treatment.converted.mean() - df_control.converted.mean()
obs_diff
```

```
-0.0015782389853555567
```

```
# plot line for observed statistic
plt.hist(p_diffs)
plt.axvline(x=obs_diff, color='r', label="Observed difference")
plt.xlabel('p_diffs')
plt.ylabel('Frequency')
plt.title('Simulated Difference of new_page & old_page converted under the Null');
plt.legend()
plt.show()
```



```
#P-value Algorithm
p_diffs = np.array(p_diffs)
sd = np.std(p_diffs)
z = (obs_diff - np.mean(p_diffs)) / sd
pvalue = 1 - stats.norm.cdf(z)
print(pvalue)
```

```
0.905339060380073
```

```
#Another P-value Algorithm
#calculate the proportion of p_diffs greater than the observe difference
(p_diffs > obs_diff).mean()
```

```
0.9005
```

91% is the proportion of the p_diffs that are greater than the actual difference observed in ab_data.csv.

k. In words, explain what you just computed in part **j.** What is this value called in scientific studies? What does this value mean in terms of whether or not there is a difference between the new and old pages?

91% is the proportion of the p_diffs that are greater than the actual difference observed in ab_data.csv. In scientific studies this value is also called p-value. This value means that we cannot reject the null hypothesis and that we do not have sufficient evidence that the new_page has a higher conversion rate than the old_page.

l. We could also use a built-in to achieve similar results. Though using the built-in might be easier to code, the above portions are a walkthrough of the ideas that are critical to correctly thinking about statistical significance. Fill in the below to calculate the number of conversions for each page, as well as the number of individuals who received each page. Let `n_old` and `n_new` refer the the number of rows associated with the old page and new pages, respectively.

```
import statsmodels.api as sm

n_new = len(df2.query('landing_page == "new_page"'))
n_old = len(df2.query('landing_page == "old_page"'))
convert_new = len(df2.query('landing_page == "new_page" & converted == 1'))
convert_old = len(df2.query('landing_page == "old_page" & converted == 1'))
```

```
convert_new, convert_old
```

```
(17264, 17489)
```

```
n_new, n_old
```

```
(145310, 145274)
```

m. Now use `stats.proportions_ztest` to compute your test statistic and p-value. Here is a helpful link on using the built in.

```
z_score, p_value = sm.stats.proportions_ztest([convert_old, convert_new], [n_old, n_new],value=None, alternative='smaller', prop_var=False)
```

```
z_score, p_value
```

```
(1.3109241984234394, 0.9050583127590245)
```

n. What do the z-score and p-value you computed in the previous question mean for the conversion rates of the old and new pages? Do they agree with the findings in parts **j.** and **k.**?

The z-score and the p_value mean that one doesn't reject the Null. The Null being the converted rate of the old_page is the same or greater than the converted rate of the new_page. The p_value is 0.91 and is higher than 0.05 significance level. That means we can not be confident with a 95% confidence level that the converted rate of the new_page is larger than the old_page.

Part III - A regression approach (optional)

1. In this final part, you will see that the result you acheived in the previous A/B test can also be acheived by performing regression.

a. Since each row is either a conversion or no conversion, what type of regression should you be performing in this case?

The dependent variable is a binary variable (converted vs not converted). Thus, you need to use a logistic regression.

b. The goal is to use **statsmodels** to fit the regression model you specified in part **a.** to see if there is a significant difference in conversion based on which page a customer receives. However, you first need to create a column for the intercept, and create a dummy variable column for which page each user received. Add an **intercept** column, as well as an **ab_page** column, which is 1 when an individual receives the **treatment** and 0 if **control**.

```
df2[['control','treatment']]= pd.get_dummies(df2['group'])
df2 = df2.drop('control',axis = 1)

df2.head()
```

	user_id	timestamp	group	landing_page	converted	treatment
0	851104	2017-01-21 22:11:48.556739	control	old_page	0	0
1	804228	2017-01-12 08:01:45.159739	control	old_page	0	0
2	661590	2017-01-11 16:55:06.154213	treatment	new_page	0	1
3	853541	2017-01-08 18:28:03.143765	treatment	new_page	0	1
4	864975	2017-01-21 01:52:26.210827	control	old_page	1	0

```
df3 = df2.rename(columns={'treatment': 'ab_page'})
df3.head()
```

	user_id	timestamp	group	landing_page	converted	ab_page
0	851104	2017-01-21 22:11:48.556739	control	old_page	0	0
1	804228	2017-01-12 08:01:45.159739	control	old_page	0	0
2	661590	2017-01-11 16:55:06.154213	treatment	new_page	0	1
3	853541	2017-01-08 18:28:03.143765	treatment	new_page	0	1
4	864975	2017-01-21 01:52:26.210827	control	old_page	1	0

c. Use **statsmodels** to import your regression model. Instantiate the model, and fit the model using the two columns you created in part **b.** to predict whether or not an individual converts.

```
from scipy import stats

df3['intercept'] = 1
df3 = df3.dropna()

lm = sm.Logit(df3['converted'],df3[['intercept','ab_page']])
results = lm.fit()
results.summary()
```

```
Optimization terminated successfully.
         Current function value: 0.366118
         Iterations 6
```

Logit Regression Results

Dep. Variable:	converted	**No. Observations:**	290584
Model:	Logit	**Df Residuals:**	290582
Method:	MLE	**Df Model:**	1
Date:	Thu, 20 Jul 2023	**Pseudo R-squ.:**	8.077e-06
Time:	22:59:59	**Log-Likelihood:**	-1.0639e+05
converged:	True	**LL-Null:**	-1.0639e+05
Covariance Type:	nonrobust	**LLR p-value:**	0.1899

	coef	std err	z	P>|z|	[0.025	0.975]
intercept	-1.9888	0.008	-246.669	0.000	-2.005	-1.973

d. Provide the summary of your model below, and use it as necessary to answer the following questions.

See above

e. What is the p-value associated with **ab_page**? Why does it differ from the value you found in **Part II**?

Hint: What are the null and alternative hypotheses associated with your regression model, and how do they compare to the null and alternative hypotheses in the **Part II**?

The p-value associated with ab_page is 0.19. It is higher than 0.05. Thus, the coefficient is not significant.

Alternative hypothesis from part II: the conversion rate of the old_page is less than the conversion rate of the new_page. This assumes a one-tailed test. In Part III, the alternative hypothesis can be formulated as follows: (1) The landing_page type influences (positively or negatively) the conversion rate or (2) the conversion rate of the old_page is different to the conversion rate of the new_page. This assumes a two-tailed test.

in both cases, the results do not support the alternative hypothesis sufficiently.

The p-value is very different. In part II the p-value is 0.91. This might be because the tests of the regression model (not the A/B test) assumes an intercept and because of differences in one or two-tailed testing.

f. Now, you are considering other things that might influence whether or not an individual converts. Discuss why it is a good idea to consider other factors to add into your regression model. Are there any disadvantages to adding additional terms into your regression model?

It is a good idea to consider other factors in order to identify other potencial influences on the conversion rate.

A disadvantage is that the model gets more complex.

g. Now along with testing if the conversion rate changes for different pages, also add an effect based on which country a user lives. You will need to read in the **countries.csv** dataset and merge together your datasets on the approporiate rows. Here are the docs for joining tables.

Does it appear that country had an impact on conversion? Don't forget to create dummy variables for these country columns - **Hint: You will need two columns for the three dummy variables.** Provide the statistical output as well as a written response to answer this question.

```
countries_df = pd.read_csv('/content/drive/My Drive/of-ds/项目/abtest/countries.csv')
df_new = countries_df.set_index('user_id').join(df3.set_index('user_id'), how='inner')
```

```
df_new.head()
```

user_id	country	timestamp	group	landing_page	converted	ab_page	intercept
834778	UK	2017-01-14 23:08:43.304998	control	old_page	0	0	1
928468	US	2017-01-23 14:44:16.387854	treatment	new_page	0	1	1
822059	UK	2017-01-16 14:04:14.719771	treatment	new_page	1	1	1
711597	UK	2017-01-22 03:14:24.763511	control	old_page	0	0	1
710616	UK	2017-01-16 13:14:44.000513	treatment	new_page	0	1	1

```
df_new.country.unique()
```

```
array(['UK', 'US', 'CA'], dtype=object)
```

```
#mean of conversion rate
df_new.ab_page.mean()
```

```
0.5000619442226688
```

```
#mean conversion rate by country
df_new.groupby(['country'], as_index=False).mean()
```

```
<ipython-input-43-504710461664>:2: FutureWarning: The default value of numeric_only in DataFrameGroupBy.mean is deprecated. In a future versio
  df_new.groupby(['country'], as_index=False).mean()
```

	country	converted	ab_page	intercept
0	CA	0.115318	0.503552	1.0
1	UK	0.120594	0.498247	1.0

```
#mean conversion rate by landing_page
df_new.groupby(['ab_page'], as_index=False).mean()
```

```
<ipython-input-44-b07633596b6b>:2: FutureWarning: The default value of numeric_only in DataFrameGroupBy.mean is deprecated. In a future versio
  df_new.groupby(['ab_page'], as_index=False).mean()
```

	ab_page	converted	intercept
0	0	0.120386	1.0
1	1	0.118808	1.0

```
# Create the necessary dummy variables
df_new[['CA','UK', 'US']]= pd.get_dummies(df_new['country'])

df_new.head()
```

user_id	country	timestamp	group	landing_page	converted	ab_page	intercept	CA	UK	US
834778	UK	2017-01-14 23:08:43.304998	control	old_page	0	0	1	0	1	0
928468	US	2017-01-23 14:44:16.387854	treatment	new_page	0	1	1	0	0	1
822059	UK	2017-01-16 14:04:14.719771	treatment	new_page	1	1	1	0	1	0
711597	UK	2017-01-22 03:14:24.763511	control	old_page	0	0	1	0	1	0
710616	UK	2017-01-16 13:14:44.000513	treatment	new_page	0	1	1	0	1	0

```
### Fit Your Linear Model And Obtain the Results

df_new['intercept'] = 1

lm = sm.Logit(df_new['converted'],df_new[['intercept','ab_page','CA','US']])
results = lm.fit()
results.summary()
```

```
Optimization terminated successfully.
         Current function value: 0.366113
         Iterations 6
```

Logit Regression Results

Dep. Variable:	converted	**No. Observations:**	290584
Model:	Logit	**Df Residuals:**	290580
Method:	MLE	**Df Model:**	3
Date:	Thu, 20 Jul 2023	**Pseudo R-squ.:**	2.323e-05
Time:	23:01:02	**Log-Likelihood:**	-1.0639e+05
converged:	True	**LL-Null:**	-1.0639e+05
Covariance Type:	nonrobust	**LLR p-value:**	0.1760

	coef	std err	z	P>|z|	[0.025	0.975]
intercept	-1.9794	0.013	-155.415	0.000	-2.004	-1.954
ab_page	-0.0149	0.011	-1.307	0.191	-0.037	0.007
CA	-0.0506	0.028	-1.784	0.074	-0.106	0.005
US	-0.0099	0.013	-0.743	0.457	-0.036	0.016

The country does not appear to have influence on the convertion rate. P-values for the two dummy country variables are above 0.05. Note the CA variable get closes to 0.05.

h. Though you have now looked at the individual factors of country and page on conversion, we would now like to look at an interaction between page and country to see if there significant effects on conversion. Create the necessary additional columns, and fit the new model.

Provide the summary results, and your conclusions based on the results.

```
#mean conversion rate by country and landing_page -
#checking for possible interactions (whether the influence of landing_page
#is different for the countries)

df_new.groupby(['country','ab_page'], as_index=False).mean()
```

```
<ipython-input-47-5ef9ab549bc3>:5: FutureWarning: The default value of numeric_only in DataFrameGroupBy.mean is deprecated. In a future versio
  df_new.groupby(['country','ab_page'], as_index=False).mean()
```

	country	ab_page	converted	intercept	CA	UK	US
0	CA	0	0.118783	1.0	1.0	0.0	0.0

By looking at an interaction, I will explore whether the influence of the landing_page might work in the US but not in the other countries, or Canada but not in other countries. Or the other way around.

```
df_new.head()
df_new['interaction_us_ab_page'] = df_new.US *df_new.ab_page
df_new['interaction_ca_ab_page'] = df_new.CA *df_new.ab_page

df_new.head()
```

user_id	country	timestamp	group	landing_page	converted	ab_page	intercept	CA	UK	US	interaction_us_ab_page	interacti
834778	UK	2017-01-14 23:08:43.304998	control	old_page	0	0	1	0	1	0	0	
928468	US	2017-01-23 14:44:16.387854	treatment	new_page	0	1	1	0	0	1	1	
822059	UK	2017-01-16 14:04:14.719771	treatment	new_page	1	1	1	0	1	0	0	
711597	UK	2017-01-22 03:14:24.763511	control	old_page	0	0	1	0	1	0	0	
710616	UK	2017-01-16 13:14:44.000513	treatment	new_page	0	1	1	0	1	0	0	

```
df_new['intercept'] = 1

lm = sm.Logit(df_new['converted'],df_new[['intercept','ab_page','US','interaction_us_ab_page','CA','interaction_ca_ab_page']])
results = lm.fit()
results.summary()
```

```
Optimization terminated successfully.
         Current function value: 0.366109
         Iterations 6
```

Logit Regression Results

Dep. Variable:	converted	**No. Observations:**	290584
Model:	Logit	**Df Residuals:**	290578
Method:	MLE	**Df Model:**	5
Date:	Thu, 20 Jul 2023	**Pseudo R-squ.:**	3.482e-05
Time:	23:01:12	**Log-Likelihood:**	-1.0639e+05
converged:	True	**LL-Null:**	-1.0639e+05
Covariance Type:	nonrobust	**LLR p-value:**	0.1920

	coef	std err	z	P>|z|	[0.025	0.975]
intercept	-1.9922	0.016	-123.457	0.000	-2.024	-1.961
ab_page	0.0108	0.023	0.475	0.635	-0.034	0.056
US	0.0057	0.019	0.306	0.760	-0.031	0.043
interaction_us_ab_page	-0.0314	0.027	-1.181	0.238	-0.084	0.021

Summary and conclusion on regression

The p_value for both interaction terms is higher than 0.05.

Thus, the influence of landing_page in the US is not different to the influence of landing_page in the other countries.

And the influence of landing_page in Canada is not different to the influence of landing_page in the other countries.

Conclusions

In conclusion, there is not enough evidence that the new_page increases the conversion rate as compared to the old_page. This is based on the probability figures, A/B testand regression. There is no strong evidence that the countries (US, CA and UK) influence the conversion rate.

Since the sample size is large continuing the testing of the new_page is likely not necessary. It is best to focus on the development of another new landing page.

✓ 0s completed at 6:12 PM