Analyze A/B Test Results

Introduction

A/B tests are very commonly performed by data analysts and data scientists. It is important that you get some practice working with the difficulties of these

For this project, you will be working to understand the results of an A/B test run by an e-commerce website. Your 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.

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Part I - Probability

To get started, let's import our libraries.

In [1]:
```
import pandas as pd
import numpy as np
import random
import matplotlib.pyplot as plt
%matplotlib inline
#We are setting the seed to assure you get the same answers on quizzes as w
random.seed(42)
```

`1.` Now, read in the `ab_data.csv` data. Store it in `df`. **Use your dataframe to answer the questions in Quiz 1 of the classroom.**

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

In [2]:
```
df=pd.read_csv('/content/ab_data.csv')
df.head()
```

Out[2]:

	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

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

In [3]:
```
df.shape
```

Out[3]: (294478, 5)

c. The number of unique users in the dataset.

In [4]:
```
df['user_id'].nunique()
```

Out[4]: 290584

d. The proportion of users converted.

In [5]:
```
converted=df.query('converted==1')
proportion = len(converted['converted'])/ len(df['user_id'])
proportion
```

Out[5]: 0.11965919355605512

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

In [6]:
```
New_page_No_treatment=df.query('landing_page=="new_page"')
New_page_No_treatment= New_page_No_treatment.query('group!="treatment"')

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

The_Number=len(New_page_No_treatment)+len(treatment_No_New_page)
The_Number
```

Out[6]: 3893

f. Do any of the rows have missing values?

In [7]:
```
#The sum of missing values in rows
df.isnull().any(axis = 1).sum()
```

Out[7]: 0

`2.` For the rows where **treatment** does not match with **new_page** or **control** does not match with **old_page**, we cannot be sure if this row truly received the new or old page. Use **Quiz 2** in the classroom to figure out how we should handle these rows.

a. Now use the answer to the quiz to create a new dataset that meets the specifications from the quiz. Store your new dataframe in **df2**.

In [8]:
```
#I will do tow df and i will Customize ech of them than i will add in  df2
Np_treatment=df.query('landing_page=="new_page"')
Np_treatment=Np_treatment.query('group=="treatment"')

Op_control=df.query('landing_page=="old_page"')
Op_control=Op_control.query('group=="control"')

df2=Np_treatment.append(Op_control)

df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 290585 entries, 2 to 294476
Data columns (total 5 columns):
 #   Column        Non-Null Count   Dtype
---  ------        --------------   -----
 0   user_id       290585 non-null  int64
 1   timestamp     290585 non-null  object
 2   group         290585 non-null  object
 3   landing_page  290585 non-null  object
 4   converted     290585 non-null  int64
dtypes: int64(2), object(3)
memory usage: 13.3+ MB
```

In [9]:
```
# Double Check all of the correct rows were removed - this should be 0
df2[((df2['group'] == 'treatment') == (df2['landing_page'] == 'new_page'))
```

Out[9]: 0

`3.` Use **df2** and the cells below to answer questions for **Quiz3** in the classroom.

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

In [10]:
```
df2.user_id.nunique()
```

Out[10]: 290584

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

In [11]:
```
sum(df2.user_id.duplicated())
```

Out[11]: 1

In [12]:
```
df2[df2.user_id.duplicated()]
```

Out[12]:

	user_id	timestamp	group	landing_page	converted
2893	773192	2017-01-14 02:55:59.590927	treatment	new_page	0

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

In [13]:
```
df2[df2.user_id.duplicated()]
```

Out[13]:

	user_id	timestamp	group	landing_page	converted
2893	773192	2017-01-14 02:55:59.590927	treatment	new_page	0

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

In [14]:
```
df2=df2.drop(index=2893)
```

In [15]:
```
sum(df2.user_id.duplicated())
```

Out[15]: 0

`4.` Use **df2** in the cells below to answer the quiz questions related to **Quiz 4** in the classroom.

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

In [16]:
```
#i will calculate the mean of (converted) for both recive old or new page
convert=df2.converted.mean()
convert
```

Out[16]: 0.11959708724499628

In [17]:
```
df2.head()
```

Out[17]:

	user_id	timestamp	group	landing_page	converted
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
6	679687	2017-01-19 03:26:46.940749	treatment	new_page	1
8	817355	2017-01-04 17:58:08.979471	treatment	new_page	1
9	839785	2017-01-15 18:11:06.610965	treatment	new_page	1

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

In [18]:
```
control=df2.query('group=="control"')
P_control_converted=control['converted'].mean()
P_control_converted
```

Out[18]: 0.1203863045004612

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

In [19]:
```
treatment=df2.query('group=="treatment"')
P_treatment_converted=treatment['converted'].mean()
P_treatment_converted
```

Out[19]: 0.11880806551510564

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

In [20]:
```
new_page=df2.query('landing_page=="new_page"')
P_received_new_page = len(new_page['landing_page'])/ len(df2['user_id'])
P_received_new_page
```

Out[20]: 0.5000619442226688

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

I think the vision is still not clear. We need more analysis and statistics. The numbers are very similar, so there is not enough evidence for me to prove that the new treatment page leads to more conversions.

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.

- H_{null} $(H_0): P_{new}$ - P_{old} <= 0
- H_{alt} $(H_1): P_{new}$ - P_{old} > 0

`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. You can use **Quiz 5** in the classroom to make sure you are on the right track.

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

In [21]:
```
#new_page=df2.query('landing_page=="new_page"')
#converted_new_page=new_page.converted.mean()
#converted_new_page

converted_new_page=df2.converted.mean()
converted_new_page
```

Out[21]: 0.11959708724499628

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

In [22]:
```
#old_page=df2.query('landing_page=="old_page"')
#converted_old_page=old_page.converted.mean()
#converted_old_page

converted_old_page=df2.converted.mean()
converted_old_page
```

Out[22]: 0.11959708724499628

c. What is n_{new}, the number of individuals in the treatment group?

In [23]:
```
new_page=df2.query('landing_page=="new_page"')
numper_new_page=len(new_page.user_id)
numper_new_page
```

Out[23]: 145310

d. What is n_{old}, the number of individuals in the control group?

In [24]:
```
old_page=df2.query('landing_page=="old_page"')
numper_old_page=len(old_page.user_id)
numper_old_page
```

Out[24]: 145274

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

In [25]:
```
converted_new_page=df2.converted.mean()
converted_new_page2=1-converted_new_page
numper_new_page=len(old_page.user_id)
array=[0,1]

Simulate_new_page= np.random.choice(array,numper_new_page,p=[converted_new_
Simulate_new_page
```

Out[25]: array([1, 0, 1, ..., 1, 1, 1])

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

In [26]:
```
converted_old_page=df2.converted.mean()
converted_old_page2=1-converted_old_page
numper_old_page=len(old_page.user_id)
array=[0,1]

Simulate_old_page=np.random.choice(array,numper_old_page,p=[converted_old_p
Simulate_old_page
```

Out[26]: array([1, 1, 1, ..., 1, 1, 0])

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

In [27]:
```
#Simulate_new_page= np.random.choice(array,numper_new_page,p=[1-converted_n
#Simulate_old_page=np.random.choice(array,numper_old_page,p=[1-converted_ol
Mean_Pold=Simulate_old_page.mean()
Mean_Pnew=Simulate_new_page.mean()
variance_pnew_pold=Mean_Pnew - Mean_Pold
variance_pnew_pold
```

Out[27]: -0.00025469113537179844

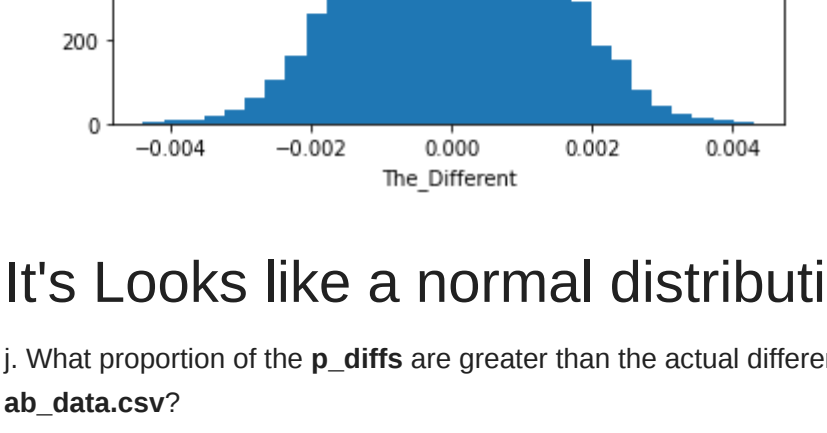
h. Create 10,000 p_{new} - p_{old} values using the same simulation process you used in parts (a) through (g) above. Store all 10,000 values in a NumPy array called **p_diffs**.

In [28]:
```
#converted_new_page=0.11959708724499628
#numper_new_page=len(old_page.user_id)==145310
#converted_old_page=0.11959708724499628
#numper_old_page=len(old_page.user_id)==145274
p_diffs=[]
array=[0,1]
i=0
while i<10000:
   Simulate_new_page= np.random.choice(array,numper_new_page,p=[converted_n

   Simulate_old_page=np.random.choice(array,numper_old_page,p=[converted_ol

   Mean_Pold=Simulate_old_page.mean()
   Mean_Pnew=Simulate_new_page.mean()
   variance_pnew_pold=Mean_Pnew - Mean_Pold
   p_diffs.append(variance_pnew_pold)
   i=i+1
```

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.

In [29]:
```
#Creat histogram for p_diffs to discover them

plt.hist(p_diffs,bins=30)
plt.ylabel('Number_of_count') ,plt.xlabel('The_Different')
```

Out[29]: (Text(0, 0.5, 'Number_of_count'), Text(0.5, 0, 'The_Different'))



It's Looks like a normal distribution

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

In [30]:
```
#we will calculate a actual difference
control=df2.query('group=="control"')
P_control_converted=control['converted'].mean()
P_control_converted

treatment=df2.query('group=="treatment"')
P_treatment_converted=treatment['converted'].mean()
P_treatment_converted

actual_diff=P_treatment_converted - P_control_converted
actual_diff
```

Out[30]: -0.0015782389853555567

In [31]:
```
#we will Make show p_diffs as array to able to del with it
p_diffs_array=np.array(p_diffs)
p_diffs_array_mean=p_diffs_array.mean()

diff=p_diffs_array_mean-actual_diff
p_diffs_array_mean,diff
```

Out[31]: (8.918319864532686e-06, 0.0015871573052200895)

In [32]:
```
#What proportion of the p_diffs are greater than the actual difference to f
proportion_p_diffs_g_actual=(p_diffs_array > actual_diff)
proportion_p_diffs_g_actual=proportion_p_diffs_g_actual.mean()
proportion_p_diffs_g_actual
```

Out[32]: 0.9061

k. Please explain using the vocabulary you've learned in this course 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?

The value that is I computed in part j his name (p-value), This value mean there is No difference between a N*page and O* pages.

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.

In [33]:
```
import statsmodels.api as sm
import scipy.stats as st
New_page=df2.query('landing_page=="new_page"')
New_page_converted= New_page.query('converted == 1')

Old_page=df2.query('landing_page=="old_page"')
Old_page_converted= Old_page.query('converted == 1')

convert_old = len(Old_page_converted)
convert_new = len(New_page_converted)
n_old = len(Old_page)
n_new = len(New_page)
```

```
/usr/local/lib/python3.6/dist-packages/statsmodels/tools/_testing.py:19: Fu
tureWarning: pandas.util.testing is deprecated. Use the functions in the pu
blic API at pandas.testing instead.
  import pandas.util.testing as tm
```

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

In [34]:
```
z_score, p_value = sm.stats.proportions_ztest([convert_old, convert_new],[n
z_score , p_value
```

Out[34]: (1.3109241984234394, 0.9050583127590245)

In [35]:
```
#also i can get the value of p_value from z_score
p_values = st.norm.sf(abs(z_score))
```

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.**?

In [36]:
```
#z-score cumulative distribution
z_scores=st.norm.cdf(z_score)
#The critical value is 95% confidence. Let's explain this further
Residual=0.95 #out of 100%
critical_value=st.norm.ppf(Residual)

critical_value,z_scores
```

Out[36]: (1.6448536269514722, 0.9050583127590245)

So what we notice here: Notice that z_score = 1.3 On the other hand, we note that the critical value = 1.64 Therefore, we conclude that the critical value is greater than the value of z_scores, and this means that we fail to reject the null hypothesis, and this result we got is the same as we got in parts j. and k.

Part III - A regression approach

`1.` In this final part, you will see that the result you achieved in the A/B test in Part II above can also be achieved 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?

Logistic Regression Because In logistic regression, the dependent variable is binary in nature (having two categories). Independent variables can be continuous or binary. In multinomial logistic regression, you can have more than two categories in your dependent variable.

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 in df2 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**.

In [37]:
```
#Create intercept column in df2
df2['intercept'] = 1

#Create dummy variable column
#ab_page= pd.Series([])

#for i in range(len(df2)):
  #if df2['group'][i]== "treatment":
   #ab_page[i]= 1
  #else:
   #ab_page[i]= 0


#df2.insert(6, "ab_page", ab_page)


#Create dummy variable column name ab_page in df2
df2['ab_page'] = pd.get_dummies(df2['group'])['treatment']

df2.tail(4)
```

Out[37]:

	user_id	timestamp	group	landing_page	converted	intercept	ab_page
294473	751197	2017-01-03 22:28:38.630509	control	old_page	0	1	0
294474	945152	2017-01-12 00:51:57.078372	control	old_page	0	1	0
294475	734608	2017-01-22 11:45:03.439544	control	old_page	0	1	0
294476	697314	2017-01-15 01:20:28.957438	control	old_page	0	1	0

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

In [38]:
```
log_reg = sm.Logit(df2.converted,df2[['ab_page','intercept']]).fit()
log_reg
```

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

Out[38]: <statsmodels.discrete.discrete_model.BinaryResultsWrapper at 0x7fcda9c3e400
>

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

In [39]:
```
log_reg.summary()
```

Out[39]:

Logit Regression Results

Dep. Variable:	converted	No. Observations:	290584
Model:	Logit	Df Residuals:	290582
Method:	MLE	Df Model:	1
Date:	Tue, 01 Dec 2020	Pseudo R-squ.:	8.077e-06
Time:	10:45:53	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]
ab_page	-0.0150	0.011	-1.311	0.190	-0.037	0.007
intercept	-1.9888	0.008	-246.669	0.000	-2.005	-1.973

In [40]:
```
log_reg.summary2()
```

Out[40]:

Model:	Logit	Pseudo R-squared:	0.000
Dependent Variable:	converted	AIC:	212780.3502
Date:	2020-12-01 10:45	BIC:	212801.5095
No. Observations:	290584	Log-Likelihood:	-1.0639e+05
Df Model:	1	LL-Null:	-1.0639e+05
Df Residuals:	290582	LLR p-value:	0.18988
Converged:	1.0000	Scale:	1.0000
No. Iterations:	6.0000		

	Coef.	Std.Err.	z	P>|z|	[0.025	0.975]
ab_page	-0.0150	0.0114	-1.3109	0.1899	-0.0374	0.0074
intercept	-1.9888	0.0081	-246.6690	0.0000	-2.0046	-1.9730

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 **Part II**?

What is the p-value associated with ab_page? The p-value associated with ab_page is 0.19 Notic in Part II was 0.90 Why does it differ from the value you found in Part II? So in Part II was the null hypotheses gives the p_old is greater or equal(>=) p_new and the alternative hypotheses gives the p_old is less than(<) p_new. / But in Part ||| was the null hypotheses gives the p_old is equal(=) p_new and the alternative hypotheses gives the p_old is not equal(!=) p_new.

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 better to consider other factors because it is not possible to rely on one or two factors. It is better to consider all the factors that are relevant in our analysis and add them to the regression model, Yes, there are disadvantages if you add additional factors has a high correlation or high depending Withe anther factors ,Why that? becuse that high correlation between them leads to Incorrect estimates and incorrect or inaccurate results in the regression mode.

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

In [41]:
```
df_countries=pd.read_csv('/content/countries.csv')
df_country=df2.set_index('user_id').join(df_countries.set_index('user_id'))
df_country.head()
```

Out[41]:

user_id	timestamp	group	landing_page	converted	intercept	ab_page	country
661590	2017-01-11 16:55:06.154213	treatment	new_page	0	1	1	US
853541	2017-01-08 18:28:03.143765	treatment	new_page	0	1	1	US
679687	2017-01-19 03:26:46.940749	treatment	new_page	1	1	1	CA
817355	2017-01-04 17:58:08.979471	treatment	new_page	1	1	1	UK
839785	2017-01-15 18:11:06.610965	treatment	new_page	1	1	1	CA

As for the country with the page, in fact, there were not enough results or clear evidence to be able to confirm whether the user turns the page or not according to the country.

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.

I dont see the significant effects on conversion by countryes

In [42]:
```
df_country.country.unique()
```

Out[42]: array(['US', 'CA', 'UK'], dtype=object)

In [43]:
```
df_country['CA_country'] = pd.get_dummies(df_country['country'])['CA']

df_country['UK_country'] = pd.get_dummies(df_country['country'])['UK']

df_country.head()
```

Out[43]:

user_id	timestamp	group	landing_page	converted	intercept	ab_page	country	CA_c
661590	2017-01-11 16:55:06.154213	treatment	new_page	0	1	1	US	
853541	2017-01-08 18:28:03.143765	treatment	new_page	0	1	1	US	
679687	2017-01-19 03:26:46.940749	treatment	new_page	1	1	1	CA	
817355	2017-01-04 17:58:08.979471	treatment	new_page	1	1	1	UK	
839785	2017-01-15 18:11:06.610965	treatment	new_page	1	1	1	CA	

In [50]:
```
df_country['US_new'] = df_country['CA_country'] * df_country['ab_page']
df_country['UK_new'] = df_country['UK_country'] * df_country['ab_page']

df_country.head()
```

Out[50]:

user_id	timestamp	group	landing_page	converted	intercept	ab_page	country	CA_c
661590	2017-01-11 16:55:06.154213	treatment	new_page	0	1	1	US	
853541	2017-01-08 18:28:03.143765	treatment	new_page	0	1	1	US	
679687	2017-01-19 03:26:46.940749	treatment	new_page	1	1	1	CA	
817355	2017-01-04 17:58:08.979471	treatment	new_page	1	1	1	UK	
839785	2017-01-15 18:11:06.610965	treatment	new_page	1	1	1	CA	

In [51]:
```
log_reg_country = sm.Logit(df_country.converted,df_country[['ab_page','CA_c
log_reg_country
```

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

Out[51]: <statsmodels.discrete.discrete_model.BinaryResultsWrapper at 0x7fcd929b26d8
>

In [52]:
```
log_reg_country.summary()
```

Out[52]:

Logit Regression Results

Dep. Variable:	converted	No. Observations:	290584
Model:	Logit	Df Residuals:	290578
Method:	MLE	Df Model:	5
Date:	Tue, 01 Dec 2020	Pseudo R-squ.:	3.482e-05
Time:	11:00:50	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]
ab_page	-0.0206	0.014	-1.505	0.132	-0.047	0.006
CA_country	-0.0175	0.038	-0.465	0.642	-0.091	0.056
UK_country	-0.0057	0.019	-0.306	0.760	-0.043	0.031
intercept	-1.9865	0.010	-206.344	0.000	-2.005	-1.968
US_new	-0.0469	0.054	-0.872	0.383	-0.152	0.059
UK_new	0.0314	0.027	1.181	0.238	-0.021	0.084

In [53]:
```
log_reg_country.summary2()
```

Out[53]:

Model:	Logit	Pseudo R-squared:	0.000
Dependent Variable:	converted	AIC:	212782.6602
Date:	2020-12-01 11:00	BIC:	212846.1381
No. Observations:	290584	Log-Likelihood:	-1.0639e+05
Df Model:	5	LL-Null:	-1.0639e+05
Df Residuals:	290578	LLR p-value:	0.19199
Converged:	1.0000	Scale:	1.0000
No. Iterations:	6.0000		

	Coef.	Std.Err.	z	P>|z|	[0.025	0.975]
ab_page	-0.0206	0.0137	-1.5052	0.1323	-0.0473	0.0062
CA_country	-0.0175	0.0377	-0.4652	0.6418	-0.0914	0.0563
UK_country	-0.0057	0.0188	-0.3057	0.7598	-0.0426	0.0311
intercept	-1.9865	0.0096	-206.3440	0.0000	-2.0053	-1.9676
US_new	-0.0469	0.0538	-0.8718	0.3833	-0.1523	0.0585
UK_new	0.0314	0.0266	1.1807	0.2377	-0.0207	0.0835

Conclusions:

In conclusion, and through our Analyze A / B Test, we conclude the following Through my Analyze, I found that the old page was much better than the new page, and this means that the null hypothesis failed and is rejected.

Sources:

- https://www.statology.org/z-score-python/
- https://stackoverflow.com/
- https://www.researchgate.net/post/Can_a_p-value_be_10
- https://www.geeksforgeeks.org/logistic-regression-using-statsmodels/
- https://www.listendata.com/2018/03/regression-analysis.html
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