Analyze A/B Test Results

This project will assure you have mastered the subjects covered in the statistics lessons. The hope is to have this project be as comprehensive of these topics as possible. Good luck!

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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.

As you work through this notebook, follow along in the classroom and answer the corresponding quiz questions associated with each question. The labels for each classroom concept are provided for each question. This will assure you are on the right track as you work through the project, and you can feel more confident in your final submission meeting the criteria. As a final check, assure you meet all the criteria on the RUBRIC (https://review.udacity.com/#!/projects/37e27304-ad47-4eb0-a1ab-8c12f60e43d0/rubric).

Part I - Probability

To get started, let's import our libraries.

In [2]:

```
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 we set
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 [3]:

```
df=pd.read_csv('ab_data.csv')
df.head()
```

Out[3]:

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

In [4]:

```
df.shape[0]
```

Out[4]:

```
294478
```

c. The number of unique users in the dataset.

In [5]:

```
df.user_id.nunique()
```

Out[5]:

```
290584
```

d. The proportion of users converted.

In [6]:

```
df.converted.mean()  #returns average of a value
```

Out[6]:

```
0.11965919355605512
```

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

In [7]:

```
df.query('group=="control"& landing_page=="new_page"').user_id.count()
```

Out[7]:

```
1928
```

In [8]:

```
df.isnull().sum()
```

Out[8]:

```
user_id         0
timestamp       0
group           0
landing_page    0
converted       0
dtype: int64
```

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. Use **Quiz 2** in the classroom to provide 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 [9]:

```
df[((df['group'] == 'treatment') == (df['landing_page'] == 'new_page')) == False]
```

Out[9]:

```
3893
```

In [10]:

```
df2=df.query('group=="treatment" and landing_page!="new_page" or group=="control"
df2
```

Out[10]:

```
array([     22,     240,     308, ..., 294252, 294253, 294331])
```

In [11]:

```
df2=df.drop(df2)
```

In [12]:

```
df2[((df2['group'] == 'treatment') == (df2['landing_page'] == 'new_page')) == Fal
```

Out[12]:

```
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 [13]:

```
df2.user_id.nunique()
```

Out[13]:

```
290584
```

In [14]:

```
df2.shape
```

Out[14]:

```
(290585, 5)
```

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

In [15]:

```
df2[df2.duplicated(['user_id'],keep=False)]
```

Out[15]:

	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**?

In [16]:

```
df2[df2.duplicated(subset="user_id", keep=False)]
```

Out[16]:

	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

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

In [17]:

```
df2.drop(1899)
```

Out[17]:

	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
5	936923	2017-01-10 15:20:49.083499	control	old_page	0
6	679687	2017-01-19 03:26:46.940749	treatment	new_page	1
7	719014	2017-01-17 01:48:29.539573	control	old_page	0
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
10	929503	2017-01-18 05:37:11.527370	treatment	new_page	0
11	834487	2017-01-21 22:37:47.774891	treatment	new_page	0
12	803683	2017-01-09 06:05:16.222706	treatment	new_page	0
13	944475	2017-01-22 01:31:09.573836	treatment	new_page	0
14	718956	2017-01-22 11:45:11.327945	treatment	new_page	0
15	644214	2017-01-22 02:05:21.719434	control	old_page	1
16	847721	2017-01-17 14:01:00.090575	control	old_page	0
17	888545	2017-01-08 06:37:26.332945	treatment	new_page	1
18	650559	2017-01-24 11:55:51.084801	control	old_page	0
19	935734	2017-01-17 20:33:37.428378	control	old_page	0
20	740805	2017-01-12 18:59:45.453277	treatment	new_page	0
21	759875	2017-01-09 16:11:58.806110	treatment	new_page	0
23	793849	2017-01-23 22:36:10.742811	treatment	new_page	0
24	905617	2017-01-20 14:12:19.345499	treatment	new_page	0
25	746742	2017-01-23 11:38:29.592148	control	old_page	0
26	892356	2017-01-05 09:35:14.904865	treatment	new_page	1
27	773302	2017-01-12 08:29:49.810594	treatment	new_page	0
28	913579	2017-01-24 09:11:39.164256	control	old_page	1
29	736159	2017-01-06 01:50:21.318242	treatment	new_page	0
30	690284	2017-01-13 17:22:57.182769	control	old_page	0
...	...	...	...	...	...
294448	776137	2017-01-12 05:53:12.386730	treatment	new_page	0
294449	883344	2017-01-22 23:15:58.645325	treatment	new_page	0
294450	825594	2017-01-06 12:37:08.897784	treatment	new_page	0

294451	875688	2017-01-14 07:19:49.042869	control	old_page	0
294452	927527	2017-01-12 10:52:11.084740	control	old_page	0
294453	789177	2017-01-17 18:17:56.215378	control	old_page	0
294454	937338	2017-01-19 03:23:22.236666	treatment	new_page	0
294455	733101	2017-01-23 12:52:58.711914	treatment	new_page	0
294456	679096	2017-01-02 16:43:49.237940	treatment	new_page	0
294457	691699	2017-01-09 23:42:35.963486	treatment	new_page	0
294458	807595	2017-01-22 10:43:09.285426	treatment	new_page	0
294459	924816	2017-01-20 10:59:03.481635	control	old_page	0
294460	846225	2017-01-16 15:24:46.705903	treatment	new_page	0
294461	740310	2017-01-10 17:22:19.762612	control	old_page	0
294462	677163	2017-01-03 19:41:51.902148	treatment	new_page	0
294463	832080	2017-01-19 13:18:27.352570	control	old_page	0
294464	834362	2017-01-17 01:51:56.106436	control	old_page	0
294465	925675	2017-01-07 20:38:26.346410	treatment	new_page	0
294466	923948	2017-01-09 16:33:41.104573	control	old_page	0
294467	857744	2017-01-05 08:00:56.024226	control	old_page	0
294468	643562	2017-01-02 19:20:05.460595	treatment	new_page	0
294469	755438	2017-01-18 17:35:06.149568	control	old_page	0
294470	908354	2017-01-11 02:42:21.195145	control	old_page	0
294471	718310	2017-01-21 22:44:20.378320	control	old_page	0
294472	822004	2017-01-04 03:36:46.071379	treatment	new_page	0
294473	751197	2017-01-03 22:28:38.630509	control	old_page	0
294474	945152	2017-01-12 00:51:57.078372	control	old_page	0
294475	734608	2017-01-22 11:45:03.439544	control	old_page	0
294476	697314	2017-01-15 01:20:28.957438	control	old_page	0
294477	715931	2017-01-16 12:40:24.467417	treatment	new_page	0

290584 rows × 5 columns

`4.` Use **df2** in the below cells 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 [18]:

```
df2.converted.mean()
```

Out[18]:

0.11959667567149027

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

In [19]:

```
df2.query('group=="control"').converted.mean()
```

Out[19]:

0.1203863045004612

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

In [20]:

```
df2.query('group=="treatment"').converted.mean()
```

Out[20]:

0.11880724790277405

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

In [21]:

```
df3=df2.query('landing_page=="new_page"')
len(df3)/len(df2)
```

Out[21]:

0.5000636646764286

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 that the treatment page leads to more conversions. If we were to conclude from the above numbers, it suggests that control pages have 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.

$$H_0: p_{new} <= p_{old}$$
$$H_1: p_{new} > p_{old}$$

`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 **convert rate** for p_{new} under the null?

In [22]:

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

Out[22]:

```
0.11880724790277405
```

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

In [23]:

```
p_old=df2.query('group=="control"')['converted'].mean()
p_old
```

Out[23]:

```
0.1203863045004612
```

c. What is n_{new} ?

In [24]:

```
n_new=df2.query('group=="treatment"')['converted'].count()
n_new
```

Out[24]:

```
145311
```

d. What is n_{old} ?

In [25]:

```
n_old=df2.query('group=="control"')['converted'].count()
n_old
```

Out[25]:

```
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**.

In [26]:

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

Out[26]:

```
0.11810530517304264
```

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**.

In [27]:

```
old_page_converted =  np.random.binomial(1, p = p_new,size = n_old)
old_page_converted.mean()
```

Out[27]:

```
0.11915415008879772
```

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

In [28]:

```
diff=new_page_converted.mean()-old_page_converted.mean()
diff
```

Out[28]:

```
-0.001048844915755076
```

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**.

In [29]:

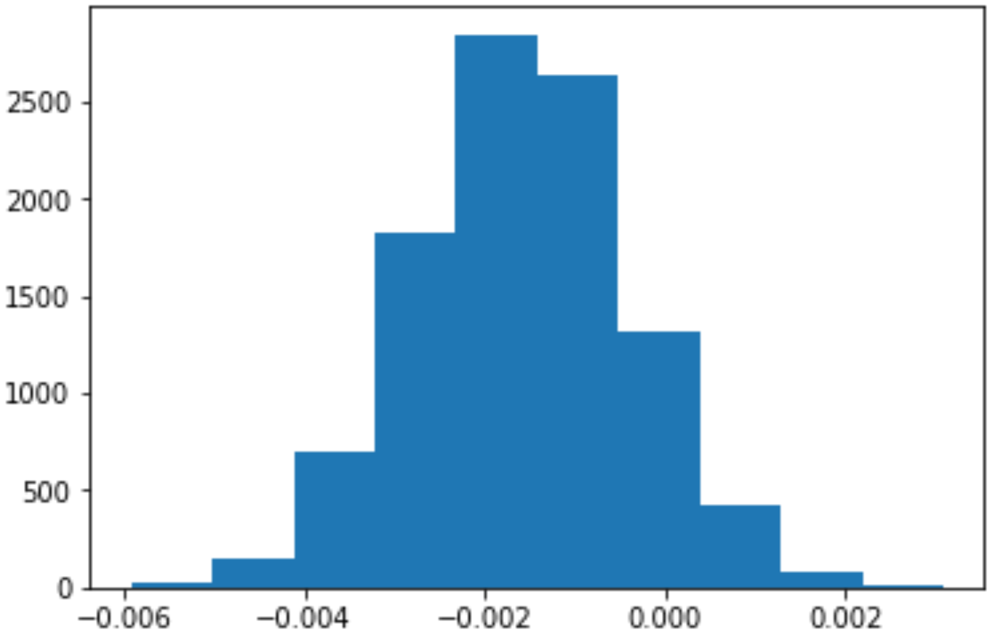
```
p_diffs = []

new_convert = np.random.binomial(n_new,p_new,10000)/n_new
old_convert = np.random.binomial(n_old,p_old,10000)/n_old
p_diffs = new_convert - old_convert
```

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.

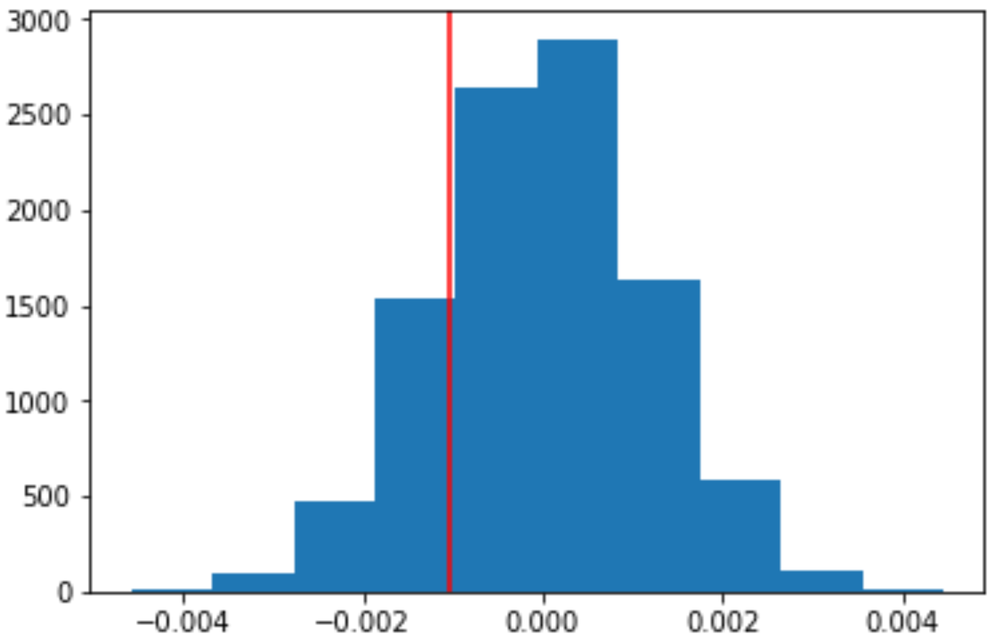
In [30]:

```
plt.hist(p_diffs);
```



In [31]:

```
p_diffs=np.array(p_diffs)
null_vals=np.random.normal(0,p_diffs.std(),p_diffs.size)
plt.hist(null_vals)
plt.axvline(diff,c='red');
```



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

In [32]:

```
(p_diffs>diff).mean()
```

Out[32]:

```
0.3256
```

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?

This is the P-value, which suggests if there is a significant difference between 2 groups for a hypothesis. In this case, the new page doesn't have better conversion rates than the old page because the value 0.9 is much higher than the alpha, 0.05.

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

convert_old = df2.query('landing_page=="old_page" and converted==1').count()[0]
convert_new = df2.query('landing_page=="new_page" and converted==1').count()[0]
n_old = df2.query('landing_page=="old_page"').count()[0]
n_new = df2.query('landing_page=="new_page"').count()[0]
```

m. Now use `stats.proportions_ztest` to compute your test statistic and p-value. [Here (http://knowledgetack.com/python/statsmodels/proportions_ztest/)](http://knowledgetack.com/python/statsmodels/proportions_ztest/) is a helpful link on using the built in.

In [34]:

```
z_score, p_value = sm.stats.proportions_ztest([convert_new, convert_old], [n_new,
print(p_value)
print(z_score)
```

```
0.905173705140591
-1.3116075339133115
```

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 is the number of standard deviation a data-point is from the population mean. It is greater than the value of -0.1645 (one-tail test) and hence it suggests that we can't reject the null. And the p-value determines the significance of our resuls. The values are different from parts j and k but it still suggests that there is no statistically significant difference betweem the new and the old page.

Part III - A regression approach

`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?

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**.

In [35]:

```
df2['intercept']=1
df2[['control', 'ab_page']]=pd.get_dummies(df2['group'])
df2.drop(labels=['control'], axis=1, inplace=True)
df2.head()
```

Out[35]:

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

In [36]:

```
import statsmodels.api as sm

mod = sm.Logit(df2['converted'], df2[['intercept','ab_page']])
results = mod.fit()
```

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

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

In [37]:

```
results.summary()
```

Out[37]:

Logit Regression Results

Dep. Variable:	converted	**No. Observations:**	290585
Model:	Logit	**Df Residuals:**	290583
Method:	MLE	**Df Model:**	1
Date:	Sat, 18 May 2019	**Pseudo R-squ.:**	8.085e-06
Time:	04:13:58	**Log-Likelihood:**	-1.0639e+05
converged:	True	**LL-Null:**	-1.0639e+05
		LLR p-value:	0.1897

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
intercept	-1.9888	0.008	-246.669	0.000	-2.005	-1.973
ab_page	-0.0150	0.011	-1.312	0.190	-0.037	0.007

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 here suggests that that new page is not statistically significant as 0.19 > 0.05. The values are different because in part 2 we randomly sampled the data 10000 times and the sample could have overlapped or been mutually exclusive to an extent to give different values such that differet p-values were received than what we got in logistic regression.

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?

Considering other factors/explanatory variables makes our hypothesis results more reliable as it can improve the r-sqaured values plus we might miss other influencing factors of out response variables. But if multicolinearity exists, that is correlation between explanatory variables then our results will be wrong. So we need to make sure that there is no multicolinearity.

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 (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.join.html)](https://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.join.html) 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 [38]:

```
countries_df = pd.read_csv('./countries.csv')
df_new = countries_df.set_index('user_id').join(df2.set_index('user_id'), how='in
df_new.head()
```

Out[38]:

	country	timestamp	group	landing_page	converted	intercept	ab_page
user_id							
630000	US	2017-01-19 06:26:06.548941	treatment	new_page	0	1	1
630001	US	2017-01-16 03:16:42.560309	treatment	new_page	1	1	1
630002	US	2017-01-19 19:20:56.438330	control	old_page	0	1	0
630003	US	2017-01-12 10:09:31.510471	treatment	new_page	0	1	1
630004	US	2017-01-18 20:23:58.824994	treatment	new_page	0	1	1

In [39]:

```
df_new[['CA','US','UK']] = pd.get_dummies(df_new['country'])[['CA','US','UK']]
df_new.head()
```

Out[39]:

user_id	country	timestamp	group	landing_page	converted	intercept	ab_page	CA
630000	US	2017-01-19 06:26:06.548941	treatment	new_page	0	1	1	0
630001	US	2017-01-16 03:16:42.560309	treatment	new_page	1	1	1	0
630002	US	2017-01-19 19:20:56.438330	control	old_page	0	1	0	0
630003	US	2017-01-12 10:09:31.510471	treatment	new_page	0	1	1	0
630004	US	2017-01-18 20:23:58.824994	treatment	new_page	0	1	1	0

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.

In [40]:

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

```
Optimization terminated successfully.
         Current function value: 0.366112
         Iterations 6
```

Out[40]:

Logit Regression Results

Dep. Variable:	converted	**No. Observations:**	290585
Model:	Logit	**Df Residuals:**	290581
Method:	MLE	**Df Model:**	3
Date:	Sat, 18 May 2019	**Pseudo R-squ.:**	2.324e-05
Time:	04:14:04	**Log-Likelihood:**	-1.0639e+05
converged:	True	**LL-Null:**	-1.0639e+05
		LLR p-value:	0.1758

	coef	std err	z	P>|z|	[0.025	0.975]
intercept	-1.9794	0.013	-155.414	0.000	-2.004	-1.954
CA	-0.0506	0.028	-1.784	0.074	-0.106	0.005
US	-0.0099	0.013	-0.744	0.457	-0.036	0.016
ab_page	-0.0150	0.011	-1.308	0.191	-0.037	0.007

Conclusions

There is no difference between the old and the new page. It is better not to change the page.