Analyze_ab_test_results_notebook

December 9, 2018

0.1 Analyze A/B Test Results

You may either submit your notebook through the workspace here, or you may work from your local machine and submit through the next page. Either way assure that your code passes the project RUBRIC. **Please save regularly

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!

0.2 Table of Contents

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.

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 we set up
        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('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

```
In [3]: df.timestamp.max(), df.timestamp.min()
```

```
Out[3]: ('2017-01-24 13:41:54.460509', '2017-01-02 13:42:05.378582')
```

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

```
In [4]: df.shape
```

```
Out[4]: (294478, 5)
```

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()
```

```
Out[6]: 0.11965919355605512
```

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

```
In [7]: # Either new_page with control OR old_page with treatment
        df.query('landing_page == "new_page" and group == "control"').shape[0] + df.query('landi
```

```
Out[7]: 3893
```

f. Do any of the rows have missing values?

```
In [8]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 294478 entries, 0 to 294477
Data columns (total 5 columns):
user_id         294478 non-null int64
timestamp       294478 non-null object
group           294478 non-null object
landing_page    294478 non-null object
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. 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]: df0 = df.query('landing_page == "old_page" and group != "treatment"')
        df0.shape[0]

Out[9]: 145274

In [10]: df1 = df.query('landing_page == "new_page" and group != "control"')
         df1.shape[0]

Out[10]: 145311

In [11]: df2 = df0.append(df1)
         df2.head()

Out[11]:    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
         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
         7   719014  2017-01-17 01:48:29.539573  control     old_page          0

In [12]: # Double Check all of the correct rows were removed - this should be 0
         df2[((df2['group'] == 'treatment') == (df2['landing_page'] == 'new_page')) == False].sh

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
```

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

```
In [14]: df2['user_id'].value_counts()
```

```
Out[14]: 773192    2
         630732    1
         811737    1
         797392    1
         795345    1
         801490    1
         799443    1
         787157    1
         793302    1
         817882    1
         842446    1
         815835    1
         805596    1
         803549    1
         809694    1
         807647    1
         895712    1
         840399    1
         836301    1
         899810    1
         834242    1
         936604    1
         934557    1
         940702    1
         938655    1
         830144    1
         828097    1
         832195    1
         838348    1
         821956    1
                  ..
         734668    1
         736717    1
         730574    1
         775632    1
         771538    1
         642451    1
         773587    1
         783828    1
         785877    1
         779734    1
         781783    1
```

```
759256    1
726472    1
748999    1
746950    1
753093    1
751044    1
740803    1
738754    1
744897    1
742848    1
634271    1
632222    1
636316    1
630169    1
650647    1
648598    1
654741    1
652692    1
630836    1
Name: user_id, Length: 290584, dtype: int64
```

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

```
In [15]: df2[df2['user_id'] == 773192]
```

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

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

```
In [16]: df2.drop_duplicates(subset=['user_id'], keep='first', inplace=True)
         df2[df2['user_id'] == 773192]
```

Out[16]:

	user_id	timestamp	group	landing_page	converted
1899	773192	2017-01-09 05:37:58.781806	treatment	new_page	0

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 [17]: (df2['converted'] == 1).mean()
```

```
Out[17]: 0.11959708724499628
```

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

```
In [18]: control_prob =(df2.query('group == "control"')['converted'] == 1).mean()
         control_prob
```

```
Out[18]: 0.1203863045004612
```

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

```
In [19]: treat_prob = (df2.query('group == "treatment"')['converted'] == 1).mean()
         treat_prob
```

```
Out[19]: 0.11880806551510564
```

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

```
In [20]: new = df2[df2['landing_page'] == "new_page"].count().landing_page
         new_prob = new / df2.shape[0]
         new_prob
```

```
Out[20]: 0.50006194422266881
```

e. Use the results in the previous two portions of this question to suggest if you think there is evidence that one page leads to more conversions? Write your response below.

The results are almost the same and so, it is hard to conclude that one page leads to more conversions or not.

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: = ALt: >

’’’

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 [21]: p_new = (df2['converted'] == 1).mean()
         p_new

Out[21]: 0.11959708724499628
```

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

```
In [22]: p_old = (df2['converted'] == 1).mean()
         p_old

Out[22]: 0.11959708724499628
```

c. What is n_{new}?

```
In [23]: n_new = df2[df2['landing_page'] == "new_page"].count().landing_page
         n_new

Out[23]: 145310
```

d. What is n_{old}?

```
In [24]: n_old = df2[df2['landing_page'] == "old_page"].count().landing_page
         n_old

Out[24]: 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 [25]: new_page_converted = np.random.choice(2, n_new, p_new)
```

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 [26]: old_page_converted = np.random.choice(2, n_old, p_old)
```

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

```
In [27]: diff = new_page_converted.mean() - old_page_converted.mean()
         diff

Out[27]: 0.0012732476214868393
```

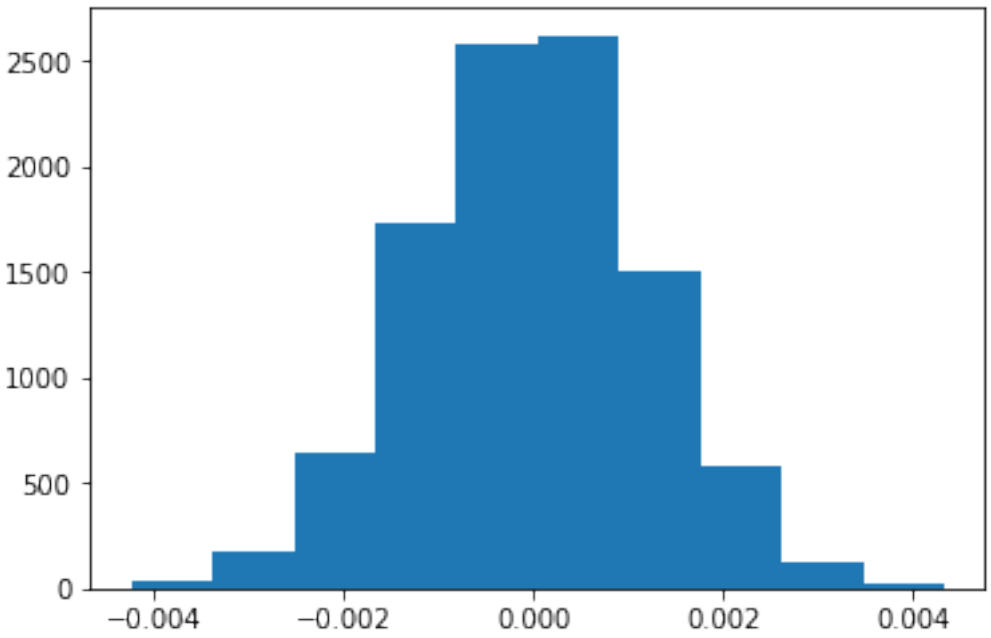
h. Simulate 10,000 p_{new} - p_{old} values using this same process similarly to the one you calculated in parts **a. through g.** above. Store all 10,000 values in **p_diffs**.

```
In [28]: p_diffs = np.random.binomial(n_new, p_new, 10000)/n_new - np.random.binomial(n_old, p_o
         p_diffs

Out[28]: array([ -7.77610743e-05,   2.86955919e-04,   2.52499259e-05, ...,
                 -5.46051841e-04,  -1.72962580e-03,  -2.49367533e-03])
```

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



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

```
In [30]: new = df2[df2['landing_page'] == "new_page"].count().landing_page
         new_prob = new / df.shape[0]
         new_prob

Out[30]: 0.49344942576355449

In [31]: old = df2[df2['landing_page'] == "old_page"].count().landing_page
         old_prob = old / df.shape[0]
         old_prob

Out[31]: 0.49332717554452288

In [32]: actual_diff = new_prob - old_prob
         actual_diff

Out[32]: 0.00122250219031616 59

In [33]: df_diffs = pd.DataFrame(p_diffs)
         df_diffs.columns = ['p_diffs']
```

```
In [34]: proportion=len(df_diffs.query('p_diffs > @ actual_diff'))/len(df_diffs)
         proportion

Out[34]: 0.457
```

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?

We have calculated the number of values (differences) in our simulation greater than the actual difference (probability), this value is the P_Value and it tells us that we fail to reject the null hypothesis and that the new page is not better or the same as the old one.

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 [35]: import statsmodels.api as sm

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

```
/opt/conda/lib/python3.6/site-packages/statsmodels/compat/pandas.py:56: FutureWarning: The panda
  from pandas.core import datetools


17489 17264
145274 145310
```

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 [36]: z_score, p_value = sm.stats.proportions_ztest([convert_old, convert_new], [n_old, n_new
         z_score, p_value

Out[36]: (1.3109241984234394, 0.18988337448195103)
```

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 p-value both are greater than 0.05 which mean that we fail to reject the null hypothesis (Z score is between -1.96 and +1.96 and so the p-value is larger than 0.05, we cannot reject the null hypothesis), which means that conversion rates are not high and there is no difference between the old page and the new one. They agree with findings in parts j and k.

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?

Since these values are categorical variables we need to use the 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 colun 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]: df2['intercept'] = 1

         df2['ab_page'] = (df2['group'] == "treatment").astype(int)
         df2.head()
```

Out[37]:

	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	
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	
7	719014	2017-01-17 01:48:29.539573	control	old_page	0	

	intercept	ab_page
0	1	0
1	1	0
4	1	0
5	1	0
7	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 [38]: import statsmodels.api as sm
         model = sm.Logit(df2['converted'], df2[['intercept','ab_page']])
         result = model.fit()
         result.summary()
```

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

```
Out[38]: <class 'statsmodels.iolib.summary.Summary'>
"""
                           Logit Regression Results
==============================================================================
Dep. Variable:              converted   No. Observations:               290584
Model:                          Logit   Df Residuals:                   290582
Method:                           MLE   Df Model:                            1
Date:                Sun, 09 Dec 2018   Pseudo R-squ.:               8.077e-06
Time:                        07:19:22   Log-Likelihood:            -1.0639e+05
converged:                       True   LL-Null:                   -1.0639e+05
                                        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
ab_page       -0.0150      0.011     -1.311      0.190      -0.037       0.007
==============================================================================
"""
```

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

We can see from the above summary that the intercept = -1.9888 and the slope = -0.0150. The p-value of the ab_page is larger than the critical value we would reject the null, in this case, we can say that the specific page does not affect the change in the dependent variable (the coefficient for the specific country is not significant)

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

p-value for ab_page = 0.190, in part II the null and the alternative associated with the same conversion rate regardless of the type of page, in the regression model we see the conversion based on which page a customer receives.

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?

Other factors can help in predicting what may affect our response variable, and in trying to find the best model to predict it. No disadvantages came from the additional terms, they provide more evidence relating to our hypothesis

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 varaibles.** Provide the statistical output as well as a written response to answer this question.

In [39]:
```
df3 = pd.read_csv('countries.csv')
df3.head()
```

Out[39]:

	user_id	country
0	834778	UK
1	928468	US
2	822059	UK
3	711597	UK
4	710616	UK

In [40]:
```
df4 = df3.set_index('user_id').join(df2.set_index('user_id'), how='inner')
df4.head()
```

Out[40]:

user_id	country	timestamp	group	landing_page	converted	intercept	ab_page
834778	UK	2017-01-14 23:08:43.304998	control	old_page	0	1	0
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	1	0
710616	UK	2017-01-16 13:14:44.000513	treatment	new_page	0	1	1

In [41]:
```
df4.country.unique()
```

Out[41]:
```
array(['UK', 'US', 'CA'], dtype=object)
```

In [42]:
```
df4[['UK', 'US', 'CA']] = pd.get_dummies(df4['country'])
df4.head()
```

Out[42]:

user_id	country	timestamp	group	landing_page	converted	intercept	ab_page	UK	US	CA
834778	UK	2017-01-14 23:08:43.304998	control	old_page	0	1	0	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	1	0	0	1	0
710616	UK	2017-01-16 13:14:44.000513	treatment	new_page	0	1	1	0	1	0

In [43]:
```
#df4 = df4.drop('CA', axis = 1)
df4.head()
```

Out[43]:

user_id	country	timestamp	group	landing_page	converted	intercept	ab_page	UK	US	CA
834778	UK	2017-01-14 23:08:43.304998	control	old_page	0	1	0	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	1	0	0	1	0
710616	UK	2017-01-16 13:14:44.000513	treatment	new_page	0	1	1	0	1	0

In [44]:
```
model2 = sm.Logit(df4['converted'], df4[['intercept','UK', 'US','ab_page']])
result2 = model2.fit()
result2.summary()
```

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

Out[44]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                           Logit Regression Results
==============================================================================
Dep. Variable:              converted   No. Observations:               290584
Model:                          Logit   Df Residuals:                   290580
Method:                           MLE   Df Model:                            3
Date:                Sun, 09 Dec 2018   Pseudo R-squ.:               2.323e-05
Time:                        07:19:23   Log-Likelihood:            -1.0639e+05
converged:                       True   LL-Null:                   -1.0639e+05
                                        LLR p-value:                    0.1760
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
intercept     -1.9893      0.009   -223.763      0.000      -2.007      -1.972
UK            -0.0408      0.027     -1.516      0.130      -0.093       0.012
US             0.0099      0.013      0.743      0.457      -0.016       0.036
ab_page       -0.0149      0.011     -1.307      0.191      -0.037       0.007
==============================================================================
"""
```

We can see that for the US we predict an increase in conversion by 0.0099 holding other variables constant. For every 100% increase in the UK, the predicted decrease in conversion is -0.0408. The only p-value that is statistically significant is the intercept and in this case, we can say that a specific country does not affect the change in the conversion

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 [45]: df4['ab_test_page'] = (df4['landing_page'] == "new_page").astype(int)
         df4.head()
```

Out[45]:

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

```
In [46]: #df4 = df4.drop('CA', axis = 1)
         df4.head()
```

Out[46]:

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

```
In [47]: model3 = sm.Logit(df4['ab_test_page'], df4[['intercept','UK', 'US']])
         result3 = model3.fit()
         result3.summary()

Optimization terminated successfully.
         Current function value: 0.693144
         Iterations 3


Out[47]: <class 'statsmodels.iolib.summary.Summary'>
         """
                                   Logit Regression Results
         ==============================================================================
         Dep. Variable:           ab_test_page   No. Observations:               290584
         Model:                          Logit   Df Residuals:                   290581
         Method:                           MLE   Df Model:                            2
         Date:                Sun, 09 Dec 2018   Pseudo R-squ.:               4.442e-06
         Time:                        07:19:24   Log-Likelihood:            -2.0142e+05
         converged:                       True   LL-Null:                   -2.0142e+05
                                                 LLR p-value:                    0.4088
         ==============================================================================
                          coef    std err          z      P>|z|      [0.025      0.975]
         ------------------------------------------------------------------------------
         intercept      0.0018      0.004      0.414      0.679      -0.007       0.011
         UK             0.0124      0.017      0.720      0.472      -0.021       0.046
         US            -0.0088      0.009     -1.023      0.306      -0.026       0.008
         ==============================================================================
         """
```

We can see that for the UK we predict an increase in conversion by 0.0124 holding other variables constant. For every 100% increase in the US, the predicted decrease in conversion is -0.0088. p-values are not statistically significant, and the coefficient for the specific country is not significant

0.2.1 Conclusions

Considering all these factors along with the timestamp for this experiment, we can conclude that the duration of this experiment is not enough to decide whether the new page is better or not. Country and Page factors do not affect the change in the conversion rate and the coefficients are not significant and so, we fail to reject the null hypothesis. The company needs to run the experiment longer to make their decision.

Finishing Up

Congratulations! You have reached the end of the A/B Test Results project! This is the final project in Term 1. You should be very proud of all you have accomplished!

Tip: Once you are satisfied with your work here, check over your report to make sure that it is satisfies all the areas of the rubric (found on the project submission page at the end of the lesson). You should also probably remove all of the "Tips" like this one so that the presentation is as polished as possible.

0.3 Directions to Submit

Before you submit your project, you need to create a .html or .pdf version of this notebook in the workspace here. To do that, run the code cell below. If it worked correctly, you should get a return code of 0, and you should see the generated .html file in the workspace directory (click on the orange Jupyter icon in the upper left).

Alternatively, you can download this report as .html via the **File** > **Download as** submenu, and then manually upload it into the workspace directory by clicking on the orange Jupyter icon in the upper left, then using the Upload button.

Once you've done this, you can submit your project by clicking on the "Submit Project" button in the lower right here. This will create and submit a zip file with this .ipynb doc and the .html or .pdf version you created. Congratulations!

```
In [ ]: from subprocess import call
        call(['python', '-m', 'nbconvert', 'Analyze_ab_test_results_notebook.ipynb'])
```