Analyze_ab_test_results_notebook_II

July 8, 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

- Section **??**
- Section **??**
- Section **??**
- Section **??**

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]:
```
# libraries
import random
import numpy as np
import pandas as pd
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]: # dataset
        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

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

```
In [3]: # rows
        df.shape[0]
```

```
Out[3]: 294478
```

c. The number of unique users in the dataset.

```
In [4]: # unique users in total
        df.user_id.nunique()
```

```
Out[4]: 290584
```

d. The proportion of users converted.

```
In [5]: # proportion of conversion
        df.converted.mean()
```

```
Out[5]: 0.11965919355605512
```

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

```
In [6]: # treatment group not receiving the new page
        cond_1 = '(group == "treatment" and landing_page != "new_page")'

        # control group not receiving the old page
        cond_2 = '(group != "treatment" and landing_page == "new_page")'

        # total
        df.query(cond_1 + ' or ' + cond_2).shape[0]
```

```
Out[6]: 3893
```

f. Do any of the rows have missing values?

```
In [7]: # info
        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 [8]: # treatment group receiving the new page
        cond_3 = '(group == "treatment" and landing_page == "new_page")'

        # control group receiving the old page
        cond_4 = '(group == "control" and landing_page == "old_page")'

        # total
        df2 = df.query(cond_3 + ' or ' + cond_4)

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

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]: # unique users in total
         df2.user_id.nunique()

Out[10]: 290584
```

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

```
In [11]: # repeated user
         df2.user_id[df2.user_id.duplicated() == True]
```

```
Out[11]: 2893    773192
         Name: user_id, dtype: int64
```

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

```
In [12]: # repeated user
         df.iloc[2893]
```

```
Out[12]: user_id                            773192
         timestamp       2017-01-14 02:55:59.590927
         group                            treatment
         landing_page                      new_page
         converted                                0
         Name: 2893, dtype: object
```

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

```
In [13]: # drop repeated
         df2 = df2.drop(2893)
         df2.info()
```

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

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 [14]: # overall proportion of conversion
         p_overall = df2.converted.mean()
         p_overall
```

```
Out[14]: 0.11959708724499628
```

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

```
In [15]: # control group proportion of conversion
         p_control = df2.query('group == "control"').converted.mean()
         p_control
```

```
Out[15]: 0.1203863045004612
```

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

```
In [16]: # treatment group proportion of conversion
         p_treatment = df2.query('group == "treatment"').converted.mean()
         p_treatment

Out[16]: 0.11880806551510564
```

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

```
In [17]: # probability of new page
         (df2.landing_page == "new_page").mean()

Out[17]: 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.

Answer

Almost half of the users recevied the new page. Only 11.88 percent of them got converted. This is actually quite similar to the conversion rate of the people who received the old page (12.04 percent). Because the conversion rates are so similar it seems that there is no evidence that one page is better than the other in terms of conversions.

End of answer

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 do you continue for it 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 the case where 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.

Answer

$$H_0 : p_{\text{old}} \geq p_{\text{new}}$$

$$H_1 : p_{\text{old}} < p_{\text{new}}$$

End of answer

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 [18]: # new page conversion rate under null
         p_new = df2.converted.mean()
         p_new
```

```
Out[18]: 0.11959708724499628
```

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

```
In [19]: # old page conversion rate under null
         p_old = p_new
         p_old
```

```
Out[19]: 0.11959708724499628
```

c. What is n_{new}?

```
In [20]: # number of new-page users
         n_new = df2.query('group == "treatment"').shape[0]
         n_new
```

```
Out[20]: 145310
```

d. What is n_{old}?

```
In [21]: # number of old-page users
         n_old = df2.query('group == "control"').shape[0]
         n_old
```

```
Out[21]: 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 [22]: # simulation
         # n_new transactions with rate p_new (under null)
         new_page_converted = np.random.choice(a=[0, 1],
                                               p=[1-p_new, p_new],
                                               size=n_new)
         new_page_converted
```

```
Out[22]: array([0, 0, 0, ..., 0, 0, 0])
```

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 [23]:
```
# simulation
# n_old transactions with rate p_old (under null)
old_page_converted = np.random.choice(a=[0, 1],
                                      p=[1-p_old, p_old],
                                      size=n_old)

old_page_converted
```

Out[23]:
```
array([0, 0, 0, ..., 0, 0, 0])
```

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

In [24]:
```
# sample proportion of new page conversion under null
p_new_sample = new_page_converted.mean()

# sample proportion of old page conversion under null
p_old_sample = old_page_converted.mean()

# difference
p_new_sample - p_old_sample
```

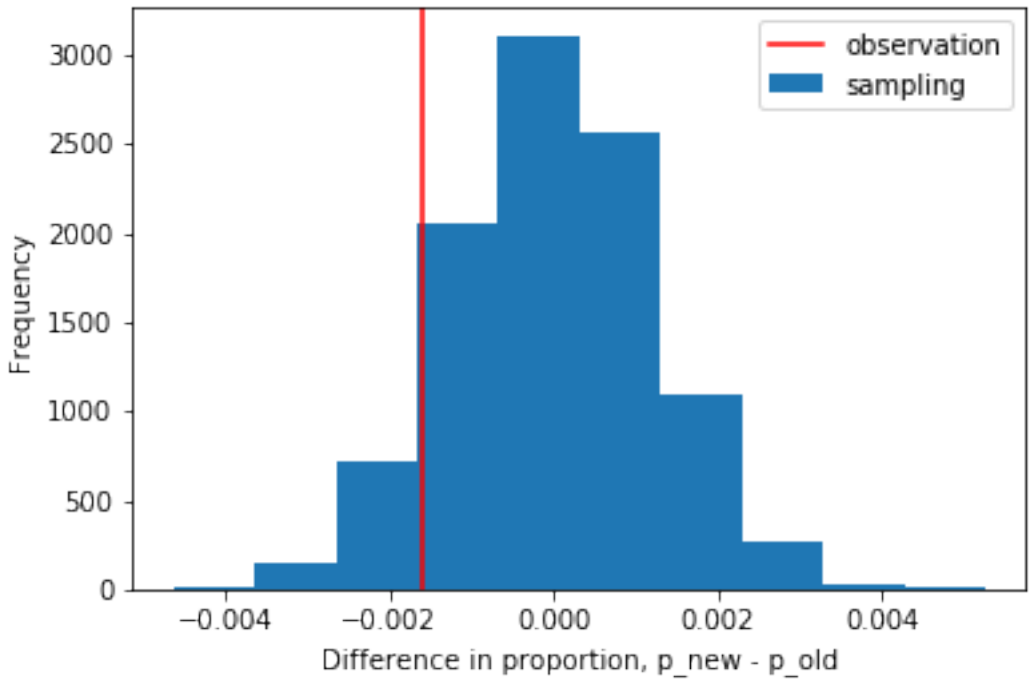
Out[24]:
```
0.00021812729857900726
```

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 [25]:
```
p_diffs = []

# simulation
# sampling distribution for sample proportion difference under null
for _ in range(int(1e4)):
    p_n_s = np.random.choice([0, 1], size=n_new, p=[1-p_new, p_new]).mean()
    p_o_s = np.random.choice([0, 1], size=n_old, p=[1-p_old, p_old]).mean()
    p_diffs.append(p_n_s - p_o_s)

# A much more implementation would be
# p_diffs = (np.random.binomial(n_new, p_new, 10000)/n_new
#            - np.random.binomial(n_old, p_old, 10000)/n_old)
```

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 [26]:
```
p_diffs = np.array(p_diffs)

# histogram
# sampling distribution for sample proportion difference under null
plt.hist(p_diffs, label='sampling')
plt.axvline(p_treatment-p_control, c='r', label='observation')
plt.xlabel('Difference in proportion, p_new - p_old')
plt.ylabel('Frequency')
plt.legend();
```



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

```
In [27]: # p-value
         (p_diffs > p_treatment - p_control).mean()
```

```
Out[27]: 0.90190000000000003
```

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?

Answer

In part **j** we calculated the probability under the null hypothesis of obtaining the observed statistic or one more extreme value in favor of the alternate hypothesis. By definition, this is the p-value!

We see that the p-vlaue is much larger than the allowed threshold of 0.05. It is not at all unlikely to obtain the observed value under the null hypothesis

$$H_0 : p_{\text{old}} \geq p_{\text{new}}.$$

Therefore, we fail to reject the null hypothesis that the new page is no better than the old page in terms of conversion.

End of answer

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 cell 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 [28]: import statsmodels.api as sm

         # old page conversions
         convert_old = df2.query('group == "control"').converted.sum()

         # new page conversions
         convert_new = df2.query('group == "treatment"').converted.sum()

         # old pages
         n_old = df2.query('group == "control"').shape[0]

         # new pages
         n_new = df2.query('group == "treatment"').shape[0]

         convert_old, convert_new, n_old, n_new
```

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

```
Out[28]: (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 [29]: # z test
         z_score, p_value = sm.stats.proportions_ztest(
             count = [convert_old, convert_new],
             nobs = [n_old, n_new],
             alternative='smaller')

         z_score, p_value
```

```
Out[29]: (1.3109241984234394, 0.90505831275902449)
```

```
In [30]: from scipy.stats import norm

         # significance of z-score
         norm.cdf(z_score)
```

```
Out[30]: 0.90505831275902449
```

```
In [31]: # critical z-score at 95% confidence
         norm.ppf(1-0.05)
```

```
Out[31]: 1.6448536269514722
```

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.**?

Answer

We see that the z-score is below the minimum acceptable score (at 95% confidence level) of 1.645, and similarly the p-value is much greater than the maximum acceptable value of 0.05. We therefore fail to reject the null hypothesis that the new page is no better than the old page for conversion.

End of answer

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?

Answer: 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 [32]: # add intercept
         df2['intercept'] = 1
         df2.head()
```

```
Out[32]:    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

            intercept
         0          1
         1          1
         2          1
         3          1
         4          1
```

```
In [33]: # dummy variables for landing page
         df2[['ab_page', 'drop_it']] = pd.get_dummies(df2['landing_page'])
         df2.head()
```

Out[33]:

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

In [34]:
```
# drop the unnecessary dummy column
df2.drop('drop_it', axis=1, inplace=True)
df2.head()
```

Out[34]:

	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 [35]:
```
# import the model
from statsmodels.api import Logit

# instantiate the model
model = Logit(df2['converted'], df2[['intercept', 'ab_page']])

# fit the model
results = model.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 [36]: # summary
         results.summary()

Out[36]: <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:                Fri, 15 Jun 2018   Pseudo R-squ.:               8.077e-06
         Time:                        05:35:33   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
         ==============================================================================
         """
```

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**?

Answer

The p-value for ab_page is 0.190. This is different from the value we found in **Part II.** We get two different p-values because the two tests are different.

In the current test, the null hypothesis is that the new page makes no difference for conversion ($H_0 : p_{\text{old}} = p_{\text{new}}$). The alternative hypothesis is that the new page makes a difference ($H_1 : p_{\text{old}} \neq p_{\text{new}}$), for better or for worse.

In **Part II**, on the other hand, the null hypothesis was that the new page makes no positive difference compared to the old page ($H_0 : p_{\text{old}} \geq p_{\text{new}}$). The alternative hypothesis is that the new page is better ($H_1 : p_{\text{old}} < p_{\text{new}}$).

End answer

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?

Answer

While doing statistical investigations, there is always a chance of Simpson's paradox. For example, from the above calculations we may conclude that the new page made no difference on conversion. It may so happen that there is a confounding variable that makes this conclusion

invalid. For the country data below, for example (and I am writing this before I have done the analysis), it is possible that the conversion rate is low in a certin group of countries and most of the treatment group belonged to this group. Then, it is possible that the conversion rate in each for the new page is higher even though the overall conversion rate is slightly lower (compared to the old page).

Even if the situation is not this extreme, is cannot be concluded that users in different countries respond the same way to the new page. We have to investigate.

There are of course disadvantages as well. We may have correlated variables and face collinearity or multicollinearity, which will affect the interpretability of the model.

End answer

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 [37]: # load country data
         df_countries = pd.read_csv('countries.csv')
         df_countries.head()
```

Out[37]:

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

```
In [38]: # add country data to previous data
         df2 = df2.join(df_countries.set_index('user_id'), on='user_id')
         df2.head()
```

Out[38]:

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

```
In [39]: # unique country values
         df2.country.unique()
```

```
Out[39]: array(['US', 'CA', 'UK'], dtype=object)
```

```
In [40]: # dummy variables for the country column
         df2[['CA', 'UK', 'US']] = pd.get_dummies(df2['country'])
         df2.head(10)
```

```
Out[40]:    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

            intercept  ab_page country  CA  UK  US
         0          1        0      US   0   0   1
         1          1        0      US   0   0   1
         2          1        1      US   0   0   1
         3          1        1      US   0   0   1
         4          1        0      US   0   0   1
         5          1        0      US   0   0   1
         6          1        1      CA   1   0   0
         7          1        0      US   0   0   1
         8          1        1      UK   0   1   0
         9          1        1      CA   1   0   0
```

```
In [41]: # instantiate the model
         model_country = Logit(df2['converted'],
                               df2[['intercept', 'CA', 'UK']])

         # fit the model
         results_country = model_country.fit()

         # summary
         results_country.summary()
```

```
Optimization terminated successfully.
         Current function value: 0.366116
         Iterations 6
```

```
Out[41]: <class 'statsmodels.iolib.summary.Summary'>
         """
                                 Logit Regression Results
         ==============================================================================
```

```
Dep. Variable:              converted   No. Observations:              290584
Model:                          Logit   Df Residuals:                  290581
Method:                           MLE   Df Model:                           2
Date:                Fri, 15 Jun 2018   Pseudo R-squ.:               1.521e-05
Time:                        05:35:34   Log-Likelihood:           -1.0639e+05
converged:                       True   LL-Null:                  -1.0639e+05
                                        LLR p-value:                    0.1984
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
intercept     -1.9967      0.007   -292.314      0.000      -2.010      -1.983
CA            -0.0408      0.027     -1.518      0.129      -0.093       0.012
UK             0.0099      0.013      0.746      0.456      -0.016       0.036
==============================================================================
"""
```

Interpretation

It does not seem like the countries have significant impact on conversion. A person in Canada is only 4 percent less likely to convert whereas a person in United Kingdom is about one percent more likely to convert. This lack of significance is evident from p-values as well. In each case (Canada and United Kingdom) the p-value is high enough that we cannot discard the possibility that the differences are purely due to chance.

End interpretation

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.

No interactions

```
In [42]: model_w_country = sm.Logit(df2['converted'],
                                   df2[['intercept', 'ab_page', 'CA', 'UK']])
         results_w_country = model_w_country.fit()
         results_w_country.summary()

Optimization terminated successfully.
         Current function value: 0.366113
         Iterations 6


Out[42]: <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:                Fri, 15 Jun 2018   Pseudo R-squ.:               2.323e-05
```

```
Time:                         05:35:35   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
ab_page       -0.0149      0.011     -1.307      0.191      -0.037       0.007
CA            -0.0408      0.027     -1.516      0.130      -0.093       0.012
UK             0.0099      0.013      0.743      0.457      -0.016       0.036
==============================================================================
"""
```

With interactions

In [43]:
```
# treatment group in UK
df2['ab_page_and_UK'] = df2['ab_page']*df2['UK']

# treatment group in Canada
df2['ab_page_and_CA'] = df2['ab_page']*df2['CA']

df2.head(10)
```

Out[43]:

	user_id	timestamp	group	landing_page	converted	intercept	ab_page	country	CA	UK	US	ab_page_and_UK	ab_page_and_CA
0	851104	2017-01-21 22:11:48.556739	control	old_page	0	1	0	US	0	0	1	0	0
1	804228	2017-01-12 08:01:45.159739	control	old_page	0	1	0	US	0	0	1	0	0
2	661590	2017-01-11 16:55:06.154213	treatment	new_page	0	1	1	US	0	0	1	0	0
3	853541	2017-01-08 18:28:03.143765	treatment	new_page	0	1	1	US	0	0	1	0	0
4	864975	2017-01-21 01:52:26.210827	control	old_page	1	1	0	US	0	0	1	0	0
5	936923	2017-01-10 15:20:49.083499	control	old_page	0	1	0	US	0	0	1	0	0
6	679687	2017-01-19 03:26:46.940749	treatment	new_page	1	1	1	CA	1	0	0	0	1
7	719014	2017-01-17 01:48:29.539573	control	old_page	0	1	0	US	0	0	1	0	0
8	817355	2017-01-04 17:58:08.979471	treatment	new_page	1	1	1	UK	0	1	0	1	0
9	839785	2017-01-15 18:11:06.610965	treatment	new_page	1	1	1	CA	1	0	0	0	1

In [44]:
```
# instantiate the model
model_w_int = Logit(df2['converted'],
```

```
                                    df2[['intercept', 'ab_page', 'CA', 'UK',
                                        'ab_page_and_CA', 'ab_page_and_UK']])

        # fit the model
        results_w_int = model_w_int.fit()

        # summary
        results_w_int.summary()

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

Out[44]:

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                           Logit Regression Results
==============================================================================
Dep. Variable:              converted   No. Observations:               290584
Model:                          Logit   Df Residuals:                   290578
Method:                           MLE   Df Model:                            5
Date:                Fri, 15 Jun 2018   Pseudo R-squ.:               3.482e-05
Time:                        05:35:36   Log-Likelihood:            -1.0639e+05
converged:                       True   LL-Null:                   -1.0639e+05
                                        LLR p-value:                    0.1920
===============================================================================================
                     coef    std err          z      P>|z|      [0.025      0.975]
-----------------------------------------------------------------------------------------------
intercept         -1.9865      0.010   -206.344      0.000      -2.005      -1.968
ab_page           -0.0206      0.014     -1.505      0.132      -0.047       0.006
CA                -0.0175      0.038     -0.465      0.642      -0.091       0.056
UK                -0.0057      0.019     -0.306      0.760      -0.043       0.031
ab_page_and_CA    -0.0469      0.054     -0.872      0.383      -0.152       0.059
ab_page_and_UK     0.0314      0.027      1.181      0.238      -0.021       0.084
===============================================================================================
"""
```

Interpretation

It does not seem like the interactions have any effect. Standard errors are high and so are the p-values. This is on top of lost interpretability of the model due to interactions.

End interpretation

Conclusions

We see that the new page did not have any statistical significance in terms of conversion. In fact it was slightly worse, though the difference is not significant. It also did not matter which country the user belongs to.

On the face of it, the above analyses seem to be a strong case for the rejection of the new page. Not necessarily. Maybe the new page is part of a broader initiative to redesign the infrastructure. Maybe it makes the webpage load much faster. Maybe the new page is based on a new and

relevant language, and is much more customizable. If any of these is the case, one should perhaps switch to the new page. After all, it was not statistically worse than the old page!

```
In [46]: from subprocess import call
         call(['python', '-m', 'nbconvert', 'Analyze_ab_test_results_notebook.ipynb'])
```

```
Out[46]: 0
```