Analyze_ab_test_results_notebook

March 30, 2021

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
- Part I - Probability
- Part II - A/B Test
- Part III - Regression

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.

[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:

[2]:
```
df = pd.read_csv("ab_data.csv")
df.head()
```

[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.

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

[3]:
```
(294478, 5)
```

c. The number of unique users in the dataset.

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

[4]:
```
290584
```

d. The proportion of users converted.

[5]:
```
df.query('converted == 1').shape[0] / df.shape[0]
```

[5]:
```
0.11965919355605512
```

[6]:
```
df.query('converted == 1').user_id.nunique() / df.user_id.nunique()
```

[6]:
```
0.12104245244060237
```

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

[7]:
```
df.query('group == "treatment" and landing_page != "new_page"').shape[0] + df.
 ↪query('group == "control" and landing_page == "new_page"').shape[0]
```

[7]:
```
3893
```

f. Do any of the rows have missing values?

[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** 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**.

[9]:
```
df_tempa = df.query('group == "treatment" and landing_page == "new_page"')
df_tempb = df.query('group == "control" and landing_page == "old_page"')
df2 = pd.DataFrame()
df2 = df2.append([df_tempa, df_tempb])
df2.shape
```

[9]:
```
(290585, 5)
```

[10]:
```
# Double Check all of the correct rows were removed - this should be 0
df2[((df2['group'] == 'treatment') == (df2['landing_page'] == 'new_page')) ==␣
 ↪False].shape[0]
```

[10]:
```
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**?

[11]:
```
df2.user_id.nunique()
```

[11]:
```
290584
```

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

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

[12]:
```
2893    773192
Name: user_id, dtype: int64
```

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

[13]:
```
df2[df2['user_id'].duplicated(keep=False)]
```

[13]:

	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**.

[14]:
```
df2.drop_duplicates(subset='user_id', inplace=True)
df2.shape
```

[14]:
```
(290584, 5)
```

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?

[15]:
```
df2.converted.mean()
```

[15]:
```
0.11959708724499628
```

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

[16]:
```
df2.query('group == "control"').converted.mean()
```

[16]:
```
0.1203863045004612
```

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

[17]:
```
df2.query('group == "treatment"').converted.mean()
```

[17]:
```
0.11880806551510564
```

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

[18]:
```
df2.query('landing_page == "new_page"').shape[0] / df2.shape[0]
```

[18]:
```
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.

It appears that the new page's conversion is no better than the old page's conversion. Therefore at this point there is no sufficient evidence to reject the old page (null hypothesis).

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.

$$H_0 : p_{new} - p_{old} \leq 0$$

$$H_1 : p_{new} - p_{old} > 0$$

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.

[19]:
```
df2.head(1)
```

[19]:

	user_id	timestamp	group	landing_page	converted
2	661590	2017-01-11 16:55:06.154213	treatment	new_page	0

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

[20]:
```
df2.converted.mean()
```

[20]:
```
0.11959708724499628
```

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

[21]:
```
df2.converted.mean()
```

[21]:
```
0.11959708724499628
```

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

[22]:
```
n_new = df2.query('group == "treatment"').shape[0]
n_new
```

[22]:
```
145310
```

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

[23]:
```
n_old = df2.query('group == "control"').shape[0]
n_old
```

[23]: 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**.

[24]:
```
new_page_converted = np.random.choice([0, 1], n_new, p=[1-df2.converted.mean(),␣
↪df2.converted.mean()])
new_page_converted.mean()
```

[24]: 0.12054228889959397

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**.

[25]:
```
old_page_converted = np.random.choice([0, 1], n_old, p=[1-df2.converted.mean(),␣
↪df2.converted.mean()])
old_page_converted.mean()
```

[25]: 0.11931935514957942

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

[26]:
```
new_page_converted.mean() - old_page_converted.mean()
```

[26]: 0.001222933750014546

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**.

[27]:
```
# Setting single probability value for null testing purpose
p = df2.converted.mean()

# Simulating binomial distribution taking given p into account
newp_conv = np.random.binomial(n_new, p, int(1e4))/n_new
oldp_conv = np.random.binomial(n_old, p, int(1e4))/n_old

# Calculating mean conversion differences
p_diffs = newp_conv - oldp_conv
p_diffs.mean()
```

[27]: 1.2451989387239457e-05

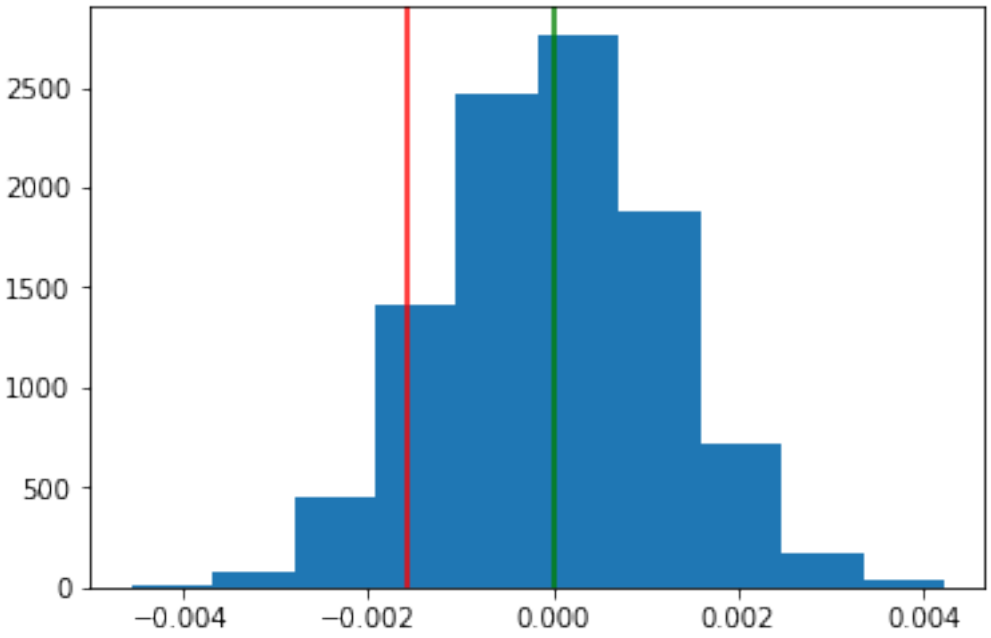
i. Plot a histogram of the **p_diffs**. Does this plot look like what you expected? Use the matching problem in the classroom to assure you fully understand what was computed here.

[28]:
```
# Calculating observed difference in converesion means
# for marking it in histogram and for future calculations
obs_diff = df2.query('group == "treatment"').converted.mean() - df2.
↪query('group == "control"').converted.mean()
```

```
# Displaying observed difference and standard deviation for future reference
obs_diff, p_diffs.std()
```

[28]: (-0.0015782389853555567, 0.0012032803783433657)

[29]:
```
# Plotting the histogram
plt.hist(p_diffs)
plt.axvline(obs_diff, color='r')
plt.axvline(p_diffs.mean(), color='g');
```



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

[30]:
```
pval1 = (p_diffs > obs_diff).mean()
pval1
```

[30]: 0.90600000000000003

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?

Part j. outcome is a **p-value**.
P-value is the probability of observing a statistic (here: mean difference in conversion rate) if the null hypothesis is true.

In this case, a **very high p-value of roughly 0.91** (meaning 91% probability) suggests we should definitely **not reject the null hypothesis**.

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.

[31]:
```
df2.head(1)
```

[31]:
```
   user_id                   timestamp      group landing_page  converted
2   661590  2017-01-11 16:55:06.154213  treatment     new_page          0
```

[32]:
```
convert_old = df2.query('group == "control"').converted
```

[33]:
```
# importing statsmodels
import statsmodels.api as sm

# Assigning values for z-test: old page and new page convertion proportions
convert_old = df2.query('group == "control" and converted == 1').shape[0]
convert_new = df2.query('group == "treatment" and converted == 1').shape[0]
n_old = df2.query('group == "control"').shape[0]
n_new = df2.query('group == "treatment"').shape[0]
```

```
/opt/conda/lib/python3.6/site-packages/statsmodels/compat/pandas.py:56:
FutureWarning: The pandas.core.datetools module is deprecated and will be
removed in a future version. Please use the pandas.tseries module instead.
  from pandas.core import datetools
```

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

[34]:
```
from statsmodels.stats.proportion import proportions_ztest

zscore, pval2 = proportions_ztest([convert_new, convert_old], [n_new, n_old],␣
 ↪alternative='larger')
zscore, pval2
```

[34]:
```
(-1.3109241984234394, 0.90505831275902449)
```

[35]:
```
# Compare ztest results to earlier calculations
print(zscore * p_diffs.std() - obs_diff )
print(pval2 - pval1)
```

```
8.29619897127e-07
-0.000941687240976
```

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 (stat) of -1.31** tells that the observed statistic is **1.31 standard deviations smaller than the mean** - in this case we are testing the null hypothesis, so the mean is 0.

The **p-value (pval) denotes probability for the statistic or a more extreme value to be observed if the null hypothesis is true**.

The values correspond with those in parts j. and k., therefore again we **fail to reject the null hypothesis**.

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

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**.

[36]:
```
import statsmodels.api as sm

df2['intercept'] = 1
```

[37]:
```
df2.head(1)
```

[37]:
```
   user_id                   timestamp      group landing_page  converted  \
2   661590  2017-01-11 16:55:06.154213  treatment     new_page          0

   intercept
2          1
```

[38]:
```
df2['ab_page'] = 0
df2.loc[df2.group == 'treatment', 'ab_page'] = 1
```

[39]:
```
df2.head(1)
```

[39]:
```
   user_id                   timestamp      group landing_page  converted  \
2   661590  2017-01-11 16:55:06.154213  treatment     new_page          0

   intercept  ab_page
2          1        1
```

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.

[40]:
```
log_mdl = sm.Logit(df2.converted, df2[['intercept', 'ab_page']])
results = log_mdl.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.

[41]:
```
# Fixing deprecated funcion
from scipy import stats
stats.chisqprob = lambda chisq, df: stats.chi2.sf(chisq, df)

# Showing results
results.summary()
```

[41]:
```
<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, 19 Mar 2021   Pseudo R-squ.:               8.077e-06
Time:                        22:15:20   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 **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**?

P-value associated with ab_page is **0.19**.
It differs from p-values in Part II because in this case the p-value comes from a two-tailed test. That is here, this is a **probability that the observed statistic** - the difference in means - **is not equal to zero**.

With p-value well over 5% (.05), version of the page does **not seem statistically significant** in relation to the conversion rate.

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?

In this particular case introducing other factors into the regression model makes much sense simply **because we haven't yet found the answer to the original question**. That is, we can't conclude whether the new page is better than the old one.

Potential problems include: - R-squared value becomes less useful, - Multicollinearity (when explanatory variables are related to each other), - A linear relationship may not exist at all.

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.

[42]:
```
df_ctr = pd.read_csv("countries.csv")
df_ctr.head(1)
```

[42]:
```
   user_id country
0   834778      UK
```

[43]:
```
print(df_ctr.country.nunique())
print(df_ctr.country.unique())
```

```
3
['UK' 'US' 'CA']
```

[44]:
```
# Joining dataframes
df2 = df2.join(df_ctr.set_index('user_id'), on='user_id')
df2.head(1)
```

[44]:
```
   user_id                   timestamp      group landing_page  converted  \
2   661590  2017-01-11 16:55:06.154213  treatment     new_page          0

   intercept  ab_page country
2          1        1      US
```

[45]:
```
# Creating dummy columns for countries
df2[['CA', 'UK', 'US']] = pd.get_dummies(df2.country)
```

[46]:
```
# Verifying
df2.head()
```

[46]:
```
   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

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

[47]:
```
# Fitting a model and displaying summary
log_mdl2 = sm.Logit(df2.converted, df2[['intercept', 'ab_page', 'CA', 'UK']])
results2 = log_mdl2.fit()
results2.summary()
```

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

[47]:
```
<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, 19 Mar 2021   Pseudo R-squ.:               2.323e-05
Time:                        22:15:21   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
==============================================================================
"""
```

[48]:
```
# Exponentiating coefficients
np.exp(-0.0149), np.exp(-0.0408), np.exp(0.0099)
```

[48]:
```
(0.9852104557227469, 0.96002111497165088, 1.0099491671175422)
```

The model suggests there is **no statistically significant impact of user's country** in relation to conversion rate. Values of exponentiated coefficients being **close to 1** means that with a change in country or page version, conversion is roughly **one times more likely**, holding all else constant.

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 are 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.

[49]:
```
# Creating interaction columns
df2['ab_page_CA'] = df2.ab_page * df2.US
df2['ab_page_UK'] = df2.ab_page * df2.UK
```

[50]:
```
df2.head(3)
```

[50]:

	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	

	intercept	ab_page	country	CA	UK	US	ab_page_CA	ab_page_UK
2	1	1	US	0	0	1	1	0
3	1	1	US	0	0	1	1	0
6	1	1	CA	1	0	0	0	0

[51]:
```
log_mdl3 = sm.Logit(df2.converted, df2[['intercept', 'ab_page', 'CA', 'UK',␣
↪'ab_page_CA', 'ab_page_UK']])
results3 = log_mdl3.fit()
results3.summary()
```

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

[51]:
```
<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, 19 Mar 2021   Pseudo R-squ.:               3.482e-05
Time:                        22:15:22   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       -0.0674      0.052     -1.297      0.195      -0.169       0.034
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_CA     0.0469      0.054      0.872      0.383      -0.059       0.152
ab_page_UK     0.0783      0.057      1.378      0.168      -0.033       0.190
==============================================================================
"""
```

Adding page-country interactions to the model provides **lower p-values** compared to when considering country influence independently (ab_page_CA, ab_page_UK).
However, these p-values are still **higher than the .05 threshold of significance**.

Therefore, **using all above methods we can conclude the same**:
There is **no statistical nor practical significance in rejecting the null hypothesis and deploying the new page**, based on the assessed data.
This might be subject to change if for example users are given more time for testing and getting accustomed with the new page layout.

Based on the above analysis I would **not switch to the new page**.

Finishing Up

> Congratulations! You have reached the end of the A/B Test Results project! 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!

[52]:
```
from subprocess import call
call(['python', '-m', 'nbconvert', 'Analyze_ab_test_results_notebook.ipynb'])
```

[52]: 0