Analyze_ab_test_results_notebook

November 23, 2021

1 Analyze A/B Test Results

This project will assure you have mastered the subjects covered in the statistics lessons. We have organized the current notebook into the following sections:

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

Specific programming tasks are marked with a **ToDo** tag.

Introduction

A/B tests are very commonly performed by data analysts and data scientists. 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 webpage, - Keep the old webpage, or - Perhaps run the experiment longer to make their decision.

Each **ToDo** task below has an associated quiz present in the classroom. Though the classroom quizzes are **not necessary** to complete the project, they help ensure you are on the right track as you work through the project, and you can feel more confident in your final submission meeting the rubric specification.

Part I - Probability

To get started, let's import our libraries.

```
In [1]: import pandas as pd
        import numpy as np
        import datetime as dt
        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)
```

1.0.1 ToDo 1.1

Now, read in the `ab_data.csv` data. Store it in `df`.

a. Read in the dataset from the `ab_data.csv` file and take a look at the top few rows here:

```
In [2]: # importing 'ab_data.csv' data file
        df = pd.read_csv ("ab_data.csv")
        # Display the top five rows from the loaded data file
        df.head()
```

Out[2]:

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

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

```
In [3]: # Display the number of rows
        df.shape[0]
```

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

c. The number of unique users in the dataset.

```
In [4]: # Display the number of unique users
        df['user_id'].nunique()
```

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

d. The proportion of users converted.

```
In [5]: # The proportion of users converted
        df['converted'].mean()
        # Alternative code
        df['converted'].sum()/df.shape[0]
```

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

e. The number of times when the "group" is `treatment` but "landing_page" is not a `new_page`.

```
In [6]: # Display the number of times the "group" is treatment but "landing_page" is not a new_p
        df.query('group == "treatment" & landing_page != "new_page"').shape[0]
```

```
Out[6]: 1965
```

f. Do any of the rows have missing values?

```
In [7]: # Display the number of rows having null values
        df.shape[0] - df.dropna().shape[0]
```

```
Out[7]: 0
```

No rows with missing data in the dataset

1.0.2 ToDo 1.2

The rows where `treatment` does not match with `new_page` or `control` does not match with `old_page`, we cannot be sure if such rows truly received the new or old wepage.

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]: # Remove the inaccurate rows where the 'group' and 'landing_page' columns don't match, a
        df2 = df.drop(df.query('group == "treatment" & landing_page != "new_page" | group == "co
        df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 290585 entries, 0 to 294477
Data columns (total 5 columns):
user_id         290585 non-null int64
timestamp       290585 non-null object
group           290585 non-null object
landing_page    290585 non-null object
converted       290585 non-null int64
dtypes: int64(2), object(3)
memory usage: 13.3+ MB
```

```
In [9]: # Double Check all of the incorrect rows were removed from df2 -
        # Output of the statement below should be 0
        df2[((df2['group'] == 'treatment') == (df2['landing_page'] == 'new_page')) == False].sha
```

```
Out[9]: 0
```

1.0.3 ToDo 1.3

Use **df2** and the cells below to answer questions for **Part 1.3**.

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

```
In [10]: # The number of unique users in df2 from 'user_id' column
         df2['user_id'].nunique()
```

```
Out[10]: 290584
```

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

```
In [11]: # Display the duplicated users from 'user_id' column
         df2[df2['user_id'].duplicated()]['user_id']
```

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

c. Display the rows for the duplicate **user_id**?

```
In [12]: # Display a row with duplicated 'user_id' information
         df2[df2['user_id'].duplicated()]
```

Out[12]:

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

d. Remove **one** of the rows with a duplicate **user_id**, from the **df2** dataframe.

```
In [13]: # Remove one of the rows with a duplicate user_id..
         # Hint: The dataframe.drop_duplicates() may not work in this case because the rows with
         df2 = df2.drop(df2[df2.duplicated(['user_id'])].index)
         # Check again if the row with a duplicate user_id is deleted or not
         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
```

1.0.4 ToDo 1.4

Use **df2** and the cells below to answer questions for **Part 1.4**.

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

```
In [14]: # Display the probability of an individual converting
         #This is also the overall "converted" success rate in the population (p-population).
         conversion_rate = df2['converted'].mean()
         conversion_rate
```

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

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

```
In [15]: # Display the probability of an individual converting from the "control" group
         control_propability = df2.query('group == "control" & converted == 1').shape[0] / df2.q
         control_propability
```

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

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

```
In [16]: # Display the probability of an individual converting from the "treatment" group
         treatment_propability = df2.query('group == "treatment" & converted == 1').shape[0] / d
         treatment_propability
```

```
Out[16]: 0.11880806551510564

In [17]: # Calculate the actual difference (obs_diff) between the conversion rates for the two g
         obs_diff = treatment_propability - control_propability
         obs_diff

Out[17]: -0.0015782389853555567
```

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

```
In [18]: # Display the probability of an individual received the new page
         new_page_propability = df2.query('landing_page == "new_page"').count()[0] / df.shape[0]
         new_page_propability

Out[18]: 0.49344942576355449
```

e. Consider your results from parts (a) through (d) above, and explain below whether the new `treatment` group users lead to more conversions.

The difference in **conversion rate** between the `control` and the `treatment` groups is **15%**; Such a minor difference in the conversion rate does not indicate any sufficient evidence to suggest: The new treatment page leads to more conversions.

Part II - A/B Test

Since a timestamp is associated with each event, you could run a hypothesis test continuously as long as you observe the events.

However, then the hard questions would be: - 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.

1.0.5 ToDo 2.1

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 be your null and alternative hypotheses (H_0 and H_1)?

You can state your hypothesis in terms of words or in terms of p_{old} and p_{new}, which are the "converted" probability (or rate) for the old and new pages respectively.

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

1.0.6 ToDo 2.2 - Null Hypothesis H_0 Testing

Under the null hypothesis H_0, assume that p_{new} and p_{old} are equal. Furthermore, assume that p_{new} and p_{old} both are equal to the **converted** success rate in the `df2` data regardless of the page. So, our assumption is:

$p_{new} = p_{old} = p_{population}$

Use the cells below to provide the necessary parts of this simulation.

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

```
In [19]: conversion_rate
```

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

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

```
In [20]: conversion_rate

Out[20]: 0.11959708724499628
```

c. What is n_{new}, the number of individuals in the treatment group? *Hint*: The treatment group users are shown the new page.

```
In [21]: n_new = df2.query('group == "treatment"').shape[0]
         n_new

Out[21]: 145310
```

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

```
In [22]: n_old = df2.query('group == "control"').shape[0]
         n_old

Out[22]: 145274
```

e. Simulate Sample for the `treatment` Group Simulate n_{new} transactions with a conversion rate of p_{new} under the null hypothesis. Store these n_{new} 1's and 0's in the `new_page_converted` numpy array.

```
In [23]: # Simulate a Sample for the treatment Group
         # new_page_converted = np.random.choice(2, n_new, replace = True, p=[(1-conversion_rate
         new_page_converted = np.random.choice(2, n_new, conversion_rate)
         new_page_converted

Out[23]: array([0, 1, 1, ..., 1, 0, 0])
```

f. Simulate Sample for the `control` Group Simulate n_{old} transactions with a conversion rate of p_{old} under the null hypothesis. Store these n_{old} 1's and 0's in the `old_page_converted` numpy array.

```
In [24]: # Simulate a Sample for the control Group
         old_page_converted = np.random.choice(2, n_old, conversion_rate)
         old_page_converted

Out[24]: array([1, 0, 0, ..., 0, 1, 0])
```

g. Find the difference in the "converted" probability $(p'_{new}$ - $p'_{old})$ for your simulated samples from the parts (e) and (f) above.

```
In [25]: p_new = new_page_converted.mean()
         p_old = old_page_converted.mean()
         converted_probability_diff = p_new - p_old
         converted_probability_diff
```

```
Out[25]: -0.00293901927266077
```

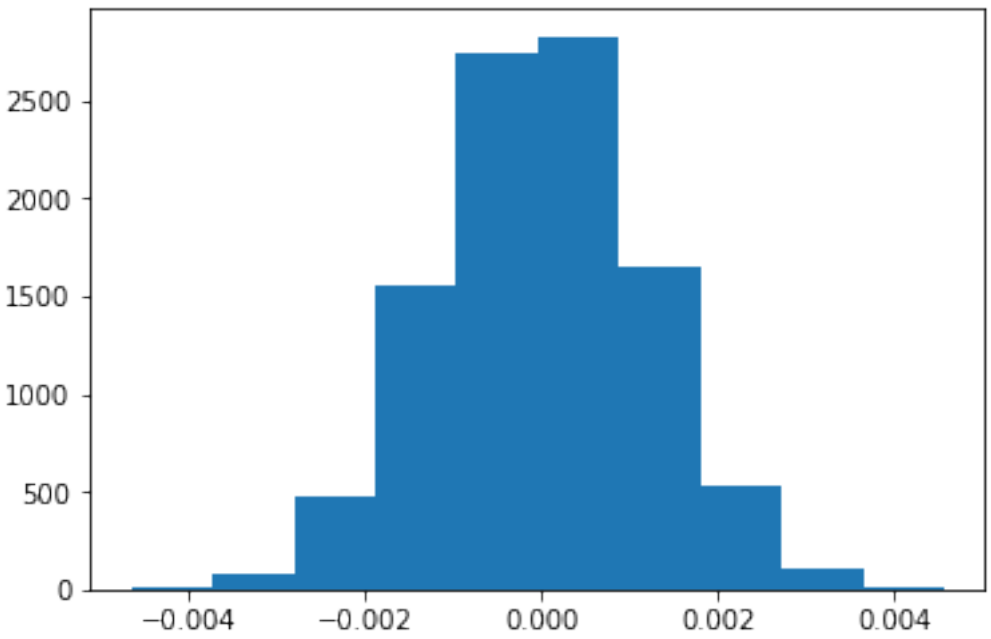
h. Sampling distribution Re-create `new_page_converted` and `old_page_converted` and find the $(p'_{new} - p'_{old})$ value 10,000 times using the same simulation process you used in parts (a) through (g) above. Store all $(p'_{new} - p'_{old})$ values in a NumPy array called `p_diffs`.

```
In [26]: # Sampling distribution
         p_diffs = []
         p_new = conversion_rate
         p_old = conversion_rate
         new_simulation = np.random.binomial(n_new, p_new, 10000)/n_new
         old_simulation = np.random.binomial(n_old, p_old, 10000)/n_old
         p_diffs = new_simulation - old_simulation
         p_diffs
```

```
Out[26]: array([ -1.11698013e-03,  -1.59885551e-03,   3.69532869e-04, ...,
                 -9.82889201e-05,  -1.57145776e-03,  -7.45695087e-04])
```

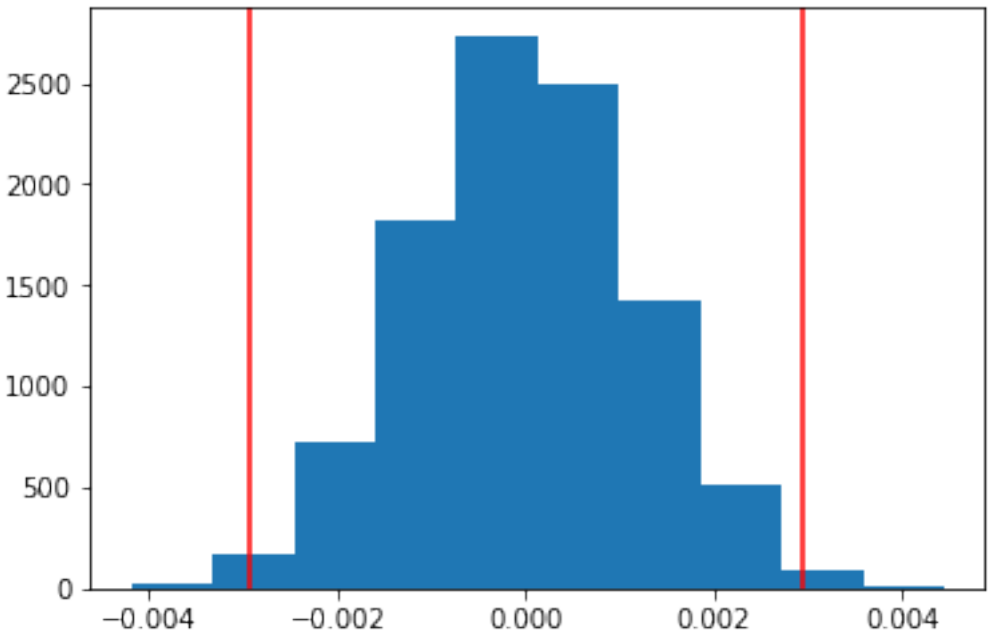
i. Histogram Plot a histogram of the **p_diffs**. Does this plot look like what you expected? Use the matching problem in the classroom to assure you fully understand what was computed here. Also, use `plt.axvline()` method to mark the actual difference observed in the `df2` data (recall `obs_diff`), in the chart.

```
In [27]: plt.hist(p_diffs)
         plt.show()
```



```
In [28]: h_null = np.random.normal(0, np.std(p_diffs),10000)

         plt.hist(h_null);
         plt.axvline(converted_probability_diff, color = 'red');
         plt.axvline(-converted_probability_diff, color = 'red');
```



j. What proportion of the **p_diffs** are greater than the actual difference observed in the `df2` data?

```
In [29]: (p_diffs > obs_diff).mean()
```

```
Out[29]: 0.90620000000000001
```

k. Please explain in words what you have just computed in part **j** above.
- What is this value called in scientific studies?
- What does this value signify in terms of whether or not there is a difference between the new and old pages? *Hint*: Compare the value above with the "Type I error rate (0.05)".

- What we computed in point **(j)** was the `p-value`, which is the probability that we will observe this statistic, in the case that the null hypnothesis is true.
- Since the `p-value` is higher than the **Type I error rate** of (5%), **we fail to reject the null hypothesis** and the treatment page does not have higher conversion rates than the control page on a statistical basis.

l. Using Built-in Methods for Hypothesis Testing 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 walk-through of the ideas that are critical to correctly thinking about statistical significance.

```
In [30]: import statsmodels.api as sm
         # number of conversions with the old_page
         convert_old = df.query('group == "control" & converted == 1').shape[0]
         # number of conversions with the new_page
         convert_new = df2.query('group == "treatment" & converted == 1').shape[0]
         # number of individuals who were shown the old_page
         n_old = df2.query("landing_page == 'old_page'").shape[0]
         # number of individuals who received new_page
         n_new = df2.query("landing_page == 'new_page'").shape[0]
         # Testing our results
         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[30]: (17723, 17264, 145274, 145310)
```

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

```
In [31]: import statsmodels.api as sm
         # ToDo: Complete the sm.stats.proportions_ztest() method arguments
         z_score, p_value = sm.stats.proportions_ztest([convert_new, convert_old], [n_new, n_old
         z_score, p_value
```

```
Out[31]: (-2.6411875940931551, 0.99586920197633411)
```

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` we computed from the test statistic suggests that the conversion rates for both old and new pages are not statistically different from one another, the `p-value` (0.09) still larger than the **type I error rate** (0.05) which also affirms **not rejecting the null hypothesis**.

Part III - A regression approach

1.0.7 ToDo 3.1

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 in the `df2` data is either a conversion or no conversion, what type of regression should you be performing in this case?

A `logistic regression` since we are looking at *binary variables*.

b. The goal is to use **statsmodels** library to fit the regression model you specified in part **a.** above to see if there is a significant difference in conversion based on the page-type a customer receives. However, you first need to create the following two columns in the `df2` dataframe: 1. `intercept` - It should be `1` in the entire column. 2. `ab_page` - It's a dummy variable column, having a value `1` when an individual receives the **treatment**, otherwise `0`.

```
In [32]: df2['intercept'] = 1
         df2['ab_page'] = pd.get_dummies(df2['group'])['treatment']
         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  ab_page
         0          1        0
         1          1        0
         2          1        1
         3          1        1
         4          1        0
```

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

```
In [33]: my_reg_model = sm.Logit(df2['converted'], df2[['intercept', 'ab_page']])
         result = my_reg_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 [34]: result.summary2()

Out[34]: <class 'statsmodels.iolib.summary2.Summary'>
         """
                                  Results: Logit
         =================================================================
         Model:              Logit            No. Iterations:   6.0000
         Dependent Variable: converted        Pseudo R-squared: 0.000
         Date:               2021-11-23 18:58 AIC:              212780.3502
         No. Observations:   290584           BIC:              212801.5095
         Df Model:           1                Log-Likelihood:   -1.0639e+05
         Df Residuals:       290582           LL-Null:          -1.0639e+05
         Converged:          1.0000           Scale:            1.0000
         -----------------------------------------------------------------
                       Coef.   Std.Err.      z      P>|z|    [0.025   0.975]
         -----------------------------------------------------------------
         intercept    -1.9888    0.0081  -246.6690  0.0000  -2.0046  -1.9730
         ab_page      -0.0150    0.0114    -1.3109  0.1899  -0.0374   0.0074
         =================================================================

         """
```

```
In [35]: np.exp(result.params)

Out[35]: intercept    0.136863
         ab_page      0.985123
         dtype: float64

In [36]: 1/np.exp(result.params)

Out[36]: intercept    7.306593
         ab_page      1.015102
         dtype: float64
```

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

- Both cases `p-value` are higher than the accepted **Type I error rate (0.05)**, the results do not support the alternative hypothesis sufficiently.
- The `p-value` is different in **part II (0.91)** from **part III (0.19)** because of using different null and alternative hypothesis here. H_0 : p_{new} - p_{old} = 0 H_1 : p_{new} - p_{old} != 0

f. Now, you are considering other things that might influence whether or not an individual converts. Discuss why it is a good idea to consider other factors to add into your regression model. Are there any disadvantages to adding additional terms into your regression model?

- It is a good idea to incorporate more factors that could potintially influence the conversion rate into the model, like `users` **(old & new)**, this data includes a single factor influencing the conversion rate `page type`.
- The disadvantages comes from the data itself, using incomplete data leads to erroneous conclusions.

g. Adding countries Now along with testing if the conversion rate changes for different pages, also add an effect based on which country a user lives in.

1. You will need to read in the **countries.csv** dataset and merge together your `df2` datasets on the appropriate rows. You call the resulting dataframe `df_merged`. Here are the docs for joining tables.

2. Does it appear that country had an impact on conversion? To answer this question, consider the three unique values, `['UK', 'US', 'CA']`, in the `country` column. Create dummy variables for these country columns.

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

```
In [37]: # Reading the countries.csv and viewing the first 5 rows of data
         countries = pd.read_csv("countries.csv")
         countries.head()

Out[37]:    user_id country
         0   834778      UK
         1   928468      US
         2   822059      UK
         3   711597      UK
         4   710616      UK
```

In [38]:
```
# Joining countries and df2 dataframes into df_merged and viewing the first 5 rows of d
df_merged = countries.merge(df2)
df_merged.head()
```

Out[38]:

	user_id	country	timestamp	group	landing_page	converted	intercept	ab_page
0	834778	UK	2017-01-14 23:08:43.304998	control	old_page	0	1	0
1	928468	US	2017-01-23 14:44:16.387854	treatment	new_page	0	1	1
2	822059	UK	2017-01-16 14:04:14.719771	treatment	new_page	1	1	1
3	711597	UK	2017-01-22 03:14:24.763511	control	old_page	0	1	0
4	710616	UK	2017-01-16 13:14:44.000513	treatment	new_page	0	1	1

In [39]:
```
# Create the necessary dummy variables
df_merged[['UK','US','CA']] = pd.get_dummies(df_merged['country'])
df_merged.head()
```

Out[39]:

	user_id	country	timestamp	group	landing_page	converted	intercept	ab_page	UK	US	CA
0	834778	UK	2017-01-14 23:08:43.304998	control	old_page	0	1	0	0	1	0
1	928468	US	2017-01-23 14:44:16.387854	treatment	new_page	0	1	1	0	0	1
2	822059	UK	2017-01-16 14:04:14.719771	treatment	new_page	1	1	1	0	1	0
3	711597	UK	2017-01-22 03:14:24.763511	control	old_page	0	1	0	0	1	0
4	710616	UK	2017-01-16 13:14:44.000513	treatment	new_page	0	1	1	0	1	0

In [40]:
```
# Fitting our model, and summarize the results
country_reg_model = sm.Logit(df_merged['converted'], df_merged[['intercept', 'ab_page',
results = country_reg_model.fit()
results.summary2()
```

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

Out[40]:
```
<class 'statsmodels.iolib.summary2.Summary'>
"""
                           Results: Logit
```

```
==============================================================================
Model:              Logit            No. Iterations:    6.0000
Dependent Variable: converted        Pseudo R-squared:  0.000
Date:               2021-11-23 18:58 AIC:               212781.1253
No. Observations:   290584           BIC:               212823.4439
Df Model:           3                Log-Likelihood:    -1.0639e+05
Df Residuals:       290580           LL-Null:           -1.0639e+05
Converged:          1.0000           Scale:             1.0000
------------------------------------------------------------------------------
               Coef.   Std.Err.     z      P>|z|    [0.025   0.975]
------------------------------------------------------------------------------
intercept     -2.0300    0.0266  -76.2488  0.0000  -2.0822  -1.9778
ab_page       -0.0149    0.0114   -1.3069  0.1912  -0.0374   0.0075
US             0.0506    0.0284    1.7835  0.0745  -0.0050   0.1063
CA             0.0408    0.0269    1.5161  0.1295  -0.0119   0.0934
==============================================================================

"""
```

```
In [41]: np.exp(results.params)
```

```
Out[41]: intercept    0.131332
         ab_page      0.985168
         US           1.051944
         CA           1.041599
         dtype: float64
```

```
In [42]: 1/np.exp(results.params)
```

```
Out[42]: intercept    7.614303
         ab_page      1.015056
         US           0.950621
         CA           0.960062
         dtype: float64
```

Statistically: - The country of residence had no impact on conversion rate **US 1.05** and **CA 1.04** are higher than **UK** (Baseline). - The difference between `US and UK` (baseline) = (1.051944 - 1) * 100 = **5.1944%** - The difference between `CA and UK` (baseline) = (1.041599 - 1) * 100 = **4.1599%**

Practically: - Countries are irrelivant to include in this analysis.

h. Fit your model and obtain the results 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 are there significant effects on conversion. **Create the necessary additional columns, and fit the new model.**

Provide the summary results (statistical output), and your conclusions (written response) based on the results.

```
In [43]: df_merged["ab_UK"] = df_merged["ab_page"] * df_merged["UK"]
         df_merged["ab_CA"] = df_merged["ab_page"] * df_merged["CA"]
```

```
In [44]: legit_model = sm.Logit(df_merged['converted'], df_merged[['intercept', 'ab_page', 'US',
         legit_fit = legit_model.fit()

Optimization terminated successfully.
         Current function value: 0.366109
         Iterations 6


In [45]: legit_fit.summary2()

Out[45]: <class 'statsmodels.iolib.summary2.Summary'>
         """
                                 Results: Logit
         =================================================================
         Model:              Logit            No. Iterations:   6.0000
         Dependent Variable: converted        Pseudo R-squared: 0.000
         Date:               2021-11-23 18:58 AIC:              212782.6602
         No. Observations:   290584           BIC:              212846.1381
         Df Model:           5                Log-Likelihood:   -1.0639e+05
         Df Residuals:       290578           LL-Null:          -1.0639e+05
         Converged:          1.0000           Scale:            1.0000
         -----------------------------------------------------------------
                        Coef.   Std.Err.     z      P>|z|    [0.025   0.975]
         -----------------------------------------------------------------
         intercept     -2.0040    0.0364  -55.0077  0.0000  -2.0754  -1.9326
         ab_page        0.0108    0.0228    0.4749  0.6349  -0.0339   0.0555
         US             0.0118    0.0398    0.2957  0.7674  -0.0663   0.0899
         CA             0.0175    0.0377    0.4652  0.6418  -0.0563   0.0914
         ab_UK         -0.0783    0.0568   -1.3783  0.1681  -0.1896   0.0330
         ab_CA         -0.0314    0.0266   -1.1807  0.2377  -0.0835   0.0207
         =================================================================

         """

In [46]: np.exp(legit_fit.params)

Out[46]: intercept    0.134794
         ab_page      1.010893
         US           1.011854
         CA           1.017682
         ab_UK        0.924703
         ab_CA        0.969090
         dtype: float64

In [47]: 1/np.exp(legit_fit.params)

Out[47]: intercept    7.418713
         ab_page      0.989224
         US           0.988285
```

```
CA           0.982625
ab_UK        1.081428
ab_CA        1.031896
dtype: float64
```

```
In [48]: # Checnking duration of the experiment
         df_merged['timestamp'] = df_merged['timestamp'].apply(lambda x : pd.to_datetime(str(x))
         df_merged['dates'] = df_merged['timestamp'].dt.date
```

```
In [49]: ((df_merged['dates'].max() - df_merged['dates']. min()), 'days')
```

```
Out[49]: (datetime.timedelta(22), 'days')
```

Statistically: - The conversion by country has no statistical significance since all `p_values` are large in all casses we failed to reject null.

Practically: - The impact of `converion by country` is with **no significance**, the conversion rate for both US and CA is higher than UK.

Final Conclusion

- Countries conversion rate was irrelevant to the case.
- Duration of the experiment was 22 days.
- There is **15%** difference in the conversion rate between the `control` and `treatment` groups from the dataset itself, which imposed almost no effect to influence the decision to switch to the new page.
- We failed to reject the `Null` in all the 3 cases, **Descriptive analysis**, **A/B Testing**, and **Regression Modelling**.

Run the code cell below to create a .html version of this notebook in the workspace. If it worked correctly, you should get a return code of 0

```
In [50]: from subprocess import call
         call(['python', '-m', 'nbconvert', 'Analyze_ab_test_results_notebook.ipynb'])
```

```
Out[50]: 0
```