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:

- Introduction
- Part I - Probability
- Part II - A/B Test
- Part III - Regression
- Final Check
- Submission

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.

In [59]:
```python
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)
```

Now, read in the `ab_data.csv` data. Store it in `df`. Below is the description of the data, there are a total of 5 columns:

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

In [60]:
```python
df = pd.read_csv('ab_data.csv')
df.head()
```

Out[60]:

	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 [61]:
```python
number_of_rows = df.shape[0]
number_of_rows
```

Out[61]: 294478

c. The number of unique users in the dataset.

In [62]:
```python
number_of_unique_users = df.user_id.nunique()
number_of_unique_users
```

Out[62]: 290584

d. The proportion of users converted.

In [63]:
```python
pr_of_converted = df.converted.mean()
pr_of_converted
```

Out[63]: 0.11965919355605512

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

In [64]:
```python
treat_and_old = df[((df['group'] == 'treatment') == (df['landing_page'] == 'new_page')) == False].shape[0]
treat_and_old
```

Out[64]: 3893

f. Do any of the rows have missing values?

In [65]:
```python
df.isnull().sum().sum()
```

Out[65]: 0

for 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.

Use **Quiz 2** in the classroom to figure out how should we handle the rows where the group and landing_page columns don't match?

In [66]:
```python
# Remove the inaccurate rows, and store the result in a new dataframe df2
treat_and_new = df.query(" group == 'treatment' and landing_page == 'new_page'")
control_and_old =df.query(" group == 'control' and landing_page == 'old_page'")
df2 = treat_and_new.append(control_and_old)
df2.head()
```

Out[66]:

	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

In [67]:
```python
# 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].shape[0]
```

Out[67]: 0

Use **df2** and the cells below to answer questions for **Quiz 3** in the classroom.

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

In [68]:
```python
unique_user_ids = df2.user_id.nunique()
unique_user_ids
```

Out[68]: 290584

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

In [69]:
```python
print('The repeated user_id is ',(df2.user_id.value_counts()).index[0])
```

```
The repeated user_id is  773192
```

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

In [70]:
```python
duplicated_user_id = df[df['user_id'] == (df2.user_id.value_counts()).index[0]]
duplicated_user_id
```

Out[70]:

	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**, from the **df2** dataframe.

In [71]:
```python
# 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 duplicate user_id are not entirely identical.
df2.drop(duplicated_user_id.index[0] , axis =0 , inplace =True)
# Check again if the row with a duplicate user_id is deleted or not
(df2.user_id.value_counts()).iloc[0]
```

Out[71]: 1

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?

In [72]:
```python
ppopulation = df2.converted.mean()
ppopulation
```

Out[72]: 0.11959708724499628

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

In [73]:
```python
p_control = df2.query(" group == 'control'")['converted'].mean()
p_control
```

Out[73]: 0.1203863045004612

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

In [74]:
```python
p_treatment = df2.query(" group == 'treatment'")['converted'].mean()
p_treatment
```

Out[74]: 0.11880806551510564

In [75]:
```python
# Calculate the actual difference (obs_diff) between the conversion rates for the two groups.
obs_diff = p_treatment - p_control
obs_diff
```

Out[75]: -0.0015782389853555567

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

In [76]:
```python
p_new = df2.query("landing_page == 'new_page' ").shape[0] / df2.landing_page.shape[0]
p_new
```

Out[76]: 0.5000619442226688

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

> **Your answer goes here.**

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?

the null hypothesis is old page perform better than or equal the new page , and the alternative hypothesis is the new page perform better than the old page

H_0 **:** p_{new} **-** p_{old} **≤ 0**

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

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.

In this section, you will:

- Simulate (bootstrap) sample data set for both groups, and compute the "converted" probability p for those samples.
- Use a sample size for each group equal to the ones in the `df2` data.
- Compute the difference in the "converted" probability for the two samples above.
- Perform the sampling distribution for the "difference in the converted probability" between the two simulated-samples over 10,000 iterations; and calculate an estimate.

Use the cells below to provide the necessary parts of this simulation. You can use **Quiz 5** in the classroom to make sure you

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

In [77]:
```python
p_new = df2['converted'].mean()
p_new
```

Out[77]: 0.11959708724499628

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

In [78]:
```python
p_old = df2['converted'].mean()
p_old
```

Out[78]: 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 [79]:
```python
new = df2.query(" landing_page == 'new_page'")
n_of_new = new.user_id.nunique()
n_of_new
```

Out[79]: 145310

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

In [80]:
```python
old = df2.query(" landing_page == 'old_page'")
n_of_old = old.user_id.nunique()
n_of_old
```

Out[80]: 145274

In [81]:
```python
# Calculate the actual difference (obs_diff) between the conversion rates for p_new and .p_old under the null
difference_rate = p_new - p_old
difference_rate
```

Out[81]: 0.0

e. Simulate Sample for the `treatment` Group
Simulate n_{new} transactions with a conversion rate of p_{new} under the null hypothesis.

In [82]:
```python
# Simulate a Sample for the treatment Group
new_page_converted = np.random.choice([0,1] ,p = ( 1-p_new , p_new), size= n_of_new )
new_page_converted.mean()
```

Out[82]: 0.12030830637946459

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 [83]:
```python
# Simulate a Sample for the control Group
old_page_converted = np.random.choice([0,1] ,p = (1-p_new,p_new),size =n_of_old )
old_page_converted.mean()
```

Out[83]: 0.11765353745336399

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

In [84]:
```python
differenc = ( new_page_converted.mean() - old_page_converted.mean() )
differenc
```

Out[84]: 0.0026547689261006008

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.

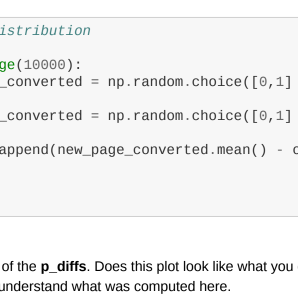
Store all $(p'_{new} - p'_{old})$ values in a NumPy array called `p_diffs`.

In [85]:
```python
# Sampling distribution
p_diffs = []
for i in range(10000):
    new_page_converted = np.random.choice([0,1] ,p = ( 1-p_new , p_new), size= n_of_new )

    old_page_converted = np.random.choice([0,1] ,p = (1-p_new,p_new),size =n_of_old )

    p_diffs.append(new_page_converted.mean() - old_page_converted.mean())
```

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

In [86]:
```python
plt.hist(p_diffs);
plt.axvline( x = obs_diff , color ='r');
```



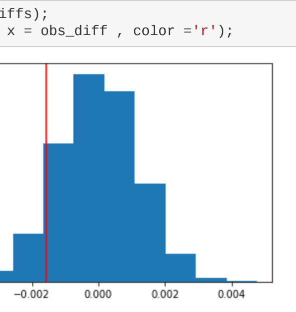
j. What proportion of the **p_diffs** are greater than the actual difference observed in the `df2` data?

In [87]:
```python
# convert p_diffs to array
p_diffs = np.array( p_diffs)
```

In [88]:
```python
# simulate distribution under the null hypothesis
null_vals = np.random.normal(0 ,  p_diffs.std() ,  p_diffs.size)
```

In [89]:
```python
# plot the the null distribution and the observed statistic
plt.hist( p_diffs);
plt.axvline(x = obs_diff , color='red')
```

Out[89]: <matplotlib.lines.Line2D at 0x7f773ad37940>



In [90]:
```python
(null_vals > obs_diff).mean()
```

Out[90]: 0.90910000000000002

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?

In part j , we computed the p_value which means that the probability of observing our statistic (or one more extreme in favor of the alternative) if the null hypothesis is true ,where if (p < α) then we suggest to reject the null.
And we get that the p_value = 0.90 which is greater than α = 0.05 so we do not have any evidence to reject the null

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 walkthrough of the ideas that are critical to correctly thinking about statistical significance.

Fill in the statements below to calculate the:

- `convert_old`: number of conversions with the old_page
- `convert_new`: number of conversions with the new_page
- `n_old`: number of individuals who were shown the old_page
- `n_new`: number of individuals who were shown the new_page

In [91]:
```python
import statsmodels.api as sm

# number of conversions with the old_page
convert_old = df2.query(" landing_page == 'old_page' ")['converted'].sum()

# number of conversions with the new_page
convert_new = df2.query(" landing_page == 'new_page' ")['converted'].sum()

# number of individuals who were shown the old_page
n_old = df2.query(" landing_page == 'old_page' ")['user_id'].nunique()

# number of individuals who received new_page
n_new = df2.query(" landing_page == 'new_page' ")['user_id'].nunique()
```

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

In [92]:
```python
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],alternative='larger' )
print(z_score, p_value)
```

```
-1.31092419842 0.905058312759
```

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.**?

From j we get that p = 0.9 greater than α = 0.05 and from k we get that z_score = -1.31 is smaller than z_α = 1,645 , as we tested the hypothesis in right_tailed so we decide that we can't reject H0 and that means the new page had not improve the conversion rate and company should keep the old webpage

Part III - A regression approach

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.

we will fit Logestic regression

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 [93]:
```python
import statsmodels.api as sm

df2['intercept'] = 1
df2[['control','ab_page']] = pd.get_dummies(df2['group'])
df2.head()
```

Out[93]:

	user_id	timestamp	group	landing_page	converted	intercept	control	ab_page
2	661590	2017-01-11 16:55:06.154213	treatment	new_page	0	1	0	1
3	853541	2017-01-08 18:28:03.143765	treatment	new_page	0	1	0	1
6	679687	2017-01-19 03:26:46.940749	treatment	new_page	1	1	0	1
8	817355	2017-01-04 17:58:08.979471	treatment	new_page	1	1	0	1
9	839785	2017-01-15 18:11:06.610965	treatment	new_page	1	1	0	1

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 [94]:
```python
lm = sm.Logit(df2['converted'],df2[['intercept','ab_page']])
```

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

In [95]:
```python
results = lm.fit()
results.summary2()
```

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

Out[95]:

Model:	Logit	No. Iterations:	6.0000
Dependent Variable:	converted	Pseudo R-squared:	0.000
Date:	2022-01-19 18:51	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

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

the null hypothesis in this regression model is there is no a realationship between the conversion and the new page , thus the alternative hypothesis is there is a relation between the new page and convarsion where if the company use the new page the conversion rate will improve.

In partII we suggested that the null hypothesis is the old page performs better than or equal the new page , and the

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

Of course if we added more information about users like country , gender , age ,or the culture , we will get

that the conversion rate will be affected and this will display the hidden details in the new conversion of the new

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.
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.

In [96]:
```python
# Read the countries.csv
c_df = pd.read_csv('countries.csv')
c_df.head()
```

Out[96]:

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

In [97]:
```python
# Join with the df2 dataframe
df_merged = df2.set_index('user_id').join(c_df.set_index('user_id'))
df_merged.head()
```

Out[97]:

user_id	timestamp	group	landing_page	converted	intercept	control	ab_page	country
661590	2017-01-11 16:55:06.154213	treatment	new_page	0	1	0	1	US
853541	2017-01-08 18:28:03.143765	treatment	new_page	0	1	0	1	US
679687	2017-01-19 03:26:46.940749	treatment	new_page	1	1	0	1	CA
817355	2017-01-04 17:58:08.979471	treatment	new_page	1	1	0	1	UK
839785	2017-01-15 18:11:06.610965	treatment	new_page	1	1	0	1	CA

In [98]:
```python
# Create the necessary dummy variables
df_merged[['CA','UK','US']] = pd.get_dummies(df_merged['country'])
df_merged.head()
```

Out[98]:

user_id	timestamp	group	landing_page	converted	intercept	control	ab_page	country	CA	UK	US
661590	2017-01-11 16:55:06.154213	treatment	new_page	0	1	0	1	US	0	0	1
853541	2017-01-08 18:28:03.143765	treatment	new_page	0	1	0	1	US	0	0	1
679687	2017-01-19 03:26:46.940749	treatment	new_page	1	1	0	1	CA	1	0	0
817355	2017-01-04 17:58:08.979471	treatment	new_page	1	1	0	1	UK	0	1	0
839785	2017-01-15 18:11:06.610965	treatment	new_page	1	1	0	1	CA	1	0	0

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.**

In [99]:
```python
# Fit your model, and summarize the results

lm2 = sm.Logit(df_merged['converted'],df_merged[['intercept' , 'ab_page' , 'US','UK']])
results2 = lm2.fit()
results2.summary2()
```

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

Out[99]:

Model:	Logit	No. Iterations:	6.0000
Dependent Variable:	converted	Pseudo R-squared:	0.000
Date:	2022-01-19 18:51	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	0.0408	0.0269	1.5161	0.1295	-0.0119	0.0934
UK	0.0506	0.0284	1.7835	0.0745	-0.0050	0.1063

from the summary we get that the baseline here is the users from 'CA' which refear to Canada , and we get that no one from the country showes statistically significant because the every p_value is >0.05, so we decide that countries

In [100]:
```python
#look at an interaction between page and country to see if are there significant effects on conversion
df_merged['ca_new'] = df_merged['CA']*df_merged['ab_page']
df_merged['us_new'] = df_merged['US']*df_merged['ab_page']
df_merged['uk_new'] = df_merged['UK']*df_merged['ab_page']
df_merged.head()
```

Out[100]:

user_id	timestamp	group	landing_page	converted	intercept	control	ab_page	country	CA	UK	US	ca_new	us_
661590	2017-01-11 16:55:06.154213	treatment	new_page	0	1	0	1	US	0	0	1	0	
853541	2017-01-08 18:28:03.143765	treatment	new_page	0	1	0	1	US	0	0	1	0	
679687	2017-01-19 03:26:46.940749	treatment	new_page	1	1	0	1	CA	1	0	0	1	
	2017-01-04												

In [101]:
```python
#fit the model and summary results
lm3 = sm.OLS(df_merged['converted'] ,df_merged[['intercept','ab_page' , 'UK','US' ,'uk_new','us_new']] )
results3 = lm3.fit()
results3.summary2()
```

Out[101]:

Model:	OLS	Adj. R-squared:	0.000
Dependent Variable:	converted	AIC:	170541.0521
Date:	2022-01-19 18:51	BIC:	170604.5300
No. Observations:	290584	Log-Likelihood:	-85265.
Df Model:	5	F-statistic:	1.466
Df Residuals:	290578	Prob (F-statistic):	0.197
R-squared:	0.000	Scale:	0.10529

	Coef.	Std.Err.	t	P>|t|	[0.025	0.975]
intercept	0.1188	0.0038	31.0570	0.0000	0.1113	0.1263
ab_page	-0.0069	0.0054	-1.2766	0.2018	-0.0174	0.0037
UK	0.0012	0.0042	0.2960	0.7672	-0.0070	0.0094
US	0.0018	0.0040	0.4667	0.6407	-0.0059	0.0096
uk_new	0.0080	0.0059	1.3599	0.1739	-0.0035	0.0196
us_new	0.0047	0.0056	0.8454	0.3979	-0.0062	0.0156

Omnibus:	125549.436	Durbin-Watson:	2.000
Prob(Omnibus):	0.000	Jarque-Bera (JB):	414285.945
Skew:	2.345	Prob(JB):	0.000
Kurtosis:	6.497	Condition No.:	26

from the ols results we get that , althouh we added a new interaction terms (ca_new , us_new ,uk_new) to the regression model , this terms didn't provide an statistical evidence that there is any relation between country of user

In [102]:
```python
from subprocess import call
call(['python', '-m', 'nbconvert', 'Analyze_ab_test_results_notebook.ipynb'])
```

Out[102]: 0