

Analyze_ab_test_results_notebook

May 7, 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

- 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 [38]: import pandas as pd
import numpy as np
import random
import matplotlib.pyplot as plt
%matplotlib inline
#We are setting the seed to assure you get the same answers on quizzes as we set up
random.seed(42)
```

1. Now, read in the `ab_data.csv` data. Store it in `df`. Use your dataframe to answer the questions in Quiz 1 of the classroom.

a. Read in the dataset and take a look at the top few rows here:

```
In [3]: df = pd.read_csv('ab_data.csv')
        df.head()
```

```
Out[3]:
```

	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 [4]: df.shape[0]
```

```
Out[4]: 294478
```

c. The number of unique users in the dataset.

```
In [5]: num = df.user_id.nunique()
```

d. The proportion of users converted.

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

```
Out[6]: 0.12104245244060237
```

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

```
In [7]: GroupT = df.query('group == "treatment"')
        GroupT_old = GroupT.query('landing_page == "old_page"')
        GroupT_old.shape[0]
        GroupC = df.query('group == "control"')
        GroupC_new = GroupC.query('landing_page == "new_page"')
        GroupT_old.shape[0]+GroupC_new.shape[0]
```

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

f. Do any of the rows have missing values?

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 294478 entries, 0 to 294477
Data columns (total 5 columns):
user_id      294478 non-null int64
```

```

timestamp      294478 non-null object
group          294478 non-null object
landing_page   294478 non-null object
converted      294478 non-null int64
dtypes: int64(2), object(3)
memory usage: 11.2+ MB

```

2. For the rows where **treatment** 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**.

```
In [9]: GroupC_new.shape[0]
```

```
Out[9]: 1928
```

```
In [10]: idx = GroupC_new.isin(df).index
         df1 = df.drop(labels=idx, axis=0)
         df1.shape[0] == (df.shape[0]-GroupC_new.shape[0])
```

```
Out[10]: True
```

```
In [11]: idx2 = GroupT_old.isin(df1).index
         df2 = df1.drop(labels=idx2, axis=0)
         df2.shape[0] == (df1.shape[0]-GroupT_old.shape[0])
```

```
Out[11]: True
```

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

```
Out[12]: 0
```

3. Use **df2** and the cells below to answer questions for **Quiz3** in the classroom.

- a. How many unique **user_ids** are in **df2**?

```
In [13]: df2.shape[0]-df2.user_id.nunique()
```

```
Out[13]: 1
```

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

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

```
Out[14]:
```

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

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

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

```
/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:1: UserWarning: Boolean Series key
    """Entry point for launching an IPython kernel.
```

```
Out[15]:
```

	user_id	timestamp	group	landing_page	converted
1899	773192	2017-01-09 05:37:58.781806	treatment	new_page	0
2893	773192	2017-01-14 02:55:59.590927	treatment	new_page	0

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

```
In [16]: df2 = df2.drop(labels=1899, axis=0)
df2.shape[0]-df2.user_id.nunique()
```

```
Out[16]: 0
```

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?

```
In [17]: (df2[df2['converted']==1].shape[0])/df2.shape[0]
```

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

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

```
In [18]: control_group = df2.query('group == "control"')
control_group[control_group['converted']==1].shape[0]/control_group.shape[0]
```

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

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

```
In [19]: treatment_group = df2.query('group == "treatment"')
treatment_group[treatment_group['converted']==1].shape[0]/treatment_group.shape[0]
```

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

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

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

```
Out[20]: 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 is hard to conclude that the more people are converting from old to new page without checking the confidence intervals and the p-value to know if it is less than Type I error or not

Part II - A/B Test

Notice that because of the time stamp associated with each event, you could technically run a hypothesis test continuously as each observation was observed.

However, then the hard question is do you stop as soon as one page is considered significantly better than another or does it need to happen consistently for a certain amount of time? How long do you run to render a decision that neither page is better than another?

These questions are the difficult parts associated with A/B tests in general.

1. For now, consider you need to make the decision just based on all the data provided. If you want to assume that the old page is better unless the new page proves to be definitely better at a Type I error rate of 5%, what should your null and alternative hypotheses be? You can state your hypothesis in terms of words or in terms of p_{old} and p_{new} , which are the converted rates for the old and new pages.

The null hypotheses shall be that the conversion rate from the old page $P(old)$ is equal or less than the conversion rate from the new page $P(new)$. The alternative hypotheses shall be that $P(old)$ is higher than $P(new)$. $H_0: P(old) - P(new) = 0$ or < 0 $H_1: P(old) - P(new) > 0$

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.

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

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

```
Out[39]:
```

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

```
In [79]: #since under null hypotheses p_new = p_old
p_new = df2['converted'].mean()
p_new
```

```
Out[79]: 0.11959708724499628
```

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

```
In [80]: p_old = p_new
```

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

```
In [84]: n_new = len(df2.query('group == "treatment"))
n_new
```

```
Out[84]: 145310
```

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

```
In [68]: control_group.shape[0]
```

```
Out[68]: 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**.

```
In [121]: bos = df2.sample(treatment_group.shape[0], replace=True)
treatment = bos.query('group == "treatment"')
pnew = treatment[treatment['converted']==1].shape[0]/treatment.shape[0]
new_page_converted = treatment['converted']
P_new = new_page_converted.mean()
```

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**.

```
In [122]: bos = df2.sample(control_group.shape[0], replace=True)
control = bos.query('group == "control"')
pold = control[control['converted']==1].shape[0]/control.shape[0]
old_page_converted = control['converted']
P_old = old_page_converted.mean()
```

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

```
In [123]: obs_diffs = P_new - P_old
obs_diffs
```

```
Out[123]: -0.0021029038762673674
```

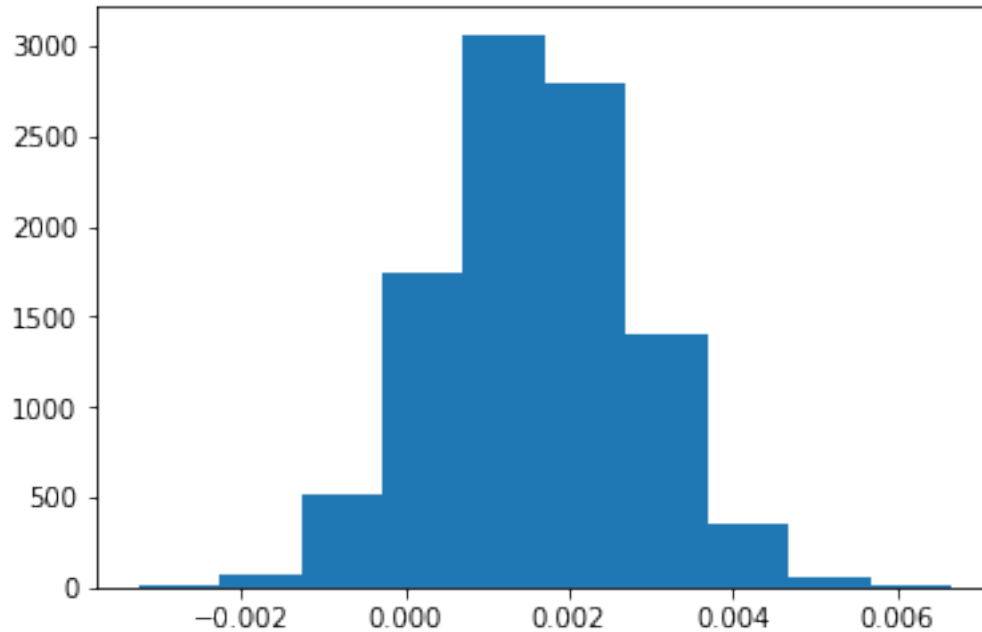
h. Create 10,000 $p_{new} - p_{old}$ values using the same simulation process you used in parts (a) through (g) above. Store all 10,000 values in a NumPy array called **p_diffs**.

```
In [73]: p_diffs = []
for i in range(10000):
    bootstrap = df2.sample(df2.shape[0], replace=True)
    tre = bootstrap.query('group == "treatment"')
    new_con = tre[tre['converted']==1].shape[0]/tre.shape[0]
    cot = bootstrap.query('group == "control"')
    old_con = cot[cot['converted']==1].shape[0]/cot.shape[0]
    p_diffs.append(old_con - new_con)

p_diffs = np.array(p_diffs)
```

- 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 [75]: plt.hist(p_diffs);
```



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

```
In [124]: (p_diffs > obs_diffs).mean()
```

```
Out[124]: 0.99880000000000002
```

- 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?

This value is called the p-value. If this value is higher than the Type 1 error, which we specified it to be 0.05, then the null hypotheses is true. Otherwise we reject the null hypotheses. Since the value is greater than 0.05 then we don't reject the null hypotheses as there is no difference between the conversion rate of both old and new page.

Note that we took the values above the null or observed one since we used the sign (= or <) in our hypotheses.

- 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 to the number of rows associated with the old page and new pages, respectively.

```
In [113]: import statsmodels.api as sm
          from statsmodels.stats.proportion import proportions_ztest
          convert_old = df2.query('landing_page=="old_page"')['converted'].mean()
          convert_new = df2.query('landing_page=="new_page"')['converted'].mean()
          n_old = df2.query('landing_page=="old_page"').shape[0]
          n_new = df2.query('landing_page=="new_page"').shape[0]
```

- 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 [119]: s1 = np.array([convert_old, convert_new])
          s2 = np.array([n_old, n_new])
          stat, pval = proportions_ztest(s1, s2)
          print('z_stat: %0.3f, p_value: %0.3f' % (stat, pval))
```

```
z_stat: 0.003, p_value: 0.997
```

- 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.?

Since the p-value is matching in m. and j., I can state that the null hypotheses can't be rejected. Hence, there are no difference between the the old and new conversion propotion

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?

Since this is only one of two out comes, then we use 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**.

```
In [129]: df2['intercept'] = 1
          df2[['treatment', 'control']] = pd.get_dummies(df2['landing_page'])
          df2.drop('control', axis=1, inplace=True)
          df2.rename(columns={'treatment': 'ab_page'}, inplace=True)
```

```
In [140]: df2.head()
```

```
Out[140]:   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., then fit the model using the two columns you created in part b. to predict whether or not an individual converts.

```
In [145]: result= sm.Logit(df2['converted'], df2[['ab_page', 'intercept']]).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 [147]: result.summary2()
```

```

Out[147]: <class 'statsmodels.iolib.summary2.Summary'>
        """
                                Results: Logit
        =====
Model:                Logit                No. Iterations:    6.0000
Dependent Variable:   converted              Pseudo R-squared:    0.000
Date:                2021-05-07 18:02      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]
-----
ab_page        -0.0150    0.0114    -1.3109  0.1899   -0.0374    0.0074
intercept      -1.9888    0.0081   -246.6690  0.0000   -2.0046   -1.9730
        =====
        """

```

- 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**?

As per the regression model, the null hypotheses is that the page type whether new or old has no effect. Since the p-value is higher than 0.05, it means that ab_page parameter has no statistical significance over the conversion rate. the two p-values are actually confirming each other and not the opposite, and let me explain why:

1- the original hypotheses was stating that the old page and the new page conversion rate is the same. Hence, it is not effected by whether the page is old or new.

2- the regression hypotheses is confirming the first point by stating that the ab_page term has no statistical significance over the conversion rate.

3- from a value point a view, it has to be remmebered that p-value in part 2 is for the whole population while the p-value in regression is concerned with individuals.

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?

I belive having additional term will help determining the conversion rate on individual level.

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.

```
In [150]: df_country = pd.read_csv('countries.csv')
          df3 = df2.set_index('user_id').join(df_country.set_index('user_id'))
          df3.head()
```

```
Out[150]:
```

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

	intercept	ab_page	country
user_id			
851104	1	0	US
804228	1	0	US
661590	1	1	US
853541	1	1	US
864975	1	0	US

h. Though you have now looked at the individual factors of country and page on conversion, we would now like to look at an interaction between page and country to see if there significant effects on conversion. Create the necessary additional columns, and fit the new model.

Provide the summary results, and your conclusions based on the results.

```
In [153]: df3[['CA', 'UK', 'US']] = pd.get_dummies(df3['country'])
          df3.head()
          results= sm.Logit(df3['converted'], df3[['ab_page', 'intercept', 'CA', 'UK']]).fit()
          results.summary2()
```

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

```
Out[153]: <class 'statsmodels.iolib.summary2.Summary'>
        """
                Results: Logit
=====
Model:                Logit                No. Iterations:    6.0000
Dependent Variable:   converted              Pseudo R-squared:    0.000
Date:                2021-05-07 18:23 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]
-----
ab_page         -0.0149    0.0114    -1.3069  0.1912   -0.0374    0.0075
intercept       -1.9893    0.0089  -223.7628  0.0000   -2.0067   -1.9718
CA              -0.0408    0.0269    -1.5161  0.1295   -0.0934    0.0119
UK               0.0099    0.0133     0.7433  0.4573   -0.0162    0.0359
=====
        """
```

Conclusion

As shown through the report, and proved by numbers and statistics, it is best to stay with the old page rather than transferring to a new page. It was shown that the the conversion from the old page is less or at best equal to the conversion rate from the new page to old. The p-values on both aggregation and individual level are supporting and confirming each other.

On aggregation level the p-value is higher than type 1 error value, it found to be 0.99. This means we can't reject the null hypotheses. Finally, when the regression model was checked it further confirmed that the type of page has no effect or statistical significance over the conversion term. Hence, reaching the conclusion mentioned earlier.

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** sub-menu, and then manually upload it into the workspace directory by clicking on the orange Jupyter icon in the upper left, then using the Upload button.

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

```
In [154]: from subprocess import call
          call(['python', '-m', 'nbconvert', 'Analyze_ab_test_results_notebook.ipynb'])
```

```
Out[154]: 0
```

```
In [ ]:
```