Analyze_ab_test_results_notebook

October 8, 2020

0.1 Analyze A/B Test Results

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.

[1]:
```
import pandas as pd
import numpy as np
import random
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns; sns.set_theme()
#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', parse_dates=['timestamp'])
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 below cell to find the number of rows in the dataset.

[3]:
```
df.shape[0]
```

[3]:
```
294478
```

c. The number of unique users in the dataset.

[4]:
```
print(f'The number of unique users: {df.user_id.nunique()}')
```

```
The number of unique users: 290584
```

d. The proportion of users converted.

[5]:
```
print(f'The proportion of users converted is: {df.converted.mean(): .0%}')
```

```
The proportion of users converted is:  12%
```

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

[6]:
```
unmatched = df.query('group == "treatment" & landing_page != "new_page" | group␣
↪!= "treatment" & landing_page == "new_page"').shape[0]
print(f'The number of unmatched group with the right landing page: {unmatched}')
```

```
The number of unmatched group with the right landing page: 3893
```

f. Do any of the rows have missing values?

[7]:
```
df.isnull().any().sum()
```

[7]:
```
0
```

2. For the rows where **treatment** is not aligned with **new_page** or **control** is not aligned with **old_page**, we cannot be sure if this row truly received the new or old page. Use **Quiz 2** in the classroom to provide how we should handle these rows.

a. Now use the answer to the quiz to create a new dataset that meets the specifications from the quiz. Store your new dataframe in **df2**.

[8]:
```
df2 = df.query('group == "control" & landing_page == "old_page" | group ==␣
↪"treatment" & landing_page == "new_page"')
```

[9]:
```
# 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]
```

[9]:
```
0
```

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

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

[10]:
```
print(f'The number of unique users: {df2.user_id.nunique()}')
```

```
The number of unique users: 290584
```

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

[11]:
```
repeated_user_id = df2.user_id.value_counts().index[0]
print(f'The repeated user id: {repeated_user_id}')
```

```
The repeated user id: 773192
```

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

[12]:
```
df2.query('user_id ==  @repeated_user_id')
```

[12]:

	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**.

[13]:
```
print(f'Shape of the data frame before removing the dublicated row: {df2.
↪shape[0]}')
df2 = df2.drop_duplicates('user_id')
print(f'Shape of the data frame after removing the dublicated row: {df2.
↪shape[0]}')
df2.query('user_id ==  @repeated_user_id')
```

```
Shape of the data frame before removing the dublicated row: 290585
Shape of the data frame after removing the dublicated row: 290584
```

[13]:

	user_id	timestamp	group	landing_page	converted
1899	773192	2017-01-09 05:37:58.781806	treatment	new_page	0

4. Use **df2** in the below cells to answer the quiz questions related to **Quiz 4** in the classroom.

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

[14]:
```
print(f'The probabilty of converting regardless of the page the reveive : {df2.
↪converted.mean(): .2%}')
```

```
The probabilty of converting regardless of the page the reveive :  11.96%
```

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

[15]:
```
control_converted_mean = df2[df2['group'] == 'control'].converted.mean()
print(f"The probabilty of converting given that an individual was in control␣
↪group : {control_converted_mean: .2%}")
```

```
The probabilty of converting given that an individual was in control group :
12.04%
```

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

[16]:
```
treatment_converted_mean = df2[df2['group'] == 'treatment'].converted.mean()
print(f"The probabilty of converting given that an individual was in treatment␣
↪group : {treatment_converted_mean: .2%}")
```

```
The probabilty of converting given that an individual was in treatment group :
11.88%
```

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

[17]:
```
p_new = df2[df2['landing_page'] == 'new_page'].shape[0] / df2.shape[0]
print(f"The probabilty of receiving the new page : {p_new: .2%}")
```

```
The probabilty of receiving the new page :  50.01%
```

[18]:
```
obs_diff = treatment_converted_mean - control_converted_mean
obs_diff
```

[18]:
```
-0.0015782389853555567
```

[19]:
```
print(f'The duration for this experment was: {df2.timestamp.max() - df2.
↪timestamp.min()}')
```

```
The duration for this experment was: 21 days 23:59:49.081927
```

e. Consider your results from a. through d. above, and explain below whether you think there is sufficient evidence to say that the new treatment page leads to more conversions.

The probabilty of converting given the new page is `11.88%` and givin the old one is `12.04%` with the information we have until now they should stay with the old page as it apears that the probabilty of converting is more than the new one but we need to wait for more time for the old users to get use to the new page design.

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.

$$H_0 : P_{new} - P_{old} \leq 0$$
$$H_1 : P_{new} - P_{old} > 0$$
$$\alpha = 0.05$$

`2.` Assume under the null hypothesis, p_{new} and p_{old} both have "true" success rates equal to the **converted** success rate regardless of page - that is p_{new} and p_{old} are equal. Furthermore, assume they are equal to the **converted** rate in **ab_data.csv** regardless of the page.

Use a sample size for each page equal to the ones in **ab_data.csv**.

Perform the sampling distribution for the difference in **converted** between the two pages over 10,000 iterations of calculating an estimate from the null.

Use the cells below to provide the necessary parts of this simulation. If this doesn't make complete sense right now, don't worry - you are going to work through the problems below to complete this problem. You can use **Quiz 5** in the classroom to make sure you are on the right track.

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

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

[20]:
```
0.11959708724499628
```

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

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

[21]:
```
0.11959708724499628
```

c. What is n_{new}?

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

[22]: 145310

d. What is n_{old}?

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

[23]: 145274

e. Simulate n_{new} transactions with a convert rate of p_{new} under the null. Store these n_{new} 1's and 0's in **new_page_converted**.

[24]:
```
new_page_converted = np.random.binomial(1, p_new, n_new)
```

f. Simulate n_{old} transactions with a convert rate of p_{old} under the null. Store these n_{old} 1's and 0's in **old_page_converted**.

[25]:
```
old_page_converted = np.random.binomial(1, p_old, n_old)
```

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

[26]:
```
from IPython.display import display, Math, Latex
display(Math(rf'P_{{new}} - P_{{old}} = {obs_diff:.7f}'))
```

$$P_{new} - P_{old} = -0.0015782$$

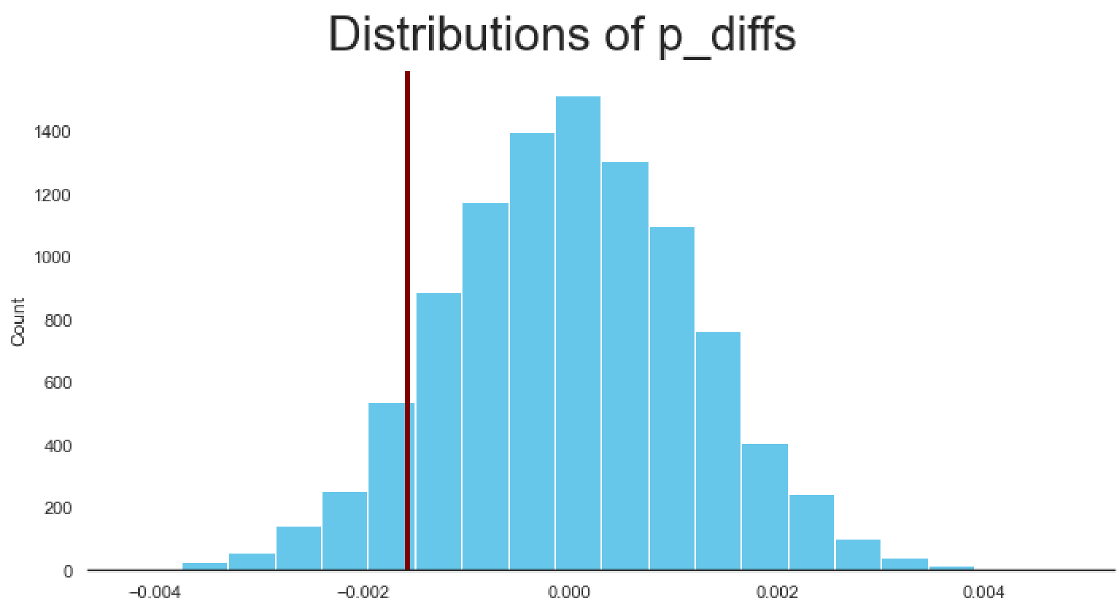
h. Simulate 10,000 p_{new} - p_{old} values using this same process similarly to the one you calculated in parts **a. through g.** above. Store all 10,000 values in a numpy array called **p_diffs**.

[27]:
```
p_diffs = []
for _ in range(10000):
    new_page_mean = np.random.binomial(1, p_new, n_new).mean()
    old_page_mean = np.random.binomial(1, p_old, n_old).mean()
    p_diffs.append(new_page_mean - old_page_mean)
```

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.

[29]:
```
p_diffs = np.array(p_diffs)

sns.set_style('white')
sns.displot(p_diffs, bins=20, height=5, aspect=2, color='#33b5e5')
sns.despine(left=True)
plt.figtext(.5,1,'Distributions of p_diffs',fontsize=30,ha='center')
plt.axvline(x=obs_diff, color='#800000', linewidth=3)
plt.show()
```



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

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

[30]: 0.9086

k. In words, explain what you just computed in part **j.** What is this value called in scientific studies? What does this value mean in terms of whether or not there is a difference between the new and old pages?

- We just computed p value or the probabilty of observing our statistic or more extreme in favor of the alternative given that the null hypothesis is true.
- Here we fail to reject the null and so we containue with the old page.

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]:
```
import statsmodels.api as sm

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]
```

```
print(f'convert_old: {convert_old}\n\
      n_old: {n_old}\n\
convert_new: {convert_new}\n\
      n_new: {n_new}')
```

```
convert_old: 17489
      n_old: 145274
convert_new: 17264
      n_new: 145310
```

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

[32]:
```
z_score, p_value = sm.stats.proportions_ztest([convert_old, convert_new],␣
↪[n_old, n_new], alternative='smaller')
print(f'Z score is: {z_score:.3f}\nand the P value is: {p_value:.3f}')
```

```
Z score is: 1.311
and the P value is: 0.905
```

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.**?

- Here also our conclusion is the same as in part j we fail to reject the null as we got similar results as we expected.

Part III - A regression approach

`1.` In this final part, you will see that the result you acheived in the previous A/B test can also be acheived by performing regression.

a. Since each row is either a conversion or no conversion, what type of regression should you be performing in this case?

- Logistic Regression

b. The goal is to use **statsmodels** to fit the regression model you specified in part **a.** to see if there is a significant difference in conversion based on which page a customer receives. However, you first need to create a 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**.

[33]:
```
df2['intercept'] = 1

df2['ab_page'] = pd.get_dummies(df2['group'])['treatment']

df2.head()
```

[33]:
```
   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 import your regression model. Instantiate the model, and fit the model using the two columns you created in part **b.** to predict whether or not an individual converts.

[34]:
```python
y = df2.converted
X = df2[['intercept','ab_page']]
model = sm.Logit(y, X)
results = model.fit()
```

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

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

[35]:
```python
results.summary()
```

[35]:
```
<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:                Thu, 08 Oct 2020   Pseudo R-squ.:               8.077e-06
Time:                        02:08:11   Log-Likelihood:            -1.0639e+05
converged:                       True   LL-Null:                   -1.0639e+05
Covariance Type:            nonrobust   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 the **Part II**?

In logistic regression we have a 2 sided test there fore the null and alternetive hypothesis are:

$$H_0 : P_{new} - P_{old} = 0$$

$$H_1 : P_{new} - P_{old} \neq 0$$

and before we had a one side test as:

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

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

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?

- We should consider other things that might influence wether or not an individual converts like having more details about the users as their sex, location and age and we then we can test for each group and see if the page have more inpact in once category than the other
- And the disadvantages for this approach it will consume more time, efforts and it will cost more.

g. Now along with testing if the conversion rate changes for different pages, also add an effect based on which country a user lives. You will need to read in the **countries.csv** dataset and merge together your datasets on the approporiate rows. Here are the docs for joining tables.

Does it appear that country had an impact on conversion? Don't forget to create dummy variables for these country columns - **Hint: You will need two columns for the three dummy variables.** Provide the statistical output as well as a written response to answer this question.

[36]:
```
countries_df = pd.read_csv('./countries.csv')
df_new = countries_df.set_index('user_id').join(df2.set_index('user_id'),␣
 ↪how='inner')
df_new.head()
```

[36]:
```
        country                   timestamp      group landing_page  converted  \
user_id
834778       UK  2017-01-14 23:08:43.304998    control     old_page          0
928468       US  2017-01-23 14:44:16.387854  treatment     new_page          0
822059       UK  2017-01-16 14:04:14.719771  treatment     new_page          1
711597       UK  2017-01-22 03:14:24.763511    control     old_page          0
710616       UK  2017-01-16 13:14:44.000513  treatment     new_page          0

         intercept  ab_page
user_id
834778           1        0
928468           1        1
822059           1        1
711597           1        0
```

```
710616            1         1
```

[37]:
```python
### Create the necessary dummy variables
df_new = df_new.join(pd.get_dummies(df_new['country']))
df_new.head()
```

[37]:
```
        country                  timestamp      group landing_page  converted  \
user_id
834778       UK 2017-01-14 23:08:43.304998    control     old_page          0
928468       US 2017-01-23 14:44:16.387854  treatment     new_page          0
822059       UK 2017-01-16 14:04:14.719771  treatment     new_page          1
711597       UK 2017-01-22 03:14:24.763511    control     old_page          0
710616       UK 2017-01-16 13:14:44.000513  treatment     new_page          0

         intercept  ab_page  CA  UK  US
user_id
834778           1        0   0   1   0
928468           1        1   0   0   1
822059           1        1   0   1   0
711597           1        0   0   1   0
710616           1        1   0   1   0
```

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.

[38]:
```python
### Fit Your Linear Model And Obtain the Results
y = df_new.converted
X = df_new[['intercept','ab_page', 'US', 'UK']]
model = sm.Logit(y, X)
results = model.fit()
results.summary()
```

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

[38]:
```
<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:                Thu, 08 Oct 2020   Pseudo R-squ.:               2.323e-05
Time:                        02:08:36   Log-Likelihood:            -1.0639e+05
```

```
converged:                       True   LL-Null:                   -1.0639e+05
Covariance Type:            nonrobust   LLR p-value:                    0.1760
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
intercept     -2.0300      0.027    -76.249      0.000      -2.082      -1.978
ab_page       -0.0149      0.011     -1.307      0.191      -0.037       0.007
US             0.0408      0.027      1.516      0.130      -0.012       0.093
UK             0.0506      0.028      1.784      0.074      -0.005       0.106
==============================================================================
"""
```

[46]:

```
interpretation = pd.DataFrame(results.params, columns=['coef']).
 ↪drop('intercept', axis=0)
interpretation['exp'] = interpretation.coef.astype('float').apply(lambda x: np.
 ↪exp(x) if x > 0 else 1/np.exp(x))
interpretation
```

[46]:

	coef	exp
ab_page	-0.014943	1.015056
US	0.040757	1.041599
UK	0.050640	1.051944

0.3 Conclusions

- All the p values for the explanatory variables are larger than α there for we fail to reject the null hypothesis again.
- For the new page the chance of conversion is less than the old page by 1.02%.
- For US the chance of conversion is more than CA by 1.04%.
- For UK the chance of conversion is more than CA by 1.05%.

[ ]: