Analyze_ab_test_results_notebook

December 21, 2018

0.1 Analyze A/B Test Results

0.2 Table of Contents

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

Part I - Probability
To get started, let's import our libraries.

```
In [ ]: 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 [102]: df = pd.read_csv('ab_data.csv')
          df.head()
```

Out[102]:

	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.

```
In [104]: df.shape[0]
```

```
Out[104]: 294478
```

c. The number of unique users in the dataset.

```
In [105]: df.user_id.nunique()
```

```
Out[105]: 290584
```

d. The proportion of users converted.

```
In [106]: df.converted.mean()
```

```
Out[106]: 0.11965919355605512
```

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

```
In [107]: df.query('landing_page == "new_page" and group == "control"').count()[0] + df.query('l
```

```
Out[107]: 3893
```

f. Do any of the rows have missing values?

```
In [108]: df.isnull().values.any()
```

```
Out[108]: False
```

```
In [109]: 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** 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**.

```
In [110]: #Filter on lines where new page and control are aligned
          npcontrol = df[(df.landing_page == "new_page") & (df.group == "control")]

          #Filter on lines where old page and treatment are aligned
          optreatment = df[(df.landing_page == "old_page") & (df.group == "treatment")]
```

```
#Concatenate the inaccurate lines
inaccurate = pd.concat([npcontrol, optreatment])

#Assign the index for these lines
inaccurate_index = inaccurate.index

#Drop the lines with the indexes assigned above
df2 = df.drop(inaccurate_index)
```

In [111]:
```
# Double Check all of the correct rows were removed - this should be 0
df2[((df2['group'] == 'treatment') == (df2['landing_page'] == 'new_page')) == False].s
```

Out[111]: 0

In [112]:
```
#Check the new data frame
df2.head()
```

Out[112]:

	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

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**?

In [113]:
```
#Number of unique users
df2['user_id'].nunique()
```

Out[113]: 290584

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

In [114]:
```
#Find the duplicate id
df2[df2.duplicated('user_id')]
```

Out[114]:

	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 [115]:
```
#Match the lines with the duplicate id found above
df2[df2.user_id == 773192]
```

Out[115]:

	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 [116]: #Remove one of the duplicate lines
          df2.drop(labels = 1899, axis=0, inplace=True)
```

```
In [117]: #Confirm removal of one of the lines
          df2[df2.user_id == 773192]
```

Out[117]:

	user_id	timestamp	group	landing_page	converted
2893	773192	2017-01-14 02:55:59.590927	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?

```
In [118]: #Since 1 is considered True, we don't need to specify the condition "converted == 1".
          df2['converted'].mean()
```

```
Out[118]: 0.11959708724499628
```

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

```
In [119]: #Probability of a user converted in control group
          df2[df2['group'] == "control"]['converted'].mean()
```

```
Out[119]: 0.1203863045004612
```

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

```
In [120]: #Probability of a user converted in treatment group
          df2[df2['group'] == "treatment"]['converted'].mean()
```

```
Out[120]: 0.11880806551510564
```

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

```
In [121]: #Probability of a user landing on new_page
          (df2.landing_page == "new_page").mean()
```

```
Out[121]: 0.50006194422266881
```

e. Use the results in the previous two portions of this question to suggest if you think there is evidence that one page leads to more conversions? Write your response below.

According to above proportions, there is a small difference between users converted from treatment group and from control group, and, therefore we cannot conclude that the new treatment page leads to more conversions. ### 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.

Put your answer here.

`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?

```
In [122]: #Find the proportion of converted rate assuming p_new and p_old are equal
          p_new = df2['converted'].mean()
          p_new
```

```
Out[122]: 0.11959708724499628
```

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

```
In [123]: #Find the proportion of converted rate assuming p_new and p_old are equal
          p_old = df2['converted'].mean()
          p_old
```

```
Out[123]: 0.11959708724499628
```

c. What is n_{new}?

```
In [124]: #Number of users landing on new page
          n_new = df2.query('group == "treatment"')['user_id'].count()
          n_new = int(n_new)
          n_new
```

```
Out[124]: 145310
```

d. What is n_{old}?

```
In [125]: #Number of users landing on old page
          n_old = df2.query('group == "control"')['user_id'].count()
          n_old = int(n_old)
          n_old

Out[125]: 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**.

```
In [126]: #Draw samples from a binomial distribution
          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**.

```
In [127]: #Draw samples from a binomial distribution
          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).

```
In [128]: #Number of rows from new page are higher than the ones on old page, therefore we trunc
          #page and compute the difference
          new_page_converted = new_page_converted[:145274]
          new_page_converted.mean() - old_page_converted.mean()

Out[128]: -0.0025056100885223753
```

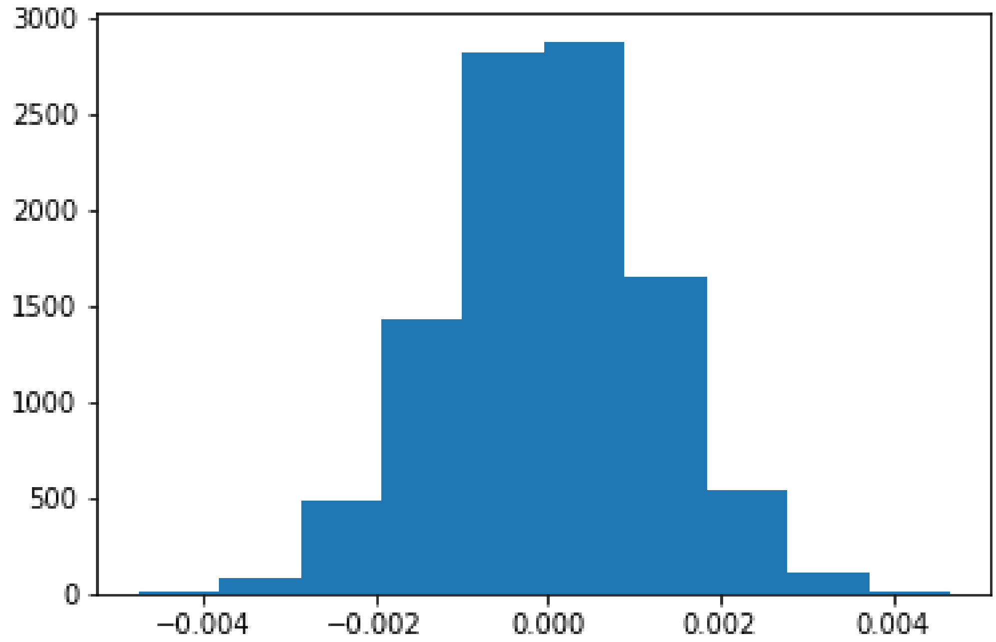
h. Simulate 10,000 p_{new} - p_{old} values using this same process similarly to the one you calculated in parts **a. through g.** above. Store all 10,000 values in **p_diffs**.

```
In [129]: #Simulate 10000 samples of the differences in conversion rates
          p_diffs = []

          for _ in range(10000):
              new_page_converted = np.random.binomial(1, p_new, n_new)
              old_page_converted = np.random.binomial(1, p_old, n_old)
              new_page_p = new_page_converted.mean()
              old_page_p = old_page_converted.mean()
              p_diffs.append(new_page_p - old_page_p)
```

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 [132]: #Show the histogram
          plt.hist(p_diffs);
```



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

```
In [133]: #Actual difference of converted rates
          actual_diff = (df2[df2['group'] == "treatment"]['converted'].mean()) - (df2[df2['group
          actual_diff
```

```
Out[133]: -0.0015782389853555567
```

```
In [134]: #Convert to numpy array and calculate the p-value
          p_diffs = np.array(p_diffs)
          (p_diffs > actual_diff).mean()
```

```
Out[134]: 0.90159999999999996
```

Actual difference represents the difference between converted rates of new page and old page, based on our data.

p-diffs represents the simuated difference between converted rates of new page and old page, based on 10000 simulated samples.

The percentage of 90.5 is called scientifically p-value, which determines the probability of obtaining our observed statistic (or one more extreme in favor of the alternative) if the null hypothesis is true.

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.

In [135]:
```
import statsmodels.api as sm

#Number of conversions for each page
convert_old = sum(df2.query('group == "control"')['converted'])
convert_new = sum(df2.query('group == "treatment"')['converted'])

#Number of individuals who received each page
n_old = df2.query("group == 'control'")['user_id'].count()
n_new = df2.query("group == 'treatment'")['user_id'].count()

#Convert figures to integers
n_old = int(n_old)
n_new = int(n_new)
```

```
/opt/conda/lib/python3.6/site-packages/statsmodels/compat/pandas.py:56: FutureWarning: The panda
  from pandas.core import datetools
```

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

In [136]:
```
#Two-sample Proportion Hypothesis Testing
z_score, p_value = sm.stats.proportions_ztest([convert_new, convert_old], [n_new, n_ol
z_score
```

Out[136]: -1.3109241984234394

In [137]:
```
p_value
```

Out[137]: 0.90505831275902449

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.**?

A negative z-score suggests and the value of p-value suggests that we should fail to reject the null hypothesis.

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 colun 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 [138]:
```
#Create intercept column
df2['intercept']=1

#Create dummies
ab_page = ['treatment', 'control']
df2['ab_page'] = pd.get_dummies(df2.group)['treatment']
```

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.

In [139]:
```
logit = 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 [140]:
```
results = logit.fit()
results.summary()
```

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

Out[140]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                           Logit Regression Results
==============================================================================
Dep. Variable:              converted   No. Observations:               290584
Model:                          Logit   Df Residuals:                   290582
Method:                           MLE   Df Model:                            1
Date:                Fri, 21 Dec 2018   Pseudo R-squ.:               8.077e-06
Time:                        21:16:14   Log-Likelihood:            -1.0639e+05
converged:                       True   LL-Null:                   -1.0639e+05
                                        LLR p-value:                    0.1899
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
intercept     -1.9888      0.008   -246.669      0.000      -2.005      -1.973
ab_page       -0.0150      0.011     -1.311      0.190      -0.037       0.007
==============================================================================
"""
```

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

The p-value associated with ab_page column is 0.19 which is lower than the p-value calculated using the z-score function. The reason why is different is due to the intercept added.

The logistic regression determines only two possible outcomes. If the new page is equal to the old page or different.

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

$$H_1 : p_{new} - p_{old}! = 0$$

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?

We could consider introducing the timestamp metric to determine in which part of the day the individuals converted the most. For example, if we find that the evening is the period that users spend most of their time on the internet we might also take it into consideration.

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

In [141]:
```
countries_df = pd.read_csv('./countries.csv')
df_new = countries_df.set_index('user_id').join(df2.set_index('user_id'), how='inner')
```

In [142]:
```
### Create the necessary dummy variables
df_new[['CA', 'US']] = pd.get_dummies(df_new['country'])[['CA','US']]
df_new.head()
```

Out[142]:
```
        country                   timestamp      group landing_page  \
user_id
834778       UK  2017-01-14 23:08:43.304998    control     old_page
928468       US  2017-01-23 14:44:16.387854  treatment     new_page
822059       UK  2017-01-16 14:04:14.719771  treatment     new_page
```

```
711597       UK  2017-01-22 03:14:24.763511    control     old_page
710616       UK  2017-01-16 13:14:44.000513  treatment     new_page

         converted  intercept  ab_page  CA  US
user_id
834778           0          1        0   0   0
928468           0          1        1   0   1
822059           1          1        1   0   0
711597           0          1        0   0   0
710616           0          1        1   0   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.

In [143]:
```python
### Fit Your Linear Model And Obtain the Results
df_new['intercept'] = 1
log_mod = sm.Logit(df_new['converted'], df_new[['CA', 'US', 'intercept', 'ab_page']])
results = log_mod.fit()
results.summary()
```

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

Out[143]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                           Logit Regression Results
==============================================================================
Dep. Variable:              converted   No. Observations:               290584
Model:                          Logit   Df Residuals:                   290580
Method:                           MLE   Df Model:                            3
Date:                Fri, 21 Dec 2018   Pseudo R-squ.:               2.323e-05
Time:                        21:21:29   Log-Likelihood:            -1.0639e+05
converged:                       True   LL-Null:                   -1.0639e+05
                                        LLR p-value:                    0.1760
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
CA            -0.0506      0.028     -1.784      0.074      -0.106       0.005
US            -0.0099      0.013     -0.743      0.457      -0.036       0.016
intercept     -1.9794      0.013   -155.415      0.000      -2.004      -1.954
ab_page       -0.0149      0.011     -1.307      0.191      -0.037       0.007
==============================================================================
"""
```

0.3 Conclusions

According to the analysis performed I found that the old page was better than the new page, therefore I fail to reject the null hypothesis. Moreover, the histogram shows that the new page is not better than the old page.

From the regression above we see that the p-value is higher in US than in Canada, which means that users in the US are more likely to convert, but still not enough evidence to reject the null hypothesis.

```
In [144]: from subprocess import call
          call(['python', '-m', 'nbconvert', 'Analyze_ab_test_results_notebook.ipynb'])

Out[144]: 0

In [ ]:
```