Analyze_ab_test_results

January 17, 2019

0.1 Analyze A/B Test Results

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Introduction

For this project, I will be working to understand the results of an A/B test run by an e-commerce website. My 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.

Part I - Probability

To get started, let's import required libraries.

```
In [1]: import pandas as pd
        import numpy as np
        import random
        import matplotlib.pyplot as plt
        import statsmodels.api as sm
        %matplotlib inline
        #I'm setting the seed to assure you get the same answers on quizzes as I set up
        random.seed(42)
```

```
C:\Users\Simin\Anaconda3\lib\site-packages\statsmodels\compat\pandas.py:56: FutureWarning: The
  from pandas.core import datetools
```

```
In [2]: # Firsr read in the `ab_data.csv` data and store it in `df`.
        df= pd.read_csv('ab_data.csv')
```

```
In [3]: 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
```

```
In [4]: # Find the number of rows in the dataset
        df.shape

Out[4]: (294478, 5)

In [5]: # Check to see if there is any duplicate in the dataset
        sum(df.duplicated())

Out[5]: 0

In [6]: # The number of unique users in the dataset
        df['user_id'].nunique()

Out[6]: 290584

In [7]: # The proportion of users converted
        df['converted'].mean()

Out[7]: 0.11965919355605512

In [8]: # The number of times the new_page and treatment don't line up
        df.query(('group == "treatment" and landing_page != "new_page" or group != "treatment"

Out[8]: 3893

In [9]: #Check if the rows have missing values?
        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
```

For the rows where **treatment** is not aligned with **new_page** or **control** is not aligned with **old_page**, I cannot be sure if this row truly received the new or old page. I drop these rows and store the results in df2.

```
In [10]: df2= df.query('group == "treatment" and landing_page == "new_page" or group == "contro

In [11]: # Double Check all of the incorrect rows were removed - this should be 0
         df2[((df2['group'] == 'treatment') == (df2['landing_page'] == 'new_page')) == False].s

Out[11]: 0
```

In [12]:
```
# Number of unique user_id's in df2
df2['user_id'].nunique()
```

Out[12]: 290584

In [13]:
```
#repeated user_id in df2
df2[df2['user_id'].duplicated()]
```

Out[13]:

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

In [14]:
```
#the row information for the repeated user_id
df2[df2['user_id']==773192]
```

Out[14]:

	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

In [15]:
```
# Drop the duplicated user
df2.drop([1899,], axis='rows', inplace = True)
```

```
/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
```

In [16]:
```
#Check the results
df2[df2['user_id']==773192]
```

Out[16]:

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

In [17]:
```
# The probability of an individual converting regardless of the page they receive?
df2['converted'].mean()
```

Out[17]: 0.11959708724499628

In [18]:
```
# Given that an individual was in the `control` group, what is the probability they c
df2.query('group == "control"')['converted'].mean()
```

Out[18]: 0.1203863045004612

In [19]:
```
# Given that an individual was in the treatment group, what is the probability they c
df2.query('group == "treatment"')['converted'].mean()
```

Out[19]: 0.11880806551510564

In [20]:
```
#The probability that an individual received the new page
(df2.group == "treatment").mean()
```

```
Out[20]: 0.50006194422266881
```

Results: Based on the results of what I've done so far, there is no evidence that one page leads to more conversions. Half of the users are in the "treatment" and the other half are in the "control" group, and the rate of conversion is 0.12 for both.

Part II - A/B Test

Because of the time stamp associated with each event, I could technically run a hypothesis test continuously as each observation was observed.

However the hard question is do I 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 I 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, I want to make the decision just based on all the data provided. I assume that the old page is better unless the new page proves to be definitely better at a Type I error rate of 5%. The null and alternative hypotheses are as followed:

p_{old} and p_{new} are the converted rates for the old and new pages.

** Hypothesis **

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

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

2. I'll 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, I'll assume they are equal to the **converted** rate in **ab_data.csv** regardless of the page.

I'll use a sample size for each page equal to the ones in **ab_data.csv**.

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

I'll use the cells below to provide the necessary parts of this simulation.

a. The **convert rate** for p_{new} under the null

```
In [21]: p_new = df2['converted'].mean()
         p_new
```

```
Out[21]: 0.11959708724499628
```

b. The **convert rate** for p_{old} under the null

```
In [22]: p_old = df2['converted'].mean()
         p_old
```

```
Out[22]: 0.11959708724499628
```

c. n_{new}

```
In [23]: n_new = df2.query('landing_page == "new_page"')['landing_page'].count()
         n_new
```

```
Out[23]: 145310
```

d. n_{old}

```
In [24]: n_old = df2.query('landing_page == "old_page"')['landing_page'].count()
         n_old
```

```
Out[24]: 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 [25]: new_page_converted = np.random.binomial(n=1, p=p_new, size=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 [26]: old_page_converted = np.random.binomial(n=1, p=p_old, size=n_old)
```

g. Find p_{new} - p_{old}

```
In [27]: new_page_converted.mean()-old_page_converted.mean()
```

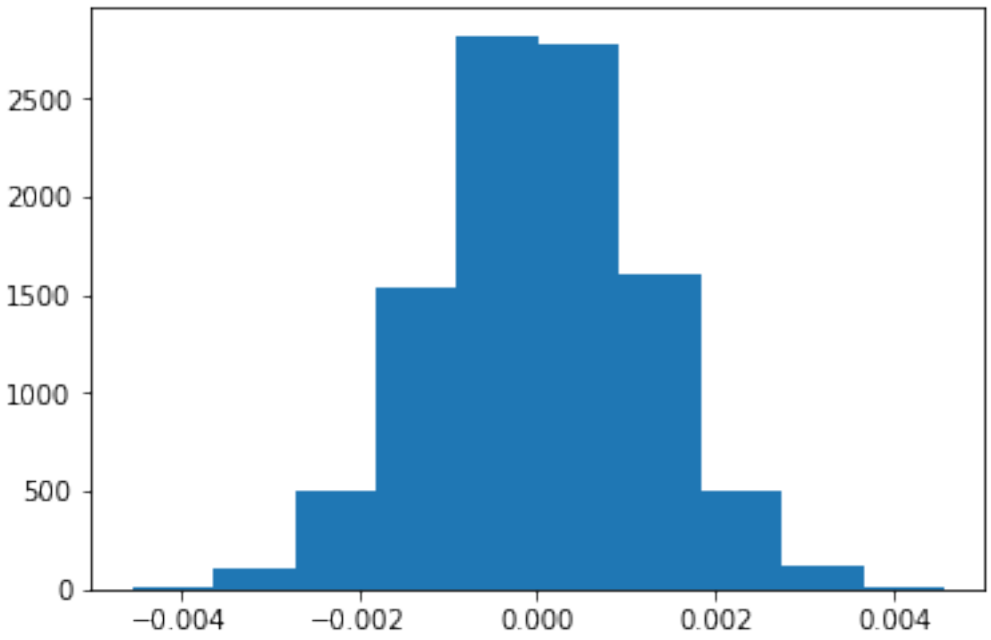
```
Out[27]: 0.00051401567146014404
```

h. Simulate 10,000 p_{new} - p_{old} values using the same process in parts a. through g. above and store all 10,000 values in **p_diffs**.

```
In [28]: p_diffs = []
         for _ in range(10000):
             new_bootsamp = np.random.binomial(n=1, p=p_new, size=n_new)
             old_bootsamp = np.random.binomial(n=1, p=p_old, size=n_old)
             p_diffs.append(new_bootsamp.mean() - old_bootsamp.mean())
```

i. Plot a histogram of the **p_diffs**.

```
In [29]: plt.hist(p_diffs);
```



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

```
In [30]: obs_diff = df2.query('group == "treatment"')['converted'].mean()-df2.query('group == '
```

```
In [31]: (p_diffs > obs_diff).mean()
```

```
Out[31]: 0.91139999999999999
```

k. What I computed in part **j.** was the **p-value**. p_value is the proportion of values in the null distribution which are greater than my observed difference. Since the p-value is a large number, I fail to reject null hypothesis. It means there is no significant difference between the new and old pages.

l. I could also use a built-in to achieve similar results by calculating the number of conversions for each page, as well as the number of individuals who received each page. `n_old` and `n_new` refer the the number of rows associated with the old page and new pages, respectively.

```
In [32]: import statsmodels.api as sm

         convert_old = df2.query('group == "control"')['converted'].sum()
         convert_new = df2.query('group == "treatment"')['converted'].sum()
         n_old = df2.query('landing_page == "old_page"')['landing_page'].count()
         n_new = df2.query('landing_page == "new_page"')['landing_page'].count()
         convert_old, convert_new, n_old ,n_new
```

```
Out[32]: (17489, 17264, 145274, 145310)
```

m. Now I use `stats.proportions_ztest` to compute my test statistic and p-value.

```
In [33]: z_score, p_value = sm.stats.proportions_ztest([convert_new,convert_old], [n_new, n_old
         p_value, z_score

Out[33]: (0.18988337448195103, -1.3109241984234394)
```

I calculated p_value under two_tail test, because I left the 'alternative' with default value of "two_sided" . p_value is differnt than the one I calculated in **j.** section. The p_value calculated in section **j.** is for a one_tail test(p_new - p_old <= 0)

```
In [34]: import statsmodels.api as sm
         z_score, p_value = sm.stats.proportions_ztest([convert_new,convert_old], [n_new, n_old
         p_value, z_score

Out[34]: (0.90505831275902449, -1.3109241984234394)
```

I set the 'alternative' to "larger", and get the same p_value calculated in **j.** section. with this p_value I fail to reject null hypothesis.

Part III - A regression approach

In this final part, will see that the result I 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, I should perform Logistic Regression in this case.

b. The goal is to use **statsmodels** to fit the regression model I specified in part **a.** to see if there is a significant difference in conversion based on which page a customer receives. However I first need to create a column for the **intercept**, as well as an **ab_page** column, which is 1 when an individual receives the **treatment** and 0 if **control**.

```
In [35]: df2.head()

Out[35]:    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 [36]: df2['intercept'] = 1
         df2['ab_page'] = pd.get_dummies(df2['landing_page'])['new_page']
         df2.head()

/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
  """Entry point for launching an IPython kernel.
```

```
/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
```

Out[36]:

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

c. Use **statsmodels** to import logistic regression model.

```
In [37]: log_mod = sm.Logit(df2['converted'], df2[['intercept', 'ab_page']])
         results = log_mod.fit()

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

d. Provide the summary of the results.

```
In [38]: results.summary()
```

Out[38]:

```
<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:                Wed, 30 May 2018   Pseudo R-squ.:               8.077e-06
Time:                        17:38:30   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
==============================================================================
"""
```

The p-value associated with ab_page is 0.19.

In linear regression, I discuss if there is a significant linear relationship between the dependent variable/column X(in my case ab_page) and independent variable/column Y(converted). The null hypothesis assosiated with regression is that there is no significant relationship between ab_page and converted columns which means conversion rate is not dependent on the page visited by user(old/new page). and the alternative hypothesis is that there is a relationship between ab_page and converted columns. These cause a two_tail hypothesis.

** Hypothesis: **

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

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

The p_value I calculated in the regression model is under a two_tail test. In Part II, section m. under a two_tail test I found the same value for p_value, however under a one_tail hypothesis the p_value was 0.91.

** f. Is it a good idea to consider other factors to add into my regression model? what are the pros and cons? ** Considering other factors to add into my regression model could help us to predict the result better or finding more associated variables, on the other hand it could cause complexity in interpreting the results or collinearity which is correlation between predictor variables that can lead to coefficients being flipped from the direction I expect from simple linear regression.

g. Now along with testing if the conversion rate changes for different pages, I also add an effect based on which country a user lives. I will read in the **countries.csv** dataset and merge together my datasets on the approporiate rows.
I want to see if country had an impact on conversion?

```
In [39]: #reading countries.csv file
         countries_df = pd.read_csv('countries.csv')
         countries_df.head()
```

Out[39]:

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

```
In [40]: #checking for null values in countries.df dataset
         countries_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 290584 entries, 0 to 290583
```

```
Data columns (total 2 columns):
user_id    290584 non-null int64
country    290584 non-null object
dtypes: int64(1), object(1)
memory usage: 4.4+ MB
```

```
In [41]: #checing if I have the same row number in df2 as countries_df
         df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 290584 entries, 0 to 294477
Data columns (total 7 columns):
user_id         290584 non-null int64
timestamp       290584 non-null object
group           290584 non-null object
landing_page    290584 non-null object
converted       290584 non-null int64
intercept       290584 non-null int64
ab_page         290584 non-null uint8
dtypes: int64(3), object(3), uint8(1)
memory usage: 15.8+ MB
```

```
In [42]: #Joining the two datasets and saving the results in df3
         df3 = df2.set_index('user_id').join(countries_df.set_index('user_id'))
         df3.head()
```

Out[42]:

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

```
In [43]: #finding the existing country in my dataset to help us create necessary dummy variabl
         df3.country.value_counts()
```

```
Out[43]: US    203619
         UK     72466
```

```
CA     14499
Name: country, dtype: int64
```

```
In [44]: #creating dummy variables for exising countries
         df3[['CA', 'UK', 'US']] = pd.get_dummies(df3['country'])
         df3 = df3.drop('CA', axis=1)
         df3.head()
```

Out[44]:

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

h. Though I have now looked at the individual factors of country and page on conversion, I would now like to look at an interaction between page and country to see if there is significant effects on conversion.

```
In [45]: log_mod =sm.Logit(df3['converted'], df3[['intercept', 'ab_page', 'UK', 'US']])
         results = log_mod.fit()
         results.summary()
```

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

Out[45]:

```
<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:                Wed, 30 May 2018   Pseudo R-squ.:               2.323e-05
Time:                        17:38:32   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]
------------------------------------------------------------------------------
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
UK             0.0506      0.028      1.784      0.074      -0.005       0.106
US             0.0408      0.027      1.516      0.130      -0.012       0.093
==============================================================================
"""
```

According to the results, because all the p-values are greater than 0.05, there isn't any statistically significant relationship between the variables and the response variable(converted)

```
In [46]: from subprocess import call
         call(['python', '-m', 'nbconvert', 'Analyze_ab_test_results_notebook.ipynb'])
```

```
Out[46]: 0
```