Analyze_ab_test_results_notebook

September 27, 2019

0.1 Analyze A/B Test Results

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Introduction
A/B tests are very commonly performed by data analysts and data scientists.

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

```
In [1]: 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.read in the `ab_data.csv` data. Store it in `df`.

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

```
In [2]: df = pd.read_csv('ab_data.csv')
        df.head()
```

Out[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.the number of rows in the dataset.

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

```
Out[3]: 294478
```

c. The number of unique users in the dataset.

```
In [4]: df['user_id'].nunique()
```

```
Out[4]: 290584
```

d. The proportion of users converted.

```
In [5]: df['converted'].mean()
```

```
Out[5]: 0.11965919355605512
```

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

```
In [6]: df.query('landing_page=="new_page" and group !="treatment"').shape[0]
```

```
Out[6]: 1928
```

f. Missing values

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

```
Out[7]: user_id         0
        timestamp       0
        group           0
        landing_page    0
        converted       0
        dtype: int64
```

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.

a. We should remove these rows as we cant be confident in them and store our new dataframe in **df2**.

```
In [8]: #We should remove these rows as we cant be confident in them
        df2= df.query(('landing_page=="new_page" and group =="treatment" or landing_page=="old_p
        df2['landing_page'].unique()
```

```
Out[8]: array(['old_page', 'new_page'], dtype=object)
```

```
In [9]: # Double Check all of the correct rows were removed - this should be 0
        df2[((df2['group'] == 'treatment') == (df2['landing_page'] == 'new_page')) == False].sha
```

```
Out[9]: 0
```

3.

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

```
In [10]: df2['user_id'].nunique()
```

```
Out[10]: 290584
```

```
In [11]: df3 = df2.copy()
         df3['is_duplicated']= df3['user_id'].duplicated()
         df3.query('is_duplicated == True')
```

```
Out[11]:       user_id                   timestamp      group landing_page  converted  \
         2893   773192  2017-01-14 02:55:59.590927  treatment     new_page          0

               is_duplicated
         2893           True
```

b. **user_id** repeated in **df2**.

```
In [12]: df2.query('user_id == 773192')
```

```
Out[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
```

c. Information for the repeat **user_id**

```
In [13]: df2.query('user_id == 773192')
```

```
Out[13]:       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 our dataframe as **df2**.

```
In [14]: df2.drop(2893, inplace = True)
```

```
/opt/conda/lib/python3.6/site-packages/pandas/core/frame.py:3697: 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#
  errors=errors)
```

4. a. The probability of an individual converting regardless of the page they receive.

```
In [15]: df2['converted'].mean()
```

```
Out[15]: 0.11959708724499628
```

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

```
In [16]: convert_old = df2.query('group =="control"')['converted'].mean()
         convert_old
```

```
Out[16]: 0.1203863045004612
```

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

```
In [17]: convert_new = df2.query('group =="treatment"')['converted'].mean()
         convert_new
```

```
Out[17]: 0.11880806551510564
```

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

```
In [18]: df2.query('landing_page == "new_page"').shape[0]/df2.shape[0]
```

```
Out[18]: 0.5000619442226688
```

Considering the proportion of control and treatment groups is 50%. The probability that individual will convert is higher in the control group (old version) is 0.1204 and 0.1188 in experiment group. The company should consider keeping the old version, however, there are might be other underlying factors and the further tests might be conducted.

Part II - A/B Test

Because of the time stamp associated with each event, we 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.` I will make the decision just based on all the data provided.

H0: $p_{new} <= p_{old}$

H1: $p_{new} > p_{old}$

`2.` Let's say 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, let's assume they are equal to the **converted** rate in **ab_data.csv** regardless of the page.

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

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

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

```
In [19]: p_old = df2['converted'].mean()
         p_old
```

```
Out[19]: 0.11959708724499628
```

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

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

Out[20]: 0.11959708724499628

c. n_{new}

```
In [21]: n_new = df2.query('group =="treatment"')['converted'].shape[0]
         n_new
```

```
Out[21]: 145310
```

d.n_{old}

```
In [22]: n_old = df2.query('group =="control"')['converted'].shape[0]
         n_old
```

```
Out[22]: 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 [23]: p_null = p_old
         new_page_converted = np.random.binomial(1,p_null, 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 [24]: old_page_converted = np.random.binomial(1, p_null, n_new)
```

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

```
In [25]: obs_diff = (df2[df2['group'] == "treatment"]['converted'].mean()) - (df2[df2['group'] =
         obs_diff
```

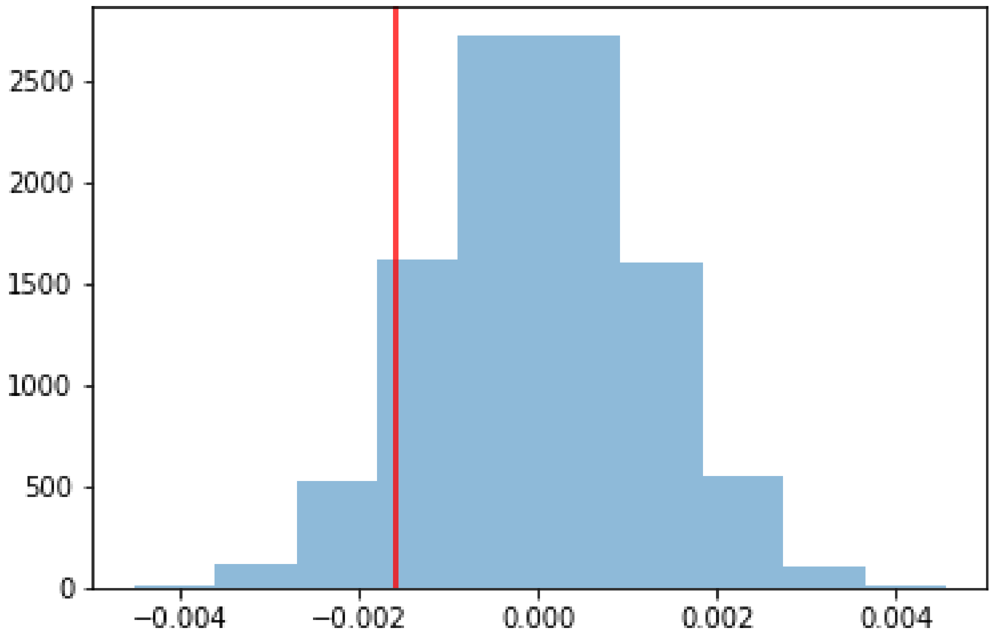
```
Out[25]: -0.0015782389853555567
```

h. Simulation of 10,000 p_{new} - p_{old} values to store all 10,000 values in **p_diffs**.

```
In [26]: # p_diffs = []
         # size= df2.shape[0]
         # for _ in range(10000):
         #     b_samp = df2.sample(size, replace=True)
         #     control_df = b_samp.query('group == "control"')
         #     treatment_df = b_samp.query('group == "treatment"')
         #     exp_diff = treatment_df['converted'].mean()-control_df['converted'].mean()
         #     p_diffs.append(exp_diff)
         p_diffs = np.random.binomial(n_new, p_null, 10000)/n_new - np.random.binomial(n_old, p_
```

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

```
In [27]: plt.hist(p_diffs, alpha = 0.5);
         # plot line for observed statistic
         plt.axvline(x= obs_diff, color = 'r');
```




```
In [28]: (p_diffs>obs_diff).mean()
```

```
Out[28]: 0.9073
```

In part j I tried to determine if the result is not due to the chance and it has a significant difference by computing the p-value. It looks like the statistic comes from null distribution. The p-value of 0.9 is more than alpha. The result is not significant and the company should reject the alternative hypothesis. The new page has no better conversion rate compare to the old page and company should keep the old page.

l. I could also use a built-in to achieve similar results. Though using the built-in might be easier to code.

```
In [29]: 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"').shape[0]
         n_new = df2.query('landing_page == "new_page"').shape[0]
         convert_old, convert_new, n_old, n_new
```

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

```
Out[29]: (17489, 17264, 145274, 145310)
```

m.stats.proportions_ztest to compute test statistic and p-value.

```
In [30]: z_score, p_value = sm.stats.proportions_ztest([convert_new, convert_old], [n_new, n_old
         z_score, p_value
```

```
Out[30]: (-1.3109241984234394, 0.18988337448195103)
```

```
In [31]: from scipy.stats import norm

         print(norm.cdf(z_score)) # Tells us how significant our z-score is

         print(norm.ppf(1-(0.05/2))) # Tells us what our critical value at 95% confidence is
```

```
0.094941687241
1.95996398454
```

Since the z-score exceeds the critical value of -1.959963984540054, we reject the alternative hypothesis

Landing page new (17264/145311) is statistically not different or better than landing page old (17489/145274).

Despite the result is slightly different in part I and part II, they agree in between towards null hypothesis. The p-value of 0.9 in part I and p-value of .19 more than alpha. We would expect their long-term performance to be no different from one another.

Part III - A regression approach

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

Logistic regression

b. The goal, now, 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, first I need to create a colun for the intercept, and create a dummy variable column for which page each user received.

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

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

```
Out[32]:    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

            control  treatment  intercept
```

```
0         1           0           1
1         1           0           1
2         0           1           1
3         0           1           1
4         1           0           1
```

c. I use **statsmodels** to import our regression model.

```
In [33]: lm = sm.Logit(df_new['converted'], df_new[['intercept', 'treatment']])
         results = lm.fit()
```

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

d.The summary of our model below.

```
In [34]: results.summary()
```

```
Out[34]: <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, 27 Sep 2019   Pseudo R-squ.:               8.077e-06
         Time:                        02:54:53   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
         treatment     -0.0150      0.011     -1.311      0.190      -0.037       0.007
         ==============================================================================
         """
```

In regression models, the slope and the intercept are equal to 0 in the null hypothesis. The alternative hypothesis by default is a computation of p-value to determine if p is equal or not equal to 0. We can interpret this as saying that under the null hypothesis there is no trend and the best estimate/predictor of a new observation is the mean which is 0 in the case of no intercept. To compare regression results with the result in Part II, both outcomes tend towards the null hypothesis and the treatment group doesn't have a significant influence on the result.

Other things that might have an effect are novelty affect and change aversion. However, if we talk about other factors we might test in the regression model could include, seasonal trends and geographical location of the users. The disadvantages of adding the new factors lay in a core or regression model as we want to make sure that parameters have correlation on the result but not between each other.

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.

```
In [35]: df_countries = pd.read_csv('countries.csv')
         df_countries.head()
```

```
Out[35]:    user_id country
         0   834778      UK
         1   928468      US
         2   822059      UK
         3   711597      UK
         4   710616      UK
```

```
In [36]: df_new1 = df_new.merge(df_countries, on = 'user_id')
         df_new1.head()
```

```
Out[36]:    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

            control  treatment  intercept country
         0        1          0          1      US
         1        1          0          1      US
         2        0          1          1      US
         3        0          1          1      US
         4        1          0          1      US
```

```
In [37]: country_page = pd.get_dummies(df_new1['country'])
         df_new1 = df_new1.join(country_page)
         df_new1.head()
```

```
Out[37]:    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

            control  treatment  intercept country  CA  UK  US
         0        1          0          1      US   0   0   1
         1        1          0          1      US   0   0   1
         2        0          1          1      US   0   0   1
         3        0          1          1      US   0   0   1
         4        1          0          1      US   0   0   1
```

```
In [38]: lm = sm.Logit(df_new1['converted'], df_new1[['intercept', 'treatment','UK','US']])
         results = lm.fit()
         results.summary()
```

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

Out[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:                Fri, 27 Sep 2019   Pseudo R-squ.:               2.323e-05
Time:                        02:54:54   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
treatment     -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
==============================================================================
"""
```

In [39]:

```
df_new1['CA_new_page'] = df_new1['treatment']*df_new1['CA']
df_new1['US_new_page'] = df_new1['treatment']*df_new1['US']
df_new1['UK_new_page'] = df_new1['treatment']*df_new1['UK']
df_new1['CA_old_page'] = df_new1['control']*df_new1['CA']
df_new1['US_old_page'] = df_new1['control']*df_new1['US']
df_new1['UK_old_page'] = df_new1['control']*df_new1['UK']
df_new1.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

   control  treatment  intercept country  CA  UK  US  CA_new_page  \
0        1          0          1      US   0   0   1            0
1        1          0          1      US   0   0   1            0
2        0          1          1      US   0   0   1            0
3        0          1          1      US   0   0   1            0
4        1          0          1      US   0   0   1            0
```

```
   US_new_page  UK_new_page  CA_old_page  US_old_page  UK_old_page
0            0            0            0            1            0
1            0            0            0            1            0
2            1            0            0            0            0
3            1            0            0            0            0
4            0            0            0            1            0
```

In [40]:
```python
lm = sm.Logit(df_new1['converted'], df_new1[['intercept', 'treatment','CA_new_page','US
results = lm.fit()
results.summary()
```

```
Optimization terminated successfully.
         Current function value: 0.366109
         Iterations 6
```

Out[40]:
```
<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, 27 Sep 2019   Pseudo R-squ.:               3.351e-05
Time:                        02:54:55   Log-Likelihood:            -1.0639e+05
converged:                       True   LL-Null:                   -1.0639e+05
                                        LLR p-value:                   0.06785
===============================================================================
                  coef    std err          z      P>|z|      [0.025      0.975]
-------------------------------------------------------------------------------
intercept      -1.9888      0.008   -246.669      0.000      -2.005      -1.973
treatment       0.0074      0.018      0.410      0.682      -0.028       0.043
CA_new_page    -0.0901      0.040     -2.225      0.026      -0.169      -0.011
US_new_page    -0.0257      0.019     -1.363      0.173      -0.063       0.011
===============================================================================
"""
```

From the section g, it can be observed that the slopes of variables are different, in simple words it identifies that different countries convert differently, to test if there is a relationship between countries and old or new pages on the covertions rate we can multiply these variables and add to our model. Interpreting the results, we can see that none of the countries has statistical significance on result regardless of, new or old page users visited. Still, the country with the smallest p-value has the highest influence. This country is Canada with the new landing page.