Analyze_ab_test_results_notebook

June 6, 2021

0.1 Analyze A/B Test Results Project

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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.

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. Now, 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(10)
```

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
5	936923	2017-01-10 15:20:49.083499	control	old_page	0

```
6   679687  2017-01-19 03:26:46.940749  treatment    new_page          1
7   719014  2017-01-17 01:48:29.539573    control    old_page          0
8   817355  2017-01-04 17:58:08.979471  treatment    new_page          1
9   839785  2017-01-15 18:11:06.610965  treatment    new_page          1
```

b. Use the cell below to find 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.nunique()
```

```
Out[4]: user_id         290584
        timestamp       294478
        group                2
        landing_page         2
        converted            2
        dtype: int64
```

d. The proportion of users converted.

```
In [5]: df_converted= len(df.query('converted ==1 '))/len(df['converted'])
        print(df_converted)
```

```
0.11965919355605512
```

```
In [6]: #df.query('converted ==1 & landing_page =="new_page"').count()
```

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

```
In [7]: new_page_n = df.query('group !="treatment" & landing_page =="new_page"')
        treatment_n = df.query('group =="treatment" & landing_page !="new_page"')
        no_times= len(new_page_n)+ len(treatment_n)
        print(no_times)
```

```
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. Store your new dataframe in **df2**.

```
In [9]: clean_df=df
        clean_df = df[((df.group=='treatment') & (df.landing_page=='new_page')) | ((df.group=='c
        df2=clean_df
```

```
In [10]: # Double Check all of the correct rows were removed - this should be 0
         df2[((df2['group'] == 'treatment') == (df2['landing_page'] == 'new_page')) == False].sh
```

```
Out[10]: 0
```

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

```
In [11]: df2['user_id'].nunique()
```

```
Out[11]: 290584
```

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

```
In [12]: len(df2['user_id'].duplicated())
```

```
Out[12]: 290585
```

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

```
In [13]: df2[df2.duplicated(['user_id'],keep=False)]
```

```
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 your dataframe as **df2**.

```
In [14]: df2=df2.drop_duplicates(subset=['user_id'], keep='first')
```

```
In [15]: len(df2.duplicated())
```

```
Out[15]: 290584
```

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

```
In [16]: df_convert= len(df2.query('converted ==1 '))/len(df2['converted'])
         print(df_convert)
```

```
0.11959708724499628
```

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

```
In [17]: control_group = len(df2.query('group=="control" and converted==1'))/len(df2.query('grou
         print(control_group)
```

```
0.1203863045004612
```

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

```
In [18]: treatment_group = len(df2.query('group=="treatment" and converted==1'))/len(df2.query('
         print(treatment_group)
```

```
0.11880806551510564
```

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

```
In [19]: received_new= len(df2.query('landing_page=="new_page"'))/len(df2['landing_page'])
         print(received_new)
```

```
0.5000619442226688
```

e.Is there a sufficient evidence to conclude that the new treatment page leads to more conversions?

I can't say that there is enough evidance to conclude that there is more conversion in new treatment page.As we see in the previous Statistics not all of users has recievied the new page only half of them and the percent of converted users that recieved is very close about 12% control group.While about 11% treatment.So overall the conversion rate did not increase.but its a very small difference.

Part II - A/B Test

`1.` For now, 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? p_{old} and p_{new}, which are the converted rates for the old and new pages.

H0: p_{new} - p_{old} <= 0

H1: p_{new} - p_{old} > 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.

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

```
In [20]: df2.head()
```

```
Out[20]:    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 [21]: pnew = len(df.query('converted ==1 '))/len(df['converted'])
         print(pnew)
```

```
0.11965919355605512
```

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

```
In [22]: pold = len(df.query('converted ==1 '))/len(df['converted'])
         print(pold)
```

```
0.11965919355605512
```

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

```
In [23]: no_treatment = len(df2.query('group=="treatment"'))
         print(no_treatment)
```

```
145310
```

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

```
In [24]: no_control = len(df2.query('group=="control"'))
         print(no_control)
```

```
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 [25]: new_page_converted = np.random.choice([0, 1], no_treatment, p = [pnew, 1-pnew])
         print(new_page_converted)
```

```
[1 0 1 ..., 1 1 0]
```

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 [26]: old_page_converted = np.random.choice([0, 1], no_control, p = [pold, 1-pold])
         print(old_page_converted)
```

```
[1 1 1 ..., 1 1 1]
```

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

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

```
0.000167269318727
```

```
In [28]: pvalue_diff = pnew-pold
         print(pvalue_diff)
```

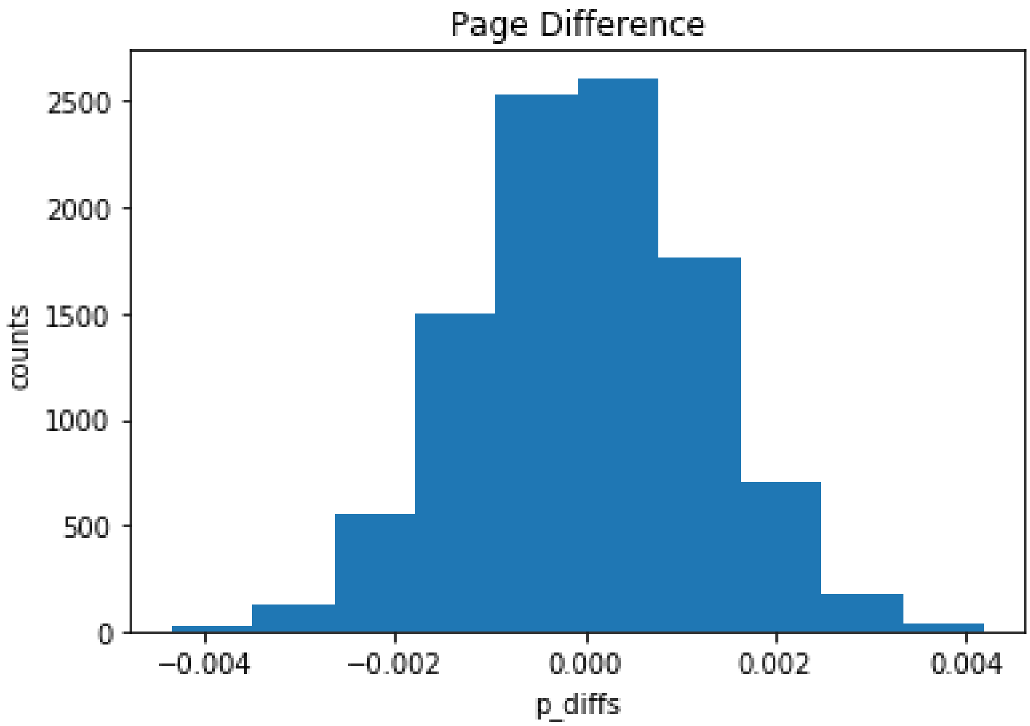
```
0.0
```

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 [29]: p_diffs=[]
         for _ in range(10000):
             new= np.random.choice([0,1],no_treatment, replace=True, p= [pnew, 1-pnew])
             old= np.random.choice([0,1],no_control, replace=True, p= [pold, 1-pold])
             new_mean= new.mean()
             old_mean= old.mean()
             p_diffs.append(new_mean - old_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.

```
In [30]: p_diffs = np.array(p_diffs)
         plt.hist(p_diffs);
         plt.title ('Page Difference');
         plt.xlabel('p_diffs');
         plt.ylabel('counts');
```

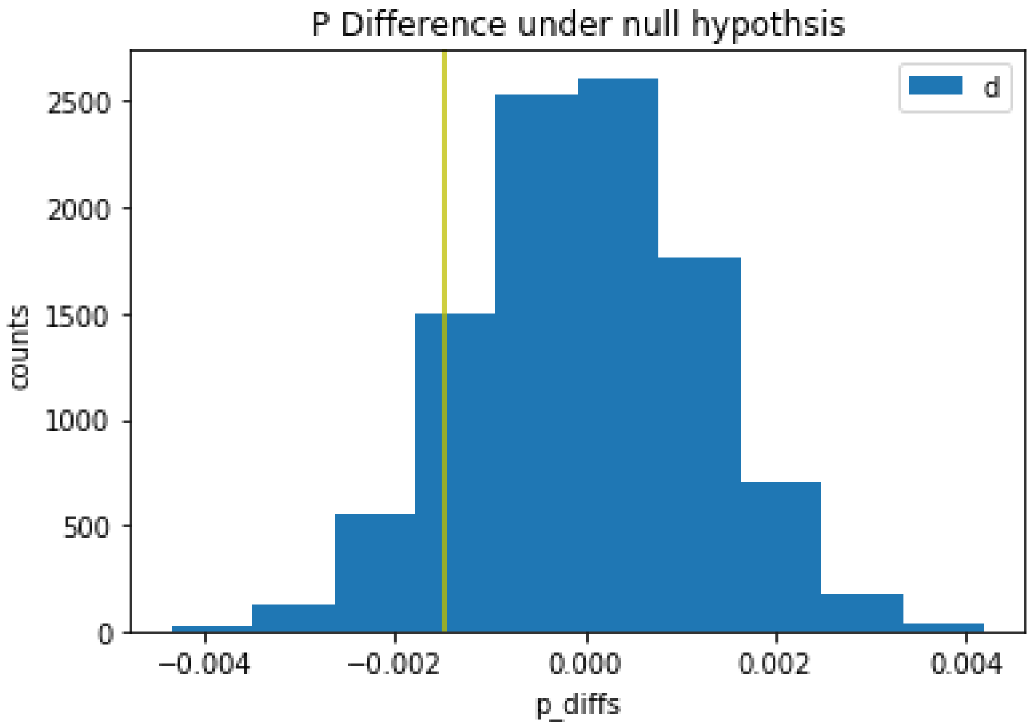


j. What proportion of the **p_diffs** are greater than the actual difference observed in **ab_data.csv**?

In [31]:
```
ab_new= df.query('group =="treatment"').converted.mean()
ab_old= df.query('group =="control"').converted.mean()
ab_diff= ab_new - ab_old
(p_diffs > ab_diff).mean()
```

Out[31]:
```
0.89170000000000005
```

In [32]:
```
plt.hist(p_diffs);
plt.title ('P Difference under null hypothsis');
plt.xlabel('p_diffs');
plt.ylabel('counts');
plt.legend("difference between old and new");
plt.axvline(x=ab_diff, color='y');
```



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?

The proportion of p-difference is about 89% .p-value is large, so the population is above diffrence which mean that the new-page is not doing better with comparison to the old one, the result is it would be better if we stick to the null hypothesis.

l. below calculation 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 that the number of rows associated with the old page and new pages, respectively.

```
In [33]: import statsmodels.api as sm
         from scipy.stats import norm
         convert_old = len(df2.query('landing_page == "old_page" & converted == 1'))
         convert_new = len(df2.query('landing_page == "new_page" & converted == 1'))
         n_old = len(df2.query('landing_page == "old_page"'))
         n_new = len(df2.query('landing_page == "new_page"'))
```

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

```
In [34]: print('n_old',n_old)
         print('n_new',n_new)
```

```
n_old 145274
n_new 145310
```

```
In [35]: print('convert_old',convert_old)
         print('convert_new',convert_new)
```

```
convert_old 17489
convert_new 17264
```

```
In [36]: z_score, p_value = sm.stats.proportions_ztest([convert_old,convert_new], [n_old, n_new]
         print(z_score,p_value)
```

```
1.31092419842 0.905058312759
```

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.**?

```
In [37]: print(norm.cdf(z_score))
```

```
0.905058312759
```

```
In [38]: print(norm.ppf(1-(0.05)))
```

```
1.64485362695
```

It's mean null hypothesis of old page conversion rate is greater than the new page conversion.As the p-value is 0.9 and z-score equal to 1.3 (should be equal or more 1.644) less than critical value of 95% confidence,so as result we can't reject null hypothesis.

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 we have a 2 variable wethier converted or not so Logistic Regression is the suitable regression type.

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.

```
In [42]: df2['intercept']=1
         df2[['control', 'treatment']] = pd.get_dummies(df2['group'])
         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/pandas/core/frame.py:3140: 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#
  self[k1] = value[k2]
```

```
Out[42]:    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  control  treatment
         0          1        1          0
         1          1        1          0
         2          1        0          1
         3          1        0          1
         4          1        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 [43]: model = sm.Logit(df2['converted'],df2[['intercept','treatment']])
```

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

```
In [45]: results = model.fit()

Optimization terminated successfully.
         Current function value: 0.366118
         Iterations 6


In [47]: results.summary2()

Out[47]: <class 'statsmodels.iolib.summary2.Summary'>
         """
                                  Results: Logit
         ==================================================================
         Model:              Logit            No. Iterations:   6.0000
         Dependent Variable: converted        Pseudo R-squared: 0.000
```

```
Date:                2021-06-06 20:52 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]
-------------------------------------------------------------------
intercept    -1.9888    0.0081  -246.6690  0.0000  -2.0046  -1.9730
treatment    -0.0150    0.0114    -1.3109  0.1899  -0.0374   0.0074
==================================================================

"""
```

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**?

Z,P-value = -1.3109 , 0.1899
Regression hypotheses is :
H0: pnew=pold
H1: pnew!=pold
while the hypotheses in part 2 is:
H0: - <= 0
H1: - > 0
The p-value is different from part 2. In part II the p-value is 0.9.This may be due to the regression model test that put an intercept.

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 think it's good to consider other factors too because this may help to know other things could affect conversion rate.on the other side i think will be alittle bit complex and that could be the disadvantages.

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 i will need to read in the **countries.csv** dataset and merge together your datasets on the appropriate rows.

In [48]:
```python
countries_df = pd.read_csv('countries.csv')
df_cont = countries_df.set_index('user_id').join(df2.set_index('user_id'), how='inner')
df_cont.head()
```

Out[48]:
```
        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  control  treatment
user_id
834778           0          1        1          0
928468           0          1        0          1
822059           1          1        0          1
711597           0          1        1          0
710616           0          1        0          1
```

In [53]:
```python
df_cont.country.unique()
```

Out[53]:
```
array(['UK', 'US', 'CA'], dtype=object)
```

In [54]:
```python
df_cont.describe()
```

Out[54]:
```
           converted  intercept        control      treatment
count  290584.000000   290584.0  290584.000000  290584.000000
mean        0.119597        1.0       0.499938       0.500062
std         0.324490        0.0       0.500001       0.500001
min         0.000000        1.0       0.000000       0.000000
25%         0.000000        1.0       0.000000       0.000000
50%         0.000000        1.0       0.000000       1.000000
75%         0.000000        1.0       1.000000       1.000000
max         1.000000        1.0       1.000000       1.000000
```

In [55]:
```python
df_cont.groupby(['country']).mean()
```

Out[55]:
```
         converted  intercept   control  treatment
country
CA        0.115318        1.0  0.496448   0.503552
UK        0.120594        1.0  0.501753   0.498247
US        0.119547        1.0  0.499541   0.500459
```

In [57]:
```python
df_cont[['CA','UK', 'US']]= pd.get_dummies(df_cont['country'])
```

In [58]:
```python
df_cont.head()
```

Out[58]:
```
        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  control  treatment  CA  UK  US
user_id
```

```
834778              0            1          1            0    0    1    0
928468              0            1          0            1    0    0    1
822059              1            1          0            1    0    1    0
711597              0            1          1            0    0    1    0
710616              0            1          0            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.

In [72]:
```
df_cont['intercept'] = 1
logistic_reg = sm.Logit(df_cont['converted'], df_cont[['intercept','treatment','CA','UK
```

In [73]:
```
results1= logistic_reg.fit()
```

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

In [74]:
```
results1.summary2()
```

Out[74]:
```
<class 'statsmodels.iolib.summary2.Summary'>
"""
                            Results: Logit
=====================================================================
Model:                Logit              No. Iterations:    6.0000
Dependent Variable:   converted          Pseudo R-squared:  0.000
Date:                 2021-06-06 22:36   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]
---------------------------------------------------------------------
intercept -1.4997 203295.7991 -0.0000 1.0000 -398453.9442 398450.9448
treatment -0.0149      0.0114 -1.3069 0.1912      -0.0374      0.0075
CA        -0.5304 203295.7991 -0.0000 1.0000 -398452.9749 398451.9142
UK        -0.4797 203295.7991 -0.0000 1.0000 -398452.9242 398451.9648
US        -0.4896 203295.7991 -0.0000 1.0000 -398452.9341 398451.9549
=====================================================================

"""
```

0.2.1 Conclusions

P-values has no signficant change.So we accept the Null Hypotheses.There is no evidence that new page increase the conversion rate with comparing to the old one.Also the countries coeffecient is very close (specially UK & US, canada is slightly differ) as whole can't say that interaction to pages is very different from each others.there is no indication for the user choice from the different 3 countries.

```
In [75]: from subprocess import call
         call(['python', '-m', 'nbconvert', 'Analyze_ab_test_results_notebook.ipynb'])

Out[75]: 0

In [ ]:
```