Analyze A/B Test Results

You may either submit your notebook through the workspace here, or you may work from your local machine and submit through the next page. Either way assure that your code passes the project RUBRIC (https://review.udacity.com/#!/projects/37e27304-ad47-4eb0-a1ab-8c12f60e43d0/rubric). **Please save regularly.**

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!

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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.

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 (https://review.udacity.com/#!/projects/37e27304-ad47-4eb0-a1ab-8c12f60e43d0/rubric).

Part I - Probability

To get started, let's import our libraries.

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` . **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 [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

In [3]:

```
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
```

In [4]:

```
df.describe()
```

Out[4]:

	user_id	converted
count	294478.000000	294478.000000
mean	787974.124733	0.119659
std	91210.823776	0.324563
min	630000.000000	0.000000
25%	709032.250000	0.000000
50%	787933.500000	0.000000
75%	866911.750000	0.000000
max	945999.000000	1.000000

b. Use the cell below to find the number of rows in the dataset.

In [5]:

```
df.shape
```

Out[5]:

```
(294478, 5)
```

c. The number of unique users in the dataset.

In [6]:

```
df.user_id.nunique()
```

Out[6]:

```
290584
```

d. The proportion of users converted.

In [7]:

```
df.describe()
```

Out[7]:

	user_id	converted
count	294478.000000	294478.000000
mean	787974.124733	0.119659
std	91210.823776	0.324563
min	630000.000000	0.000000
25%	709032.250000	0.000000
50%	787933.500000	0.000000
75%	866911.750000	0.000000
max	945999.000000	1.000000

In [8]:

```
df.converted.mean()
```

Out[8]:

```
0.11965919355605512
```

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

In [9]:

```
treatment=df.query("group=='treatment' and landing_page=='old_page'").count()
control=df.query("group=='control' and landing_page=='new_page'").count()
treatment+control
```

Out[9]:

```
user_id         3893
timestamp       3893
group           3893
landing_page    3893
converted       3893
dtype: int64
```

f. Do any of the rows have missing values?

In [10]:

```
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
```

In [11]:

```
df.notnull().count()
```

Out[11]:

```
user_id         294478
timestamp       294478
group           294478
landing_page    294478
converted       294478
dtype: int64
```

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. Use **Quiz 2** in the classroom to figure out 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 [12]:

```
df2=df.copy()
df2=df2.query("(group == 'treatment' and landing_page == 'new_page') or (group == 'control'
df2.count()
```

Out[12]:

```
user_id         290585
timestamp       290585
group           290585
landing_page    290585
converted       290585
dtype: int64
```

In [13]:

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

Out[13]:

```
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**?

In [14]:

```
df2.user_id.nunique()
```

Out[14]:

```
290584
```

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

In [15]:

```
df2[df2.duplicated('user_id',False)]
```

Out[15]:

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

In [16]:

```
df2[df2.duplicated('user_id',False)]
```

Out[16]:

	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 [17]:

```
df2.drop_duplicates('user_id',keep='first',inplace=True)
```

In [18]:

```
df2[df2.duplicated('user_id',False)]
```

Out[18]:

	user_id	timestamp	group	landing_page	converted

In [19]:

```
df2.query("user_id=='773192'")
```

Out[19]:

	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 cells below 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 [20]:

```
df2.converted.mean()
```

Out[20]:

```
0.11959708724499628
```

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

In [21]:

```
control=df2.query("group=='control'").converted.mean()
control
```

Out[21]:

```
0.1203863045004612
```

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

In [22]:

```
treatment=df2.query("group=='treatment'").converted.mean()
treatment
```

Out[22]:

```
0.11880806551510564
```

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

In [23]:

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

Out[23]:

```
0.5000619442226688
```

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

Your answer goes here.

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.

H0:page_new<=page_old

H1:page_new>page_old

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.

In [24]:

```
df2.converted.value_counts()
```

Out[24]:

```
0    255831
1     34753
Name: converted, dtype: int64
```

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

In [25]:

```
p_new=df2.converted.mean()
p_new
```

Out[25]:

```
0.11959708724499628
```

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

In [26]:

```
p_old=df2.converted.mean()
p_old
```

Out[26]:

```
0.11959708724499628
```

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

In [27]:

```
n_new=df2.query("group=='treatment'").count()[0]
n_new
```

Out[27]:

```
145310
```

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

In [28]:

```
n_old=df2.query("group=='control'").count()[0]
n_old
```

Out[28]:

```
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 [29]:

```
new_page_converted=np.random.binomial(1,p_new,n_new)
new_page_converted
```

Out[29]:

```
array([0, 1, 1, ..., 0, 0, 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 [30]:

```
old_page_converted=np.random.binomial(1,p_old,n_old)
old_page_converted
```

Out[30]:

```
array([0, 0, 0, ..., 0, 0, 0])
```

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

In [31]:

```
dif=new_page_converted.mean()-old_page_converted.mean()
dif
```

Out[31]:

```
-0.00019490240709425788
```

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 [32]:

```
p_diffs = []
for _ in range(10000):
    new_page_converted = np.random.binomial(n_new,p_new)/n_new
    old_page_converted = np.random.binomial(n_old, p_old)/n_old
    p_diffs.append(new_page_converted-old_page_converted)
```

A try for sampling distribution:

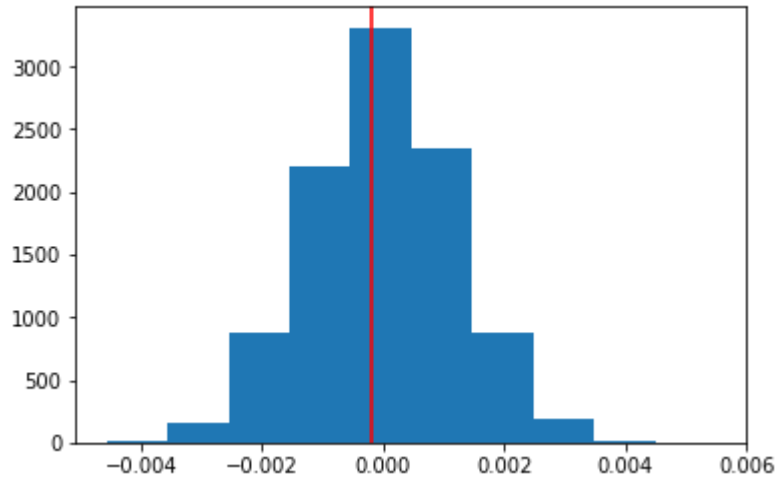
In [49]:

```
diffs=[]
for _ in range(10000):
    boot_samp=df2.sample(df2.shape[0],replace=True)
    boot_p_new=boot_samp.converted.mean()
    boot_p_old=boot_samp.converted.mean()
    boot_n_new=boot_samp.query("group=='treatment'").count()[0]
    boot_n_old=boot_samp.query("group=='control'").count()[0]
    boot_new_page_converted=np.random.binomial(boot_n_new,boot_p_new)/boot_n_new
    boot_old_page_converted=np.random.binomial(boot_n_old,boot_p_old)/boot_n_old
    diffs.append(boot_new_page_converted-boot_old_page_converted)
```

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.

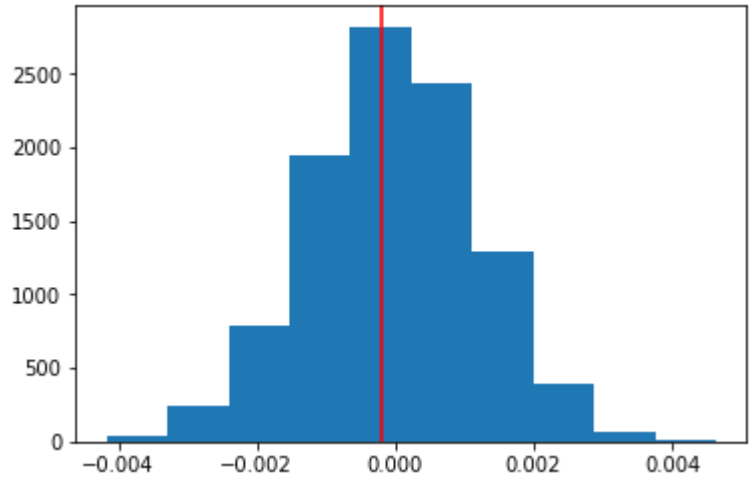
In [50]:

```
p_diffs=np.array(p_diffs)
plt.hist(p_diffs);
plt.axvline(dif,color='red');
```



In [51]:

```
diffs=np.array(diffs)
plt.hist(diffs);
plt.axvline(dif,color='red');
```



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

In [52]:

```
(p_diffs>dif).mean()
```

Out[52]:

```
0.5588
```

In [53]:

```
(diffs>dif).mean()
```

Out[53]:

```
0.559
```

In [85]:

```
df_diff=df2.query("group=='treatment'").converted.mean()-df2.query("group=='control'").conv
print(df_diff)
```

```
-0.0015782389853555567
```

In [88]:

```
(p_diffs>df_diff).mean()
```

Out[88]:

```
0.9
```

k. Please explain using the vocabulary you've learned in this course 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?

Put your answer here.

The type 1 error(alpha) is 5% which is 0.05,Which means the p value should be less than 0.05 then the alternative hypothesis will be true but in our case,The new page didnot have a better rate than the old page because the value is 0.5588 is greater than the alpha value.

final words is that we have failed to eliminate the null hypothesis because the new page has the larger rate than 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.

In [65]:

```
import statsmodels.api as sm

convert_old=df2.query("landing_page=='old_page' and converted=='1'").count()[0]
convert_new=df2.query("landing_page=='new_page' and converted=='1'").count()[0]
n_old=df2.query("landing_page=='old_page'").count()[0]
n_new=df2.query("landing_page=='new_page'").count()[0]
```

In [66]:

```
convert_old
```

Out[66]:

```
17489
```

In [67]:

```
convert_new
```

Out[67]:

```
17264
```

In [68]:

```
n_old
```

Out[68]:

```
145274
```

In [69]:

```
n_new
```

Out[69]:

```
145310
```

m. Now use `stats.proportions_ztest` to compute your test statistic and p-value. Here (http://knowledgetack.com/python/statsmodels/proportions_ztest/) is a helpful link on using the built in.

In [70]:

```
from statsmodels.stats.proportion import proportions_ztest
z_score, p_value = sm.stats.proportions_ztest([convert_new, convert_old], [n_new,n_old], al
```

In [71]:

```
z_score
```

Out[71]:

```
-1.3109241984234394
```

In [72]:

```
p_value
```

Out[72]:

```
0.9050583127590245
```

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.**?

Put your answer here.

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?

Put your answer here.

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 in df2 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**.

In [132]:

```
import statsmodels.api as sm
df2['intercept']=1
df2[['control','treatment']]=pd.get_dummies(df2['group'])
```

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 [204]:

```
lm=sm.OLS(df2[['converted']],df2[['intercept','treatment']])
results=lm.fit()
```

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

In [205]:

```
results.summary()
```

Out[205]:

OLS Regression Results

Dep. Variable:	converted	**R-squared:**	0.000
Model:	OLS	**Adj. R-squared:**	0.000
Method:	Least Squares	**F-statistic:**	1.719
Date:	Wed, 24 Apr 2019	**Prob (F-statistic):**	0.190
Time:	16:52:32	**Log-Likelihood:**	-85267.
No. Observations:	290584	**AIC:**	1.705e+05
Df Residuals:	290582	**BIC:**	1.706e+05
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
intercept	0.1204	0.001	141.407	0.000	0.119	0.122
treatment	-0.0016	0.001	-1.311	0.190	-0.004	0.001

Omnibus:	125553.456	**Durbin-Watson:**	1.995
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	414313.355
Skew:	2.345	**Prob(JB):**	0.00
Kurtosis:	6.497	**Cond. No.**	2.62

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

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**?

the p-value is 0.190

As i mentioned above to meet the alternative hypothesis or to reject the null hypothesis the type 1 error(alpha) should me less than 0.05. but here we have got 0.19 which means that we have again failed to reject the null hypothesis. where 0.19>0.05

H0:page_new<=page_old

H1:page_new(not=)page_old

The values in the part 2 is different because we randomly sampled the data 10000 times and the sample would have been overlapped.which means that there was a different measurement occurred in the calculation that we see in the regression part.

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?

it is a good idea to consider the other factors to develop our test results and can make a good decisions.

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. You will need to read in the **countries.csv** dataset and merge together your datasets on the appropriate rows. Here (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.join.html) 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.

In [209]:

```
df_count=pd.read_csv('countries.csv')
df_count.head()
```

Out[209]:

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

In [210]:

```
df2=pd.merge(df2,df_count,on=['user_id'])
```

In [211]:

```
df2.head(10)
```

Out[211]:

	user_id	timestamp	group	landing_page	converted	intercept	control	treatment	c
0	851104	2017-01-21 22:11:48.556739	control	old_page	0	1	1	0	
1	804228	2017-01-12 08:01:45.159739	control	old_page	0	1	1	0	
2	661590	2017-01-11 16:55:06.154213	treatment	new_page	0	1	0	1	
3	853541	2017-01-08 18:28:03.143765	treatment	new_page	0	1	0	1	
4	864975	2017-01-21 01:52:26.210827	control	old_page	1	1	1	0	
5	936923	2017-01-10 15:20:49.083499	control	old_page	0	1	1	0	
6	679687	2017-01-19 03:26:46.940749	treatment	new_page	1	1	0	1	
7	719014	2017-01-17 01:48:29.539573	control	old_page	0	1	1	0	
8	817355	2017-01-04 17:58:08.979471	treatment	new_page	1	1	0	1	
9	839785	2017-01-15 18:11:06.610965	treatment	new_page	1	1	0	1	

In [212]:

```
df2.country.value_counts()
```

Out[212]:

```
US    203619
UK     72466
CA     14499
Name: country, dtype: int64
```

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 [225]:

```
df2[['US','UK','CA']]=pd.get_dummies(df2['country'])
```

In [230]:

```
lm_count=sm.OLS(df2['converted'],df2[['intercept','UK','CA']])
result_count=lm_count.fit()
result_count.summary()
```

Out[230]:

OLS Regression Results

Dep. Variable:	converted	**R-squared:**	0.000
Model:	OLS	**Adj. R-squared:**	0.000
Method:	Least Squares	**F-statistic:**	1.605
Date:	Wed, 24 Apr 2019	**Prob (F-statistic):**	0.201
Time:	16:58:59	**Log-Likelihood:**	-85267.
No. Observations:	290584	**AIC:**	1.705e+05
Df Residuals:	290581	**BIC:**	1.706e+05
Df Model:	2		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
intercept	0.1153	0.003	42.792	0.000	0.110	0.121
UK	0.0053	0.003	1.787	0.074	-0.001	0.011
CA	0.0042	0.003	1.516	0.130	-0.001	0.010

Omnibus:	125552.384	**Durbin-Watson:**	1.995
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	414306.036
Skew:	2.345	**Prob(JB):**	0.00
Kurtosis:	6.497	**Cond. No.**	9.94

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [234]:

```
lm_count=sm.OLS(df2['converted'],df2[['intercept','CA','US','UK']])
result_count=lm_count.fit()
result_count.summary()
```

Out[234]:

OLS Regression Results

Dep. Variable:	converted	**R-squared:**	0.000
Model:	OLS	**Adj. R-squared:**	0.000
Method:	Least Squares	**F-statistic:**	1.050
Date:	Wed, 24 Apr 2019	**Prob (F-statistic):**	0.369
Time:	17:08:05	**Log-Likelihood:**	-85267.
No. Observations:	290584	**AIC:**	1.705e+05
Df Residuals:	290580	**BIC:**	1.706e+05
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
intercept	-4.242e+09	1.37e+10	-0.309	0.757	-3.11e+10	2.26e+10
CA	4.242e+09	1.37e+10	0.309	0.757	-2.26e+10	3.11e+10
US	4.242e+09	1.37e+10	0.309	0.757	-2.26e+10	3.11e+10
UK	4.242e+09	1.37e+10	0.309	0.757	-2.26e+10	3.11e+10

Omnibus:	125552.427	**Durbin-Watson:**	1.995
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	414306.321
Skew:	2.345	**Prob(JB):**	0.00
Kurtosis:	6.497	**Cond. No.**	5.76e+13

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 1.4e-22. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

Conclusion:

Looking at the above results we come under a decision that there no need to implement the new page. which means that the company need to stay in the old page rather than implementing the new page. As there is no evidence against the old page to implement the new page.

Finishing Up

Congratulations! You have reached the end of the A/B Test Results project! You should be very proud of all you have accomplished!

Tip: Once you are satisfied with your work here, check over your report to make sure that it is satisfies all the areas of the rubric (found on the project submission page at the end of the lesson). You should also probably remove all of the "Tips" like this one so that the presentation is as polished as possible.

Directions to Submit

Before you submit your project, you need to create a .html or .pdf version of this notebook in the workspace here. To do that, run the code cell below. If it worked correctly, you should get a return code of 0, and you should see the generated .html file in the workspace directory (click on the orange Jupyter icon in the upper left).

Alternatively, you can download this report as .html via the **File** > **Download as** submenu, and then manually upload it into the workspace directory by clicking on the orange Jupyter icon in the upper left, then using the Upload button.

Once you've done this, you can submit your project by clicking on the "Submit Project" button in the lower right here. This will create and submit a zip file with this .ipynb doc and the .html or .pdf version you created. Congratulations!

In [ ]:

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