

## A/B Test - Translation

A France-based users company have a much higher conversion rate in French than in any other Frenchspeaking country. The solution was to have one translation written by a local, aiming to improve the conversion rate. However, based on the test the localized translation was doing worse!

The structure of this notebook is as follows:

- Load Dataset
- Exploratory Data Analysis
- Two-sample Z-test on entire dataset
- Conversion rate by variable
- Conversion rate by country

```
In [176]: import warnings
#scripting.disable_filter('Ignore')

import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.stats import ttest_ind
import plotlylib inline
```

### Load Dataset

```
In [177]: test = pd.read_csv('test_table.csv', parse_dates=['date'])
test.head()
```

```
Out[177]:
```

	user_id	date	source	device	browser_language	ads_channel	browser	conversion	test
0	315281	2015-12-03	Direct	Web	FR	NaN	IE	1	0
1	497851	2015-12-04	Ads	Web	FR	Google	IE	0	1
2	848402	2015-12-04	Ads	Web	FR	Facebook	Chrome	0	0
3	290051	2015-12-03	Ads	Mobile	Other	Facebook	Android_App	0	1
4	548435	2015-11-30	Ads	Web	FR	Google	FireFox	0	1

```
In [179]: user = pd.read_csv('user_table.csv')
user.head()
```

```
Out[179]:
```

	user_id	sex	age	country
0	765821	M	20	Democratic Republic of the Congo
1	343561	F	27	Luxembourg
2	118744	M	23	Canada
3	987753	F	27	Switzerland
4	554597	F	20	France

```
In [180]: # Merge two tables
data = pd.merge(left=test, right=user, how='left', on='user_id')
data.head()
```

```
Out[180]:
```

	user_id	date	source	device	browser_language	ads_channel	browser	conversion	test	sex	age	c
0	315281	2015-12-03	Direct	Web	FR	NaN	IE	1	0	M	32.0	Fran
1	497851	2015-12-04	Ads	Web	FR	Google	IE	0	1	M	21.0	Dem Rep of the C
2	848402	2015-12-04	Ads	Web	FR	Facebook	Chrome	0	0	M	34.0	Fran
3	290051	2015-12-03	Ads	Mobile	Other	Facebook	Android_App	0	1	F	22.0	Dem Rep of the C
4	548435	2015-11-30	Ads	Web	FR	Google	FireFox	0	1	M	19.0	Dem Rep of the C

### Exploratory Data Analysis

```
In [181]: test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 453321 entries, 0 to 453320
Data columns (total 9 columns):
user_id      453321 non-null int64
date         453321 non-null datetime64[ns]
source       453321 non-null object
device       453321 non-null object
browser_language 453321 non-null object
ads_channel  181877 non-null object
browser      453321 non-null object
conversion   453321 non-null int64
test         453321 non-null int64
dtypes: datetime64[ns](1), float64(1), object(5)
memory usage: 31.1+ MB
```

```
In [182]: test.describe()
```

```
Out[182]:
```

	user_id	conversion	test
count	453321.000000	453321.000000	453321.000000
mean	499937.514728	0.049579	0.476446
std	288676.264784	0.217073	0.499445
min	1.000000	0.000000	0.000000
25%	249816.000000	0.000000	0.000000
50%	500919.000000	0.000000	0.000000
75%	749522.000000	0.000000	1.000000
max	1000000.000000	1.000000	1.000000

```
In [183]: user.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 452867 entries, 0 to 452866
Data columns (total 4 columns):
user_id      452867 non-null int64
sex          452867 non-null object
age          452867 non-null int64
country      452867 non-null object
dtypes: int64(2), object(2)
memory usage: 13.8+ MB
```

```
In [184]: user.describe()
```

```
Out[184]:
```

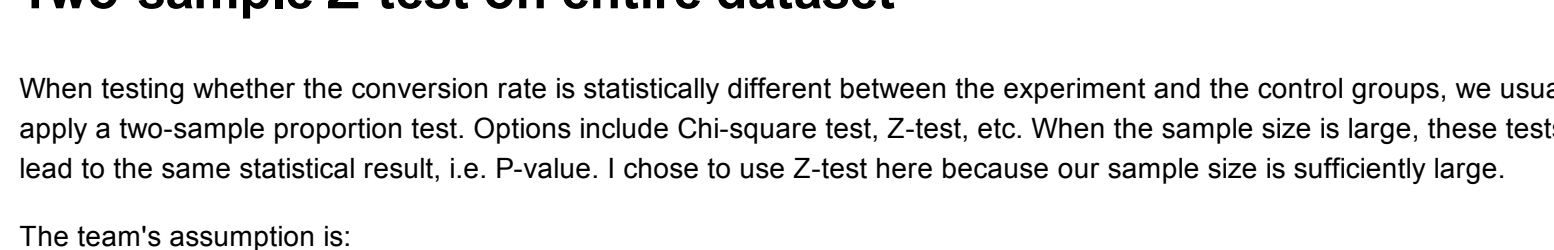
	user_id	age
count	452867.000000	452867.000000
mean	499944.805166	27.130740
std	288676.264784	6.776678
min	1.000000	18.000000
25%	249819.000000	22.000000
50%	500919.000000	26.000000
75%	749543.000000	31.000000
max	1000000.000000	70.000000

```
In [185]: data.info()
```

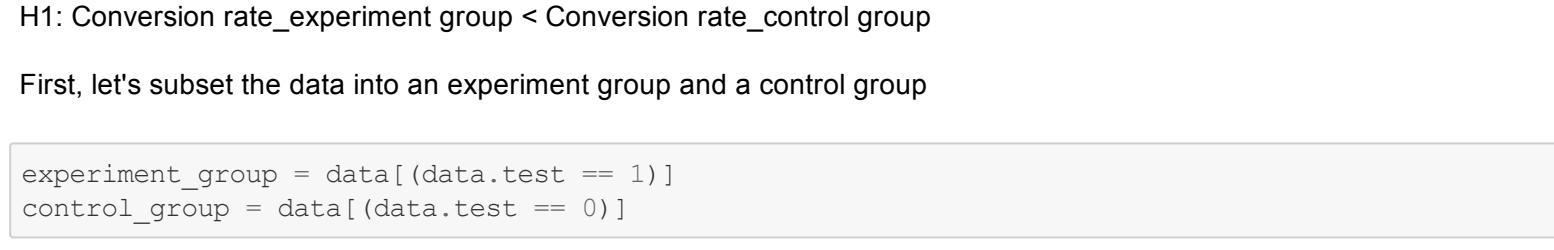
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 453321 entries, 0 to 453320
Data columns (total 12 columns):
user_id      453321 non-null int64
date         453321 non-null datetime64[ns]
source       453321 non-null object
device       453321 non-null object
browser_language 453321 non-null object
ads_channel  181877 non-null object
browser      453321 non-null object
conversion   453321 non-null int64
test         453321 non-null int64
sex          452867 non-null object
age          452867 non-null float64
country      452867 non-null object
dtypes: datetime64[ns](1), float64(1), int64(3), object(7)
memory usage: 45.0+ MB
```

```
In [186]: # First check that France converts much better than the rest of LatAm countries
groupby_country = data[data['test'] == 0][['conversion', 'country']].groupby('country').mean()
groupby_country = groupby_country.reset_index()
groupby_country = groupby_country.sort_values('conversion', ascending=False)
```

```
# Visualization
fig, ax = plt.subplots(figsize=(30,10))
sns.barplot(x='country', y='conversion', data=groupby_country, ax=ax)
plt.show()
```



```
In [187]: # Visualization
fig, ax = plt.subplots(figsize=(35, 10))
sns.barplot(x='country', y='conversion', hue='test', data=data, ax=ax)
plt.show()
```



Eventually, let's remove France and samples that have missing country values from the dataset because:

Nothing has changed for France Number of missing values is small, so they won't affect statistical tests much

```
In [188]: data = data[data.country != 'France'] & data.country != 'missing']
data.shape
```

```
Out[188]: (401519, 12)
```

### Two-sample Z-test on entire dataset

When testing whether the conversion rate is statistically different between the experiment and the control groups, we usually apply a two-sample proportion test. Options include Chi-square test, Z-test, etc. When the sample size is large, these tests lead to the same statistical result, i.e. P-value. I chose to use Z-test here because our sample size is sufficiently large.

The team's assumption is:

H0: Conversion\_rate\_experiment group = Conversion\_rate\_control group

H1: Conversion\_rate\_experiment group < Conversion\_rate\_control group

First, let's subset the data into an experiment group and a control group

```
In [189]: experiment_group = data[data.test == 1]
control_group = data[data.test == 0]
```

We can see from below that initial comparison of the conversion rates between the experiment and the control groups indicates that the non-localized translation was doing better.

```
In [190]: control_group.conversion.mean()
```

```
Out[190]: 0.0483042316066309
```

```
In [191]: experiment_group.conversion.mean()
```

```
Out[191]: 0.043424713982118966
```

```
In [192]: import statsmodels.api as sm
def two_sample_z_test(df, alternative='two-sided'):
    """
    This function returns the P-value from a two-sample Z-test
    """
    test_df = df[df.test == 1]
    control_df = df[df.test == 0]

    test_convert = test_df.conversion.sum()
    control_convert = control_df.conversion.sum()

    test_n = len(test_df.conversion)
    control_n = len(control_df.conversion)
    z, p_value = sm.stats.proportions_test([test_convert, control_convert],
                                         [test_n, control_n],
                                         alternative=alternative)

    return(z, p_value)

z, pvalue = two_sample_z_test(data, alternative='smaller')
print('Z-score is: {}'.format(z))
print('P-value is: {}'.format(pvalue))

Z-score is: -7.422021422012666
P-value is: 5.707307540762427e-14
```

From the test result we see that what the team observed was true, the conversion rate of the test group is indeed less than that of the control group.

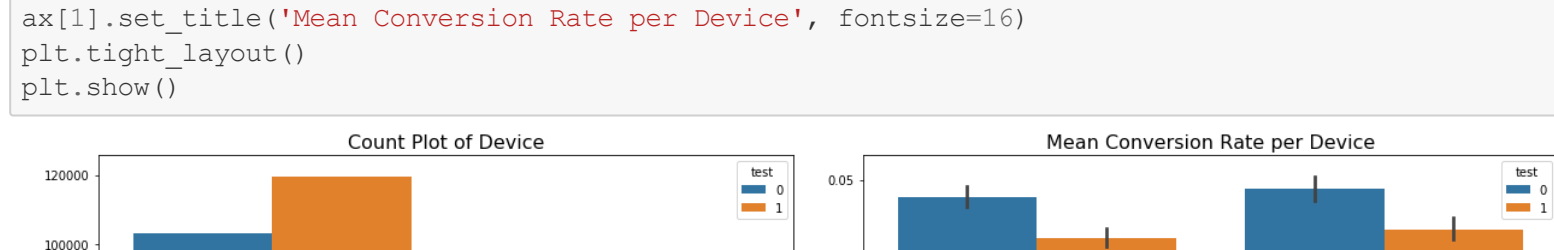
### Conversion rate by variable

Is there any confounding variable?

A confounding variable is an outside influence that changes the effect of an independent variable on the dependent variable

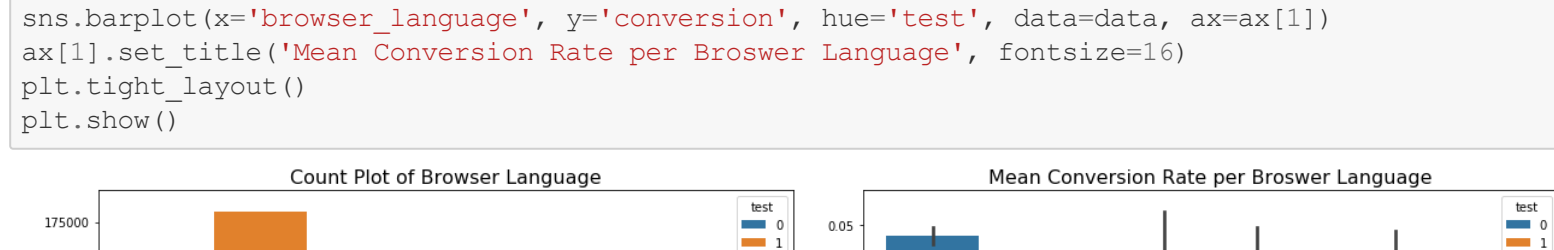
```
In [203]: # Visualization of different dates
fig, ax = plt.subplots(nrows=2, ncols=2, figsize=(18, 6))
sns.countplot(x='date', hue='test', data=data, ax=ax[0])
ax[0].set_title('Count Plot of Date', fontsize=16)

sns.barplot(x='date', y='conversion', hue='test', data=data, ax=ax[1])
ax[1].set_title('Mean Conversion Rate per Date', fontsize=16)
plt.tight_layout()
plt.show()
```



```
In [204]: # Visualization of different source
fig, ax = plt.subplots(nrows=2, ncols=2, figsize=(18, 6))
sns.countplot(x='source', hue='test', data=data, ax=ax[0])
ax[0].set_title('Count Plot of Source', fontsize=16)

sns.barplot(x='source', y='conversion', hue='test', data=data, ax=ax[1])
ax[1].set_title('Mean Conversion Rate per Source', fontsize=16)
plt.tight_layout()
plt.show()
```



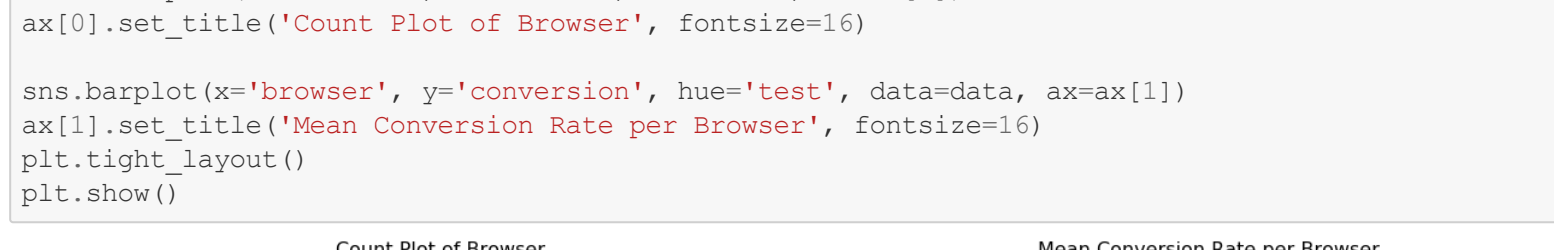
```
In [205]: # Visualization of different device
fig, ax = plt.subplots(nrows=2, ncols=2, figsize=(18, 6))
sns.countplot(x='device', hue='test', data=data, ax=ax[0])
ax[0].set_title('Count Plot of Device', fontsize=16)

sns.barplot(x='device', y='conversion', hue='test', data=data, ax=ax[1])
ax[1].set_title('Mean Conversion Rate per Device', fontsize=16)
plt.tight_layout()
plt.show()
```



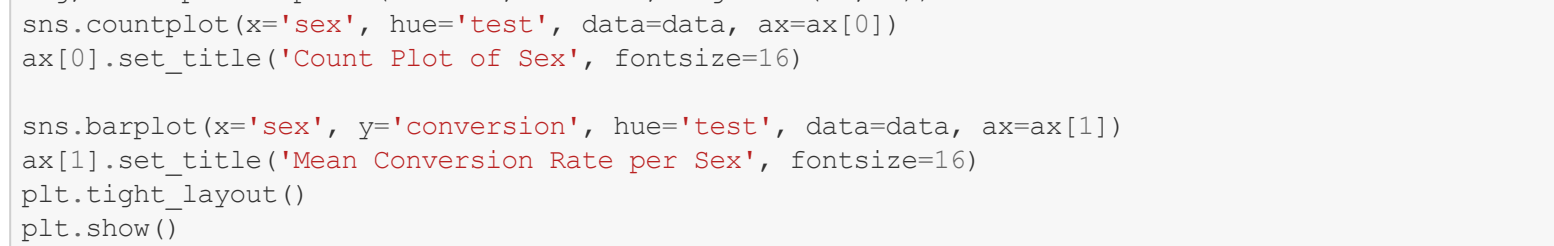
```
In [206]: # Visualization of different browser language
fig, ax = plt.subplots(nrows=2, ncols=2, figsize=(18, 6))
sns.countplot(x='browser_language', hue='test', data=data, ax=ax[0])
ax[0].set_title('Count Plot of Browser Language', fontsize=16)

sns.barplot(x='browser_language', y='conversion', hue='test', data=data, ax=ax[1])
ax[1].set_title('Mean Conversion Rate per Browser Language', fontsize=16)
plt.tight_layout()
plt.show()
```



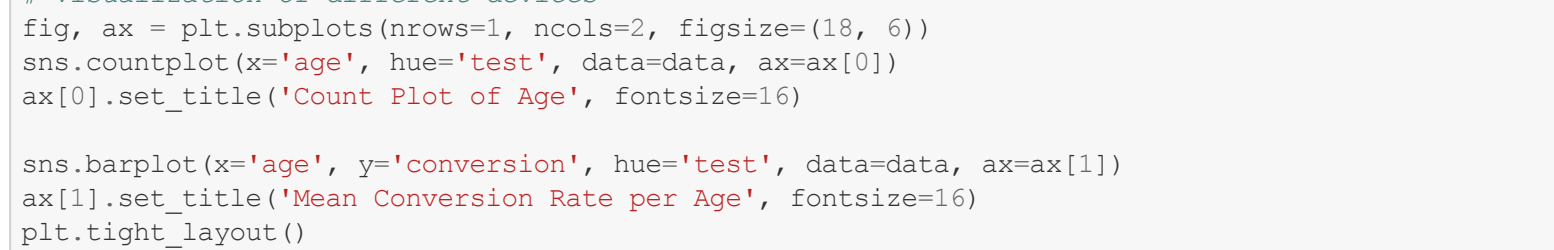
```
In [207]: # Visualization of different devices
fig, ax = plt.subplots(nrows=2, ncols=2, figsize=(18, 6))
sns.countplot(x='ads_channel', hue='test', data=data, ax=ax[0])
ax[0].set_title('Count Plot of Ads Channel', fontsize=16)

sns.barplot(x='ads_channel', y='conversion', hue='test', data=data, ax=ax[1])
ax[1].set_title('Mean Conversion Rate per Ads Channel', fontsize=16)
plt.tight_layout()
plt.show()
```



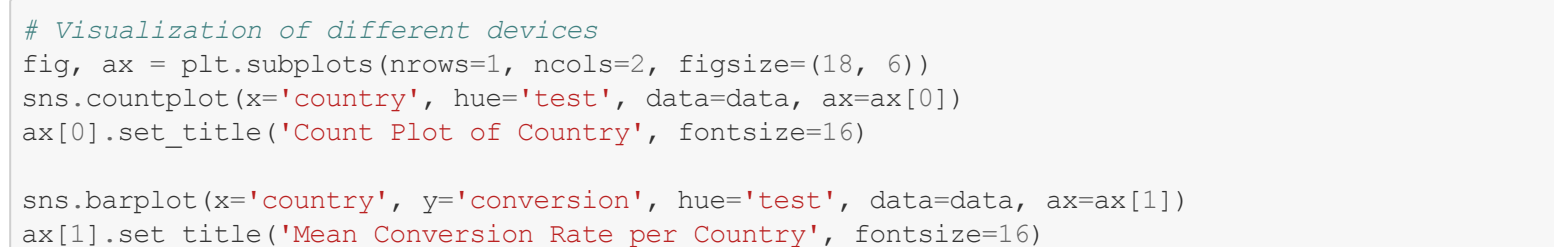
```
In [208]: # Visualization of different devices
fig, ax = plt.subplots(nrows=2, ncols=2, figsize=(18, 6))
sns.countplot(x='browser', hue='test', data=data, ax=ax[0])
ax[0].set_title('Count Plot of Browser', fontsize=16)

sns.barplot(x='browser', y='conversion', hue='test', data=data, ax=ax[1])
ax[1].set_title('Mean Conversion Rate per Browser', fontsize=16)
plt.tight_layout()
plt.show()
```



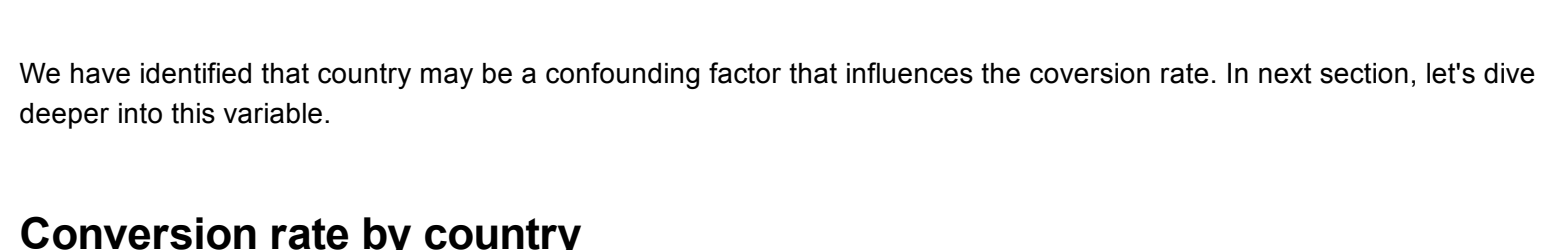
```
In [209]: # Visualization of different devices
fig, ax = plt.subplots(nrows=2, ncols=2, figsize=(18, 6))
sns.countplot(x='sex', hue='test', data=data, ax=ax[0])
ax[0].set_title('Count Plot of Sex', fontsize=16)

sns.barplot(x='sex', y='conversion', hue='test', data=data, ax=ax[1])
ax[1].set_title('Mean Conversion Rate per Sex', fontsize=16)
plt.tight_layout()
plt.show()
```



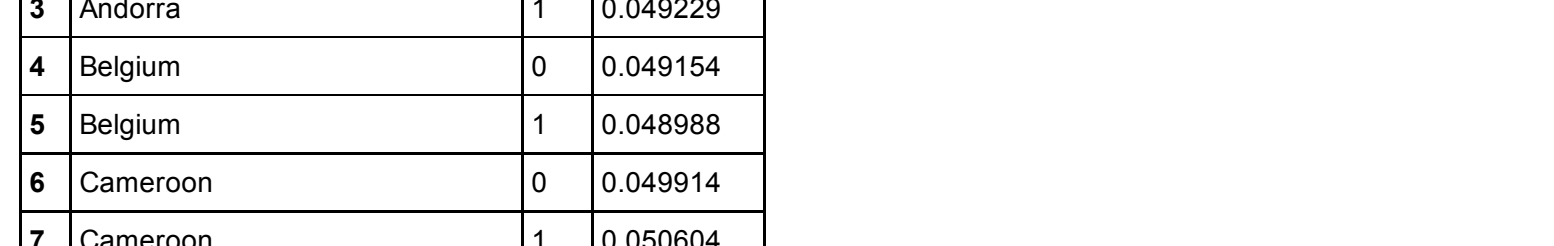
```
In [210]: # Visualization of different devices
fig, ax = plt.subplots(nrows=2, ncols=2, figsize=(18, 6))
sns.countplot(x='age', hue='test', data=data, ax=ax[0])
ax[0].set_title('Count Plot of Age', fontsize=16)

sns.barplot(x='age', y='conversion', hue='test', data=data, ax=ax[1])
ax[1].set_title('Mean Conversion Rate per Age', fontsize=16)
plt.tight_layout()
plt.show()
```



```
In [211]: # Visualization of different devices
fig, ax = plt.subplots(nrows=2, ncols=2, figsize=(18, 6))
sns.countplot(x='country', hue='test', data=data, ax=ax[0])
ax[0].set_title('Count Plot of Country', fontsize=16)

sns.barplot(x='country', y='conversion', hue='test', data=data, ax=ax[1])
ax[1].set_title('Mean Conversion Rate per Country', fontsize=16)
plt.tight_layout()
plt.show()
```



We have identified that country may be a confounding factor that influences the conversion rate. In next section, let's dive deeper into this variable.

### Conversion rate by country

In this section, let's look at conversion rate by country and check how many countries have a higher conversion rate in the experiment group than the control.

From the table below, we see that several countries have a higher conversion rate in the experiment group.

```
In [124]: conversion_by_country = data.groupby(['country', 'test']).conversion.mean().reset_index()
conversion_by_country
```

```
Out[124]:
```

	country	test	conversion
0	Algeria	0	0.015071
1	Algeria	1	0.013725
2	Andorra	0	0.048493
3	Andorra	1	0.049229
4	Belgium	0	0.049154
5	Belgium	1	0.048988
6	Cameroon	0	0.049914
7	Cameroon	1	0.050604
8	Canada	0	0.052089
9	Canada	1	0.050571
10	Democratic Republic of the Congo	0	0.049495
11	Democratic Republic of the Congo	1	0.051186
12	Gabon	0	0.052256
13	Gabon	1	0.054738
14	Haiti	0	0.049369
15	Haiti	1	0.047801
16	Luxembourg	0	0.052647
17	Luxembourg	1	0.054177
18	Mauritius	0	0.012048
19	Mauritius	1	0.012807
20	Morocco	0	0.048107
21	Morocco	1	0.051295
22	Republic of the Congo	0	0.053554
23	Republic of the Congo	1	0.047947
24	Senegal	0	0.050906
25	Senegal	1	0.047540
26	Seychelles	0	0.046796
27	Seychelles	1	0.049370
28	Spain	0	0.079719
29	Switzerland	0	0.050344
30	Switzerland	1	0.049578
31	Tunisia	0	0.050643
32	Tunisia	1	0.048847

```
In [125]: data.groupby(['country', 'test']).conversion.count()
```

```
Out[125]:
```

	country	test	conversion
0	Algeria	1	9356
1	Algeria	0	37377
2	Andorra	0	3650
3	Andorra	1	182
4	Belgium	1	3697
5	Belgium	0	8036
6	Cameroon	1	7859
7	Cameroon	0	16869
8	Canada	1	16972
9	Canada	0	27088
10	Democratic Republic of the Congo	0	28972
11	Democratic Republic of the Congo	1	64275
12	Gabon	0	2660
13	Gabon	1	2649
14	Haiti	0	5550
15	Haiti	1	5574
16	Luxembourg	0	3419
17	Luxembourg	1	3304
18	Mauritius	0	415
19	Mauritius	1	3719
20	Morocco	0	8653
21	Morocco	1	9884
22	Republic of the Congo	0	4108
23	Republic of the Congo	1	4067
24	Senegal	0	4361
25	Senegal	1	4207
26	Seychelles	0	1966
27	Seychelles	1	1985
28	Spain	0	51782
29	Switzerland	0	16149
30	Switzerland	1	15925
31	Tunisia	0	7622
32	Tunisia	1	7503

```
In [127]: data.groupby(['country', 'test']).conversion.sum()
```

```
Out[127]:
```

	country	test	conversion
0	Algeria	0	141
1	Algeria	1	513
2	Andorra	0	177
3	Andorra	1	182
4	Belgium	0	395
5	Belgium	1	389
6	Cameroon	0	842
7	Cameroon	1	850
8	Canada	0	1411
9	Canada	1	1364
10	Democratic Republic of the Congo	0	3178
11	Democratic Republic of the Congo	1	3290
12	Gabon	0	139
13	Gabon	1	145
14	Haiti	0	274
15	Haiti	1	267
16	Luxembourg	0	180
17	Luxembourg	1	5
18	Mauritius	1	48
19	Morocco	0	474
20	Morocco	1	507
21	Republic of the Congo	0	220
22	Republic of the Congo	1	195
23	Senegal	0	222
24	Senegal	1	200
25	Seychelles	0	92
26	Seychelles	1	98
27	Spain	0	4128
28	Switzerland	0	813
29	Switzerland	1	779
30	Tunisia	0	386
31	Tunisia	1	365

Overall, we found that 27% of countries have higher conversion rates in the experiment group than the control group. But are these differences statistically significant?

```
In [134]: tol = 0
for i in range(1, len(conversion_by_country.conversion)):
    if conversion_by_country.conversion[i] > conversion_by_country.conversion[i - 1]:
        tol = 1
print('Proportion of countries that have a higher conversion rate in the experiment group: {}'.format(tol/len(conversion_by_country.conversion)))
```

Proportion of countries that have a higher conversion rate in the experiment group: 0.2727272727272727

Next, let's use a Z-test to check whether the difference of conversion rates are statistically significant. We have the following hypotheses:

H0: Conversion rate experiment group = Conversion rate control group

H1: Conversion rate experiment group < Conversion rate control group

When performing a two-sided Z-test for each country where, we found that all p-values are above the 0.05 significance level, therefore, we cannot reject the null hypothesis mentioned above.

```
In [173]: country_df = data.groupby(['country'])
pvalue_df = country_df.apply(lambda x: two_sample_z_test(x, 'smaller')[1]).reset_index()
pvalue_df.columns = ['country', 'pvalue']
pvalue_df
```

```
Out[173]:
```

	country	pvalue
0	Algeria	0.160878
1	Andorra	