ABTesting

October 27, 2021

1 Using A/B testing to determine whether a company should keep its old homepage

Finding out whether a company should keep its old page or its new page, or take further time to collect data and make a decision.

This project used A/B testing to determine one of the above options.

1.1 Data Wrangling

The data was collected by the company and provided by Udacity.

1.1.1 Information about the data

Converted: whether or not the user bought the product. 1 means yes, 0 means no. Landing_page: Whether the user returned to the old page or the new page. Group: Whether the user belonged to the control or the treatment group (treatment group tried out the new page). TimeStamp: Date and time. User_id: Unique ID of the user.

The data was read in below:

[1]:
```
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np
```

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

[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

Obtaining basic information about the dataset. This information is listed in the next section:

[3]:
```
ab_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 294478 entries, 0 to 294477
Data columns (total 5 columns):
 #   Column        Non-Null Count   Dtype
---  ------        --------------   -----
 0   user_id       294478 non-null  int64
 1   timestamp     294478 non-null  object
 2   group         294478 non-null  object
 3   landing_page  294478 non-null  object
 4   converted     294478 non-null  int64
dtypes: int64(2), object(3)
memory usage: 11.2+ MB
```

[4]:
```
ab_data.loc[(ab_data['group']=='treatment') & (ab_data['landing_page'] ==␣
↪'old_page')]
```

[4]:

	user_id	timestamp	group	landing_page	converted
308	857184	2017-01-20 07:34:59.832626	treatment	old_page	0
327	686623	2017-01-09 14:26:40.734775	treatment	old_page	0
357	856078	2017-01-12 12:29:30.354835	treatment	old_page	0
685	666385	2017-01-23 08:11:54.823806	treatment	old_page	0
713	748761	2017-01-10 15:47:44.445196	treatment	old_page	0
…	…	…	…	…	…
293773	688144	2017-01-16 20:34:50.450528	treatment	old_page	1
293817	876037	2017-01-17 16:15:08.957152	treatment	old_page	1
293917	738357	2017-01-05 15:37:55.729133	treatment	old_page	0
294014	813406	2017-01-09 06:25:33.223301	treatment	old_page	0
294252	892498	2017-01-22 01:11:10.463211	treatment	old_page	0

[1965 rows x 5 columns]

So 1965 rows are incorrectly labelled so that "treatment" is mapped to "old_page".

Checking whether control users were given "old_page":

[5]:
```
ab_data.loc[(ab_data['group']=='control') & (ab_data['landing_page'] ==␣
↪'new_page')]
```

[5]:

	user_id	timestamp	group	landing_page	converted
22	767017	2017-01-12 22:58:14.991443	control	new_page	0
240	733976	2017-01-11 15:11:16.407599	control	new_page	0
490	808613	2017-01-10 21:44:01.292755	control	new_page	0
846	637639	2017-01-11 23:09:52.682329	control	new_page	1
850	793580	2017-01-08 03:25:33.723712	control	new_page	1
…	…	…	…	…	…
293894	741581	2017-01-09 20:49:03.391764	control	new_page	0
293996	942612	2017-01-08 13:52:28.182648	control	new_page	0
294200	928506	2017-01-13 21:32:10.491309	control	new_page	0
294253	886135	2017-01-06 12:49:20.509403	control	new_page	0

```
294331   689637  2017-01-13 11:34:28.339532  control     new_page          0

[1928 rows x 5 columns]
```

So 1928 rows are incorrectly labelled.

Finding how many unique users there were:

[6]:
```
ab_data.nunique()
```

[6]:
```
user_id         290584
timestamp       294478
group                2
landing_page         2
converted            2
dtype: int64
```

[7]:
```
ab_data.loc[(ab_data['converted'] == 1)]
```

[7]:
```
        user_id                   timestamp      group landing_page  converted
4        864975  2017-01-21 01:52:26.210827    control     old_page          1
6        679687  2017-01-19 03:26:46.940749  treatment     new_page          1
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
15       644214  2017-01-22 02:05:21.719434    control     old_page          1
…          …                          …          …          …          …
294396   838593  2017-01-15 09:56:31.455023  treatment     new_page          1
294405   712217  2017-01-11 10:34:30.176801    control     old_page          1
294420   795742  2017-01-09 01:06:58.299207    control     old_page          1
294430   733871  2017-01-21 17:54:08.810964  treatment     new_page          1
294443   665217  2017-01-10 23:29:01.767720    control     old_page          1

[35237 rows x 5 columns]
```

[8]:
```
ab_data.isnull().sum()
```

[8]:
```
user_id         0
timestamp       0
group           0
landing_page    0
converted       0
dtype: int64
```

Drop the incorrectly labelled data:

[9]:
```
treatment = ab_data[(ab_data['group']=='treatment') & (ab_data['landing_page']␣
↪== 'new_page')]
```

[10]:
```
control = ab_data[(ab_data['group']=='control') & (ab_data['landing_page'] ==
↪'old_page')]
```

[11]:
```
ab_cleaned = pd.concat([treatment,control], ignore_index='True')
```

[12]:
```
ab_cleaned.head()
```

[12]:
```
   user_id                   timestamp      group landing_page  converted
0   661590  2017-01-11 16:55:06.154213  treatment     new_page          0
1   853541  2017-01-08 18:28:03.143765  treatment     new_page          0
2   679687  2017-01-19 03:26:46.940749  treatment     new_page          1
3   817355  2017-01-04 17:58:08.979471  treatment     new_page          1
4   839785  2017-01-15 18:11:06.610965  treatment     new_page          1
```

[13]:
```
ab_cleaned.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 290585 entries, 0 to 290584
Data columns (total 5 columns):
 #   Column        Non-Null Count   Dtype
---  ------        --------------   -----
 0   user_id       290585 non-null  int64
 1   timestamp     290585 non-null  object
 2   group         290585 non-null  object
 3   landing_page  290585 non-null  object
 4   converted     290585 non-null  int64
dtypes: int64(2), object(3)
memory usage: 11.1+ MB
```

[14]:
```
ab_cleaned.nunique()
```

[14]:
```
user_id         290584
timestamp       290585
group                2
landing_page         2
converted            2
dtype: int64
```

The number of unique users is 290584.

[15]:
```
print(ab_cleaned[ab_cleaned.duplicated()])
```

```
Empty DataFrame
Columns: [user_id, timestamp, group, landing_page, converted]
Index: []
```

[16]:
```
ab_cleaned.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 290585 entries, 0 to 290584
```

```
Data columns (total 5 columns):
 #   Column        Non-Null Count   Dtype 
---  ------        --------------   ----- 
 0   user_id       290585 non-null  int64 
 1   timestamp     290585 non-null  object
 2   group         290585 non-null  object
 3   landing_page  290585 non-null  object
 4   converted     290585 non-null  int64 
dtypes: int64(2), object(3)
memory usage: 11.1+ MB
```

[17]:
```
N_conversions = ab_cleaned[(ab_cleaned['converted'] == 1)].count()
N_rows = ab_cleaned.count()
```

[18]:
```
p_convert = N_conversions/N_rows
p_convert
```

[18]:
```
user_id         0.119597
timestamp       0.119597
group           0.119597
landing_page    0.119597
converted       0.119597
dtype: float64
```

Now calculating the probability of converting given that the individual was in the control group:

[19]:
```
control = ab_cleaned[ab_cleaned['group']=='control'].count()
p_old = ab_cleaned[ab_cleaned['group']=='control']['converted'].sum()/control
p_old
```

[19]:
```
user_id         0.120386
timestamp       0.120386
group           0.120386
landing_page    0.120386
converted       0.120386
dtype: float64
```

[20]:
```
control
```

[20]:
```
user_id         145274
timestamp       145274
group           145274
landing_page    145274
converted       145274
dtype: int64
```

[21]:
```
treatment = ab_cleaned[ab_cleaned['group']=='treatment'].count()
```

```
p_new = ab_cleaned[ab_cleaned['group']=='treatment']['converted'].sum()/
 ↪treatment
p_new
```

[21]:
```
user_id         0.118807
timestamp       0.118807
group           0.118807
landing_page    0.118807
converted       0.118807
dtype: float64
```

[22]:
```
new_page = ab_cleaned[ab_cleaned['landing_page']=='new_page'].count()
new_page
```

[22]:
```
user_id         145311
timestamp       145311
group           145311
landing_page    145311
converted       145311
dtype: int64
```

[23]:
```
p_new_page = new_page['landing_page']/N_rows
p_new_page
```

[23]:
```
user_id         0.500064
timestamp       0.500064
group           0.500064
landing_page    0.500064
converted       0.500064
dtype: float64
```

[24]:
```
obs_diff = abs(p_new - p_old)
obs_diff
```

[24]:
```
user_id         0.001579
timestamp       0.001579
group           0.001579
landing_page    0.001579
converted       0.001579
dtype: float64
```

1.1.2 Does the new treatment group have a higher probability of converting?

The previous calculations show that the dataset is split 50/50 into treatment and control data.

The probability of converting on the old page is 0.1549% greater.

The probability difference requires further investigation as it is a difference, but it is not clear whether we can be confident it is statistically significant.

1.1.3 Hypothesis testing

Hypothesis O: The pages have the same conversion rates, so that p_new = p_old = p_convert Hypothesis 1: The old page has a significantly higher conversion rate, with a confidence interval of 95%.

Now we simulate 10000 samples and calculate the probability differences for each one:

[25]:
```
treatment['landing_page']
```

[25]:
```
145311
```

[26]:
```
p_new = p_new['landing_page']
```

[27]:
```
N_new = treatment['landing_page']
new_converted_simulation = np.random.binomial(N_new,p_new,10000)/N_new
new_converted_simulation
```

[27]:
```
array([0.11819477, 0.11864897, 0.11817412, …, 0.11782315, 0.12006662,
       0.1187866 ])
```

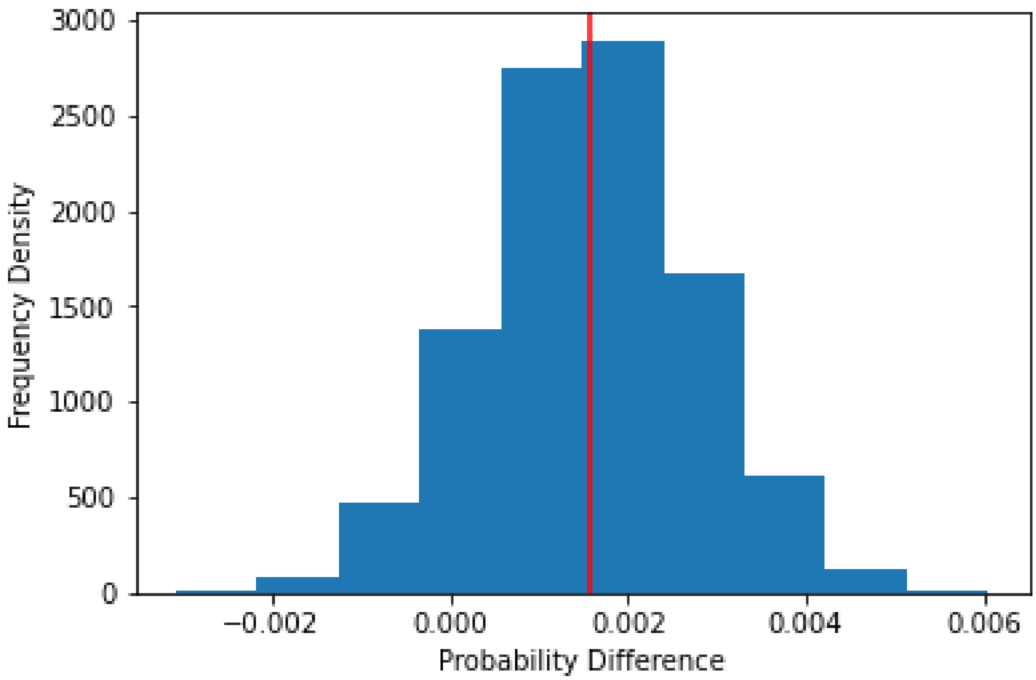
[28]:
```
N_old = control['landing_page']
p_old = p_old['landing_page']
old_converted_simulation = np.random.binomial(N_old,p_old,10000)/N_old
old_converted_simulation
```

[28]:
```
array([0.12141884, 0.1208475 , 0.11837631, …, 0.12051021, 0.11830747,
       0.1209301 ])
```

[29]:
```
p_diffs = old_converted_simulation - new_converted_simulation
obs_diff = obs_diff['landing_page']
```

Plotting a histogram of the results:

[30]:
```
plt.hist(p_diffs)
plt.axvline(x=obs_diff,color='r')
plt.ylabel('Frequency Density')
plt.xlabel('Probability Difference')
plt.show()
```



The above graph shows that it is very likely the null hypothesis should be rejected, as about half the values simulated are above the observed difference.

Now calculating what proportion of the simulated probability differences are greater than the observed probability difference calculated earlier. This will confirm or deny H_0.

[31]:
```
obs_diff
```

[31]: 0.0015790565976871451

[57]:
```
proportion = (p_diffs > obs_diff).sum()
proportion_value = proportion/len(p_diffs)
```

[58]:
```
proportion_value
```

[58]: 0.4965

Here we see that nearly 50% of the simulated probability differences are greater than the observed difference. This suggests that the observed difference lies close to the center of the probability difference distribution and therefore is not statistically significant.

However it is also clear that the mean probabilty difference is greater than 0, which seems to contradict the null hypothesis.

1.1.4 Computing the Z-score using statsmodel.api

[34]:
```
import statsmodels.api as sm


import numpy as np
from statsmodels.stats.proportion import proportions_ztest

convert_new = ab_cleaned[ab_cleaned['group']=='treatment']['converted'].sum()
convert_old = ab_cleaned[ab_cleaned['group']=='control']['converted'].sum()

n_old = control['landing_page']
n_new = treatment['landing_page']

# array with the numbers of converted customers in both control and treatment␣
↪groups
count = np.array([convert_old, convert_new])
# total number of observations in each group
number_of_obs = np.array([n_old, n_new])
# Calculates the p-value for these two samples
stat, pval = proportions_ztest(count, number_of_obs, alternative='larger')
```

[35]:
```
print(pval)
```

```
0.09482629485940902
```

The p-value here is 9.48%. This is much greater than the significance level chosen of 5%. Therefore the result here is *not* statistically significant and the null hypothesis, the conversion rates for both old and new pages are equal, is accepted.

1.2 Performing an A/B test using regression

As this is a classification problem, logistic regression was used.

Some pre-processing was necessary:

1. A new column 'intercept' was created.
2. A column 'ab_page' which essentially encodes the treatment as '1' and the control as '0'.

[36]:
```
ab_cleaned['intercept'] = 1
ab_cleaned.head()
```

[36]:
```
   user_id                   timestamp      group landing_page  converted  \
0   661590  2017-01-11 16:55:06.154213  treatment     new_page          0
1   853541  2017-01-08 18:28:03.143765  treatment     new_page          0
2   679687  2017-01-19 03:26:46.940749  treatment     new_page          1
3   817355  2017-01-04 17:58:08.979471  treatment     new_page          1
4   839785  2017-01-15 18:11:06.610965  treatment     new_page          1

   intercept
```

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

[37]:
```
from sklearn.preprocessing import LabelBinarizer
lb = LabelBinarizer()
ab_cleaned['ab_page'] = lb.fit_transform(ab_cleaned['group'])
```

[38]:
```
ab_cleaned.head()
```

[38]:
```
   user_id                   timestamp      group landing_page  converted  \
0   661590  2017-01-11 16:55:06.154213  treatment     new_page          0
1   853541  2017-01-08 18:28:03.143765  treatment     new_page          0
2   679687  2017-01-19 03:26:46.940749  treatment     new_page          1
3   817355  2017-01-04 17:58:08.979471  treatment     new_page          1
4   839785  2017-01-15 18:11:06.610965  treatment     new_page          1

   intercept  ab_page
0          1        1
1          1        1
2          1        1
3          1        1
4          1        1
```

[39]:
```
ab_cleaned.tail()
```

[39]:
```
        user_id                   timestamp    group landing_page  converted  \
290580   718310  2017-01-21 22:44:20.378320  control     old_page          0
290581   751197  2017-01-03 22:28:38.630509  control     old_page          0
290582   945152  2017-01-12 00:51:57.078372  control     old_page          0
290583   734608  2017-01-22 11:45:03.439544  control     old_page          0
290584   697314  2017-01-15 01:20:28.957438  control     old_page          0

        intercept  ab_page
290580          1        0
290581          1        0
290582          1        0
290583          1        0
290584          1        0
```

Using logistic regression model to fit the data:

[55]:
```
x = ab_cleaned[['intercept','ab_page']]
y = ab_cleaned['converted']
model = sm.Logit(y,x)
results = model.fit()
```

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

[56]:
```python
results.summary()
```

[56]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                           Logit Regression Results
==============================================================================
Dep. Variable:              converted   No. Observations:               290585
Model:                          Logit   Df Residuals:                   290583
Method:                           MLE   Df Model:                            1
Date:                Wed, 27 Oct 2021   Pseudo R-squ.:               8.085e-06
Time:                        09:26:02   Log-Likelihood:            -1.0639e+05
converged:                       True   LL-Null:                   -1.0639e+05
Covariance Type:            nonrobust   LLR p-value:                    0.1897
==============================================================================
                 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     -1.312      0.190      -0.037       0.007
==============================================================================
"""
```

1.2.1 Conclusions based on this Logistic Regression model:

The p-value of this model is 19.0%. This is much higher than the significance level of 5%. It means that the difference in probabilities of conversion is statistically insignificant.

In this case, the p-value calculated is different because the logistic regression model uses a sigma function as the probability distribution, whereas calculating z-scores relies on the normal distribution. These are two very differently shaped distributions and they produce different results.

1.2.2 What is the impact of the user's country, if there is any impact, on the conversion rate?

A new set of data had to be imported and joined to the cleaned A/B testing data on the column 'user_id'.

This was then used to estimate the impact of the user's country on the conversion rate.

[59]:
```python
countries = pd.read_csv('countries.csv')
```

[60]:
```python
countries.head()
```

[60]:

	user_id	country
0	834778	UK
1	928468	US
2	822059	UK

```
3   711597      UK
4   710616      UK
```

[61]:
```
df_merged = pd.merge(countries,ab_cleaned, how='left', on=['user_id'])
```

[62]:
```
df_merged.head()
```

[62]:
```
   user_id country                   timestamp      group landing_page  \
0   834778      UK  2017-01-14 23:08:43.304998    control     old_page
1   928468      US  2017-01-23 14:44:16.387854  treatment     new_page
2   822059      UK  2017-01-16 14:04:14.719771  treatment     new_page
3   711597      UK  2017-01-22 03:14:24.763511    control     old_page
4   710616      UK  2017-01-16 13:14:44.000513  treatment     new_page

   converted  intercept  ab_page
0          0          1        0
1          0          1        1
2          1          1        1
3          0          1        0
4          0          1        1
```

[67]:
```
df_merged.tail()
```

[67]:
```
        user_id  country                   timestamp      group landing_page  \
290580   653118        0  2017-01-09 03:12:31.034796    control     old_page
290581   878226        0  2017-01-05 15:02:50.334962    control     old_page
290582   799368        0  2017-01-09 18:07:34.253935    control     old_page
290583   655535        1  2017-01-09 13:30:47.524512  treatment     new_page
290584   934996        0  2017-01-09 00:30:08.377677    control     old_page

        converted  intercept  ab_page
290580          0          1        0
290581          0          1        0
290582          0          1        0
290583          0          1        1
290584          0          1        0
```

Turning the categorical data for ‘countries’ into binary values:

[64]:
```
df_merged['country'] = pd.get_dummies(df_merged['country'])
```

[66]:
```
df_merged['country']
```

[66]:
```
0          0
1          0
2          0
3          0
4          0
```

```
          ..
290580    0
290581    0
290582    0
290583    1
290584    0
Name: country, Length: 290585, dtype: uint8
```

[65]:
```
df_merged.head()
```

[65]:
```
   user_id  country                   timestamp      group landing_page  \
0   834778        0  2017-01-14 23:08:43.304998    control     old_page
1   928468        0  2017-01-23 14:44:16.387854  treatment     new_page
2   822059        0  2017-01-16 14:04:14.719771  treatment     new_page
3   711597        0  2017-01-22 03:14:24.763511    control     old_page
4   710616        0  2017-01-16 13:14:44.000513  treatment     new_page

   converted  intercept  ab_page
0          0          1        0
1          0          1        1
2          1          1        1
3          0          1        0
4          0          1        1
```

Now fitting the logistic regression model, but with two independent variables instead of one:

[68]:
```
model2 = sm.Logit(df_merged['converted'],df_merged[['intercept',␣
 ↪'ab_page','country']])
results = model2.fit()
```

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

[69]:
```
results.summary()
```

[69]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                           Logit Regression Results
==============================================================================
Dep. Variable:              converted   No. Observations:               290585
Model:                          Logit   Df Residuals:                   290582
Method:                           MLE   Df Model:                            2
Date:                Wed, 27 Oct 2021   Pseudo R-squ.:               2.065e-05
Time:                        09:41:33   Log-Likelihood:            -1.0639e+05
converged:                       True   LL-Null:                   -1.0639e+05
Covariance Type:            nonrobust   LLR p-value:                    0.1112
==============================================================================
```

```
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
intercept     -1.9867      0.008   -243.359      0.000      -2.003      -1.971
ab_page       -0.0150      0.011     -1.309      0.191      -0.037       0.007
country       -0.0434      0.027     -1.627      0.104      -0.096       0.009
==============================================================================
"""
```

1.2.3 Conclusions:

The model provides a p-value of 11.1%.

The null hypothesis is that country has no effect on the result. This was tested with a significance level of 5%. It is a right-tailed test.

The outcome is that the calculated p-value is greater than the significance level of 5%.

This leads us to conclude that country does not have a statistically significant effect on the conversion rate.

1.2.4 Other possible factors which should be accounted for:

There are some limitations of this model.

Its result differs partly because it assumes a logistic regression rather than a normal distribution. The functions employed in both cases are quite different.

Further questions to be explored:

- 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?