A/B Test for an e-commerce website (Using python)

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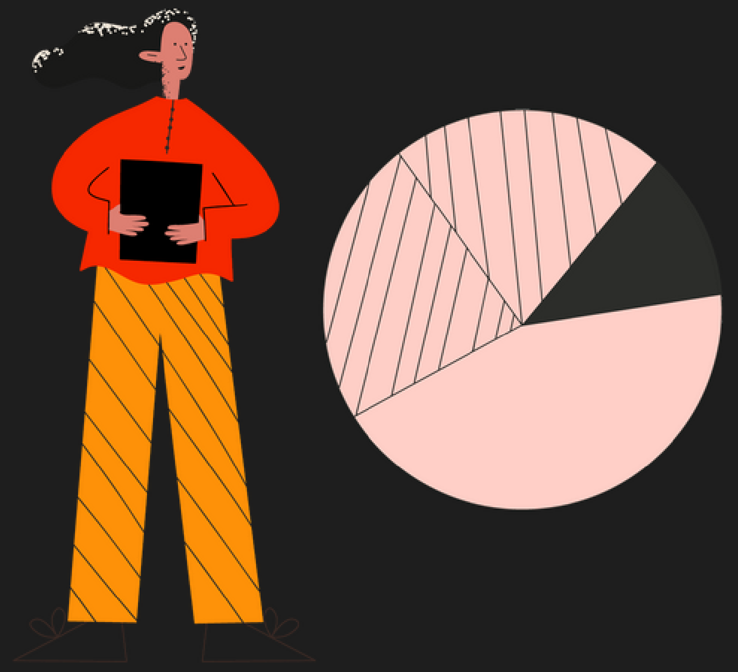


Understanding the case

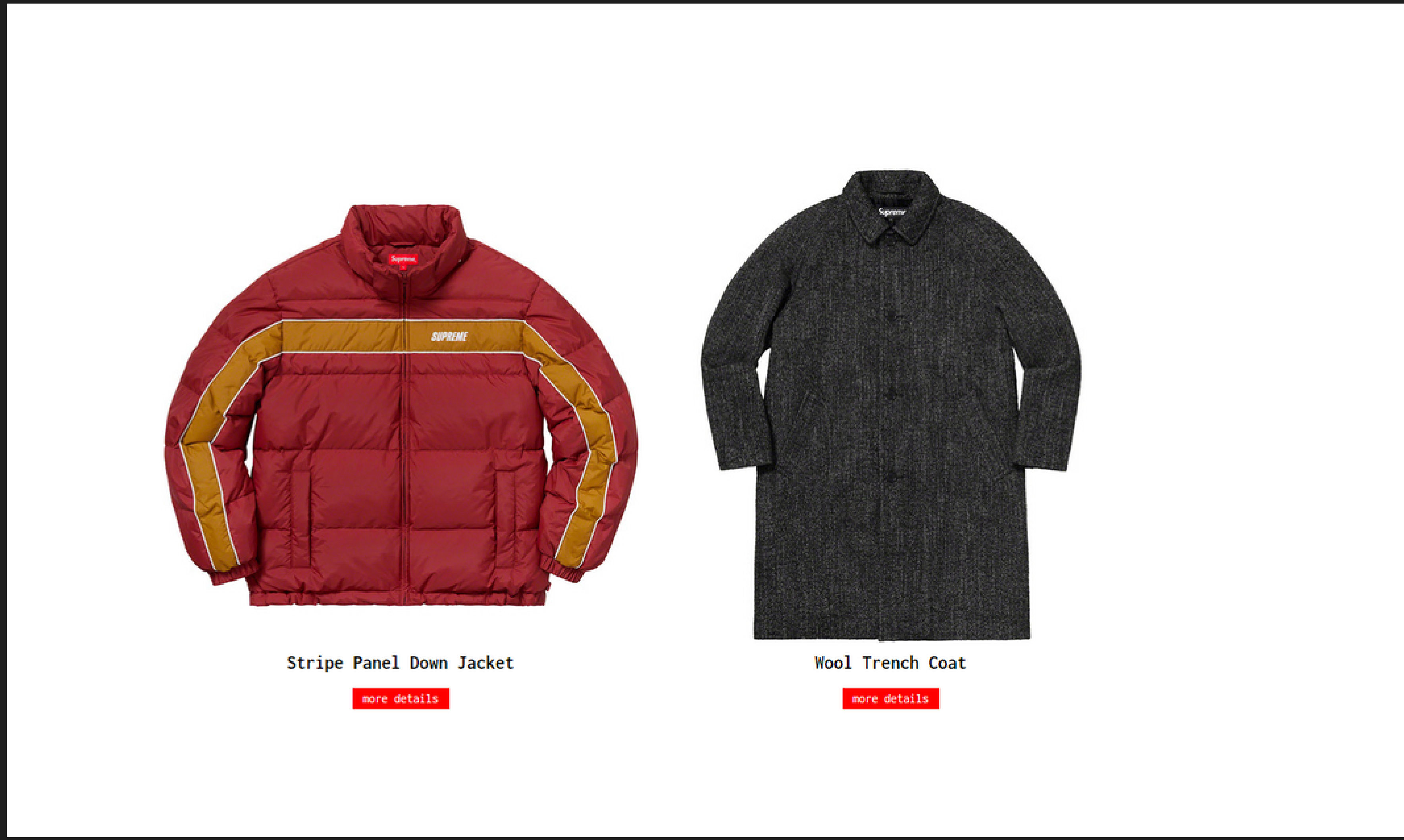
A medium-sized e-commerce business has a current conversion rate i.e., consumers buying a product, of 12%, the firm wants to increase the conversion rate to 14%. To help increase the conversion rate, the firm asks the design team to redesign their website.

$$12\% \longrightarrow 14\%$$

Conversion rate   Conversion rate

As analysts of the e-commerce firm, we need to test the effect of the new website on the conversion rate. The new design of the website will be implemented if the conversion rate rises to 14%.

OLD VS NEW WEBPAGE



Old webpage

Source

New webpage

Source

The Hypothesis

Null hypothesis (H0) -

A certain e-commerce website visitors that receive the new website design will not have a higher conversion rate compared to visitors that receive the old website design.

H0: P0= P1

Alternate hypothesis (H1) -

A certain e-commerce website visitors that receive the new website layout will have a higher conversion rate compared to visitors that receive the old website design.

H1: P0 = P1

Choosing the sample size

Since we cannot test our hypothesis on the whole population that visit our website, we need to use a sample number of visitors to test our hypothesis. The more number of samples, the more precise is our result.

On the contrary, the higher the number of samples, the more expensive our test becomes.
To find the right number of samples we use power analysis. Power is the probability that we will correctly reject the null hypothesis.

Power analysis in python -

```python
import statsmodels.stats.api as sms

effect_size = sms.proportion_effectsize(0.12, 0.14)

required_sample_size = sms.NormalIndPower().solve_power(effect_size, power= 0.8, alpha= 0.05, ratio= 1)

required_sample_size = round(required_sample_size)

print(required_sample_size)
```

A/B Test I

Z- Test

We finally test and analyze our hypothesis. Since the number of samples is large, we use Z-test to calulate the z-statistic and p-value.

To conduct the Z-test we use statsmodels.stats.proportion.

Z-Test in python and its results -

```
from statsmodels.stats.proportion import proportions_ztest, proportion_confint

z_statistic, p_value = proportions_ztest(result, nobs= count)
(lower_control, lower_treatment), (upper_control, upper_treatment) = proportion_confint(result, nobs= count, alpha=0.05)

print(f'The p-value from Z-test is: {p_value:.3f}')
print(f'The Z-statistic from Z-test is: {z_statistic:.3f}')
```

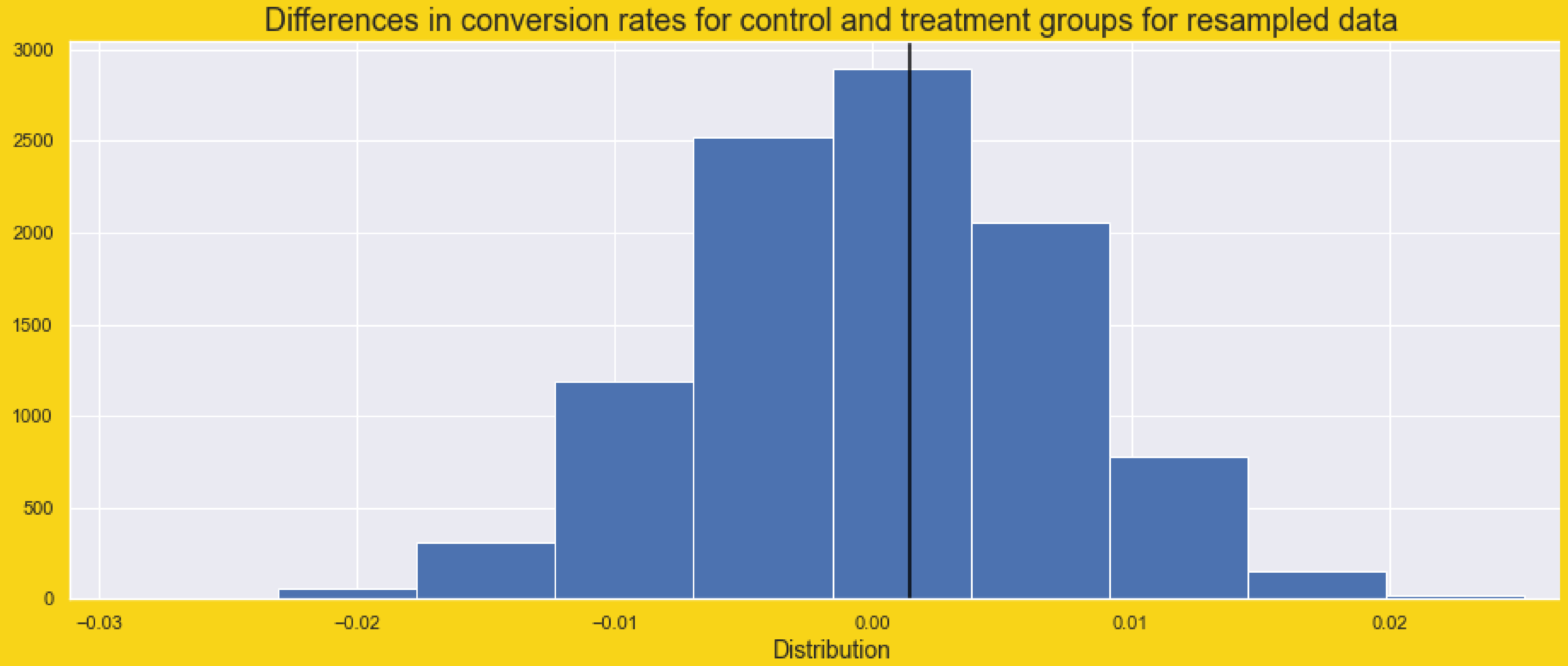
```
p-value from Z-test is: 0.439
Z-statistic from Z-test is: -0.774
```

A/B Test II

To further strengthen our findings from the Z-test, we simulate differences in the conversion rates between sampled control and sampled treatment groups under the null hypothesis.

To simulate these differences we first sample the data using np.random.choice and find out the difference between the conversion rates of the resampled data. We simulate the data 10000 times to find statistical significance between the control and treatment groups.

Plotting our simulated conversion differences of the conversion rate gives an idea of the distribution of data. -



P-value : 0.4152

Interpretation and Conclusion

- The p-value from our Z-test is 0.439 which is way higher than the α= 0.05 threshold we had anticipated. Since p-value > α we fail to reject the null hypothesis.
- The p-value derived from A/B Test II confirms our findings of A/B Test I. The p-value of 0.4049 is greater than the alpha of 0.05. Hence we fail to reject our null hypothesis.
- Since we fail to reject the null hypothesis, our new webpage did not perform significantly better than the old webpage.
  The conclusion of the whole study is that the firm needs to re-evaluate its decision to roll out the new webpage and further experiment with its designs.

Thank You