Mobile App A/B Test

Introduction

There is a mobile app with two variations for an enrollment button. A says 'Secure Free Trial', and B says 'Enroll Now'. The goal is to see if changing to B will result in more clicks and boost the company's sales. In this experiment a one-tailed z-test for comparing two proportions will be used.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from scipy.stats import norm
```

$$H_0 : \mu_B \leq \mu_A$$
$$H_1 : \mu_B > \mu_A$$

Data

In [2]:
```
def measure_click(ctr):
    return 1 if np.random.uniform(0,1) < ctr else 0

def measure_a():
    return measure_click(ctr=0.005)

def measure_b():
    return measure_click(ctr=0.007)
```

Pilot Study

- This pilot study is set up for a power of 80% and a false positive rate of 5%. The practical significance determined by the company is 0.1%. So in addition to statistical significance, B needs to be atleast 0.1% better than A. A sample of 1,000 is being used to determine the number of measurements needed.

In [3]:
```
def design_ab_test():
    def pilot_study(num_pilot_measurements):
        clicked_pre_a = np.array([measure_a() for _ in range(num_pilot_measurements)])
        clicked_pre_b = np.array([measure_b() for _ in range(num_pilot_measurements)])
        sd_1 = np.sqrt(clicked_pre_a.std()**2 + clicked_pre_b.std()**2)
        return sd_1
    sd_1 = pilot_study(1000)
    prac_sig = 0.001
    num_ind = (2.48*sd_1/prac_sig)**2
    return int(num_ind)
```

In [4]:
```
np.random.seed(17)
num_ind = design_ab_test()
num_ind
```

Out[4]: 91561

- So 91,561 individual measurements are needed to confidently detect a meaningful difference between the two variants.

Run A/B Test

In [5]:
```
def run_ab_test(num_ind):
    clicked_a = []
    clicked_b = []
    for n in range(num_ind // 2):
        clicked_a.append(measure_a())
        clicked_b.append(measure_b())

    return np.array(clicked_a), np.array(clicked_b)
```

In [6]:
```
np.random.seed(17)
clicked_a, clicked_b = run_ab_test(num_ind)
```

Comparing CTRs

In [7]:
```
df_a = pd.DataFrame({'click': clicked_a, 'group': 'A'})
df_b = pd.DataFrame({'click': clicked_b, 'group': 'B'})
df   = pd.concat([df_a, df_b], ignore_index=True)
```

In [8]:
```
df['group'].value_counts()
```

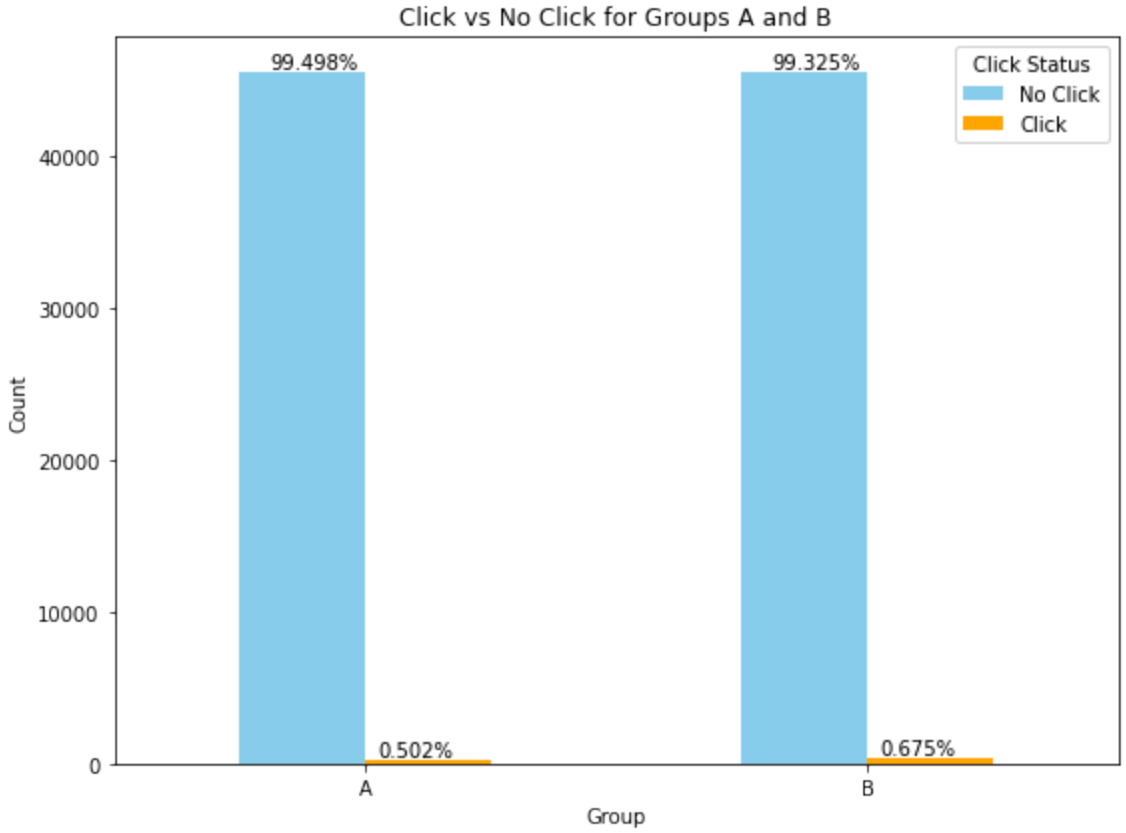
Out[8]:
```
group
A    45780
B    45780
Name: count, dtype: int64
```

- By design, the samples sizes for A and B were balanced to provide more accurate results with reduced variability.

In [9]:
```
print(f"A was clicked {sum(df[df.group=='A'].click)} times.")
print(f"B was clicked {sum(df[df.group=='B'].click)} times.")
```

```
A was clicked 230 times.
B was clicked 309 times.
```

In [10]:
```
#↔
```



Analyzing Results

In [11]:
```
def analyze_a_b_test(clicked_a, clicked_b):
    mean_a = clicked_a.mean()
    mean_b = clicked_b.mean()
    std_a = clicked_a.std()
    std_b = clicked_b.std()
    m = mean_b - mean_a
    se = np.sqrt((std_a**2+std_b**2)/num_ind)
    z = m/se

    return z, mean_a, mean_b, std_a, std_b
```

In [12]:
```
z, mean_a, mean_b, std_a, std_b = analyze_a_b_test(clicked_a, clicked_b)
```

In [13]:
```
np.random.seed(17)
clicked_a, clicked_b = run_ab_test(num_ind)
print(z.round(2))
```

```
4.83
```

- The value of the test statistic being greater than the critical of 1.64 indicates strong evidence against the null hypothesis.

In [14]:
```
alpha=0.05
p_value = 1 - norm.cdf(z)
if p_value < alpha:
    print('Reject the null hypothesis')
```

```
Reject the null hypothesis
```

- Because the p value is less than our chosen alpha of 0.05 we reject the null hypothesis and conclude the mean ctr of B is significantly higher than the mean ctr of A.

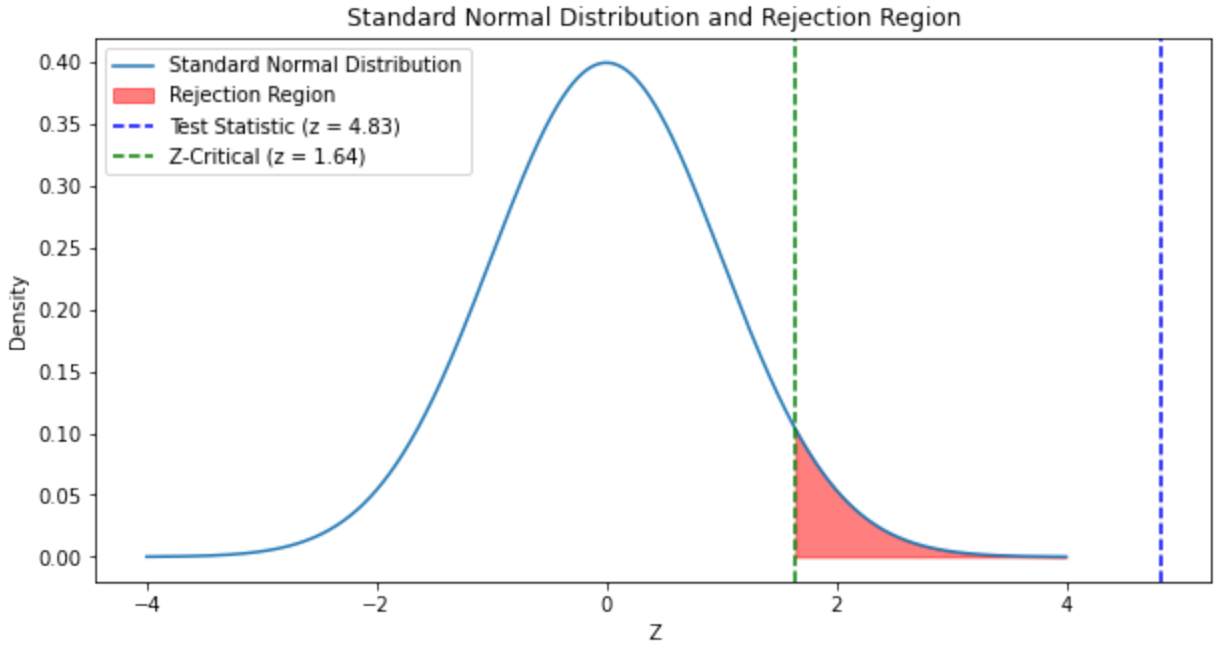
Standard Normal Distribution with Rejection Region

In [15]:

```
x = np.linspace(-4, 4, 1000)
y = norm.pdf(x)

z_critical = 1.64

plt.figure(figsize=(10, 5))
plt.plot(x, y, label="Standard Normal Distribution")
plt.fill_between(x, y, where=(x >= z_critical), color="red", alpha=0.5, label="Rejection Region")
plt.axvline(z, color="blue", linestyle="--", label=f"Test Statistic (z = {z:.2f})")
plt.axvline(z_critical, color="green", linestyle="--", label=f"Z-Critical (z = {z_critical})")
plt.title("Standard Normal Distribution and Rejection Region")
plt.xlabel("Z")
plt.ylabel("Density")
plt.legend()
plt.show()
```



- This graph shows our test statistic, z, being well within the rejection region.

95% Confidence Interval

In [16]:
```
mean_diff = mean_b - mean_a
std_err = np.sqrt((std_a**2 + std_b**2) / num_ind)

lower_bound = mean_diff - 1.64 * std_err
upper_bound = mean_diff + 1.64 * std_err

print(f"95% Confidence Interval: ({lower_bound:.6f}, {upper_bound:.6f})")
```

```
95% Confidence Interval: (0.001139, 0.002312)
```

- The lower bound of the CI is higher than our practical significance of 0.001.

Conclusion

- In conclusion, the A/B test above indicates variant B performs significantly better than variant A both statistically and practically. Therefore the mean CTR of B is greater than A, and that difference is large enough for motivation to change the product.