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Google colab link: CSTT_A10.ipynb

Screenshots of the code:

Graphs are added for better understanding.

```
1 # Load Ad Click Prediction Dataset
2 ad_df = pd.read_csv('/content/ad_click_dataset.csv')
3
4 print(ad_df)

Tid full_name age gender device_type ad_position \
0 670 User670 22.0 NaN Desktop Top
1 3044 User6924 NaN Male Desktop Top
2 5912 User5912 41.0 Non-Binary NaN Side
3 5418 User5418 34.0 Mon-Binary NaN NaN
4 9452 User9452 39.0 Non-Binary NaN NaN
510 User6910 NaN NaN NaN
510 User6910 NaN NaN NaN NaN
511 User9452 39.0 Non-Binary NaN NaN
512 User9452 39.0 Non-Binary NaN NaN
513 User9451 NaN NaN Hobile Top
5995 7843 User7843 NaN Female Desktop Bottom
5996 7843 User9314 NaN Hole Hobile Side
5996 7840 User3014 NaN NaN NaN NaN
59999 3856 User3856 44.0 Male Tablet Top
59999 3856 User3856 A4.0 Male Tablet Top
59999 Afternoon 1
1 Shopping Afternoon 1
2 Education NaN 0
59996 Education NaN 0
59996 Entertainment Evening 1
4 Social Media Morning 0
59997 NaN Morning 0
59999 Social Media Morning 0
610000 rows x 9 columns]
```

```
2. Perform necessary data cleaning and preprocessing: Handle missing values Convert categorical columns (e.g., gender, ad_position)
    0
                         3 ad_df=ad_df.dropna()
                       4
5#convert into catagorical columns
6 ad_df['gender']=ad_df['gender'].astype('category').cat.codes
7 ad_df['ad_position']=ad_df['ad_position'].astype('category').cat.codes
                       9 print(ad df)

        id
        full_name
        age
        gender
        device_type
        ad_position
        browsing_history
        \
            News

        188
        User188
        56.0
        0
        Tablet
        0
        News

        4890
        User4890
        43.0
        1
        Tablet
        0
        Education

        4985
        User4985
        37.0
        1
        Mobile
        2
        News

        9888
        User9888
        49.0
        1
        Mobile
        2
        News

        8201
        User8201
        59.0
        0
        Desktop
        0
        Social Media

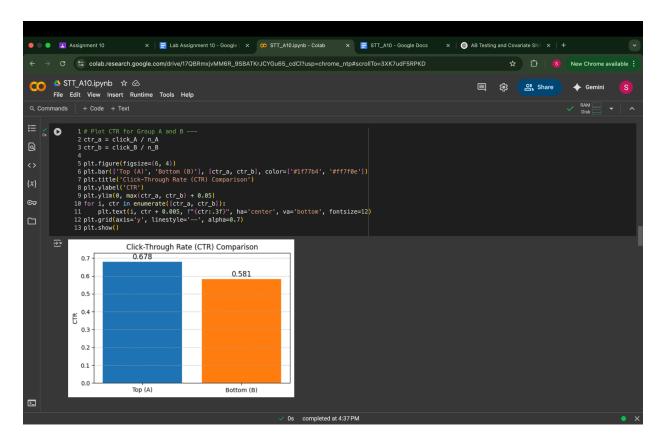
                                                                                                                                                                         0 Social Hedia
0 News
1 Education
2 Entertainment
0 Shopping
2 Social Media
                               7268 User7268
5912 User5912
9638 User9638
5574 User5574
3056 User3056
                                                                            28.0
41.0
64.0
52.0
44.0
                                                                                                                            Desktop
Mobile
Desktop
Desktop
Tablet
                9951
9952
9960
9986
9999
                              time_of_day click
Morning 1
Afternoon 1
Evening 0
Morning 1
Morning 0
               17
25
33
52
102
                9951
9952
9960
9986
9999
                                  Evening
Night
Morning
Afternoon
Morning
                                                                                                                                                                                          ✓ 0s completed at 4:37 PM
       3.Split the dataset into two groups: Group A: Users with ad_position = 0 (Top) Group B: Users with ad_position = 1 (Bottom)
                    1 # Split into two groups
2 group_A = ad_df[ad_df['ad_position'] == 0] # Top position
3 group_B = ad_df[ad_df['ad_position'] == 1] # Bottom position
)
0s
                           5 print('group A:\n',group_A)
6 print('group B:\n',group_B)
       → group A:
                                                                                                   A:
    id full_name age
    188    User188    56.0
4890    User4890    43.0
8201    User8201    59.0
118    User118    43.0
3062    User3062    34.0
                                  6989 User6989
7267 User7267
5574 User5574
7268 User7268
5574 User5574
                                                                              28.0
20.0
52.0
28.0
52.0
                    9866
9904
9925
9951
9986
                                                                                                                                                                                                                  Shopping
                                                                                                                                   Mobile
                                                                                                                                Desktop
Desktop
Desktop
Desktop
                                                                                                                                                                                                                   Shopping
Shopping
Shopping
News
                                time_of_day click
Morning 1
                   17
25
102
154
170
                                     Morning
Afternoon
Morning
Night
Evening
                   9866
9904
9925
9951
9986
                                    Afternoon
Night
Afternoon
                                     Evening
Afternoon
                     id full_name age
5484 User5484 64.0
5703 User5703 55.0
820 User820 39.0
4630 User4630 19.0
6167 User6167 20.0
                                                                                        gender device_type ad_position browsing_history \
0 Mobile 1 Education
0 Tablet 1 Shopping
2 Mobile 1 Social Media
2 Tablet 1 Shopping
1 Mobile 1 Shopping
      122
135
140
146
244
                                                                                                                      Tablet
Desktop
Desktop
Mobile
                     2812 User2812 25.0
2602 User2602 61.0
6075 User6075 32.0
4620 User4620 43.0
5912 User5912 41.0
                                                                                                                                                                                               Shopping
Shopping
Social Media
      9843
9845
9917
9926
9952
                                                                                                                                                                                          Entertainment
Education
                                                                                                                           Mobile
                    time_of_day click
Morning 0
Night 0
Afternoon 0
Evening 0
Night 1
      122
135
140
146
244
      9843
9845
9917
9926
9952
                          Morning
Afternoon
Night
Night
Night
```

```
4. Use the statsmodel's proportions_ztest function to perform an independent two-sample z-test between Group A and Group B.
[8]
       2 click_A = group_A['click'].sum()
3 n_A = len(group_A) #total entries with top position
       5 click_B = group_B['click'].sum()
       6 n_B = len(group_B) #total entries with bottom position
       9 count = np.array([click_A, click_B])
      10 nobs = np.array([n_A, n_B])
      11 z_stat, p_value = proportions_ztest(count, nobs)
  5. Print the following: The z-score The p-value
0
       1 #outputs
       2 print(f"Clicks (Top): {click_A} / {n_A}")
       3 print(f"Clicks (Bottom): {click_B} / {n_B}")
4 print(f"Z-score: {z_stat}")
       5 print(f"P-value: {p_value}")
Clicks (Bottom): 150 / 258
Z-score: 2.3380678956239453
    P-value: 0.019383726320686367
```

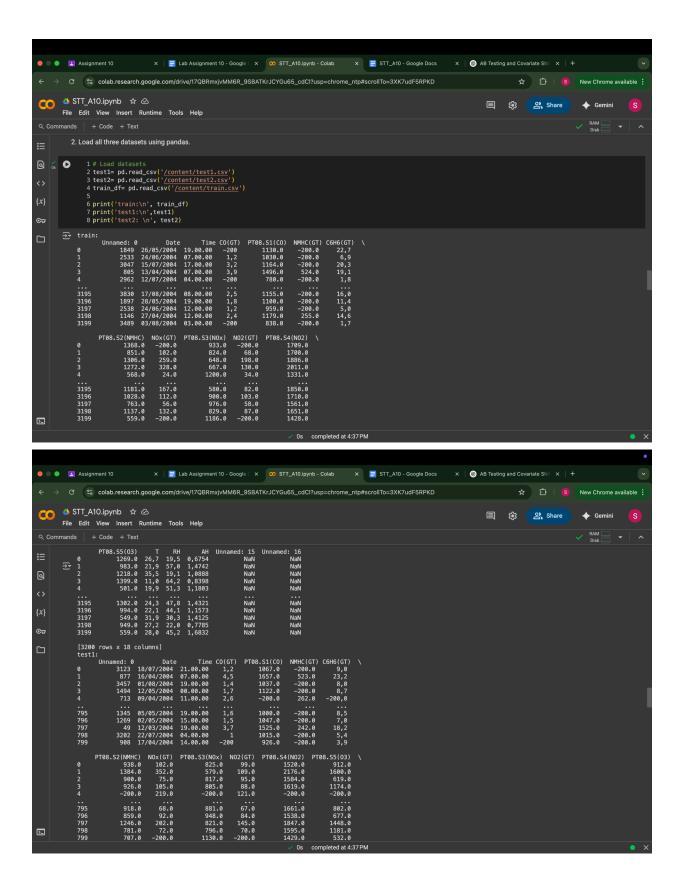
6. Interpret the result: Is there a statistically significant difference in click-through rates between the two groups? Justify your answer.

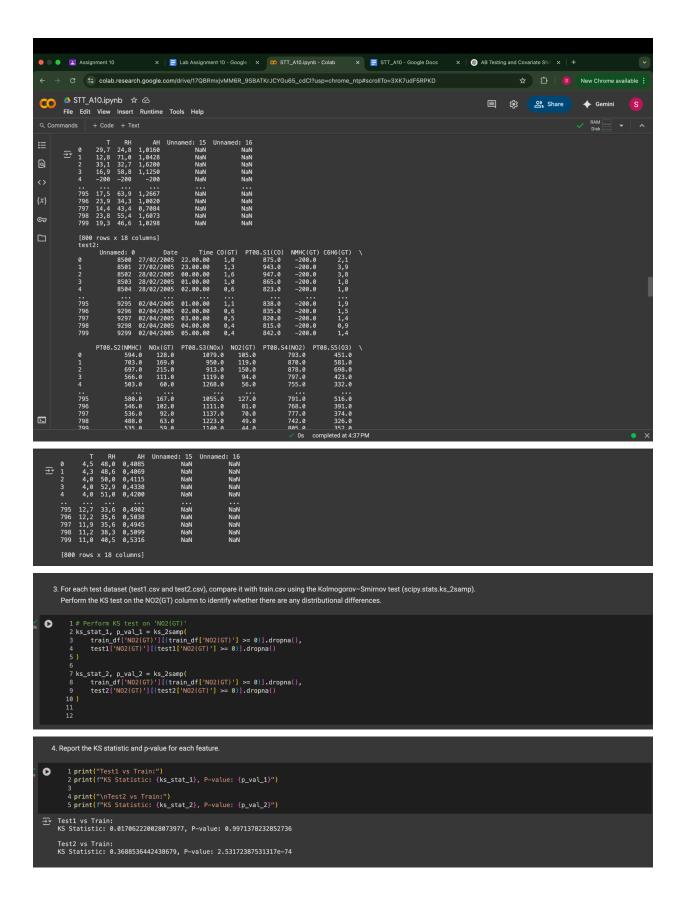
Yes, there is a statistically significant difference in click-through rates between the two groups.

Based on the outputs of the two-sample z-test, we can observe that the p-value is less than the commonly used threshold which is 0.05. This shows that we can reject the null hypothesis, which assumed that there is no difference in the click-through rates between ads placed at the top (Group A) and those placed at the bottom (Group B). In other words, the data provides statistically significant evidence that ad position does influence user behavior. Specifically, users are more likely to click on ads displayed at the top of the page compared to those shown at the bottom. This insight can be valuable for marketing teams and advertisers, as it suggests that prioritizing top-position ad placements could lead to higher engagement and better campaign performance.



Part 2: Covariate Shift Detection Using Air Quality Data 1. You are provided with 3 datasets via this Google Drive link: train.csv test1.csv test2.csv





```
5. Determine which of the two test datasets (test1.csv or test2.csv) exhibits a covariate shift relative to the training dataset (train.csv).

Use the results of the Kolmogorov-Smirnov test to support your answer.

[13] 1 # Determine covariate shift according to Ks test on only NO2(GT)
2 if p_val_1 < 0.05:
3 print("\nConclusion: Test1 shows covariate shift w.r.t training set.")
4 else:
5 print("\nConclusion: Test1 does NOT show significant covariate shift w.r.t training set.")
6 7 if p_val_2 < 0.05:
8 print("Conclusion: Test2 shows covariate shift w.r.t training set.")
9 else:
10 print("Conclusion: Test2 does NOT show significant covariate shift w.r.t training set.")

**Conclusion: Test1 does NOT show significant covariate shift w.r.t training set.

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```

The null hypothesis states that the two samples being compared are drawn from the same distribution.

If the p value is less than 0.05 that means we can reject the null hypothesis, which means those samples are not taken form the same distribution, that indicates covariate whiff

To determine which test dataset exhibits a covariate shift relative to the training dataset, we conducted the Kolmogorov–Smirnov (KS) test on the NO2(GT) feature. The results for Test1 vs Train showed a KS Statistic of 0.017 and a p-value of 0.99, which indicates a high similarity between their distributions. Since the p-value is much greater than 0.05, we fail to reject the null hypothesis, suggesting that there is no significant distributional difference between Test1 and the training set for this feature.

on the other hand, the results for Test2 vs Train showed a KS Statistic of 0.36 and an extremely small p-value, which is far less than the significance threshold which is 0.05. This provides strong evidence to reject the null hypothesis, indicating that Test2's NO2(GT) distribution is significantly different from that of the training data.

Therefore, based on the KS test results, we conclude that Test2 exhibits a covariate shift relative to the training dataset, while Test1 does not.

```
1 import seaborn as sns
2
3 def plot_distribution_comparison(train_col, test_col, feature_name, test_name):
4    plt.figure(figsize=(8, 5))
5    sns.kdeplot(train_col.dropna(), label='Train', fill=True, alpha=0.5)
6    sns.kdeplot(test_col.dropna(), label=test_name, fill=True, alpha=0.5)
7    plt.title(fibistribution Comparison: Train vs {test_name} for {feature_name}')
8    plt.xlabel(feature_name)
9    plt.ylabel('Density')
10    plt.legend()
11    plt.grid(True)
12    plt.show()
13
14    # Example:
15 plot_distribution_comparison(train_df['NO2(GT)'], test1['NO2(GT)'], 'NO2(GT)', 'Test1')
16 plot_distribution_comparison(train_df['NO2(GT)'], test2['NO2(GT)'], 'NO2(GT)', 'Test2')
17
```

