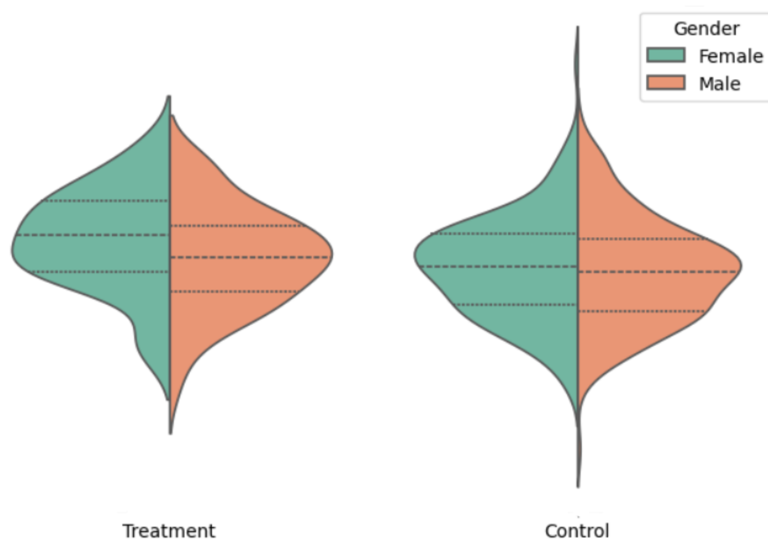
Segmenting Promo Code Impact by Gender: A/B Testing Insights

A Work Sample in Segmentation and A/B Testing Analysis

By JH, M.S.c.

March 05, 2025



Note: Full code and simulated dataset available upon request.

Project Overview

RetailW aimed to optimize its promotional strategy by understanding how promo codes affect customer behavior across gender segments. This A/B test analyzed a 10% discount promo code's impact on average order value (AOV), comparing Treatment (promo code) and Control (no promo code) groups within Male and Female subgroups. **The objective was to identify which gender responds most strongly, enabling targeted marketing**.

This work sample showcases segmentation analysis, statistical rigor, custom coding, and visualization, delivering insights to enhance precision marketing.

Data and Analytical Approach

Dataset Overview

The analysis leverages a simulated dataset of 425 customer records from a retail experiment to emulate the real one I used when worked at the Consultancy Firm supporting a retail company in USA. Columns include Customer_ID (int), Group (Control/Treatment, object), Promo_Code_Applied (object), Order_Value (float), and Gender (object). No missing values were present. Example rows: [Customer_ID: 1, Group: Control, Order_Value: 68.45, Gender: M], [Customer_ID: 2, Group: Treatment, Order_Value: 82.30, Gender: F].

Key Methods

Data was segmented by Gender, with statistical tests (t-tests, Levene's, Shapiro-Wilk) applied to each subgroup. Bootstrapping addressed sample imbalance, and visualizations (histograms, boxplots, violin plots) compared AOV across segments highlighting gender differences.

Code Snippet: (Statistical Assumption Checks)

[2]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import levene, shapiro, ttest_ind, mannwhitneyu
import numpy as np
```

[17]:
```
# Homogeneity of variance
levene_male_stat, levene_male_p = levene(male_treatment, male_control)
levene_female_stat, levene_female_p = levene(female_treatment, female_control)
print("\nLevene's Test for Homogeneity of Variance by Gender:")
print(f"Male: Statistic={levene_male_stat:.4f}, p-value={levene_male_p:.4f}")
print(f"Female: Statistic={levene_female_stat:.4f}, p-value={levene_female_p:.4f}")
```

```
Levene's Test for Homogeneity of Variance by Gender:
Male: Statistic=0.1524, p-value=0.6966
Female: Statistic=0.0333, p-value=0.8553
```

[27]:
```
# Normality test
shapiro_male_t = shapiro(male_treatment)
shapiro_male_c = shapiro(male_control)
shapiro_female_t = shapiro(female_treatment)
shapiro_female_c = shapiro(female_control)
print("\nShapiro-Wilk Test for Normality by Gender:")
print(f"Male Treatment: Statistic={shapiro_male_t.statistic:.4f}, p-value={shapiro_male_t.pvalue:.4f}")
print(f"Male Control: Statistic={shapiro_male_c.statistic:.4f}, p-value={shapiro_male_c.pvalue:.4f}")
print(f"Female Treatment: Statistic={shapiro_female_t.statistic:.4f}, p-value={shapiro_female_t.pvalue:.4f}")
print(f"Female Control: Statistic={shapiro_female_c.statistic:.4f}, p-value={shapiro_female_c.pvalue:.4f}")
```

```
Shapiro-Wilk Test for Normality by Gender:
Male Treatment: Statistic=0.9878, p-value=0.8347
Male Control: Statistic=0.9902, p-value=0.2675
Female Treatment: Statistic=0.9598, p-value=0.2551
Female Control: Statistic=0.9863, p-value=0.1197
```

Analysis and Visualizations

Segmented Analysis

Statistical Testing

T-tests showed a significant AOV increase for Females (p=0.0066) but not Males (p=0.0890). Bootstrapping confirmed these findings, addressing smaller subgroup sizes.

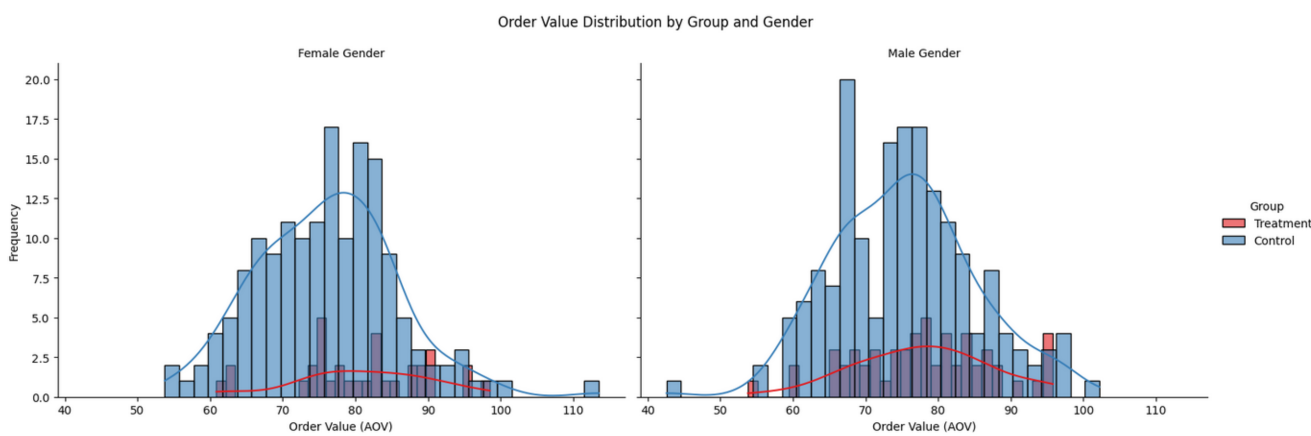
Code Snippet: (Bootstrapping)

[28]:
```
# 5. Bootstrapping by Segment

def bootstrap_diff(data1, data2, n_iterations=10000):
    diffs = [np.mean(np.random.choice(data1, len(data1), replace=True)) -
             np.mean(np.random.choice(data2, len(data2), replace=True))
             for _ in range(n_iterations)]
    return np.percentile(diffs, [2.5, 97.5]), np.mean(diffs)

ci_male, mean_diff_male = bootstrap_diff(male_treatment, male_control)
ci_female, mean_diff_female = bootstrap_diff(female_treatment, female_control)
print("\nBootstrapped Results by Gender:")
print(f"Male: 95% CI={ci_male}, Mean Difference={mean_diff_male:.4f}")
print(f"Female: 95% CI={ci_female}, Mean Difference={mean_diff_female:.4f}")
```

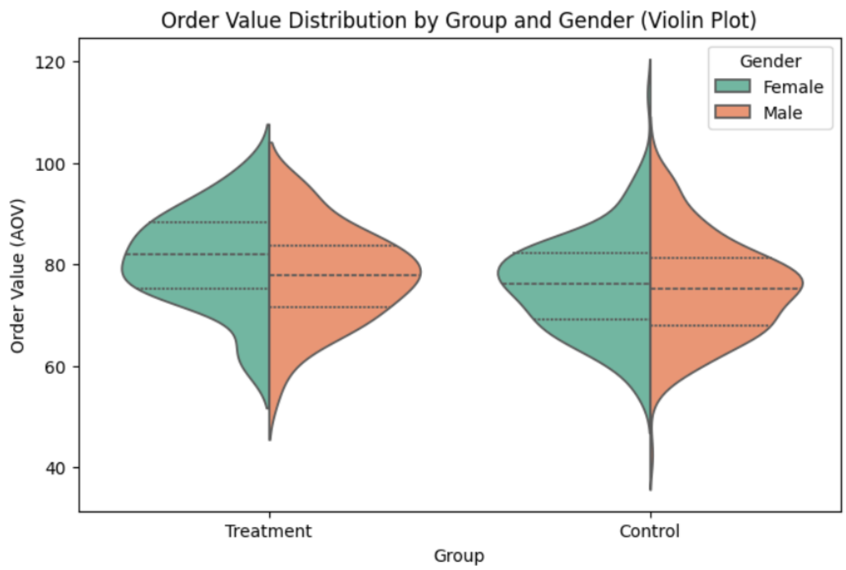
```
Bootstrapped Results by Gender:
Male: 95% CI=[-0.2948741   5.30672712], Mean Difference=2.5149
Female: 95% CI=[1.48952473 8.34281418], Mean Difference=4.9915
```

Visualization

Histograms by gender:



A violin plot illustrates AOV distributions, highlighting gender differences.



Results

Key Findings

Table

Segment	Control AOV	Treatment AOV	AOV Lift	95% CI	p-value	Cohen's d
Male	$75.80	$78.30	$2.51	-0.33 – 5.33	0.089	0.2614
Female	$75.50	$80.70	$5.00	1.53 – 8.32	0.0066	0.5279

Females exhibit a significant $5.00 AOV lift (p=0.0066, moderate effect: d=0.5279), with a 95% CI of $1.53–$8.32. Males show a non-significant $2.51 lift (p=0.0890, small effect: d=0.2614), with a 95% CI of -$0.33–$5.33.

Insights and Recommendations

Segmentation Insights

Promo codes significantly increase AOV for Females by \$5.00 ($p=0.0066$, CI: 1.53–8.32), with a moderate effect size ($d=0.5279$), indicating a reliable response. Males show a smaller, non-significant \$2.51 lift ($p=0.0890$, CI: -0.33–5.33, $d=0.2614$), suggesting an inconsistent effect. Normality (Shapiro-Wilk: Male Treatment $p=0.8347$, Male Control $p=0.2675$, Female Treatment $p=0.2551$, Female Control $p=0.1197$) and equal variance (Levene's: Male $p=0.6966$, Female $p=0.8553$) assumptions hold.

Recommendation:

Prioritize promo codes for Female customers to maximize AOV. For Males, test higher discounts or alternative incentives, and explore additional segments (e.g., age) to refine targeting.

Closing

Conclusion

This segmented A/B test demonstrates advanced analysis, statistical rigor, and visualization to optimize marketing by gender. Completed in less than10 days with two feedback rounds, it offers a framework for data-driven targeting, with Females as a key focus for promo code strategies.