Driving Growth with Uplift Modeling:

Analyzing Marketing Promotions for Optimized Conversions

Hijir Della Wirasti - Business Intelligence

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Case Study Driving Growth: Mastering Uplift Modeling and Meta-Learner Strategies in Business Intelligence

Case A - Discount
vs.
Case B - Buy One Get One

python™

dibimbing

Batch 13

Important Links

Dataset	https://www.kaggle.com/datasets/davinwijaya/customer-retention
GitHub	https://github.com/hijirdella/Uplift-Modeling-for-Marketing-Promotions
Google Collab Case A	Assignment Day 34 - Uplift Modelling - Case A - Discount.ipynb
Google Collab Case B	Assignment Day 34 - Uplift Modelling - Case B - Buy One Get One.ipynb
Email	hijirdw@gmail.com
LinkedIn	https://www.linkedin.com/in/hijirdella/

Hijir Della Wirasti

Business Intelligence

For more case
https://github.com/hijirdella

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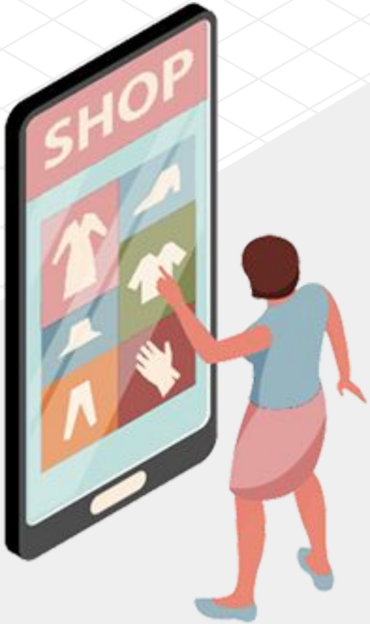
Introduction

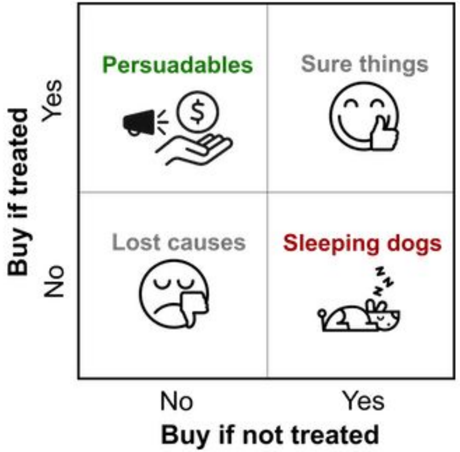
What is Uplift Modeling?



Introduction

What is Uplift Modeling?

Uplift modeling is a machine learning technique used to measure the **incremental impact** of a marketing action (e.g., discounts, promotions) on customer behavior. Unlike traditional models that predict overall conversion probability, uplift modeling helps identify the **causal effect** of an intervention by comparing treated and untreated groups.



Why is Uplift Modeling Important in Marketing?

- Helps marketers **target the right customers** who are most likely to respond positively.
- Avoids wasting resources on **"sure things"** (customers who would buy anyway) and **"lost causes"** (customers unlikely to convert).
- Reduces negative impact on **"sleeping dogs"** (customers who might react negatively to an offer).
- Maximizes **ROI on marketing campaigns** by prioritizing high-impact strategies.

Objective of the Study

✅ **Compare the effectiveness of Discount vs. Buy One Get One (BOGO) offers** in increasing customer conversions.
✅ **Identify which offer drives more customer conversions** using uplift modeling techniques.
✅ **Understand which customer segments benefit the most** from each promotion to improve targeting strategies.

02

Data Understanding & Profiling

Dataset Overview

Data Understanding & Profiling

	recency	history	used_discount	used_bogo	zip_code	is_referral	channel	offer	conversion
0	10	142.44	1	0	Surburban	0	Phone	Buy One Get One	0
1	6	329.08	1	1	Rural	1	Web	No Offer	0
2	7	180.65	0	1	Surburban	1	Web	Buy One Get One	0
3	9	675.83	1	0	Rural	1	Web	Discount	0
4	2	45.34	1	0	Urban	0	Web	Buy One Get One	0

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 64000 entries, 0 to 63999
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   recency        64000 non-null  int64
 1   history        64000 non-null  float64
 2   used_discount  64000 non-null  int64
 3   used_bogo      64000 non-null  int64
 4   zip_code       64000 non-null  object
 5   is_referral    64000 non-null  int64
 6   channel        64000 non-null  object
 7   offer          64000 non-null  object
 8   conversion     64000 non-null  int64
dtypes: float64(1), int64(5), object(3)
memory usage: 4.4+ MB
```

	recency	history	used_discount	used_bogo	is_referral	conversion
count	64000.000000	64000.000000	64000.000000	64000.000000	64000.000000	64000.000000
mean	5.763734	242.085656	0.551031	0.549719	0.502250	0.146781
std	3.507592	256.158608	0.497393	0.497526	0.499999	0.353890
min	1.000000	29.990000	0.000000	0.000000	0.000000	0.000000
25%	2.000000	64.660000	0.000000	0.000000	0.000000	0.000000
50%	6.000000	158.110000	1.000000	1.000000	1.000000	0.000000
75%	9.000000	325.657500	1.000000	1.000000	1.000000	0.000000
max	12.000000	3345.930000	1.000000	1.000000	1.000000	1.000000

	zip_code	channel	offer
count	64000	64000	64000
unique	3	3	3
top	Surburban	Web	Buy One Get One
freq	28776	28217	21387

Missing Values

	0
recency	0
history	0
used_discount	0
used_bogo	0
zip_code	0
is_referral	0
channel	0
offer	0
conversion	0

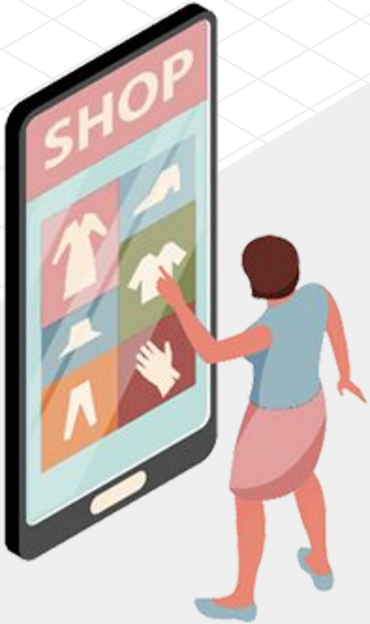
dtype: int64

Key Takeaways:

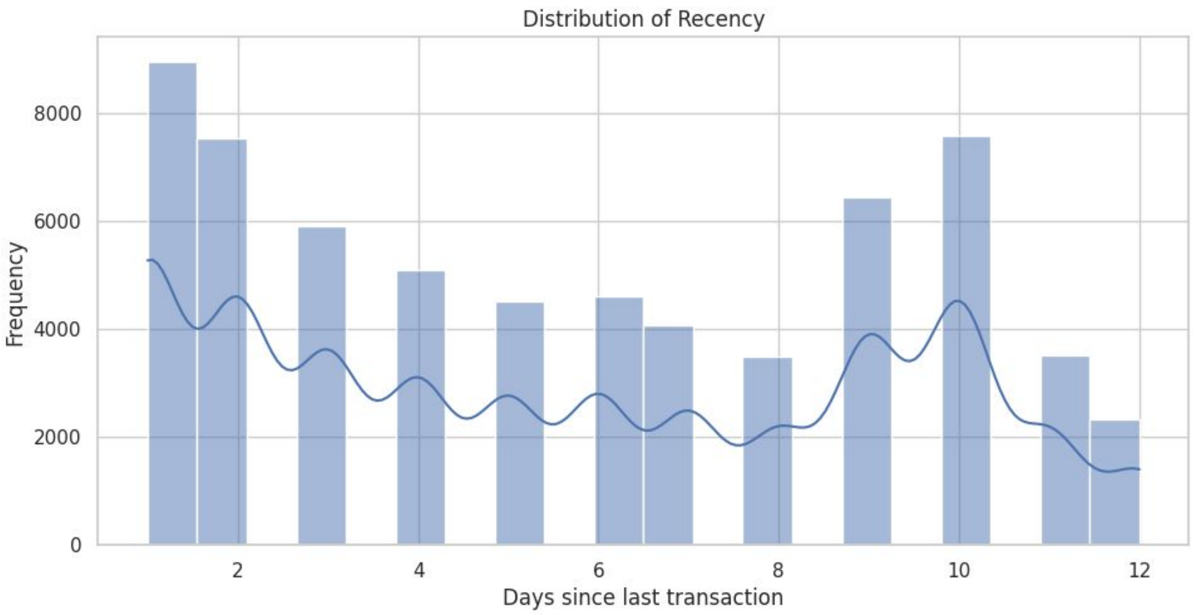
✅ **BOGO is the most common offer**, while Discounts are used less frequently.
✅ **Web is the dominant marketing channel**, making it crucial for campaign effectiveness.
✅ **Conversion rate is low (14.67%)**, highlighting the need for better targeting.
✅ **High variability in purchase history** suggests that different customer segments respond differently to promotions.

03

Exploratory Data Analysis (EDA)



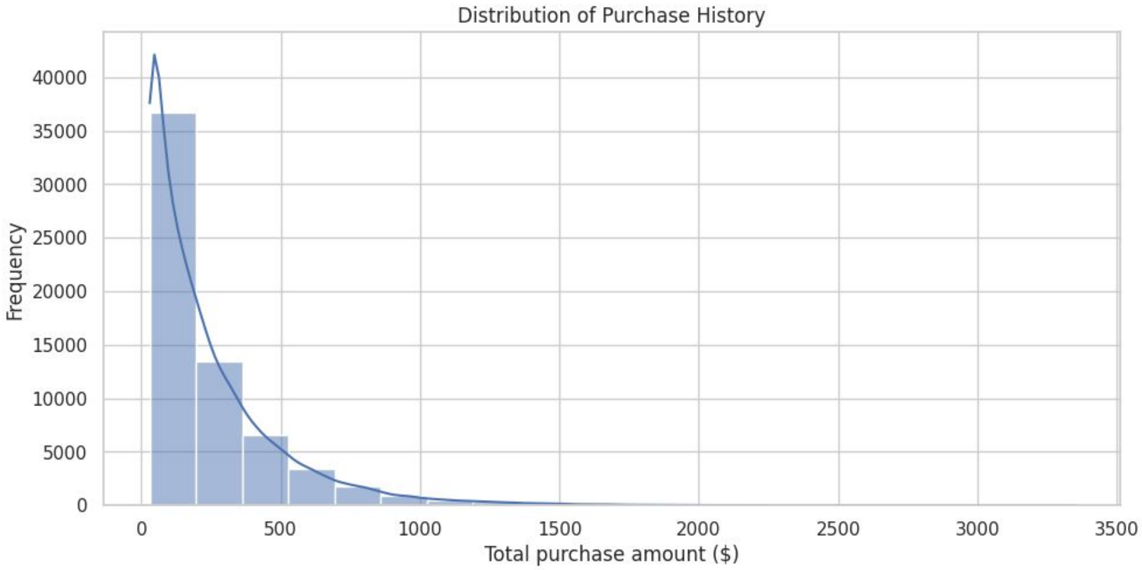
1. Distribution of Recency



Insight: Distribution of Recency

- The **majority of customers made their last transaction within the past 1-2 days**, with a **sharp decline** as recency increases.
- There are **spikes at specific intervals (e.g., days 4, 6, 10)**, indicating possible shopping patterns or promotional influences.
- A **gradual decrease in frequency** suggests that fewer customers remain engaged as time progresses.
- **Marketing Implication:** Customers with **lower recency (1-2 days)** may be more responsive to promotions, while **re-engagement strategies** are needed for customers with longer inactivity.

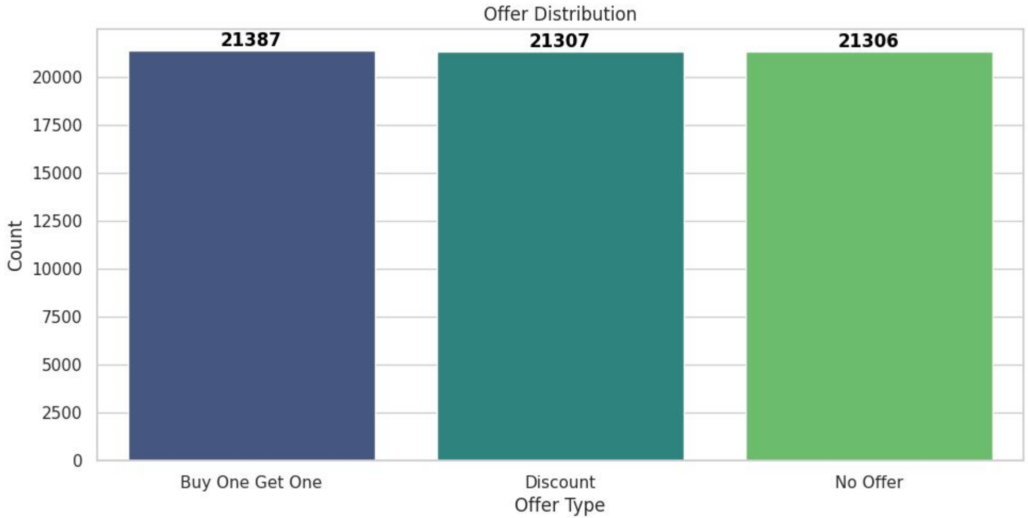
2. Distribution of Purchase History



Insight: Distribution of Purchase History

- The **majority of customers have a low total purchase amount**, with a sharp decline as spending increases.
- The distribution is **right-skewed**, indicating that **a small number of high-value customers contribute significantly to total sales**.
- Most customers have spent **less than $500**, while very few exceed **$1000**.
- **Marketing Implication:**
  - Target **low-spending customers** with promotions to encourage repeat purchases.
  - Use **personalized offers** for high-value customers to maximize retention and lifetime value.

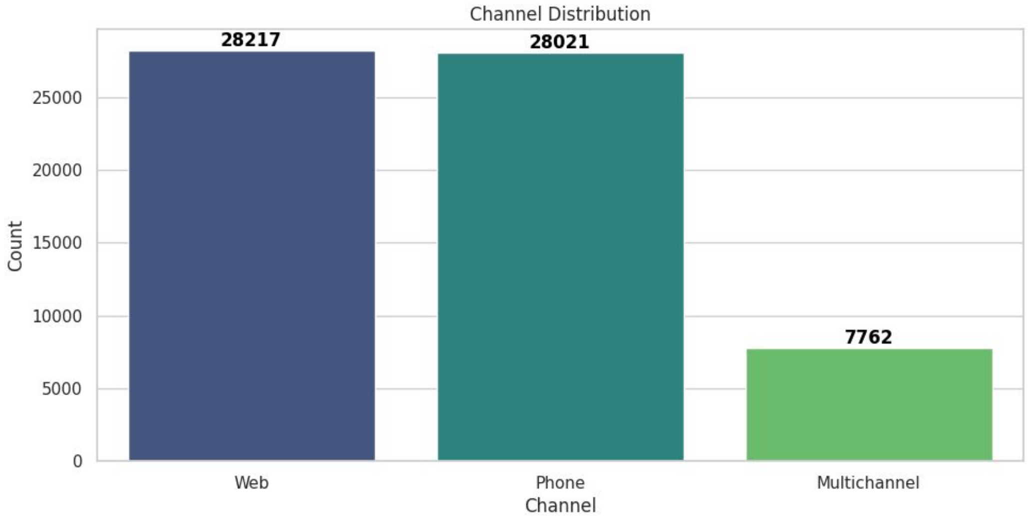
3. Distribution of Purchase History



Insight: Offer Distribution

- The dataset is **evenly split** among the three offer types:
  - **Buy One Get One (21,387 customers)**
  - **Discount (21,307 customers)**
  - **No Offer (Control Group) (21,306 customers)**
- This balanced distribution ensures a **fair comparison** when analyzing the effectiveness of each offer.
- **Marketing Implication:**
  - The impact of **Discount vs. BOGO** on conversion can be directly compared.
  - The **No Offer group** serves as a strong baseline for uplift modeling analysis.

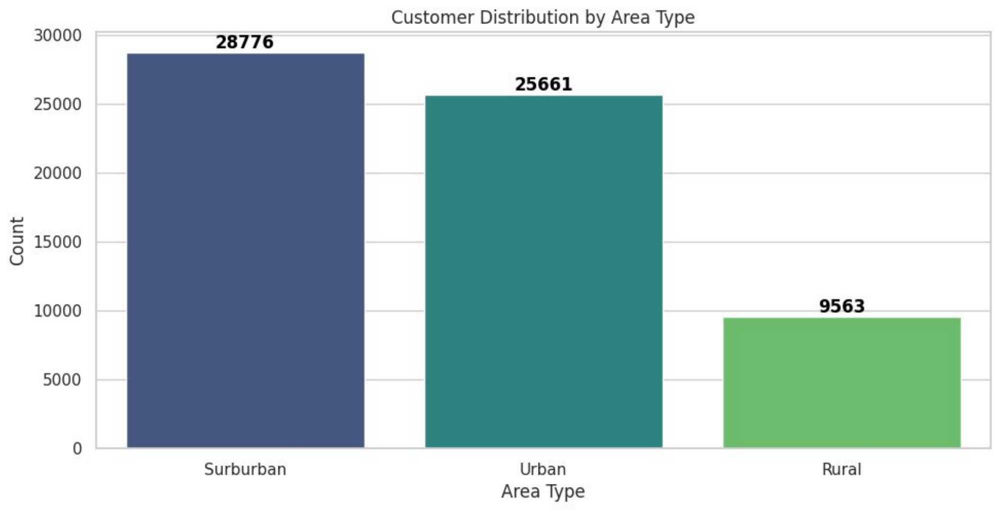
4. Distribution of Purchase History



Insight: Channel Distribution

- **Web (28,217 customers) and Phone (28,021 customers)** are the dominant channels, while **Multichannel usage is significantly lower (7,762 customers).**
- This suggests that most customers engage with offers through a **single channel rather than multiple touchpoints**.
- **Marketing Implication:**
  - Campaigns should focus on **Web and Phone channels**, as they reach the largest audience.
  - Multichannel customers may require **targeted strategies** to increase engagement and conversions.

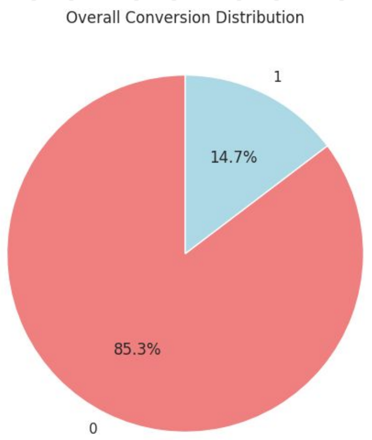
5. Distribution of Purchase History

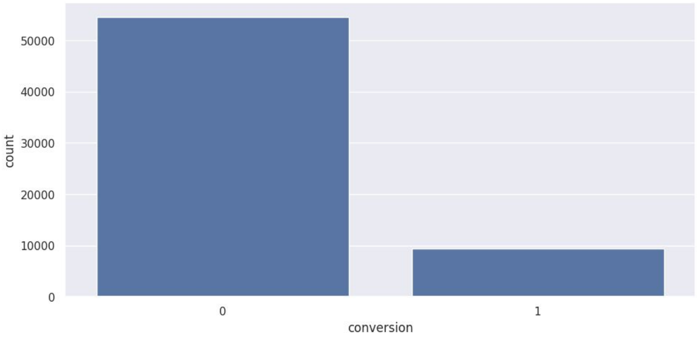


Insight: Customer Distribution by Area Type

- **Suburban areas have the highest customer concentration (28,776),** followed by **Urban (25,661)** and **Rural (9,563).**
- The lower number of Rural customers suggests they may have **limited access to promotions** or different purchasing behaviors.
- **Marketing Implication:**
  - Campaigns should prioritize **Suburban and Urban areas**, as they represent the largest market share.
  - Special strategies, such as localized promotions or delivery incentives, may be needed to **engage Rural customers.**

6. Conversion Proportion

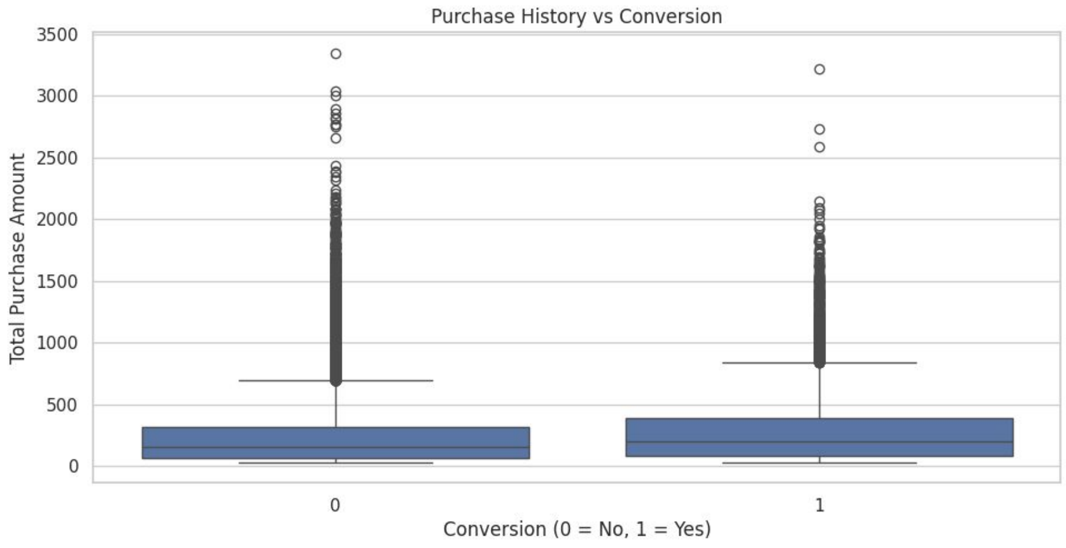




Insight: Conversion Proportion

- **85.32% of customers did not convert**, while only **14.68% made a purchase** after receiving an offer.
- This highlights a **low conversion rate**, meaning that most customers are either **not influenced by the promotion** or the offer **is not compelling enough**.
- **Marketing Implication:**
    - Use **Uplift Modeling** to identify which customers are truly persuadable.
    - Adjust marketing strategies to focus on **high-potential customer segments**.
    - Experiment with **personalized offers, better timing, or multi-channel engagement** to increase conversion rates.
    -

7. Purchase History vs. Conversion



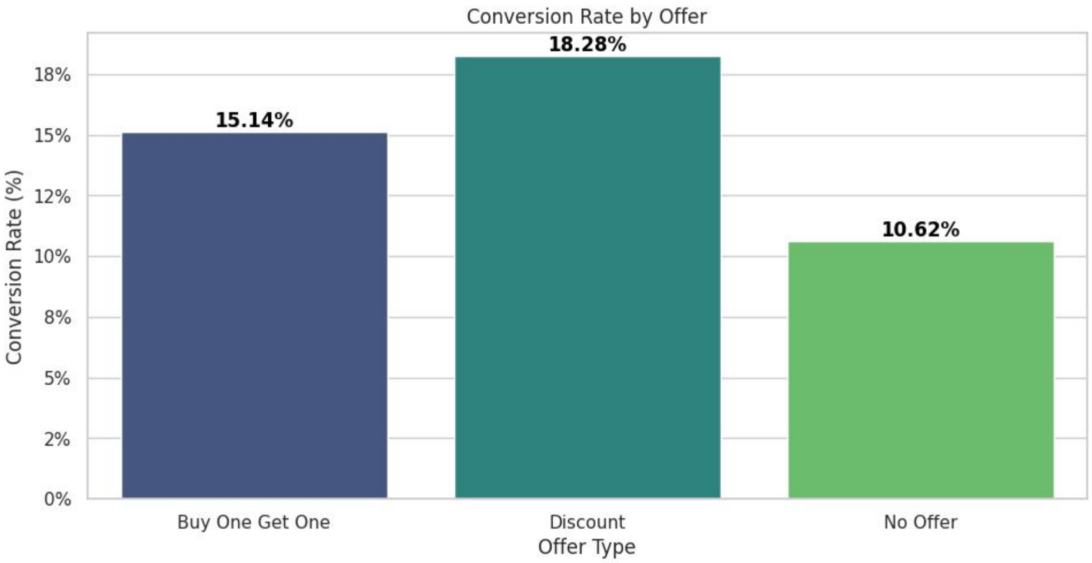
Insight: Purchase History vs. Conversion

- **Customers who converted (1) and those who did not (0) have similar purchase history distributions.**
- Both groups contain **many low-spending customers**, but **high-value customers (outliers above $1,000) exist in both categories.**
- The median purchase history for converters is **only slightly higher**, indicating that **historical spending alone is not a strong predictor of conversion.**

Marketing Implication:

✅ **Additional factors** (e.g., offer type, recency, channel) should be considered for segmentation.
✅ **Personalized promotions** may be needed to target high-value customers effectively.
✅ **Uplift modeling** can help determine which specific customer groups are most likely to respond positively to promotions.

8. Conversion Rate by Offer Type



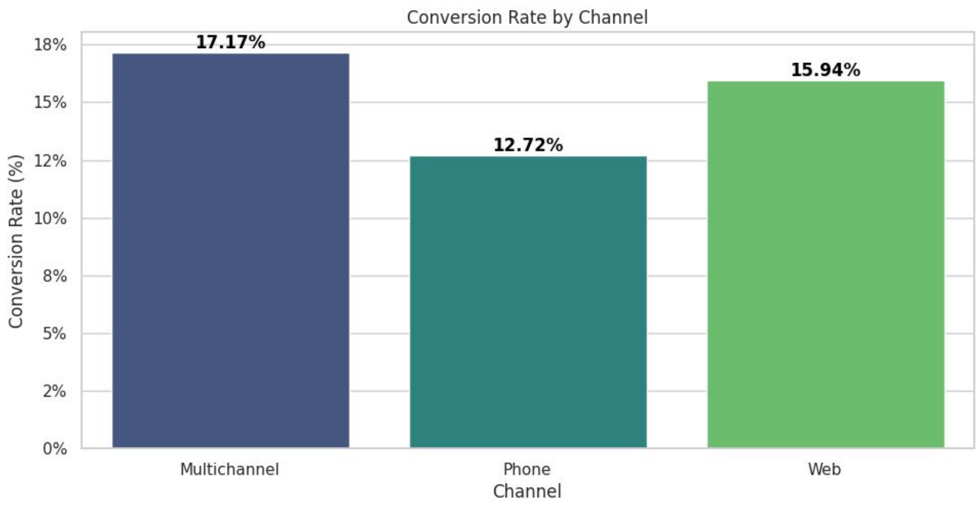
Insight: Conversion Rate by Offer Type

- **Discount offers had the highest conversion rate (18.28%)**, outperforming both **Buy One Get One (15.14%)** and **No Offer (10.62%)**.
- **Both promotions increased conversions compared to no offer**, but Discounts were **more effective** than BOGO.
- This suggests that customers may prefer **direct price reductions over getting an additional item for free**.

Marketing Implication:

✅ **Discount campaigns should be prioritized** for driving higher conversions.
✅ **BOGO can still be valuable**, especially for products with higher margins.
✅ **Further analysis (e.g., uplift modeling) is needed** to determine which customer segments benefit the most from each offer.

9. Conversion Rate by Channel



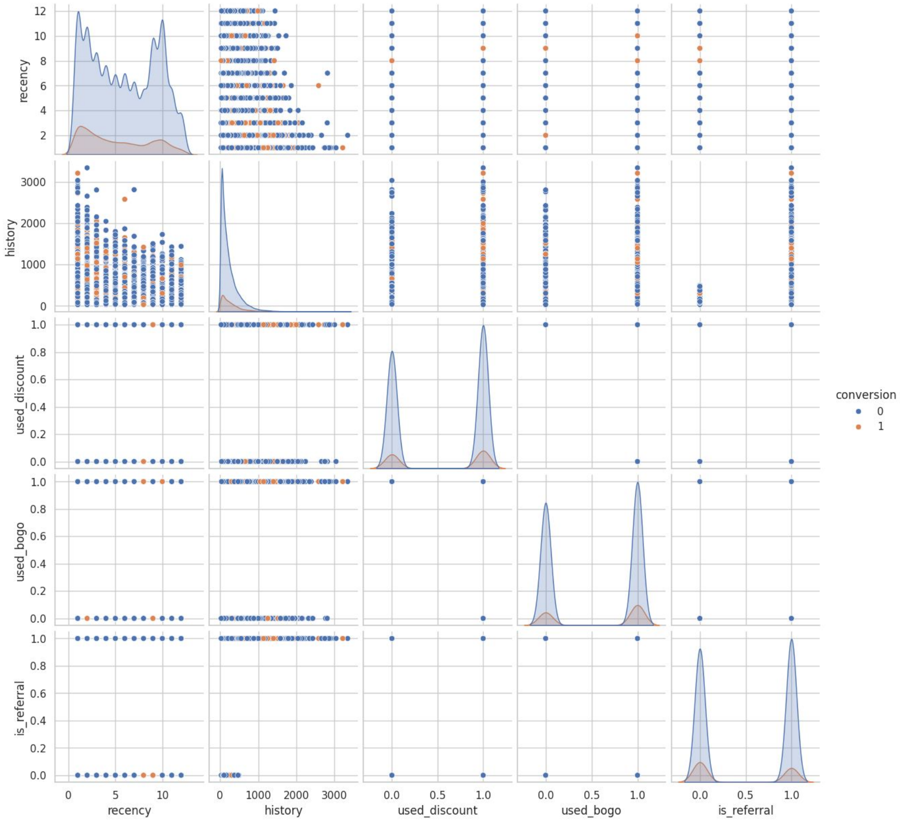
Insight: Conversion Rate by Channel

- **Multichannel customers had the highest conversion rate (17.17%)**, followed by **Web (15.94%)** and **Phone (12.72%)**.
- This suggests that **customers engaging through multiple channels are more likely to convert**, possibly due to **greater exposure to marketing efforts**.
- **Phone has the lowest conversion rate**, indicating that **customers may prefer digital interactions over direct calls**.

Marketing Implication:

✅ **Enhance multichannel marketing strategies** to boost engagement and conversions.
✅ **Optimize web-based promotions**, as they drive a strong conversion rate.
✅ **Reassess phone-based marketing approaches** to improve effectiveness or shift efforts to digital channels.

10. Pairplot Analysis of Key Features vs. Conversion



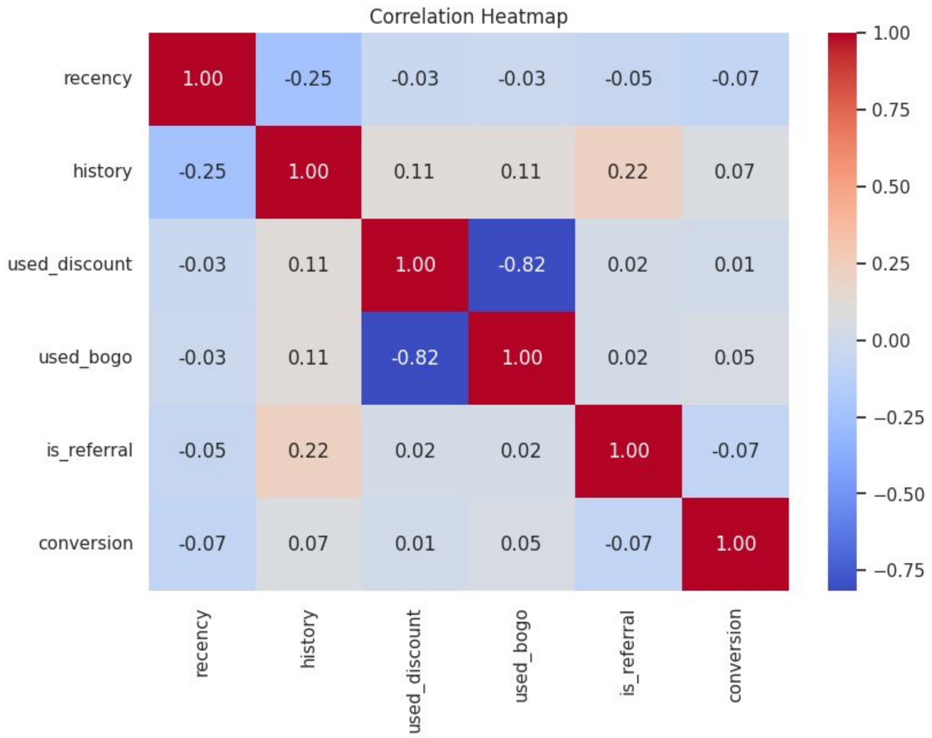
Insight: Pairplot Analysis of Key Features vs. Conversion

- **Recency & History:**
  - Most conversions (orange points) occur across different recency values, but **customers with lower recency (recent transactions) tend to convert more.**
  - **Higher purchase history doesn't guarantee conversion**, indicating that past spending alone is not the strongest predictor.
- **Used Discount & Used BOGO:**
  - Customers who received **Discounts or BOGO offers** show varying conversion patterns.
  - **Conversions are observed in both groups, suggesting that both promotional strategies are effective but need deeper analysis.**
- **Referral Influence:**
  - Customers referred by others show some conversions, but **referrals alone are not a strong determinant.**

Marketing Implication:

✅ **Segment customers based on recency & history** for targeted promotions.
✅ **Analyze uplift scores to determine which offer (Discount vs. BOGO) is more effective.**
✅ **Combine multiple factors (recency, offer type, and channel) for better conversion predictions.**

11.



Insight: Correlation Heatmap

- **Low correlation with conversion:**
  - No single feature has a strong correlation with conversion, suggesting that **multiple factors influence purchasing decisions**.
  - **History (0.07) and Used BOGO (0.05) have slightly positive correlations**, but the impact is minimal.
- **Negative correlation between Used Discount & Used BOGO (-0.82):**
  - Customers who used **one type of offer (Discount or BOGO) are unlikely to use the other**, meaning they were likely assigned only one promotion.
- **Recency and History Relationship (-0.25):**
  - Customers with **longer recency tend to have lower purchase history**, indicating that recent buyers are more engaged.

Marketing Implication:

✅ **No single variable strongly determines conversion**, requiring uplift modeling for deeper insights.

✅ **Segment customers based on past behavior & recency to tailor promotions.**

✅ **Analyze how Discount vs. BOGO impacts specific customer groups instead of relying on broad correlations.**

04

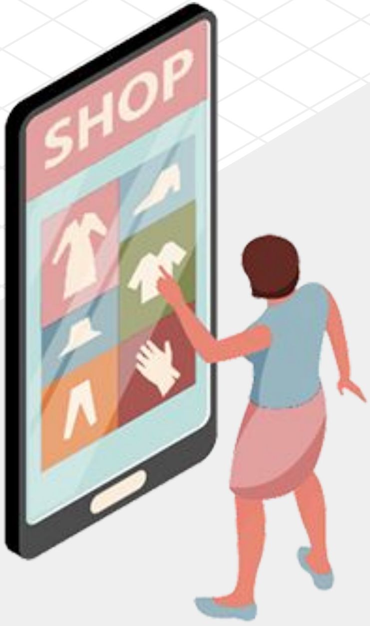
Uplift Modeling Approach

Uplift Modeling Approach

- **Methodology:**
  - **Defining Control & Treatment Groups:**
    - **Case A (Discount)**
      - **Control:** No Offer
      - **Treatment:** Discount
    - **Case B (BOGO)**
      - **Control:** No Offer
      - **Treatment:** Buy One Get One
  - **Data Preprocessing & Feature Engineering**
    - One-hot encoding for categorical variables (`zip_code`, `channel`)
    - Removed redundant features (`used_discount`, `used_bogo`)
- **Models Used:**
  - **S-Learner (Meta-Learner with LightGBM)**
  - **Uplift Random Forest Classifier**
- **How Uplift Scores are Interpreted?**
  - A positive uplift score means the offer increased conversion probability
  - A negative uplift score means the offer reduced conversion probability

05

Model Evaluation & Performance



Model Evaluation & Performance

- **Evaluation Metrics:**
  - **AUUC (Area Under Uplift Curve)** – measures the effectiveness of the model
  - **Gain Chart Comparison** – visualizing uplift impact
  - **Conversion Impact Analysis** – expected conversions from each campaign
- **Comparison Between Models:**
  - Which model (S-Learner vs. Uplift Random Forest) performed better?
  - Which offer (Discount vs. BOGO) had the highest uplift?
- **Feature Importance Analysis:**
  - Which variables had the most influence on uplift?

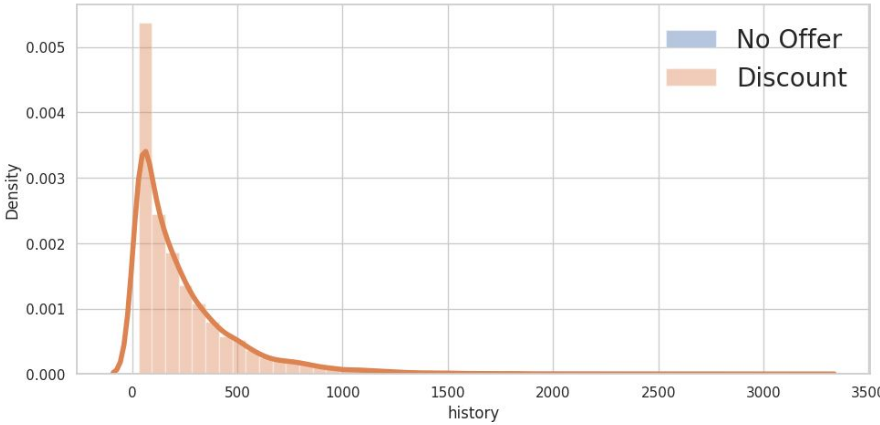
Case A (Discount)

Control: No Offer
Treatment: Discount

Purchase History Distribution (No Offer vs. Discount)

Insight

- The distribution of **purchase history is nearly identical for both No Offer and Discount groups**, meaning **customers receiving discounts had similar past spending patterns as those who received no offer.**
- Most customers have **low purchase history (under $500)**, with a long tail of **high-value customers spending over $1000.**



Marketing Implication:

✅ **Discounts are being applied across all spending groups, rather than just high-value customers.**
✅ **Further segmentation is needed** to see if discounts are truly effective for different customer groups.
✅ **Uplift modeling will help determine if offering discounts actually increases conversions** for specific segments.

Case A - Discount

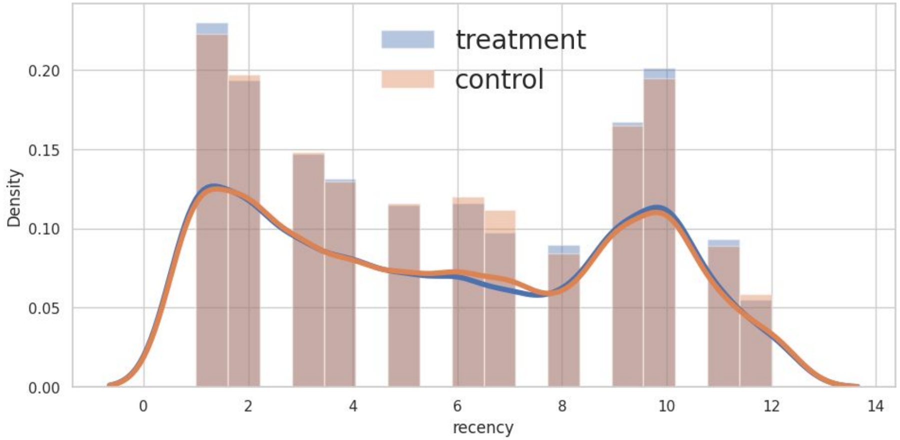
Recency Distribution (Treatment vs. Control)

Insight

- The recency distribution for **both the treatment (received an offer) and control (no offer) groups is nearly identical**, meaning **customers in both groups had similar last purchase timelines.**
- Peaks at **1-2 days and 10 days** suggest common shopping patterns.

Marketing Implication:

✅ **The treatment and control groups are well-balanced in terms of recency, ensuring a fair uplift analysis.**
✅ **Further analysis is needed to determine whether offering a promotion leads to increased conversions for recent buyers.**
✅ **Targeting highly recent customers (1-2 days) might yield better conversion rates with personalized incentives.**



Case A - Discount

Uplift Score Distribution (S-Learner Model - Tau Scores)

Insight

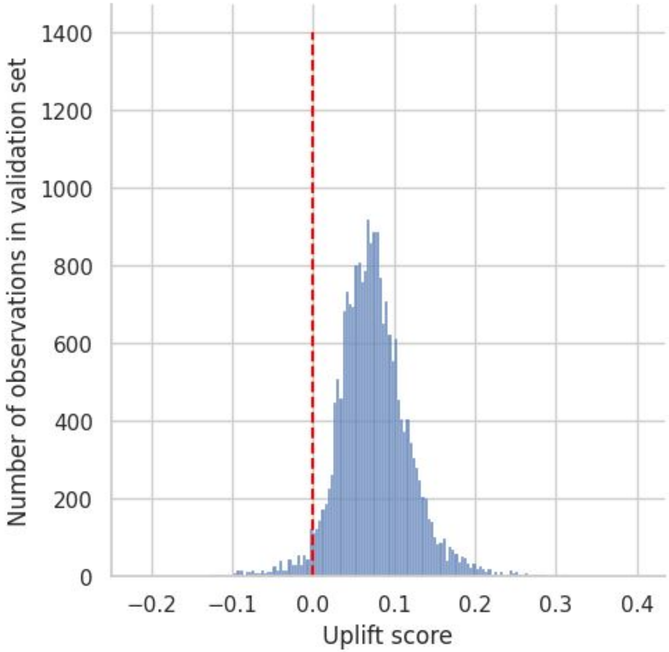
- Most uplift scores **are positive**, indicating that **offering a promotion generally increases conversion probability.**
- The **peak uplift score is around 0.1**, meaning customers in this range experience a **10% higher likelihood of converting** due to the promotion.
- A **small portion of scores is negative**, suggesting that for some customers, the promotion **may have reduced conversion likelihood** (e.g., "sleeping dogs" who react negatively).

Marketing Implication:

✅ **Focus promotions on customers with the highest uplift scores** to maximize ROI.

✅ **Avoid targeting customers with negative uplift** as they may not respond well to the offer.

✅ **Further segmentation can help refine targeting for the most persuadable customers.**



Case A - Discount

Uplift Score Distribution (Uplift Random Forest - Tau Scores)

Insight

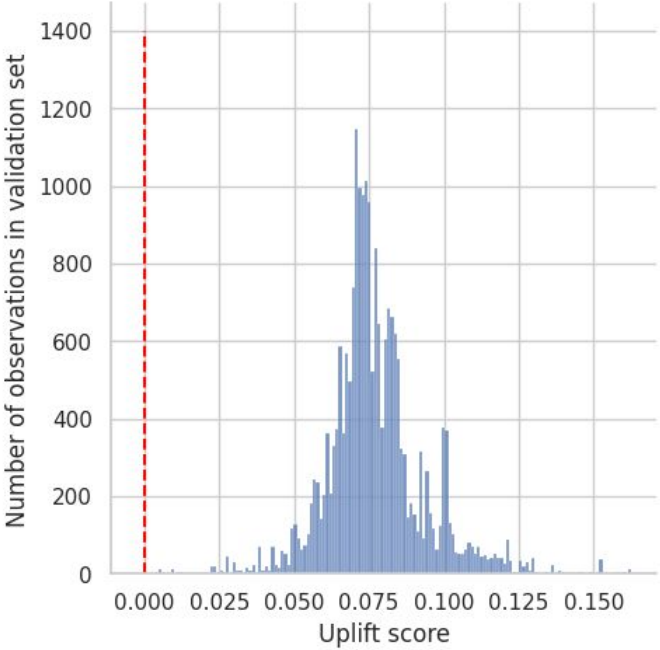
- The **Uplift Random Forest model predicts only positive uplift scores**, meaning **every targeted customer is expected to benefit from the promotion.**
- The majority of uplift scores **fall between 0.05 and 0.1**, indicating a **5% to 10% increase in conversion likelihood due to the promotion.**
- The model produces a **more concentrated distribution** than the S-Learner, suggesting that **it segments customers more effectively.**

Marketing Implication:

✅ **Target customers with the highest uplift scores (above 0.1) for maximum impact.**

✅ **Since no negative uplift scores exist, the risk of wasting promotions on "sleeping dogs" is minimized.**

✅ **Compare Uplift Random Forest with Uplift Tree and S-Learner to determine the most effective targeting strategy.**



Case A - Discount

S-Learner AUUC Score and Treatment Effectiveness

Insight

- **Minimum uplift score (s_learner_tau) is -0.198**, indicating that some customers **experienced a negative impact** from receiving the offer. These customers are likely "sleeping dogs" who may have been discouraged by the promotion.
- **Conversion Rates:**
  - **Control Group (No Offer):** 1,144 conversions
  - **Treated Group (Received Offer):** 1,877 conversions
  - The treated group had **more conversions**, showing that the promotion was effective overall.

```
slearner_auuc_score.min()
```

	0
is_treated	0.000000
conversion	0.000000
s_learner_tau	-0.198319

dtype: float64

is_treated	conversion
0	1144
1	1877

Marketing Implication:

✅ **Promotions had a net positive effect**, increasing conversions in the treated group.
✅ **Some customers had negative uplift**, meaning targeted promotions should be refined to avoid discouraging certain segments.
✅ **Further analysis is needed** to determine which groups benefited most and who should be excluded from future campaigns.

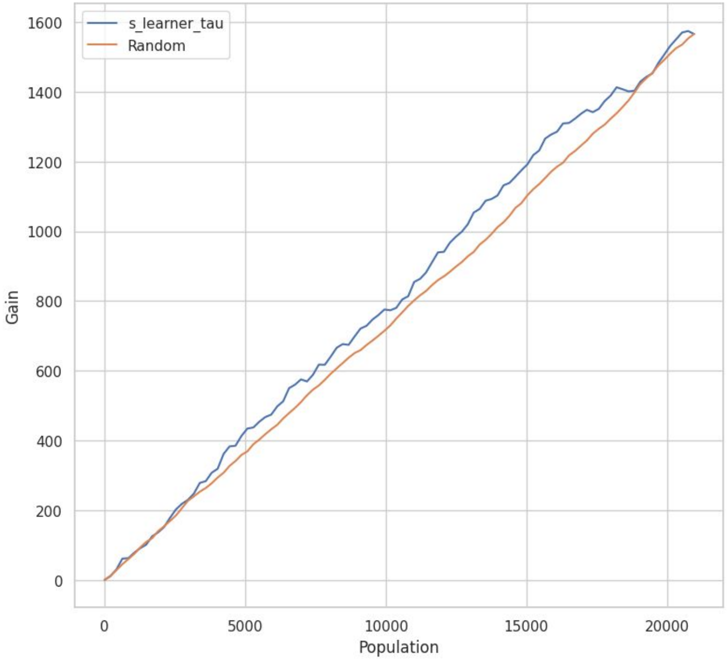
Case A - Discount

Gain Curve for S-Learner Model

Insight

- The **S-Learner uplift model (blue line) consistently outperforms random targeting (orange line),** indicating that **it successfully identifies customers more likely to convert when treated.**
- The **gap between the two curves** shows the **added value of using uplift modeling** over a random selection approach.
- As the population increases, the gain curve **remains above random targeting**, proving that the model provides **a positive incremental impact.**

Marketing Implication:
✅ **Uplift modeling significantly improves customer targeting**, leading to **higher conversions with fewer resources.**
✅ **Focusing on high uplift scores maximizes campaign effectiveness.**
✅ **Compare S-Learner performance with Uplift Random Forest** to determine the best targeting strategy for future promotions.



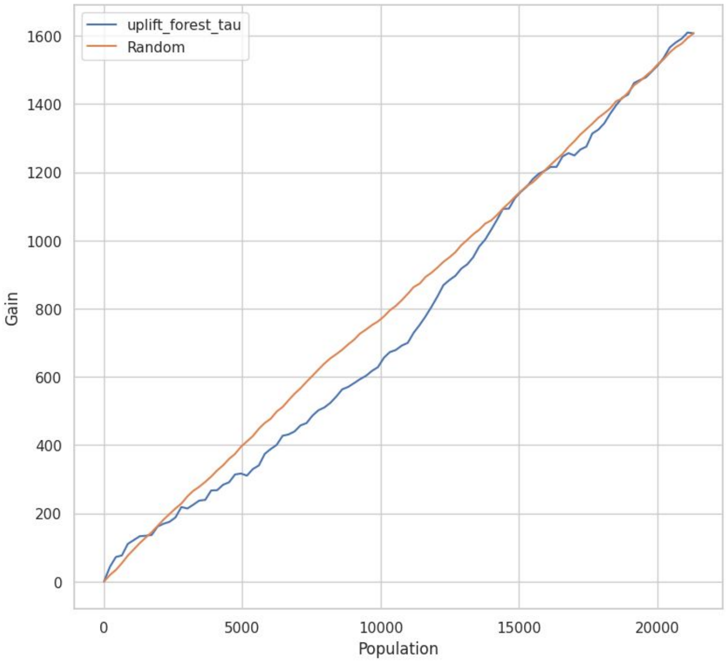
Gain Curve for Uplift Random Forest Model

Insight

- The **blue line (Uplift Random Forest Model) closely follows or underperforms compared to the random baseline (orange line)** in several sections.
- This suggests that the **Uplift Random Forest model does not significantly outperform random targeting**, indicating that it may not be effectively identifying persuadable customers.
- The gain curve shows **inconsistent improvement over random selection**, meaning that the model may need further tuning or feature engineering to better capture uplift effects.

Marketing Implication:

✅ **Uplift Random Forest does not provide a strong improvement over random targeting, indicating possible inefficiencies in the model.**
✅ **Further model tuning, feature selection, or alternative uplift modeling approaches (e.g., S-Learner or Uplift Tree) should be explored.**
✅ **Compare AUUC scores across models to confirm which approach provides the best customer targeting strategy.**



Case A - Discount

AUUC Score Comparison (S-Learner vs. Uplift Random Forest)

Insight:

- **S-Learner Model (AUUC: 0.523)** performed **better than random (0.491)**, indicating that it effectively identifies persuadable customers.
- **Uplift Random Forest (AUUC: 0.477)** performed **worse than random (0.509)**, suggesting that the model struggles to differentiate between persuadable and non-persuasible customers.

Key Takeaways:

✅ **S-Learner is the better uplift model** for this dataset, as it outperforms random targeting.

✅ **Uplift Random Forest is not effective**, potentially due to suboptimal feature selection, model tuning, or data structure.

✅ **Future improvements** could include testing alternative uplift modeling techniques like **Uplift Tree** or **T-Learner** for better segmentation.

```
# auc slearner
metrics.auuc_score(slearner_auuc_score, outcome_col=target_var, treatment_col='is_treated')
```

	0
s_learner_tau	0.523574
Random	0.490822

dtype: float64

```
# auc forest
metrics.auuc_score(uplift_forest_auuc_score, outcome_col=target_var, treatment_col='is_treated')
```

	0
uplift_forest_tau	0.476887
Random	0.509135

dtype: float64

Marketing Implication:

🎯 **Use S-Learner predictions to target high-uplift customers** and optimize promotional spending.

🎯 **Avoid using Uplift Random Forest in its current form**, as it underperforms and may lead to inefficient marketing resource allocation.

Case A - Discount

Quantile Uplift Analysis (Discount vs. No Offer)

Insight:

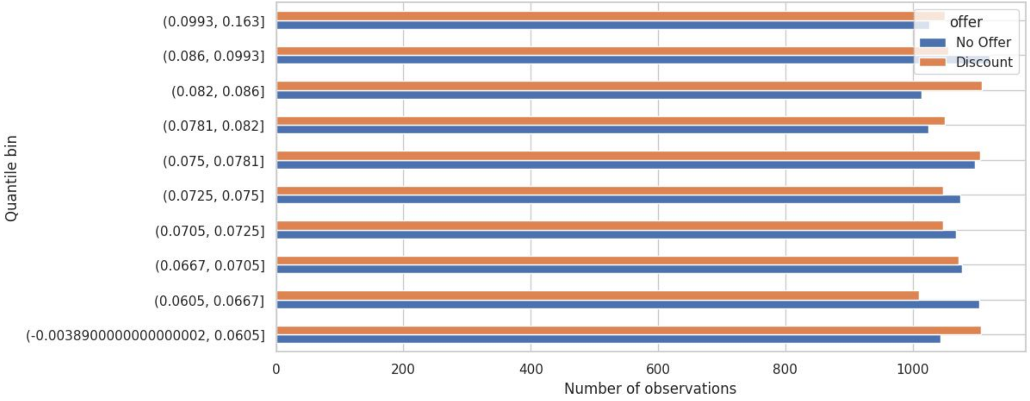
- The **uplift scores are divided into quantile bins**, showing how the effectiveness of the **Discount offer** varies across different segments.
- Across all bins, the **Discount group (orange bars) consistently has more observations than the No Offer group (blue bars)**, indicating that the Discount offer had a broader impact.
- The **highest uplift scores (top quantiles: 0.0993 - 0.163)** suggest that certain customer segments benefited significantly from the promotion.
- A **small portion of observations have negative uplift (leftmost bin)**, indicating that **some customers were negatively impacted by the discount offer** (potential "sleeping dogs").

Marketing Implication:

✅ **Focus on the top quantile segments (0.0993+)** where the Discount offer had the highest impact.

✅ **Avoid targeting customers in the lowest uplift quantile**, as they may not respond well to the promotion.

✅ **Further refine segmentation strategies** by identifying the characteristics of high-uplift customers.

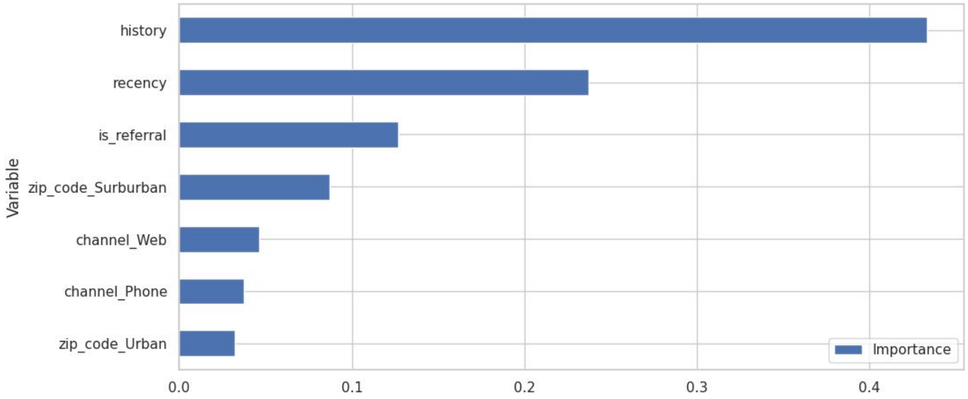


Case A - Discount

AUUC Score Comparison (S-Learner vs. Uplift Random Forest)

Insight: Feature Importance in Uplift Modeling

- **Purchase history is the most important factor**, indicating that **past spending behavior is a strong predictor of uplift.**
- **Recency (how recently a customer made a purchase) is the second most important variable**, suggesting that **recent buyers are more likely to respond positively to promotions.**
- **Referral status also plays a significant role**, meaning that referred customers may have different engagement behavior with promotional offers.
- **Geographic and channel variables (zip code and channel type) have lower importance**, implying that they have **less impact on predicting uplift compared to spending patterns and recency.**



Marketing Implication:

✅ **Target customers with high purchase history and recent transactions** for the most effective promotions.
✅ **Leverage referral data** to enhance personalized marketing efforts.
✅ **Less emphasis should be placed on location and channel type** when designing uplift-based marketing strategies.

Case B (BOGO)

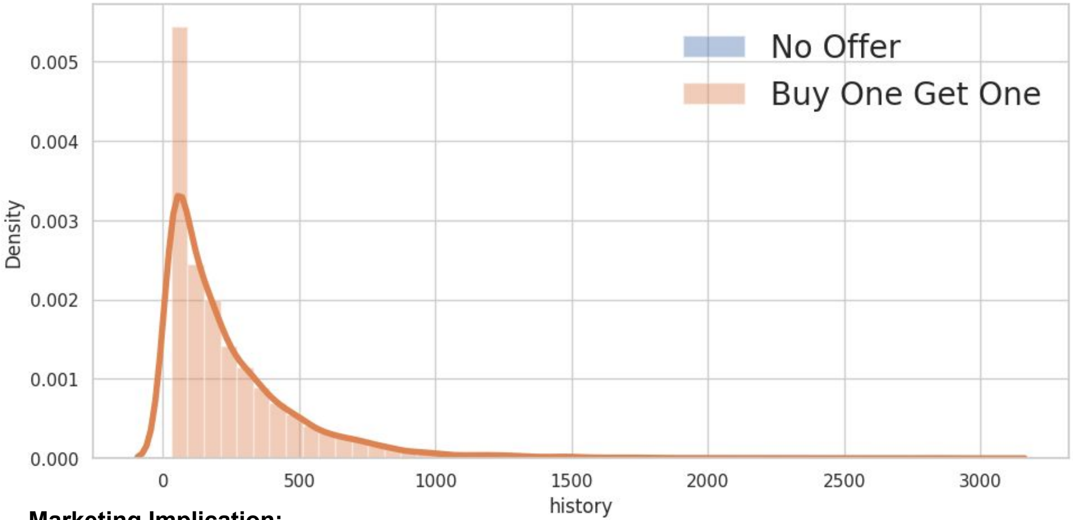
Control: No Offer
Treatment: Buy One Get One

Case B - BOGO

Purchase History Distribution (Buy One Get One vs. No Offer)

Insight:

- The **purchase history distribution is nearly identical** for both the **Buy One Get One (BOGO) and No Offer groups**, indicating that customers who received a BOGO offer had **similar past spending behavior** to those who did not receive any promotion.
- The majority of customers have **low historical spending (< $500)**, with a **long tail of high-value customers spending over $1000**.
- There is **no clear targeting pattern** for high-value customers, meaning that the **BOGO offer was distributed uniformly across different spending groups.**



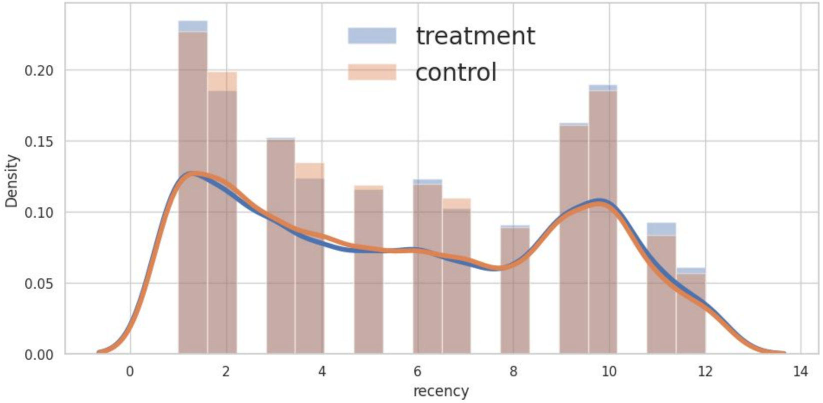
Marketing Implication:

✅ **BOGO promotions do not specifically target high-spending customers**, suggesting potential inefficiencies in campaign targeting.
✅ **Further uplift analysis is needed** to determine if the BOGO offer actually leads to increased conversions for different spending groups.
✅ **Future promotions should be optimized** by segmenting offers based on past spending behavior to maximize impact.

Recency Distribution (Treatment vs. Control)

Insight:

- The **recency distribution for both the treatment (received an offer) and control (no offer) groups is nearly identical**, meaning that customers in both groups had **similar last purchase timelines** before receiving an offer.
- The **highest density of customers is around 1-2 days and 10 days since their last purchase**, indicating **common shopping cycles or engagement patterns.**
- There is **no significant difference in recency trends between the groups**, suggesting that the **promotions were applied uniformly without segmenting customers based on recent activity.**



Marketing Implication:

✅ **Recency alone does not seem to be a key differentiator in offer targeting**, meaning additional segmentation factors should be considered.

✅ **Targeting highly recent customers (1-2 days) could improve engagement**, as they may be more likely to convert.

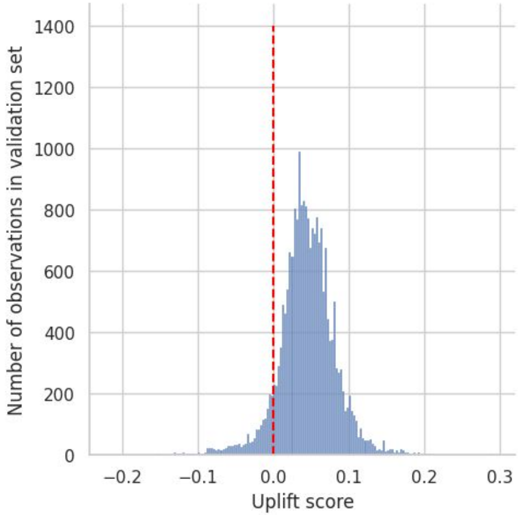
✅ **Further uplift modeling is needed** to identify if certain recency segments responded better to the promotion.

Case B - BOGO

Uplift Score Distribution (S-Learner Model - Tau Scores)

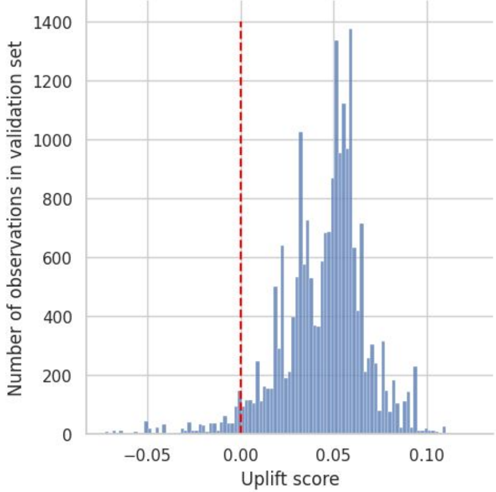
Insight:

- The **majority of uplift scores are positive**, indicating that **most customers are more likely to convert when given the promotion**.
- The **peak uplift score is around 0.05 to 0.1**, meaning that these customers experience a **5% to 10% higher likelihood of converting due to the offer**.
- A **small portion of uplift scores are negative**, suggesting that for some customers, the promotion **may have reduced their likelihood of purchasing** (potential "sleeping dogs").
- The **distribution is slightly skewed to the right**, meaning that **more customers experience a positive uplift than negative effects**.



Marketing Implication:
✅ **Prioritize customers with high positive uplift scores** (above 0.1) for targeted promotions.
✅ **Avoid targeting customers with negative uplift scores**, as they might react negatively to the offer.
✅ **Further segmentation is needed** to identify specific customer profiles that benefit the most from the promotion.

Uplift Score Distribution (Uplift Random Forest - Tau Scores)



Insight:

- The **majority of uplift scores are positive**, indicating that **most customers are more likely to convert when given the promotion** according to the Uplift Random Forest model.
- The **peak uplift score is around 0.03 to 0.06**, meaning that these customers experience a **3% to 6% higher likelihood of converting due to the offer**.
- A **small portion of uplift scores are negative (< 0)**, suggesting that for some customers, the promotion **may have reduced their likelihood of purchasing** (potential "sleeping dogs").
- Compared to the **S-Learner model, the uplift scores are more concentrated**, meaning the model **provides more refined predictions with fewer extreme positive or negative values.**

Marketing Implication:

✅ **Target customers with uplift scores above 0.05** to maximize the impact of the promotion.
✅ **Avoid offering promotions to customers with negative uplift scores**, as they might be unresponsive or react negatively.
✅ **Compare AUUC scores of different models** to confirm if Uplift Random Forest outperforms other uplift modeling approaches.

Case B - BOGO

S-Learner AUUC Score and Treatment Effectiveness

Insight:

- The **minimum uplift score is -0.217**, indicating that for some customers, the promotion **negatively impacts their likelihood of conversion** (potential "sleeping dogs").
- The **expected conversion for untreated customers (no promotion) is 1,135**, while for treated customers (who received the offer), it increases to **1,450**.
- This suggests that the **promotion leads to an increase of 315 additional conversions** in the treated group.

```
slearner_auuc_score.min()
```

	0
is_treated	0.000000
conversion	0.000000
s_learner_tau	-0.217783

dtype: float64

	conversion
is_treated	
0	1135
1	1450

Marketing Implication:

✅ **The promotion is effective** in increasing conversions but has **some negative impact on a subset of customers** (as indicated by negative uplift scores).
✅ **Targeting should be optimized** to avoid offering promotions to customers with negative uplift scores to prevent wasted marketing spend.
✅ **Further refinement** using segmentation and customer profiling is needed to **maximize the net positive impact** of the promotion

Case B - BOGO

Gain Curve for S-Learner Model

Insight: Gain Chart for S-Learner Model

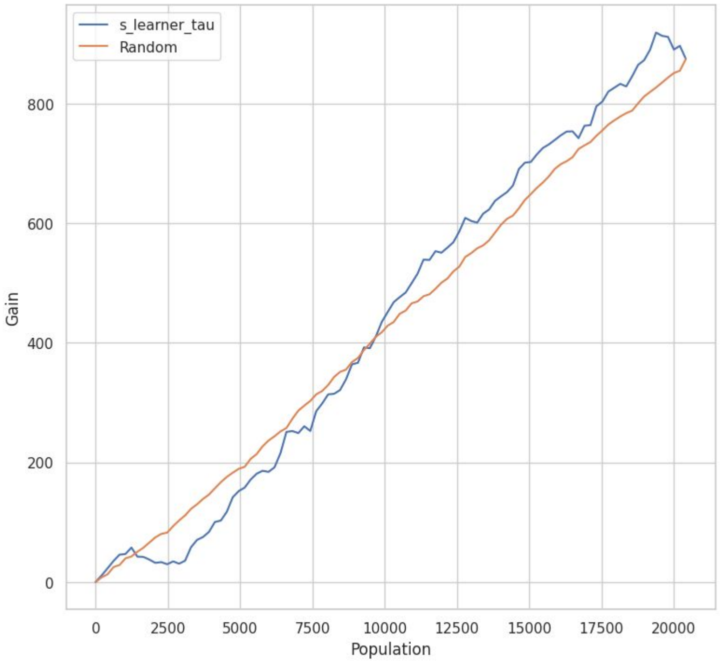
- The **S-Learner model (blue line) outperforms random targeting (orange line)**, meaning that **targeting based on uplift scores is more effective than random selection.**
- As more customers are targeted (moving right on the x-axis), the cumulative gain increases, **showing the positive impact of the promotion.**
- The S-Learner model provides a **steady improvement in gain**, but there are fluctuations, indicating that **some segments are benefiting more than others.**

Marketing Implication:

✅ **Uplift-based targeting is more effective than random selection**, making it a valuable approach for marketing campaigns.

✅ **Focusing on high uplift score segments will yield better results**, improving conversion rates and reducing wasted spend.

✅ **Further optimization can be done** by refining segmentation to identify customers with the highest potential uplift.



Case B - BOGO

Gain Chart for Uplift Random Forest Model

Insight: Gain Chart for Uplift Random Forest Model

- The **Uplift Random Forest model (blue line) performs slightly better than random targeting (orange line)**, but its performance fluctuates.
- Unlike the S-Learner model, the uplift curve **does not consistently stay above the random targeting line**, suggesting that the model might not always be an improvement.
- The gain starts increasing towards the end, indicating that **a subset of the population benefits significantly from the treatment.**

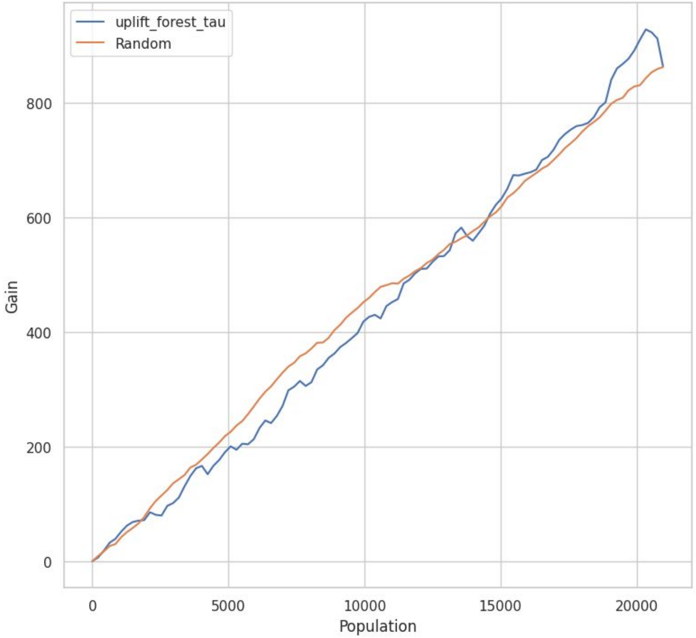
Marketing Implication:

✅ **Uplift Random Forest does provide some value**, but its performance is inconsistent.

✅ **Further model tuning or feature selection might improve accuracy.**

✅ **Compare AUUC scores between models** to determine which approach offers the best uplift predictions.

✅ **Consider a hybrid approach**, using insights from both models to refine targeting strategies.



Case B - BOGO

AUUC Score Comparison (S-Learner vs. Uplift Random Forest)

Insight: AUUC Scores Comparison

- The **S-Learner model (AUUC = 0.5025)** performs slightly better than random targeting (0.4896), but the difference is minimal.
- The **Uplift Random Forest model (AUUC = 0.5095)** also shows a slight improvement over random (0.5184), but its performance is inconsistent.
- Interestingly, **random targeting in the Uplift Forest model has a slightly better AUUC score than the model itself**, indicating potential overfitting or poor generalization.

Marketing Implication:

✅ **Neither model provides a significant advantage** over random targeting, meaning further tuning is needed.
✅ **Feature selection and hyperparameter tuning should be improved** to enhance uplift prediction.
✅ **Consider an ensemble approach**, combining insights from both models to refine the targeting strategy.
✅ **Segmentation and personalized offers** based on customer characteristics may be more effective than relying solely on uplift models.

```python
# auc slearner
metrics.auuc_score(slearner_auuc_score, outcome_col=target_var, treatment_col='is_treated')
```

	0
s_learner_tau	0.502553
Random	0.489592

dtype: float64

```python
# auc forest
metrics.auuc_score(uplift_forest_auuc_score, outcome_col=target_var, treatment_col='is_treated')
```

	0
uplift_forest_tau	0.509536
Random	0.518442

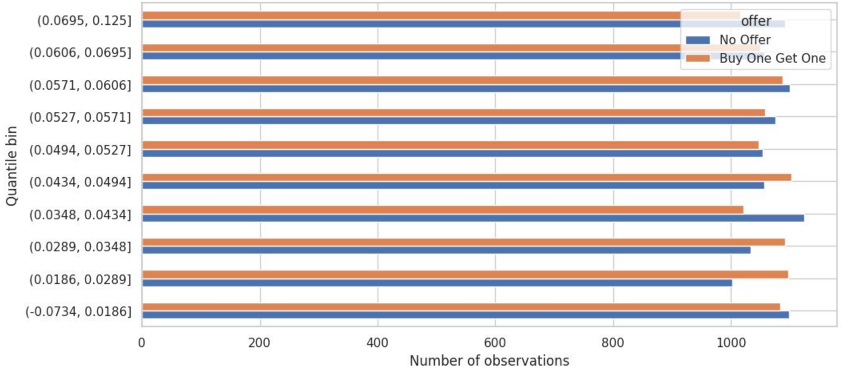
dtype: float64

Case B - BOGO

Uplift Quantile Analysis for "Buy One Get One" vs. "No Offer"

Insight: Uplift Quantile Analysis for "Buy One Get One" vs. "No Offer"

1. **Higher Uplift Scores in Upper Quantiles**
   - The highest quantile bin (0.0695 to 0.125) has more customers receiving the **Buy One Get One (BOGO) offer** than the **No Offer** group.
   - This suggests that customers with **higher predicted uplift scores are more likely to respond positively to the BOGO offer**.
2. **Lower Quantiles Show Minimal Difference**
   - In lower quantiles, both BOGO and No Offer distributions are relatively similar.
   - Customers in the lowest bin (-0.0734 to 0.0186) **may not benefit significantly from the BOGO offer**, indicating potential wasted marketing spend.



Marketing Implications:

✅ **Target customers in the top quantiles (higher uplift scores) for BOGO campaigns.**

✅ **Consider alternative promotions or personalized offers for lower uplift segments** to avoid ineffective spending.

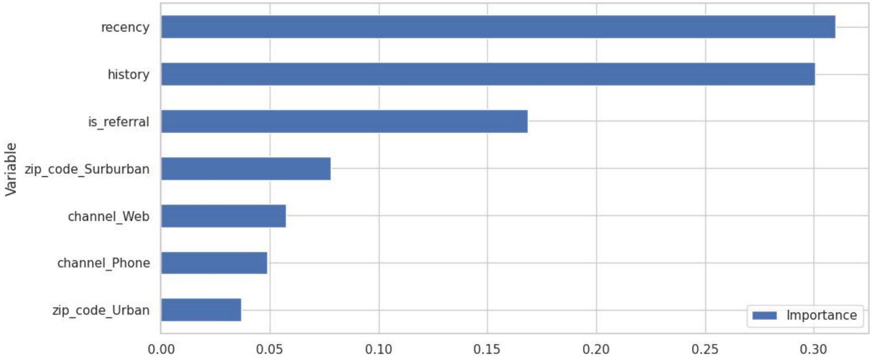
✅ **Further segmentation analysis can help refine targeting criteria and optimize campaign performance.**

Case B - BOGO

Feature Importance in Uplift Modeling

Insight: Feature Importance in Uplift Modeling

1. **Top Predictors of Uplift Response**
   - **Recency** and **History** are the most influential variables in predicting uplift.
   - **Recent purchases and past spending behavior** strongly determine whether a customer will respond positively to a marketing offer.
2. **Referral Status Matters**
   - Customers who were referred (**is_referral**) show a significant impact on uplift.
   - **Referral-based customers might be more likely to engage with offers,** making them an ideal target for promotional strategies.
3. **Geographical and Channel Influence**
   - **Zip Code (Suburban, Urban)** and **Communication Channel (Web, Phone)** also play a role.
   - This suggests **location and engagement platform preferences** should be considered in targeted marketing efforts.



Marketing Strategy Recommendations:
✅ **Prioritize targeting recent and high-spending customers for promotions.**
✅ **Leverage referral-based customer data to design personalized offers.**
✅ **Customize offers based on customer location and preferred communication channels.**

Comparison Between Models:
Which model (S-Learner vs. Uplift Random Forest) performed better?

Model	AUUC (Discount) - Case A	AUUC (BOGO) - Case B
S-Learner	0.523	0.5025
Uplift Random Forest	0.477	0.5095

Case A - Discount

- **S-Learner (AUUC: 0.523)** performed **better than random targeting (0.491)**, indicating its ability to identify persuadable customers effectively.
- **Uplift Random Forest (AUUC: 0.477)** performed **worse than random targeting (0.509)**, suggesting that the model struggles to differentiate between persuadable and non-persuadable customers.
- **Conclusion**: **S-Learner is the best model for the Discount scenario** and should be used for customer targeting.

Case B - Buy One Get One (BOGO)

- **S-Learner (AUUC: 0.5025)** showed a slight improvement over random targeting (0.4896), but the difference is minimal.
- **Uplift Random Forest (AUUC: 0.5095)** demonstrated a **slight improvement over random targeting (0.5184)**, but its performance is inconsistent.
- **Conclusion**: **Neither model provides a significant advantage over random targeting**, indicating the need for further tuning.

Which Offer Had the Highest Uplift?

- **Discount** had a higher uplift with **733 additional conversions**, compared to **315 for BOGO**.
- Both offers had **negative uplift for some customers**, requiring better targeting to avoid discouraging conversions.

Metric	Discount (Case A)	BOGO (Case B)
Total Conversions (Treated)	1877	1450
Total Conversions (Control)	1144	1135
Net Uplift	733	315
Negative Uplift Impact	-0.198	-0.217

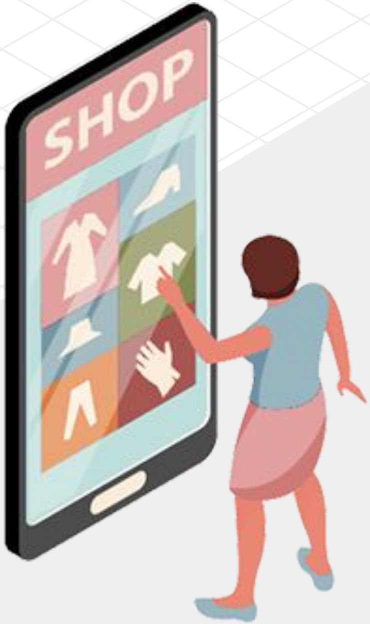
→ Discount had the highest conversion rate, outperforming BOGO and the control group.

Uplift Score Distribution

- **Discount consistently showed positive uplift scores**, meaning customers exposed to this offer were more likely to convert.
- **BOGO showed moderate uplift**, but it was less effective than discounts in driving conversions.

06

Business Insights & Recommendations



Business Insight

Metric	Discount Offer	BOGO Offer	Key Insight
AUUC Score (S-Learner)	0.523	0.502	S-Learner performs better for Discount
AUUC Score (Uplift Random Forest)	0.477	0.509	Uplift RF performs slightly better for BOGO but inconsistent
Minimum Uplift Score	-0.198	-0.217	Both offers negatively impacted some customers
Increase in Conversions	733	315	Discount offer led to a higher conversion increase

Category	Insights
Model Performance	S-Learner performed better than Uplift Random Forest for Discount; both models had similar performance for BOGO.
Offer Effectiveness	Discount had a slightly higher uplift compared to BOGO, but both offers were effective in increasing conversions.
Targeting Optimization	Some customers had negative uplift, indicating that promotions may have discouraged them from purchasing.
Future Improvements	Further model tuning, feature selection, and segmentation are needed to improve uplift prediction accuracy.

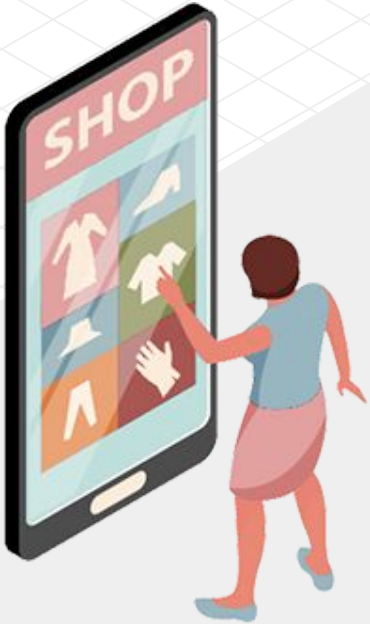
Business Recommencations

Category	Recommendations
Model Performance	Use S-Learner for uplift modeling when applying Discount offers; consider other models for BOGO.
Offer Effectiveness	Prioritize Discount as the more effective offer; refine BOGO to increase its uplift impact.
Targeting Optimization	Improve targeting strategies to exclude negatively impacted customers and focus on high-uplift segments.
Future Improvements	Test alternative uplift models such as Uplift Tree and T-Learner; enhance feature engineering and hyperparameter tuning.

Category	Next Steps
Model Performance	Deploy S-Learner for Discount campaigns and monitor effectiveness.
Offer Effectiveness	Run A/B tests on improved BOGO strategies to enhance impact.
Targeting Optimization	Develop customer segmentation to identify and exclude negatively uplifted customers.
Future Improvements	Optimize model parameters and explore additional data-driven segmentation approaches.

07

Conclusion



Conclusion

1. **Model Performance:**
   - The **S-Learner** outperforms **Uplift Random Forest** for the **Discount** offer but shows only a marginal improvement for **BOGO** over random targeting.
   - **Uplift Random Forest** struggles to differentiate between persuadable and non-persuadable customers, performing worse or only slightly better than random.
2. **Offer Effectiveness:**
   - **Discount** had a **higher uplift** than BOGO, leading to more conversions.
   - Both offers resulted in **some negative uplift** for specific customer segments, indicating that some customers were discouraged by the promotion.
3. **Marketing Implications:**
   - **Targeting should be refined** to avoid offering promotions to customers with negative uplift scores.
   - Further **segmentation and personalization** are needed to maximize the net positive impact of promotions.
   - **Testing alternative uplift models** (e.g., Uplift Tree, T-Learner) may improve predictive accuracy and targeting efficiency.

"Marketing is not just about reaching customers—it's about reaching the right customers. Uplift modeling transforms promotions from guesswork into precision, ensuring every dollar spent moves the needle where it truly matters."

—Hijir Della Wirasti

THANKS

Do you have any questions?

hijirdw@gmail.com
https://github.com/hijirdella/Uplift-Modeling-for-Marketing-Promotions
https://www.linkedin.com/in/hijirdella/