

## Introduction



Developing audience targeting strategies that can significantly boost advertisers' reach and engagement, leading to more effective and efficient marketing efforts.

### Goal

- Maximize Viewable Impressions and Clicks
- Maximize New To Brand Reach
- Optimal Bidding Strategy

## **Overall Recommendations**

#### Prioritize Weekends & Specific Months

 Amongst Feb, Mar, Apr, May focus on advertising campaigns on weekends and during February and March

#### • Refine Audience Targeting for maximum Reach

- o Categories: Women's Running Shoes, Foundation Makeup, Sheet and Pillowcase Sets
- Slots: Desktop and mobile app.

#### • Refine Audience Targeting for maximum NTB (New-to-Brand) Reach

- o Categories: Women's Running Shoes, Foundation Makeup, and Sheet and Pillowcase
- Slots : Mobileapp / Mobileweb
- Monitor & Adapt (monitor campaign performance) for any changes in future.

#### Limitations

• There could be changes in optimal bidding and campaign performance based on external factors like economy, future target audience likings, future and historical data.

## **Data cleaning And Profiling**

- Dataset Integration: Merged datasets, removed duplicates by date.
- Numerical Features: Filled missing sales/orders with 0.
- Categorical Features: Filled missing 'vertical'/'sub\_vertical' with 'Unknown', applied one-hot encoding to extract features.
- Date Feature: Extracted 'Month' and 'Day' from 'hit\_day\_utc'.

Note: Data is from Feb to May (we don't have complete data for month of May)

## **Model And Evaluation Metrics Used**

### **Evaluation Metrics**

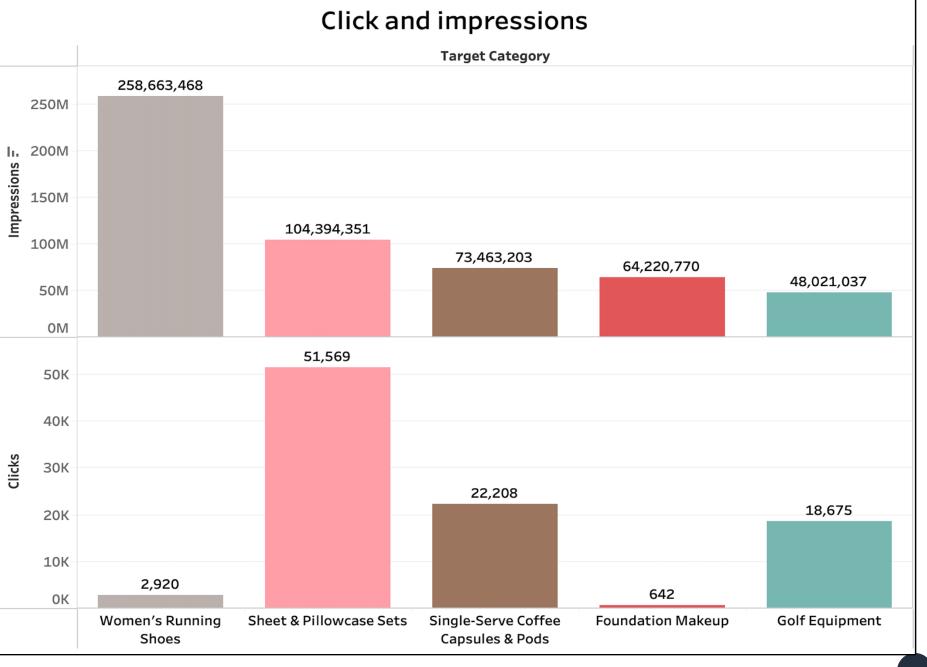
- 1. Mean Absolute Error (MAE) Average error between actual vs predicted
- 2. Mean Squared Error (MSE) Like MAE, but squares errors before averaging.
- 1. Evaluation Metric R-squared (R<sup>2</sup>)-

How well our predictions match the actual data between 0 to 100%

### **Model Approaches**

**Gradient Boosting Regressor** - Adds new decision models to correct errors made by existing models **Random Forest Regressor** - Builds multiple decision independently on random subset and averages

## Preliminary Analysis



# **IMPRESSIONS**

## Targeting for maximum Impressions: Approach

## **Objective:-**

• Predicting features influencing Impressions on whole dataset

#### **Model Selection:-**

• Model Used: Gradient Boosting Regressor

## Parameters used and Target variable:-

- Filter criteria: None
- Target: Impressions
- **Features:** clicks, placement slot, targeting secondary, vertical, sub vertical, month, day

## **Targeting for maximum Impressions**

<u>FEATURES</u>	Feature Importance Results(In decreasing order)
Placement slot	Offsite mobileapp Offsite Desktop
Targeting category:(Top 5)	<ol> <li>Women's Running Shoes</li> <li>Foundation Makeup</li> <li>Soap Opera</li> <li>Sheet and Pillowcase Sets</li> <li>Single-Serve Coffee Capsules &amp; Pods</li> </ol>
Month	<ol> <li>March</li> <li>February</li> </ol>
Day of the Week	<ol> <li>Sunday</li> <li>Saturday</li> </ol>
Model Results	R-sq = 64.45% MAE = 1,252.09 MSE = 5,092,641.23

## Optimized targeting for viewable Impressions

	Approach 1	Approach 2
Objective	Predicting features influencing impressions where some products were sold from views	Predicting features influencing impressions where there has been some clicks
Model Selecti on	Random Forest Regressor (better R-sq and less error) than Gradient Boosting	Random Forest Regressor (better R-sq and less error) than Gradient Boosting
Dataset Filter	view_attributed_units_sold > 0 (blanks treated as 0)	clicks > 0
Target	Impressions	Impressions
Features	clicks, placement slot, targeting secondary, month, day	clicks, placement slot, targeting secondary, month, day

## Optimized targeting for viewable Impressions

Feature Importance Results(In Decreasing order)

<u>FEATURES</u>	<u>Dataset with</u> <u>View attributed units sold &gt; 0</u>	<u>Dataset with Clicks &gt; 0</u>
Placement slot	Mobile App Mobile Web	Offsite Desktop
Targeting category: (Top 5)	<ol> <li>Women's Running Shoes</li> <li>Foundation Makeup</li> <li>Soap Opera</li> <li>Sheet &amp; Pillowcase Sets</li> <li>Home &amp; Kitchen</li> </ol>	<ol> <li>Sheet and Pillowcase Sets</li> <li>Women's Running Shoes</li> <li>Kid's Electronics</li> <li>Single-Serve Coffee Capsules &amp; Pods</li> <li>Foundation Makeup</li> </ol>
Month	<ol> <li>February</li> <li>March</li> </ol>	<ol> <li>February</li> <li>March</li> </ol>
Day of the Week	<ol> <li>Sunday</li> <li>Saturday</li> </ol>	<ol> <li>Sunday</li> <li>Saturday</li> </ol>
Model Results	R-sq = 84.60% MAE = 733.30 MSE = 3,243,257	R-sq = 92.22% MAE = 542.57 MSE = 1,748,221

# **CLICKS**

## Optimal targeting for maximum Clicks: Approach

## **Objective:-**

• Predicting important features influencing clicks

#### **Model Selection:-**

• Model Used: Gradient Boosting Regressor

## Parameters used and Target variable:-

- Filter criteria: click are at least 1(58674 records)
- Target: Clicks
- **Features:** impressions, placement\_slot, targeting\_secondary, vertical, sub\_vertical, month, day

## **Optimal targeting for maximum Clicks**

<u>FEATURES</u>	Feature Importance Results(In decreasing order)
Placement slot	Offsite desktop Offsite mobile web
Targeting category:(Top 5)	<ol> <li>Sheet and Pillowcase sets</li> <li>Single-Serve Coffee Capsules &amp; Pods</li> <li>Pipe Fittings &amp; Pipes</li> <li>Golf Equipment</li> <li>Bed Pillows &amp; Positioners</li> </ol>
Month	<ol> <li>February</li> <li>March</li> </ol>
Day of the Week	<ol> <li>Saturday</li> <li>Sunday</li> </ol>
Model Results	R-sq = 74.15% $MAE = 1.22$ $MSE = 3.98$

## Key Insights: Top features for better reach

Below are the features to focus to maximize impressions and clicks based on previous approaches

Placement Slot

Offsite Desktop

Offsite mobile app

Targeting Categories

#### **Impressions:**

Women's Running Shoes
Foundation Makeup
Soap Opera
Sheet and Pillowcase Sets
Kid's Electronics

#### **Clicks:**

Sheet and Pillowcase sets
Single-Serve Coffee Capsules & Pods
Pipe Fittings & Pipes

Seasonality

#### Month:

March, February

#### Day of week:

Sunday and Saturday

## NEW TO BRAND REACH

## Maximizing "new to brand" reach: Approach

#### **Objective:-**

 Predicting 'New To Brand' reach through impressions where some NTB products have been sold

#### **Model Selection:-**

- Models Used: Random Forest and Gradient Boosting Regressor
- Model Selected: Random Forest Regressor (less error and better R-sq)

#### Parameters used and Target variable:-

- **Filter criteria**: ntb\_view\_attributed\_units\_sold is not '0' and not in blank
- Target: 'impression'
- **Features:** targeting\_secondary, placement\_slot, month, day

## Maximizing "new to brand" reach

## Feature Importance Results

<u>FEATURES</u>	Feature Importance Results (In decreasing order)
Placement slot	Offsite mobileapp Offsite mobileweb
Targeting category:(Top 5)	<ol> <li>Women's Running Shoes</li> <li>Foundation Makeup</li> <li>Sheet and Pillowcase Sets</li> <li>Home &amp; Kitchen</li> <li>Oral Care Products</li> </ol>
Month	<ol> <li>March</li> <li>February</li> </ol>
Day of the Week	<ol> <li>Sunday</li> <li>Saturday</li> </ol>
Model Results	R-sq = 79.24% MAE = 904.47 MSE = 4,553,859

# OPTIMAL BIDDING

## **Optimal Bidding Strategy: Approach**

### **Objective:-**

- Predicting features for optimal bidding through maximum impressions with at least one click.
- Increased bidding on a combination of these top features based on importance and applied on Adjusted Cost to see difference

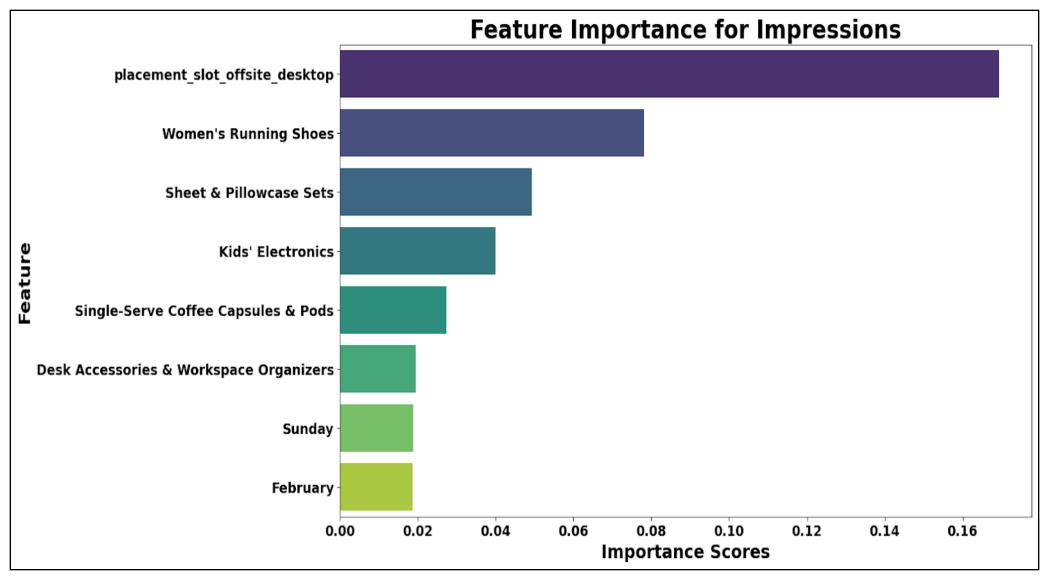
#### Model: Random Forest Regressor

- **Filter criteria**: Click is > 0
- Target: Impressions
- **Features:** 'Clicks', 'targeting\_secondary', 'placement\_slot', 'month', 'day'

#### **Results:**

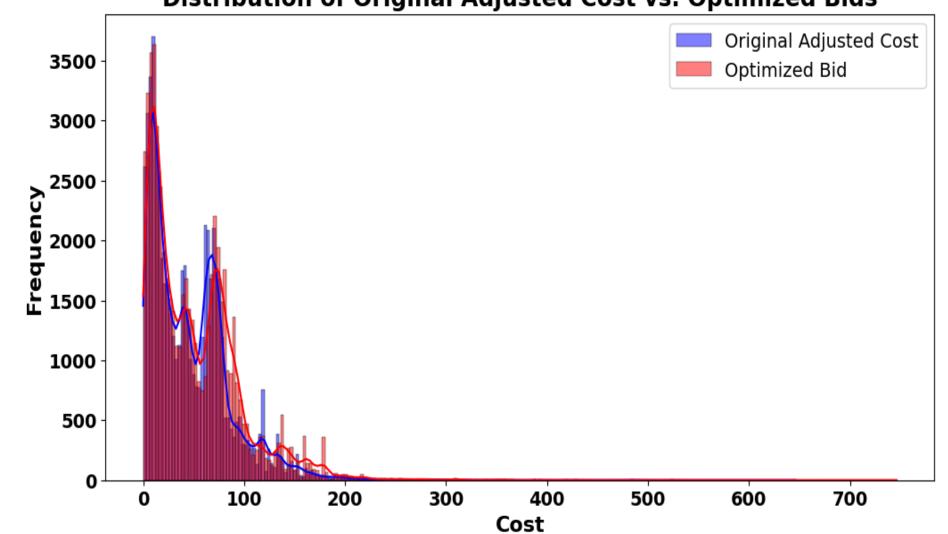
R-sq = 92.18 % MAE = 542.57 MSE = 174,221

## Features To Consider for Bidding



## **Bidding Strategy Implementation**

#### Distribution of Original Adjusted Cost vs. Optimized Bids



- Incrementing Adjusted Cost based on feature Importance:
- Placement Slot: +10% for offsite desktop
- Top 5 Categories: +5%, 4%, 3%, 2%, 1%
- Month: +5% for February
- **Day**: +5% for Sunday

# Thank you! Q&A

## **Appendix**

• Submitted document and code in Assignment to supplement this presentation.

Documentation link