



"I'm Just Browsing"

Predicting the Value of Prospective Customers

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What is a Prospective Customer?



Why are they important? Understanding the potential future value of customers who have engaged with Macy's, but have not made any purchases is critical to **new customer acquisition**

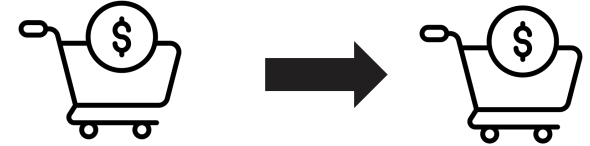


Our Project: Understand who the valuable prospective customers are, and how to activate their first purchase and retain them

Problem Overview

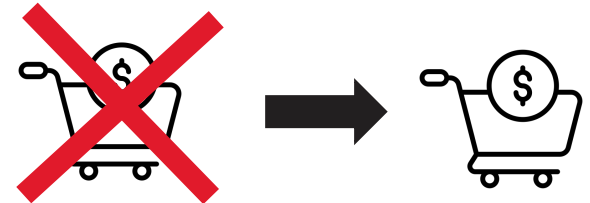
Current State

Macy's has models to predict the future value of **active customers** by using their historical purchase data



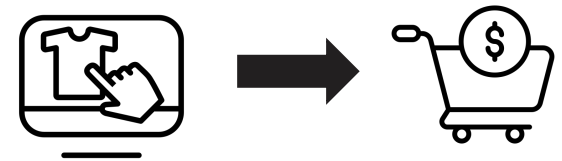
Limitation

Prospective customers, by definition, do not have purchase history



Our Approach

Use prospective customer **online activity data** to predict their value



Our Approach: Constructing the Dataset

Feb 2020 – Jan 2022

Feb 2022 – Jan 2023



Prospective customers had online activity but no purchases

Predict prospective customer **value** in 2022



Inactive Customers
Have purchase history prior to Feb 2020

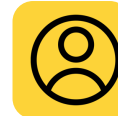
New Customers
Have never made a purchase prior to 2022

Features



Click behaviors

Search, browse, add to cart, page view, abandon cart, and others



User Profile

Loyalty status, length of loyalty, new/inactive

Data Limitations



Imbalanced Dataset

Only 8% of prospective customers made a purchase in 2022 - spend is skewed



Skewed Distribution for Online Activity

Majority of values indicate little activity



Missing Values

Removed demographic and income features

Our Approach: Predictive Modeling



3 Key Questions

Which prospective customers will make a purchase?

3 Models

Binary Classification model to predict whether a customer will purchase in next fiscal year



How much will prospective customers spend?

Regression model to predict the dollar amount that a customer will spend in next fiscal year



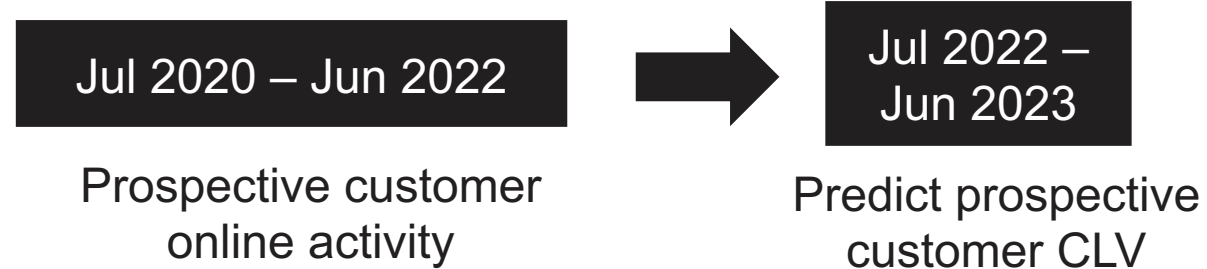
Who are the high value prospective customers?

Multi-Classification model to predict zero/low/high spend in next fiscal year

Model Validation through Backtesting

Backtesting: training on recent customer trends and testing on historical data

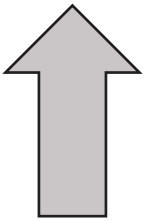
- ① Train model on more recent data

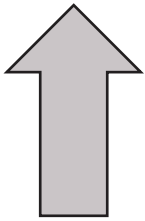


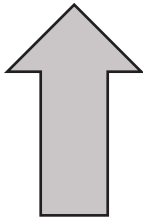
- ② Test model on older data



Our Models Improve upon Existing Methodologies

84%  **+7%**
Over Baseline
Accuracy of our
Best Model

73%  **+19%**
Over Baseline
Recall of our
Best Model

79%  **+12%**
Over Baseline
AUC of our Best
Model

Out-of-Sample Backtesting Results

Model	Accuracy	Recall	AUC
GBM Binary	0.84	0.73	0.79
GBM Multiclass	0.79	0.79	0.75
Baseline (Active Customer Churn)	0.77	0.54	0.67

Our Best Model: Binary CatBoost GBM
Baseline: Existing Customer Churn Models

Top Drivers of Prospective Customer Value



New vs. Inactive Customer

Whether a customer is new or inactive



Account Creation

Whether or not a customer signed up for a Macy's account as a loyalty member or non-loyalty member



Email Opt-In

Whether or not a customer opted-in to email marketing



Count of SMS Sent

Number of SMS messages delivered to customer



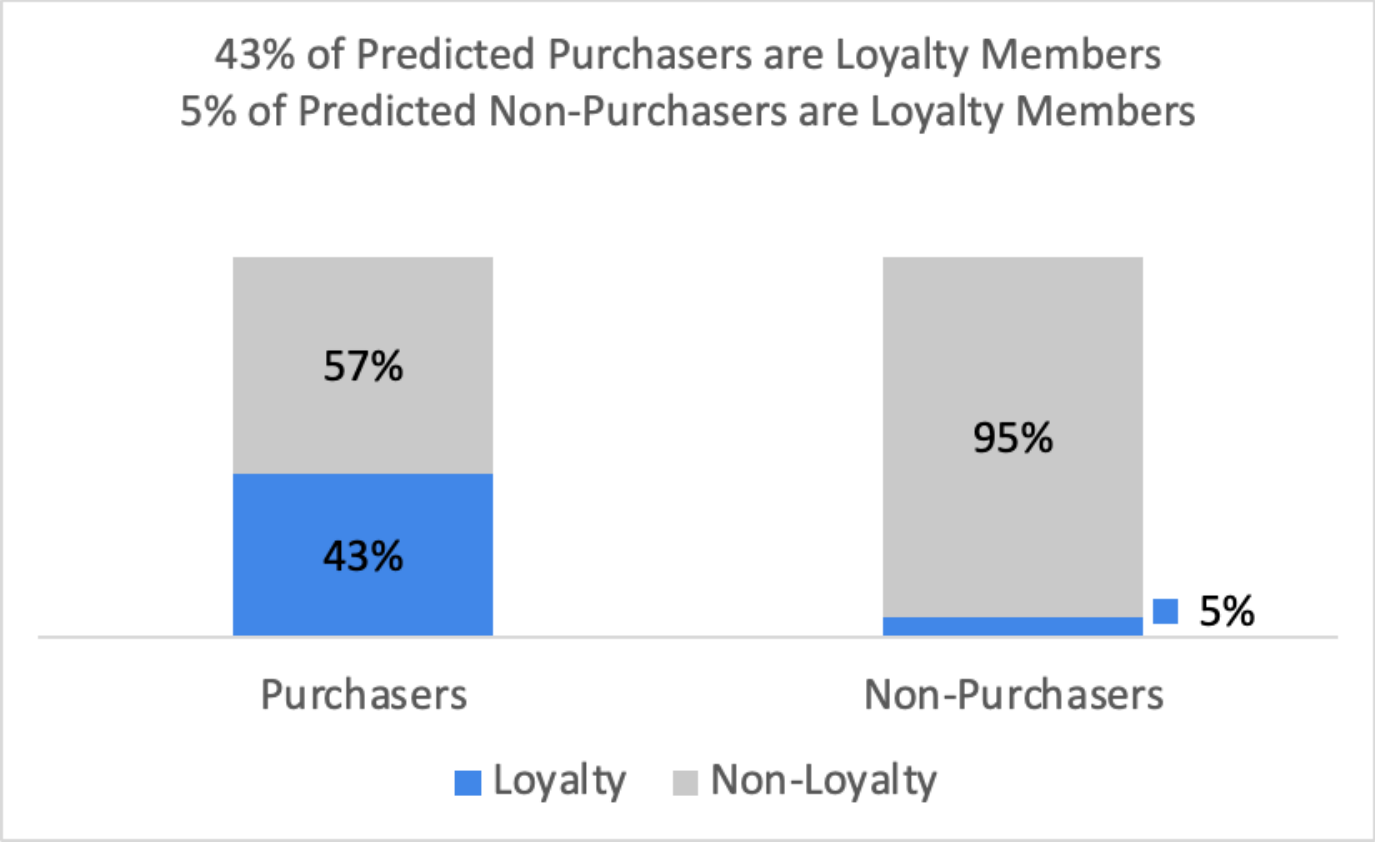
Search

Number of days with a search in the past 720 days

Post-Modeling Analysis: Binary Model

Feature	Predicted Purchasers	Predicted Non-Purchasers
% Inactive Customers	91%	0.3%
% Acct Creation Loyal	6%	1%
% Email Opt-In	6%	0.5%
Count of SMS Sent	8	0.2
Avg Number of Days w/ Searches Past 720 Days	4	3.8

Post-Modeling Analysis: Binary Model





Business Impact

- Targeted email campaigns to valuable prospective customers
- Guide customer personalization, engagement, and retention efforts and act as a data resource for teams across Macy's



Next Steps

- Integration into active customer CLV workflow
- Predict CLV for future time frame 2023-2024
- Deployment of prospective customer CLV models

Acknowledgements



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- MIT MBAn Program Team

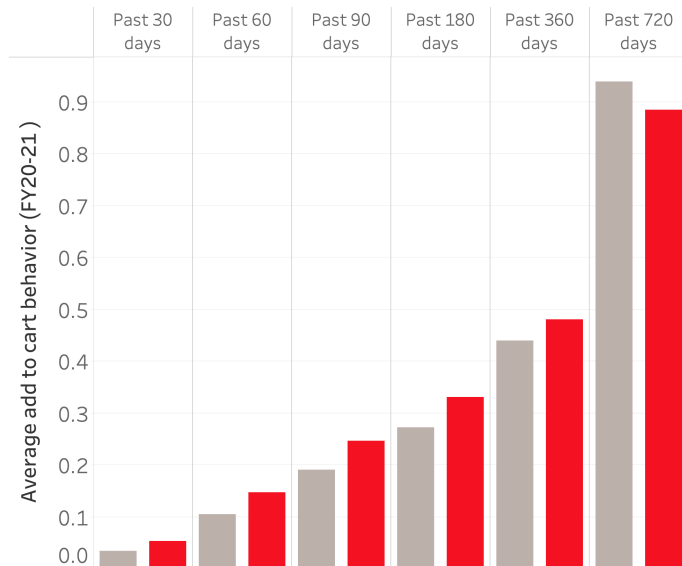
APPENDIX

Predictive Features Selected

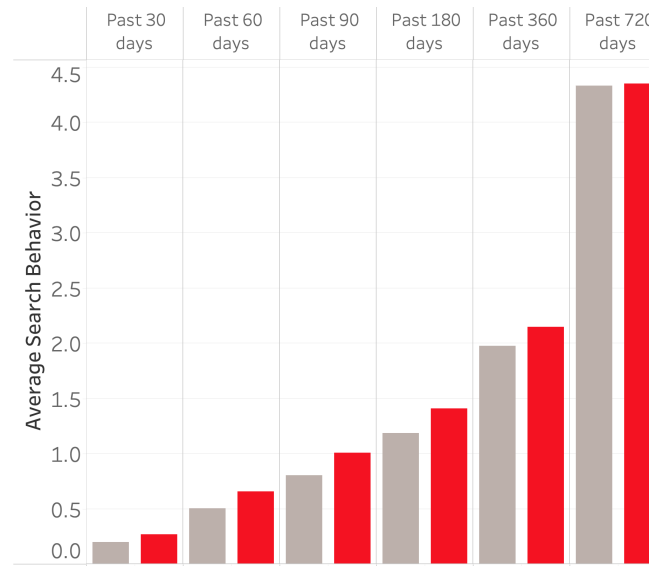
- Online activity metrics (search, browse product, page view, add to cart, abandon) *
 - Loyalty tier & age of loyalty
 - Email opt-in & SMS opt-in flag
 - App download flag
 - Prospective customer flag (1=never made a purchase)
 - Count & Duration (seconds) of visits
 - Device medium for visits (mobile phone, mobile app, tablet, desktop)
 - Source sites (Google, Facebook, Bing, etc.)
 - SMS data (sent, clicked, ordered, click rate, days since sms sent, days since sms clicked, days since sms ordered) *
- ***note: time frame: across 30, 60, 90, 180, 360, 720 days, 2 years**

Online Activity Average Counts are Similar Across Purchasers and Non-Purchasers

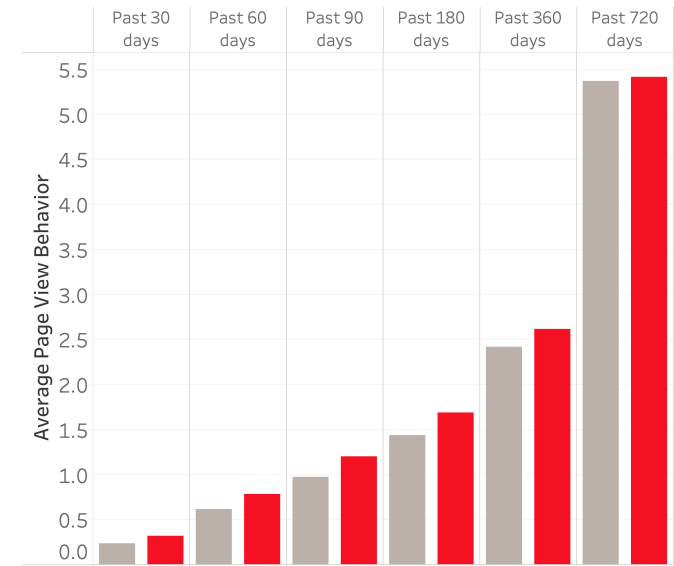
Add to Cart



Search



Page View



FY22 Purchase Flag

■ No Purchase

■ Purchase

*Outliers filtered out for all

App Download, Email Marketability, Session Length

Feature	Description
App Download Flag	<ul style="list-style-type: none">• Binary• Whether user downloaded Macy's app
Email Marketability Flag	<ul style="list-style-type: none">• Binary• Whether user was email marketable at time of downloading Macy's app
Session Length	<ul style="list-style-type: none">• Total duration spent in seconds over last 7 days

SMS Features

Feature	Description
# SMS Sent	<ul style="list-style-type: none"># of SMS messages sent to user
# SMS Clicked (Total)	<ul style="list-style-type: none"># of SMS messages clicked by user
# SMS Clicked (Unique)	<ul style="list-style-type: none"># of <u>unique</u> SMS messages clicked by user
Click Rate	<ul style="list-style-type: none"># SMS messages clicked / # sent
Days Since SMS Sent	<ul style="list-style-type: none"># of days since SMS was sent
Days Since SMS Clicked	<ul style="list-style-type: none"># of days since SMS was clicked

*Measured for all features over 30, 60, 90, 360, 720 days

Post-Modeling Analysis: Multi-Class Model

Feature	Predicted Zero Tier (spend = \$0)	Predicted Low Tier* (spend <= \$119)	Predicted High Tier (spend > \$119)
% Acct Creation Loyal	0%	10%	11%
% New Customers	99.9%	15%	19%
Avg Number of Days w/ Searches Past 360 Days	0.3	0.4	10
Avg Number of Days w/ Abandons Past 720 Days	1	0.5	3.5
Avg Number of Days w/ Page Views in Past 360 Days	0.4	0.5	12
% Email Opt-In	0%	5%	18%
Count of SMS Sent	0.4	6.6	6.8

Post-Modeling Analysis: Multi-Class Model

Feature	Predicted Zero Tier (spend = \$0)	Predicted Low Tier* (spend <= \$119)	Predicted High Tier (spend > \$119)
% Acct Creation Loyal	0%	10%	11%
% Inactive Customers	0.1%	85%	81%
Avg Number of Days w/ Searches Past 360 Days	0.3	0.4	10
% Email Opt-In	0%	5%	18%
Count of SMS Sent	0.4	6.6	6.8

*\$119 cutoff determined by median spend value

Post-Modeling Analysis: Multi-Class Model

