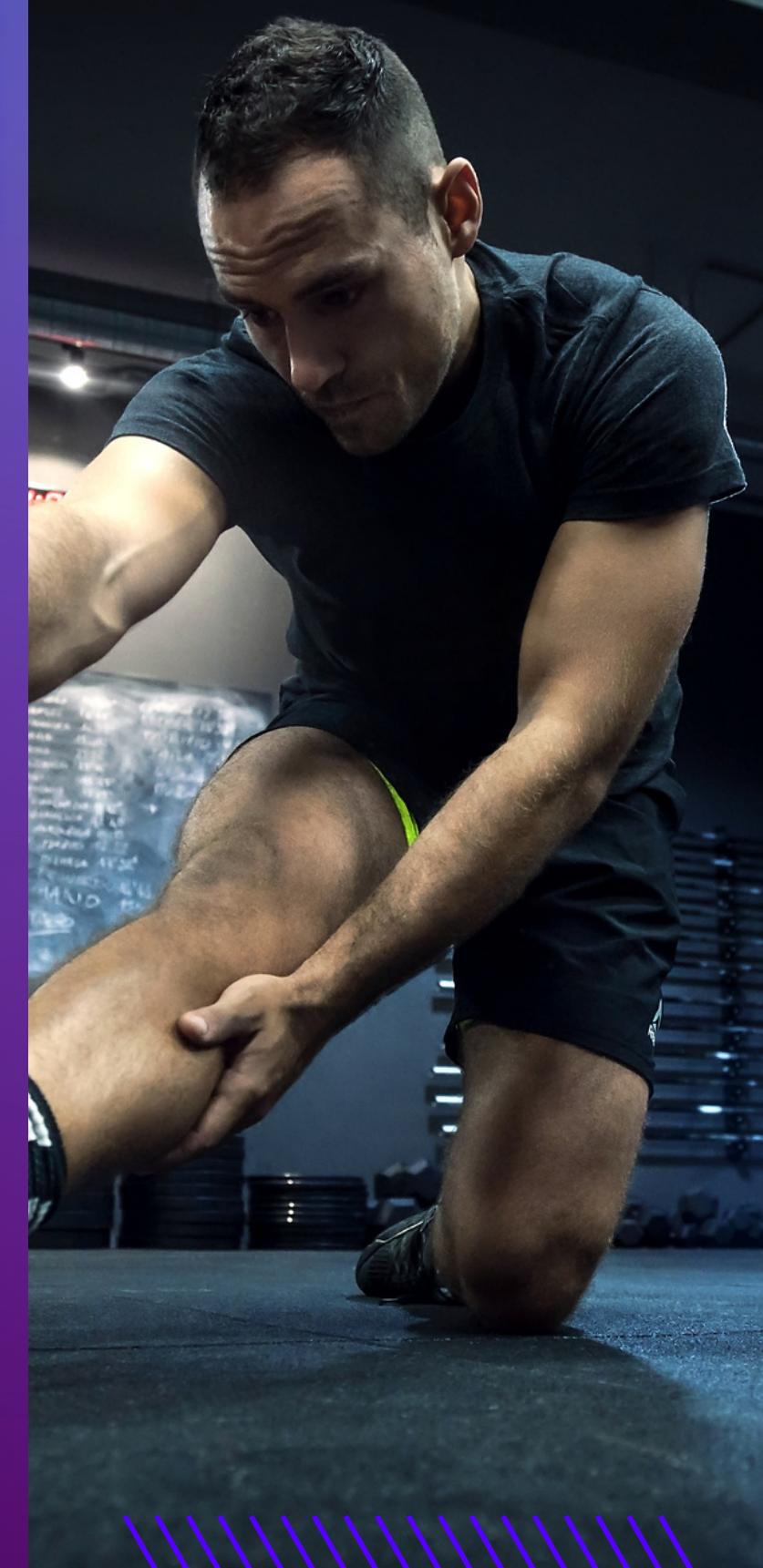


Customer Segmentation for product marketing

Our market proposal for a successful email campaign



Our Understanding of the Business Problem

Product Campaign to increase the sales of Men's Pants in Men Category

- Analysis on Customer Data (By 2020 May-Jun)
- Channel: In Store and Online
- Customer Campaign List -> ROI

Our Proposal For A Successful Email Campaign

Decision Needed: Campaign approach to distribute promotion emails

TOP CRITERIA

- + NUMBER OF MEN'S PANTS
- + TOTAL MONEY SPENT ON MEN'S
- + TOTAL # OF PRODUCTS PURCHASED
- AVERAGE VALUE OF TRANSACTIONS
- PERCENTAGE MARKDOWN ITEMS
- TOTAL WOMEN'S SPEND

SIZE OF CUSTOMERS

3015

ESTIMATED ROI

303%+

Approach to Problem



1

Study Data Insights with Exploratory Data Analysis

2

Two-Pronged Strategy - Machine Learning & RFM Model

3

Model Design - Feature Engineering

4

Results - Target Customers & ROI





Domain Research

Engagement:

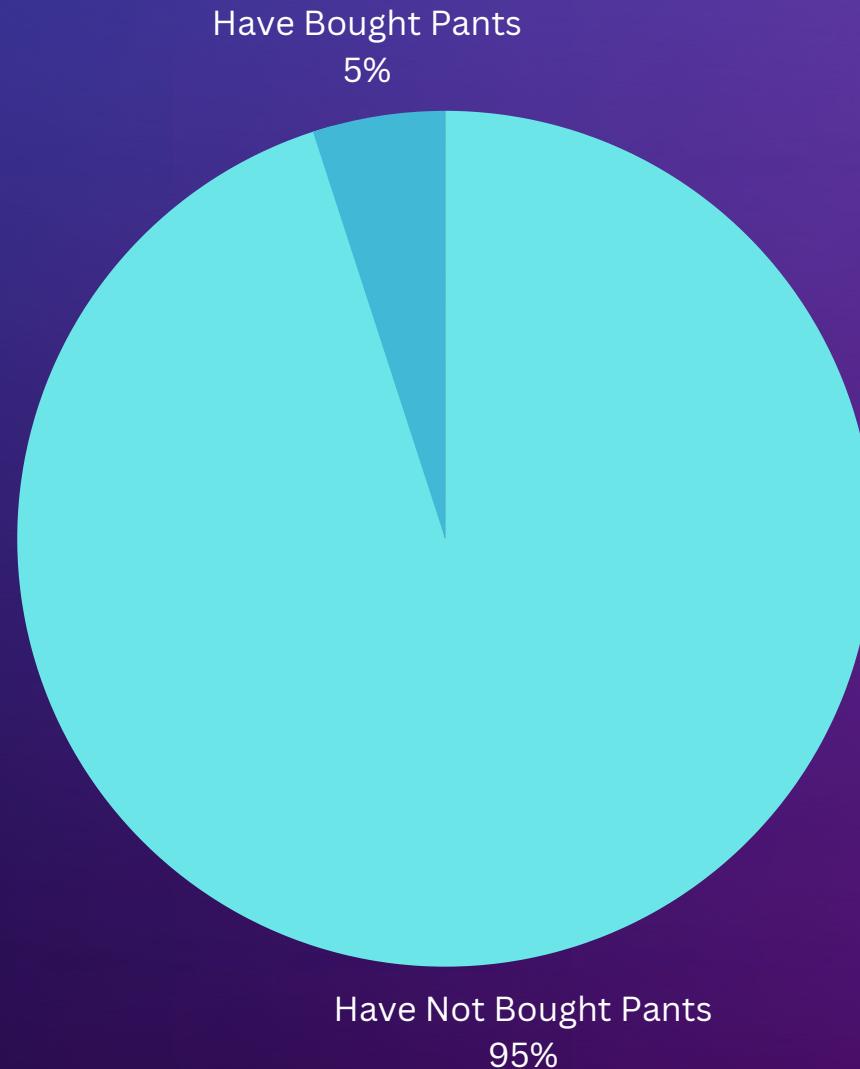
- Last visit to website.
- Email opening rate

Purchase History:

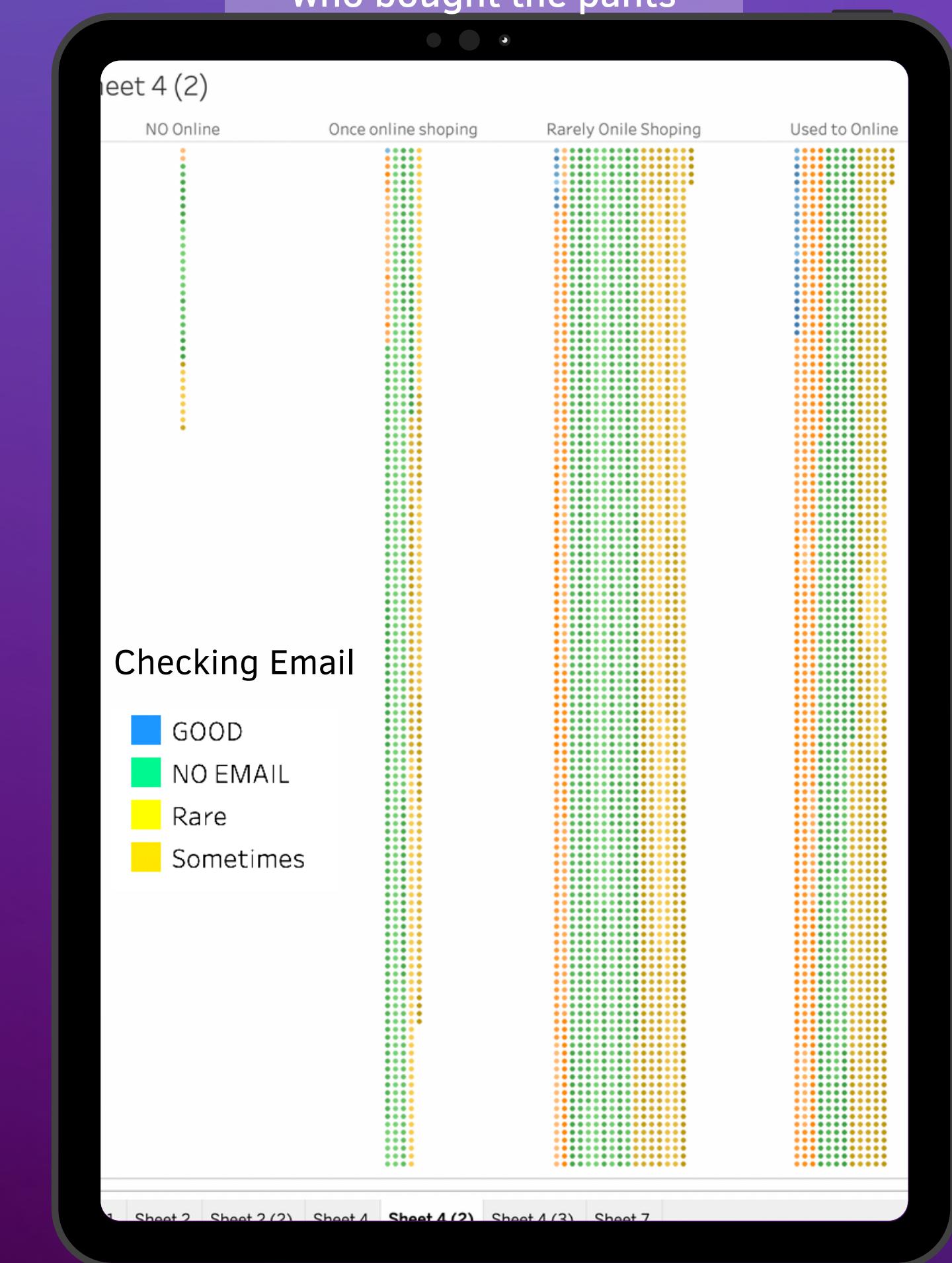
- Gender-based analysis of purchase history

Purchase Amount and Basket Size: Amount and frequency of purchases

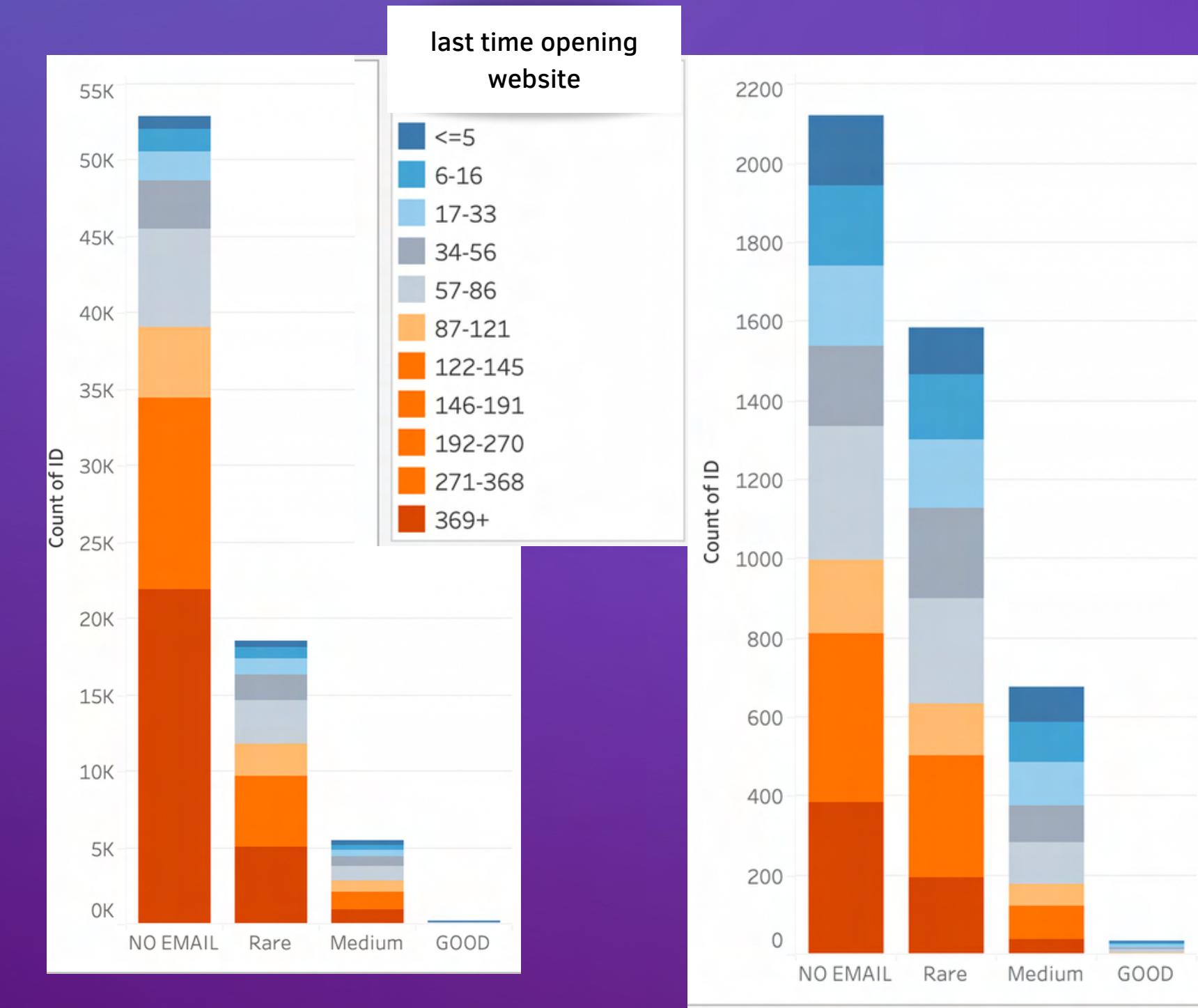
DATA INSIGHTS



Online shopping Record for
who bought the pants

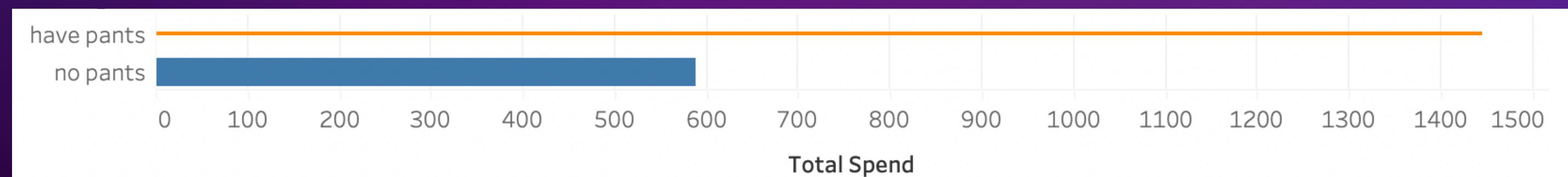


DATA INSIGHTS



costumer who did not buy
the product

costumer bought
the product



TWO-PRONGED APPROACH

RFM MODEL

User Profile Evaluation

- **Recency** score to evaluate the time gap since last purchasement
- **Frequency** score to evaluate how often a customer purchases a good
- **Monetary** score to evaluate how much a customer spend

MACHINE LEARNING MODEL

Probability Calculation

- Logistic Regression Model
 - Easy to implement
 - Efficient on binary classification problem
 - Result can be interpreted to probability

RFM MODEL DESIGN

Step 1

Calculate

Recency,
Frequency,

Monetary score

Step 2

Fulfill operation
strategy matrix

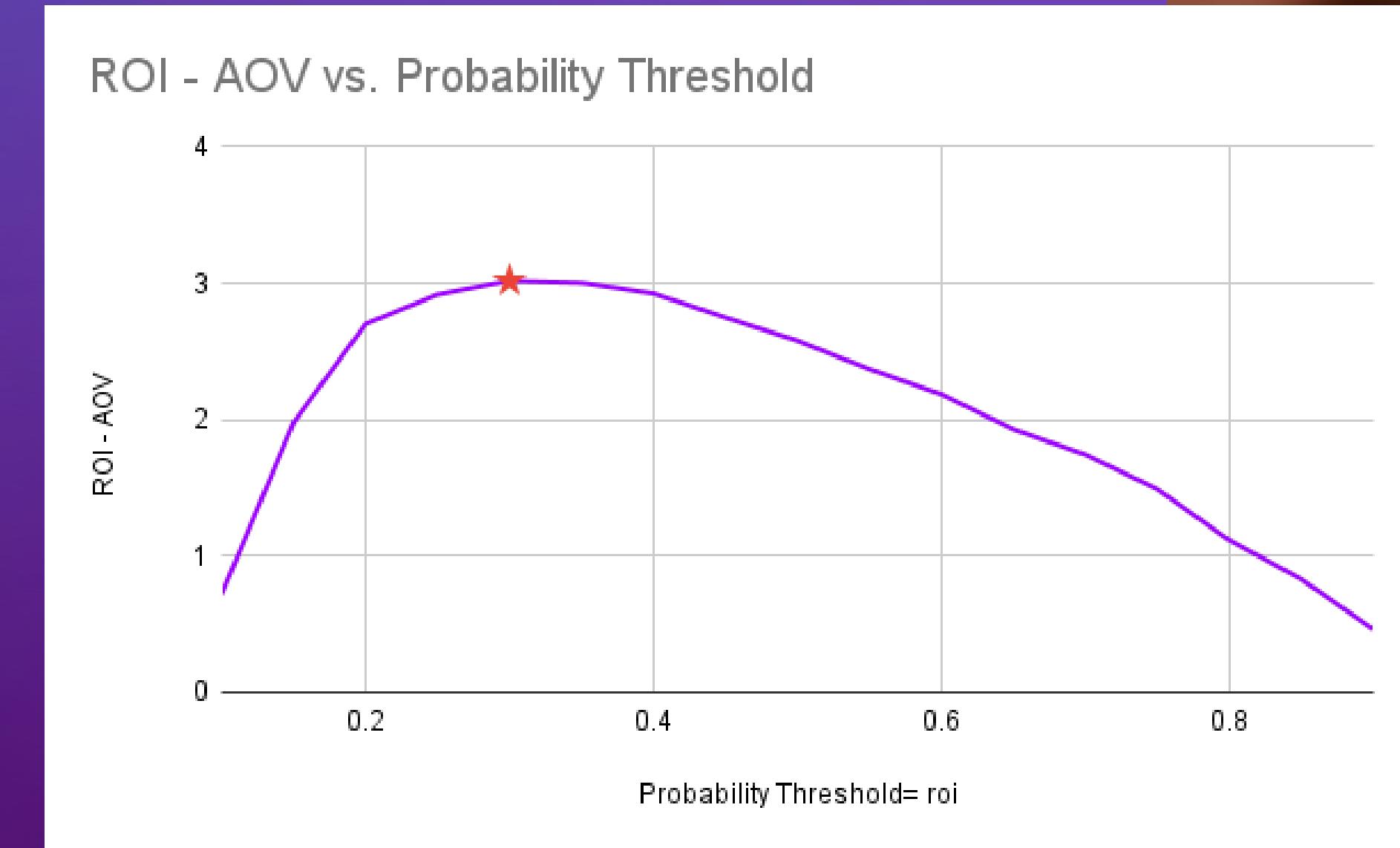
Classification	Recency	Frequency	Monetary	Operation Strategy
Critical Valuable	↑	↑	↑	Keep as-is
Critical Developable	↑	↓	↑	Improve Freq
Critical Persistent	↓	↑	↑	General Recall
Critical Preserved	↓	↓	↑	Critical Recall
General Valuable	↑	↑	↓	Boost Consumption
General Developable	↑	↓	↓	Mining Needs
General Persistent	↓	↑	↓	Loss Recall
General Preserved	↓	↓	↓	No Action (54% in dataset)

ML Model Design



Final Results and Calculations of ROI

Probability Threshold	0.3
# of Customers Identified	603
Projected # of Customers in Customer Base	3,015
Estimated Cost	52,889
Projected Potential Benefits - by AOV	212,511
Projected Potential Benefits - by Pant Unit Price	213,073
ROI - AOV	3.02
ROI - Pant Unit Price	3.03



PREDICTIONS FOR EFFECTIVENESS OF EMAIL CAMPAIGN



RFM SIDE FILTER

46% of customers
were likely to be
excellent targets for an
email campaign



SIZE OF CUSTOMERS

Based on different probability
threshold calculations, we
believe that the range of the
target customers of this
campaign is:

3015



ESTIMATED ROI

- Design Cost: \$25,000
- Email Cost: \$27,888.75
- Total Cost: \$52,888.75
- Design Amortization Cost: \$8.29/person
- Potential Benefits: \$213,073.58
- ROI: 303%+



Thank You



Chaucer Qiu



Jeff Wang



Parnian Taghipour



Rovenna Chu



Smitha Kolan



Zhi Zheng

Q&A





Appendix

Final Results and Calculations of ROI

Probability Threshold	0.25	0.3	0.35	0.45	0.55	0.65	0.7	0.75
# of Customers Identified	769	603	486	339	241	182	158	137
Projected # of Customers in Customer Base	3,845	3,015	2,430	1,695	1,205	910	790	685
Estimated Cost	60,566	52,889	47,478	40,679	36,146	33,418	32,308	31,336
Projected Potential Benefits - by AOV	237,234	212,511	190,072	152,501	121,832	97,892	88,649	78,055
Projected Potential Benefits - by Pant Unit Price	241,971	213,073	188,922	151,480	120,295	97,529	87,278	77,571
ROI - AOV	2.92	3.02	3.00	2.75	2.37	1.93	1.74	1.49
ROI - Pant Unit Price	3.00	3.03	2.98	2.72	2.33	1.93	1.70	1.48

Contribution of Each Team Member

Team Member	Contributions
Chaucer Qiu	Built RFM model with Smitha as a main factor of customer evaluation. Kick-off and worked with the team, coordinated if required. Set objectives for the team & use case.
Smitha Kolan	Fine-tuned statistical RFM model with added features based on correlation factor. Set clear objectives for the team & use case. Designed and organized the flow of the presentation.
Jeff Wang	Built the ML model from start to end, including cleaning, feature transformation, feature selection, model selection and optimization, model evaluation, probability generation.
Rovenna Chu	Prepared initial machine learning models with explanatory ML, Shaped Problem Statement and Summarizing Proposals, Prepared ROI Calculations as Final Results
Zhi Zheng	Ranked the importance of machine learning features and assisted in the feature selection; Calculated the final result based on Rovenna's work
Parnian Taghipour	Working on visualizing data and EDA, Doing domain research on the problem, Introduced the function that needed to be optimized for calculating the final number of selected costumer based on the models results