

The background features a stylized illustration of a classical bank building with columns and arched windows. To the right, a man in a dark suit and glasses stands next to a large brown money bag with a large Indian Rupee symbol (₹) on it. Next to the bag is a stack of gold coins. The overall theme is finance and banking.

# Promoting Financial Products to Bank Customers From a Prescriptive Analytics Perspective

*Machine Learning Under a Optimization Lens Final Project*




*Luca-Andrei Manea, Zeki Yan*

# PROBLEM STATEMENT






Prediction

## Customer Interests

-  Savings account
-  Mortgage account
-  Pension account

## Marketing Channel

-  Gift
-  Newsletter
-  Seminar

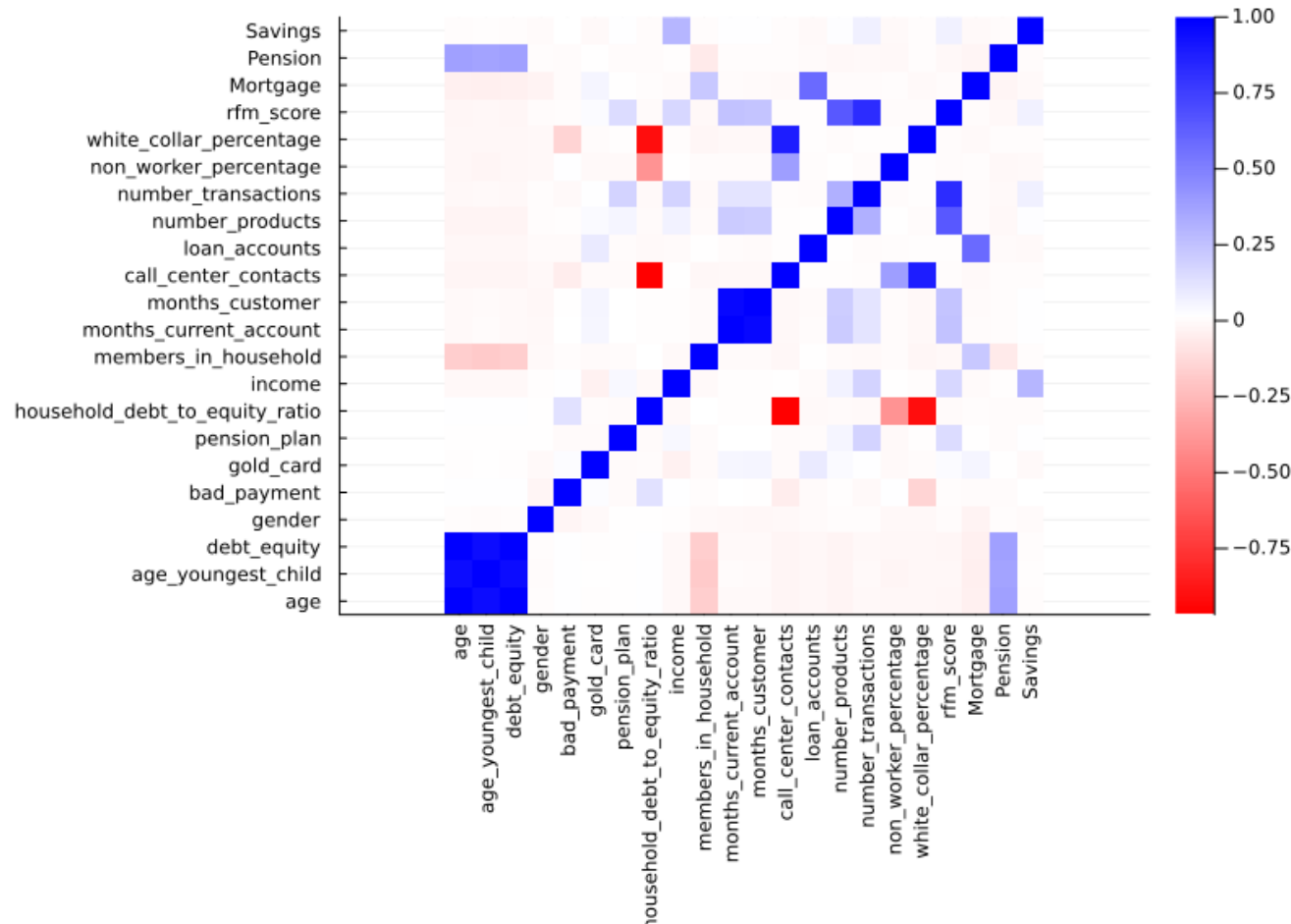
TO BE DECIDED



Decision

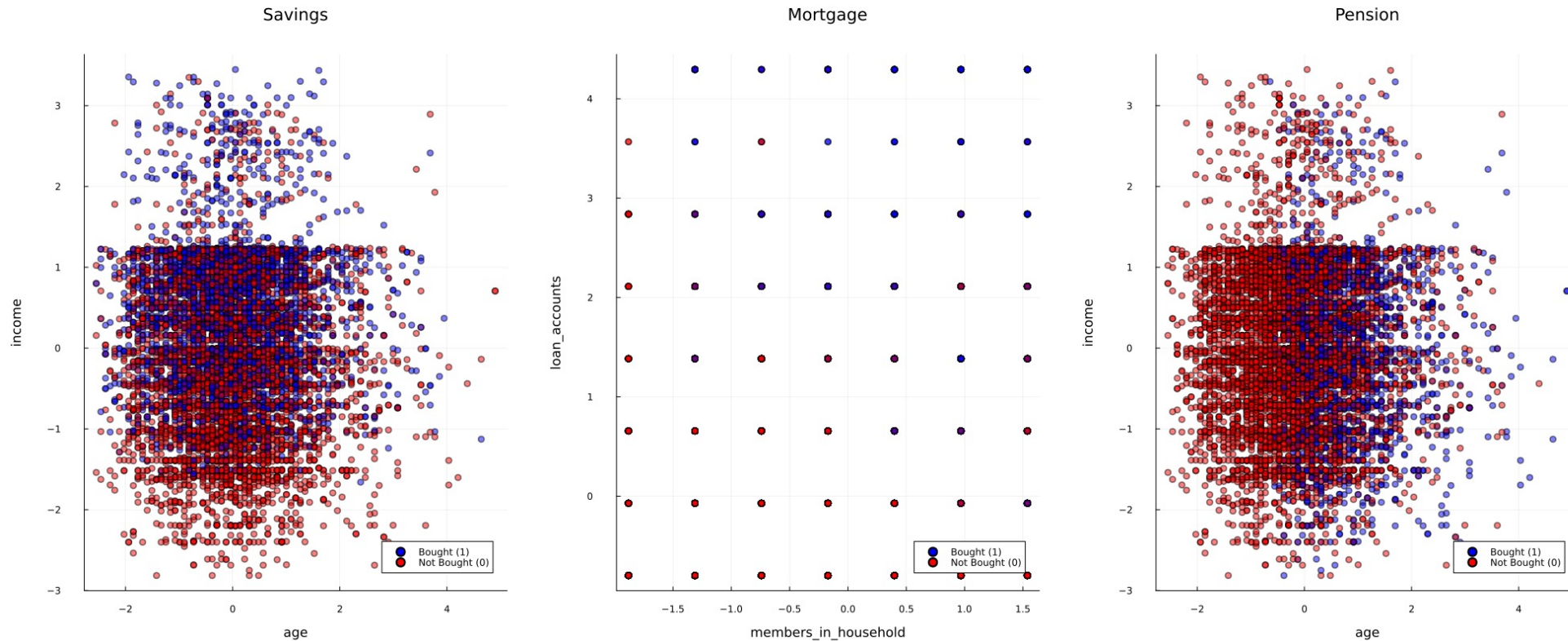
- ❓ Contact which customers?
- ❓ Promote which **product**?
- ❓ Through which **channel**?

# EDA & FEATURE ENGINEERING



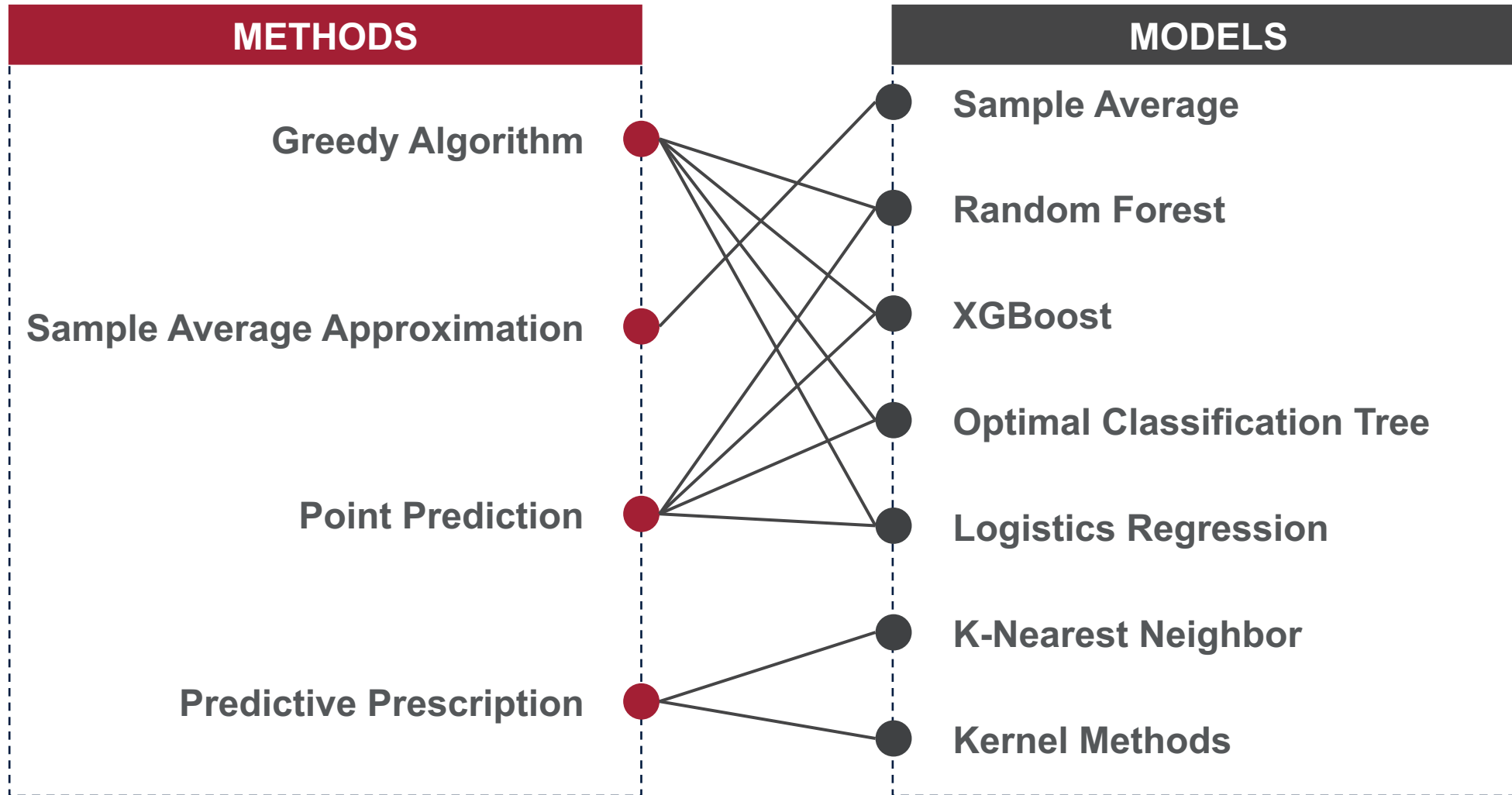
- Moderate correlation with target variables overall
- **Savings account:**
  - Income (0.2987)
- **Pension account:**
  - Age (0.3814)
  - Age of Youngest Child (0.3814)
  - Debt-to-Equity Ratio (0.3814)
  - All correlated with each other
- **Mortgage account:**
  - # Loan accounts (0.5916)
  - # Household members (0.2278)

# EDA & FEATURE ENGINEERING



Selected Features: **Age, Income, Number of members in household, Number of loan accounts**

# METHODOLOGY & PREDICTION MODELS



# GREEDY METHOD | SERVE AS BASELINE



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Greedy Algorithm (simplified pseudo code)

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**for customers from 1 to I:**

**for products from 1 to J:**

**for channels from 1 to K:**

**if (predicted) demand is not satisfied:**

**make an assignment!**

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# OPTIMIZATION METHOD | E.G. PRESCRIPTIVE



Minimize minus expected profit



$$\min \sum_{i'=1}^{I_0} \sum_{i=1}^{I_1} \sum_{j=1}^J \sum_{k=1}^K w_{I_0}^{i'}(x_i) \cdot (c_k - p_j \cdot s_k) \cdot y_{i'j} \cdot z_{ijk}$$

Budget Constraint



$$\text{s.t.} \quad \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K c_k \cdot z_{ijk} \leq B$$

Minimum promotion per channel constraint



$$\sum_{i=1}^I \sum_{j=1}^J z_{ijk} \geq 0.1 \cdot I, \quad \forall k$$

At most one channel per customer



$$\sum_{k=1}^K z_{ijk} \leq 1, \quad \forall i, j$$

At most one product per customer



$$\sum_{j=1}^J z_{ijk} \leq 1, \quad \forall i, k$$

# WEIGHTING MODEL | E.G. KERNEL METHODS



- To Estimate:  $m(x) = \mathbb{E}[Y|X = x]$

➔ 
$$\hat{m}_{I_0}(x) = \frac{\sum_{i'=1}^{I_0} y^{i'} K((x^{i'} - x_i)/h_{I_0})}{\sum_{i'=1}^{I_0} K((x^{i'} - x_i)/h_{I_0})}$$

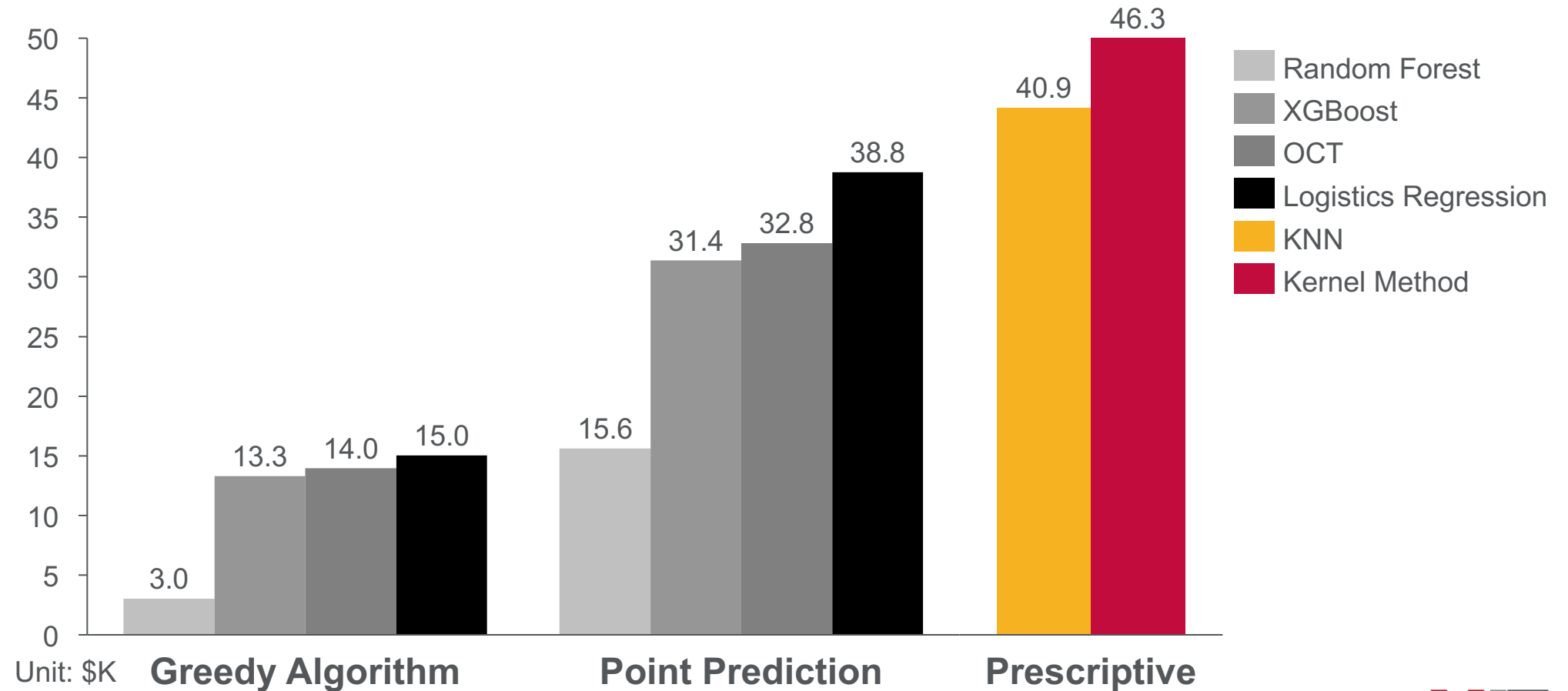
- Kernel  $K : \mathbb{R}^d \rightarrow \mathbb{R}$
- Bandwidth  $h_{I_0} > 0$
- Naive Kernel  $K(x) = \mathbb{I}[\|x\| \leq 1]$



# RESULT | BEST MODEL: PREDICTIVE PRESCRIPTION POWERED BY KERNEL METHODS



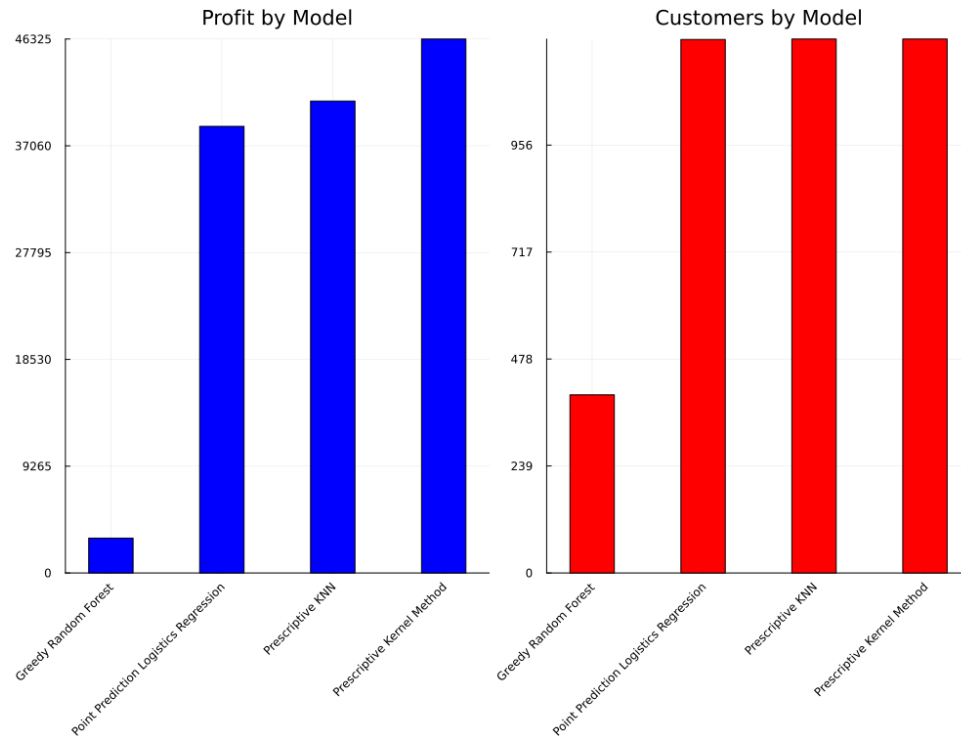
Profit generated by each method & model



# RESULT | METRIC ANALYSIS

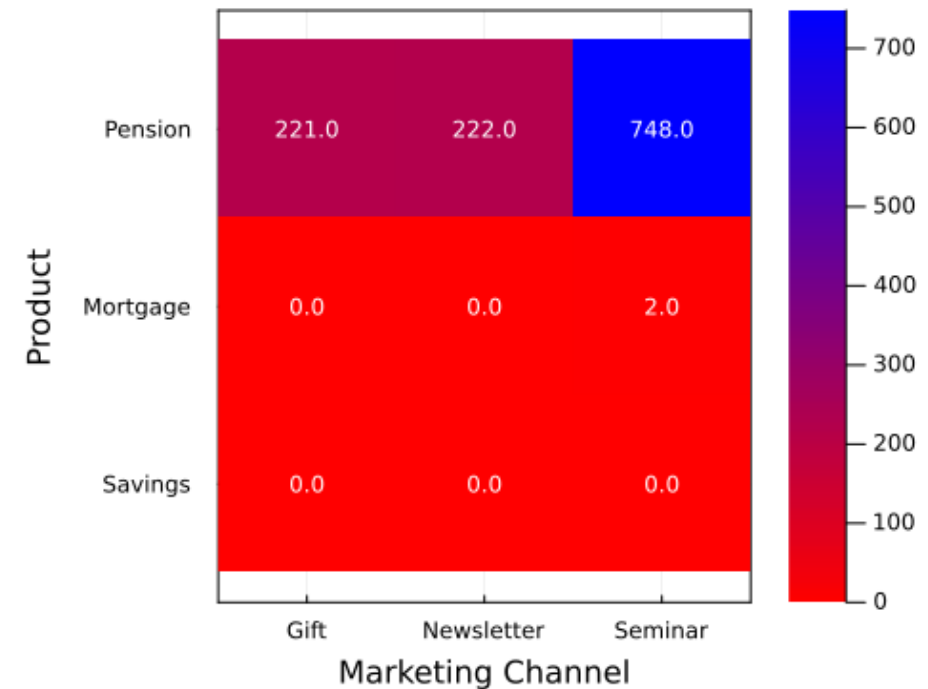


## Comparison of Profitability and Offering Ability



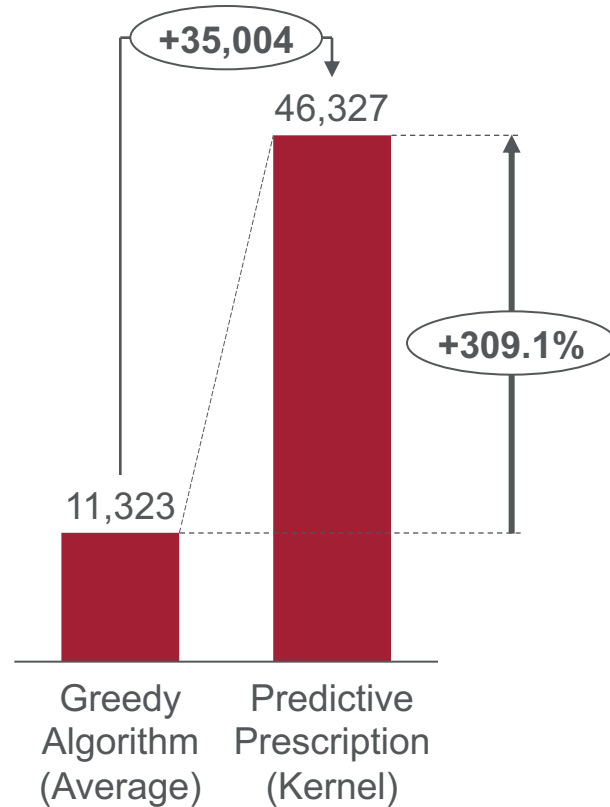
➤ Better models serve more customers

## Product Offering Channels (Prescriptive Kernel Method)

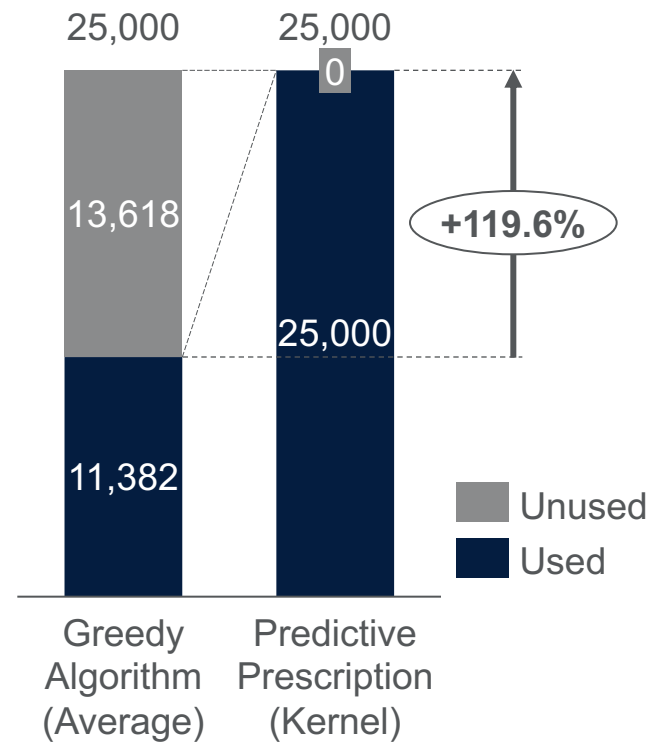


➤ Best model prioritizes profitable products/channels

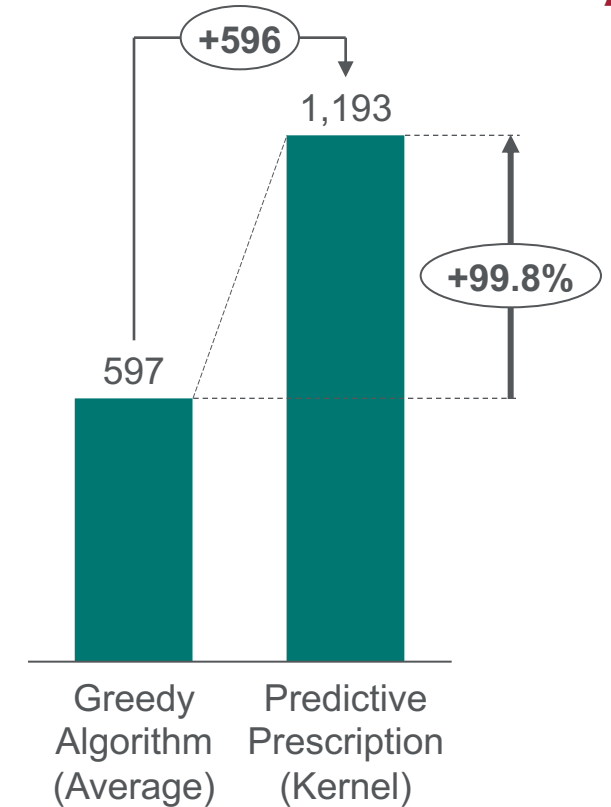
# BUSINESS IMPACT | SIGNIFICANT IMPROVEMENT



**\$ Profit Generated**  
**X 3**



**\$ Budget Utilized**  
**X 2**



**# Customers Served**  
**X 2**

**THANK YOU!**



# REFERENCES



- ❑ [1] Bertsimas, Dimitris, and Jack Dunn. "Optimal classification trees." *Machine Learning* 106 (2017): 1039-1082.
- ❑ [2] Bertsimas, Dimitris, and Nathan Kallus. "From predictive to prescriptive analytics." *Management Science* 66.3 (2020): 1025-1044.
- ❑ [3] Bertsimas, Dimitris, and Nihal Koduri. "Data-driven optimization: A reproducing kernel Hilbert space approach." *Operations Research* 70.1 (2022): 454-471.
- ❑ [4] Bertsimas, Dimitris, and Kimberly Villalobos Carballo. "Multistage Stochastic Optimization via Kernels." *arXiv preprint arXiv:2303.06515* (2023).

# APPENDIX 1 | OBJECTIVE FUNCTIONS



- Sample Average Approximation

$$\hat{z}^{SAA} \in \arg \min_{z \in Z} \frac{1}{I_0} \sum_{i=1}^{I_0} \sum_{j=1}^J \sum_{k=1}^K (c_k - p_j \cdot s_k) \cdot y_{ij} \cdot z_{jk}$$

- Point-Prediction

$$\hat{z}^{point-pred} \in \arg \min_{z \in Z} \sum_{i=1}^{I_1} \sum_{j=1}^J \sum_{k=1}^K (c_k - p_j \cdot s_k) \cdot \hat{y}_{ij} \cdot z_{ijk}$$

- Predictive Prescription

$$\hat{z}_{I_0}(x) \in \arg \min_{z \in Z} \sum_{i'=1}^{I_0} \sum_{i=1}^{I_1} \sum_{j=1}^J \sum_{k=1}^K w_{I_0}^{i'}(x_i) \cdot (c_k - p_j \cdot s_k) \cdot y_{i'j} \cdot z_{ijk}$$

# APPENDIX 2 | DATA STRUCTURE



Table 1: Dataset Structure and Explanation of Features

Column Name	Explanation
<i>customer_id</i>	id of the customer
<i>age</i>	age of customer
<i>age_youngest_child</i>	age of the customer's youngest child
<i>debt_equity</i>	debt to equity ratio of customer ( $\times 100$ )
<i>gender</i>	binary variable, male-0 ,female-1
<i>bad_payment</i>	binary variable, whether customer has bad payment history
<i>gold_card</i>	binary variable, whether customer is a gold card user
<i>pension_plan</i>	binary variable, whether customer has a pension plan
<i>household_debt_to_equity_ratio</i>	household debt to equity ratio ( $\times 100$ )
<i>income</i>	annual income of the customer (\$)
<i>members_in_household</i>	number of members in the customer's household
<i>months_current_account</i>	number of months passed since the customer opened their account
<i>months_customer</i>	number of months passed since customer registered with the bank
<i>call_center_contacts</i>	amount of time spent in contact with call center
<i>loan_accounts</i>	number of loan accounts the customer has
<i>number_products</i>	number of products (except for those to be promoted) bought
<i>number_transactions</i>	number of transactions the customer has made
<i>non_worker_percentage</i>	percentage of non-workers in the customer's household
<i>white_collar_percentage</i>	percentage of white-collar workers in the customer's household
<i>rfm_score</i>	Recency, Frequency, and Monetary (RFM) score of the customer
<b>*Mortgage</b>	whether the customer has opened Mortgage account (only in old customer dataset)
<b>*Pension</b>	whether the customer has opened Pension account (only in old customer dataset)
<b>*Savings</b>	whether the customer has opened Savings account (only in old customer dataset)

# APPENDIX 3 | MODEL BASIC EVALUATION



Table 2: Basic evaluation of each model

Method	Model	Revenue	Budget	Profit	Customers
Greedy	Random Forest	\$7,525	\$7,075	\$3,025	398
Greedy	Logistics Regression	\$22,660	\$12,818	\$15,026	663
Greedy	OCT	\$21,595	\$12,818	\$13,952	663
Greedy	XGBoost	\$20,820	\$12,818	\$13,291	663
SAA	Sample Average	\$0	\$0	\$0	0
Point Prediction	Random Forest	\$23,670	\$16,889	\$15,608	840
Point Prediction	Logistics Regression	\$52,130	\$24,985	\$38,752	1,192
Point Prediction	OCT	\$45,200	\$24,985	\$32,836	1,192
Point Prediction	XGBoost	\$43,095	\$24,295	\$31,374	1,162
Prescriptive	KNN	\$52,840	\$25,000	\$40,946	1,193
Prescriptive	Kernel Method	\$59,090	\$25,000	\$46,327	1,193



# APPENDIX 4 | PRODUCTS OFFER RESULTS



Table 3: Products offered under each model

Method	Model	Savings	Mortgage	Pension
Greedy	Random Forest	335	10	53
Greedy	Logistics Regression	206	112	345
Greedy	OCT	289	100	274
Greedy	XGBoost	320	6	337
SAA	Sample Average	0	0	0
Point Prediction	Random Forest	436	121	283
Point Prediction	Logistics Regression	308	219	665
Point Prediction	OCT	451	210	531
Point Prediction	XGBoost	501	78	583
Prescriptive	KNN	0	65	1,128
Prescriptive	Kernel Method	0	2	1,191

# APPENDIX 5 | CHANNELS USED RESULTS



Table 4: Channels used under each model

Method	Model	Gift	Newsletter	Seminar
Greedy	Random Forest	221	177	0
Greedy	Logistics Regression	221	221	221
Greedy	OCT	221	221	221
Greedy	XGBoost	221	221	221
SAA	Sample Average	0	0	0
Point Prediction	Random Forest	221	221	398
Point Prediction	Logistics Regression	221	221	750
Point Prediction	OCT	221	221	750
Point Prediction	XGBoost	221	221	720
Prescriptive	KNN	221	222	750
Prescriptive	Kernel Method	221	222	750