

# Customer Acquisition Cost Prediction



How smart media planning helps growth







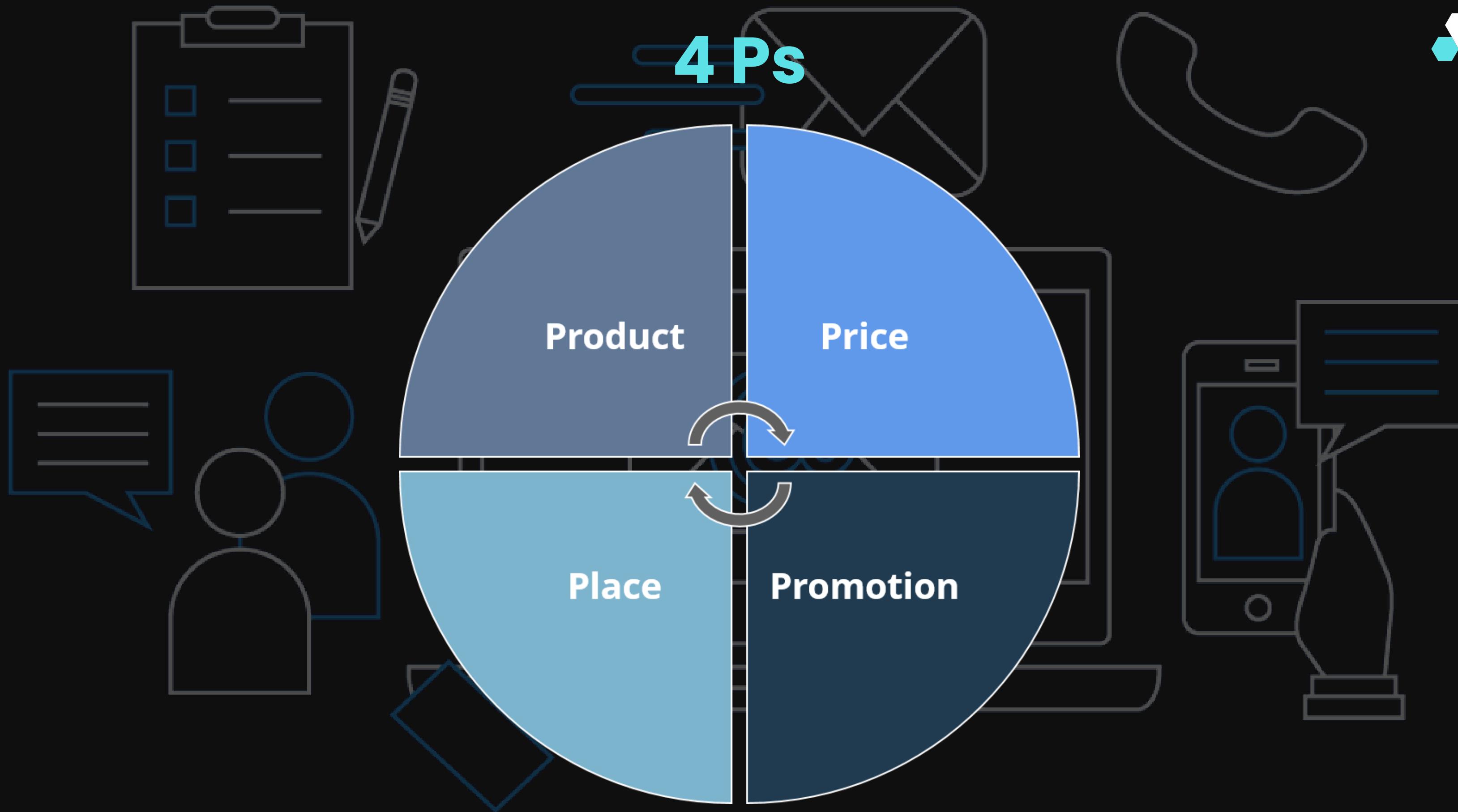
**4 Ps**

**Product**

**Price**

**Place**

**Promotion**



# Table of Content



Use Case



Data



Modelling



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Conclusion

# Who Are We?



**Emery**  
*Lead-Project Manager*



**Lucie**  
*Lead-Business Analyst*



**Chongho**  
*Data Analyst*



**Bennett**  
*Data Scientist*



**Julie**  
*Lead-Product Manager*



**Priyanka**  
*Lead-Data Analyst*



**Raman**  
*Lead-Data Scientist*





# Use Case: Framing the Problem

Context – Problem Statement – Strategy



## Context

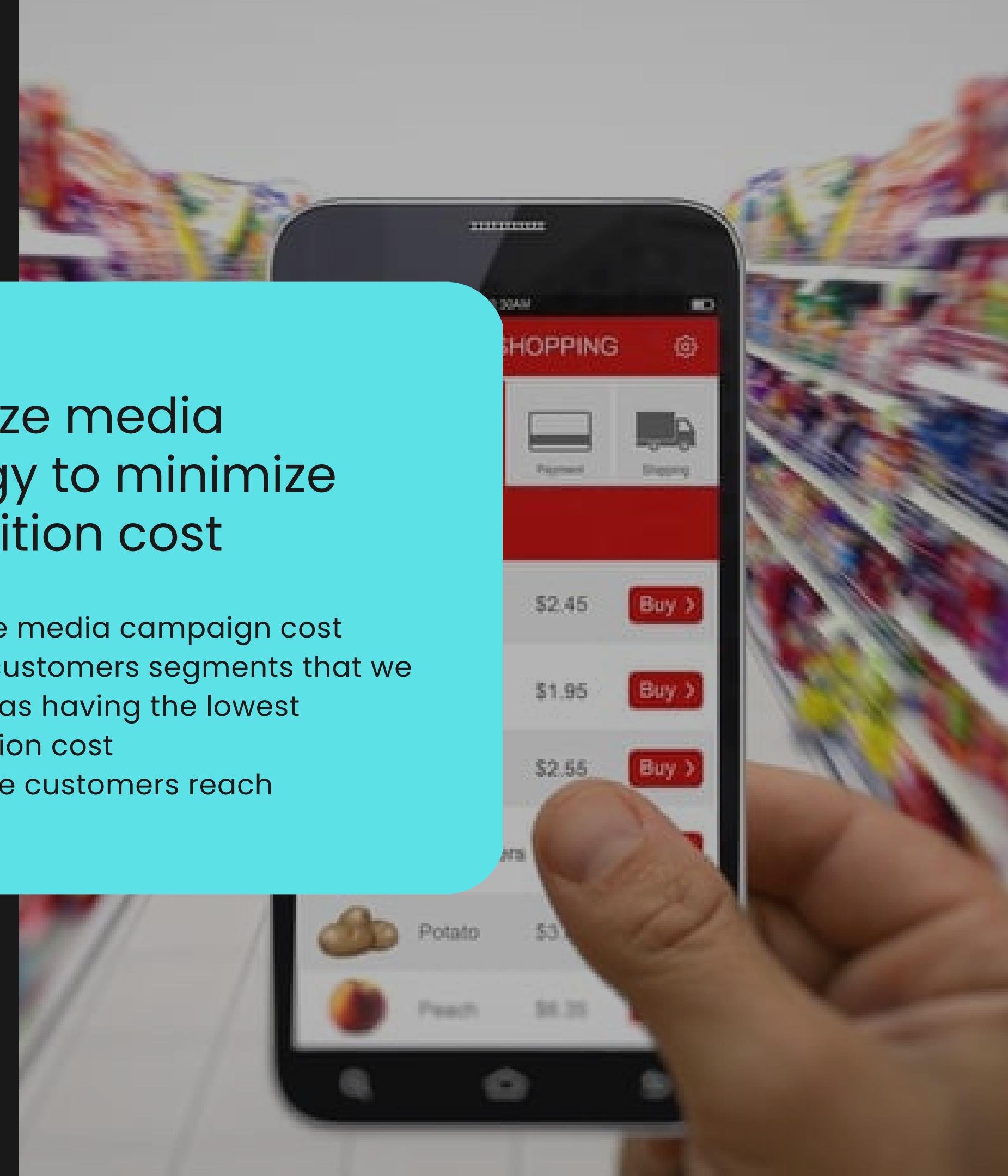
- Post- COVID
- Race for attention
- Horizontal growth
  - International extension
  - +300 stores in Canada
- Vertical investments
  - Customer segmentation
  - Loyalty Programs



# Problem Statement

Optimize media strategy to minimize acquisition cost

- Minimize media campaign cost
- Target customers segments that we identify as having the lowest acquisition cost
- Maximize customers reach



# Strategy

**Customer segmentation**



- Identify customer features
- Investigate our customer segmentation

**Predict customer acquisition cost**



- Defined the relevant factors in our predictions
- Identify cost of acquisition per segment

**Lower cost of acquisition**



- Create a strategy around an optimal customer cost of acquisition and segment to grow our business



# Data

Acquisition – Preparation – Exploration





# Data Aquisition

- Customer's acquisition Cost
- Based on more than 60k observations
  - Customers' demographic data (gender, marital status...)
  - Stores' data (sales, store's type)
  - Media campaigns' data (type, acquisition cost)



# Data Preparation Steps

## Some Key Steps

### **Key Assumptions:**

Cost - The Customer Acquisition Cost

Media Type- Type of media used for advertising. encoded by label encoding



### NAs

There were no detectable missing or null values in the datasets.

*Removed rows: 0*

### Outlier Detection

Using an isolation forest we identified and removed outliers from the datasets

*Removed rows: 3,005*

### Feature Scaling

Multi-collinearity distorts model performance. By scaling features we can reduce this effect.

### Synthesized Attributes

Attribute whose parse tree node value is determined by the attribute value at child nodes.

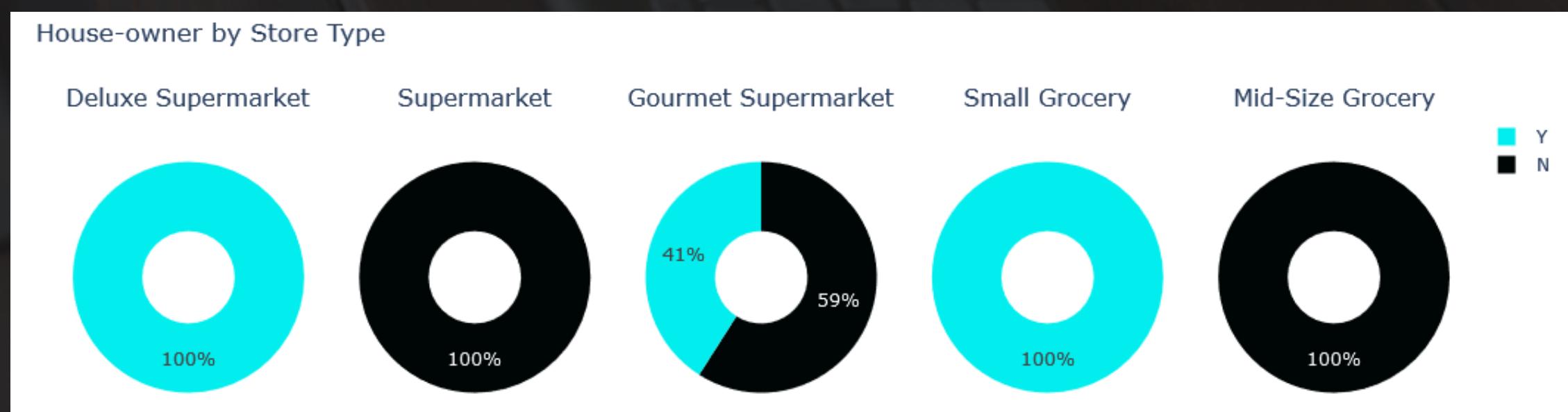
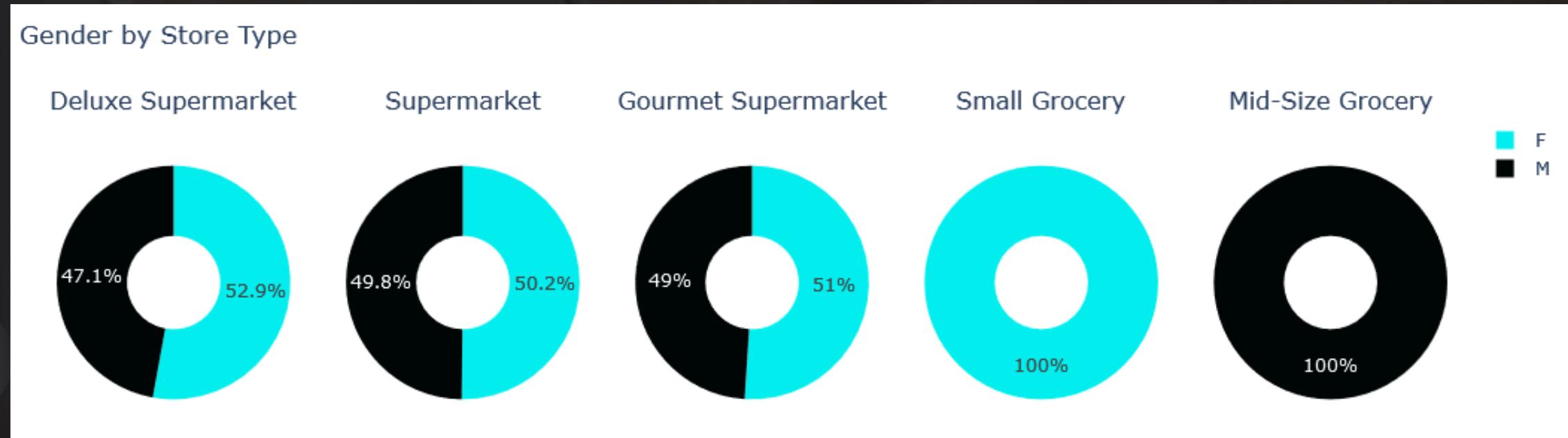
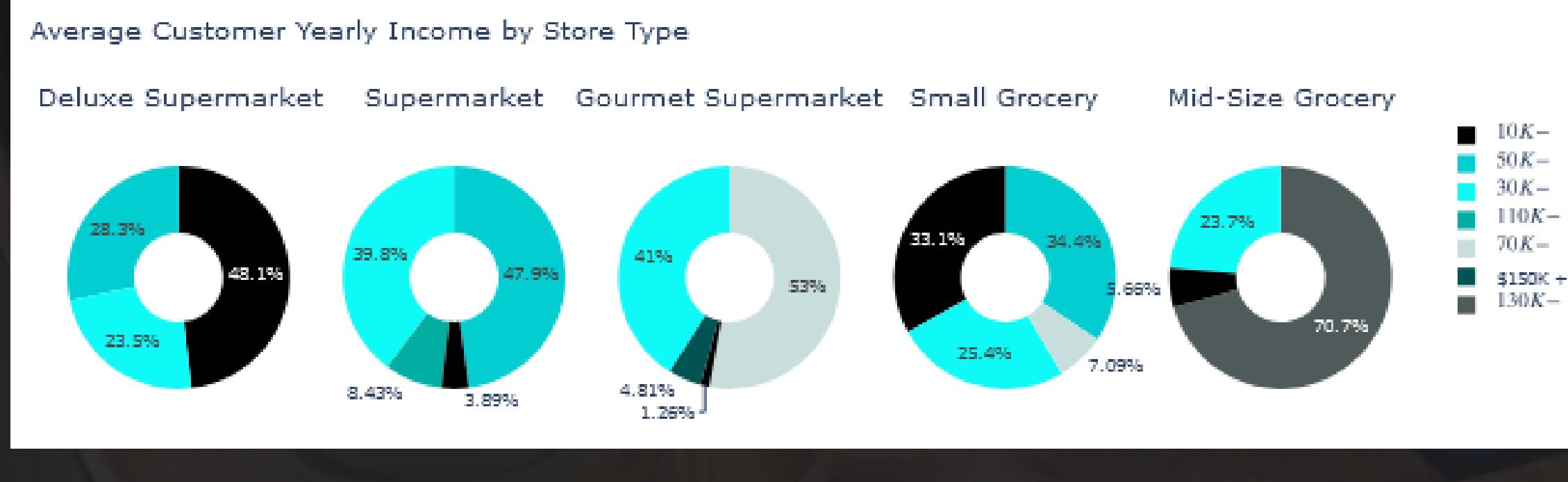
### Dummification

Any Categorical Variables were dummified based on one hot encoding



# Data Exploration

## Customer Segments



# Data Exploration

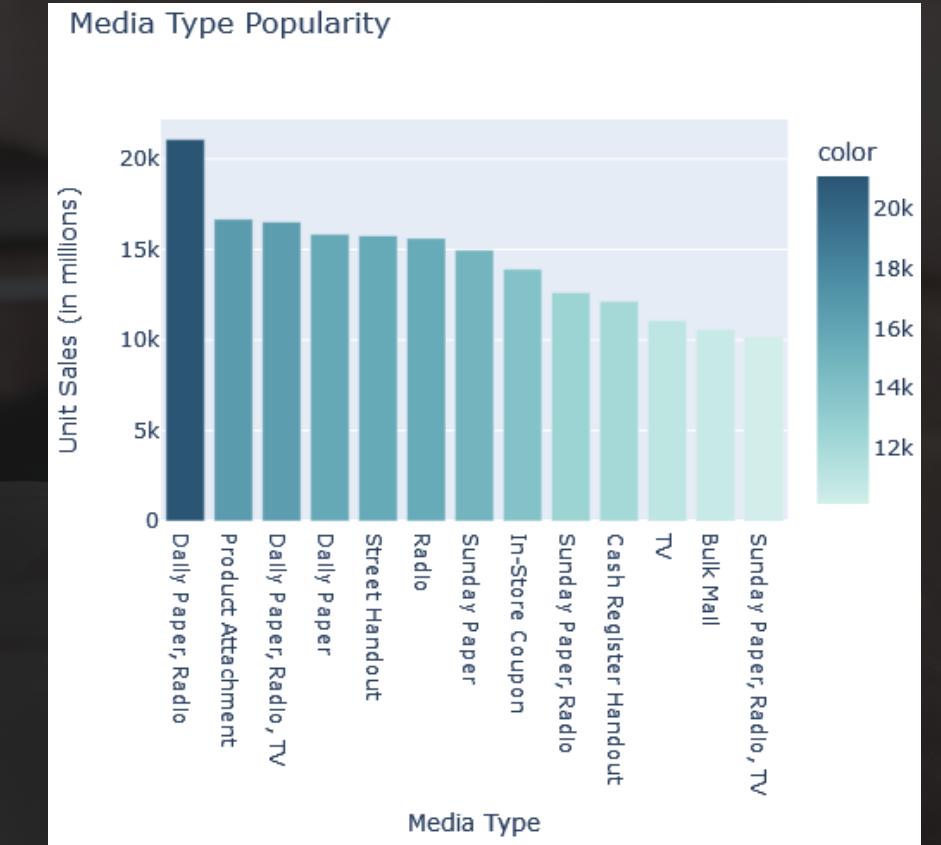
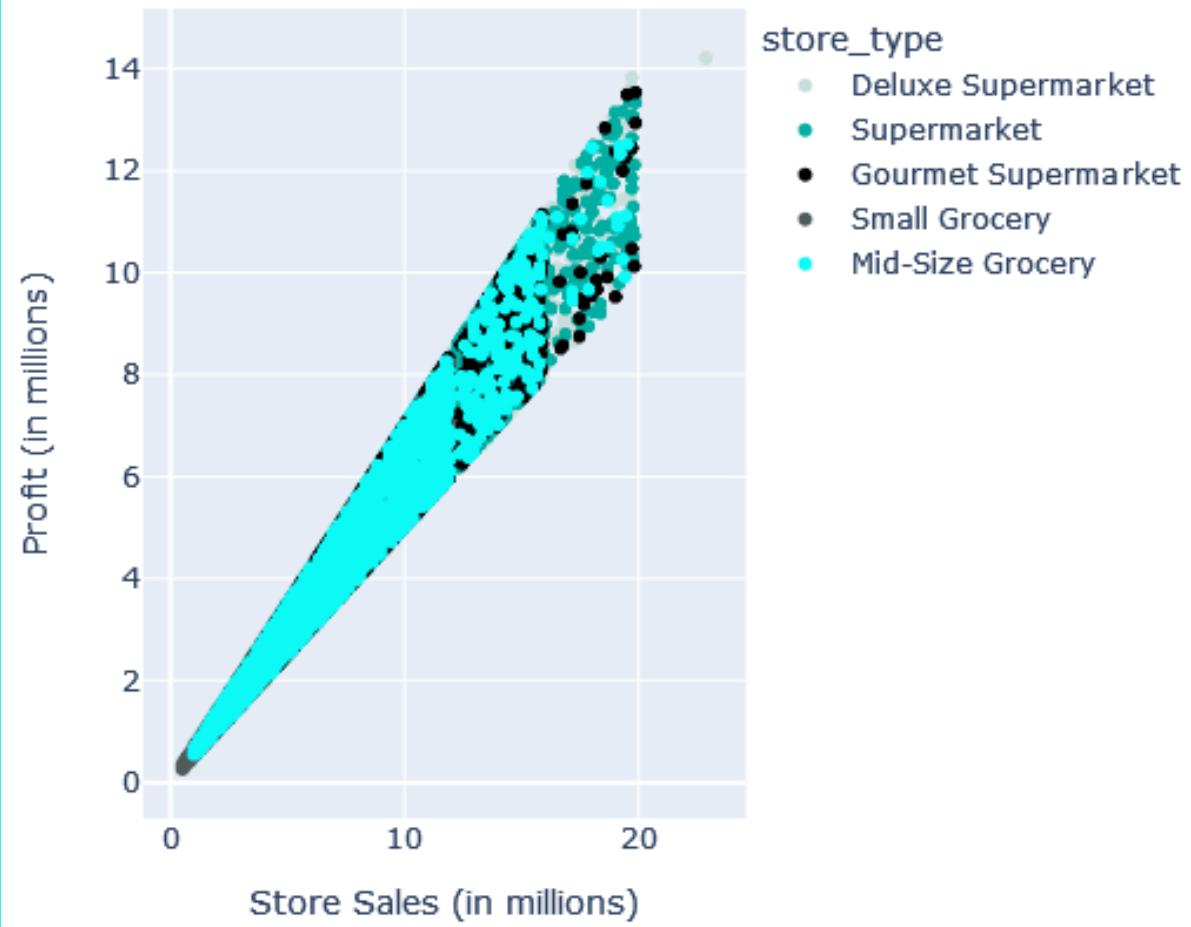
## Customer Segments



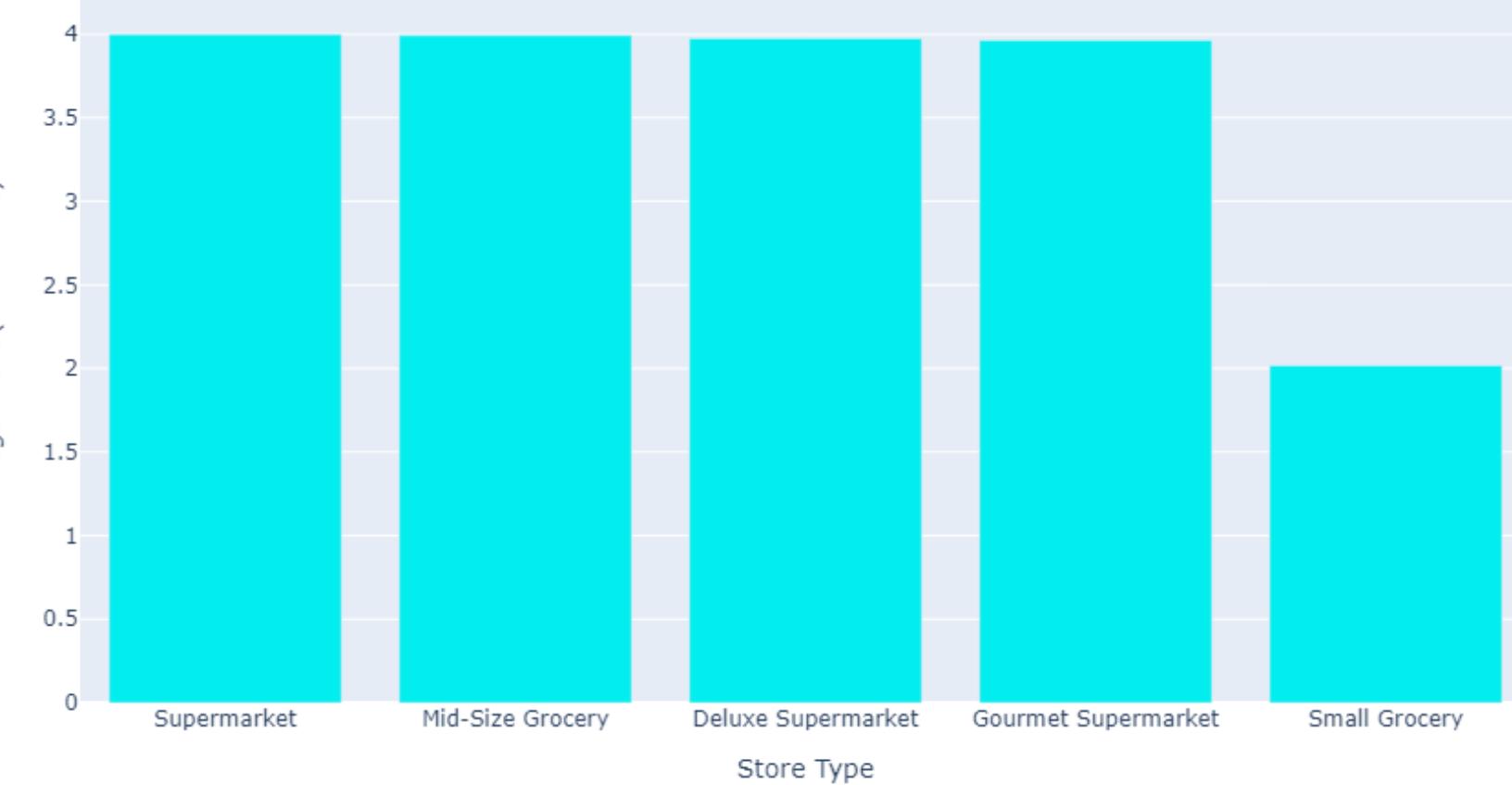
# Data Exploration

Stores and Media segment

Profit by Store Sales (with Store Type)



Average Profit (in millions) by Store Type

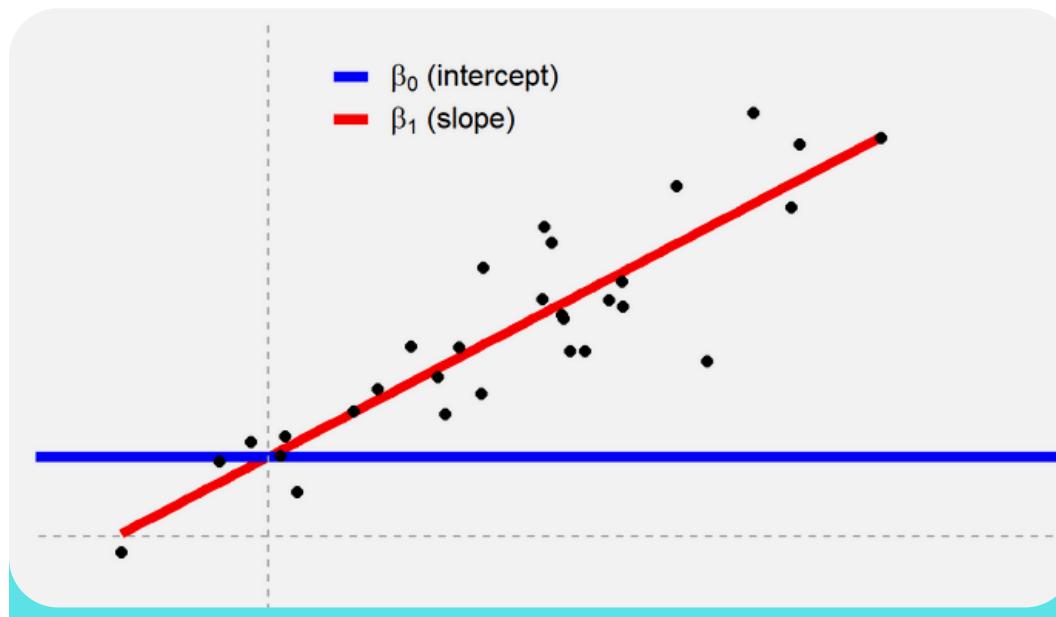
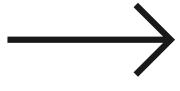




# Modeling Strategy

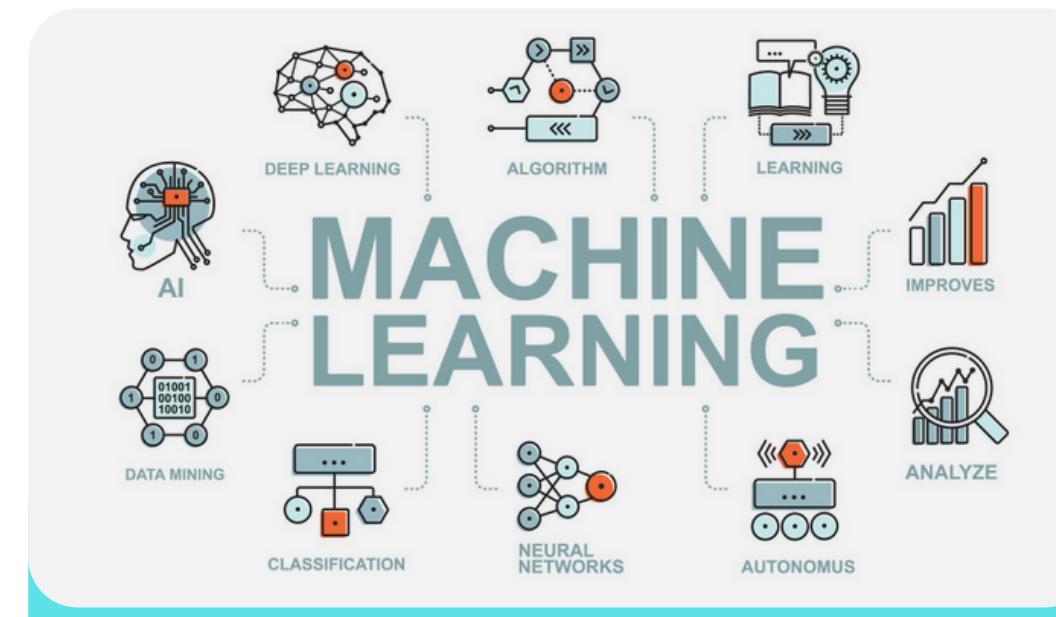
Approach - Evaluation - Selection

# Modeling Strategies



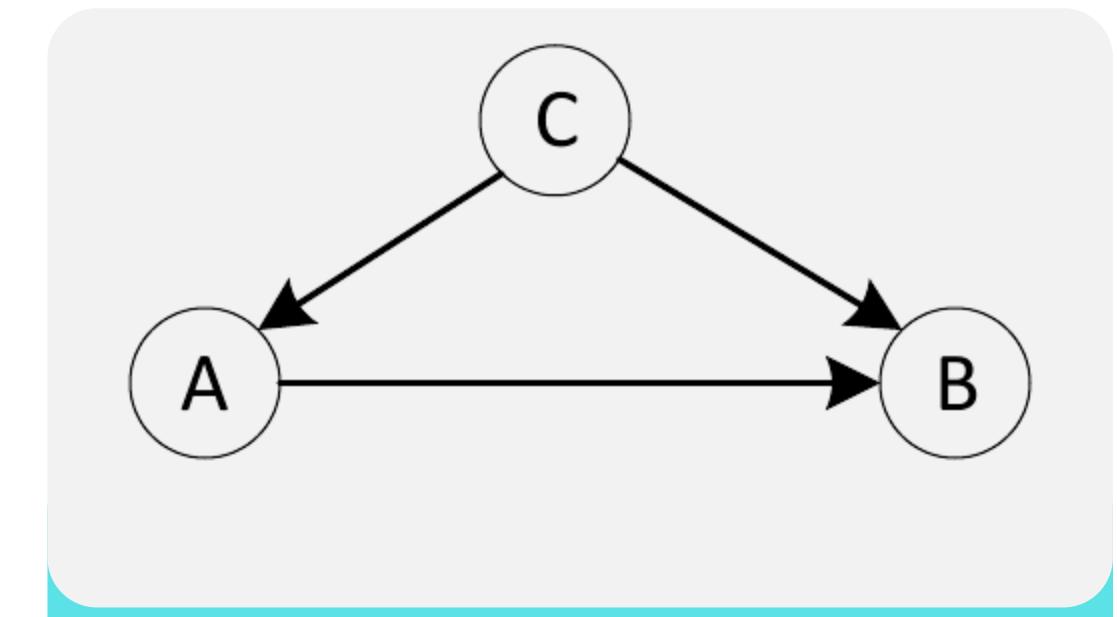
## Linear Models

We used a dummy regressor to establish a baseline and understand some factors that predict cost the error.



## Machine Learning

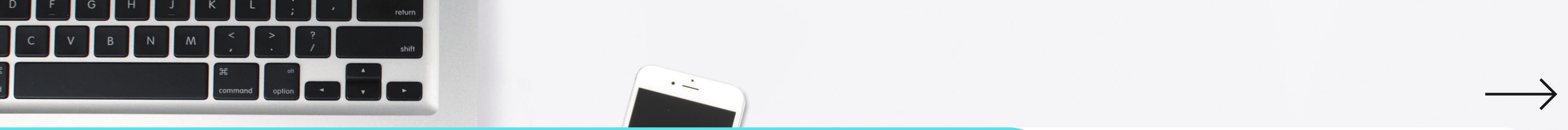
- Tree-Based Methods
- XGBoost
- Neural Networks
  - & More



## Causal Inference

We want to examine the effect of human metrics on costs.

Objective: Reduce the cost of acquisition of our customers



# Causal Inference



## Effect of Gender



**Outcome Variable**

Cost



**Treatment**

Gender

## Effect of Loyalty

Cost

Member Card

## Effect of Media Type

Cost

Media Type



**Control Variables**

All Other Variables

All Other Variables

All Other Variables

# Evaluation & Selection

Model Accuracy (MSE)

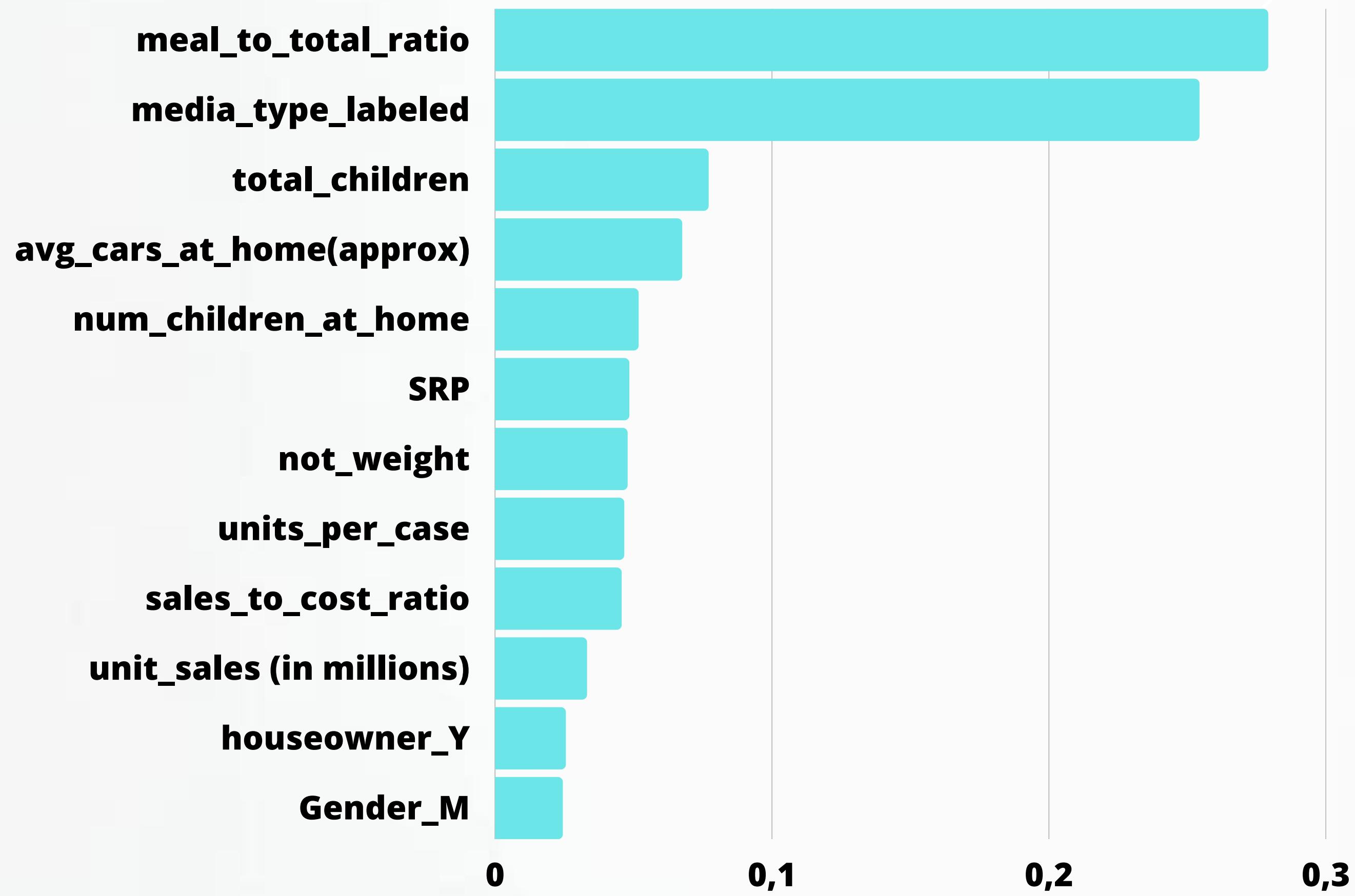




# Results

Interpretation - Insights

# Feature significance





# Key Insights



→ **Less meat**

→ **Media cost**



# Conclusion

Lessons Learned – Next Step



# Appendix

# Data Structure



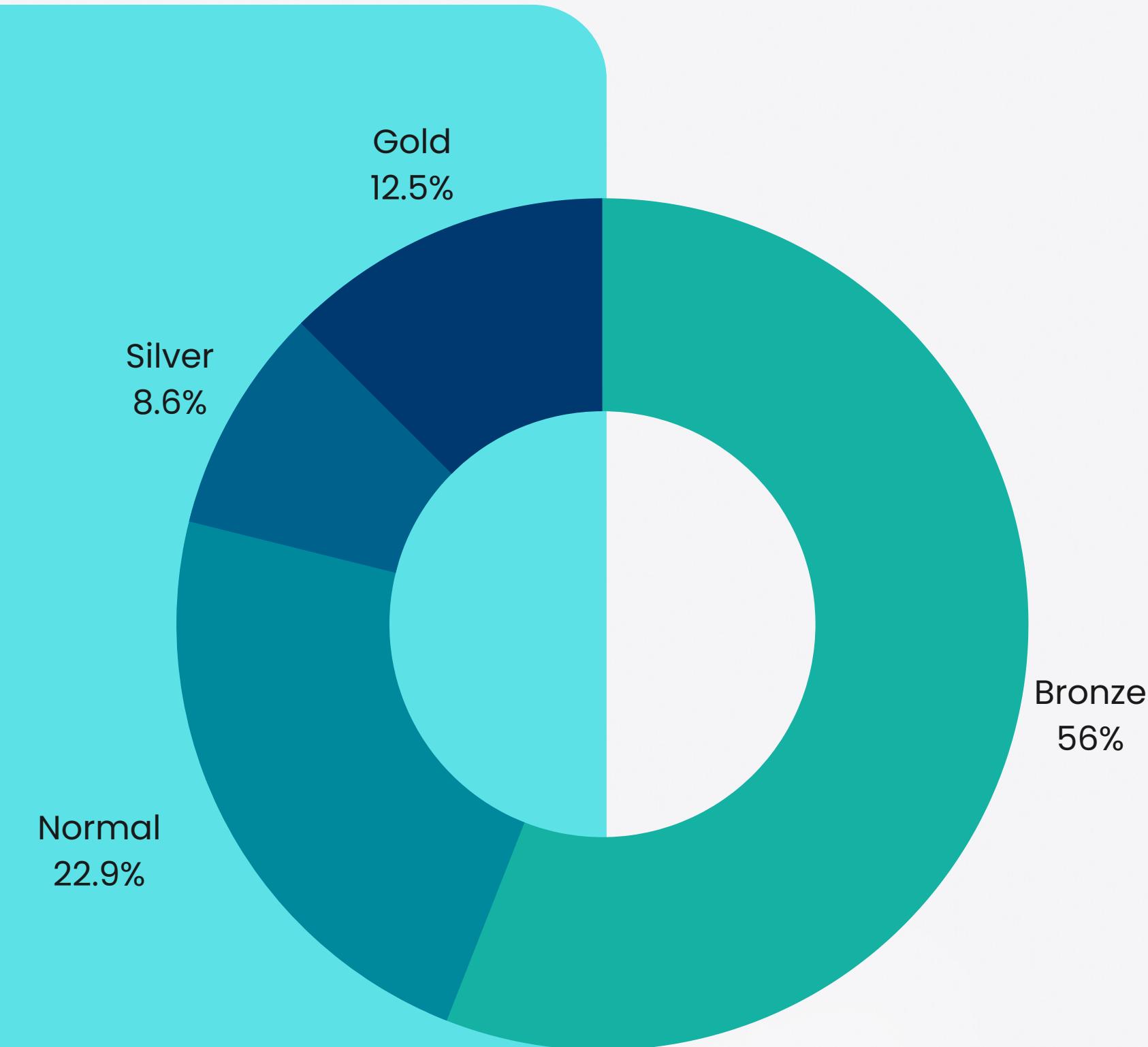
<b>Column</b>	<b>Name</b>	<b>Count</b>		<b>Type</b>
---	-----	-----	-----	-----
0	food_category	60428	non-null	object
1	food_department	60428	non-null	object
2	food_family	60428	non-null	object
3	store_sales(in millions)	60428	non-null	float64
4	store_cost(in millions)	60428	non-null	float64
5	unit_sales(in millions)	60428	non-null	float64
6	promotion_name	60428	non-null	object
7	sales_country	60428	non-null	object
8	marital_status	60428	non-null	object
9	gender	60428	non-null	object
10	total_children	60428	non-null	float64
11	education	60428	non-null	object
12	member_card	60428	non-null	object
13	occupation	60428	non-null	object
14	houseowner	60428	non-null	object
15	avg_cars_at_home(approx)	60428	non-null	float64
16	avg_yearly_income	60428	non-null	object
17	num_children_at_home	60428	non-null	float64
18	avg_cars_at_home(approx).1	60428	non-null	float64
19	brand_name	60428	non-null	object

	<b>Column</b>	<b>Name</b>	<b>Count</b>		<b>Type</b>
	20	SRP	60428	non-null	float64
	21	gross_weight	60428	non-null	float64
	22	net_weight	60428	non-null	float64
	23	recyclable_package	60428	non-null	float64
	24	low_fat	60428	non-null	float64
	25	units_per_case	60428	non-null	float64
	26	store_type	60428	non-null	object
	27	store_city	60428	non-null	object
	28	store_state	60428	non-null	object
	29	store_sqft	60428	non-null	float64
	30	grocery_sqft	60428	non-null	float64
	31	frozen_sqft	60428	non-null	float64
	32	meat_sqft	60428	non-null	float64
	33	coffee_bar	60428	non-null	float64
	34	video_store	60428	non-null	float64
	35	salad_bar	60428	non-null	float64
	36	prepared_food	60428	non-null	float64
	37	florist	60428	non-null	float64
	38	media_type	60428	non-null	object
	39	cost	60428	non-null	float64

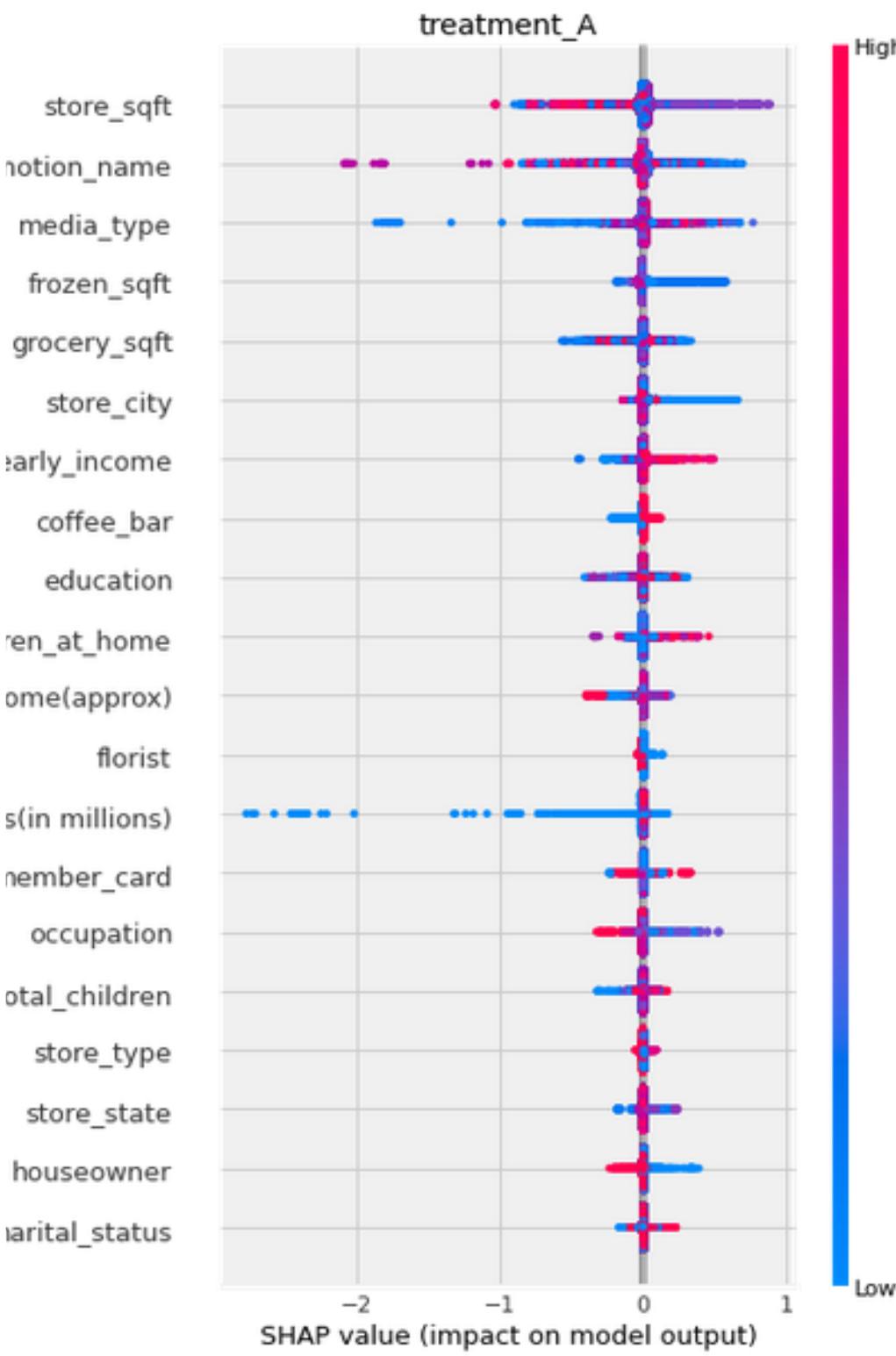
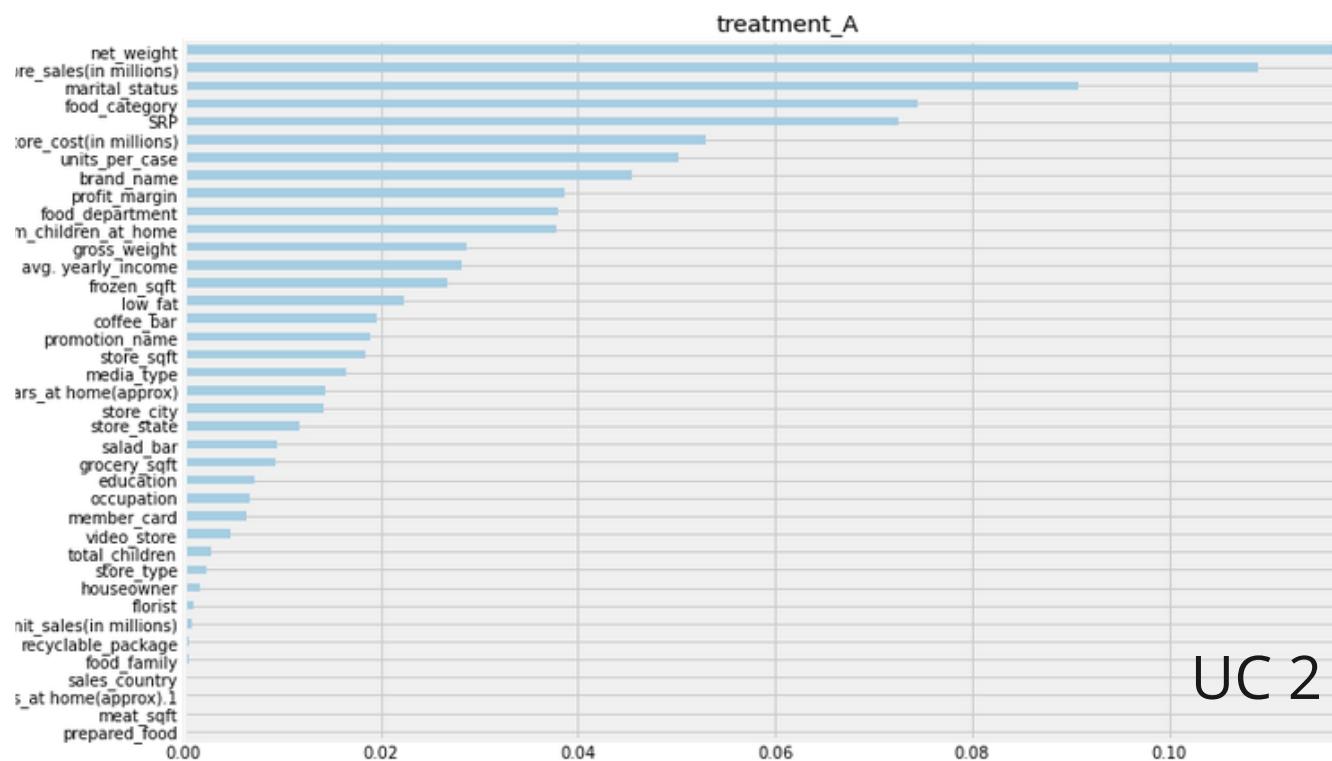
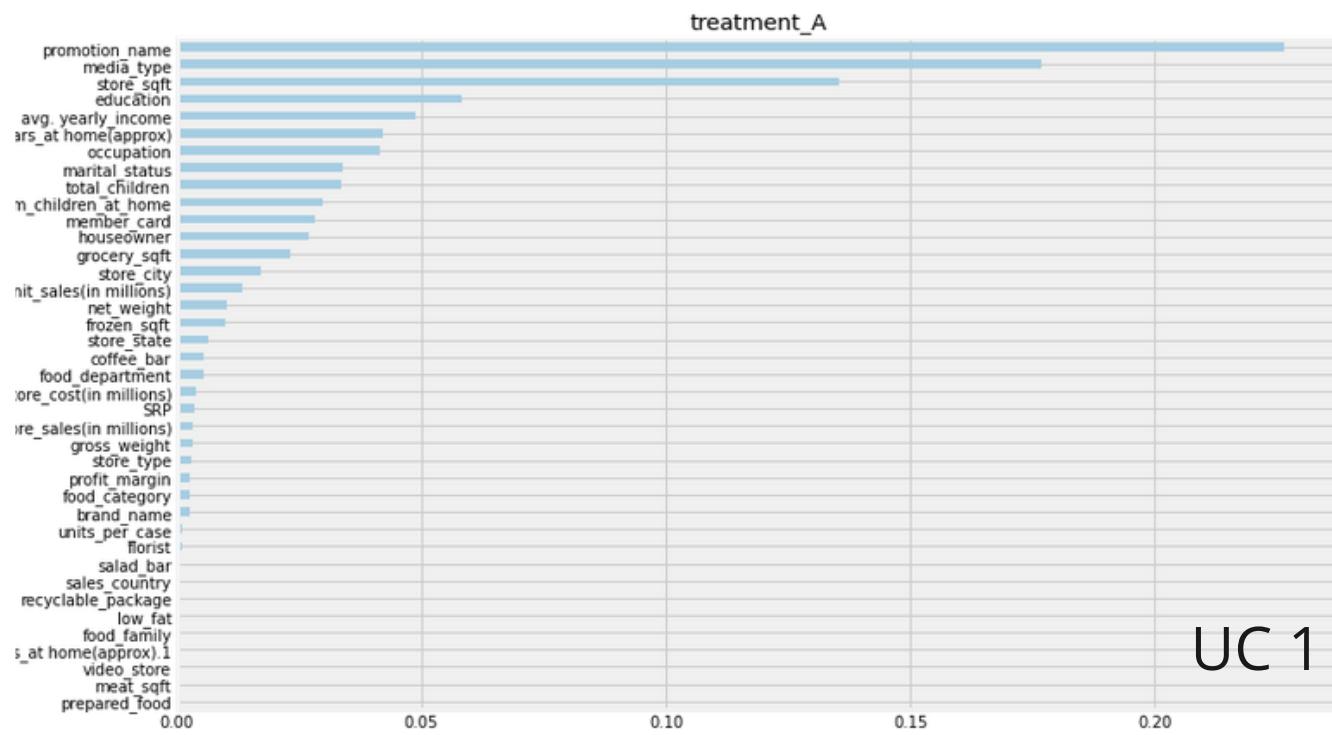
# Loyalty Program

**Distribution of customers' membership status**

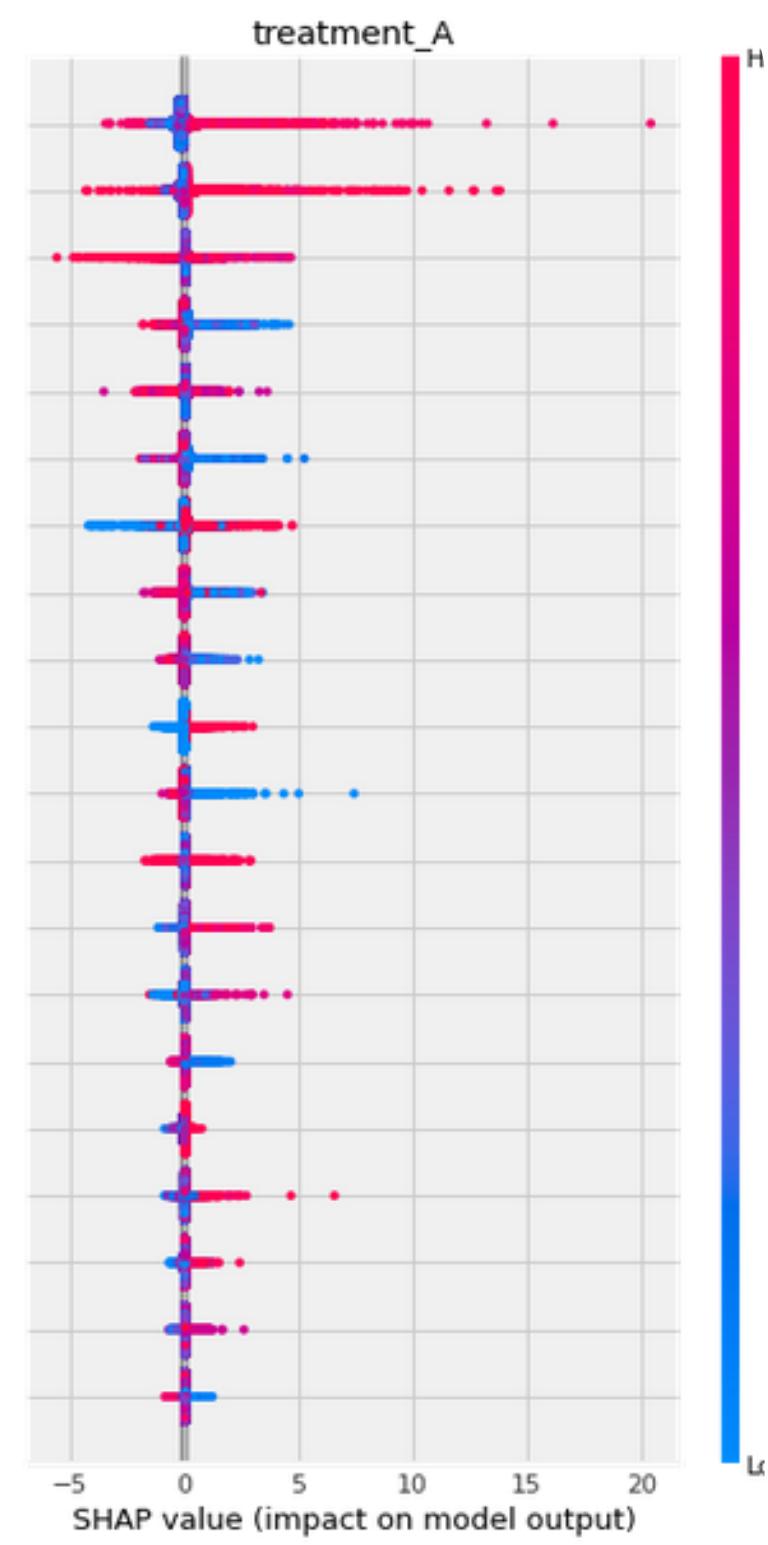
77% of customers have enrolled in the loyalty program



# Causal Inference

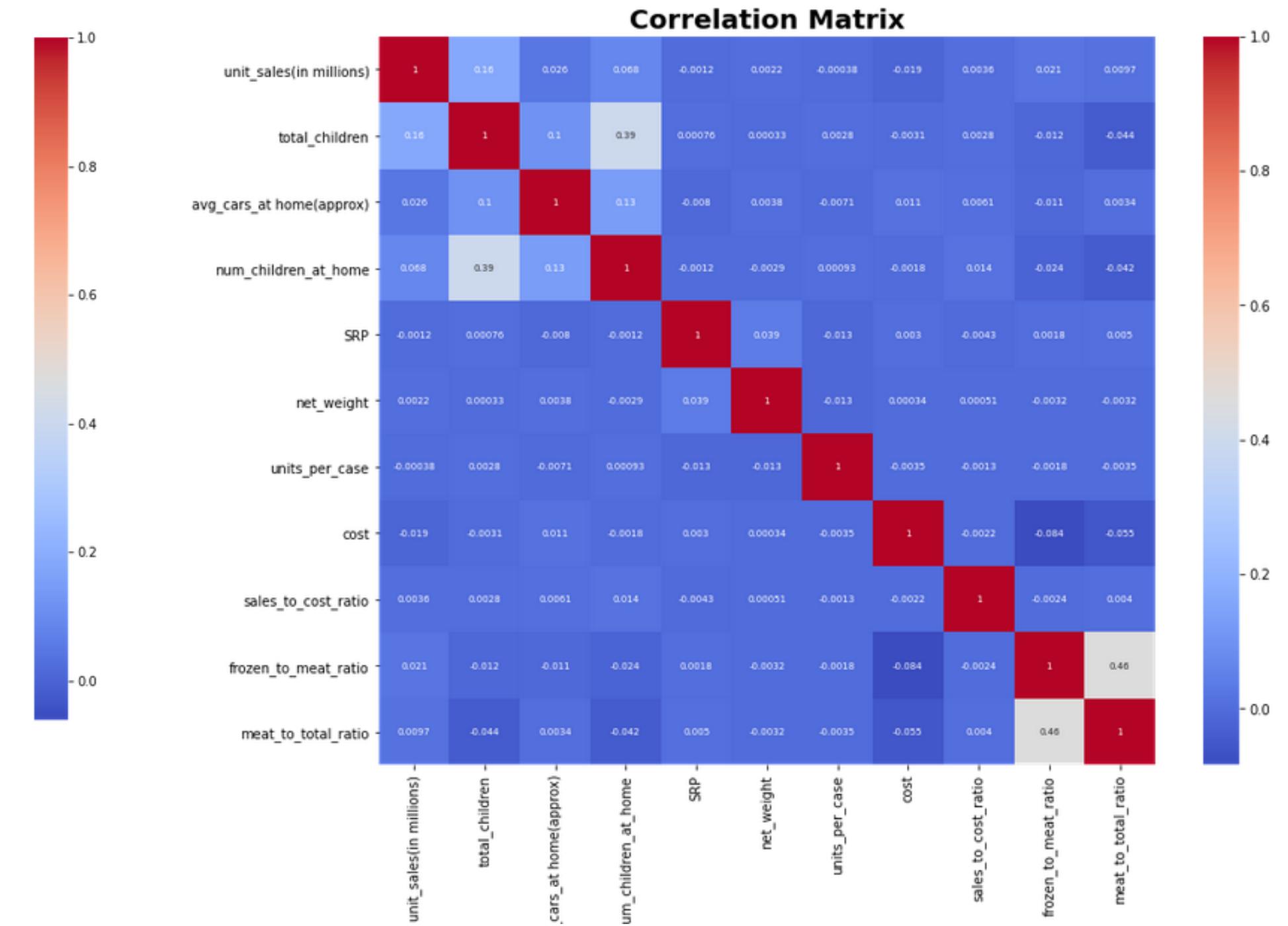
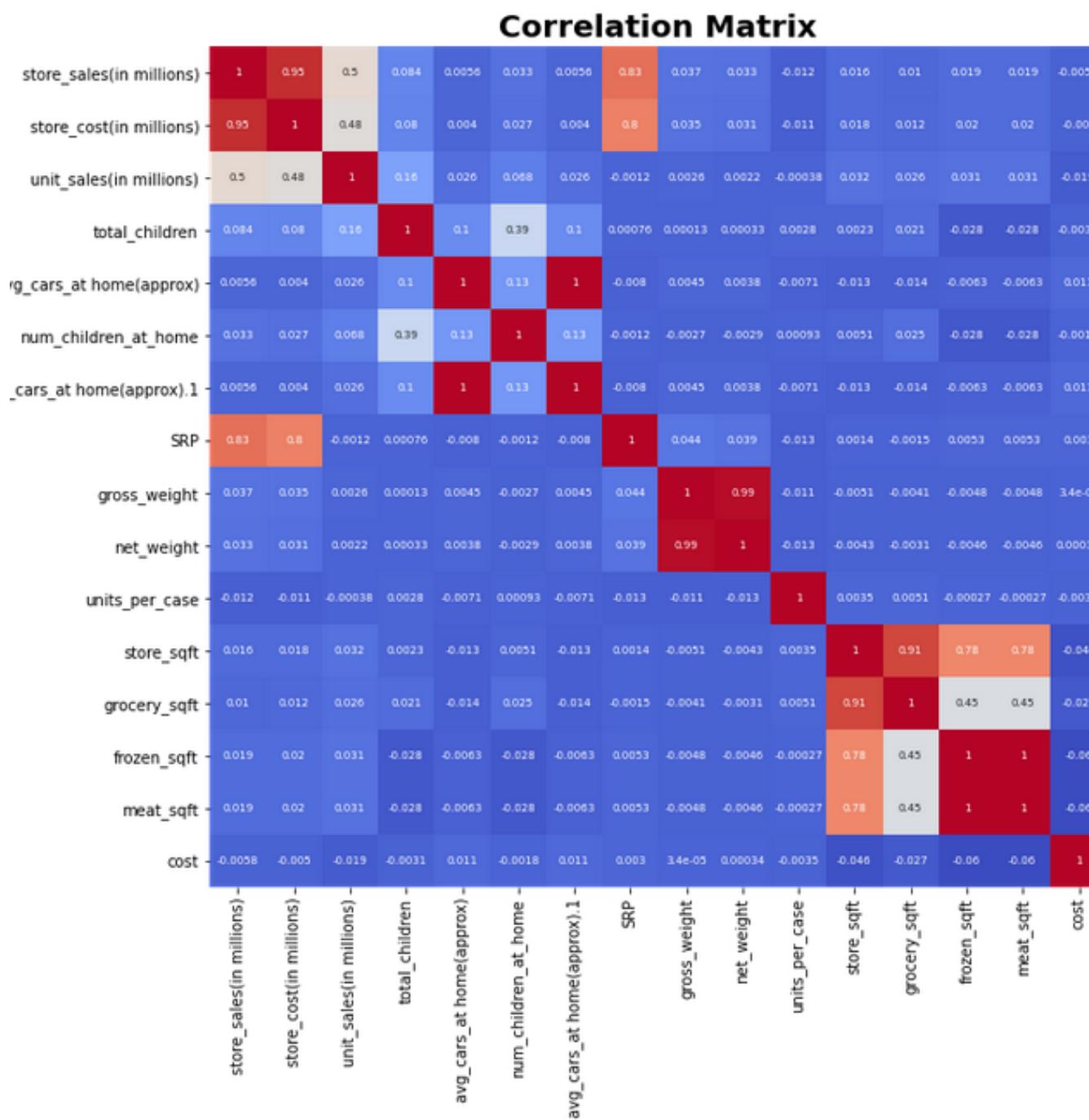


UC 1: Gender



UC 2: Loyalty

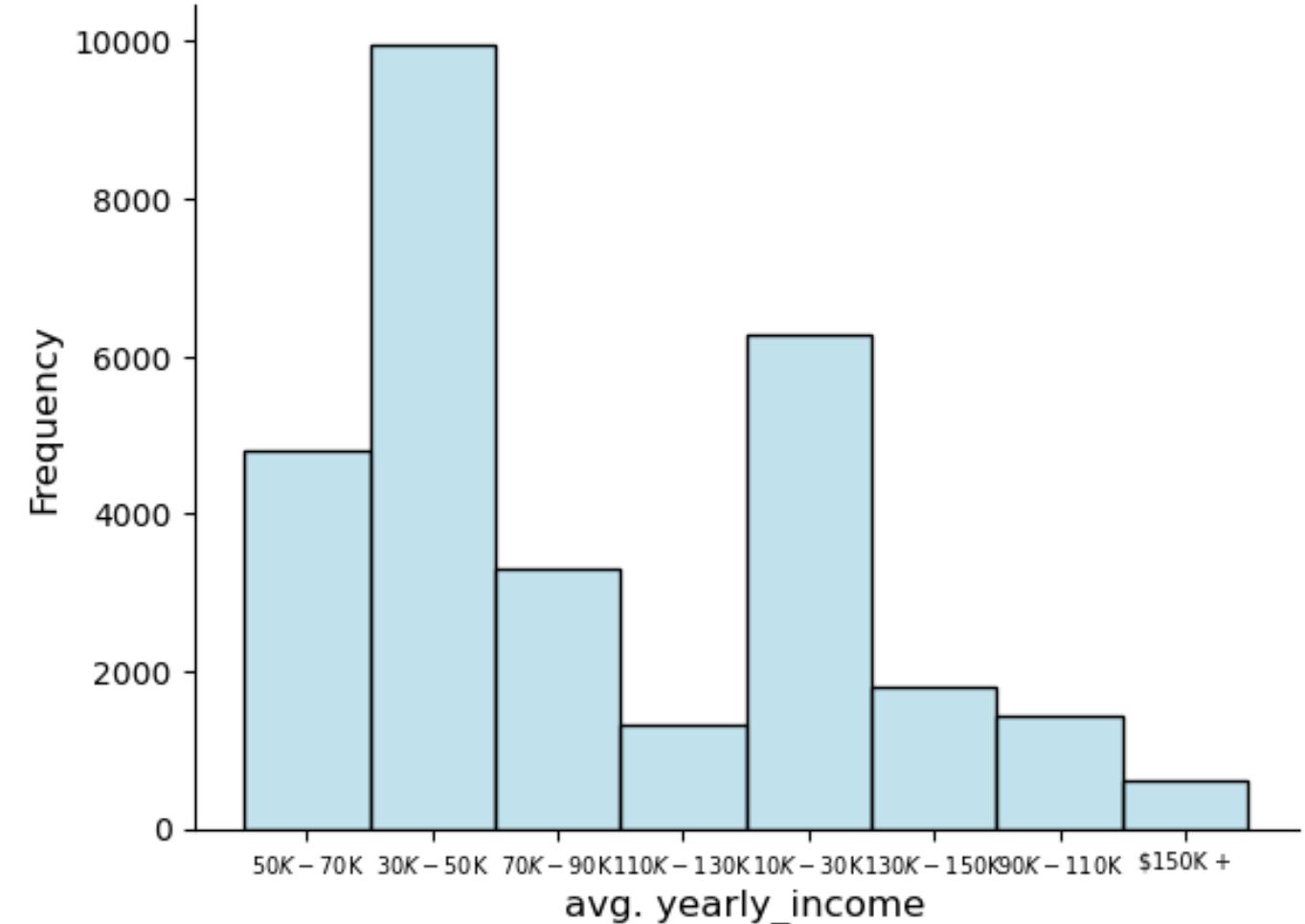
# Data Correlation



# Data Evaluation: Male

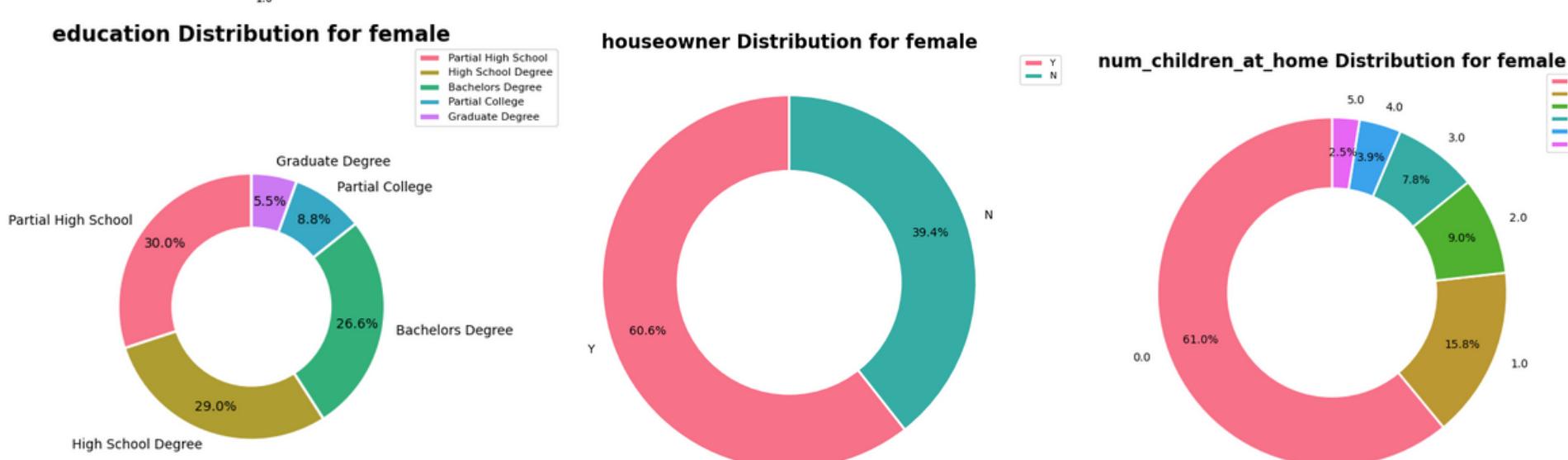
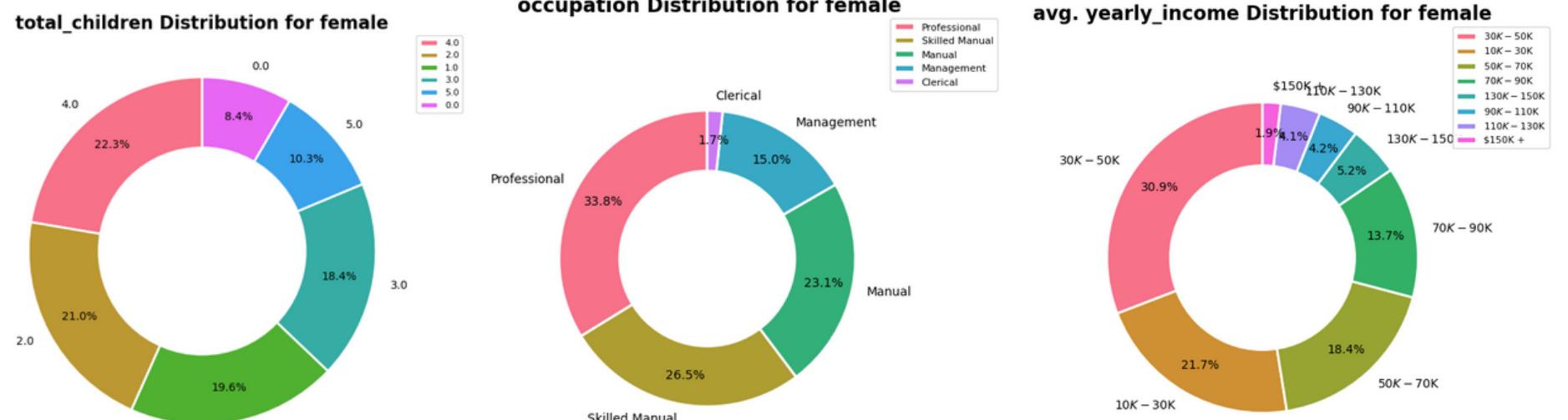
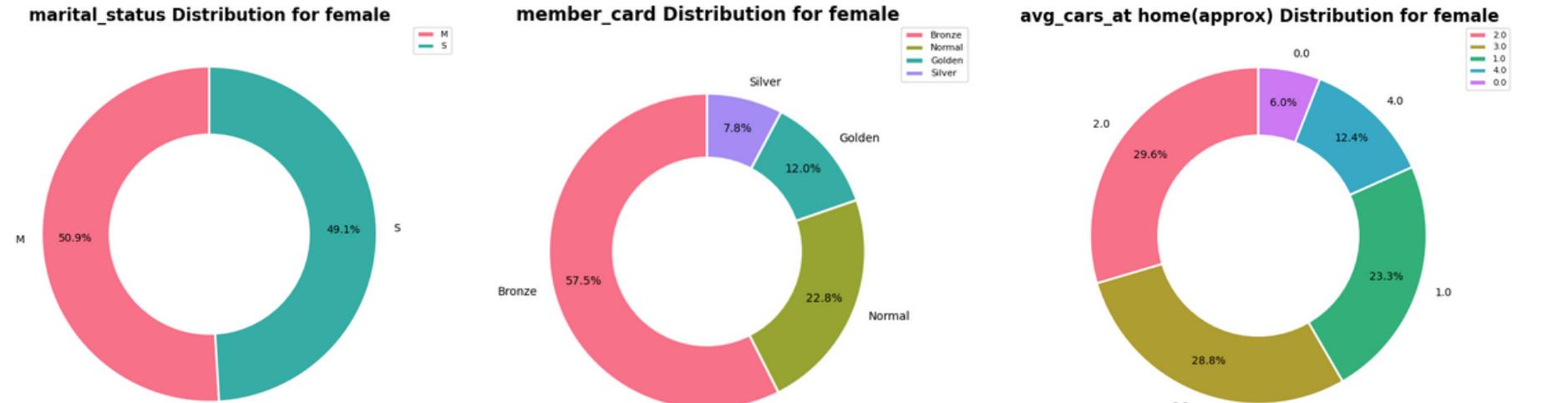


**Distribution of avg. yearly\_income male**

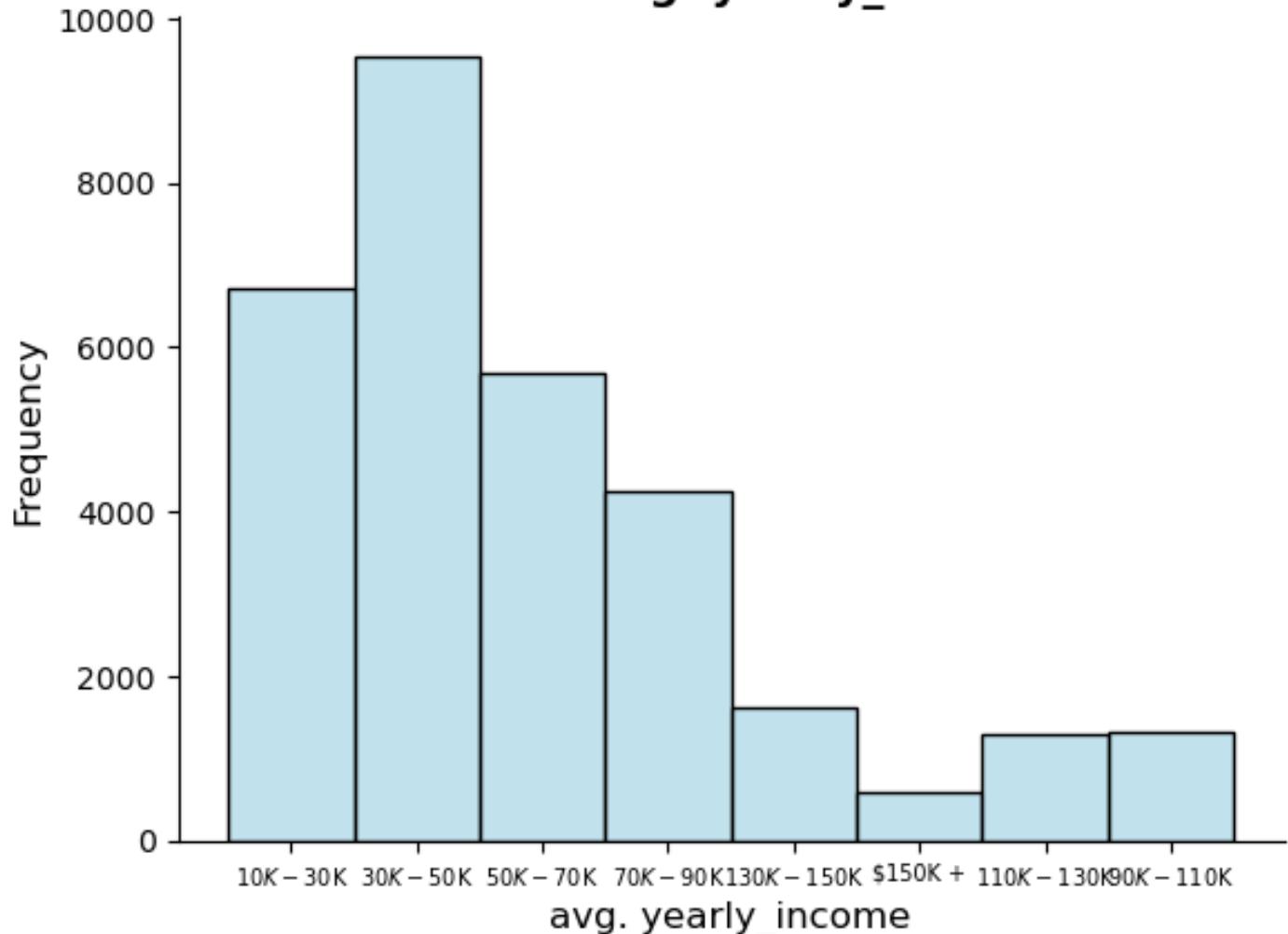


CO

# Data Evaluation: Female

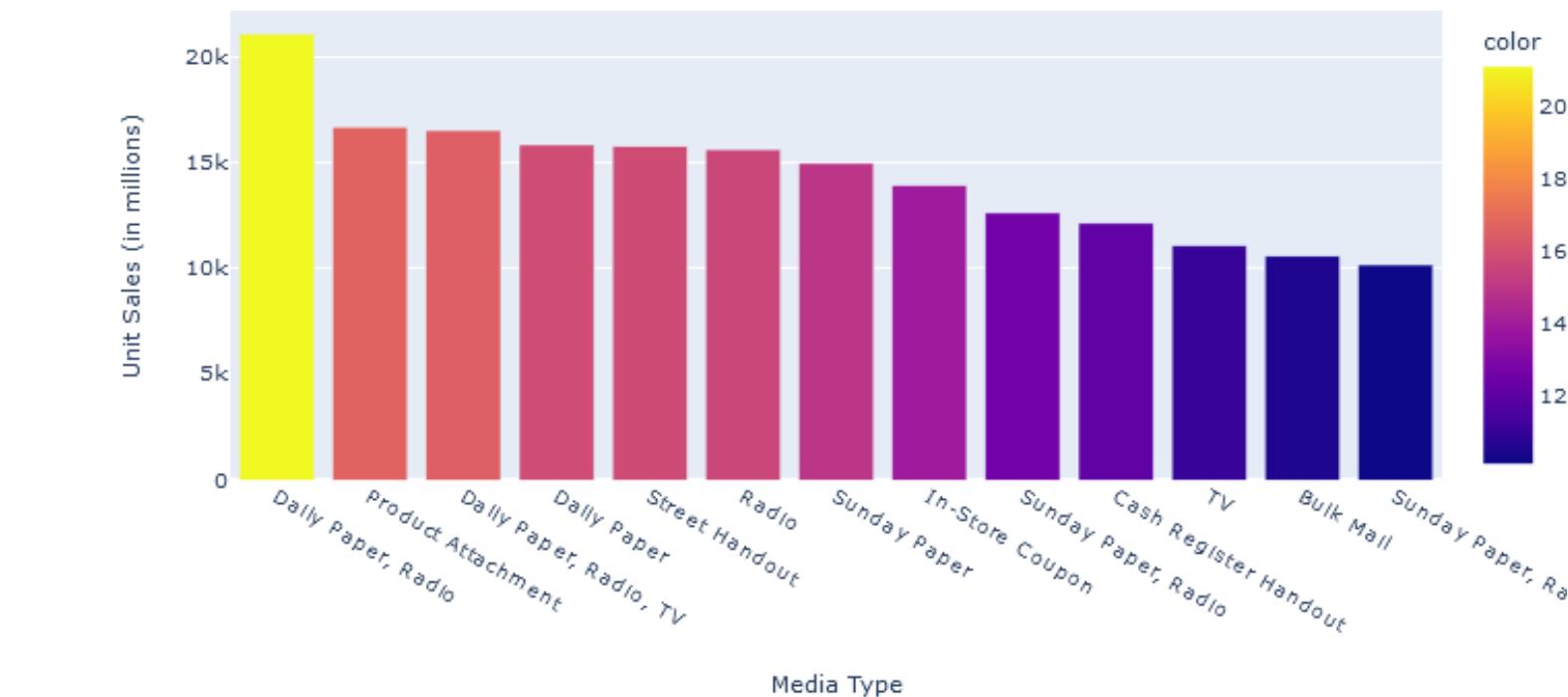
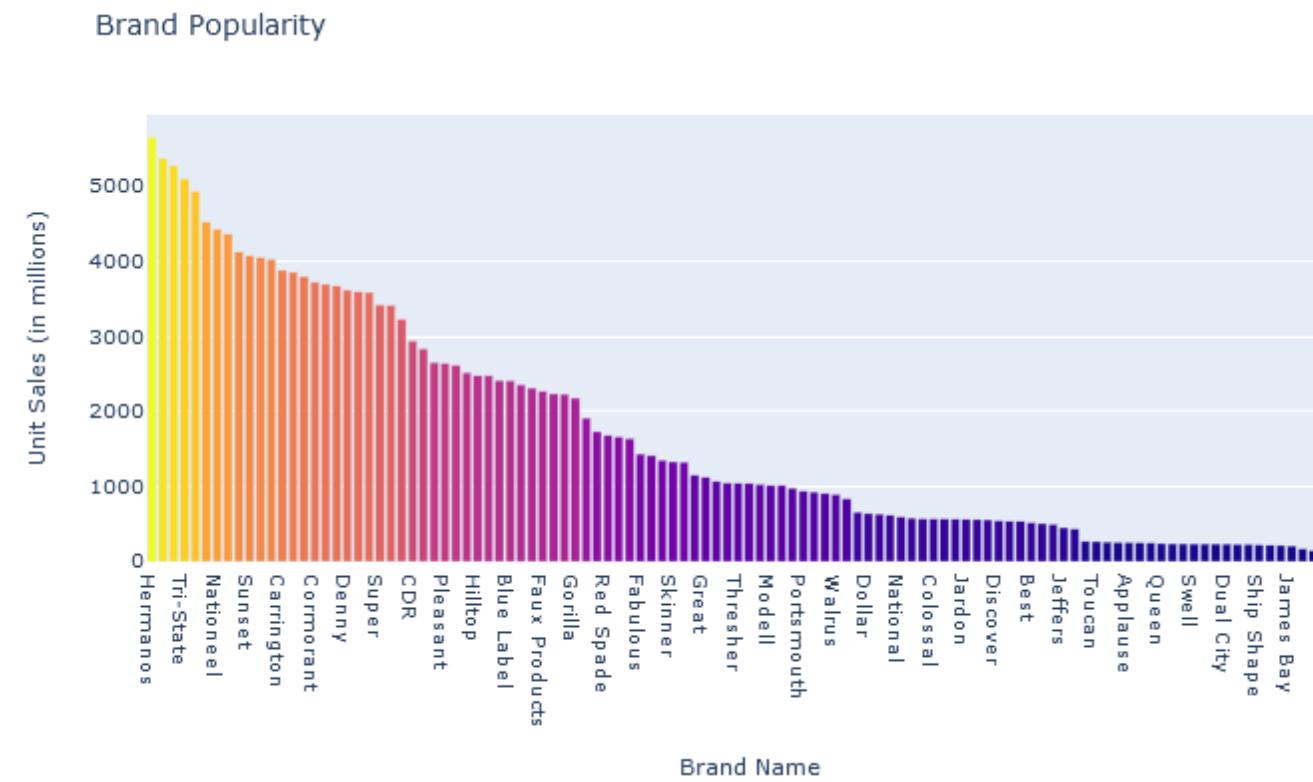


**Distribution of avg. yearly\_income female**

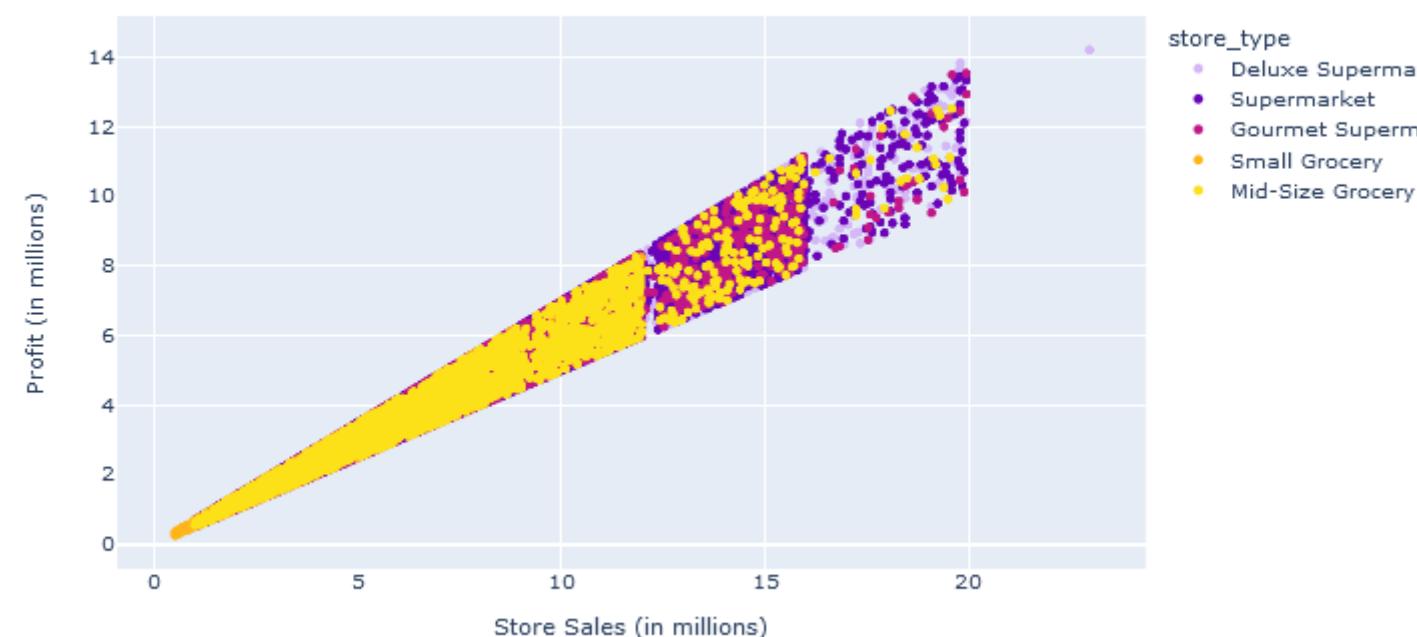


CO

# Data Evaluation



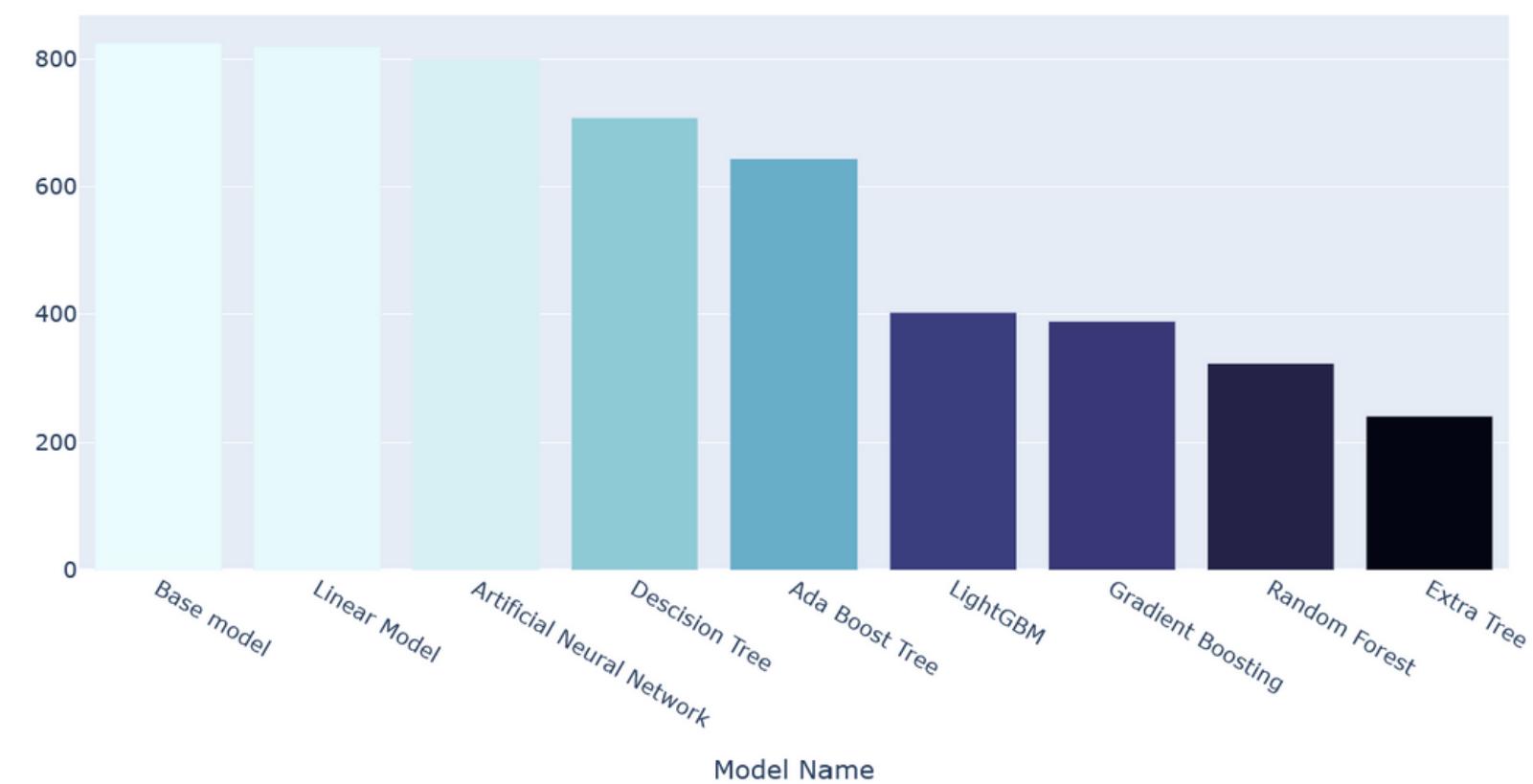
Profit by Store Sales (with Store Type)



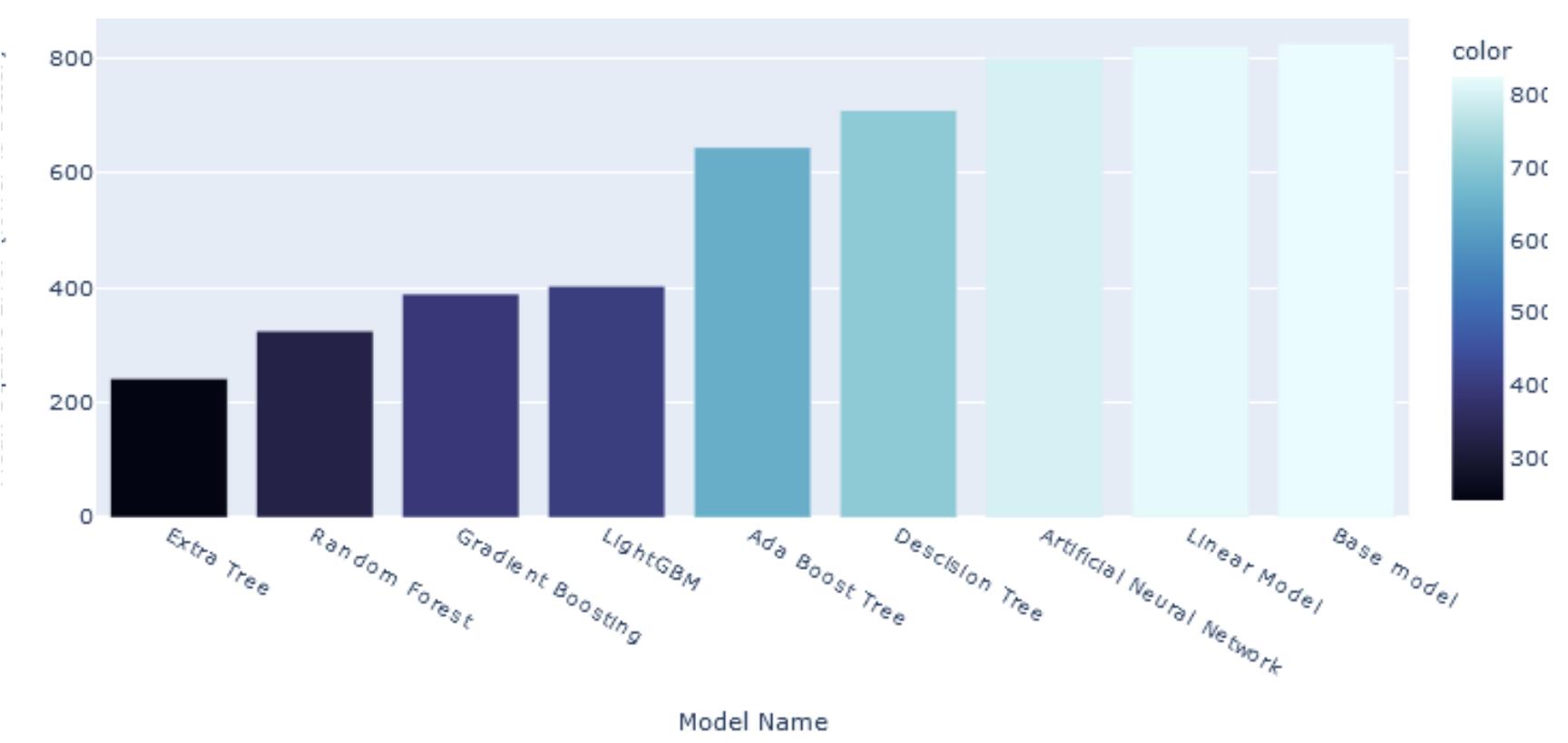
# Data Evaluation



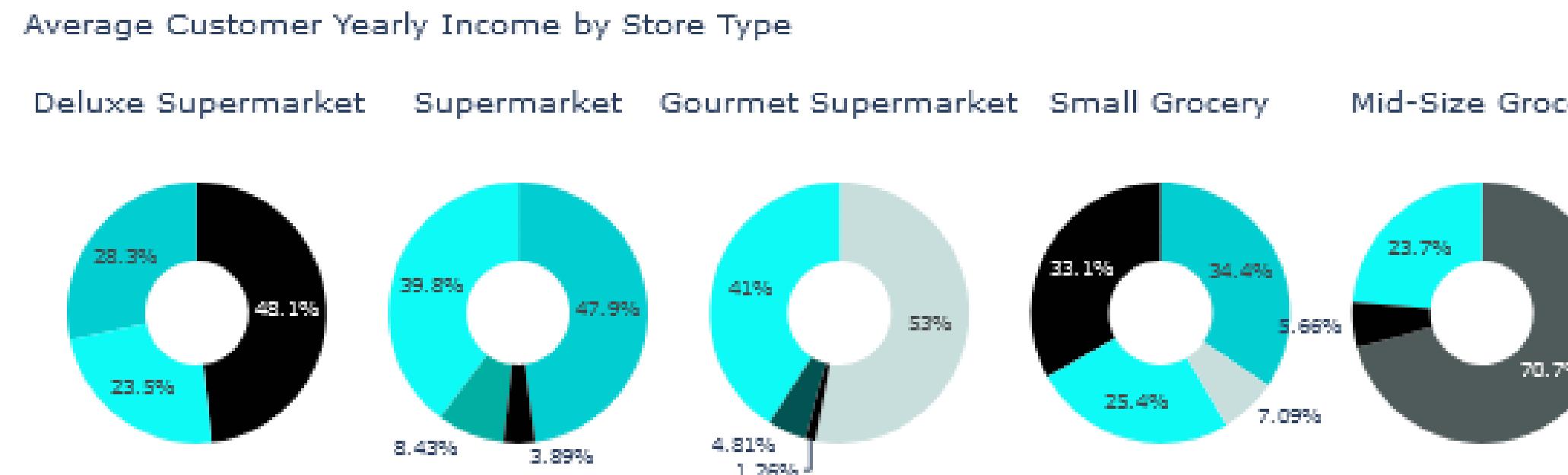
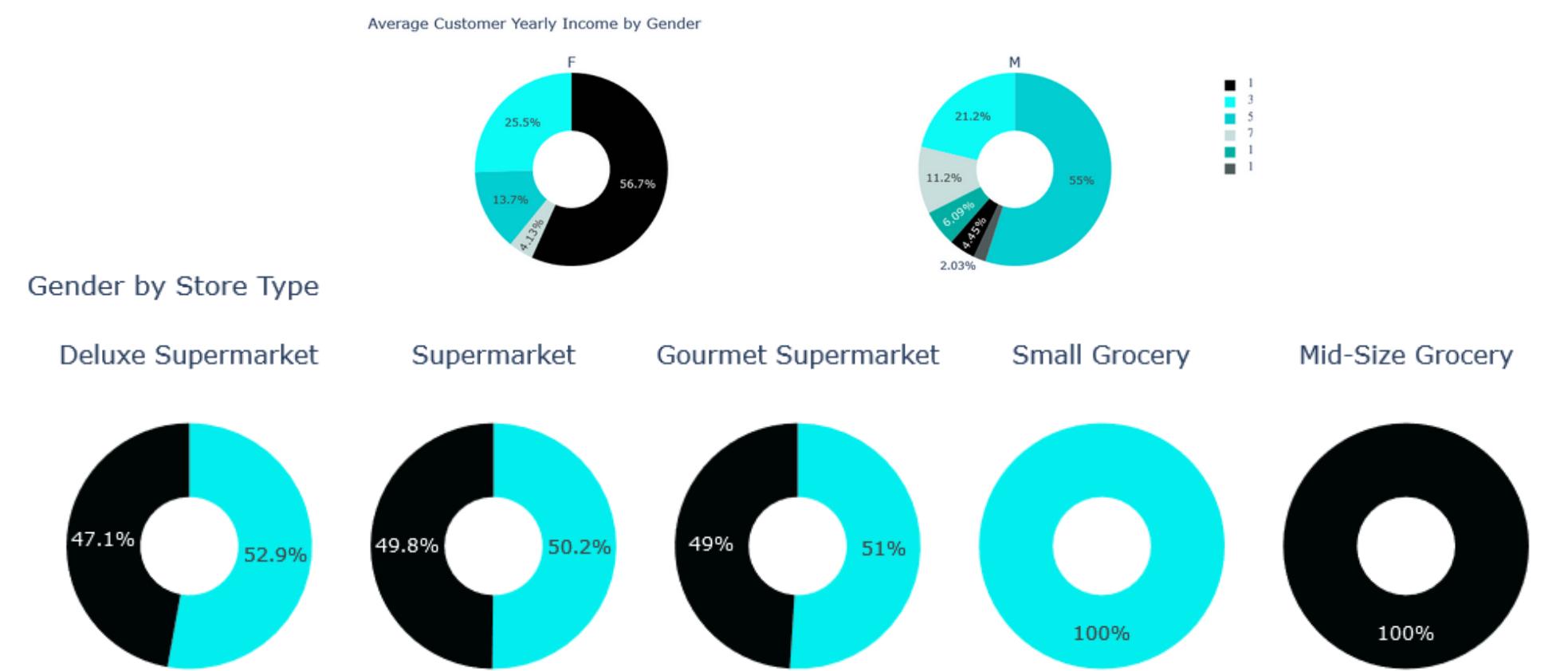
Model Accuracy



Model Accracy



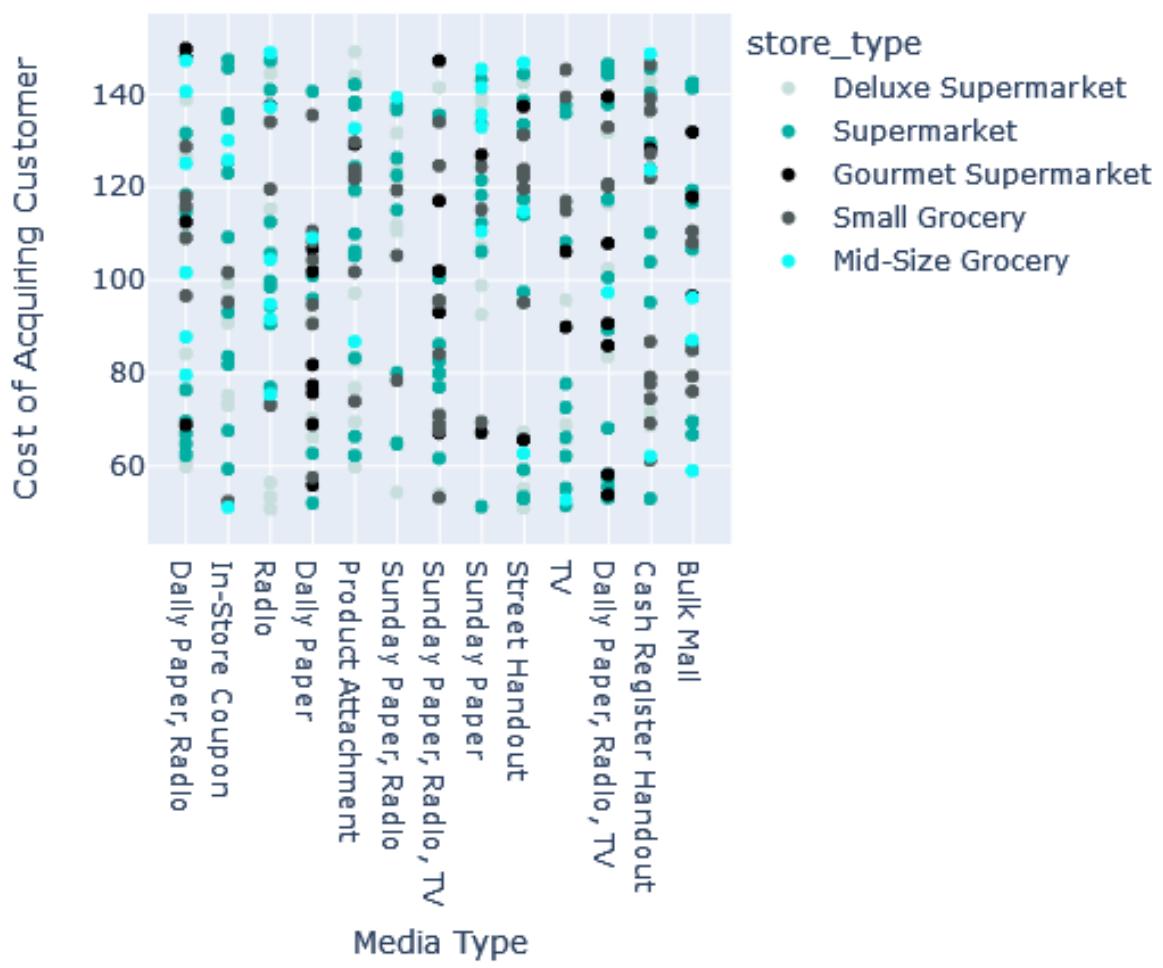
# Data Evaluation



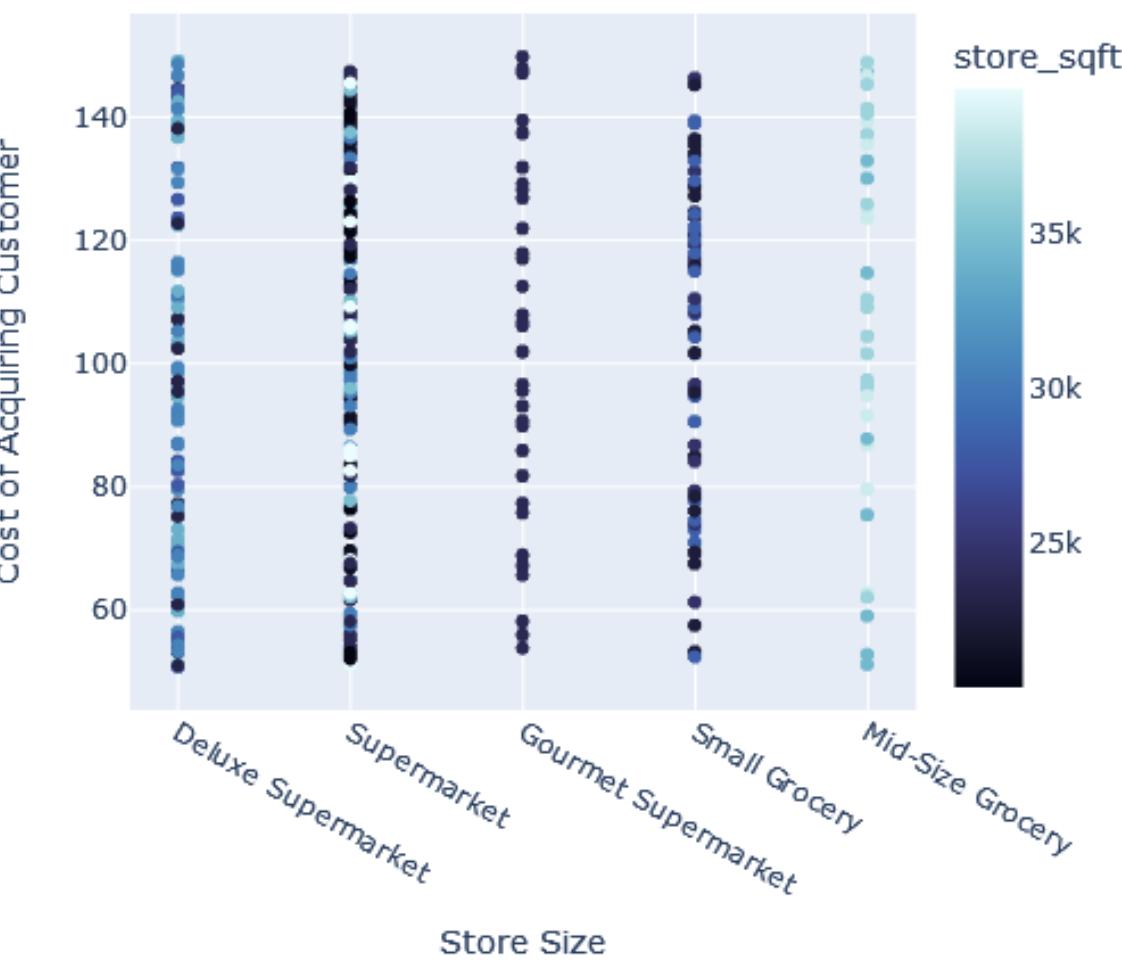
# Data Evaluation



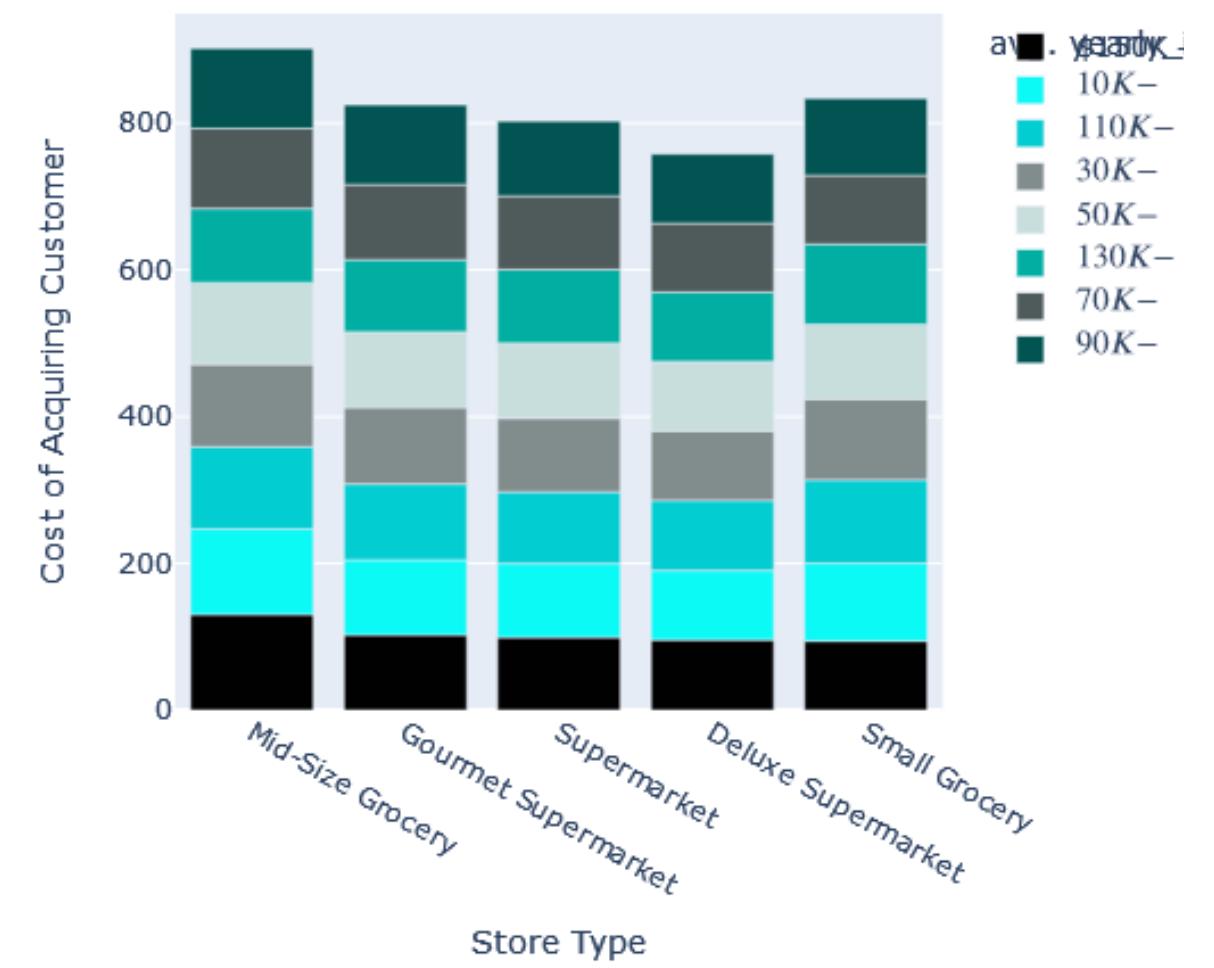
Cost of Acquiring a Customer by Media Type



Cost of Acquiring a Customer by Store Type



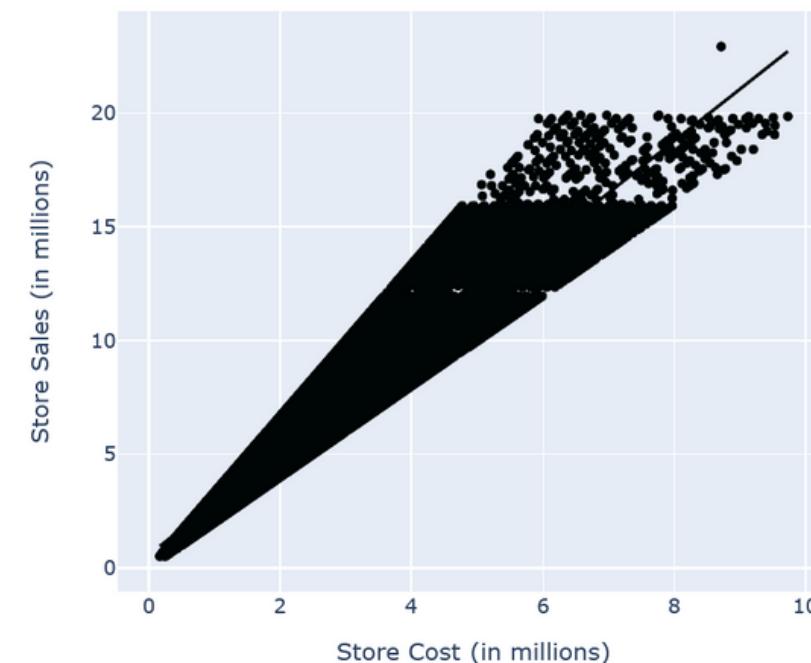
Cost of Acquiring Customer by Gender (with Average Year)



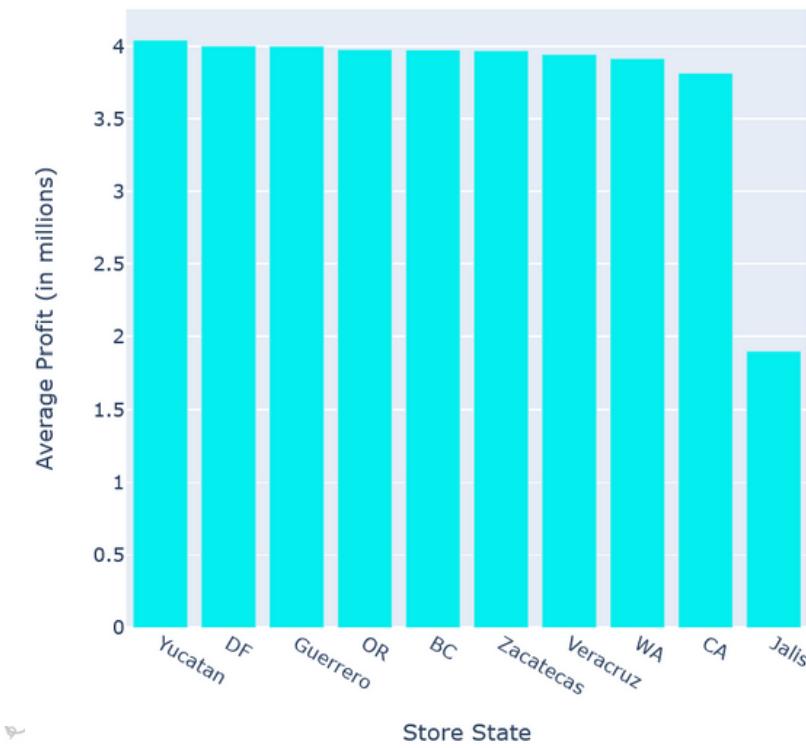
# Data Evaluation



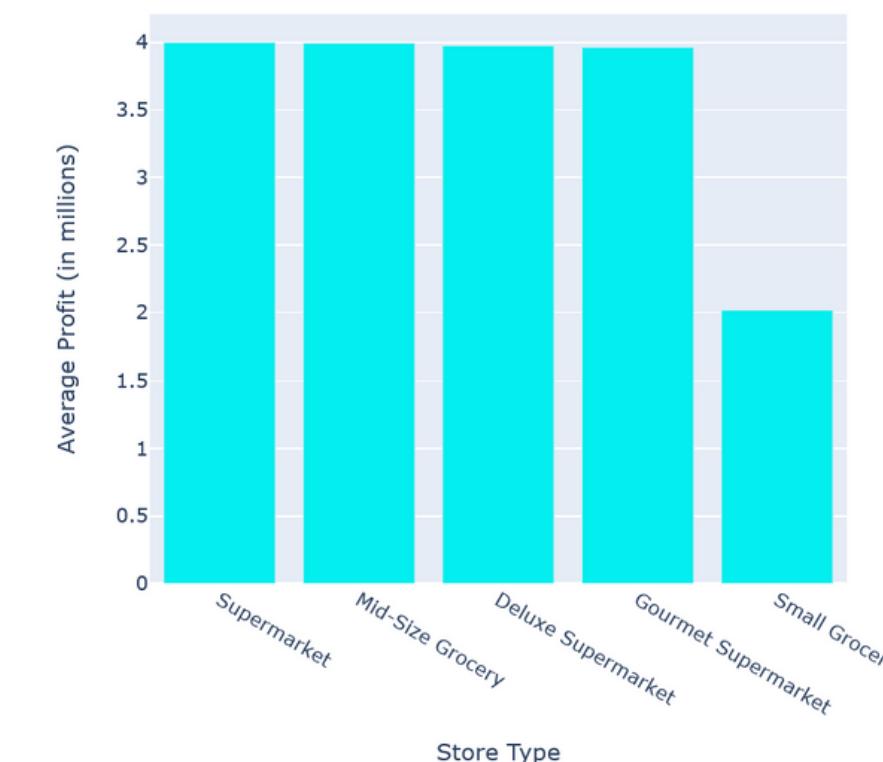
Relationship between Store Cost and Store Sales



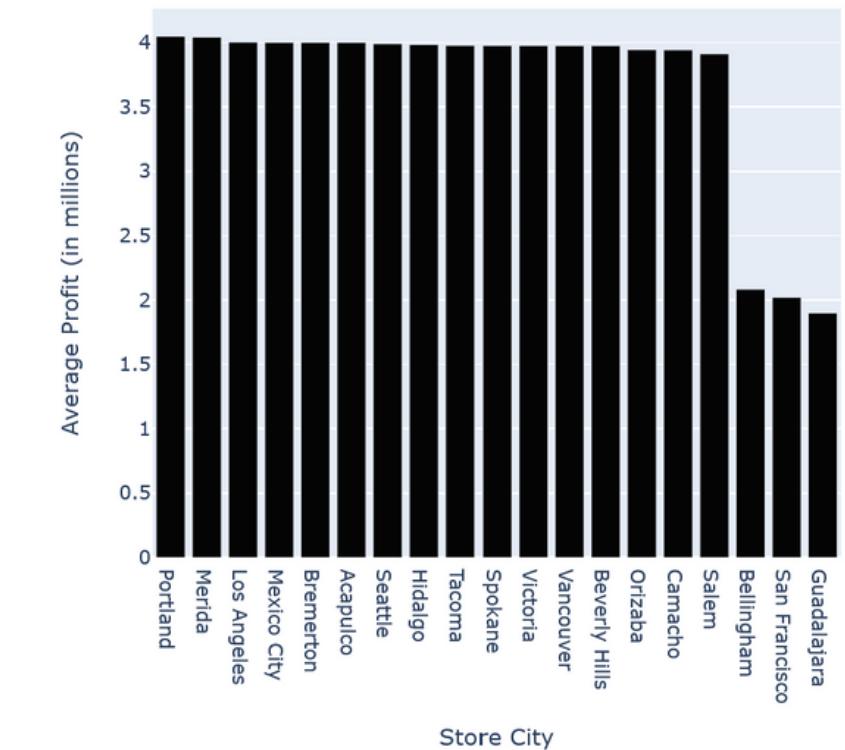
Average Profit (in millions) by Store State



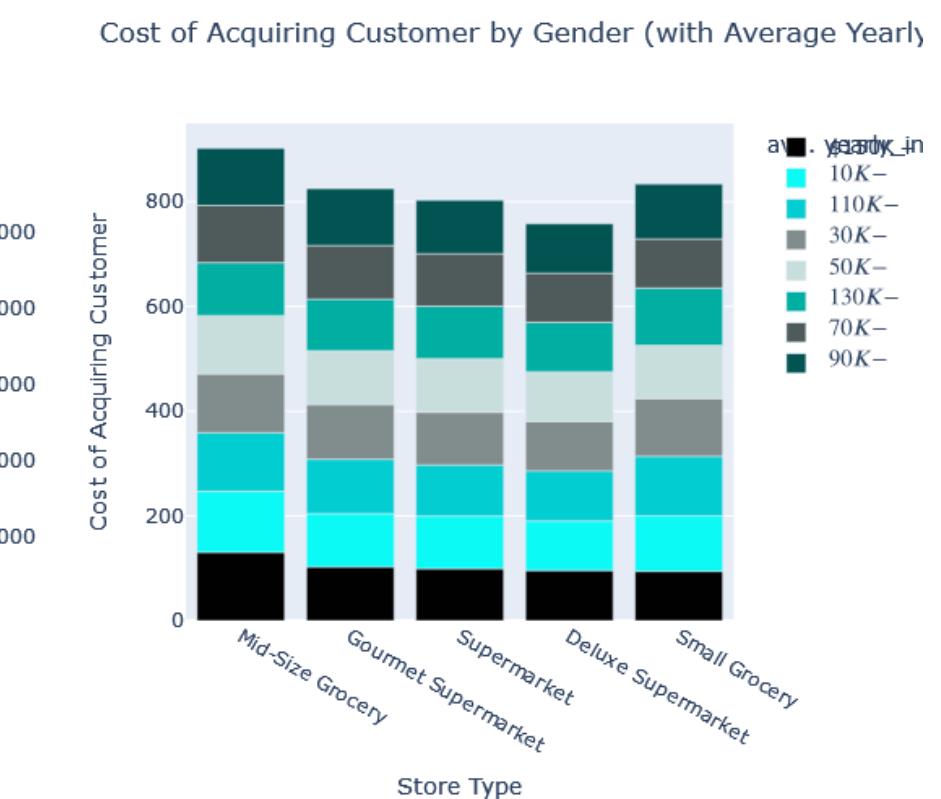
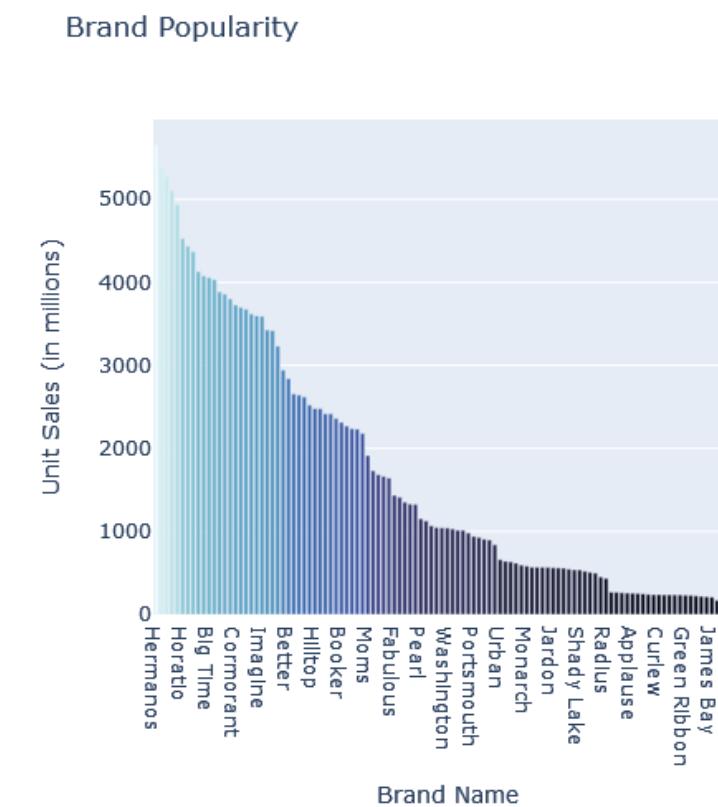
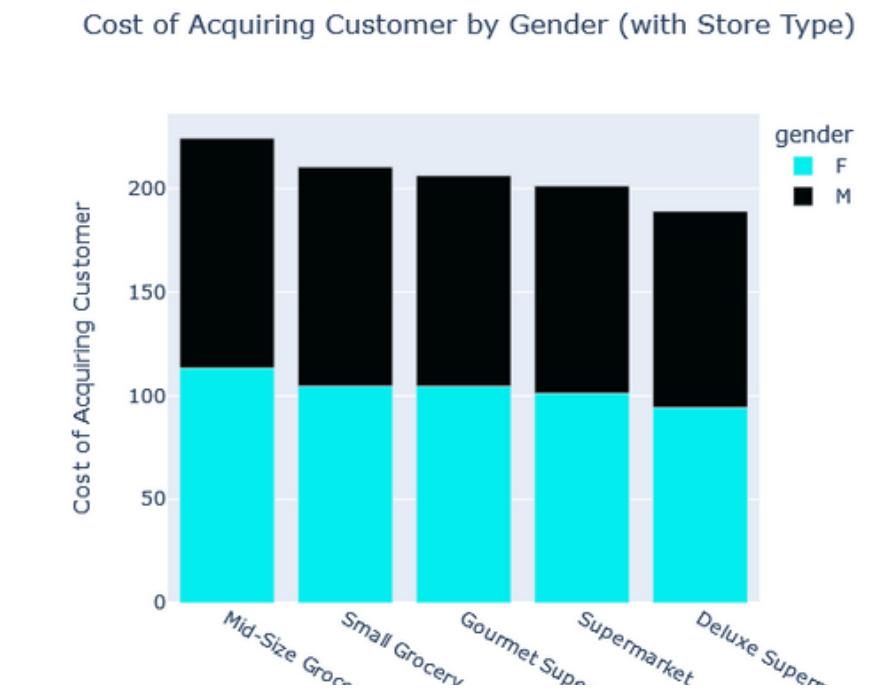
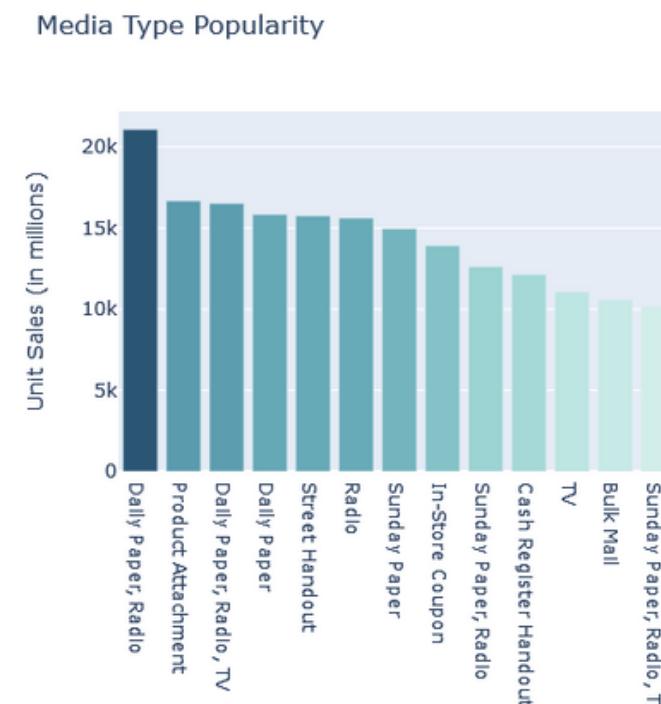
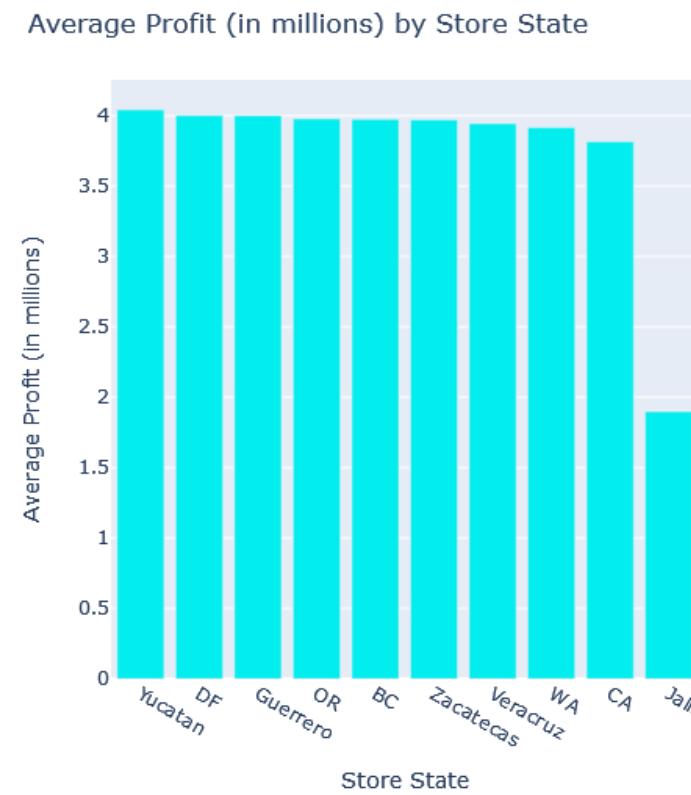
Average Profit (in millions) by Store Type



Average Profit (in millions) by Store City



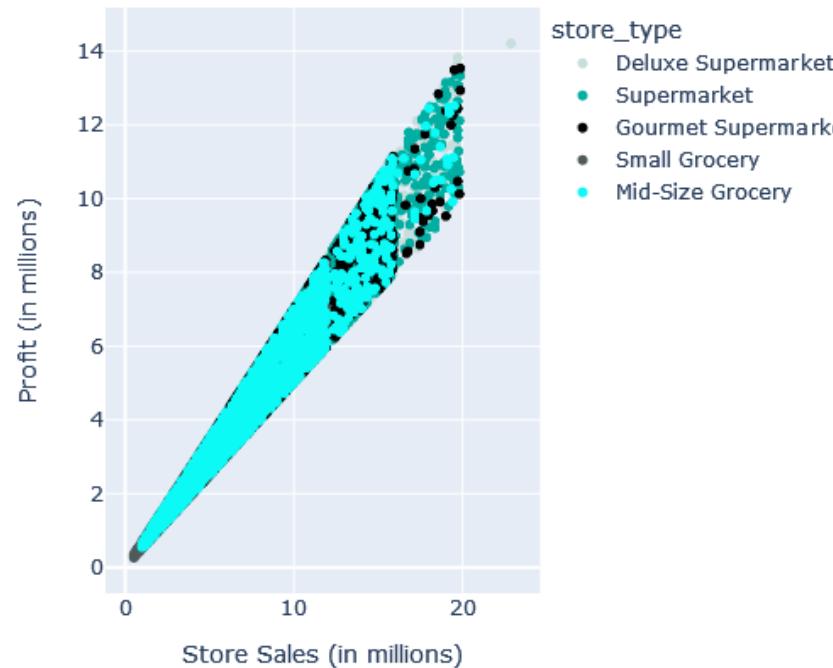
# Data Evaluation



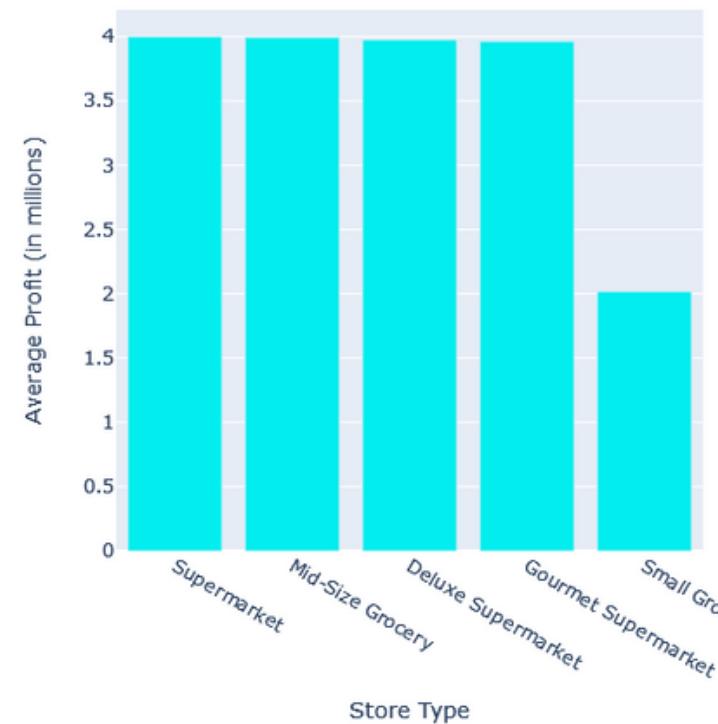
# Data Evaluation



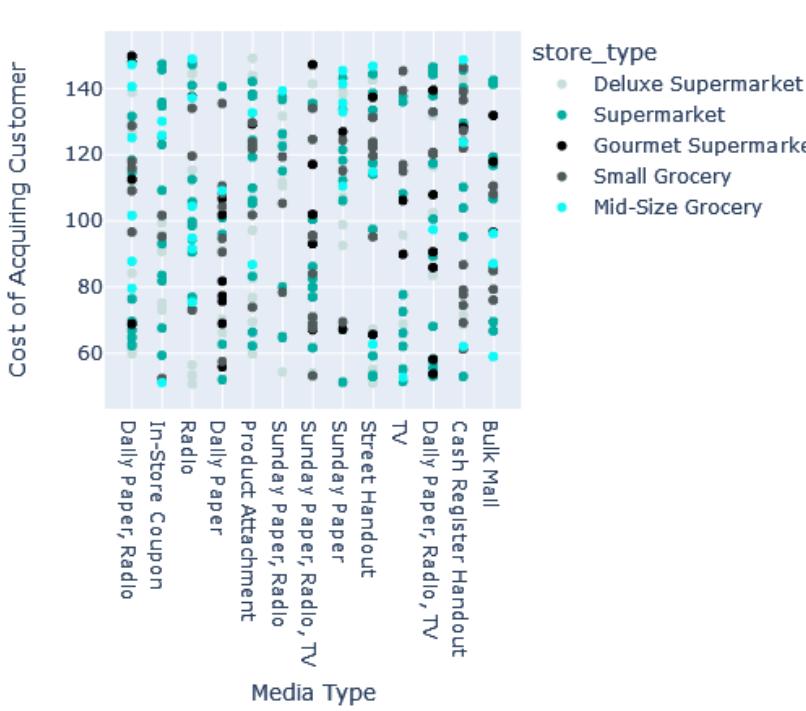
## Profit by Store Sales (with Store Type)



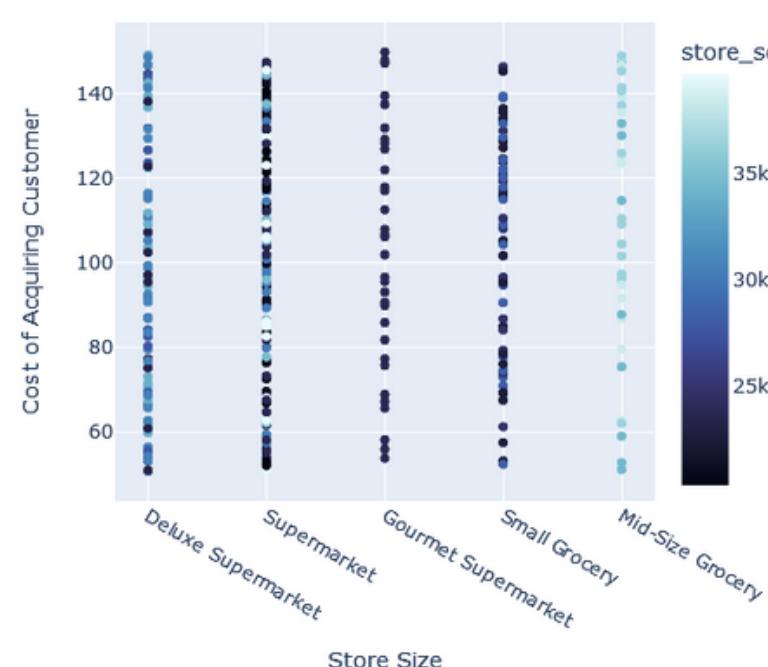
### Average Profit (in millions) by Store Type



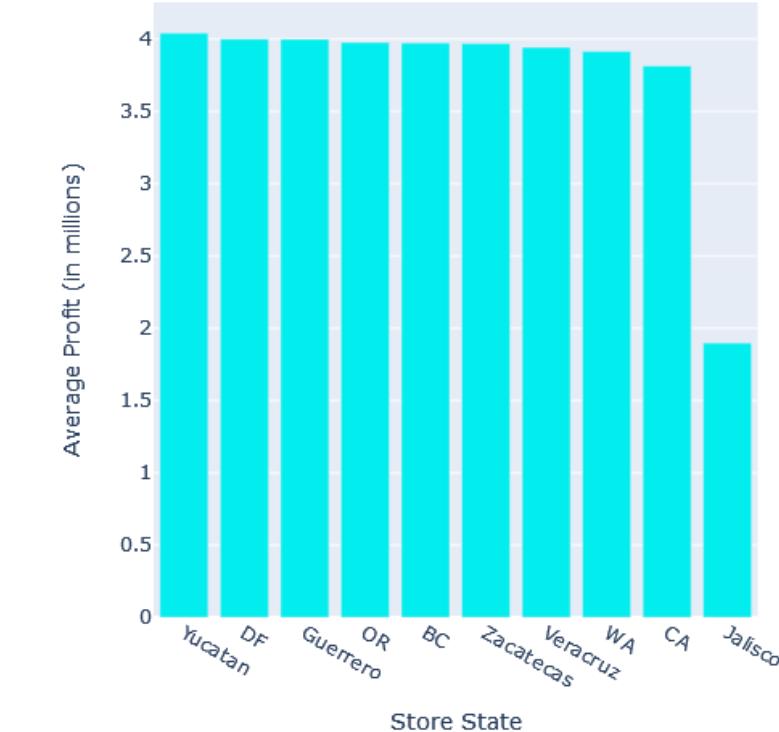
## Cost of Acquiring a Customer by Media Type



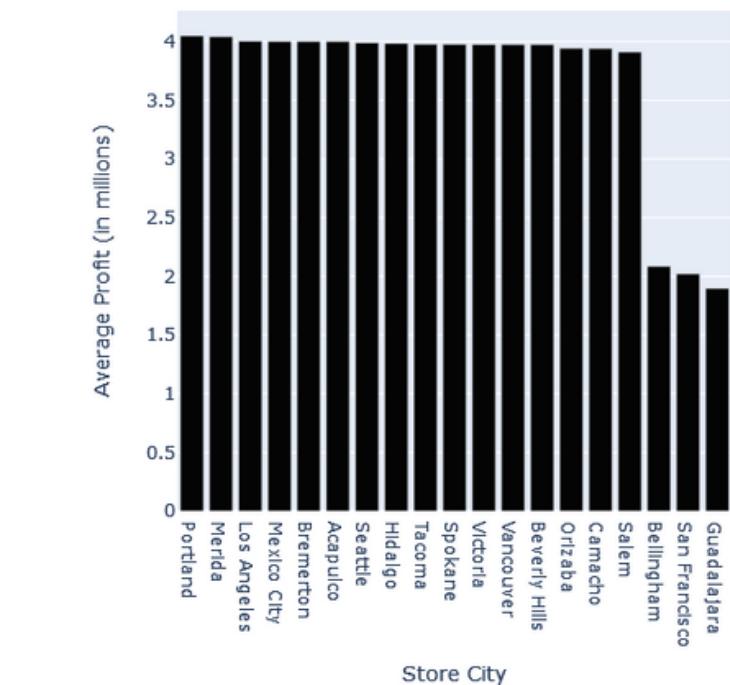
## Cost of Acquiring a Customer by Store Type



### Average Profit (in millions) by Store State



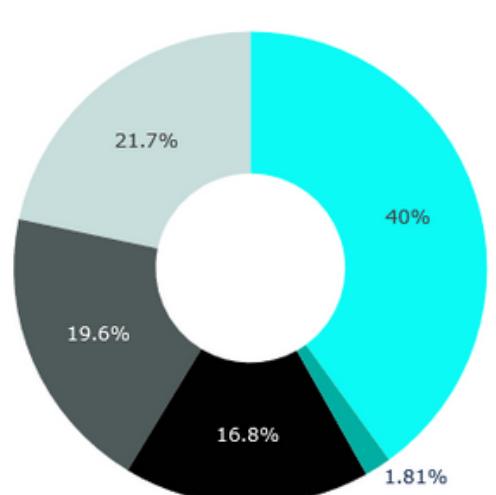
### Average Profit (in millions) by Store City



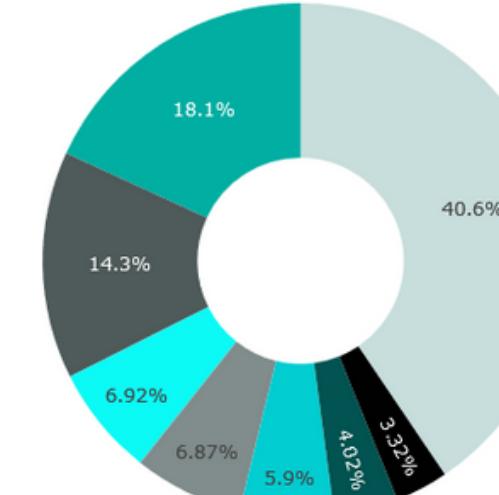
# Data Evaluation



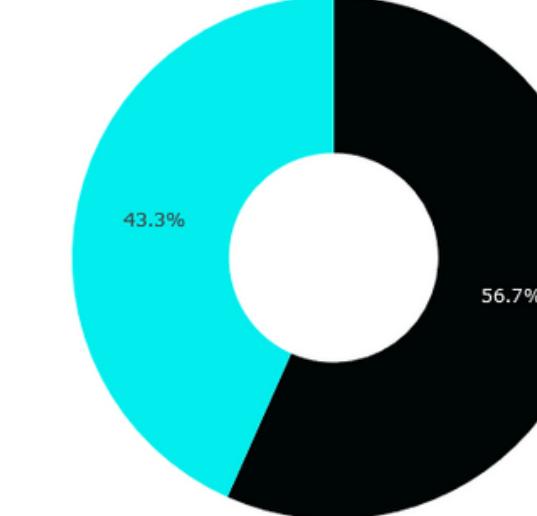
Percentage of Customers with Golden member card by Occ



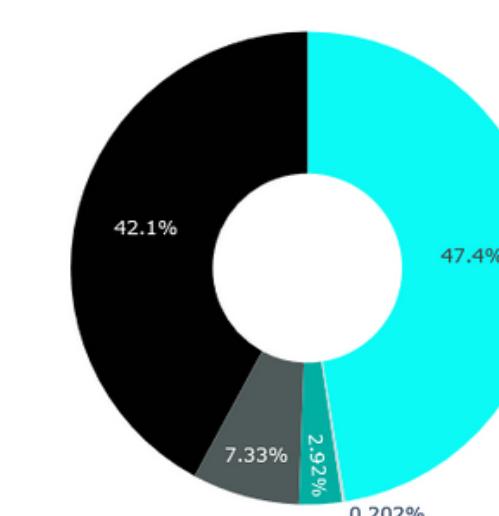
Percentage of Customers with Golden member card by Ave



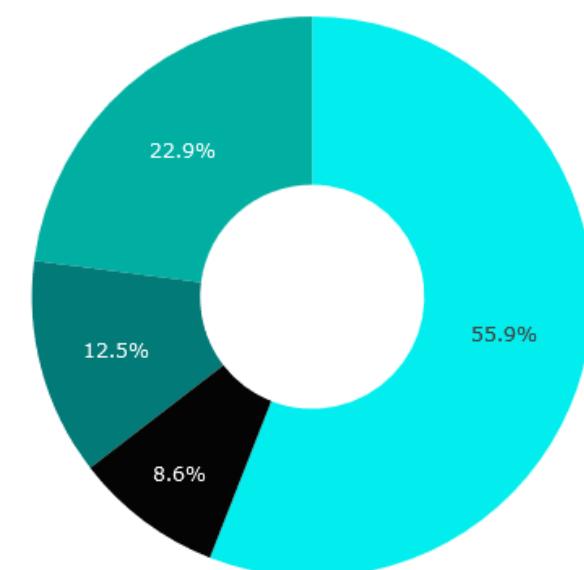
Percentage of Customers with Normal member card by Ho



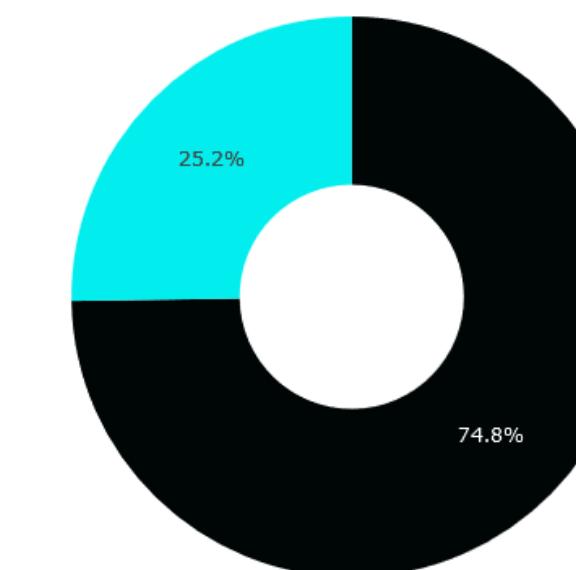
Percentage of Customers with Normal member card by Occ



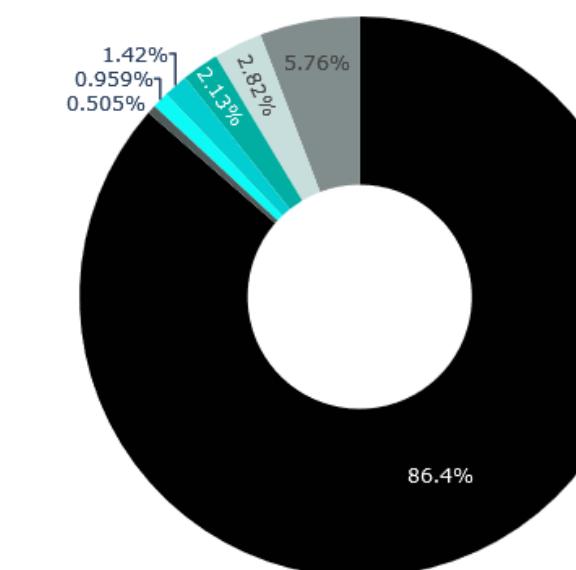
Percentage of Customers per Member Card Type



Percentage of Customers with Golden member card by Ho



Percentage of Customers with Normal member card by Ave



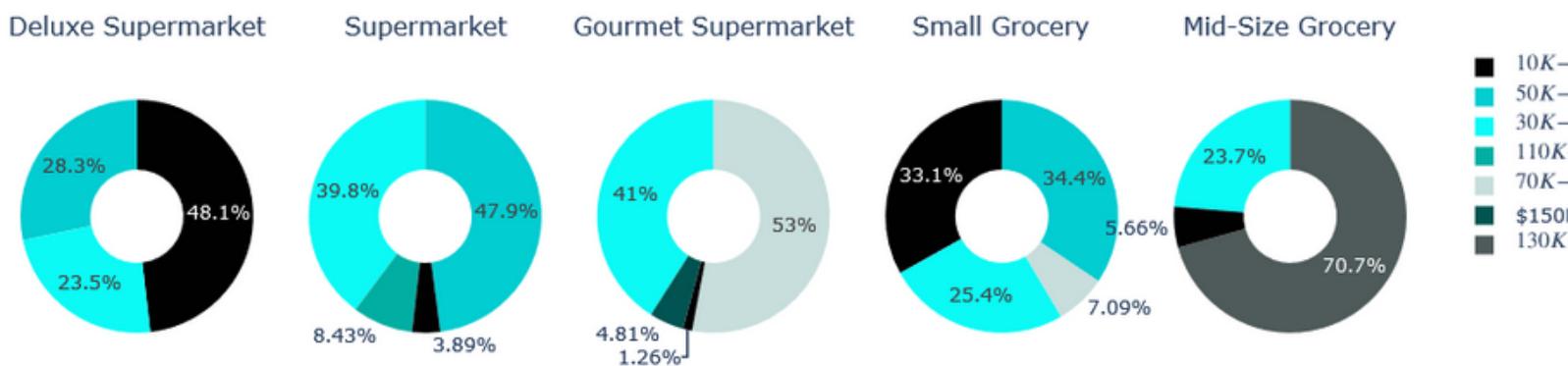
# Data Evaluation



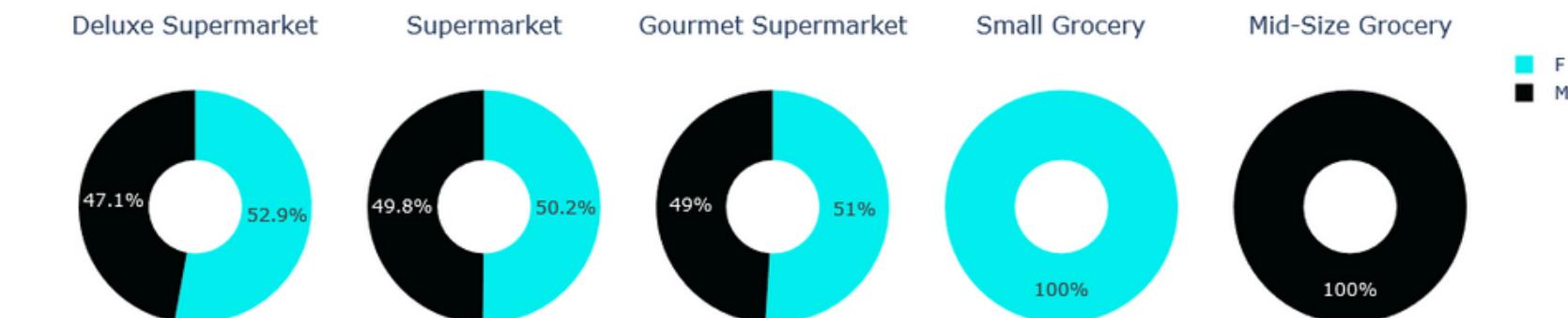
Average Customer Yearly Income by Gender



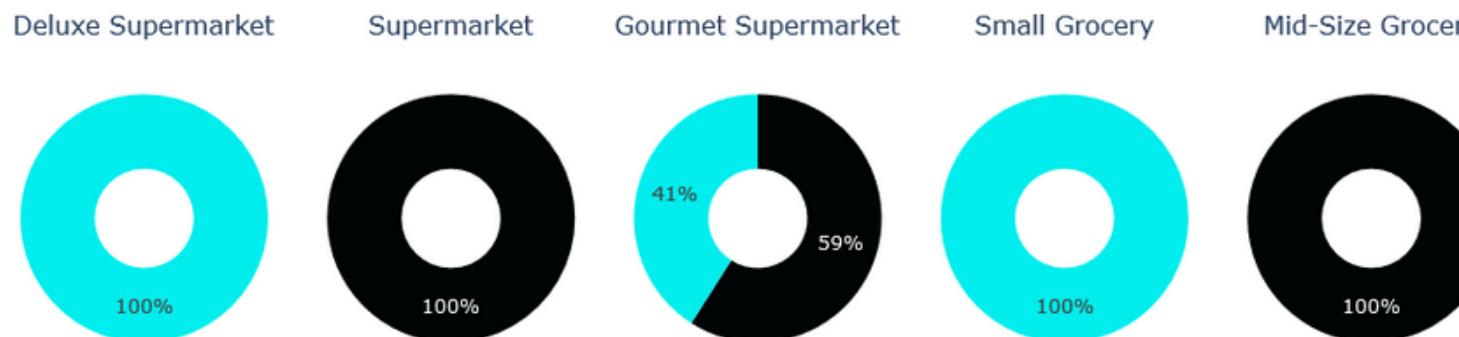
Average Customer Yearly Income by Store Type



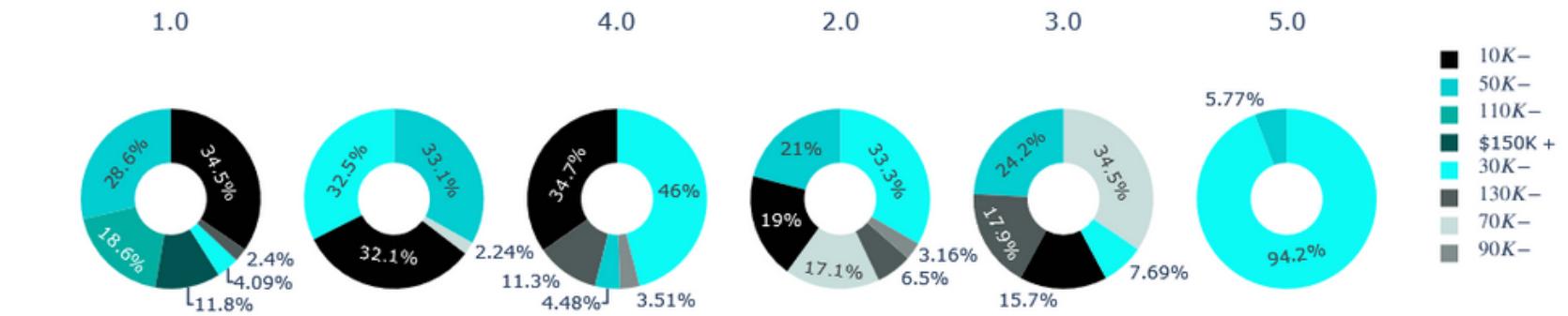
Gender by Store Type



House-owner by Store Type

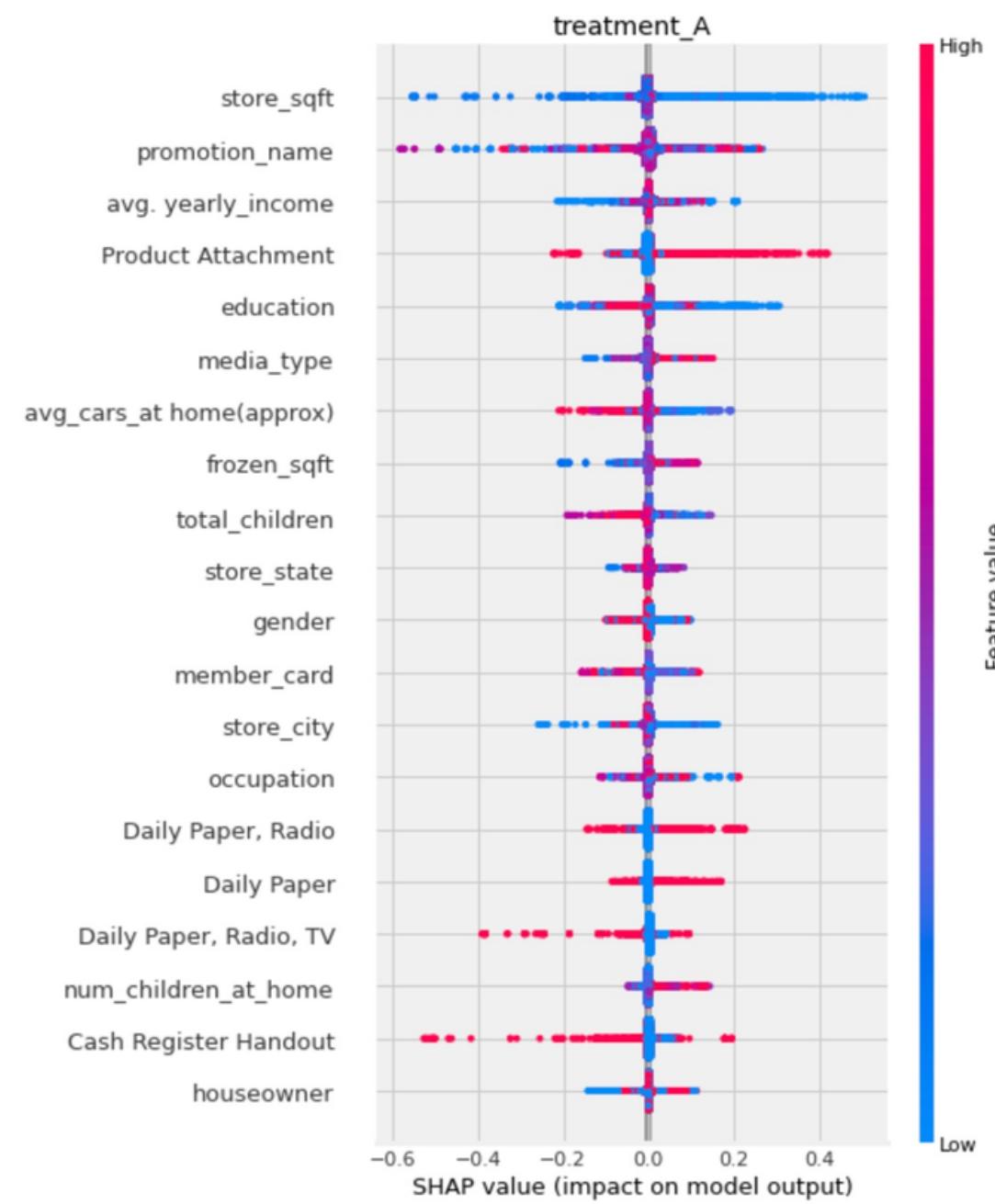


Average Customer Yearly Income by Total Number of Children

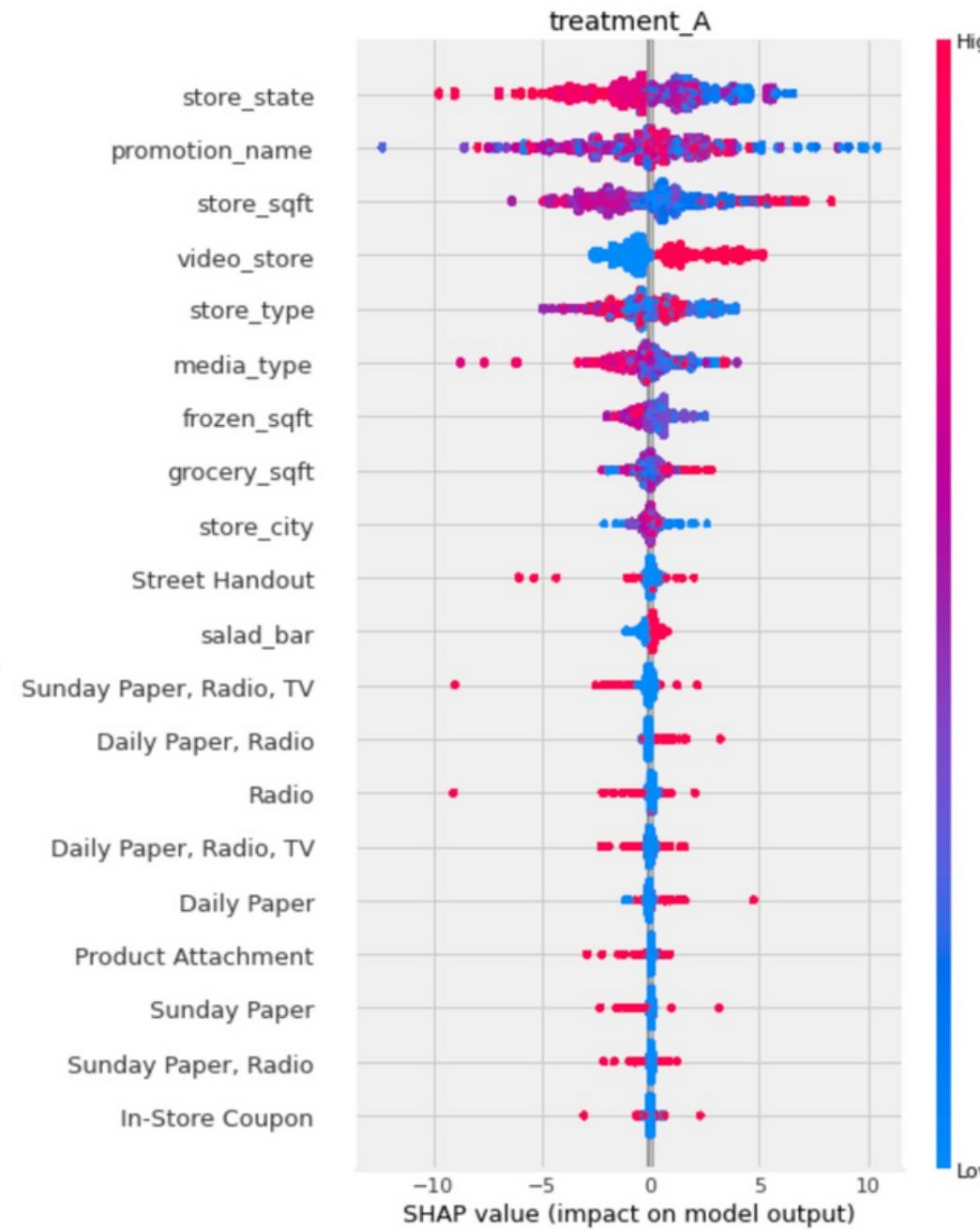


# Data Evaluation

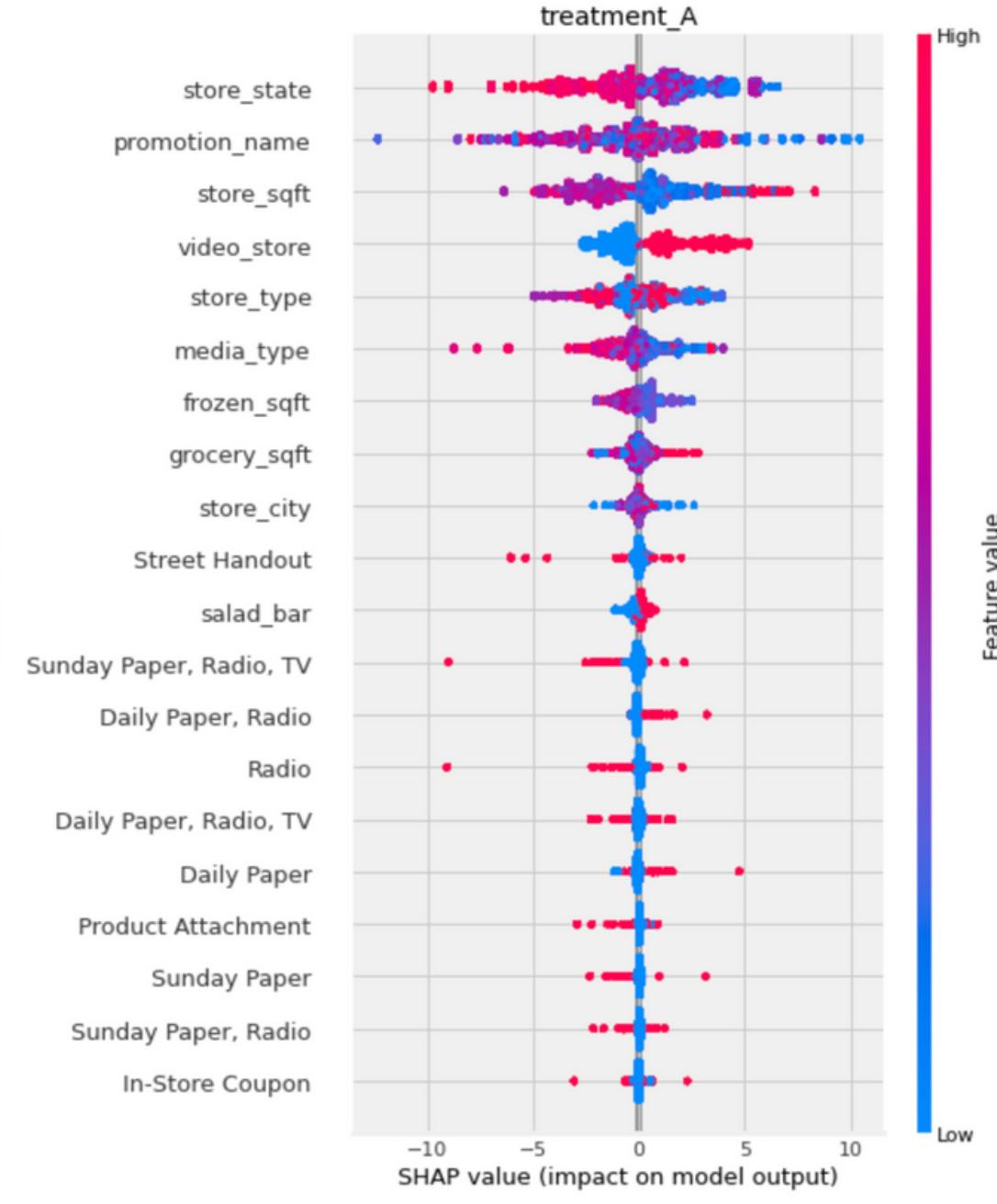
Treatment: Member card  
Target: Cost



Treatment: Media Type  
Target: Cost



Treatment: Gender  
Target: Cost



# Team Details

Name	Git ID	Git URL
Raman, Vakil	Ramanvkl	<a href="https://github.com/Ramanvkl">https://github.com/Ramanvkl</a>
Priyanka, Jahul	priyanka-cj	<a href="https://github.com/priyanka-cj">https://github.com/priyanka-cj</a>
Lucie, Peccoux	luciepcx	<a href="https://github.com/luciepcx">https://github.com/luciepcx</a>
Julie, Chanzy	Juliechz	<a href="https://github.com/Juliechz">https://github.com/Juliechz</a>
Jeongho, Pyo	chongho-pyo	<a href="https://github.com/chongho-pyo">https://github.com/chongho-pyo</a>
Emery, Dittmer	Emery-Dittmer	<a href="https://github.com/Emery-Dittmer">https://github.com/Emery-Dittmer</a>
Bennett, Fahey	bennetffahey	<a href="https://github.com/bennetffahey">https://github.com/bennetffahey</a>