SOCIAL INFLUENCE ON SHOPPING

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ABSTRACT

Understanding how social influence on purchasing affects customers is critical for businesses looking to increase customer engagement, sales, and the shopping experience. This project's main objective is the development of a model that would identify the market segment that will react effectively to attractive approaches to marketing, such as influencer marketing, social media promotions, and specific advertisements. To do this, To predict the customer responsiveness, we used a variety of regression models, including CatBoost, Random Forest, Gradient Boosting, Support Vector, and XGBoost. Using measures like Root MSE, Mean Absolute Percentage Error, R-squared & MSE, we assessed the effectiveness of various regression models. To understand the significance of various indicators in predicting consumer responsiveness, we employed SHAP values. Methods for addressing duplicate data, missing data, and scaling or normalizing numerical columns are also included in the project. The dataset used for this project includes crucial data that helps us to understand the modern young consumers' purchase decisions. The results of this research provide important details about how various customer categories respond to social influence strategies. In conclusion, Organizations must understand which market segments respond best to these techniques. It enables them to properly manage resources and target particular groups with their marketing initiatives, optimizing their return on investment. Our experiment helps organizations to improve their marketing tactics with the aid of this study. For instance, if a certain customer category is shown to be extremely sensitive to influencer marketing, a business might commit more resources to this channel to efficiently target that segment.

INTRODUCTION

The shopping factor effect is complicated has a significant influence on customer behavior and corporate performance. Understanding people through leveraging the power of social influence is essential for both customers who want to make decisions and companies trying to engage with their audience.

Influence plays a big part in buying since it influences consumer preferences, choices, and actions. It discusses how people are impacted by their social networks, cultural standards, and outside forces when they make judgments about what to buy. This explains how social media sites have become into a force in figuring out what people like and how they make judgments about what to buy. A thorough investigation is conducted to learn more about how social media impacts every aspect of shopping behavior. This article offers tips on how shops and brands may take advantage of this impact[1].

By using ml methods, the study examines how networks work in the context of internet business. Their study offers a data-driven perspective on this topic by illuminating the links between relationships and decisions made when purchasing online[2].

In this context, we will explore how different social aspects interact and influence consumers' e-commerce decision-making, illustrating connections and patterns that might not be immediately apparent[3].

It aims for better understanding of the function of social influence within the e-commerce environment is achieved by identifying and evaluating the elements that impact customers' decisions when purchasing online[4].

LITERATURE SURVEY

Table 1- Literature survey

AUTHOR & YEAR	MODEL USED	PARAMETERS	MERITS	DEMERITS/LIMITATION AND DRAWBACKS	FUTURE SCOPE
Authors- Lee, Mathew. KO. **Year**-2006	structural equation modeling, manipulation checks, PLS Analyses.	-Model specification -Component Based Research	-Social Influence moderateness -It suggests that positive information social influence influences the relation between consumers' opinions in Internet shopping & their intention toward Internet shopping.	-we did not alter the messages in web forum. -It only concentrates on the effects of positive information social influences in consumers decision in the Online shopping.	- Explore the negativity unevenness in information social influence.
Authors- Ahmad. **Year**-2013	SEM(Structural Equation Modeling)	-Measurement model analysis, -Uni-dimensionality -Measurement Model, -Parameter Estimation.	-Multivariate Analysis -Handling Missing Data -Model Comparison	- Online sampling is used to analyze how SM affects online buying.	- applying experimental techniques.
Authors- Sareen, M., & Jain, A. **Year-** 2014	UTAUT MODEL UTAU	-Effectiveness, -Social Persuasion, -Usage Intention	-The results shows that the value of convenience as a one of prioritized factors that the customer looks Internet shopping environment given by website.	-comparative analysis	-Explore more over the effect of auction site

Authors- Kim, Y. A., & Srivastava, J. **Year-**2014	Machine learning and predictive modeling	-Product rating matrix -User interaction matrix	-Determining and utilizing and Making use of social influence in Online or Internet shopping	-The main issues it focus involves merging external opinions and recommendations with an individual's intrinsic choices to shape their decision-making process.	-Should maximize social influences for effective customers purchasing behavior in Electronic Commerce
Authors- Kumar, S. S., Ramachandran **Year-**2015	SEM using AMOS v. 20software	Hypothesis Tests	-As the study focuses on actual Internet shopping behavior, the outcome can relevance business looking to enhance their online sales and engagement.	-The survey peers should activate an account in social media like Facebook , Instagram and online shopping websites or apps	-Examine how users' concerns about data privacy and trustworthiness of recommendations impact their willingness to engage in online shopping.
Authors- Pei, Z., & Paswan, A. **Year-**2018	Multivariate regression, C/D framework	Coefficient (Beta Matrix) -P values -T values	-Our surveys are very helpful in benefit of retail cost and boost the ecommerce growth and profit	-The main drawback of this research is maximum product category and the rare returns	-Explore and examine the unexpected study outcomes
Author- Marriot & Williams **Year-**2018	- Structural Equation Modelling	-Model Specification -Measurement Model -Model fit. -Goodness-of-Fit Index	-Understanding the intention of mobile shopping via extended ECT	-There's a risk of common method bias, where responses are influenced by response tendencies rather than genuine perceptions.	-Explore more on issues Trust and risks may have various opinions on users intention towards mobile shopping

Authors: Kuswanto, H., Pratama, **Year:**2019	-SEM PLS -Oriented Segmentation	Cluster Analysis, Marketing Strategy	-The SEM-PLS shows that joy, risk, and social impact significantly influencing the opinion of university students on online shopping	-Small sample size concerns -Lack of Castability	-Future research could focus on trust and security and website quality
Authors- yudantara **Year**-2020	Technolgy Acceptance Model	-validity -Communality - Reliability	-The test results show that peers have a good effect on Behavioral intention and Use of Behavior	-It influence lower than correlation construct perceived usefulness and construct Behavioral intention.	-The online shopping information system provider company should give attention to suggestions, assessments and comments on each product offered
Authors- Tam, J. K., Smith, A. B., **Year**-2020	ECM(Expectation Confirmation Model) and UTAUT2, SEM	-confirmation performance -expectancy - effort expectancy	-Intention of continuation to use the Mobile Shopping Apps	-Data collected through surveys or interviews can be subject to self-response bias and may not provide accurate app usage behaviors.	-Explore how contextual factors, such as location, time of day, and user activity, impact app usage. -Consider how adapting app functionality based on context can enhance user retention.
Authors: Davis, F., Francis Gnanasekar **Year**:2021	structural equation modeling	-Hypothesis tests Descriptive statistics -Confirmatory factor analysis -Dependent variables	-The research proposes that trust in the platform and the product significantly enhance the connection between initial factors and user actions.	-Challenges linked to self-report measures include the potential for common procedural bias, social impression bias	- Examining the proportion of rural customers who use the internet to make purchases as well as their attitudes on the activity could provide further information.

Author- Tarhini **Year-**2021	UTAUT, Structure model, DeLone-McLean Model	-Mean -Standard Deviation -Testing of Hypothesis	- Results support the conceptual model's ability to predict variance in shopping behavioral intention with an accuracy of 70.4%.	-competence to measure temporary changes of given the factors over time, when the familiarity of users increases	- Identify the findings across diverse various technologies
Authors: Zhang, M., & Shi, G. **Year**:2022	Structural Equation (SEM) - (SRMR)	-Marketing Strategy -P -Beta Values	-Identifying the problem of the online rash buying is proposed	-this research does not focus on the alter effects of other variables across influencing path.	-Explore more on consumers' Rash buying behavior
Authors: Amaral, M. A. L., & Djuang, G **Year**:2023	-SEM PLS Version 3.0.	-Hypothesis tests -SE2 and B1	- all latent variables are reliable	-SE2 and B1indicators did not satisfy the criteria of a loading factor greater than 0.6	- Focus on fashion, online shopping experience
Authors- Maduku, D. K., & Thusi, P **Year-**2023	expectation-confirmation model (ECM)	-Confirmation -Perceived Performance -Expectation. -Model Validation.	-Focus on User Experience	-The Lack of Consideration for New Information -Neglect of Affective and Emotional Aspects	-Can concern with cultural orientation

PROBLEM STATEMENT:

It has become more and more important for businesses to improve their marketing Strategies for best customer engagement in the world of online shopping. Finding the group of customers who respond most shopping experiences is an important challenge now a days. These shopping experiences include influencer marketing, social media discounts and campaigns, etc.

OVERALL SUMMARY

Lee, Mathew KO et al. (2006) [1] - Lee and his colleagues explore how customers' Internet buying choices are affected by social media and knowledge. This research, presented at the International Meeting on System Sciences, explores how suggestions and social interactions influence customer behavior when purchasing online.

Akram et al (2013) [2] - The authors look into how social media has affected Pakistani customers' online shopping behaviors during pandemic. The study looks into how social media sites affected how consumers behaved throughout the epidemic.

Sareen, M., & Jain, A. (2014) [3]- In the context of Indian internet purchasing, Sareen and Jain's research explores the effect of social media and customers' expectations of effort. It clarifies how social conditions and perceived effort impact customers' decisions.

Kim, Y. A., & Srivastava, J. (2014) [4]- Kim and Srivastava's study looks at how social media impacts choice-making in the setting of online shopping. The presentation took place during a global internet commerce convention. The study looks into how social factors affect the buying choices of consumers.

Kumar, S. S., et al (2015) [5] - The influencing elements that lead to online buying and their part in this. The study by Kumar, Ramachandra, focuses on how several factors, particularly product suggestions on Facebook, might impact consumers' online buying behavior. It looks on how social media recommendations affect consumers' purchasing decisions.

Pei, at al (2018) [6] - The study by author examines consumers' return habits while making purchases online, looking at both ethical and false return practices. The study looks into the variables that affect return choices.

Marriott, A. B et al (2018) [7] - To identify the factors influencing consumers' uncertainty and confidence in their e-commerce aims. In terms of online sales, the study by Marriott and Williams aims to look at the factors affecting consumers' views of risk and loyalty. It analyzes elements determining consumers' plans to make purchases via the internet.

Kuswant et al (2019) [8] - The research focuses on examining the internet buying habits of students in Indonesia. They refer to this as a study of students. The study seeks to determine the variables that affect students choices and behavior while they purchase online using an incomplete least square strategy.

Yudantara, et al (2020) [9] - The author examines the variables that affect how consumers act in connection to online shopping software. This study seeks to identify the critical factors that affect how people interact with shopping systems.

Tam, et al (2020) [10] - The authors' study seeks to define the variables influencing people's ongoing desire to use mobile applications, it is important for the mobile trade. The study looks into the factors that affect the initial and ongoing use of apps.

Davis et al (2021) [11]- The study by authors analyses how features of goods and trust have modifying roles in buying behavior in India. The study looks into how these elements impact customer requests and decisions.

Tarhini, et al(2021) [12] - The authors' research tries to pinpoint and comprehend the variables affecting the popularity of online shopping. Every aspect that affects customers' decisions to make buy online is investigated by the research.

M., & Shi, G.et al (2022) [13]- Authors looks at how online shoppers' fast choices are made, with a focus on how social presence affects such decisions. The study looks at the part that relationships play in impulsive purchasing.

Amaral et al (2023) [14] - The study by the authors examines how social influence, shopping habits, rash decisions, and purchase intention affect others, with a focus on used goods. The study explains the variables affecting customers' decisions to buy used goods.

Maduku, dk et al. (2023) [15]- The study explores the elements that affect consumer choices to keep using mobile shopping services and gives new data on understanding consumers' goals to continue shopping via mobile devices, especially in the conditions of South Africa.

OBJECTIVE

- Identifying which type of segment is most responsive to engaging shopping experiences, such as influencer marketing, social media discounts and campaigns, etc.
- Determine the specific demographic or segment within the target audience that exhibits the highest level of responsiveness to various shopping experiences, including influencer marketing, social media discounts, and campaigns.
- Determining which segment is most receptive, to captivating shopping experiences, such, as influencer marketing, social media promotions and targeted campaigns.

PROPOSED METHODOLOGY & ARCHITECTURE

In this project, the goal is to identify the most responsive shopping segment based on survey responses, aligning with specific business objectives such as higher engagement and conversion rates.

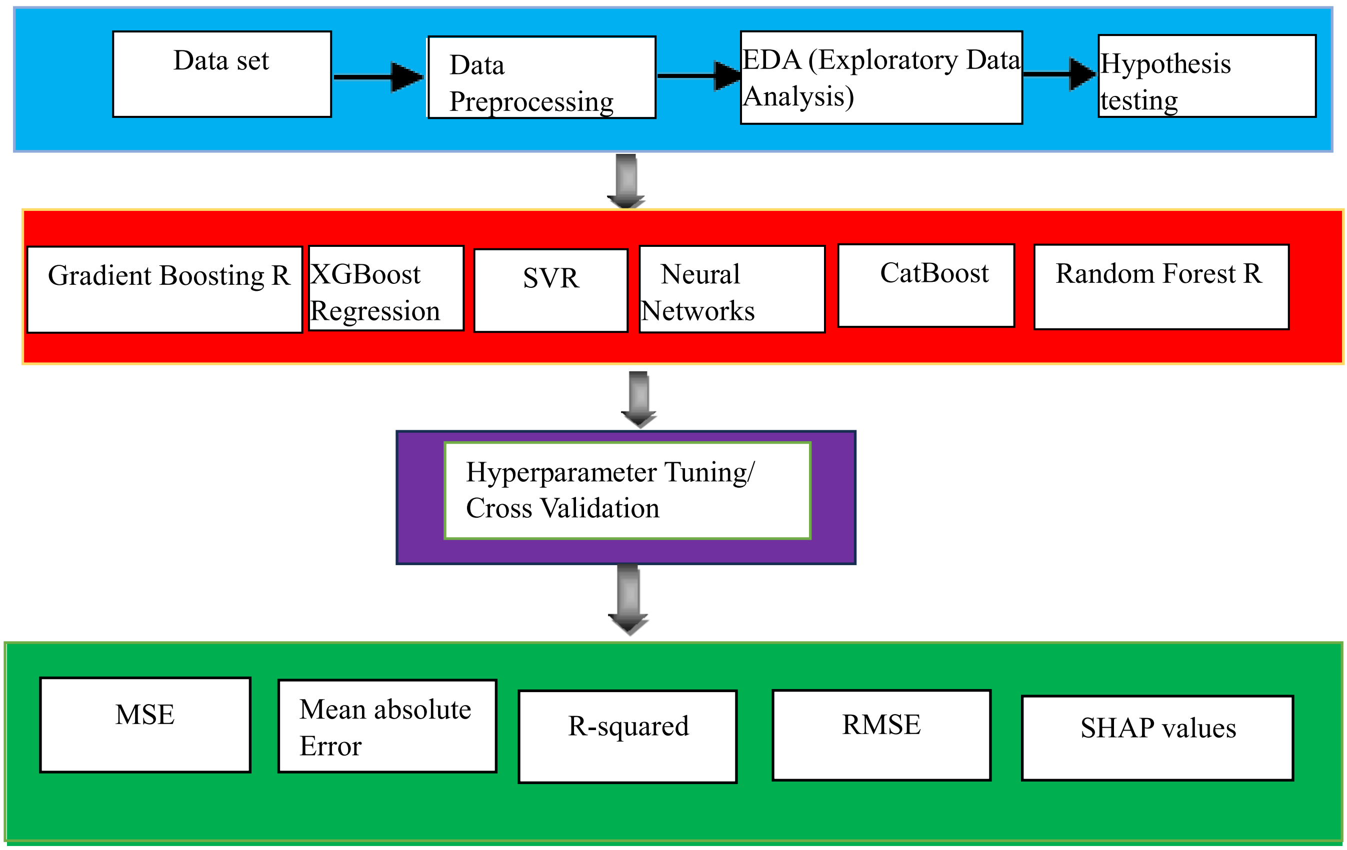

FIG 1 –PROPOSED ARCHITECTURE

1. Data Collection and Preprocessing:

We must obtain the dataset by survey process conducted by various trusted sources and handle missing values in the data then we normalize the data or scale the numerical features. To evaluate the model, divide the dataset into training and test sets.

2. Exploratory Data Analysis (EDA):

To learn more about each consumer category, do EDA. Analyze exploratory data to learn more about the dataset.

3. Hypothesis Testing/Statistical Analysis:

To find out if there are significant changes in the replies depending on the segment type or other parameters, use statistical tests (such the chi-squared test).

4.Model Selection:

We must use various regression algorithms. Some regression algorithms are CatBoost, Random Forest , Gradient Boosting (e.g., XGBoost) SV regression & Neural Networks.

5. Hyperparameter Tuning:

Using methods like grid search or random search, we optimize the hyperparameters of the selected model(s). To make sure the model is generalizable, use cross-validation.

6. Training the model:

On the training dataset, run the chosen model or models.

7. Evaluation Metrics:

We choose evaluation metrics based on the problem (e.g., MSE, RMSE, R- Squared, MAPE).

8. Model Interpretation:

Based on the model selected, consider interpreting the results. Techniques like feature importance analysis, SHAP values, can help understand what features contribute most to a segment's responsiveness.

Algorithms used:

1. **Random Forest Regression**:

An approach to collective learning is Random Forest Regression. During training, several decision trees are constructed. The average (for regression) or mode (for classification) of each tree's contribution to the final prediction is used. It is renowned for its capacity in handling different types of data and reliability against overfitting.

2. **Support Vector Regression (SVR)**:

SVR is a regression method that extends Support Vector Machines to issues related to regression. It locates a hyperplane that minimizes the error margin and most accurately matches the data. SVR works well at identifying complex patterns in data and is especially helpful when working with high-dimensional data.

3. **Gradient Boosting Regression**:

Regression is an ensemble method that repeatedly constructs several decision trees. Each tree fixes the errors of the before ones, creating a model that is precise. This is renowned for its flexibility and predictive capacity and can handle both regression and classification jobs.

4. **XGBoost Regression**:

A advanced use of gradient boosting is called XGBoost (Extreme Gradient Boosting).It is appropriate for huge datasets because of its great efficiency and flexibility. To avoid overfitting, XGBoost employs normalized trees and performs well on regression problems.

5. **CatBoost Regression**:

It is a is a gradient boosting method designed specifically to deal with categorical information. It uses techniques like ordered boosting and automatically encodes categorical data. CatBoost is known for its performance, speed, and applicability to a variety of problems related to regression.

6. **Neural Networks Regression**:

Artificial neural networks are used in neural networks regression to represent complicated connections in data. It is made up of layers of linked neurons that can recognize patterns in input data. Although very adaptable and capable of collecting complex patterns, neural networks may need careful tuning and considerable data.

EXPERIMENTAL WORK

- ✓ The process undertaken this project are as follows:
- ✓ Set Up Infrastructure.
- ✓ New Python Notebook in Colab.
- ✓ Incorporate required libraries Sklearn, Numpy, Pandas, Matplotlib and Seaborn ,shap……etc.
- ✓ Dataset Preparation.
- ✓ Process the data.
- ✓ Exploratory Data Analysis.
- ✓ Normalize the data using Sklearn'sMinMax Function.
- ✓ Split the data.
- ✓ Hypothesis Testing.
- ✓ Perform various ML models.
- ✓ Hyperparameters tuning & cross-validation performed.
- ✓ Develop Solution Model & improve using GridsearchCV.
- ✓ Ensemble top three performing models
- ✓ Now for the best model calculate SHap values.
- ✓ Mean absolute SHAP values.

DATASET

- ➢ The dataset consists of 1450 rows & 6 columns
- ➢ This data set provides an examination of the shopping behaviors of customers & how their choices are influenced by social media. By analyzing the survey responses related to this topic we can gain an understanding of how these generations interests, beliefs and desires shape their decisions. Understanding the aspects that affect the purchase decisions of the current generation is made easier with the help of this dataset.

- ➢ **columns in the dataset are:**

- **Question:** This dataset contains questions, from our survey that focus on shopping habits trust in retailers and the influence of friends and family during the purchase process.
- **Segment Type:** The "Segment Type" refers to whether an individual was part of a group targeted for a question.
- **Segment Description:** It provides details about the population surveyed for each question listed in the "Question" section.
- **Answer:** here you'll find all the responses given by each person for each question on our survey, including options like Yes, No or Unsure.
- **Count:** It contains values indicating how many respondents chose each answer option for its question. For example, it may state that 10 respondents answered No.
- **Percentage:** It presents percentage values that represent the count data found in the "Count" column. It includes all answers from any specified segments, across all questions asked in our survey platform. For instance, it might state that 30% responded No.

Here are some operations

TABLE 2 – MEAN OPERATIONS

	MEAN	SD	MIN	25%	50%	75%	MAX
COUNT	**35**	**95**	**0**	**0**	**1**	**20**	**947**
PERCENTAGE	**0.2**	**0.27**	**0**	**0**	**0.06**	**0.32**	**1**

PERFORMANCE PARAMETERS

Regression Metrics:

- **Mean absolute error :**

  It is the avg absolute difference (variance) b/w predicted & actual values.

  MAE = [Σ |Original – Predicted|] /n
- **Mean squared error**:

  It is the avg squared difference b/w predicted & actual values.

  MSE = [Σ (Original– Predicted) ^2] / n
- **Root mean squared error:**

  It is the root of MSE.

  RMSE = (MSE)^(1/2)
- **R-squared:**

  It is the proportion of the variance in the dependent variable

  R2 = 1- z

  z = y1/y2

  y1= Σ (Yi - Ŷi) ^2

  y2 = Σ (Yi - Ȳ) ^2

Dataset link: [DAFE DATASET - Google Sheets]

<u>CODE:</u>

https://github.com/chaithra6667/DAFE

RESULTS

Visualize the distribution of numerical column

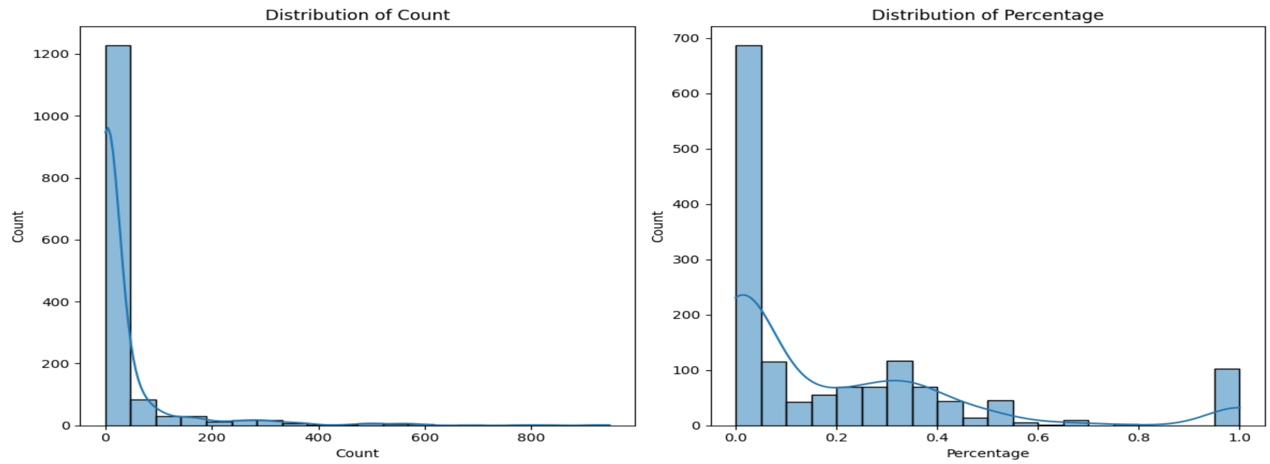

FIG 2- distribution of numerical columns

Visualize categorical variables

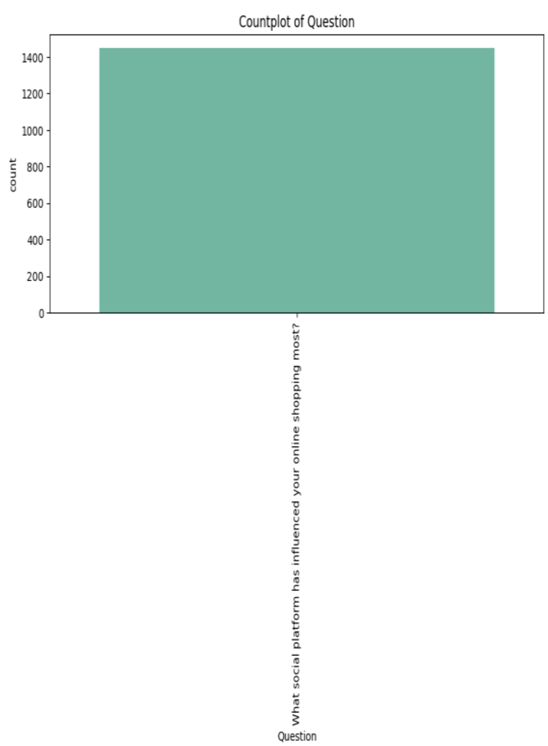

FIG-3 Question vs Count

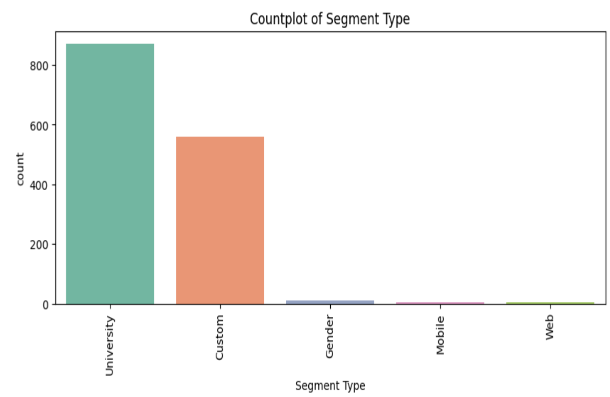

FIG 4 – Segment Type Vs count

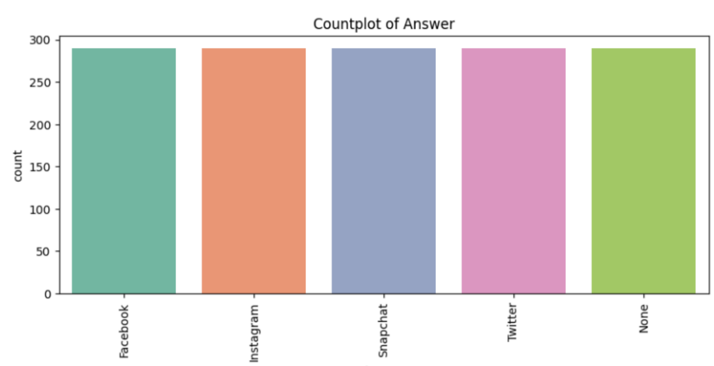

FIG 5 – Answer Vs Count

In the above graphs count of each value in column has been drawn

Correlation matrix

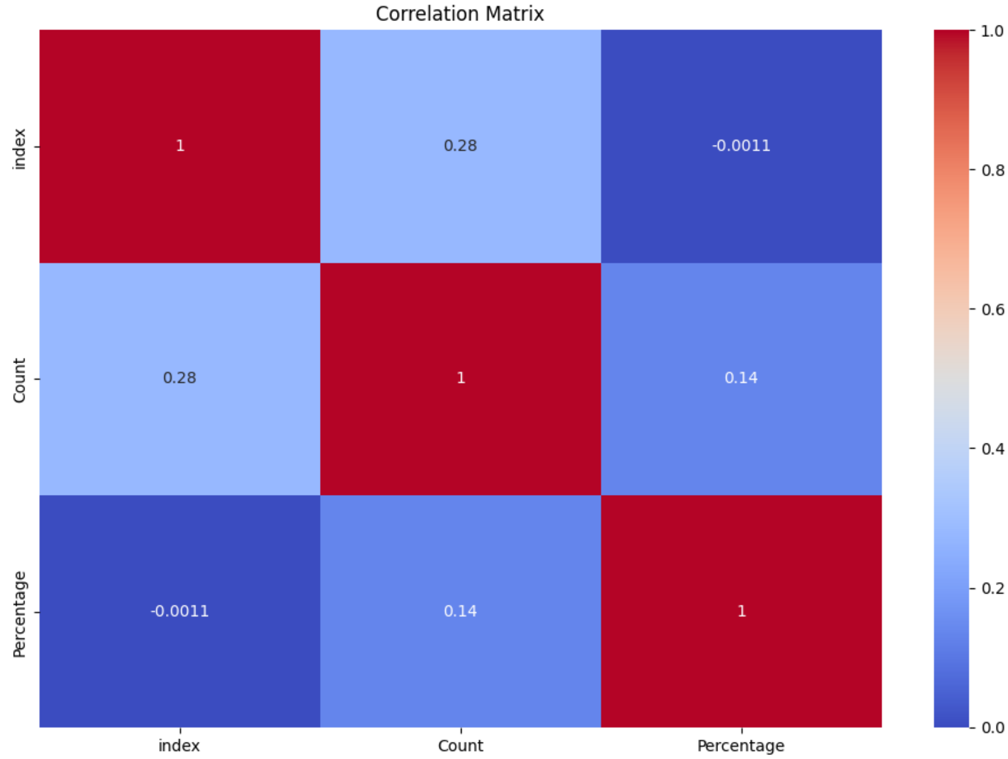

FIG – 6 Correlation matrix

Hypotheses Test

Null hypothesis:

Based on the social platform, there are no significant variations in response rates among sectors(H0)

Alternative hypothesis:

According to the social platform, there is a significant variation in response rates between sectors (H1).

Chi-Squared Statistic: 0.0

P-value: 1.0

Accept: H0

Best Hyperparameters

Random Forest R: {'maximum_depth': None, 'minimum_samp_leaf': 1, 'minimum_samp_split': 2, 'n_estim': 200}

Gradient Boosting: {'learning_rate': 0.2, 'maximum_depth': 4, 'minimum_samp_leaf': 1, 'min_samp_split': 4, 'n_estim': 300}

Support Vector: {'C': 10, 'epsilon': 0.01, 'kernel': 'rbf'}

XGBoost: {'learning_rate': 0.2, 'maximum_depth': 5, 'minimum_child_weight': 2, 'n_estima: 300}

Neural Network: {'activation': 'tanh', 'alpha': 0.01, 'hidden_layer_sizes': (200, 100, 50)}

CatBoost: {'depth': 6, 'iterations': 300, 'learning_rate': 0.2}

Table-3 Evaluation Metrics

MODELS	MSE	MAE	R-Squared	RMSE
CB	**0.00068**	**0.01099**	**0.91065**	**0.02618**
XGB	0.00124	0.01418	0.08240	0.03674
RFR	0.00118	0.01281	0.82404	0.03442
GB	0.00173	0.01759	0.77396	0.04164
SVM	0.00631	0.06552	0.17685	0.07946
NNR	0.01655	0.10112	-1.15723	0.12865

"CatBoost" holds the top position in maintaining a high level of performance. Because it has the least MSE. As a result, CatBoost Regression fits the model very well, with an MSE of 0.00068

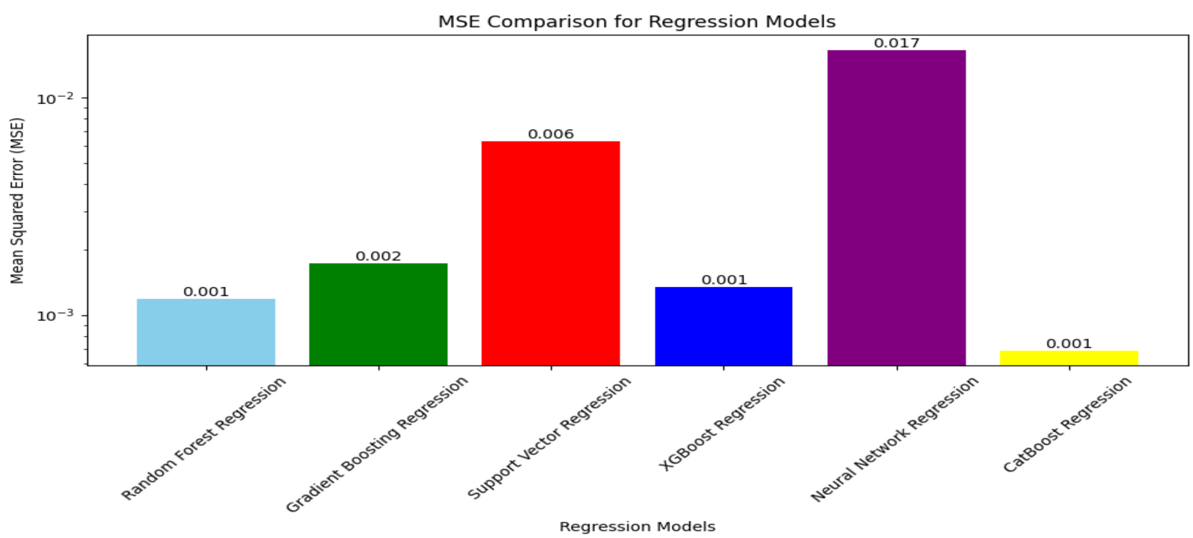

FIG - 7 MSE

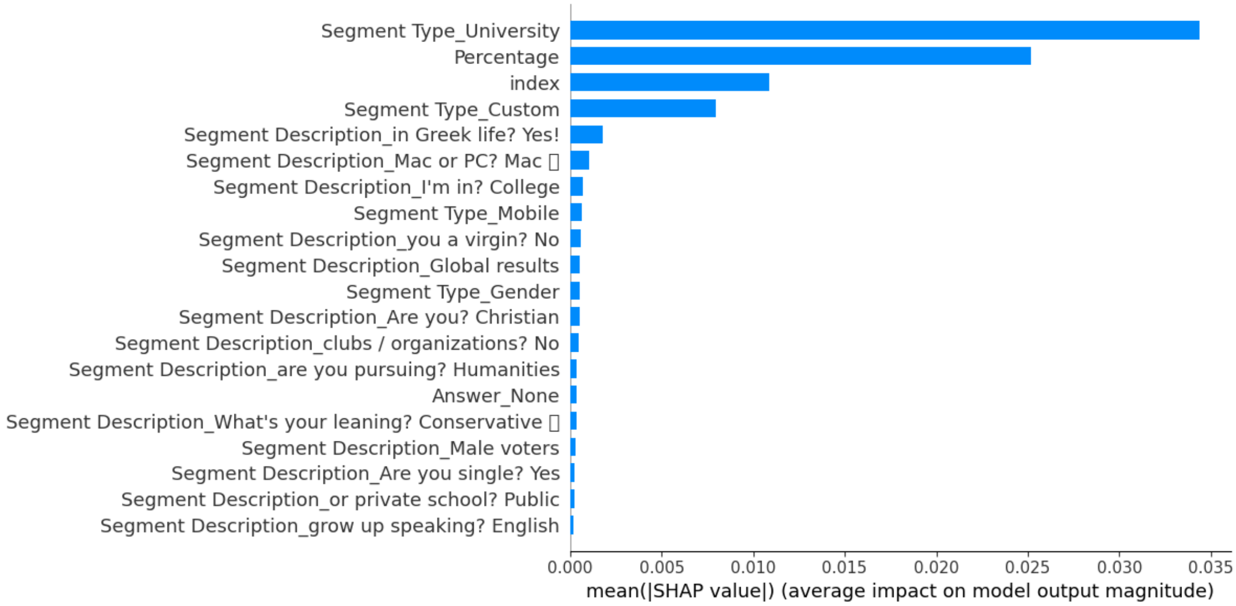

FIG 8 - Mean SHAP values

In the above graph segment university has the highest mean shap value

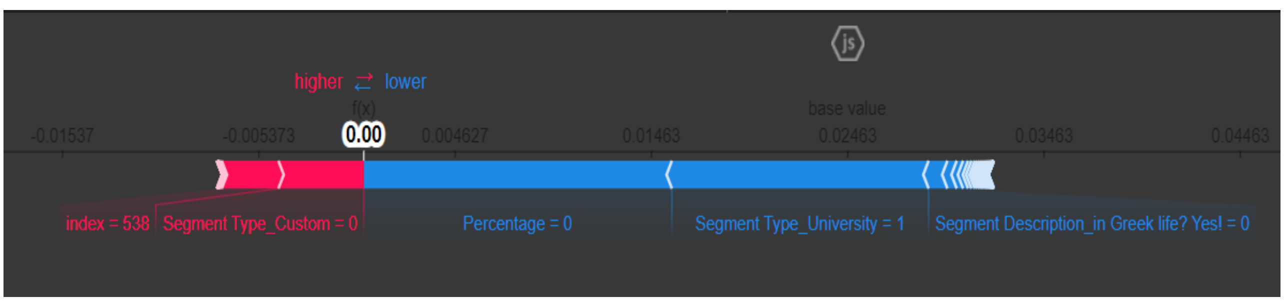

FIG 9 – Most responsive segment

We obtained the highest shap value for the segment type University, and the Mean Absolute SHAP Value is 0.03437, indicating that the segment type university is the most responsive shopping segment.

CONCLUSION

In this analysis, we determined which group of customers are more responsive to purchasing experiences, such as influencer marketing, social media sales, and campaigns. To learn more about customer response, we used data preprocessing, machine learning models, and SHAP (SHapley Additive exPlanations) interpretability approaches. This helped us in determining the variables that significantly influenced consumer behavior. Through these methods, we learned which customer categories responded better to particular marketing strategies, allowing us to target these segments more successfully.

FUTURE SCOPE:

The future scope of the social influence on shopping project for further exploration and development. The model performance can be increased by adding more features. Better insights may be obtained by investigating more client attributes or by developing new products. Investigating more advanced neural networks or machine learning models may be able to reveal complex links in the data. Marketing tactics may benefit from incorporating time-series data to examine how client responsiveness changes over time. Conducting experiments to confirm the model predictions and improve marketing strategies in real-time. Applying unsupervised learning techniques to identify new customer segments and adjusting marketing strategies accordingly.

LIMITATIONS:

- The dataset's quality is very important. Results may be affected by inaccurate or missing data.
- The models assume that past data will predict future behavior. These assumptions may not always hold in a rapidly changing market.
- While SHAP values provide insights, they might not fully address the "why" behind certain things.
- The dataset used may have an impact on the models created in this investigation. It may not always be easy to generalize results to other markets or sectors.
- various factors affect customer behavior, which is subject to change throughout time. Model retraining and ongoing monitoring are crucial.

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