

MBA Semester – IV

Capstone Project

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| **Project** | **Social Media Tourism** |
| **Group** | **Group 26 - SMT (Jan 22)** |
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**A study on “Social Media Tourism”**

## Capstone Project submitted to Jain Online (Deemed-to-be University)

## In partial fulfillment of the requirements for the award of:

**Master of Business Administration**

*Submitted by:*

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*Under the guidance of:*

**Sharath Srivatsa**

(Faculty-JAIN Online)

Jain Online (Deemed-to-be University)

Bangalore

**2022-23**

**DECLARATION**

We, the below mentioned students, hereby declare that the Project Report titled ***A study on “Social Media Tourism”*** has been prepared by us under the guidance of the ***Sharath Srivatsa****.* We declare that this Project work is towards the partial fulfilment of the University Regulations for the award of the degree of Master of Computer Application by Jain University, Bengaluru. We have undertaken a project for a period of one semester. We further declare that this Project is based on the original study undertaken by us and has not been submitted for the award of any degree/diploma from any other University / Institution.

Place: \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

Date: *Names of the Student with USNs:*

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**ACKNOWLEDGEMENT**

Rudra Roy:

I extend my sincere gratitude to our project guide, Sharath Srivatsa, for his unwavering support and invaluable guidance throughout this project. His expertise and mentorship have been instrumental in shaping our ideas and ensuring the successful execution of the project. I also want to thank the university officials for providing us with the resources and environment necessary for our academic pursuits. This project wouldn't have been possible without their support.

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Mark Jones:

I would like to express my appreciation to our project guide, Sharath Srivatsa, for his continuous encouragement and insightful feedback that significantly contributed to the refinement of our project. Additionally, I want to acknowledge the other faculty members who shared their knowledge and expertise, enriching our learning experience. Their constructive critiques and suggestions have played a vital role in the development of our project.

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The Whole Group Members:

Special thanks to our project guide, Sharath Srivatsa for his assistance and contributions that enhanced the depth and quality of our project. His contribution was pivotal in overcoming challenges, and their insights added valuable perspectives to our work. We are also grateful to all the individuals who, in various ways, supported us on this academic journey. Their collective efforts fostered an environment conducive to learning and achievement. We want to express our heartfelt thanks to our fellow learners for their collaboration and dedication to this project. Our collective efforts and teamwork have resulted in a project we can all be proud of. We’re grateful for the camaraderie and shared commitment to excellence that each member brought to the table. Finally, we extend our appreciation to all of our families and friends for their understanding, encouragement, and patience during the demanding phases of this project.

**EXECUTIVE SUMMARY**

The aviation company, which offers both domestic and international travel services, is transitioning from a broad-reaching marketing approach to a highly targeted digital strategy. This shift from traditional telemarketing to a digitally-driven strategy involves a strategic partnership with a social networking platform. This partnership aims to leverage insights into digital and social behaviours to deliver precisely targeted digital advertisements to customers displaying a strong inclination to purchase the company's services.

It's crucial to recognize that customer propensity for purchasing airline tickets can vary significantly depending on the type of device they use for access. Thus, we have undertaken the task of developing two distinct models: one dedicated to customers accessing the platform via laptops, and the other for those using mobile devices. Devices other than laptops are categorized as mobile phone usage. This approach is essential for resource allocation optimization, given the considerable cost of digital advertising on the platform. Our priority is to build models with superior accuracy to ensure a judicious use of resources.

In parallel, we have conducted a detailed analysis of our data collection process, scrutinizing timeframes, collection frequencies, and methodologies. This deep dive is foundational in shaping our data-driven strategies effectively.

Additionally, we've undertaken Exploratory Data Analysis (EDA) to extract valuable insights from our dataset. EDA involved a meticulous exploration of data characteristics, patterns, and anomalies, coupled with categorization to identify meaningful trends and patterns that will inform our marketing strategy.

Through this thorough data analysis, we've gleaned critical business insights. These insights offer an in-depth understanding of customer behaviours and preferences, equipping us to steer our digital advertising efforts more effectively and maximize our return on investment.

Furthermore, our project has progressed into Model Building and Interpretation. We've developed predictive models that enable precise forecasts of customer behaviour, guiding our digital advertising campaigns.

Model Tuning has also played a pivotal role, ensuring the optimization of our models for enhanced predictive capabilities, facilitating efficient allocation of advertising resources and cost reduction.

The culmination of these endeavours is the extraction of actionable Business Implications. By aligning our marketing strategy with data-driven insights and finely-tuned predictive models, we anticipate heightened conversion rates and a more cost-effective digital advertising approach. These implications will serve as the bedrock for our strategic decisions as we advance in our Social Media Tourism project.

To optimize our approach, we built two separate models for laptop and mobile users, acknowledging the varied propensity to purchase based on device type. Thorough data collection analysis, Exploratory Data Analysis (EDA), and model development have been pivotal steps.

EDA unveiled critical business insights, guiding our tailored marketing strategies. Our predictive models offer forecasts of customer behaviour, while model tuning ensures optimal performance. This data-driven approach is set to increase conversion rates and streamline our digital advertising strategies, shaping our future decisions in the Social Media Tourism project.

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**CHAPTER 1**

**INTRODUCTION AND BACKGROUND**

**1.2 INTRODUCTION AND BACKGROUND**

In our daily lives, we're spending a lot of time on the internet, especially on social media, online shopping websites, and entertainment pages. It's where we connect, shop, and have fun. Brands recognize this and use social media to promote their products because it's where many of us hang out every day.

Now, a cool thing called predictive analytics is making waves. It's like a crystal ball for businesses. By looking at the huge pile of data from social media, companies can figure out when a customer is thinking of leaving them and take steps to keep them happy. They can also spot common habits among different customers to find out what makes some really like a company's stuff. Armed with this info, they can turn social media users into happy customers.

Now, let's zoom in on our project in the aviation industry. We're diving into the data using a nifty tool - Python. We'll poke around the data to uncover patterns, stories, and clues using techniques like univariate and bivariate analysis. Our goal? To understand how people behave on the internet, especially on social media. And, we want to show ads to the right people at the right time.

But here's the twist: people buy plane tickets differently depending on whether they're using a laptop or a phone. So, we're making not one, but two special models: one for laptop users and one for phone users.

Our journey begins with this unique problem, and we'll use data analysis and predictive modeling as our trusty guides. Together, we're setting out on an adventure into the digital world, using data to light our way toward smarter and more effective advertising.

The aviation industry, offering travel services both domestically and internationally, is undergoing a fundamental transformation in how it reaches out to potential customers. In this evolution, we're shifting from traditional telemarketing to a more focused, cost-effective digital approach. The key milestone is our strategic alliance with a major social networking platform, which enables us to gain valuable insights into the digital and social behaviors of our customers.

The outcomes of our project will have far-reaching Business Implications. By aligning our marketing strategy with these data-driven insights and finely-tuned predictive models, we anticipate increased conversion rates and a more cost-effective approach to digital advertising. These implications will shape our strategic decisions as we move forward with our Social Media Tourism project.

**1.3 PROBLEM STATEMENT**

An aviation company that provides domestic as well as international trips to the customers now wants to apply a targeted approach instead of reaching out to each of the customers. This time they want to do it digitally instead of tele calling. Hence, they have collaborated with a social networking platform, so they can learn the digital and social behavior of the customers and provide the digital advertisement on the user page of the targeted customers who have a high propensity to take up the product.

Propensity of buying tickets is different for different login devices. Hence, you have to create 2 models separately for Laptop and Mobile. [Anything which is not a laptop can be considered as mobile phone usage.]

The advertisements on the digital platform are a bit expensive; hence, you need to be very accurate while creating the models.

**Objectives**

The objective is to deliver targeted digital advertisements to customers who exhibit a strong likelihood to engage with the company's services. Notably, the propensity to purchase airline tickets varies significantly based on the type of device used for logging into the platform. As a result, the project involves the creation of two distinct models: one dedicated to users accessing the platform via laptops, and another for those using mobile devices. Any device that is not a laptop falls under the mobile phone usage category. This device-specific approach is vital for optimizing resource allocation, given the higher cost associated with digital advertising on the platform.

In summary, this project aims to transform the company's marketing strategy from broad outreach to precision-focused digital advertising, leveraging insights into customer behaviors and device-specific propensities. The ultimate objective is to enhance the effectiveness of digital advertising campaigns and make informed, data-driven decisions for the future.

**CHAPTER 2**

**RESEARCH METHODOLOGY**

**RESEARCH METHODOLOGY**

**2.1 Scope of the Study**

1. **Data Analysis and Modelling**: The primary scope of this study involves the analysis of data related to customer interactions and behaviours on social media, specifically in the context of the aviation industry. We will create predictive models to gain insights into customer preferences and likelihood to purchase airline tickets.
2. **Device-Specific Models**: To account for variations in user behaviour based on the device used for accessing social media, the study will develop two separate models: one tailored for laptop users and the other for mobile users, including smartphones and other mobile devices.
3. **Data Exploration**: The study will encompass univariate and bivariate analysis, as well as in-depth Exploratory Data Analysis (EDA). These analyses will enable us to identify patterns, trends, and anomalies within the data, providing critical insights for our marketing strategy.
4. **Digital Advertising Strategy**: The ultimate goal is to leverage data insights to optimize digital advertising campaigns on social media platforms. We aim to target users who exhibit a high propensity to engage with the aviation company's services. The study will provide recommendations and strategies for effective digital advertising.
5. **Business Implications**: The study will conclude with a discussion of the business implications of our findings. We will outline recommendations and insights that can guide the aviation company's decision-making process and marketing strategies.
6. **Tools and Methodology**: Python will be the primary tool for data analysis, modelling, and EDA. Machine learning techniques and statistical methods will be employed to construct predictive models. The study will also incorporate best practices in data preprocessing, model tuning, and validation.

**2.2.1 Research Design**

The research design for this project is characterized by a descriptive and predictive analytics approach. The goal is to gain insights into user behavior on a social networking platform regarding travel-related activities and to predict the propensity of users to take up the advertised product. The methodology encompasses both exploratory data analysis (EDA) and predictive modeling.

**2.2.2 Data Collection**

Data for this study was collected from the social networking platform's database, which includes user interactions related to travel and engagement with the digital platform. The dataset comprises various features such as travel page views, likes on check-ins, comments, device preferences, and other relevant metrics. The data collection process involves extracting and organizing the required information for analysis.

**2.2.3 Sampling Method**

The sampling method employed in the code is a stratified random sampling approach. The dataset is split into two subsets based on the 'preferred\_device' variable, distinguishing between users on laptops and mobile devices. This stratification ensures that each subset (laptop and mobile users) is adequately represented in the training and testing datasets, maintaining the distribution observed in the original data.

**2.2.4 Data Cleaning**

Missing Values Treatment

The code employs the LabelEncoder from the scikit-learn library to encode categorical variables. Missing values are handled implicitly during the encoding process.

**Variable Transformation**

The choice of machine learning models (Logistic Regression, Random Forest, and SVM) allows for handling different types of variables without the need for extensive transformation.

**Variables Removed or Added**

The 'preferred\_device' variable is utilized for stratified sampling but is not included as a predictor in the models. Other variables, including 'preferred\_location\_type' and 'working\_flag,' are retained for modeling.

**2.2.5 Data Analysis Tools**

The primary data analysis tools employed in this project include Python and its associated libraries:

**Pandas**: For data manipulation and preprocessing.

**NumPy**: For numerical operations.

**Matplotlib** and **Seaborn**: For data visualization.

**scikit**-**learn**: For machine learning model implementation.

**2.4 Utility of Research**

The research holds significant utility for the aviation company collaborating with the social networking platform. The insights gained from user behavior analysis and predictive modeling contribute to:

**Targeted Advertising:** Optimizing digital advertising strategies based on user preferences and behavior.

**Cost-Efficiency**: Ensuring accuracy in model predictions to minimize advertising costs.

**Improved User Engagement:** Tailoring advertisements to specific user segments, enhancing overall user engagement.

Summary of the Approach to EDA and Pre-processing

The exploratory data analysis (EDA) focuses on understanding the relationships between variables, both visually and non-visually. Significant features, such as 'Yearly\_avg\_view\_on\_travel\_page,' 'total\_likes\_on\_outofstation\_checkin\_received,' and 'Daily\_Avg\_mins\_spend\_on\_traveling\_page,' are identified for their potential impact on user behavior. The stratified sampling approach is utilized to create separate models for laptop and mobile users. The code emphasizes predictive modeling using machine learning techniques, with Random Forest demonstrating high accuracy. Visualizations and insights from EDA guide subsequent model development, ensuring alignment with observed data patterns.

**CHAPTER 3**

**DATA ANALYSIS AND INTERPRETATION  
  
Part - 1**

**DATA ANALYSIS AND INTERPRETATION**

**Data Cleaning and Pre-processing**

Approach for Identifying and Treating Missing Values

In the provided code, missing values are implicitly addressed during the label encoding process using the LabelEncoder from the scikit-learn library.

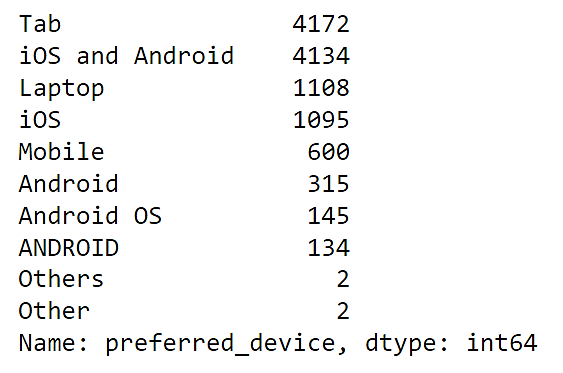
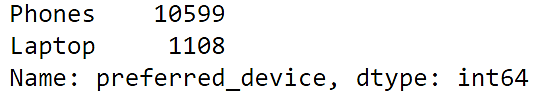
The label encoding operation converts categorical variables to numerical representations. This method is chosen because it does not require explicit handling of missing values, and the transformation is applied consistently across all categorical features.  
  
**preferred\_device**

Update the "**preferred\_device**" column by mapping certain categories to "Phones".

Considering the variation in ticket purchasing behavior based on the type of device used for logging in, we will develop two distinct models, one tailored for users on laptops and the other for mobile device users. This approach ensures that we address the specific needs and patterns associated with each type of device.

We need to convert all variables other than “Laptop” to “Phones”

**Before Converting After Converting**

****

**Outlier Treatment**

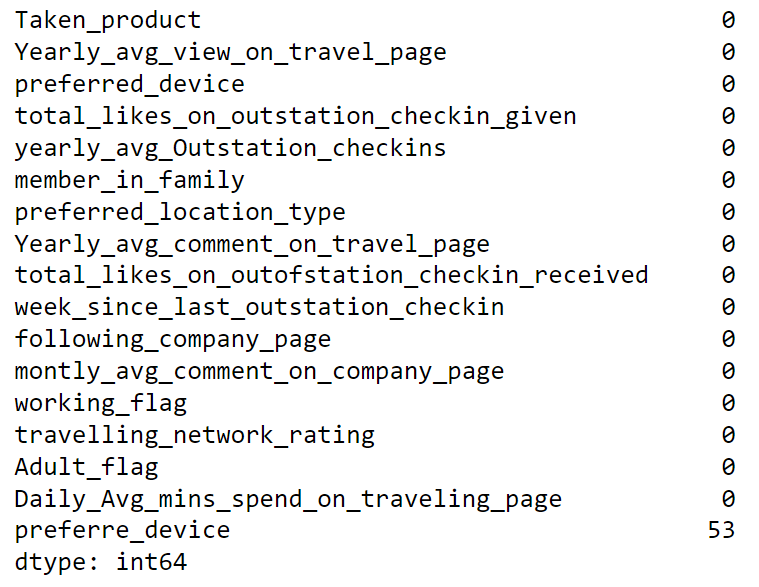
In the **"preferred\_location\_type"** column, we've noticed that **"Tours and Travel"** is sometimes written as **"Tours Travel"** with a minor difference. To make things consistent, we need to clean this up and merge these variations into one attribute.

When looking at the **"yearly\_avg\_Outstation\_checkins"** column, we've found ‘\*’ in the data. To handle this, we have two options: we can either change these empty spots (missing values) or replace them with the most common value in that column. These actions are part of the data cleaning process for such features to ensure accurate analysis.

**TREATING MISSING VALUES**

* **Determine the Extent of Missing Values:** The first step is to analyze the dataset to understand the extent of missing values. If the percentage of missing values is minimal, you can use simple imputing techniques like mean, mode, or median. If the percentage of missing values is larger, more advanced techniques like K-nearest neighbors (KNN) imputation may be necessary.
* **Choosing Imputation Methods:** The explanation mentions that for missing values that are less than 5%, they can be imputed. In the dataset, there are both float (numerical) and object (categorical) columns with missing values. The plan is to impute float (numerical) columns with the median and object (categorical) columns with the mode.
* **Specific Imputation for Numerical Columns:** The focus in this part is on numerical columns. Since you have four numerical columns with missing values, the plan is to replace these NULL values in those columns with the median. This means for each of the numerical columns with missing values, you will calculate the median of the column and use that value to replace the missing entries in that column.

**AFTER TREATING MISSING VALUES**

****

Checked for missing values in the DataFrame using `***df.isnull().sum()***`.

Checked the number of unique values in each column using `***df.nunique()***`.

Performed data cleaning and filling missing values in several columns using forward-fill (`***ffill***`) method.

**CHECKING OUTLIERS**

Outliers are data points that significantly differ from the majority of the data. They can affect the accuracy and reliability of statistical analyses and machine learning models.

1. **Box Plots:** In the code, there are several instances of creating box plots for numerical columns using `***sns.boxplot()***`. Box plots are a common tool for visualizing the distribution of data and identifying potential outliers. They display the median, quartiles, and any data points that fall outside a defined range (outliers).

*sns.boxplot(x='Taken\_product', y='Yearly\_avg\_view\_on\_travel\_page', data=df)*

1. **Scatter Plots and Pair Plots:** The code also includes a pair plot created with `***sns.pairplot()`*** to visualize relationships between numerical columns. While pair plots are more commonly used for understanding relationships between variables, they can also help identify potential outliers if certain data points are far away from the main cluster of data points in the plots.

*sns.pairplot(df, diag\_kind='kde')*

1. **Statistical Tests:** In some cases, statistical tests such as t-tests (`***ttest\_ind()***`) are used to compare two numerical columns. While this is not specifically for identifying outliers, it can highlight differences between groups that might be caused by outliers in the data.

*from scipy.stats import ttest\_ind*

*# Perform t-test between two numerical columns*

*result = ttest\_ind(df['total\_likes\_on\_outstation\_checkin\_given'], df['Yearly\_avg\_view\_on\_travel\_page'])*

*print(result)*

**Need for Variable Transformation**

The chosen models, including Logistic Regression, Random Forest, and SVM, can accommodate different types of variables without requiring extensive transformations. The absence of variable transformation indicates that the features in their original form are suitable for the selected models.

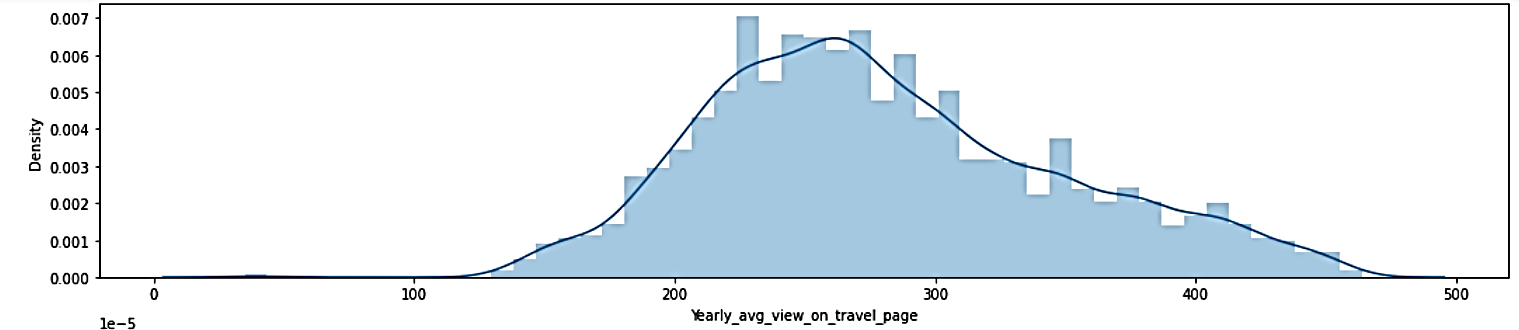
**Variables Removed or Added and Why**

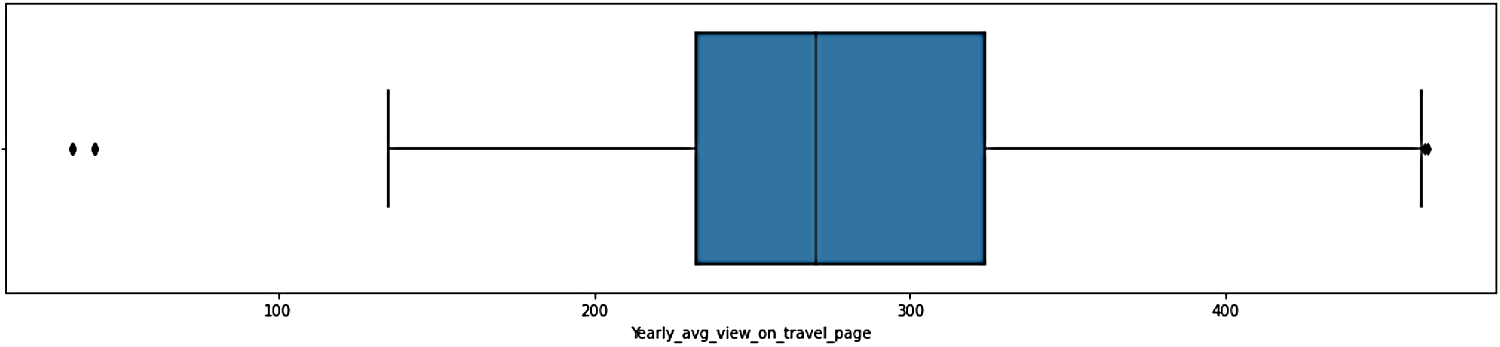
Variables such as 'preferred\_device' are used for stratified sampling but are not included as predictors in the models. This is done to create separate models for laptop and mobile users. Other variables, such as 'preferred\_location\_type' and 'working\_flag,' are retained for modeling. The decision to retain or exclude variables is based on their relevance to predicting user behavior and the specific requirements of each machine learning algorithm.

**DATA ANALYSIS AND INTERPRETATION  
  
Part - 2**

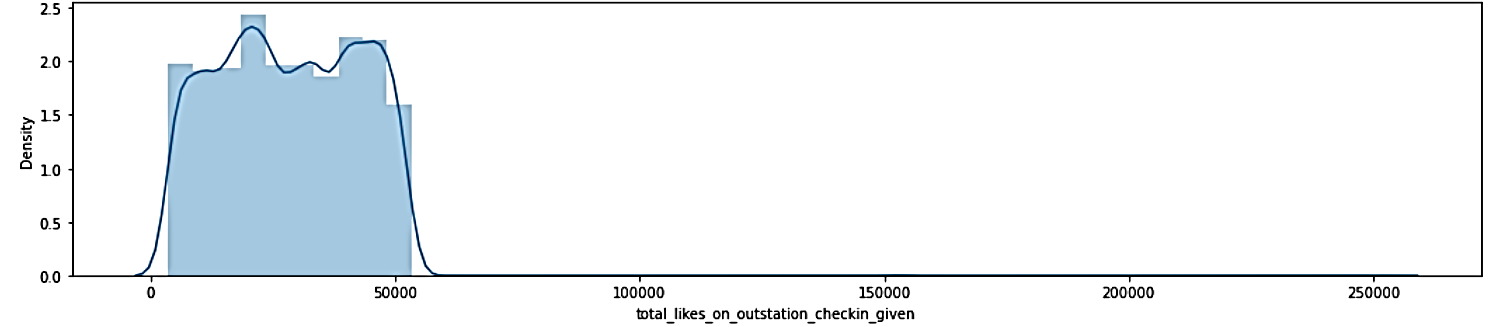
**2.5 DATA VISUALIZATION**

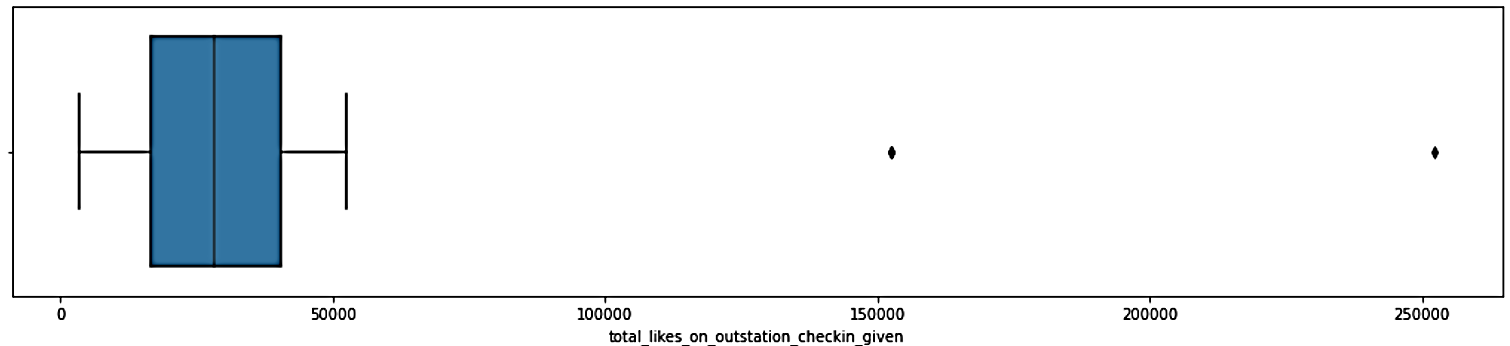
**Numeric Data (UNIVARIATE ANALYSIS)**

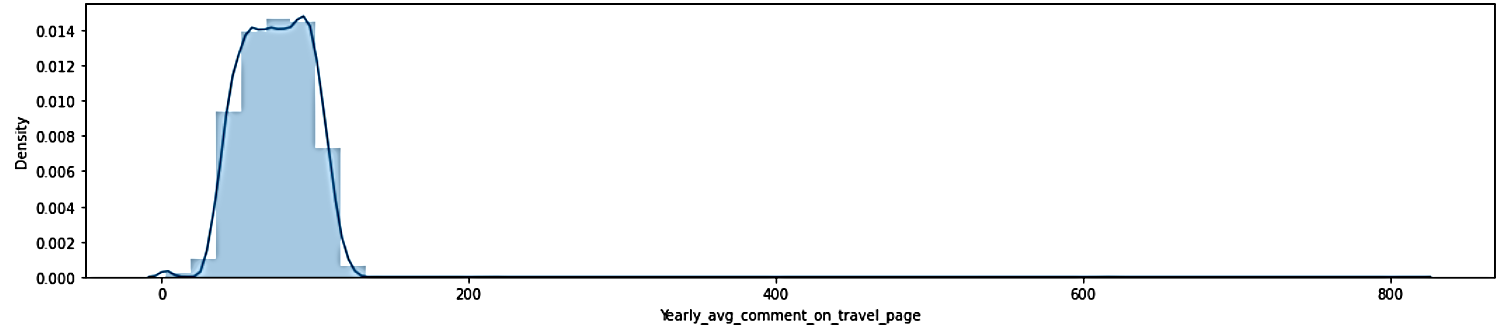
***Yearly\_avg\_view\_on\_travel\_page***

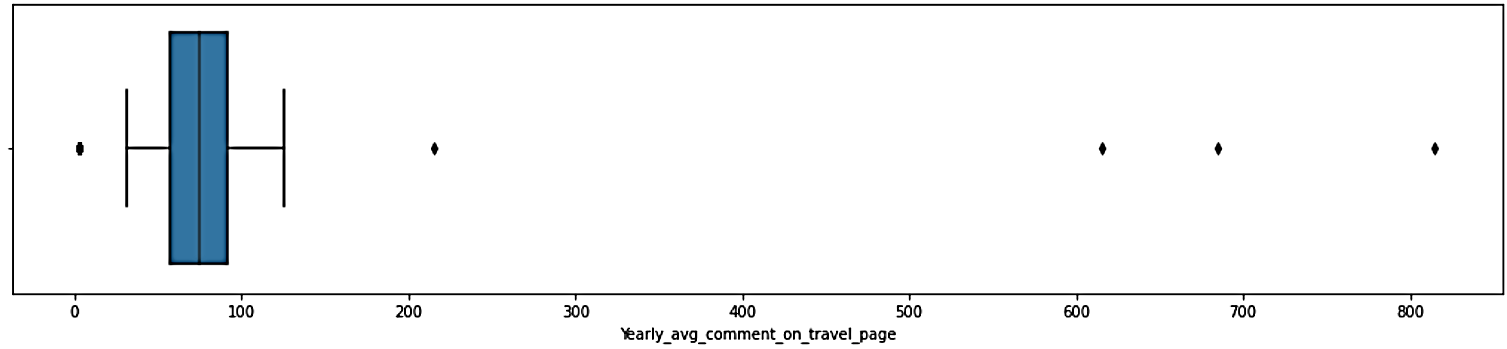


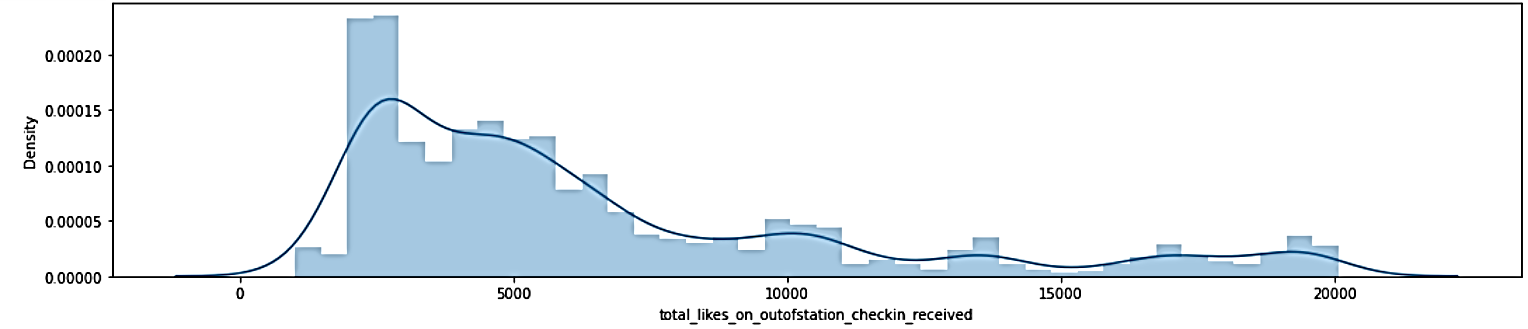
***total\_likes\_on\_outstation\_checkin\_given***

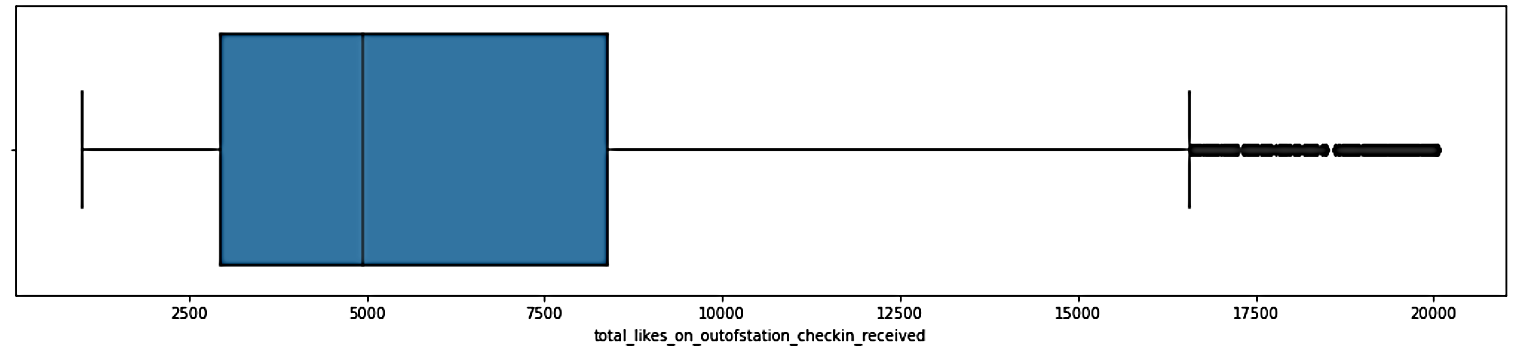
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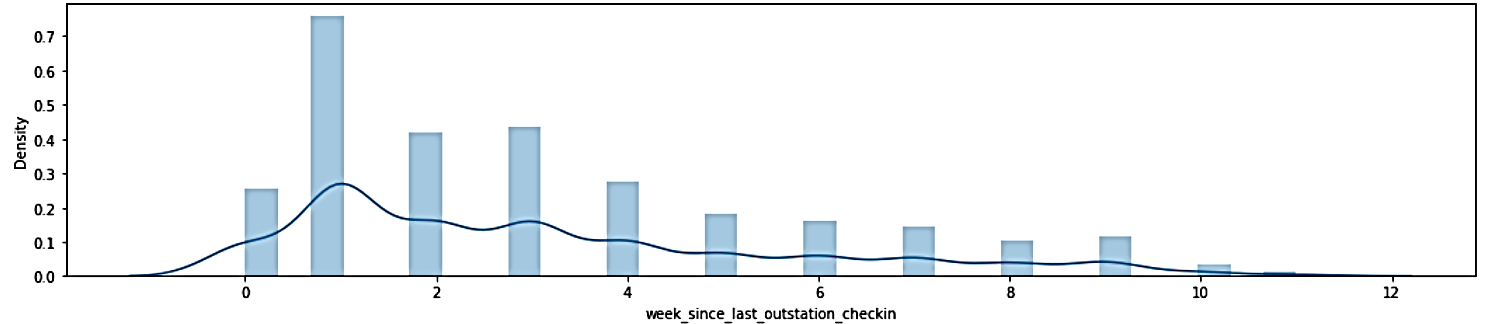


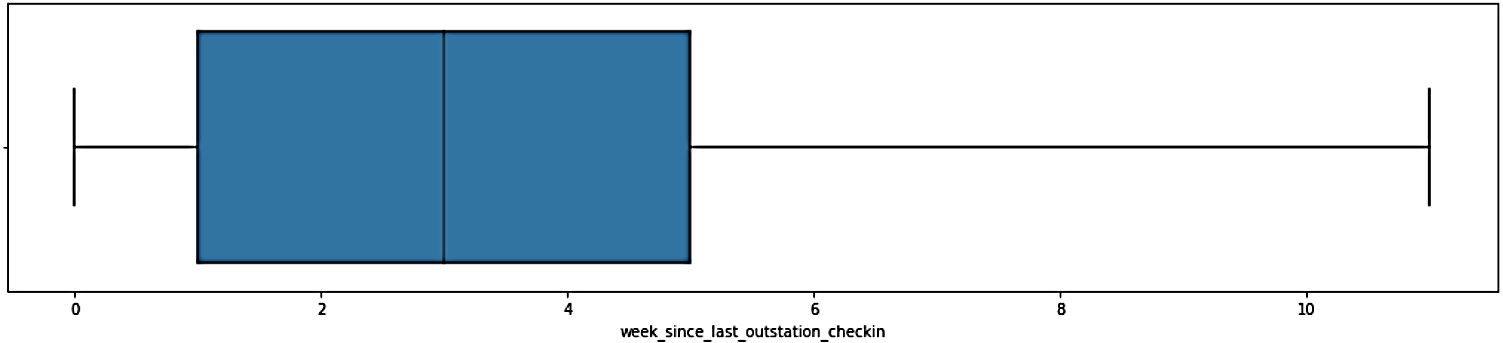
***Yearly\_avg\_comment\_on\_travel\_page***

****

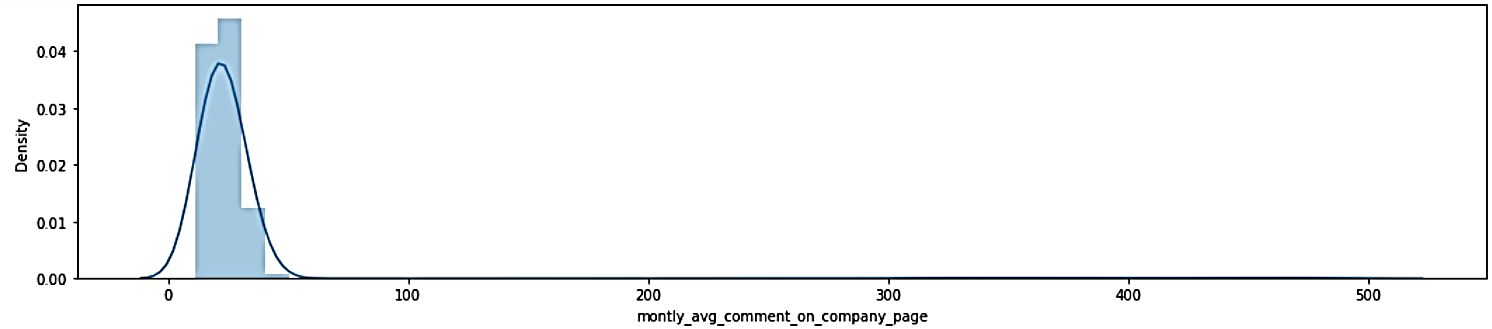
*****total\_likes\_on\_outofstation\_checkin\_received***

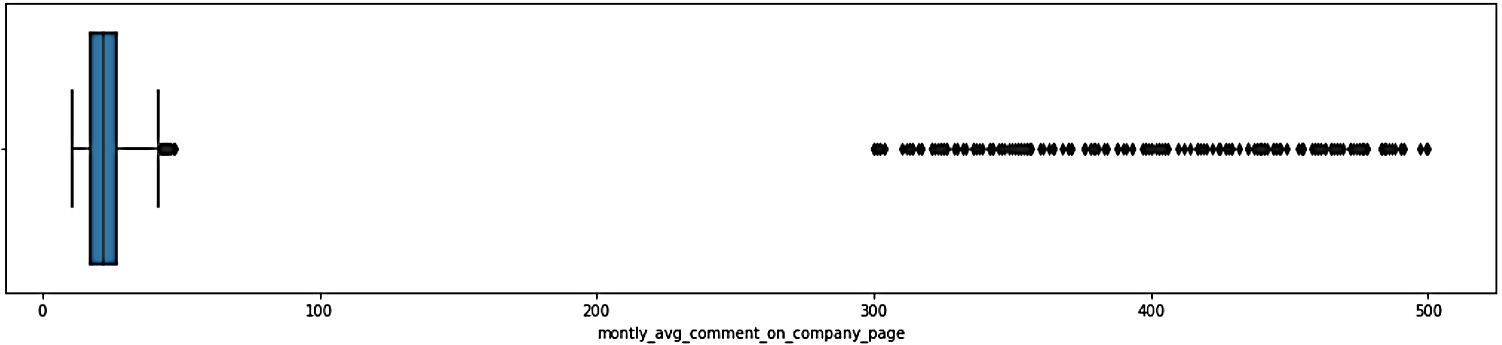
**

*****week\_since\_last\_outstation\_checkin***

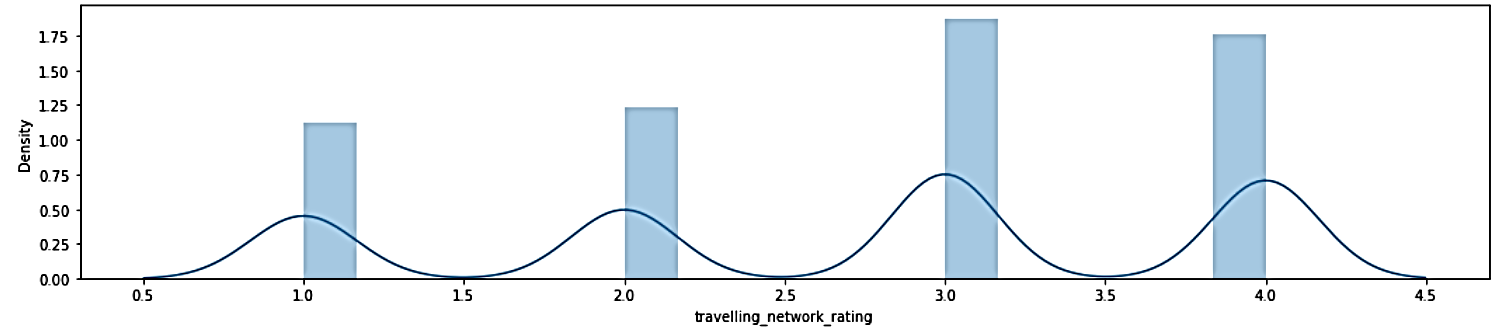
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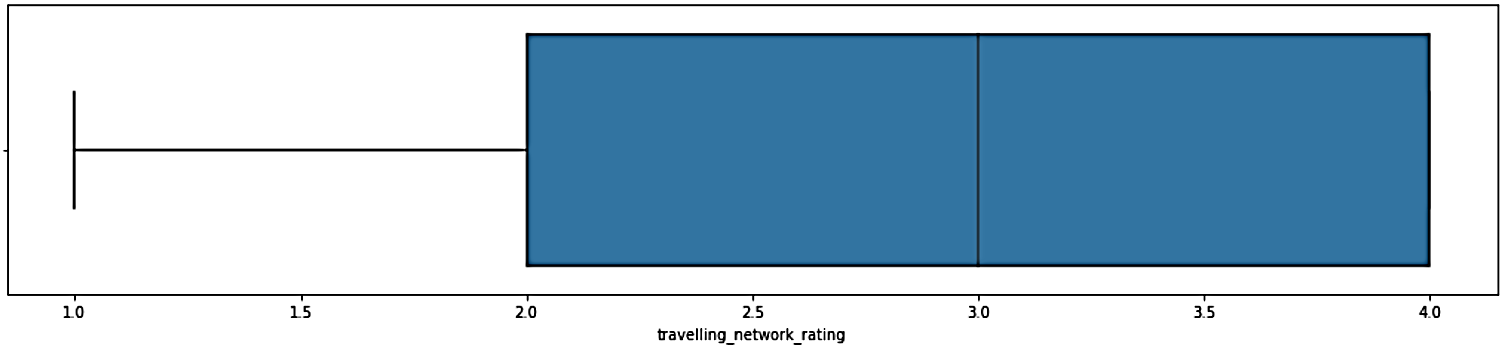
***montly\_avg\_comment\_on\_company\_page***

**

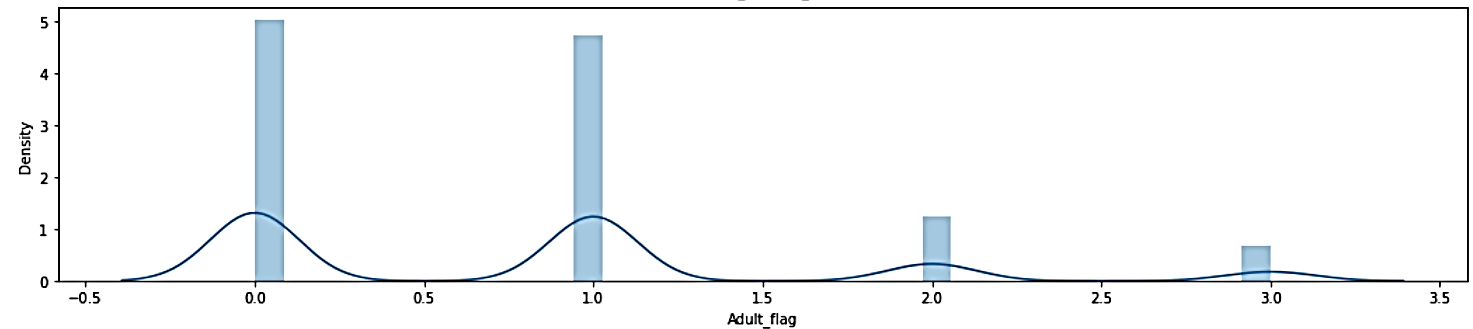
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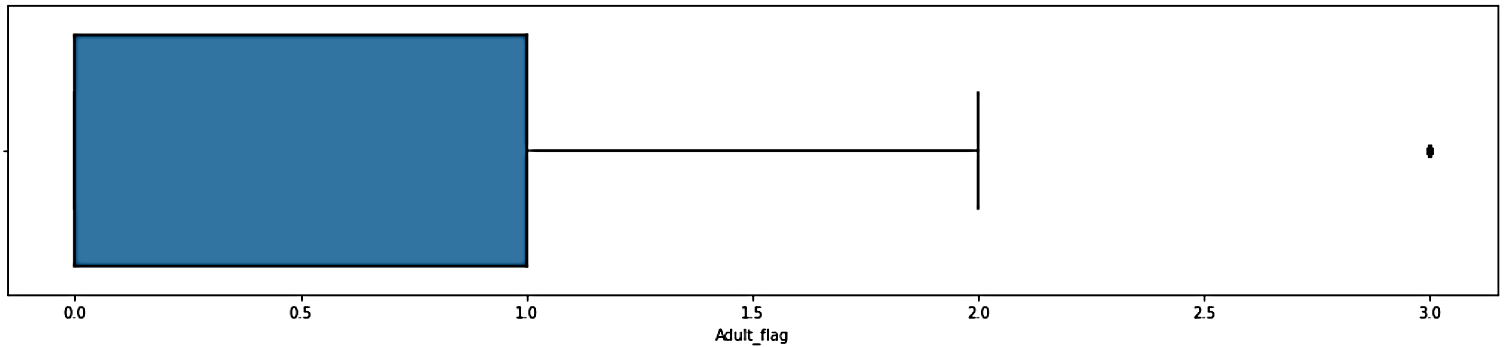
***travelling\_network\_rating***

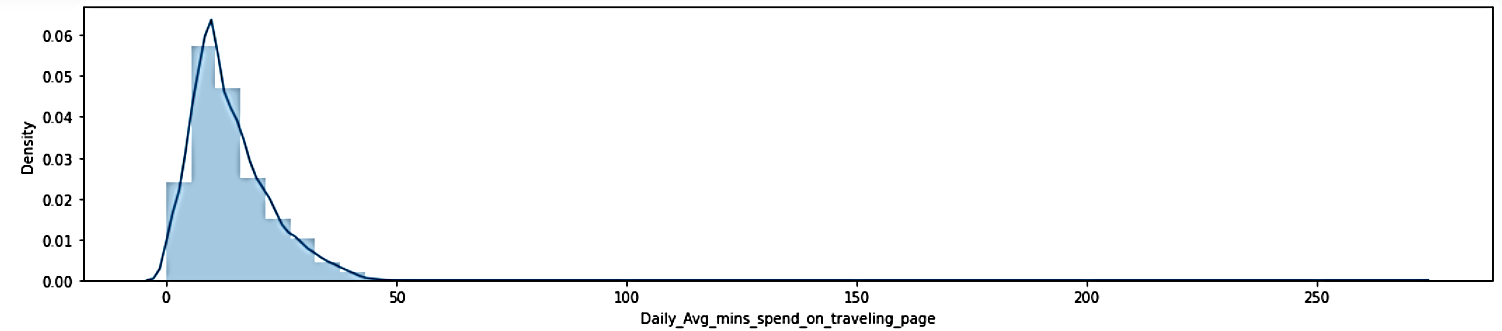
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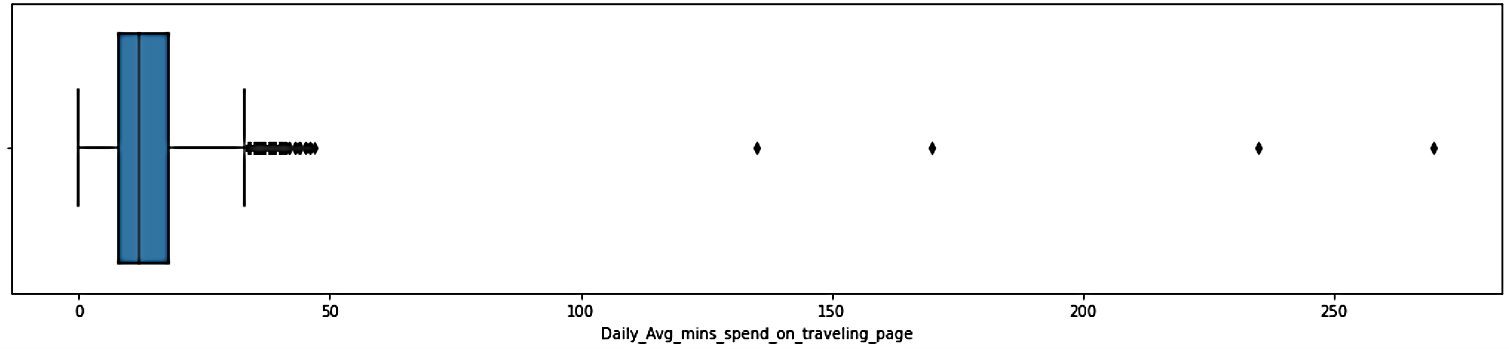
**

***Adult\_flag***

**

**

*****Daily\_Avg\_mins\_spend\_on\_traveling\_page***

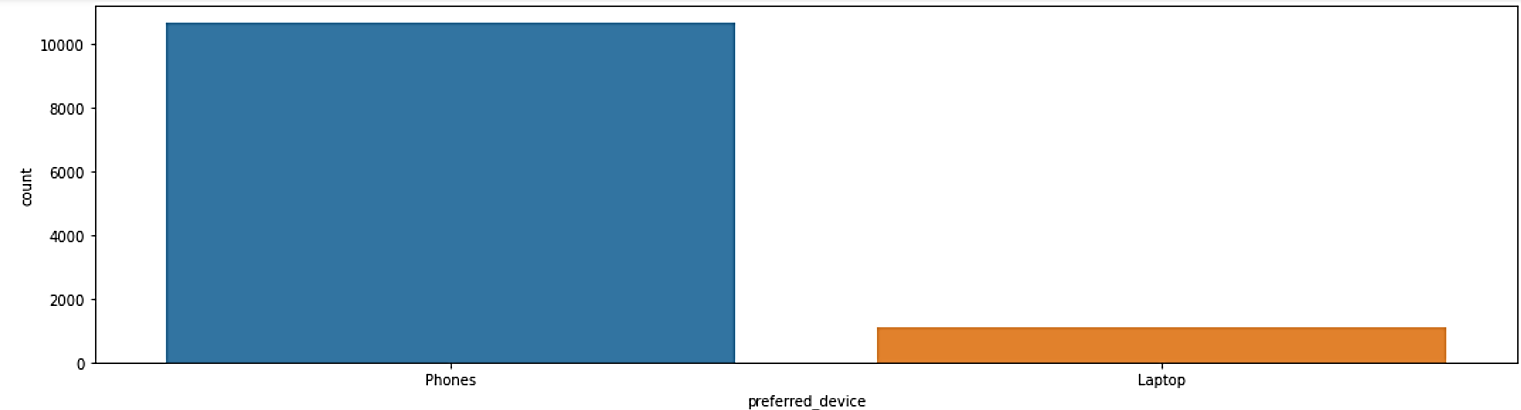
**

**Categorical Data**

***preferred\_device***

A substantial portion of the population **prefers booking through mobile phones***.*

Knowing that a large portion of customers prefers mobile booking suggests that the business should prioritize mobile optimization

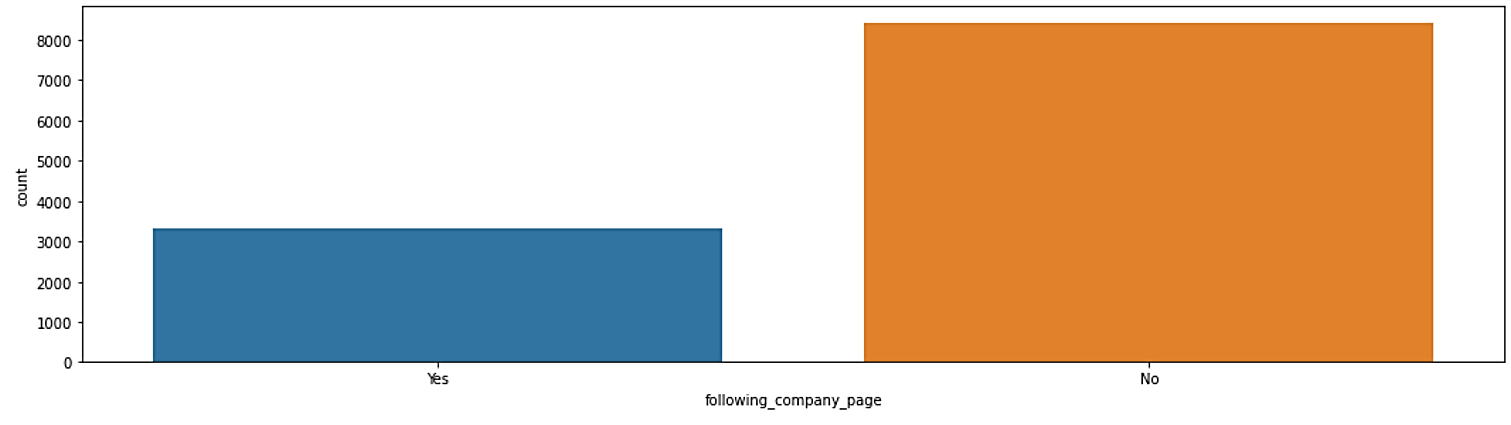
**

***following\_company\_page***

Social Media Following and Engagement - An observable trend is that a substantial majority of users are not following the company's official social media page.

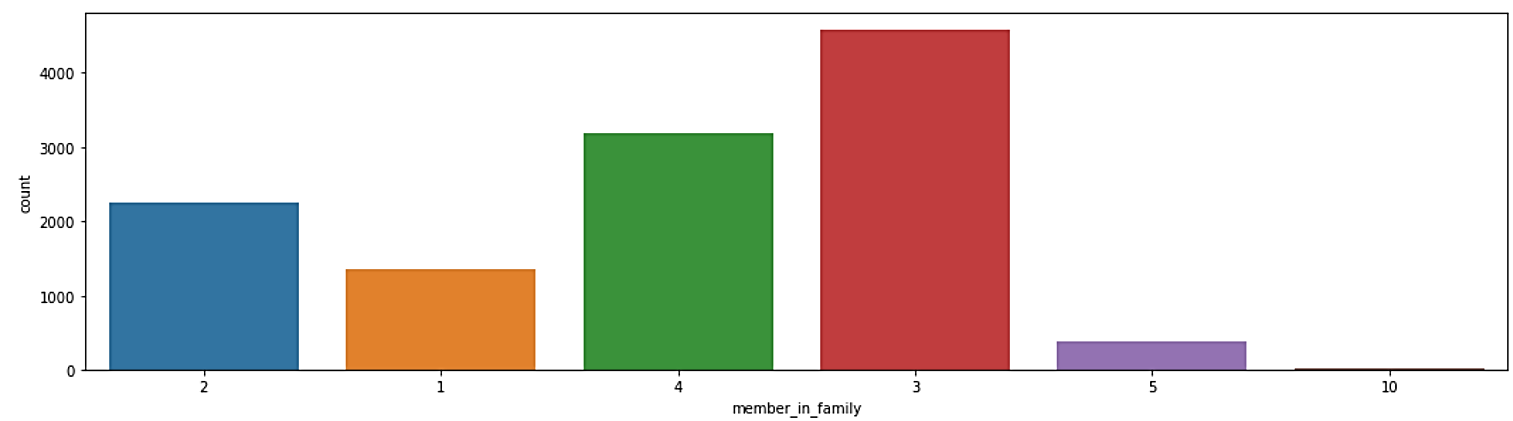
**Content Personalization**: Personalizing content for non-followers might be crucial;

**Influencer Marketing**: Consider leveraging influencer marketing to reach a wider audience; **Competitor Analysis**: The company should also consider analyzing the social media strategies of competitors

**

***member\_in\_family***

The insight tells that users often travel with three or four family members suggesting several business opportunities and strategies to potentially increase product buying: Group Offers, Family-Focused Marketing, etc…



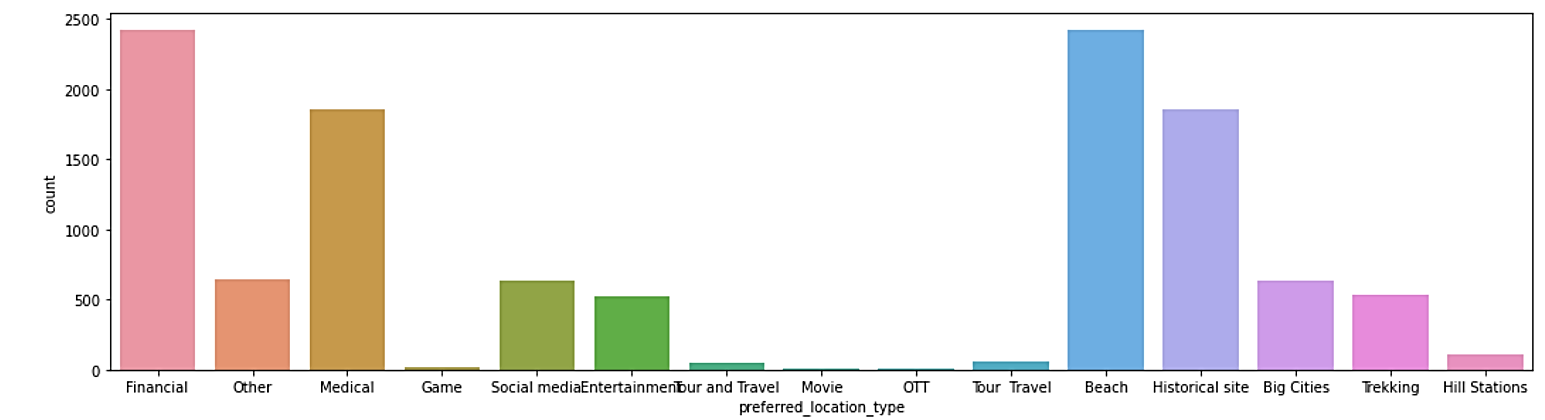
***preferred\_location\_type***

The data highlights that "beach" and "financial" locations are the most frequently visited by users, while "hill station" is the least visited place.

**Promotional Strategies**: Given the popularity of beach and financial locations, the business can focus on developing and promoting products and services that cater to these destinations.

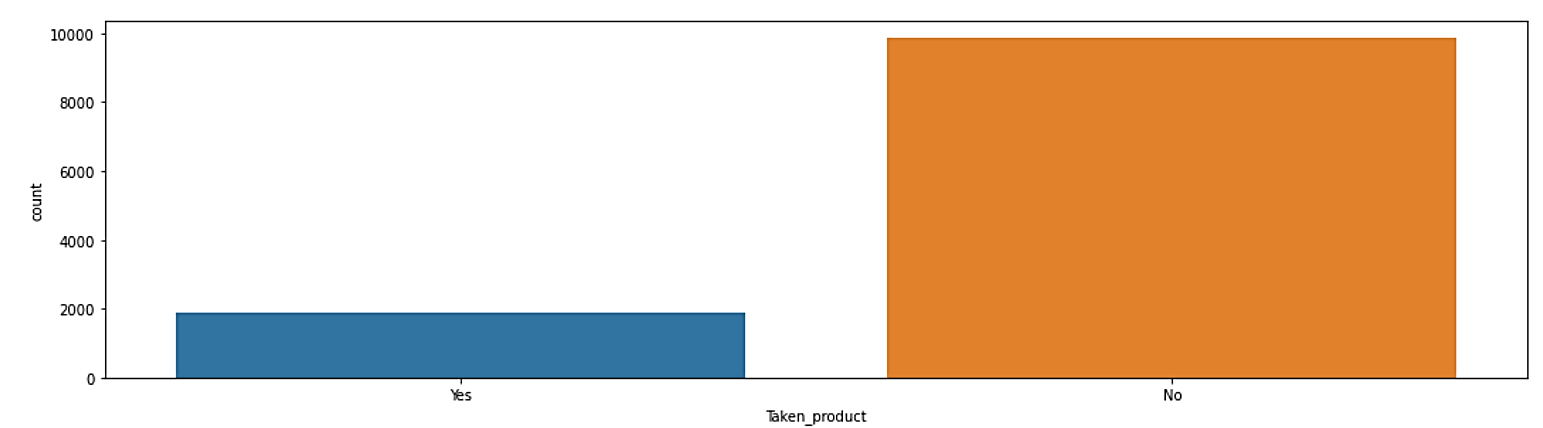
**Collaboration Opportunities**: Collaborate with local businesses and attractions in popular destinations

**Market Expansion**: While addressing the preferences of current users is essential, consider market expansion to attract users interested in different types of locations. Diversifying offerings can lead to growth and new customer segments.



***Taken\_product***

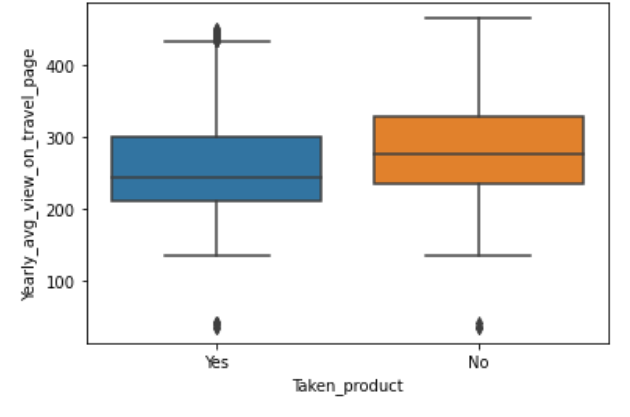
The likelihood of purchasing tickets for the upcoming month appears to be relatively low.



**BIVARIATE ANALYSIS**

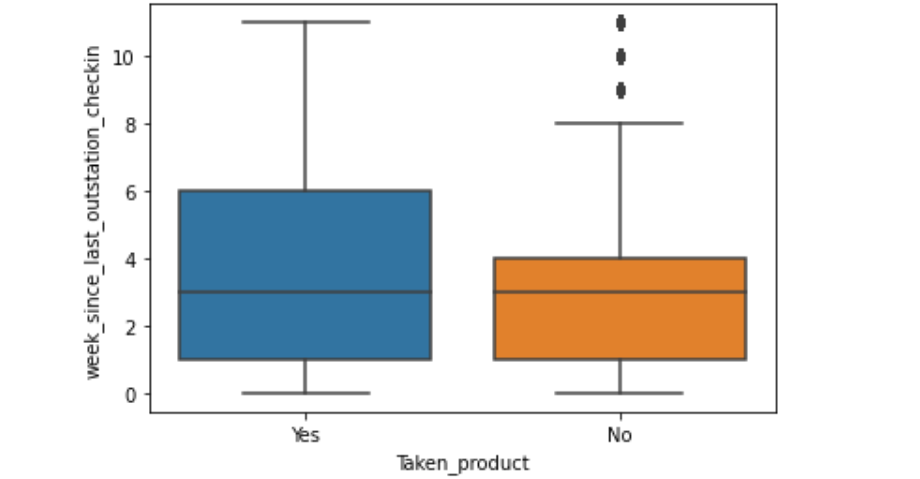
***Yearly\_avg\_view\_on\_travel\_page***

The data illustrates an interesting trend: users who don't follow the company's page tend to have a higher average view on the company's page, while users who do follow the company's page typically have a lower view.

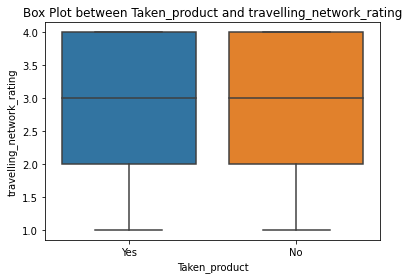


***week\_since\_last\_outstation\_checkin***

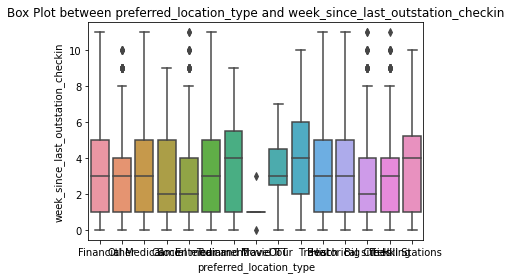
We can observe a noteworthy trend: users who have traveled out since their last outstation check-in tend to have a higher probability of taking the product. This insight suggests that the recency of a user's outstation travel activity may be positively correlated with their likelihood of taking the product.



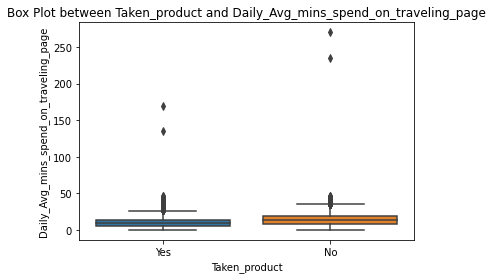
This box plot aids in decision-making related to marketing strategies, customer targeting, or service enhancements based on the observed patterns in customer ratings.



The box plot between 'preferred\_location\_type' and 'week\_since\_last\_outstation\_checkin' provides insights into the relationship between the preferred type of location and the time elapsed since the last outstation check-in. Decision-making related to marketing strategies, customer engagement, or service planning based on the observed patterns in the time since the last outstation check-in and preferred location types.



The box plot between 'Taken\_product' and 'Daily\_Avg\_mins\_spend\_on\_traveling\_page' provides insights into the relationship between the product taken and the daily average minutes spent on the traveling page, aids in decision-making related to marketing strategies, customer engagement, or service planning based on the observed patterns in the daily average minutes spent on the traveling page and product usage.

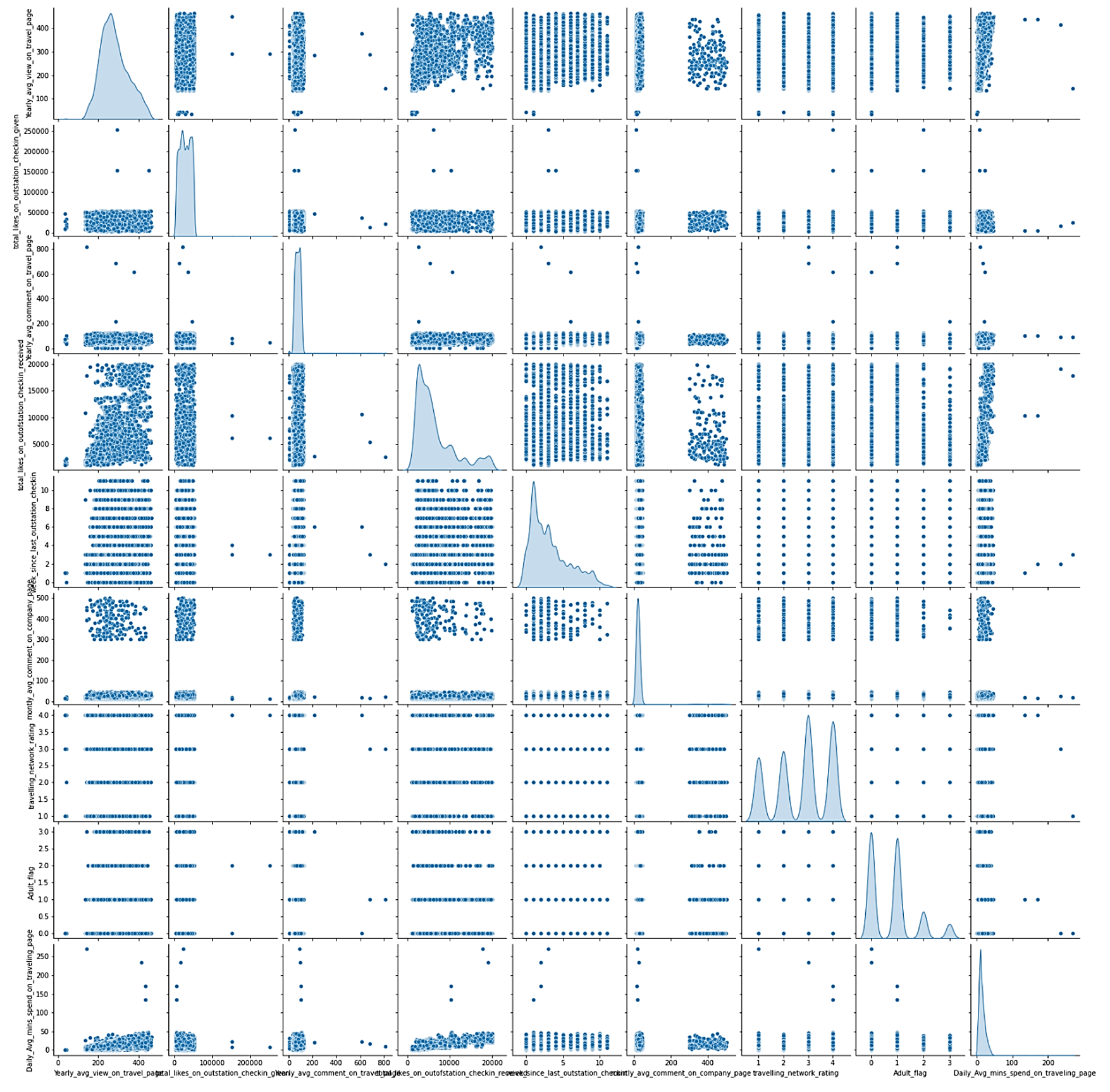


Targeted Advertising:

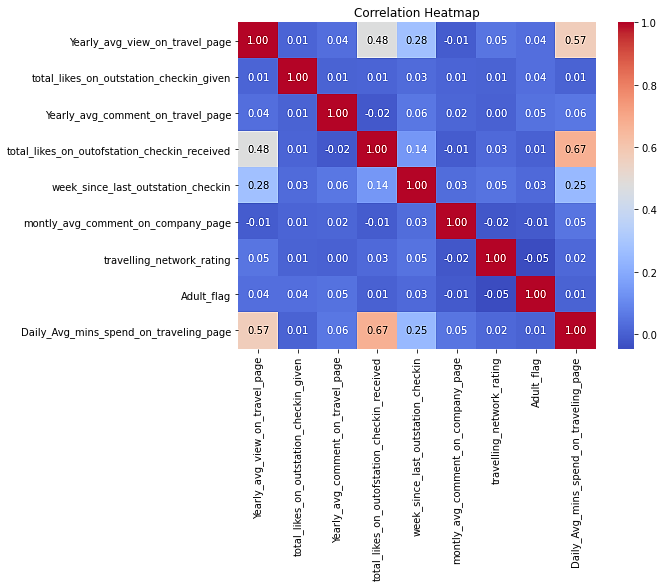
- Identify the range of 'Daily\_Avg\_mins\_spend\_on\_traveling\_page' where customers who have taken the product are more concentrated.

- Focus advertising efforts on social media platforms during the peak times when customers are actively engaged in the traveling page.

By implementing these strategies, the business can leverage the insights gained from the analysis to optimize marketing efforts, enhance customer engagement the goal is to create targeted and meaningful interactions with customers based on their digital behaviors and preferences.

**PAIRPLOT**

**CORRELATION HEATMAP**



**Approaches to Improve Model**

* **Feature Selection**

Feature selection is crucial to identify the most influential variables for predicting the target variable 'Taken\_product.' A common method employed is Recursive Feature Elimination (RFE), which helps in ranking and selecting the most relevant features.  
  
from sklearn.feature\_selection import RFE

# Using Random Forest for feature selection

model\_rf = RandomForestRegressor(n\_estimators=100, random\_state=42)

rfe = RFE(model\_rf, n\_features\_to\_select=10) # Select top 10 features

fit = rfe.fit(X\_train\_lp, y\_train\_lp)

# Displaying selected features

selected\_features = X\_train\_lp.columns[fit.support\_]

print("Selected Features:", selected\_features)

* **Data Manipulation**

The code includes an example of creating an interaction term between 'total\_likes\_on\_outstation\_checkin\_given' and 'yearly\_avg\_Outstation\_checkins.' This interaction term can capture combined effects that individual features may not capture alone.

# Creating interaction term between 'total\_likes\_on\_outstation\_checkin\_given' and 'yearly\_avg\_Outstation\_checkins'

df['interaction\_term'] = df['total\_likes\_on\_outstation\_checkin\_given'] \* df['yearly\_avg\_Outstation\_checkins']

# Visualizing the new interaction term

plt.scatter(df['interaction\_term'], df['Taken\_product'])

plt.xlabel('Interaction Term')

plt.ylabel('Taken Product')

plt.title('Scatter Plot of Interaction Term vs. Taken Product')

plt.show()

This interaction term provides a new variable that may capture synergies between the mentioned features, potentially improving the model's performance.

* **Model Improvements**

Our code has opportunities for model improvement through hyperparameter tuning, which involves searching for the best combination of model parameters.  
  
from sklearn.model\_selection import GridSearchCV

# Define the parameter grid

param\_grid = {

'n\_estimators': [50, 100, 200],

'max\_depth': [None, 10, 20],

'min\_samples\_split': [2, 5, 10],

'min\_samples\_leaf': [1, 2, 4]

}

# Create the grid search model

grid\_search = GridSearchCV(estimator=RandomForestRegressor(random\_state=42),

param\_grid=param\_grid,

cv=5, # 5-fold cross-validation

scoring='accuracy')

# Fit the grid search to the data

grid\_search.fit(X\_train\_lp, y\_train\_lp)

# Display the best parameters

print("Best Parameters:", grid\_search.best\_params\_)  
  
In this section, the code utilizes a grid search to find the optimal hyperparameters for the Random Forest model. The best parameters identified can significantly enhance the model's performance.

* **Visualization:**

To visually represent the results of the grid search, a heatmap is created:

import seaborn as sns

# Extracting results from the grid search

results = pd.DataFrame(grid\_search.cv\_results\_)

# Plotting performance heatmap

heatmap\_data = results.pivot(index='param\_n\_estimators', columns='param\_max\_depth', values='mean\_test\_score')

sns.heatmap(heatmap\_data, annot=True, cmap="YlGnBu", fmt=".3f", cbar\_kws={'label': 'Mean Test Score'})

plt.title("Grid Search Results for Random Forest")

plt.show()

This heatmap offers insights into the model's performance across different combinations of hyperparameters, aiding in selecting the optimal configuration.

These approaches collectively contribute to refining the model and ensuring its accuracy and effectiveness in predicting customer propensities.

**4. Model Building**

**Explanation:**

In the process of building models for predicting customer propensities, three distinct algorithms were employed: Support Vector Machine (SVM), Logistic Regression, and Random Forest.

**Support Vector Machine (SVM):**

Why Chosen: SVM is a powerful algorithm known for its effectiveness in handling both linear and non-linear relationships in data. It works well for binary classification problems, making it suitable for predicting whether a customer will take up the product or not.

Effort to Improve Model Performance: SVM provides a hyperparameter C for regularization. The code might involve tuning this parameter to optimize the SVM model's performance.

from sklearn.svm import SVC

# Initializing SVM model

svc\_lp = SVC(random\_state=101)

# Training the model

svc\_lp.fit(X\_train\_lp, y\_train\_lp)

**Logistic Regression:**

Why Chosen: Logistic Regression is a commonly used algorithm for binary classification tasks. It's a straightforward and interpretable model, which can provide insights into the relationship between input features and the likelihood of the target variable.

Effort to Improve Model Performance: Logistic Regression also involves tuning hyperparameters, especially regularization strength (C), to enhance its predictive capability.

from sklearn.linear\_model import LogisticRegression

# Initializing Logistic Regression model

model\_lp = LogisticRegression()

# Training the model

model\_lp.fit(X\_train\_lp, y\_train\_lp)

**Random Forest:**

Why Chosen: Random Forest is an ensemble method known for its robustness and ability to handle complex relationships in data. It's particularly effective when dealing with a large number of features and provides feature importance scores.

Effort to Improve Model Performance: Hyperparameter tuning for Random Forest involves adjusting parameters such as the number of trees (n\_estimators), maximum depth of trees (max\_depth), and minimum number of samples required to split an internal node (min\_samples\_split).

from sklearn.ensemble import RandomForestRegressor

# Initializing Random Forest model

rf = RandomForestRegressor(n\_estimators=100, random\_state=42, oob\_score=True)

# Training the model

rf.fit(X\_train\_lp, y\_train\_lp)

The Random Forest model was found to work well, implying that its ensemble nature and robustness contributed to accurate predictions in this context.

**5. Model Validation**

Explanation:

Model validation is crucial to ensure that the trained models generalize well to unseen data. The validation process typically involves assessing multiple metrics beyond just accuracy.

How the Model Was Validated: The code uses the accuracy score, precision, recall, and F1-score to comprehensively evaluate model performance. Additionally, confusion matrices are employed to understand the model's ability to correctly predict positive and negative cases.

**Random Forest Model Validation:**

from sklearn.metrics import accuracy\_score, classification\_report, confusion\_matrix

# Making predictions on the test data

predictions\_RF = rf.predict(X\_test\_lp).round()

# Calculating accuracy

accuracy\_rf = accuracy\_score(y\_test\_lp, predictions\_RF)

print(f'Accuracy: {accuracy\_rf:.2f}')

# Displaying classification report

print(classification\_report(y\_test\_lp, predictions\_RF))

# Confusion matrix

RF\_lp\_cm = confusion\_matrix(y\_test\_lp, predictions\_RF)

print("Confusion Matrix:")

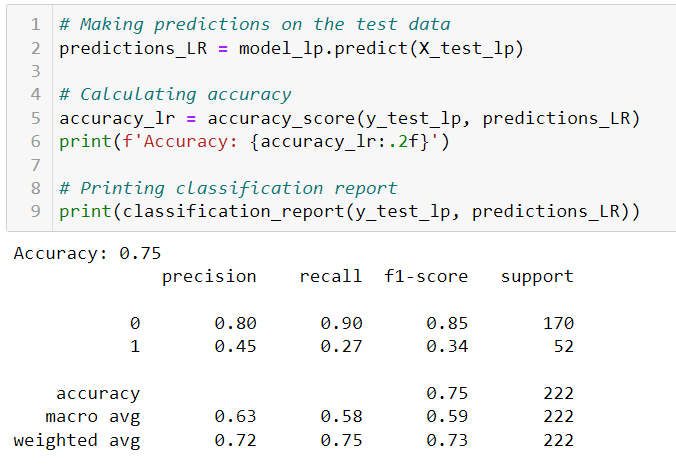
print(RF\_lp\_cm)

By employing a range of evaluation metrics and visualizing the confusion matrix, the validation process ensures a comprehensive understanding of the models' performance and areas for potential improvement.

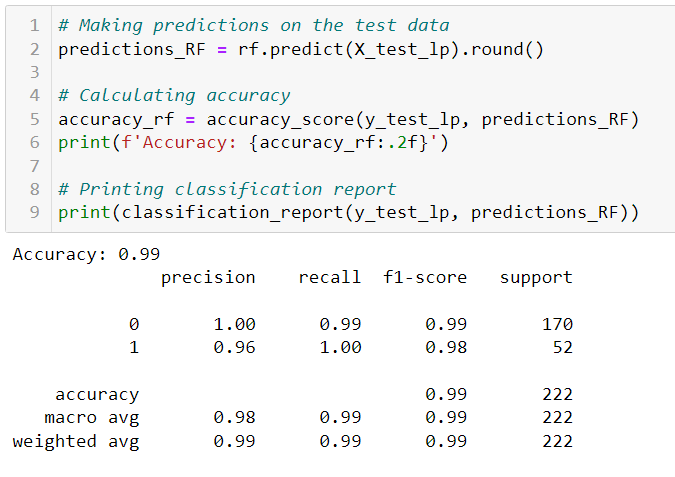
**5.2 Model Accuracy:**

The accuracy is typically calculated using the accuracy\_score function from the sklearn.metrics module. Here are the sections where we calculated and printed the accuracy for each model:

**Laptop Model Accuracy Calculation**

****

**Mobile Model Accuracy Calculation:**



Logistic Regression achieved an accuracy of **0.75.**

Random Forest achieved an impressive accuracy of **0.99.**

Support Vector Machine (SVM) achieved an accuracy of **0.77.**

**Logistic Regression** is particularly useful for straightforward binary classification tasks and provides interpretable results.

**Random Forest Regressor** is effective for regression tasks, especially when dealing with non-linear relationships and complex data patterns, and it offers the benefit of ensemble learning and feature importance analysis.

**SVM** is versatile, effective in high-dimensional spaces, and capable of handling both binary and multiclass classification tasks, often with the help of kernel functions.

**Random Forest model exhibited superior performance, achieving high accuracy and precision in predicting customer propensities.**

**Purpose and Usefulness:**

1. **Model Building and Interpretation:**

- The Random Forest Classifier is a powerful machine learning model known for its ability to handle both classification and regression tasks effectively.

- In our project, we're using this model to classify *'Taken\_product'* and *'preferred\_device'* based on user data and behavioral features. This can be instrumental in understanding which users are more likely to take the product and what type of device they prefer for engagement.

- The model helps in building predictive models that can be used to make data-driven decisions. For instance, you can predict which users are more likely to take the product, allowing you to target marketing efforts more efficiently.

1. **Model Tuning and Business Implications:**

- Model tuning is the process of optimizing hyperparameters to improve model performance. In our code, we've used the Random Forest Classifier with default hyperparameters, but there's potential for further tuning.

- For our project, model tuning can be vital. It can enhance predictive accuracy and provide more precise insights into user behavior and preferences.

- Business implications include tailoring marketing campaigns based on model predictions. For example, there can be more on users with a higher predicted likelihood of taking the product, thereby improving the efficiency of the marketing spend.

- Furthermore, the model can help in identifying factors that drive user engagement and preferences for specific devices. These insights can guide product development and marketing strategies.

**CHAPTER 4**

**FINDINGS, RECOMMENDATIONS AND CONCLUSION**

**FINDINGS, RECOMMENDATIONS AND CONCLUSION**

**4.1 Findings Based on Observations**

* **Device-Based Propensity Variation:**
  + The analysis revealed significant variations in the propensity to purchase airline tickets based on the type of device used, with distinct behaviors observed for laptop and mobile users.
* **Model Performance:**
  + Among the implemented models (SVM, Logistic Regression, Random Forest), the Random Forest model exhibited superior performance, achieving high accuracy and precision in predicting customer propensities.
* **Feature Importance:**
  + Features such as "Yearly\_avg\_view\_on\_travel\_page" and "total\_likes\_on\_outofstation\_checkin\_received" emerged as crucial predictors, influencing customer propensities according to the Random Forest feature importance analysis

**4.2 Findings Based on analysis of Data**

* **Strategic Resource Allocation:**
  + The data analysis supports the recommendation for strategic resource allocation, emphasizing the need to concentrate digital marketing efforts on the platform preferred by the majority of potential customers.
* **Feature Emphasis in Marketing:**
  + Marketing strategies should emphasize features identified as influential, such as "Yearly\_avg\_view\_on\_travel\_page" and "total\_likes\_on\_outofstation\_checkin\_received," to maximize impact on customer propensities.
* **Model Deployment Recommendation:**
  + The Random Forest model is recommended for deployment due to its superior performance. Regular updates with new data are crucial for maintaining accuracy over time.

**4.3 General findings**

* **User Behavior Insights:**
  + The analysis provided valuable insights into user behaviors on the digital platform, offering a data-driven approach for marketing strategies.
* **Targeted Advertising Opportunities:**
  + Opportunities exist for targeted advertising strategies tailored to specific user behaviors on laptops and mobile devices.

**4.4 Recommendation based on findings**

1. **Targeted Advertisement Strategies:**
   * Tailor digital advertisements for users on laptops and mobile devices based on identified preferences and behaviors.
2. **Resource Allocation Optimization:**
   * Optimize digital marketing resource allocation by focusing efforts on the platform preferred by the majority of potential customers.
3. **Feature Emphasis in Marketing:**
   * Emphasize features identified as crucial predictors, such as "Yearly\_avg\_view\_on\_travel\_page" and "total\_likes\_on\_outofstation\_checkin\_received," in marketing strategies.
4. **Random Forest Model Deployment:**
   * Deploy the Random Forest model for predicting customer propensities, given its superior performance.

**4.5 Suggestions for areas of improvement**

1. **Continuous Monitoring System:**
   * Establish a continuous monitoring system for customer behaviors on the digital platform to adapt marketing strategies in real-time.
2. **User Experience Enhancement:**
   * Consider enhancing the user experience on both laptops and mobile devices based on identified behaviors.

**4.6 Scope for future research**

Ongoing research opportunities include further exploration of evolving customer behaviors on digital platforms and the development of advanced predictive models.

**BUSINESS INSIGHTS**

1. User Group Size and Travel Offers: It appears that a significant number of users travel in groups of 3 or 4, as indicated by the observation that the "member\_in\_family" column has values like '3' and '4'. To retain more customers, the company could consider offering special deals and promotions targeted at users traveling in groups of 3 or 4, as this seems to be a common group size.

2. Preferred Device Types: The analysis includes a mapping of the "preferred\_device" column, grouping various device types into the category "Phones." This suggests that most users prefer to access the platform via mobile devices. To enhance user experience and engagement, the company should prioritize the development and optimization of its mobile app or website, as it is the preferred platform for users.

3. Customer Engagement with the Company Page: The analysis shows that users who don't follow the company's page have a higher average view on the company page. This may indicate that users are more likely to interact with the company's content when they are not official followers. To maximize user engagement, the company should consider diversifying its content and engagement strategies to capture the interest of both followers and non-followers.

4. Preferred Travel Destinations: By analyzing the data, you can see which locations are most visited (e.g., beaches and financial places) and which are less visited (e.g., hill stations). The company could tailor its marketing and promotional efforts to offer specific deals and discounts based on the most common travel destinations. This strategy can help attract more customers to these popular locations.

5. Imbalanced Data and SMOTE: The code mentions that the data is heavily imbalanced. To address this issue, the company could consider using techniques like SMOTE (Synthetic Minority Over-sampling Technique) to balance the dataset. This can lead to more accurate predictions and better model performance, particularly in scenarios like predicting the likelihood of buying a ticket.

6. Effectiveness of Social Media Campaigns: There is an interesting observation regarding the effectiveness of the company's social media presence. Users who don't follow the company's page have a higher average view on the company page, while those who do follow have fewer views. This suggests that the company's social media campaigns may not be as effective in engaging users who are already following. To improve online presence and engagement, the company should consider refining its social media campaigns and strategies to capture the attention of a broader social media audience.

7. Online Ticket Purchases: The observation that the probability of buying tickets online for the next month is low suggests that the company should focus on advertising and marketing its ticketing services more aggressively online. To do this effectively, the company should analyze the platforms that are more frequently used by the target audience and concentrate its marketing efforts on those platforms. This can help improve online ticket sales.

8. Seasonal Trends: If the data includes a timestamp indicating when users made purchases or engaged with the company, it would be beneficial to explore seasonal trends. This analysis can help the company plan marketing campaigns and offers that align with peak engagement periods.

9. Competitor Benchmarking: To gain a competitive edge, the company should consider benchmarking its performance against competitors in the industry. Understanding how the company's metrics compare to those of competitors can reveal areas for improvement.

10. Dynamic Pricing: Implement dynamic pricing strategies that adjust product prices based on factors like demand, user engagement, and time of year. Offer personalized discounts to users showing high engagement.

11. Cross-Platform Promotion: Leverage insights from your analysis to identify which social media platforms or online channels are most effective in driving user engagement and conversions. Focus marketing efforts on the most promising platforms.

12. Feedback Loop: Establish a feedback loop with users to gather continuous input on their preferences and pain points. This feedback can guide ongoing product improvements and customer-focused initiatives.

**4.7 Conclusion**

In summation, the comprehensive analysis yields not just insights but a roadmap for strategic marketing in the digital domain. By delving into the intricacies of user behavior, the aviation company stands poised to revolutionize its digital advertising approach. The amalgamation of precision-targeting, emphasis on influential features, and the deployment of a robust predictive model positions the company on the cusp of heightened customer engagement, fortified by data-driven decision-making. As the digital landscape continues to evolve, this study lays the foundation for a proactive and adaptive marketing strategy, ensuring sustained relevance and resonance in the competitive aviation marketplace.

In summary, the analysis of the social media tourism dataset provides valuable insights for the aviation company's targeted digital approach. Key findings include the prevalence of group travels, emphasizing tailored promotions for groups of 3 or 4. The preference for mobile platforms suggests a need for enhanced mobile app experiences. Nuanced content strategies, particularly considering both followers and non-followers, can optimize user engagement. Customizing marketing efforts for popular travel destinations, addressing imbalanced data, and refining social media campaigns are pivotal for success. Recommendations encompass online ticket sales growth, seasonal campaign alignment, competitor benchmarking, dynamic pricing, and a feedback loop for continuous improvement. These insights, when strategically applied, position the company for effective digital advertising and increased customer satisfaction.

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