Customer Purchase Prediction Report

1. Data Preprocessing Steps

1.1 Data Loading and Initial Exploration

- The dataset `online_shoppers_intention.csv` was loaded using `pandas`.
- The dataset contains **12,330 rows** and **18 columns**, including numerical, categorical, and boolean features.
- Basic exploration was performed using `.head()`, `.info()`, and `.describe()` to understand the structure and summary statistics of the data.

1.2 Handling Missing Values

- Missing values were checked using `.isnull().sum()`. No missing values were found in the dataset.

1.3 Encoding Categorical Variables

- One-hot encoding was applied to categorical variables (`Month`, `OperatingSystems`, `Browser`, `Region`, `TrafficType`, `VisitorType`, `Weekend`) to convert them into numerical format for modeling.

1.4 Feature Creating

- **New Features Created**:
    - `TimeSpentOnSite`: Sum of `ProductRelated_Duration`, `Administrative_Duration`, and `Informational_Duration` to capture total user engagement.
    - `VisitorType_New`: Derived from `VisitorType_Returning_Visitor` to simplify the analysis of returning visitors.

1.5 Normalization

- Normalization of the continuous variables `Administrative`, `ProductRelated`, and `BounceRates` using MinMaxScaler.

2. Exploratory Data Analysis (EDA) Findings

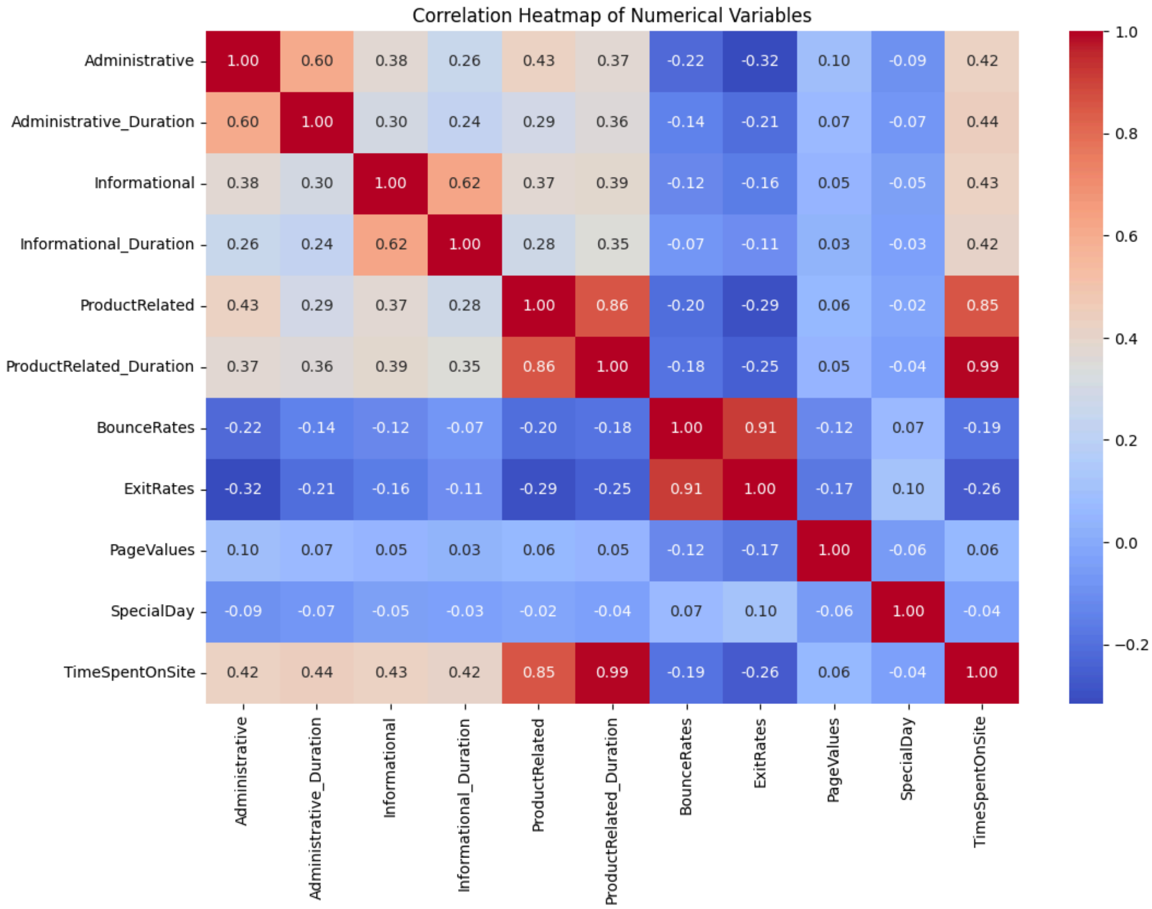
2.1 Distribution of Numerical Variables

- **Administrative Page Visits**:
  The histogram shows a right-skewed distribution, with most users visiting a small number of administrative pages. The box plot confirms the presence of outliers, indicating some users interact significantly more with administrative pages.
- **Bounce Rates**:
  The histogram reveals a right-skewed distribution, with most users having low bounce rates. The box plot shows a few outliers, indicating some users have unusually high bounce rates.
- **Exit Rates**:
  The histogram also shows a right-skewed distribution, with most users having low exit rates. The box plot highlights outliers, suggesting some users exit the site at a much higher rate.

2.2 Distribution of Categorical Variables

- **Month**:
  The bar chart shows that visits are highest in **May** and **November**, indicating seasonal trends in user activity.
- **Operating Systems**:
  The bar chart reveals that most users use **Operating System 2**, followed by **Operating System 3** and **4**.
- **Browser**:
  The bar chart highlights that **Browser 2** is the most popular, followed by **Browser 4** and **Browser 5**.
- **Traffic Type**:
  The bar chart shows that **Traffic Type 2** is the most common, followed by **Traffic Type 3** and **Traffic Type 4** .
- **Visitor Type**:
  The pie chart reveals that the dataset is evenly split between **Returning Visitors** and **New Visitors** (both 49.8%) and a small percentage of **Other** visitors.
- **Weekend**:
  The pie chart shows that **76.7%** of visits occur on weekdays, while **23.3%** occur on weekends.

2.3 Correlation Analysis



- The correlation heatmap reveals relationships between numerical variables:
  - **Strong Positive Correlations**:
    - `ProductRelated` and `ProductRelated_Duration` (0.86): Users who view more product-related pages tend to spend more time on them.
    - `Administrative` and `Administrative_Duration` (0.60): Users who visit more administrative pages also spend more time on them.
  - **Negative Correlations**:
    - `Administrative` and `ExitRates` (-0.32): Higher administrative rates are associated with lower exit rates.
    - `ExitRates` and `ProductRelated` (-0.26): Higher exit rates are linked to lower product related.

2.4 Purchase Rates: Weekend vs. Non-Weekend

- The bar plot compares purchase rates for weekend and non-weekend visits:
  - **Non-Weekend Visits**: Purchase rate is **15%.**

- **Weekend Visits**: Purchase rate is **17.5%** .
- **Insight**: While weekdays drive the majority of purchases due to higher traffic, weekend visits have a slightly higher purchase rate, indicating that weekend users may be more intentional or engaged.

2.5 Relationship Between Numerical Variables and Revenue

- **ProductRelated_Duration vs. Revenue**:
  The box plot shows that users who made a purchase (`Revenue = Yes`) spent significantly more time on product-related pages compared to non-purchasers (`Revenue = No`). This indicates that higher engagement with product content is strongly associated with conversions.
- **BounceRates vs. Revenue**:
  The box plot reveals that users who made a purchase (`Revenue = Yes`) had lower bounce rates compared to non-purchasers (`Revenue = No`). This suggests that users who engage beyond the landing page are more likely to convert.

3. Feature Engineering

3.1 New Features Created

- `TimeSpentOnSite`: Sum of `ProductRelated_Duration`, `Administrative_Duration`, and `Informational_Duration` to capture total user engagement.
- `VisitorType_New`: Derived from `VisitorType_Returning_Visitor` to simplify the analysis of returning visitors.
- `Normalization`: not required as numerical features were already scaled between 0 and 1.

3.2 Target Variable Creation

- Creation of new variable `Revenue` as Binary Target (1 for purchase, 0 for no purchase).

4. Model Development

4.1 Train-Test Split

- The dataset was split into training (80%) and testing (20%) sets, with stratification to ensure the proportion of buyers (`Revenue = 1`) and non-buyers (`Revenue = 0`) remained consistent in both sets.
    - **Training Set Class Distribution**:
        - Non-Buyers: **84.53%**
        - Buyers: **15.47%**
    - **Testing Set Class Distribution**:
        - Non-Buyers: **84.51%**
        - Buyers: **15.49%**

4.2 Models Evaluated

Three models were trained and evaluated:

- **Logistic Regression** (Scaled features using `StandardScaler`).
- **Random Forest**
- **XGBoost (Gradient Boosting)**

5. Model Comparison and Performance Metrics

5.1 Evaluation Results

The three models were evaluated using key metrics: **Accuracy**, **Precision**, **Recall**, **F1-Score**, and **ROC-AUC Score**. Below is a summary of their performance:

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Logistic Regression	0.8812	0.7380	0.3613	0.4851	0.8810
Random Forest	0.8978	0.7407	0.5236	0.6135	0.9168
XGBoost (Gradient Boosting)	**0.8950**	**0.6804**	**0.6073**	**0.6418**	**0.9213**

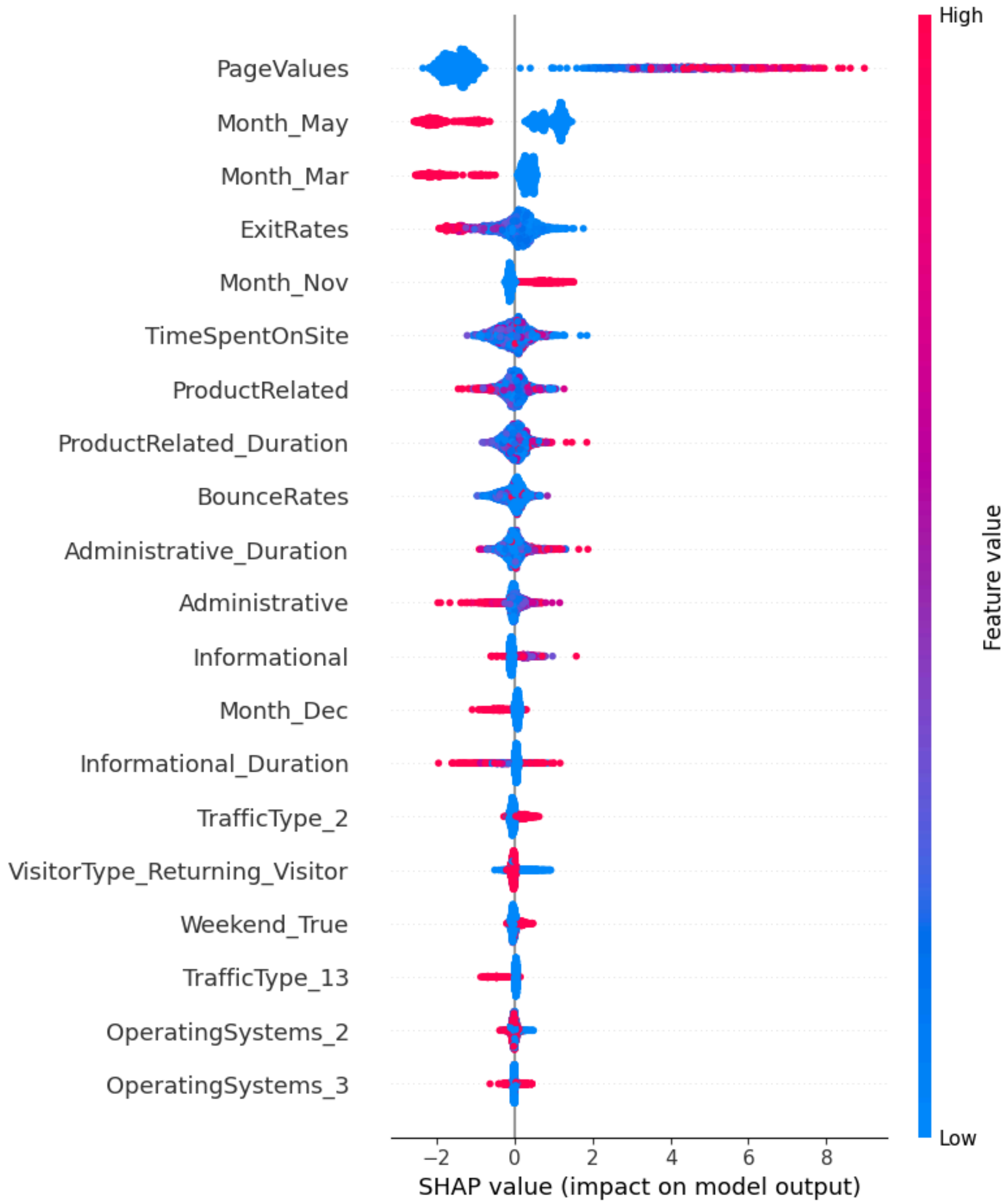
5.2 Best Model Selection

- **XGBoost** is the best-performing model overall due to its:
    - Highest **Recall (0.6073)**: Identifies more actual buyers.

- Highest **F1-Score (0.6418)**: Balances precision and recall effectively.
- Highest **ROC-AUC (0.9213)**: Best at distinguishing between buyers and non-buyers.

6. Key Business Insights

6.1 Variable Importance (SHAP Analysis)



The SHAP summary plot highlights the most influential features for predicting purchases:

1. **PageValues**:
   The average value of pages visited by a customer is the most critical factor. Higher page values correlate with higher purchase intent.
2. **Month_May and Month_Mar**:
   Visits in May and March are highly influential, indicating seasonal trends or promotions that drive purchases.
3. **ExitRates**:
   Lower exit rates are associated with higher purchase probabilities, emphasizing the importance of retaining users on the site.
4. **TimeSpentOnSite**:
   Total time spent on the site is a strong indicator of purchase intent. Engaged users are more likely to convert.
5. **ProductRelated and ProductRelated_Duration**:
   Engagement with product-related pages significantly impacts purchase decisions.
6. **BounceRates**:
   Lower bounce rates are preferable, as users who leave after viewing only one page are less likely to purchase.
7. **VisitorType_Returning_Visitor**:
   Returning visitors are more likely to make purchases, highlighting the importance of customer retention strategies.
8. **Weekend_True**:
   Weekend visits have a positive impact on purchase likelihood, likely due to users having more leisure time.

7. Recommendations to Improve Customer Retention and Purchases

7.1 Enhance Page Value

- Implement personalized recommendations and targeted promotions to increase the value of pages.

7.2 Seasonal Campaigns

- Run targeted marketing campaigns and promotions during high-impact months (May, March, December).

7.3 Reduce Exit and Bounce Rates

- Improve website usability, content relevance, and page load speed to retain users and reduce early exits.

7.4 Engage Customers with Product Content

- Ensure product-related pages are informative, visually appealing, and easy to navigate to encourage longer visits.

7.5 Retain Returning Visitors

- Implement loyalty programs, personalized offers, and email marketing to encourage repeat visits and purchases.

7.6 Weekend Promotions

- Introduce special weekend promotions, flash sales, or events to capitalize on higher purchase intent during weekends.

8. Actionable Recommendations for Marketing and Sales Teams

8.1 Target High-Value Customers

- Use the XGBoost model to identify high-value customers based on their engagement patterns (e.g., high `PageValues`, long `TimeSpentOnSite`).
- Focus on returning visitors and users who spend significant time on product-related pages.

8.2 Personalized Marketing

- Leverage insights from SHAP analysis to create personalized marketing campaigns targeting users with high purchase intent.

8.3 Optimize Website Experience

- Continuously monitor and optimize the website to reduce bounce and exit rates, ensuring a seamless user experience.

Conclusion

- The **XGBoost model** is the best-performing model for predicting customer purchases, with strong performance in recall, F1-score, and ROC-AUC.
- Key drivers of purchase intent include **PageValues**, **TimeSpentOnSite**, and **ProductRelated_Duration**.
- Actionable recommendations focus on improving user engagement, reducing bounce and exit rates, and leveraging seasonal trends to boost revenue.