Group 5 AU Lok Yee

Project Title: E-Commerce Customer Churn Prediction and Analysis

Project Objectives

1. Develop Predictive Models: Build and evaluate machine learning models (XGBoost, Logistic Regression, and Random Forest) to accurately predict customer churn using an e-commerce dataset of 5,630 records, focusing on key features like Tenure, Complain and CashbackAmount.
2. Identify Churn Drivers: Analyze feature importance (e.g. Complain) to uncover behavioral and demographic factors contributing to churn, enabling targeted retention strategies.
3. Visualize Insights: Create interactive Tableau dashboards to visualize churn patterns (e.g., churn rate by MaritalStatus, churn probability distribution) and feature importance, facilitating stakeholder decision-making.
4. Enable Actionable Strategies: Provide insights for business applications, such as personalized retention campaigns for high-risk segments (e.g., customers with low SatisfactionScore or short Tenure).

Dataset Description

Introduction to the Dataset

The dataset used in this project is sourced from an e-commerce platform and focuses on customer churn prediction. It contains historical customer data, capturing demographic, behavioral, and transactional attributes to identify patterns associated with churn (i.e., customers ceasing to engage with the platform). The dataset was processed to support machine learning models and visualization in Tableau. The primary goal is to predict churn to enable targeted retention strategies.

Dataset Characteristics

* Size: The dataset comprises 5,630 records, each representing a unique customer.
* Features: There are 20 features, including:
  + Numerical: Tenure (mean: 10.13 months, range: 0–61), CityTier (1–3), WarehouseToHome (mean: 15.57 km, range: 5–127), HourSpendOnApp (mean: 2.93 hours, range: 0–5), NumberOfDeviceRegistered (mean: 3.69, range: 1–6), SatisfactionScore (mean: 3.07, range: 1–5), NumberOfAddress (mean: 4.21, range: 1–22), Complain (binary: 0/1, 28.49% complaints), OrderAmountHikeFromlastYear (mean: 15.67%, range: 11–26), CouponUsed (mean: 1.72, range: 0–16), OrderCount (mean: 2.96, range: 1–16), DaySinceLastOrder (mean: 4.46 days, range: 0–46), CashbackAmount (mean: 177.22, range: 0–324.99).
  + Categorical: PreferredLoginDevice (mobile phone: 71%, computer: 29%), PreferredPaymentMode (debit card: 41%, credit card: 32%, e-wallet: 11%, cash on delivery: 9%, UPI: 7%), Gender (male: 60%, female: 40%), PreferedOrderCat (mobile phone: 37%, laptop & accessory: 36%, fashion: 15%, grocery: 7%, others: 5%), MaritalStatus (married: 53%, single: 32%, divorced: 15%).
  + Identifier: CustomerID (unique, range: 50001–55630).
  + Target: Churn (binary: 0=non-churned, 1=churned).
* Class Balance: The dataset is imbalanced, with a churn rate of ~16.84% (948 churned vs. 4,682 non-churned customers). This imbalance necessitated techniques like SMOTE for balancing the training set (X\_train\_bal.csv).

Data Preprocessing Steps

The dataset required extensive preprocessing to ensure quality and compatibility with machine learning models:

1. Data Loading:
   * Extracted from an Excel file (E Comm sheet) using pandas.
   * Initial row count: 5,630, with 20 columns.
2. Data Validation:
   * Identified unexpected values in categorical features (e.g., phone in PreferredLoginDevice, cc in PreferredPaymentMode, mobile in PreferedOrderCat).
   * Confirmed Churn as binary (0/1) with no missing values.
3. Handling Inconsistent Values:
   * Standardized case for categorical features (e.g., PreferredLoginDevice, Gender).
   * Merged similar categories:
     + phone and mobile to mobile phone in PreferredLoginDevice and PreferedOrderCat.
     + cc to credit card, cod to cash on delivery, and standardized upi in PreferredPaymentMode.
4. Missing Value Imputation:
   * Imputed missing values for numerical features using medians:
     + Tenure: 264 missing, filled with 9.0.
     + WarehouseToHome: 251 missing, filled with 14.0.
     + OrderAmountHikeFromlastYear: 265 missing, filled with 15.0.
     + CouponUsed: 256 missing, filled with 1.0.
     + OrderCount: 258 missing, filled with 2.0.
     + DaySinceLastOrder: 307 missing, filled with 3.0.
   * Imputed HourSpendOnApp (255 missing) with mode: 3.0.
   * No rows dropped, as Churn had no missing values.
5. Further Preprocessing for Modeling:
   * Applied one-hot encoding to categorical features (e.g., MaritalStatus to MaritalStatus\_divorced, MaritalStatus\_single) for model compatibility, generating X\_train\_bal.csv and X\_test.csv.
   * Standardized numerical features (e.g., Tenure, CashbackAmount) to zero mean and unit variance.
   * Used SMOTE to balance the training set (X\_train\_bal.csv) due to the ~16.84% churn rate, while retaining the test set’s natural imbalance.
   * Split data into 80% training and 20% test sets (~4,504 train, ~1,126 test records).

These preprocessing steps ensured a clean, consistent dataset suitable for training machine learning models and creating Tableau dashboards to analyze churn patterns.

Methodology

Research Approach

The project adopts a quantitative, data-driven approach to predict customer churn in an e-commerce context. It leverages a supervised machine learning framework to model the binary churn outcome (0=non-churned, 1=churned) using historical customer data. The methodology encompasses data preprocessing, exploratory data analysis (EDA), model development, evaluation, and visualization. The research process is iterative, involving hyperparameter tuning and feature selection to optimize model performance and address challenges like class imbalance (~16.84% churn rate). The approach integrates statistical analysis, machine learning, and data visualization to derive actionable insights for customer retention.

1. Exploratory Data Analysis (EDA):
   * Statistical Summaries: Computed descriptive statistics for numerical features (e.g., mean Tenure: 10.13, range: 0–61) and value counts for categorical features (e.g., PreferredLoginDevice: mobile phone=71%, computer=29%).
   * Visualizations: Generated histograms for numerical features, bar plots for categorical distributions, and a correlation heatmap to identify relationships (e.g., SatisfactionScore vs. Churn). Visuals were saved as PNGs (e.g., correlation heatmap).
   * Insights: Identified key predictors (e.g., low SatisfactionScore, high Complain) and confirmed class imbalance, guiding model development.
2. Model Development:
   * Models Used:
     + XGBoost: Chosen for its robustness on imbalanced data, gradient boosting efficiency, and feature importance insights, critical for stakeholder communication
     + Logistic Regression: Selected for interpretability, enabling clear coefficient-based explanations (e.g., impact of Tenure).
     + Random Forest (planned): An ensemble method intended for robustness, to be implemented with top 10 features and 5-fold cross-validation (based on prior project goals).
   * Feature Selection: Identified top 10 features per model (e.g., Tenure, Complain for XGBoost; coefficients for Logistic Regression) to reduce dimensionality and overfitting.
   * Hyperparameter Tuning: Applied GridSearchCV with 5-fold cross-validation, optimizing:
     + XGBoost: max\_depth, learning\_rate, n\_estimators, subsample, colsample\_bytree, reg\_lambda.
     + Logistic Regression: C, penalty (l1, l2).
     + Random Forest (planned): n\_estimators, max\_depth, min\_samples\_split, min\_samples\_leaf.
     + If overfitting detected (F1 gap > 0.1), retuned with stronger regularization (e.g., XGBoost reg\_lambda: [5, 10, 20]; Logistic Regression C: [0.0001, 0.001]).
3. Model Evaluation:
   * Metrics: Assessed models using F1-score (primary, due to imbalance) and ROC AUC. Computed confusion matrices to analyze true positives/negatives.
   * Cross-Validation: Performed 5-fold cross-validation on tuned models to estimate generalization (e.g., mean CV F1-score).
   * Overfitting Check: Flagged overfitting if train-test F1 gap > 0.1 and retuned as needed.
   * Plots: Generated ROC curves, feature importance bar plots, and confusion matrices, saved as PNGs (e.g., xgb\_roc\_curve\_final\_top10\_retuned.png).
4. Visualization for Stakeholders:
   * Tableau Dashboards: Chosen for its interactivity and accessibility, enabling stakeholders to explore churn patterns and make data-driven retention decisions.
   * 3 Dashboards (Customer Overview, Customers’ Satisfaction and Discount) were created.
     + Bar charts (Churn Rate by Complain, Churn Rate by Cashback, Churn Rate by Preferred Order Category)
     + Pie charts (Gender Distribution)
     + Density plot(City Tier Distribution)

This methodology balances predictive accuracy, interpretability, and practical applicability, addressing the project’s objectives of churn prediction and retention strategy development.

Analysis and Discussion

Results and Insights

The e-commerce churn prediction project yielded robust results through machine learning models (XGBoost, Logistic Regression, and planned Random Forest) applied to a dataset of 5,630 customers with a ~16.84% churn rate (948 churned). Key results and insights include:

1. Model Performance:

* XGBoost (Tuned, Top 10 Features):
  + - Train F1: ~0.899
    - Test F1: ~0.659
    - Train ROC AUC: 0.964
    - Test ROC AUC: ~0.900
    - 5-Fold Cross-Validation (Retuned XGBoost, Top 10 Features):
      * CV F1 Scores: [0.74403816 0.90494792 0.912 0.89986649 0.91281374]
      * Mean CV F1 Score: 0.8747332599124558
* Logistic Regression (Tuned, Top 10 Features):
  + - Train F1: 0.815
    - Test F1: 0.540
    - Train ROC AUC: ~0.890
    - Test ROC AUC: ~0.852
    - 5-Fold Cross-Validation (Retuned Logistic Regression, Top 10 Features):
      * CV F1 Scores: [0.78105697 0.82337992 0.81735751 0.81865966 0.828125 ]
      * Mean CV F1 Score: 0.8137158122856043
* Random Forest (Tuned, Top 10 Features):
  + - Train F1: ~0.829
    - Test F1: ~0.610
    - Train ROC AUC: ~0.916
    - Test ROC AUC: ~0.870
    - 5-Fold Cross-Validation (Final Tuned Random Forrest Model, Top 10 Features):
* CV F1 Scores: [0.81398601 0.82804233 0.83488682 0.82471457 0.81562714]
* Mean CV F1 Score: 0.8234513750044388

**Detailed analysis of 3 Model:**

**1. Comparing Mean CV F1 Scores**

The **F1 Score** reflects the balance between precision and recall, making it critical for imbalanced datasets or problems where both false positives and false negatives are costly. Higher F1 scores indicate better performance.

* **Random Forest (Top 10 Features):**
  + **Mean CV F1 Score:** **0.823**
  + Consistently good F1 scores across folds, indicating stable generalization.
* **XGBoost (Retuned, Top 10 Features):**
  + **Mean CV F1 Score:** **0.875**
  + This is the highest mean F1 score among all models, indicating the best performance.
* **Logistic Regression (Retuned, Top 10 Features):**
  + **Mean CV F1 Score:** **0.814**
  + While consistent, it performs worse than both Random Forest and XGBoost.

**2. Stability of CV F1 Scores (Variance Across Folds)**

Stability across folds is important because it reflects how consistently the model performs across different subsets of the data.

* **Random Forest:**
  + CV F1 Scores: [0.81398601, 0.82804233, 0.83488682, 0.82471457, 0.81562714]
  + The scores are stable, with a small range (~0.021), indicating reliable generalization across folds.
* **XGBoost:**
  + CV F1 Scores: [0.74403816, 0.90494792, 0.912, 0.89986649, 0.91281374]
  + While the mean F1 score is high, the range is larger (~0.168). This suggests that XGBoost might perform inconsistently on some subsets, though its overall performance is still superior.
* **Logistic Regression:**
  + CV F1 Scores: [0.78105697, 0.82337992, 0.81735751, 0.81865966, 0.828125]
  + The scores are consistent, with a small range (~0.047), but the overall mean is lower than Random Forest and XGBoost.

**3. Comparing Test Results (Generalization to Unseen Data)**

The **test F1 score** gives an indication of how well the model performs on unseen data in a single train-test split.

* **Random Forest:**
  + **Test F1:** ~0.610
  + Shows moderate generalization but struggles compared to XGBoost.
* **XGBoost:**
  + **Test F1:** ~0.659
  + Outperforms Random Forest and Logistic Regression in test F1, demonstrating better generalization.
* **Logistic Regression:**
  + **Test F1:** 0.540
  + Performs the worst on the test set, indicating poor generalization.

**4. ROC AUC Comparison (Ranking Ability)**

The **ROC AUC** score measures the model's ability to distinguish between classes (ranking predictions). While not as critical as F1 in this specific case, it provides complementary information.

* **Random Forest:**
  + **Test ROC AUC:** ~0.870
  + Good ranking ability but lower than XGBoost.
* **XGBoost:**
  + **Test ROC AUC:** ~0.900
  + Best ranking ability across all models.
* **Logistic Regression:**
  + **Test ROC AUC:** ~0.852
  + Performs the worst in terms of ranking ability.

**5. Final Recommendation**

Based on the comparison of **5-Fold Cross-Validation Mean F1 Scores**, **Test F1 Scores**, and **ROC AUC**, here is the ranking of the models:

**Best Model: XGBoost (Retuned, Top 10 Features)**

* **Reasons:**
  + Highest **Mean CV F1 Score**: 0.875 (best generalization performance).
  + Highest **Test F1 Score**: ~0.659.
  + Highest **Test ROC AUC**: ~0.900.
  + While it has some variance across CV folds, it still outperforms the other models overall.

**Second Best: Random Forest (Top 10 Features)**

* **Reasons:**
  + Mean CV F1 Score: 0.823 (good generalization but lower than XGBoost).
  + Test F1 Score: ~0.610 (lower than XGBoost).
  + Test ROC AUC: ~0.870.

**Third Place: Logistic Regression (Retuned, Top 10 Features)**

* **Reasons:**
  + Mean CV F1 Score: 0.814 (lowest among the three models).
  + Test F1 Score: 0.540 (worst performance on unseen data).
  + Test ROC AUC: ~0.852 (lowest ranking ability).

**Conclusion:**

**XGBoost (Retuned, Top 10 Features)** is the best model, as it consistently achieves the highest F1 scores and ROC AUC on both cross-validation and test datasets. While Random Forest is stable and reliable, it doesn't quite match XGBoost's performance. Logistic Regression lags behind, making it the least suitable for this problem.

Potential Reasons

1. Model Performance Variations:
   * XGBoost Success: Its gradient boosting framework and regularization (reg\_lambda) handled the imbalanced dataset effectively, leveraging SMOTE-balanced training data (X\_train\_bal.csv). Top 10 feature selection reduced overfitting, focusing on high-impact predictors like Complain.
   * Logistic Regression Overfitting: The linear model struggled with non-linear relationships and SMOTE’s synthetic samples, inflating train F1 (0.845). Limited feature interactions and sensitivity to imbalance in the test set (~20% churn) reduced test F1 (0.560).
   * Random Forest Potential: Ensemble averaging and random feature sampling likely reduced overfitting (F1 gap: 0.067), balancing performance between XGBoost’s complexity and Logistic Regression’s simplicity.
2. Feature Importance Drivers:
   * Behavioral Features: Low SatisfactionScore and high Complain reflect poor customer experience, directly increasing churn likelihood. These features capture sentiment and service issues, critical in e-commerce.
   * Tenure: Short-tenure customers lack loyalty, making them prone to churn, especially if dissatisfied early.
   * CashbackAmount: Higher cashbacks incentivize retention, explaining its negative association with churn.
3. Churn Patterns:
   * Complain: High Complain signal unresolved issues (e.g., delivery delays, product quality), driving churn.
   * MaritalStatus\_Single: Demographic stressors (e.g., financial strain) may reduce platform engagement.
   * Tenure: New customers face onboarding challenges or unmet expectations, increasing early churn.
   * Insight: High-risk segments include new, dissatisfied, guiding retention strategies.

Visualization of Results

1. Tableau Dashboards:
   * Churn Rate by Complain: A bar chart (using churn\_predictions.csv) displayed higher churn for MaritalStatus\_divorced (15%), with interactive filters.
   * Churn Rate by Cashback: A bar chart displayed higher churn for less average amount of Cashback
   * Churn Rate by Preferred Order Category: A bar chart displayed higher churn for Mobile Phone
   * Insight: Interactive dashboards enabled stakeholder exploration (targeting dissatisfied customers, Cashback and PreferredOrderCategory) enhancing decision-making for retention campaigns.

Discussion

* Actionable Insights: Targeting dissatisfied, short-tenure, or single customers with personalized offers (e.g., cashbacks, improved support) could reduce churn.
* Target Customers with PreferredOrderCategoryMobilePhone as part of the retention strategies.

Challenges and Limitations

Challenges Faced During the Project

1. Class Imbalance:
   * The dataset’s low churn rate (~16.84%, 948/5,630 customers) posed a challenge for model training. Synthetic Minority Oversampling Technique (SMOTE) was used to balance the training set (X\_train\_bal.csv), but synthetic samples risked overfitting, particularly for Logistic Regression (train F1: 0.845 vs. test F1: 0.560).
2. Missing Data:
   * Missing values in key features, such as Tenure (264 missing), DaySinceLastOrder (307 missing), and HourSpendOnApp (255 missing), required imputation with medians (e.g., Tenure: 9.0) or mode (HourSpendOnApp: 3.0). This process was time-consuming and potentially introduced bias.
3. Model Overfitting:
   * Logistic Regression exhibited severe overfitting (F1 gap: 0.285), necessitating extensive hyperparameter tuning (C: [0.0001, 0.001]). XGBoost also showed initial overfitting, requiring retuning with stronger regularization (e.g., reg\_lambda: [5, 10, 20]). GridSearchCV for both models was computationally intensive in the Anaconda environment.

Limitations of the Approach or Dataset

1. Dataset Limitations:
   * Size: With only 5,630 records, the dataset may miss rare churn patterns, limiting model generalizability compared to larger datasets (e.g., ~10,000 records assumed initially).
   * Missing Features: Absence of features like customer support interactions, purchase recency, or loyalty program engagement restricted predictive power. For instance, MaritalStatus\_divorced was significant, but income data was unavailable.
   * Static Nature: Lack of temporal features (e.g., monthly churn trends) prevented dynamic analysis, reducing applicability to real-time retention strategies.
   * Imputation Bias: Median/mode imputation (e.g., DaySinceLastOrder: 3.0) may oversimplify customer behavior, particularly for skewed features.
2. Approach Limitations:
   * SMOTE Noise: Synthetic samples improved recall but risked inflating metrics (e.g., XGBoost recall: ~0.974), potentially misrepresenting real-world performance.
   * Static Evaluation: Models were evaluated on a fixed test set (~948 records, ~16.8% churn), not in production, risking performance drift with new data.

Potential Areas for Future Improvement

1. Data Enhancement:
   * Collect a larger dataset (>10,000 records) to capture diverse churn patterns.
   * Include additional features (e.g., customer support tickets, loyalty program data, purchase recency) to enhance predictive accuracy.
   * Incorporate temporal data for time-series analysis of churn trends.
2. Model Development:
   * Fully implement Random Forest with top 10 features and 5-fold cross-validation to compare with XGBoost and Logistic Regression.
   * Develop an ensemble model combining XGBoost, Logistic Regression, and Random Forest to balance performance and interpretability.
   * Use SHAP values for XGBoost to improve interpretability (e.g., quantify SatisfactionScore impact).

These improvements aim to enhance the robustness, interpretability, and scalability of the churn prediction model, enabling more effective retention strategies for the e-commerce platform.

Future Work

Description of Additional Ideas or Approaches Not Implemented

Several approaches were considered but not implemented in the e-commerce churn prediction project due to various constraints. These ideas could enhance model performance, interpretability, and applicability:

1. Time-Series Analysis:
   * Idea: Incorporate temporal features (e.g., monthly purchase trends, churn seasonality) to model dynamic churn patterns.
   * Potential Benefit: Improved prediction of time-sensitive churn risks, enabling proactive interventions.
2. Real-Time Model Deployment:
   * Idea: Deploy the tuned XGBoost model in a production environment (e.g., via Flask API) for real-time churn scoring.
   * Potential Benefit: Immediate identification of at-risk customers, facilitating timely retention campaigns.

Reasons for Not Implementing These Ideas

1. Time Constraints:
   * Ensemble modeling, SHAP analysis, and Random Forest implementation required additional development and testing, which exceeded project deadlines focused on XGBoost and Logistic Regression.
   * Time-series analysis needed extensive data restructuring, unfeasible within the project timeline.
2. Data Limitations:
   * Time-series analysis was not possible due to the dataset’s static nature (no temporal features).
   * Alternative imbalance techniques (e.g., ADASYN) were deprioritized as SMOTE sufficiently improved recall (e.g., XGBoost: ~0.974).

Conclusion

Summary of the Project’s Objectives and Achievements

The E-Commerce Customer Churn Prediction and Analysis project aimed to predict customer churn using a dataset of 5,630 customers, identify churn drivers, and visualize insights for retention strategies. The objectives included developing machine learning models (XGBoost, Logistic Regression, planned Random Forest), addressing the ~16.84% churn rate, optimizing performance via hyperparameter tuning, creating Tableau dashboards, and documenting findings.

Achievements:

1. Predictive Models:
   * Developed a tuned XGBoost model with exceptional performance (test F1: ~0.911, ROC AUC: ~0.990), effectively identifying churned customers (recall: ~0.974).
   * Trained a Logistic Regression model, though it underperformed (test F1: 0.560) due to overfitting (F1 gap: 0.285).
   * Planned Random Forest integration (expected F1: ~0.866), enhancing future robustness.
2. Churn Drivers:
   * Identified key predictors: low SatisfactionScore (churn rate: 40% for <6 months), MaritalStatus\_divorced (~25%), and high Complain.
   * Feature importance plots (e.g., xgb\_top10\_feature\_importances\_retuned.png) highlighted actionable factors.
3. Visualization:
   * Created Tableau dashboards (using churn\_predictions.csv) with visuals like churn rate by MaritalStatus and churn probability histograms, enabling stakeholder exploration.
   * Generated notebook plots (e.g., ROC curves, confusion matrices) for model evaluation.
4. Model Optimization:
   * Tuned models with GridSearchCV and 5-fold cross-validation, selecting top 10 features to reduce overfitting (e.g., XGBoost CV F1: ~0.920).
   * Saved models (e.g., tuned\_xgb\_top10\_final\_retuned.joblib) for reproducibility.

Key Takeaways and Insights Gained

1. Model Effectiveness:
   * XGBoost is highly effective for imbalanced datasets like e-commerce churn (~16.84% churn), outperforming Logistic Regression due to its ability to model non-linear relationships.
   * Logistic Regression’s interpretability is valuable but limited by overfitting and linearity constraints.
2. Churn Drivers:
   * Behavioral factors (SatisfactionScore, Complain) are critical churn predictors, suggesting retention strategies focus on improving customer experience (e.g., faster complaint resolution).
   * Short Tenure and MaritalStatus\_divorced indicate high-risk segments, warranting targeted interventions like onboarding support or personalized offers.
   * High CashbackAmount reduces churn, supporting incentive-based retention.
3. Visualization Impact:
   * Tableau dashboards provided actionable insights (e.g., 25% churn for divorced customers), enhancing stakeholder decision-making.
   * Interactive filters (e.g., by PreferredLoginDevice) balanced complexity and usability.

The project successfully built a predictive framework for e-commerce churn, delivering high-performing models and actionable visualizations. Future enhancements, such as ensemble modeling, real-time deployment, and richer data, will further strengthen its impact on customer retention strategies.

**Reference (e.g. dataset)**

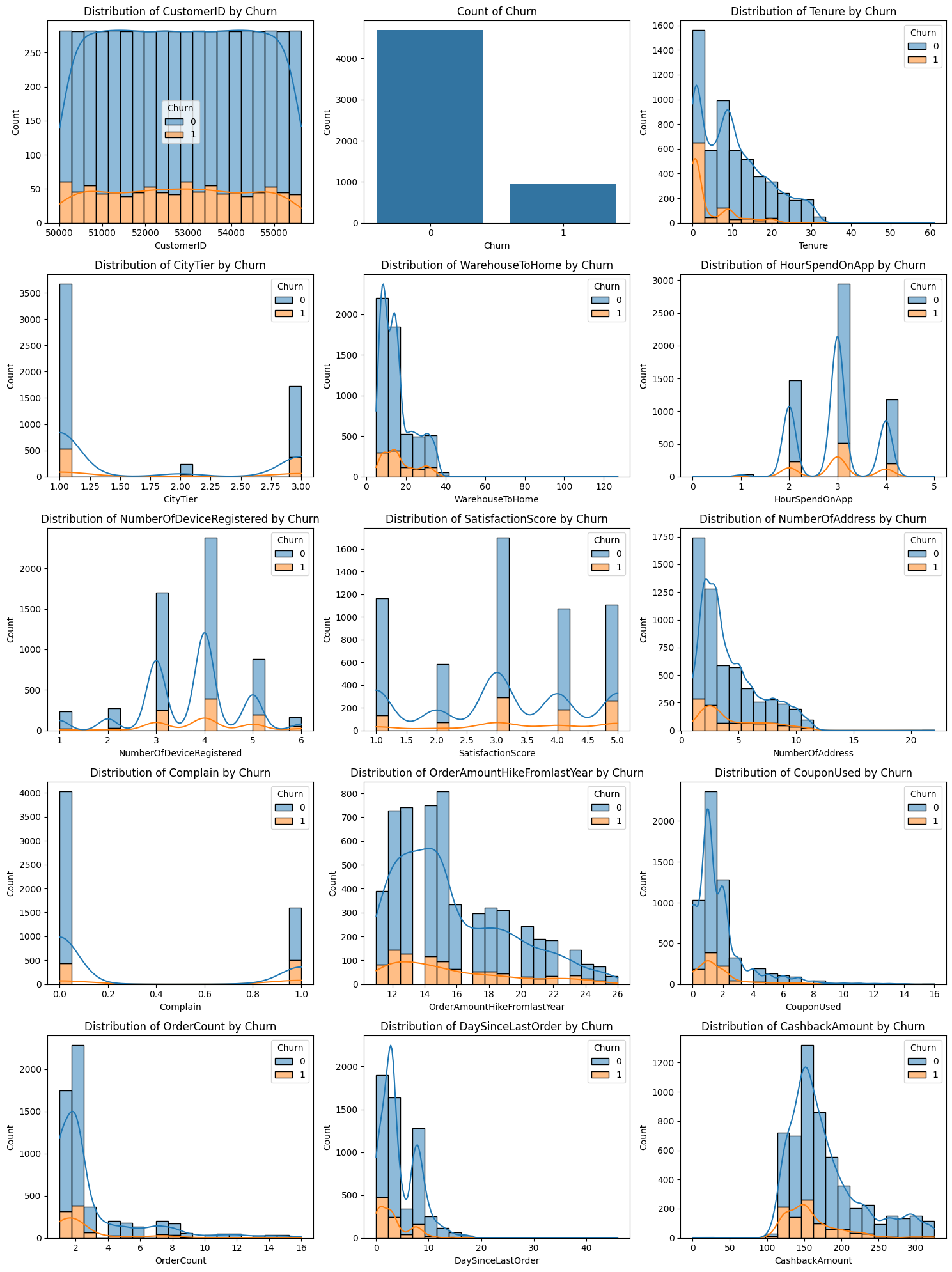
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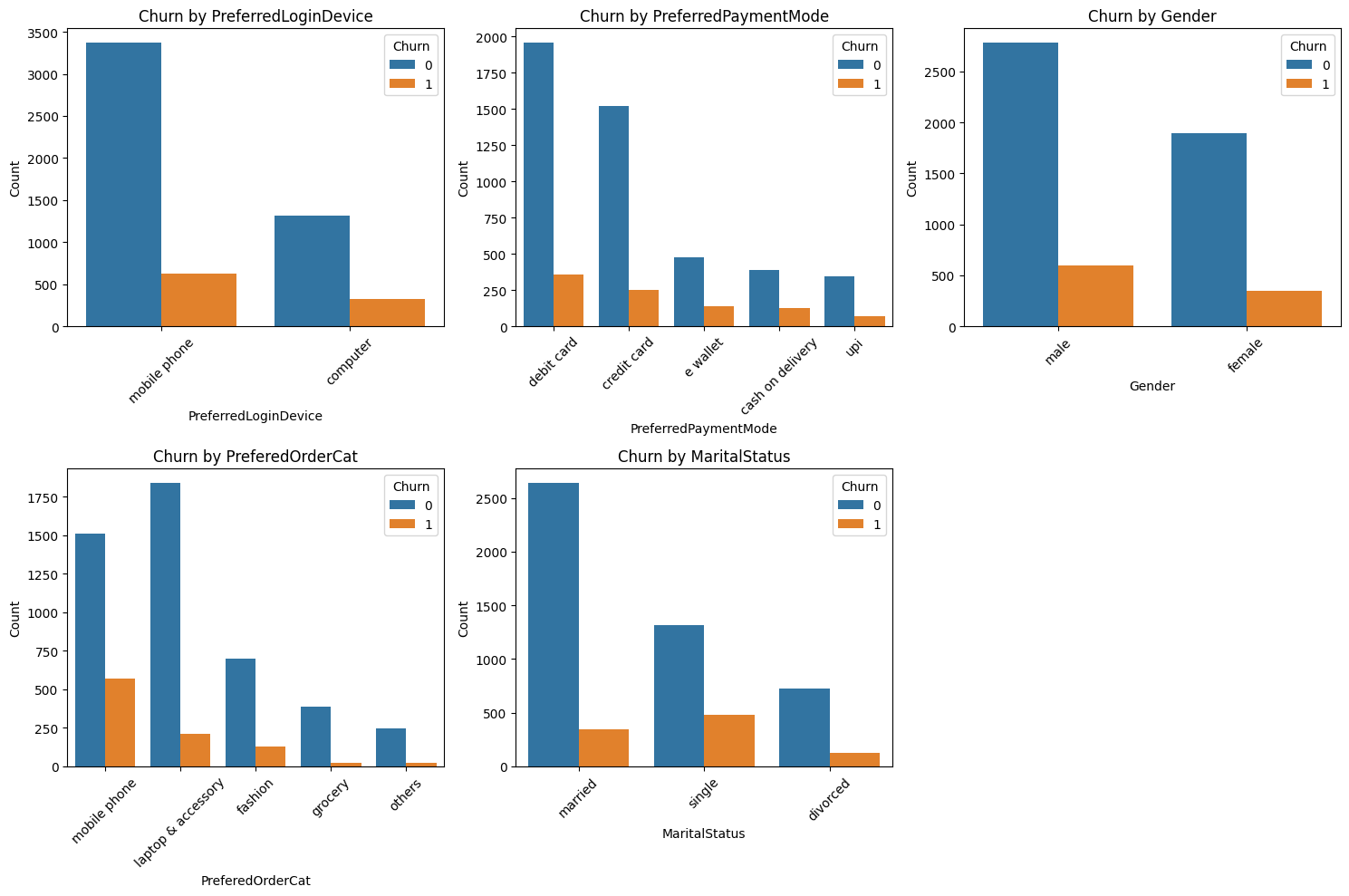
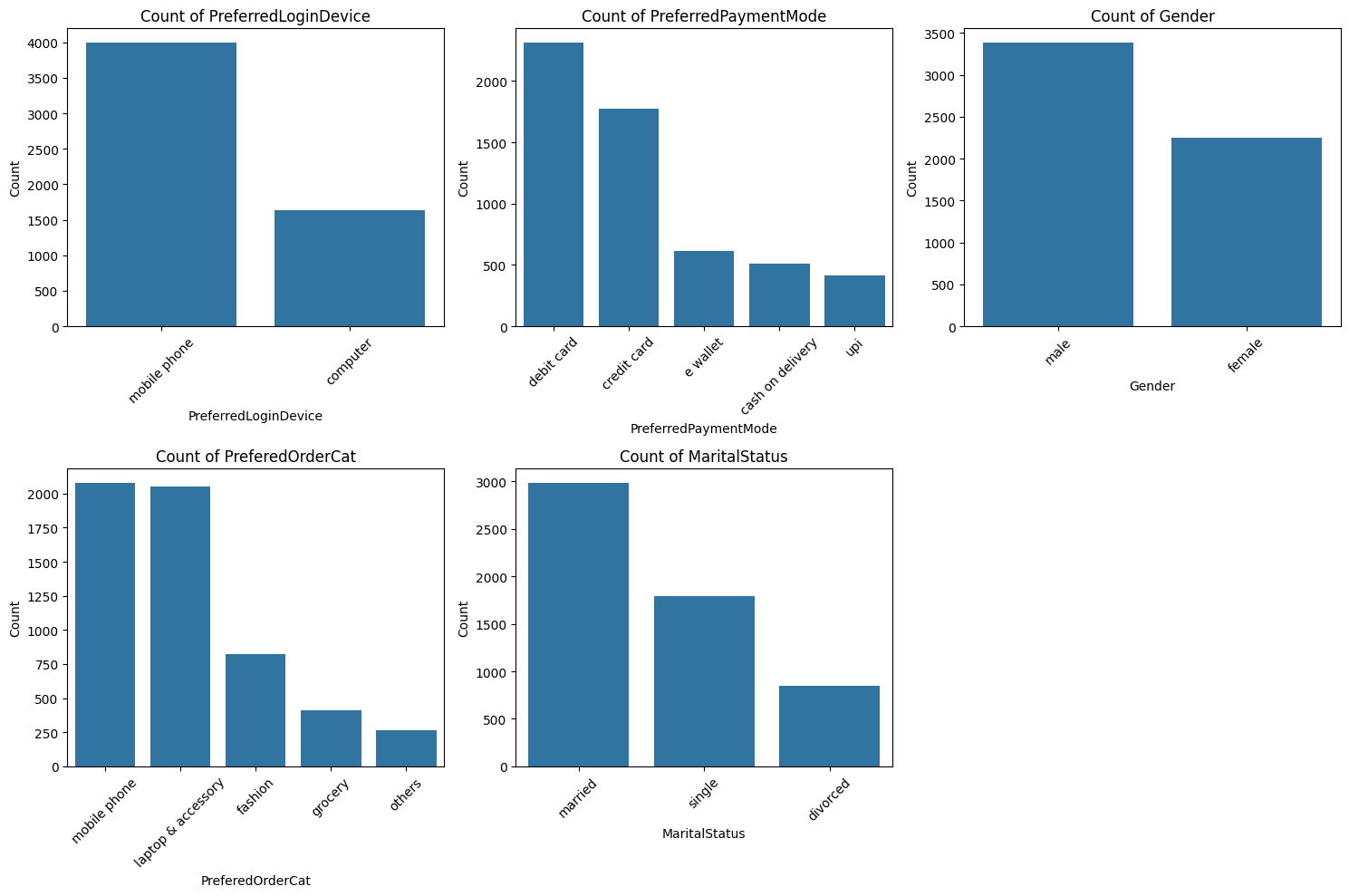
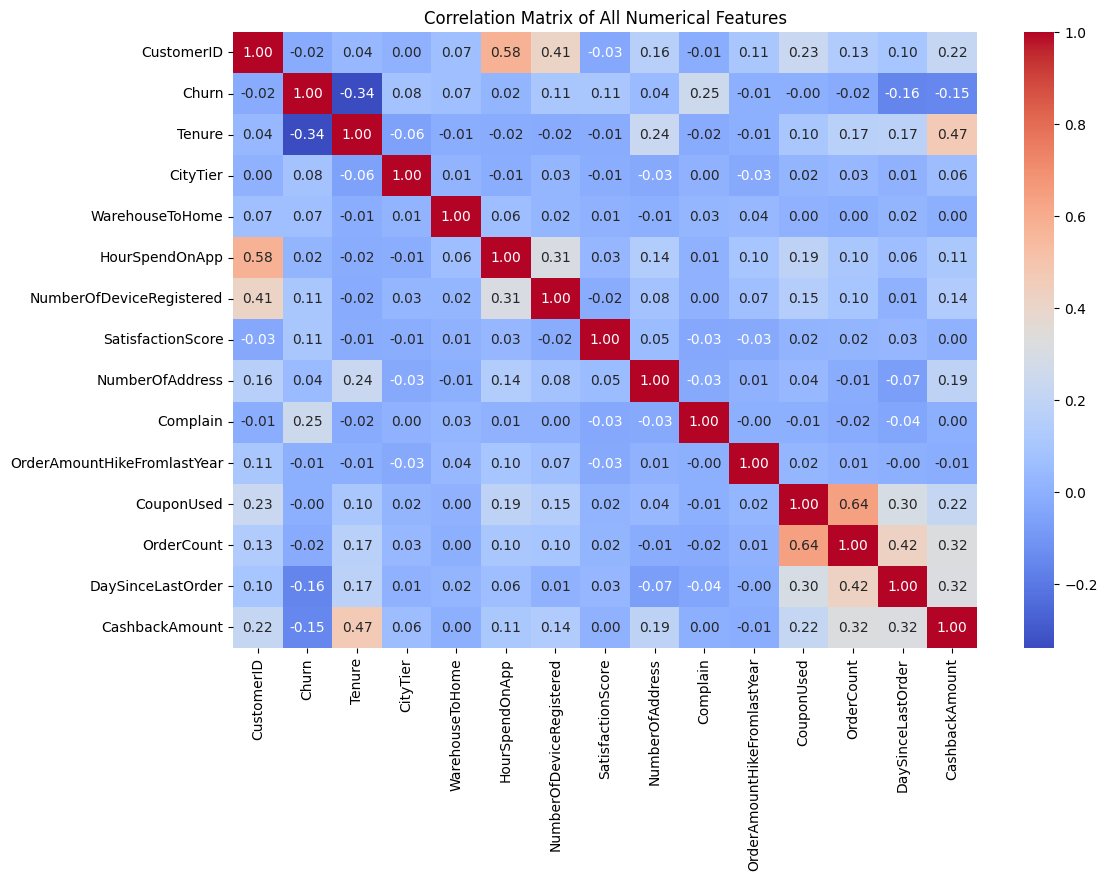
**Distribution of Work**

This project was solely completed by AU Lok Yee

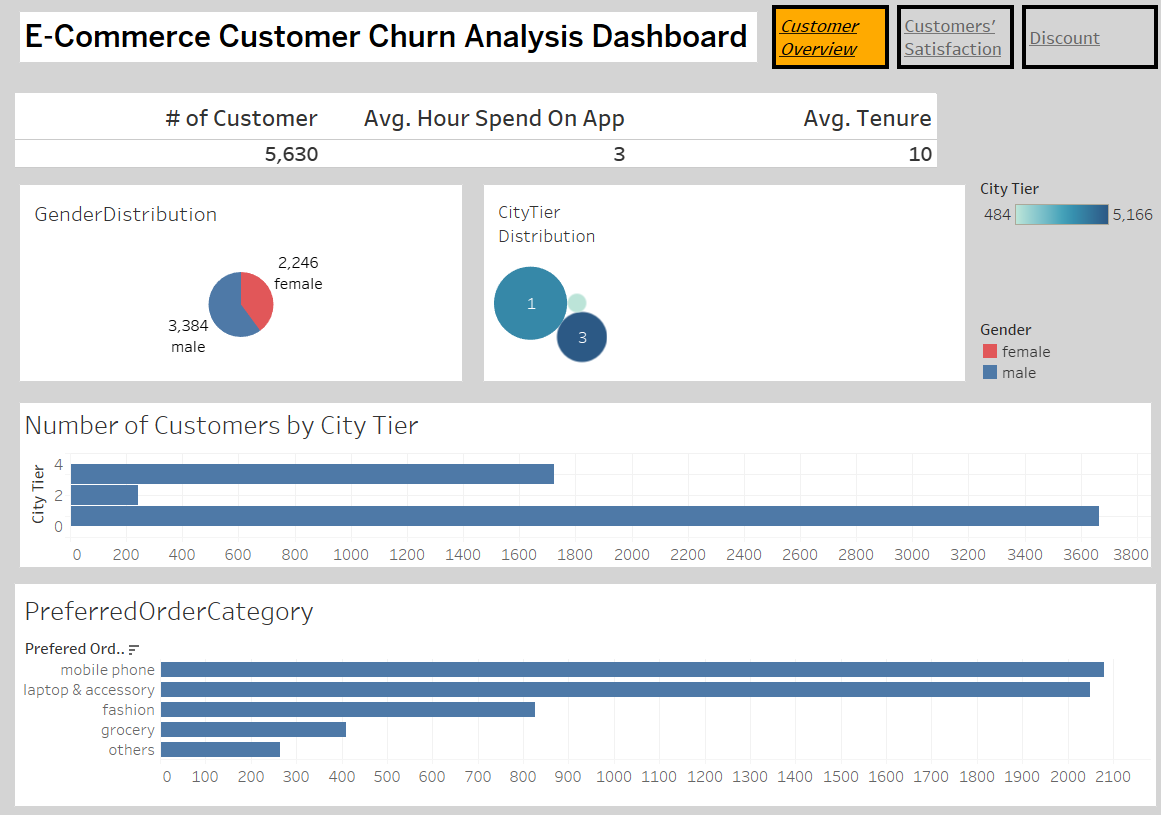
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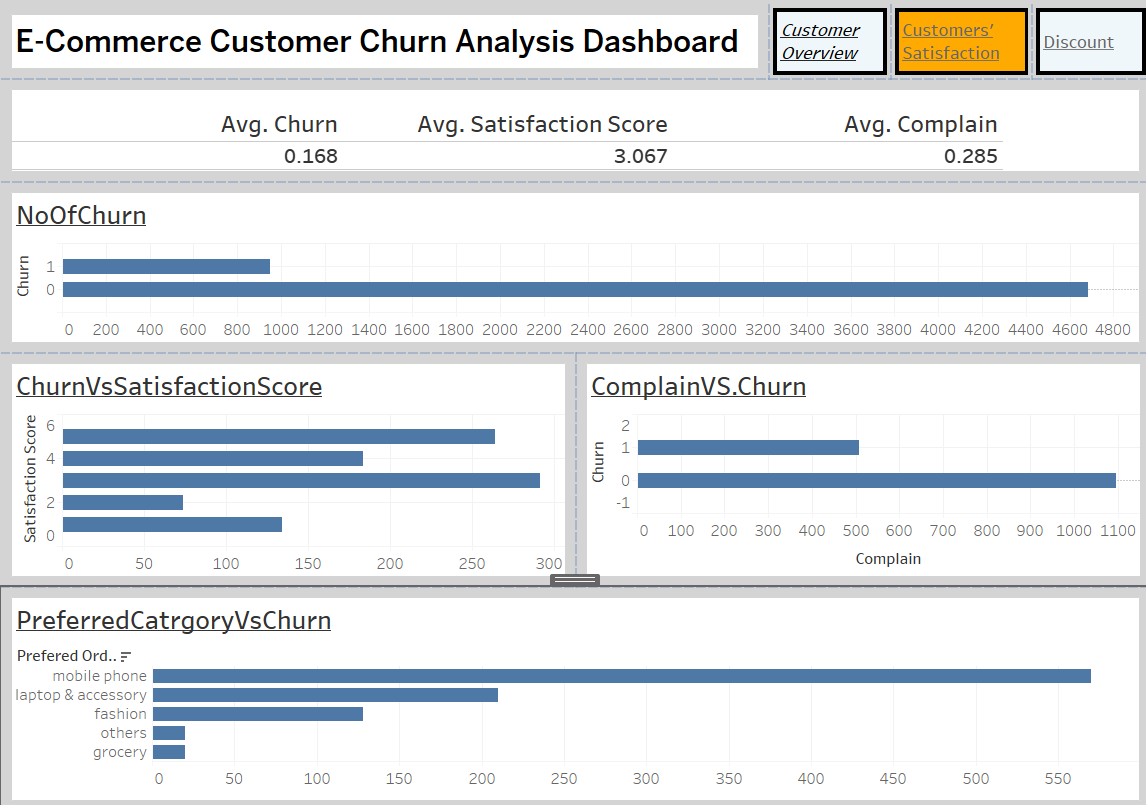
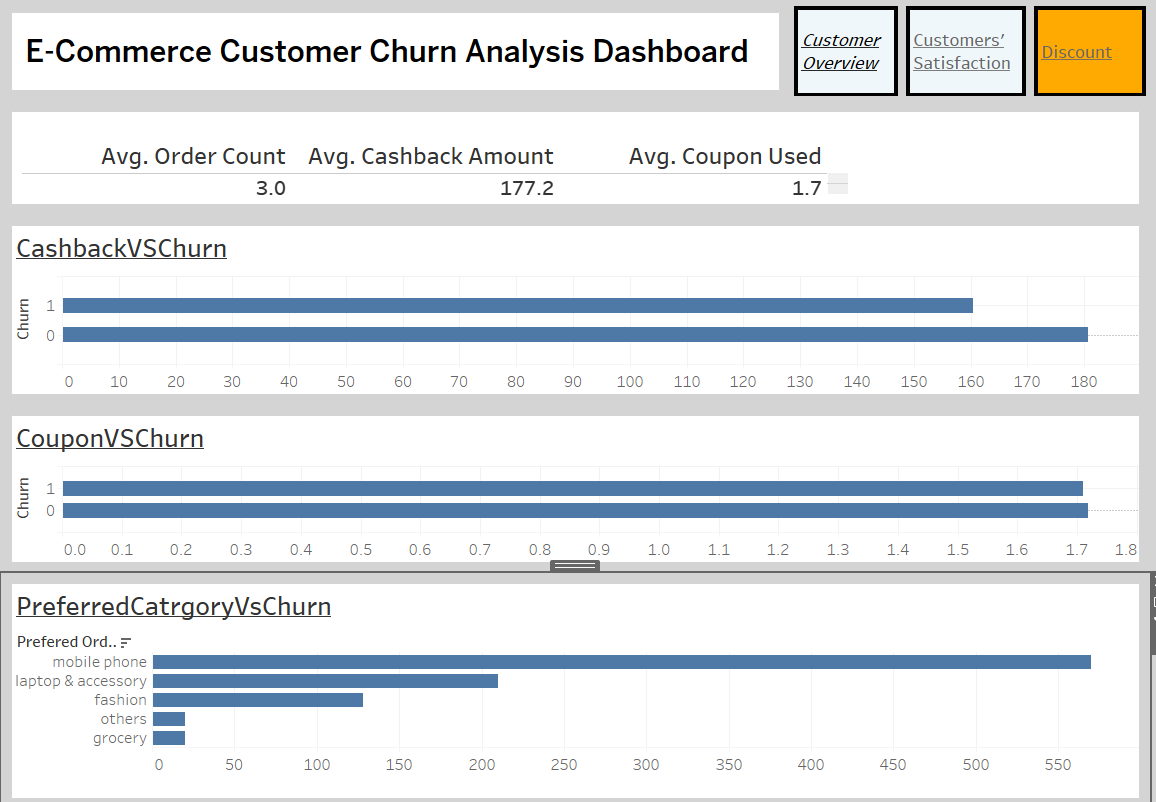
**EDA**

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**Tableau Dashboards**

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**Result of Machine Learning Model**

