Customer Churn Analysis & Prediction

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Data Exploration & Analysis

1. Dataset Overview

• 1.1 Dataset Description

Dataset Size: The dataset contains 3,333 rows (observations) and 20 columns (features).

Target Variable: The target variable is Churn, a binary feature indicating whether a customer has churned (True or False).

Features:

Categorical columns >> ['International plan', 'Voice mail plan', 'Churn'] <<

Numerical columns >> ['Account length', 'Number vmail messages', 'Total day minutes', 'Total day calls', 'Total day charge', 'Total eve minutes', 'Total eve calls', 'Total eve charge', 'Total night calls', 'Total night charge', 'Total intl minutes', 'Total intl calls', 'Total intl charge', 'Customer service calls'] <<

1.2 Data Types

Numerical Features:

Integer: Account length, Area code, Number vmail messages, Total day calls, Total eve calls, Total night calls, Total intl calls, Customer service calls.

Float: Total day minutes, Total day charge, Total eve minutes, Total eve charge, Total night minutes, Total night charge, Total intl minutes, Total intl charge.

Categorical Features:

Object: State, International plan, Voice mail plan.

Boolean: Churn.

1.3 Missing Values & Duplicated

No Missing Values & Duplicated: The dataset is complete, with no missing values in any of the columns. This simplifies preprocessing, as no imputation or removal of missing data is required.

1.4 Descriptive Statistics

Numerical Features:



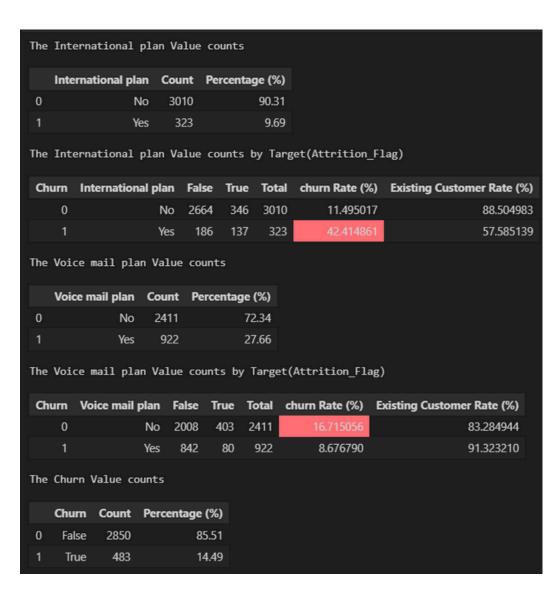
Categorical Feature:

	count	unique	top	freq
State	3333	51	WV	106
International plan	3333	2	No	3010
Voice mail plan	3333	2	No	2411
Churn	3333	2	False	2850

2- Data Analysis & Visualization with insights:

Three key functions were implemented for analysis:

- 1.value_counts: Calculates unique values' count and percentage distribution in a specified column, used for categorical features like International plan and State.
- 2.calculate_churn_rates: Computes churn and existing customer rates for categorical columns, highlighting categories with the highest churn rates.
- 3.add_custom_stats: This function calculates minimum, maximum, and average statistics for specified columns and merges them with a value counts DataFrame. It also styles the output with bar plots for better visualization.



Analyze distribution across target categories

	Churn	Count	Percentage (%)	min_Total eve calls	max_Total eve calls	avg_Total eve calls
0	False	2850	85.51%	0.00	170.00	100.04
1	True	483	14.49%	48.00	168.00	100.56
	Churn	Count	Percentage (%)	min_Total eve charge	max_Total eve charge	avg_Total eve charge
0	False	2850	85.51%	0.00	30.75	16.92
1	True	483	14.49%	6.03	30.91	18.05
	Churn	Count	Percentage (%)	min_Total night minutes	max_Total night minutes	avg_Total night minutes
0	False	2850	85.51%	23.20	395.00	200.13
1	True	483	14.49%	47.40	354.90	205.23
	Churn	Count	Percentage (%)	min_Total night calls	max_Total night calls	avg_Total night calls
0	False	2850	85.51%	33.00	175.00	100.06
1	True	483	14.49%	49.00	158.00	100.40
				min_Total night	max_Total night	avg_Total night
	Churn	Count	Percentage (%)	charge	charge	charge
0	False	2850	85.51%	1.04	17.77	9.01
1	True	483	14.49%	2.13	15.97	9.24
					=	
	Churn	Count	Percentage (%)	min_Total intl minutes	max_Total intl minutes	avg_Total intl minutes
0	False	2850	85.51%	0.00	18.90	10.16
1	True	483	14.49%	2.00	20.00	10.70
	Churn	Count	Percentage (%)	min_Account length	max_Account length	avg_Account length
0	False	2850	85.51%	1.00	243.00	100.79
1	True	483	14.49%	1.00	225.00	102.66
	Churn	Count	Percentage (%)	min_Number vmail messages	max_Number vmail messages	avg_Number vmail messages
0	False	2850	85.51%	0.00	51.00	8.60
1	True	483	14.49%	0.00	48.00	5.12

Insights

1. Churn Rate: The overall churn rate is 14.49%, with 85.51% of customers remaining active.

2. Evening Calls and Charges:

- The average number of evening calls is similar for both churned and nonchurned customers (around 100).
- Churned customers have slightly higher average evening charges (18.05)
 compared to non-churned customers (16.92).

3. Night Minutes and Charges:

 Churned customers have slightly higher average night minutes (205.23) and charges (9.24) compared to non-churned customers (200.13 and 9.01, respectively).

4.International Minutes:

Churned customers have slightly higher average international minutes (10.70)
 compared to non-churned customers (10.16).

5. Account Length:

 The average account length is slightly higher for churned customers (102.66) compared to non-churned customers (100.79), indicating that account length might not be a significant factor in churn.

6. Voicemail Messages:

 Non-churned customers have a higher average number of voicemail messages (8.60) compared to churned customers (5.12), suggesting that customers who use voicemail more frequently are less likely to churn.

7. Day Minutes and Charges:

 Churned customers have significantly higher average day minutes (206.91) and charges (35.18) compared to non-churned customers (175.18 and 29.78, respectively). This indicates that higher daytime usage might be associated with higher churn rates.

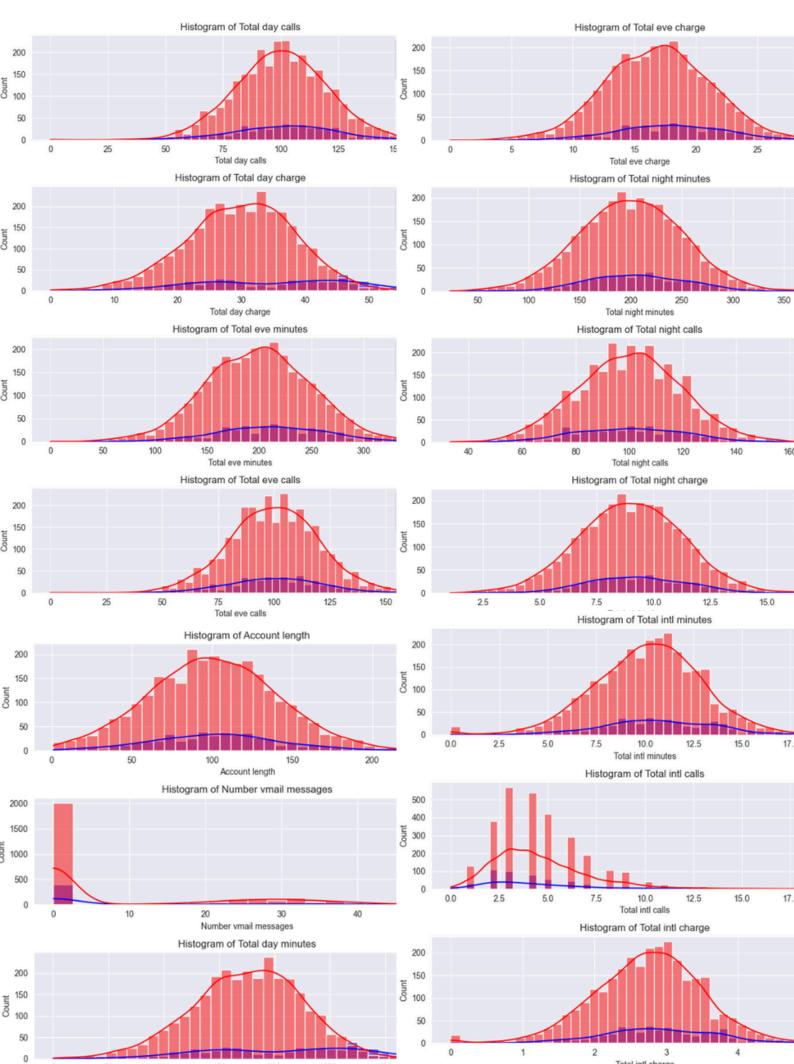
8. Day Calls:

 The average number of day calls is similar for both churned and non-churned customers (around 100), indicating that the number of calls might not be a significant factor in churn.

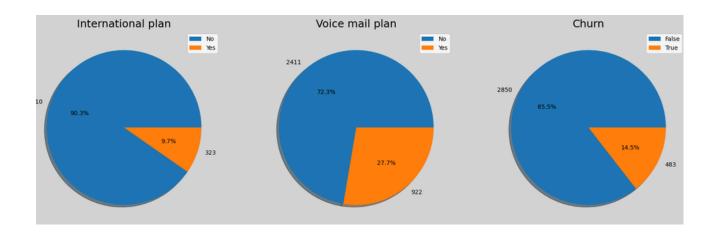
9. Evening Minutes:

 Churned customers have higher average evening minutes (212.41) compared to non-churned customers (199.04), suggesting that higher evening usage might be associated with higher churn rates.

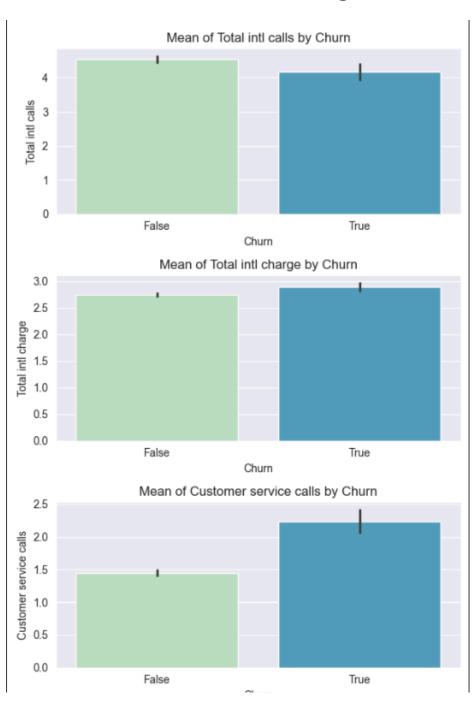
distribution of numerical features:



distribution of Categorical features



Numerical Features man by Churn Status



Preprocessing & Model building

Preprocessing:

1. Encoding:

- The target variable Churn was encoded (False: 0, True: 1).
- Categorical features (International plan and Voice mail plan) were label-encoded.

2. Train-Test Split:

 The dataset was split into features (X) and target (y), and further divided into training (80%) and testing (20%) sets.

3. Handling Class Imbalance:

- A class imbalance in Churn was observed using a count plot.
- SMOTE (Synthetic Minority Oversampling Technique) was applied to balance the training data.

4. Log Transformation:

 Log transformation was applied to skewed numerical columns (Number vmail messages, Total intl calls, Customer service calls) to normalize their distributions.

5. Scaling:

 Numerical features were standardized using StandardScaler to ensure consistent scaling across the dataset.

Model Building and Evaluation

1.XGBoost Model:

An XGBoost classifier was trained without hyperparameter tuning.

Achieved high performance:

Accuracy: 96.4%Recall: 80.6%

F1-Score: 86.2%Precision: 92.5%

2. Other Models with Hyperparameter Tuning:

- Multiple models (Logistic Regression, Naive Bayes, K-Nearest Neighbors, Decision Tree, Random Forest, AdaBoost, Gradient Boosting) were trained using GridSearchCV with recall as the scoring metric.
- o Top Performers:
 - Gradient Boosting:

• Accuracy: 96.2%

• Recall: 78.4%

F1-Score: 85.3%Precision: 93.5%

Random Forest:

Accuracy: 94.1%

• Recall: 66.67%

• F1-Score: 76%

• Precision: 88.5%

3. Model Comparison:

- XGBoost outperformed other models in terms of accuracy, recall, and F1-score.
- Gradient Boosting and Random Forest also showed strong performance, with high accuracy and balanced precision-recall trade-offs.

Key Insights

- Feature Importance:
 - XGBoost's feature importance plot highlighted the most influential features for predicting churn.

	Model	Accuracy	Recall	F1-Score	Precision	Best Parameters
0	XGBoost	0.964018	0.806452	0.862069	0.925926	{Without grid-search}
7	Gradient Boosting	0.962519	0.784946	0.853801	0.935897	{'learning_rate': 0.1, 'max_depth': 7, 'min_sa
5	Random Forest	0.941529	0.666667	0.760736	0.885714	{'criterion': 'gini', 'max_depth': 20, 'min_sa
4	Decision Tree Classifier	0.893553	0.774194	0.669767	0.590164	{'criterion': 'entropy', 'max_depth': 20, 'min
6	AdaBoost	0.887556	0.569892	0.585635	0.602273	{'learning_rate': 1, 'n_estimators': 100}
3	K-Nearest Neighbors	0.805097	0.559140	0.444444	0.368794	{'algorithm': 'auto', 'n_neighbors': 3, 'weigh
1	Logistic Regression	0.743628	0.634409	0.408304	0.301020	{'C': 0.1, 'max_iter': 100, 'penalty': 'I2'}
2	Naive Bayes	0.566717	0.741935	0.323185	0.206587	0

Confusion Matrix



