

# CHURN PREDICTION

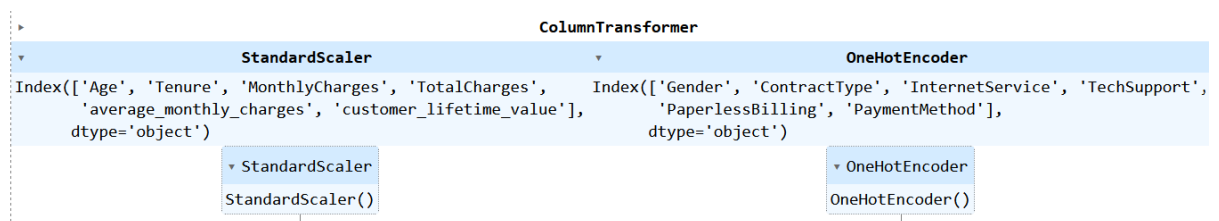
## 1. Exploratory Data Analysis (EDA)

### 1.1 Dataset Overview:

- **Features:**
  - **Age:** Integer
  - **gender:** Categorical (Female, Male)
  - **Contract:** Categorical (Month-to-month, One year, Two year)
  - **MonthlyCharges:** Float
  - **TotalCharges:** Float
  - **TechSupport:** Categorical (No, Yes)
  - **InternetService:** Categorical (DSL, Fiber optic, No)
  - **tenure:** Integer
  - **PaperlessBilling:** Categorical (No, Yes)
  - **PaymentMethod:** Categorical (Bank transfer, Credit card, Electronic check, Mail check)
  - **Churn:** Target Variable (Binary: 0 = No Churn, 1 = Churn)

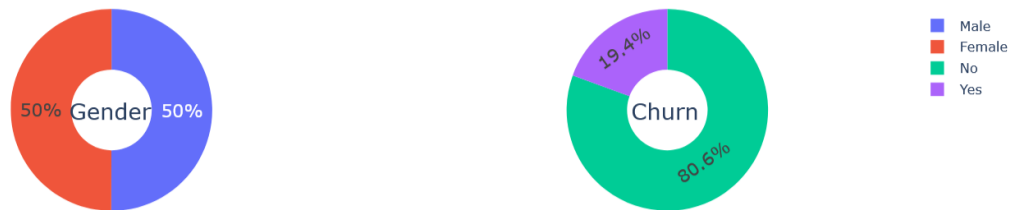
### 1.2 Data Cleaning and Preprocessing:

- Handling Missing Values: Replaced missing values in categorical columns with appropriate values or encoded as nan.
- Encoding Categorical Variables: Applied One hot Encoding to convert categorical variables into numerical values suitable for machine learning models.

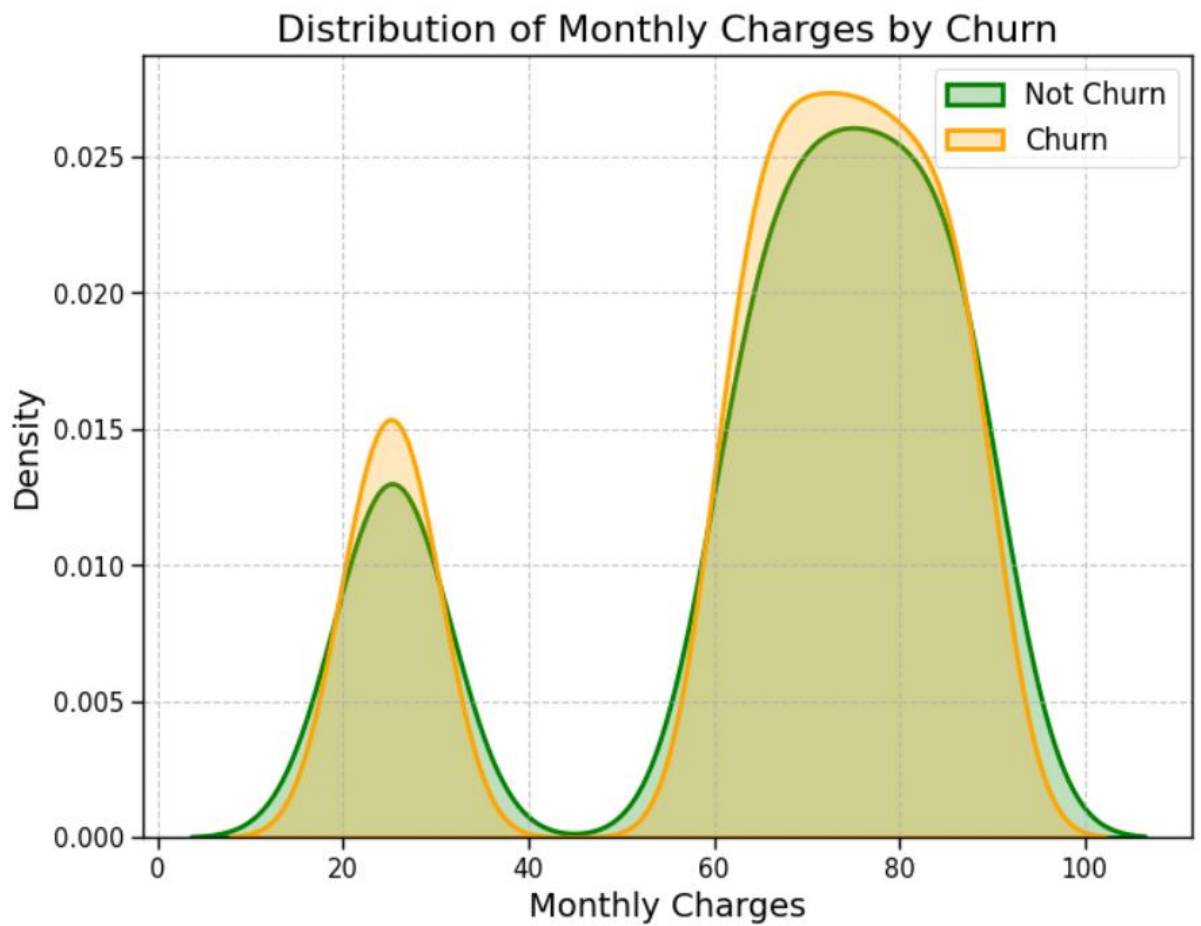


### 1.3 Visualization and Analysis:

Gender and Churn Distributions

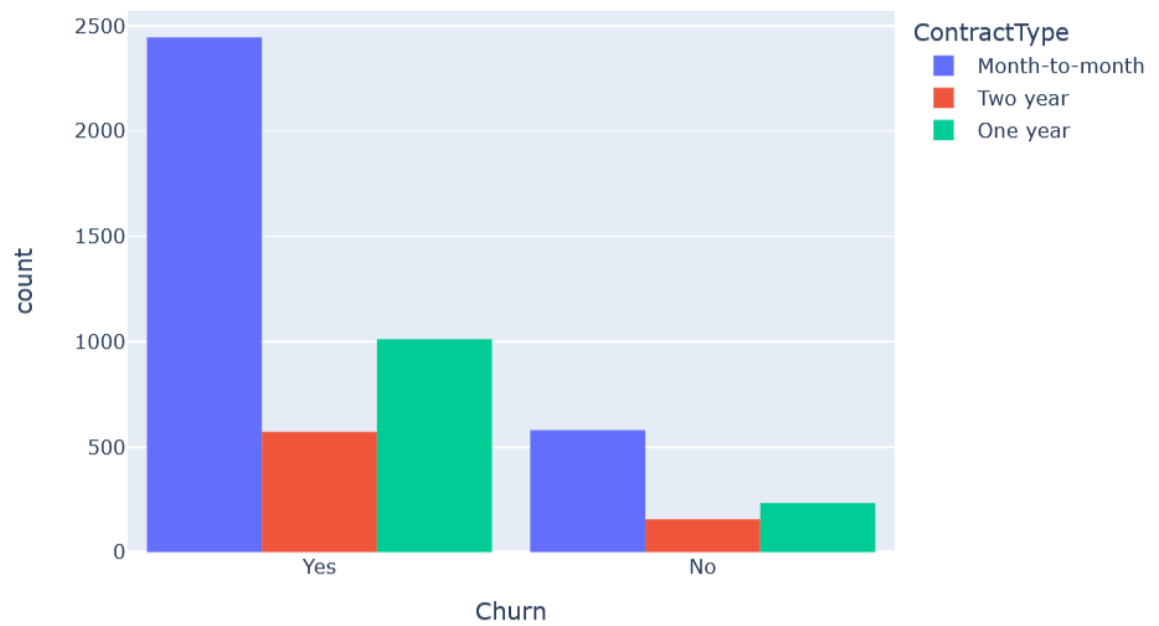


- Customer Monthly Charges Distribution w.r.t. Churn

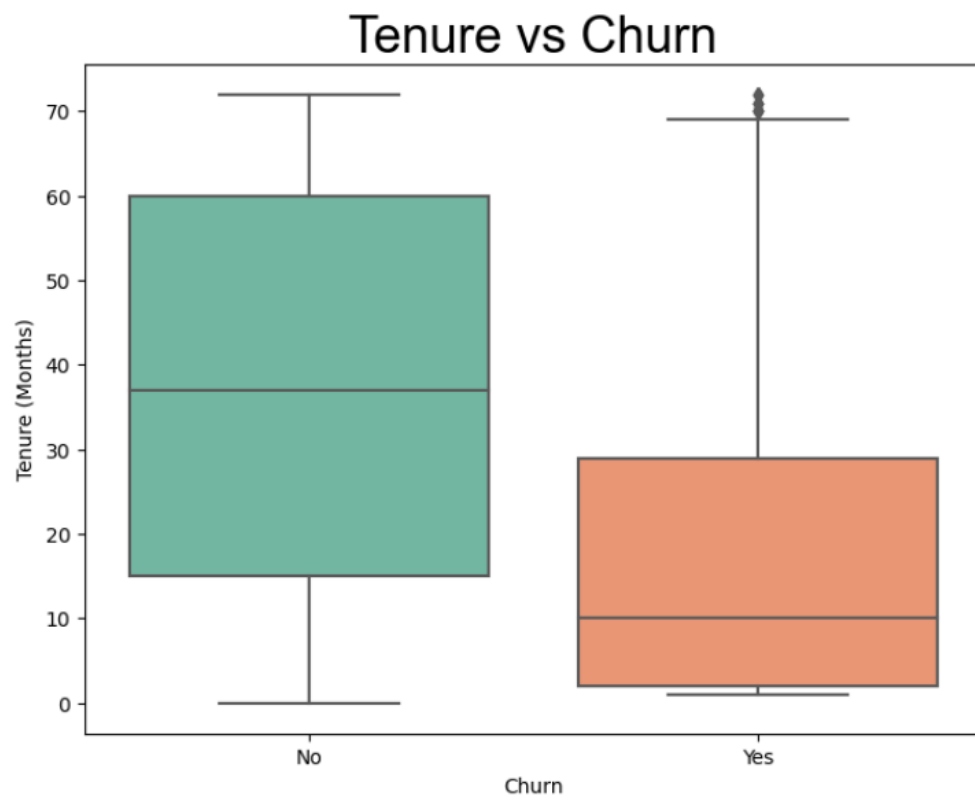


- Churn Distribution w.r.t. Contract Type

## Customer Churn



- Tenure vs Churn



## 2. Model Performance

### 2.1 Models Evaluated:

- Logistic Regression
- Decision Tree Classifier
- Random Forest Classifier
- Support Vector Machine (SVM)
- K-Nearest Neighbors (KNN)
- Gradient Boosting Classifier
- CatBoostClassifier
- XGBClassifier
- ExtraTreesClassifier

### 2.2 Performance Metrics:

- Accuracy
- Precision
- Recall
- F1-Score
- ROC Curve
- AUC (Area Under the Curve)

### 2.5 Example Metrics for Logistic Regression:

- **Accuracy:** 79.98%
- **Precision:** 0.64
- **Recall:** 0.4906
- **F1-Score:** 0.55

### 3. Model Interpretation and Insights

#### 3.1 Confusion Matrix: [[693 71]

[135 130]]

A confusion matrix was generated to visualize the performance of the classification models. It showed how many true positives, true negatives, false positives, and false negatives were identified.

#### 3.2 Recommendations:

- **Customer Retention:** Focus on customers with high MonthlyCharges and low tenure as they are more likely to churn.
- **Service Improvement:** Enhance support and service for customers using Fiber optic internet service and those without TechSupport.

### 4. Conclusion

The analysis effectively identified key factors influencing customer churn and evaluated various machine learning models to predict churn with a focus on maximizing accuracy and interpretability. The best-performing models provide actionable insights for improving customer retention strategies and refining service offerings. Further analysis and model improvements can enhance predictive accuracy and customer insights.

## 5.Final OutPut

### Customer Churn Prediction

Age:  
21

Gender:  
Female

Monthly Charges:  
29

Total Charges:  
600

Tenure:  
22

Contract Type:  
Month-to-month

Internet Service:  
DSL

Tech Support:  
No

Payment Method:  
Bank transfer

Tenure:

Contract Type:  
Month-to-month

Internet Service:  
DSL

Tech Support:  
No

Payment Method:  
Bank transfer

Paperless Billing:  
No

Average Monthly Charges:

Customer Lifetime Value:

Predict

Prediction Result: Yes Churn