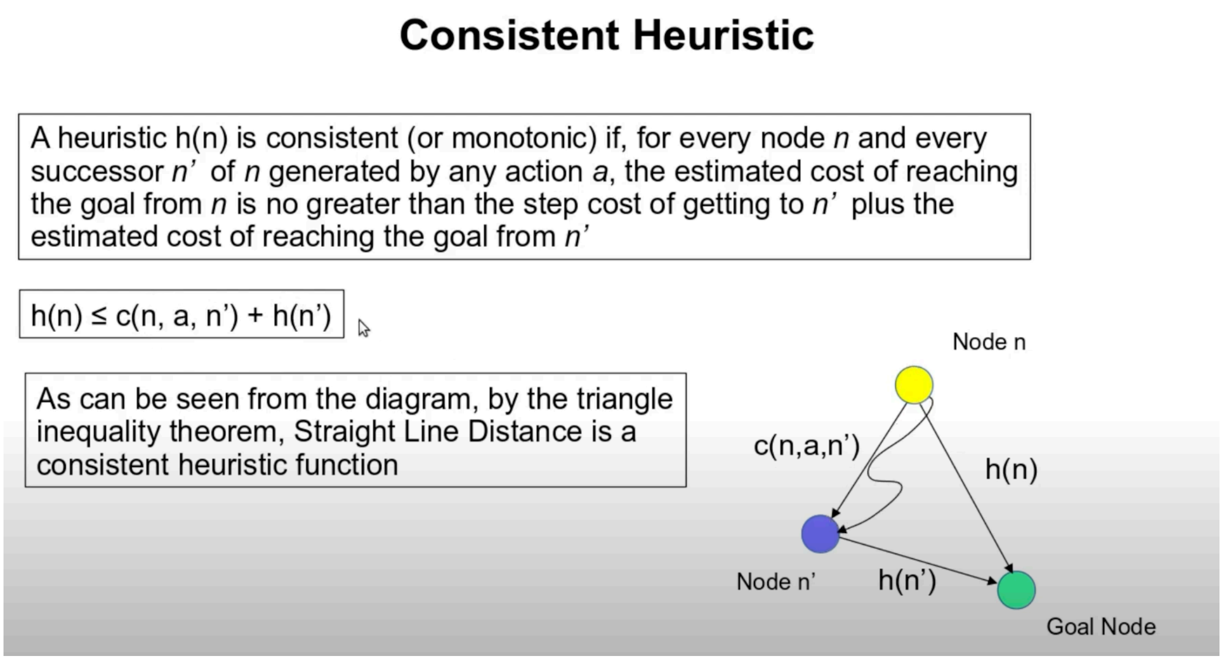
🧠

AP EDA: Framingham

Course #	5100 - Intro AI
Task	Class Lecture
Parent Class	🧠 *Intro to AI Syllabus, 🧠 🔥🔥🔥 AI FINAL PROJECT 🔥🔥🔥
Individual Class	🧠 AP XGBoost , 🧠 Random Forest Exploratory Data Analysis (EDA)
URL	https://rajagopalvenkat.com/teaching/resources/AI/
Progress	In progress
Algorithms, Formulas & Equations DB	*Artificial Intelligence, Artificial Intelligence Tutorial | AI Tutorial - GeeksforGeeks
Week	10
Office Hours	Khoury Office Hours App for all office hours (online and in-person) for efficient queue management this semester. Instructor - Raj • In-person, Meserve 303, Tuesday, 9:30 am - 11:30 am. • To schedule appointments outside of office hours, visit my appointments page. • If you decide to swing by on a whim and my office door is open, feel free to bug me
Reviewed?	☐
Textbook File	https://artint.info/3e/html/ArtInt3e.html

Masters CS Northeastern DB*

Task	Week	Class	Progress	Date	Due Date	Rea
Syllabus	1	🧠 Anaconda Setup	Submitted!			
Homework	1	🧠 Problem Set 0: Background	Submitted!		@January 17, 2025	



AI Review

▼ Exploratory Data Analysis (EDA)

"Framingham" heart disease dataset includes over 4,240 records,16 columns and 15 attributes. The goal of the dataset is to predict whether the patient has 10-year risk of future (CHD) coronary heart disease

Heart Failure Attributes

1. Age: age of the patient [years]
2. Sex: sex of the patient [M: Male, F: Female]
3. ChestPainType: chest pain type [TA: Typical Angina, ATA: Atypical Angina, NAP: Non-Anginal Pain, ASY: Asymptomatic]
4. RestingBP: resting blood pressure [mm Hg]
5. Cholesterol: serum cholesterol [mm/dl]
6. FastingBS: fasting blood sugar [1: if FastingBS > 120 mg/dl, 0: otherwise]
7. RestingECG: resting electrocardiogram results [Normal: Normal, ST: having ST-T wave abnormality (T wave inversions and/or ST elevation or depression of > 0.05 mV), LVH: showing probable or definite left ventricular hypertrophy by Estes' criteria]
8. MaxHR: maximum heart rate achieved [Numeric value between 60 and 202]
9. ExerciseAngina: exercise-induced angina [Y: Yes, N: No]
10. Oldpeak: oldpeak = ST [Numeric value measured in depression]

11. ST_Slope: the slope of the peak exercise ST segment [Up: upsloping, Flat: flat, Down: downsloping]
12. HeartDisease: output class [1: heart disease, 0: Normal]

sex	
age	
education	
currentSmoker	
cigsPerDay	
BPMeds	
prevalentStroke	
prevalentHyp	
diabetes	
totChol	
sysBP	
diaBP	
BMI	
heartRate	
glucose	
TenYearCHD	

```
male            0
age             0
education       105
currentSmoker   0
cigsPerDay      29
BPMeds          53
prevalentStroke 0
prevalentHyp    0
diabetes        0
totChol         50
sysBP           0
diaBP           0
BMI             19
heartRate       1
glucose         388
TenYearCHD      0
```

Framingham *number of missing values

▼ XGBoost v1 Results @March 11, 2025 11:55 AM

```
# 4. Train default XGBoost classifier model

#Set up basic parameters
params = {
    "objective": "binary:logistic",  # Binary classification
    "eval_metric": "auc",  # AUC is good for classification
    "seed": 42
}

# Train the model
model = xgb.train(params, dtrain, num_boost_round=100)

# Save model
model.save_model("xgboost_model.json")

----

# Define XGBoost classifier
xgb_clf = XGBClassifier(use_label_encoder=False, eval_metric="auc")

# Define hyperparameter grid
param_grid = {
    "n_estimators": [30, 40, 50, 75, 100, 150, 200, 300],  # Number of trees
    "max_depth": [3, 5, 7, 8, 9, 10, 11, 12],  # Tree depth
    "learning_rate": [0.01, 0.1, 0.2],  # Step size shrinkage
    "subsample": [0.8, 1.0],  # Percentage of samples used per tree
    "colsample_bytree": [0.8, 1.0]  # Percentage of features used per tree
}

# Run GridSearchCV
grid_search = GridSearchCV(xgb_clf, param_grid, cv=3, scoring="roc_auc", verbose=2, n_jobs=-1)
grid_search.fit(X_train, y_train)

# Best parameters
print("Best parameters:", grid_search.best_params_)

# Save best model
best_model = grid_search.best_estimator_
best_model.save_model("best_xgboost_model.json")
```

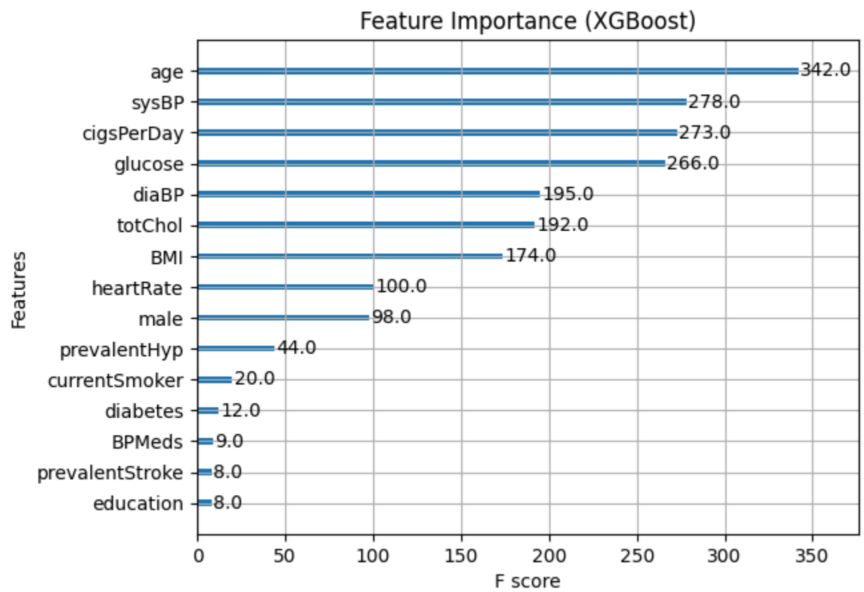
```
#Fitting 3 folds for each of 768 candidates, totalling 2304 fits

Best parameters: {'colsample_bytree': 0.8, 'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 300, 'subsample': 0.8}
```

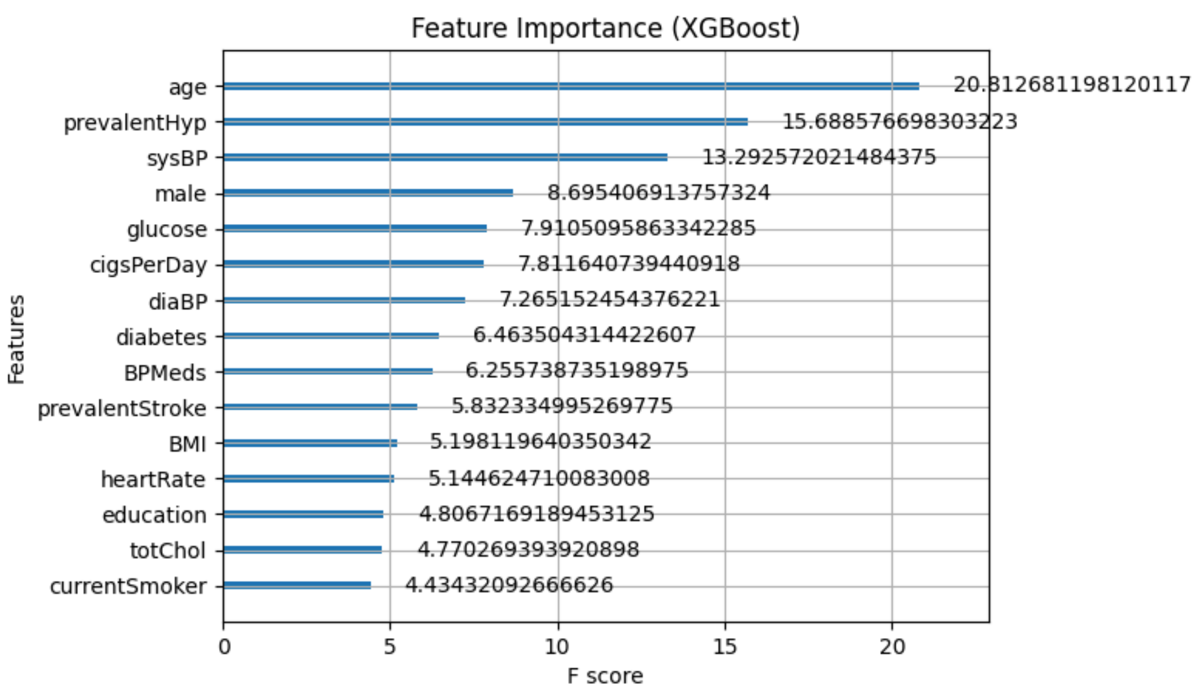
```
Accuracy: 0.8573113207547169
AUC Score: 0.7036613400616765
Confusion Matrix:
 [[725   0]
 [121   2]]
```

Plot

```
# Plot feature importance using built-in XGBoost method
xgb.plot_importance(best_model, importance_type="weight")  # "gain", "cover", or "weight"
plt.title("Feature Importance (XGBoost)")
plt.show()
```

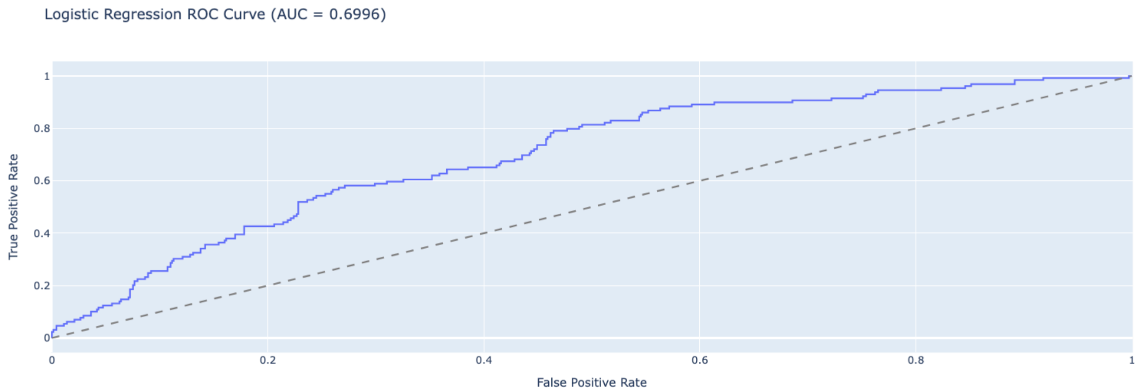
- `"weight"`: Number of times a feature appears in trees.
- `"gain"`: Improvement in performance when a feature is used.
- `"cover"`: Coverage of samples a feature influences.





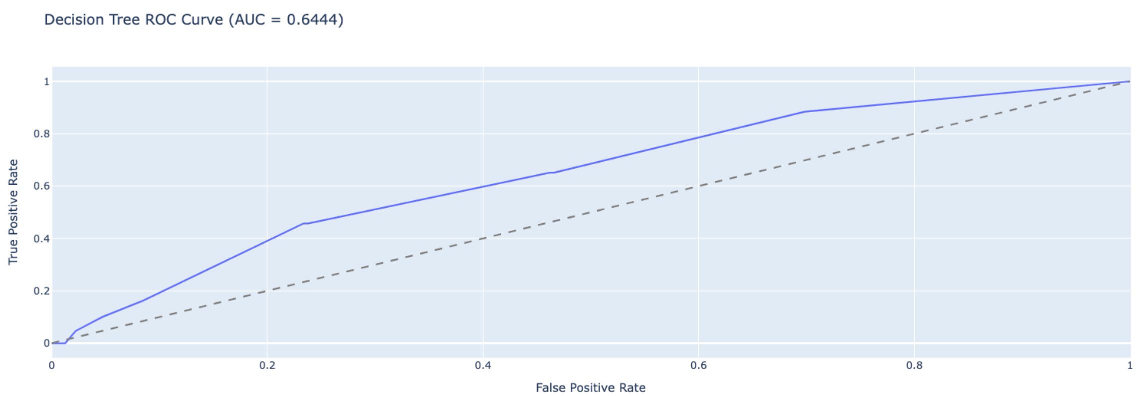
▼ **Logistic Regression Results** @March 10, 2025

```
Logistic Regression Classification Report:
              precision    recall  f1-score   support

           0       0.85      0.99      0.92       719
           1       0.47      0.05      0.10       129

    accuracy                           0.85       848
   macro avg       0.66      0.52      0.51       848
weighted avg       0.79      0.85      0.79       848

Logistic Regression ROC-AUC: 0.6995935353796724
```



▼ Decision Tree Results @March 10, 2025

```
Decision Tree Classification Report:
              precision    recall  f1-score   support

           0       0.85      0.98      0.91       719
           1       0.27      0.05      0.08       129

    accuracy                           0.84       848
   macro avg       0.56      0.51      0.49       848
weighted avg       0.76      0.84      0.78       848

Decision Tree ROC-AUC: 0.6441135373203523
```



▼ Framingham Dataset

Info	Result
Total rows	4240
df.shape	(4240, 16)

▼ Heart Failure Attributes

1. Age: age of the patient [years]

2. Sex: sex of the patient [M: Male, F: Female]
3. ChestPainType: chest pain type [TA: Typical Angina, ATA: Atypical Angina, NAP: Non-Anginal Pain, ASY: Asymptomatic]
4. RestingBP: resting blood pressure [mm Hg]
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8. MaxHR: maximum heart rate achieved [Numeric value between 60 and 202]
9. ExerciseAngina: exercise-induced angina [Y: Yes, N: No]
10. Oldpeak: oldpeak = ST [Numeric value measured in depression]
11. ST_Slope: the slope of the peak exercise ST segment [Up: upsloping, Flat: flat, Down: downsloping]
12. HeartDisease: output class [1: heart disease, 0: Normal]

▼ *After converting all features to numeric

<class	'pandas.core.frame.DataFrame'>		
Index:	4240	entries	
Data	columns	(total	
#	Column	Non-Null	
---	------	--------------	
0	male	4240	Int64
1	age	4240	Int64
2	education	4240	Int64
3	currentSmoker	4240	Int64
4	cigsPerDay	4240	Int64
5	BPMeds	4240	Int64
6	prevalentStroke	4240	Int64
7	prevalentHyp	4240	Int64
8	diabetes	4240	Int64
9	totChol	4240	Int64
10	sysBP	4240	Float64
11	diaBP	4240	Float64
12	BMI	4240	Float64
13	heartRate	4240	Int64
14	glucose	4240	Int64
15	TenYearCHD	4240	Int64
dtypes:	Float64(3)		
memory	usage:	629.4	

df.info()	#	Column	Non-Null	Count	Dtype
	0	male	4240	non-null	int64
	1	age	4240	non-null	int64

	2	education	4135	non-null	float64
	3	currentSmoker	4240	non-null	int64
	4	cigsPerDay	4211	non-null	float64
	5	BPMeds	4187	non-null	float64
	6	prevalentStroke	4240	non-null	int64
	7	prevalentHyp	4240	non-null	int64
	8	diabetes	4240	non-null	int64
	9	totChol	4190	non-null	float64
	10	sysBP	4240	non-null	float64
	11	diaBP	4240	non-null	float64
	12	BMI	4221	non-null	float64
	13	heartRate	4239	non-null	float64
	14	glucose	3852	non-null	float64
	15	TenYearCHD	4240	non-null	int64
dtypes:	float64(9),	int64(7)			
memory	usage:	530.1	KB		

```
root
 |-- male: string (nullable = true)
 |-- age: string (nullable = true)
 |-- education: string (nullable = true)
 |-- currentSmoker: string (nullable = true)
 |-- cigsPerDay: string (nullable = true)
 |-- BPMeds: string (nullable = true)
 |-- prevalentStroke: string (nullable = true)
 |-- prevalentHyp: string (nullable = true)
 |-- diabetes: string (nullable = true)
 |-- totChol: string (nullable = true)
 |-- sysBP: string (nullable = true)
 |-- diaBP: string (nullable = true)
 |-- BMI: string (nullable = true)
 |-- heartRate: string (nullable = true)
 |-- glucose: string (nullable = true)
 |-- TenYearCHD: string (nullable = true)
```

```
import pandas as pd
import numpy as np
import matplotlib.pylab as plt
import seaborn as sns
plt.style.use('ggplot')
pd.set_option('max_columns', 200)
```

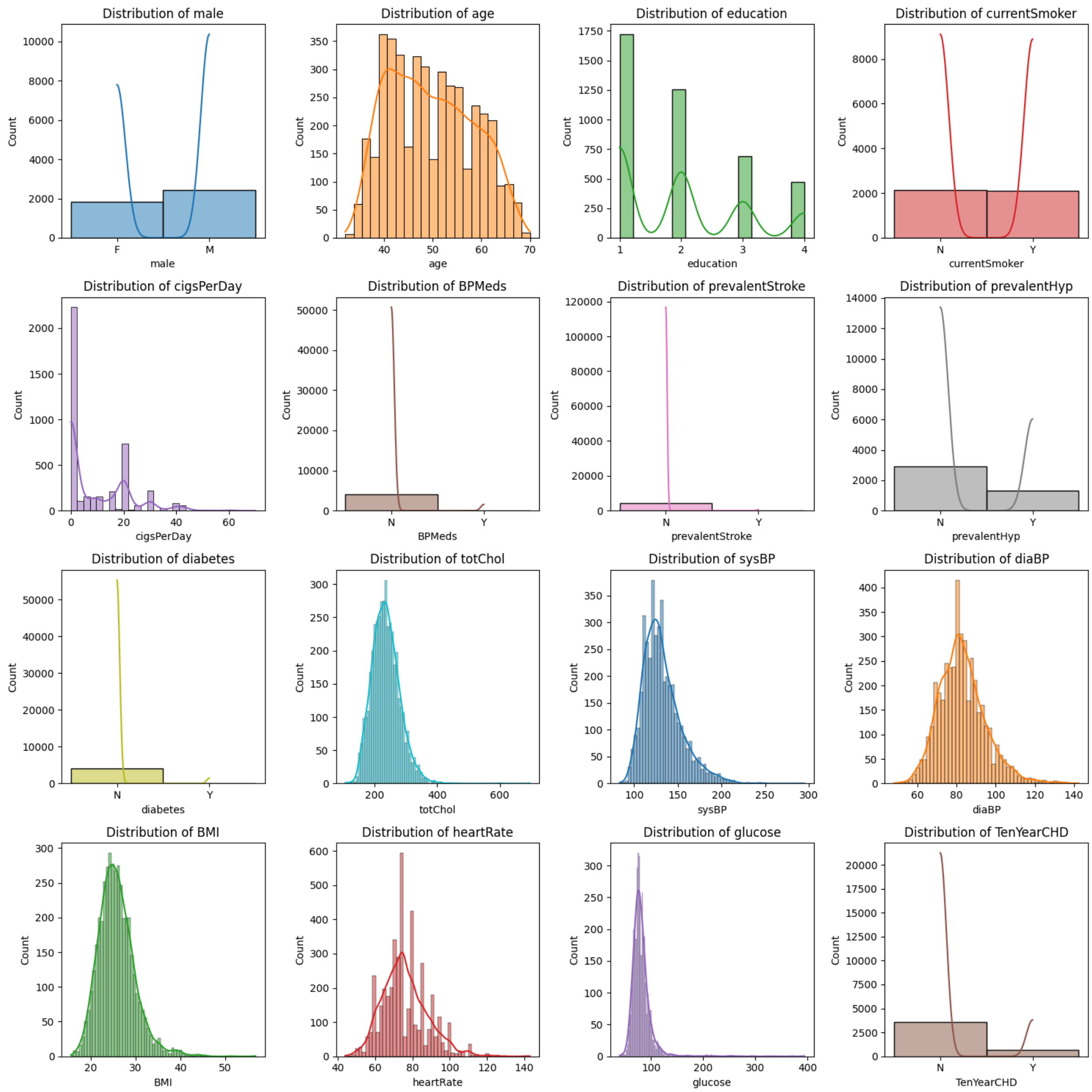
```
[5]  1  df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4240 entries, 0 to 4239
Data columns (total 16 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   male             4240 non-null   int64  
 1   age              4240 non-null   int64  
 2   education        4135 non-null   float64
 3   currentSmoker    4240 non-null   int64  
 4   cigsPerDay       4211 non-null   float64
 5   BPMeds           4187 non-null   float64
 6   prevalentStroke  4240 non-null   int64  
 7   prevalentHyp     4240 non-null   int64  
 8   diabetes         4240 non-null   int64  
 9   totChol          4190 non-null   float64
 10  sysBP            4240 non-null   float64
 11  diaBP            4240 non-null   float64
 12  BMI              4221 non-null   float64
 13  heartRate        4239 non-null   float64
 14  glucose          3852 non-null   float64
 15  TenYearCHD       4240 non-null   int64  
dtypes: float64(9), int64(7)
memory usage: 530.1 KB
```

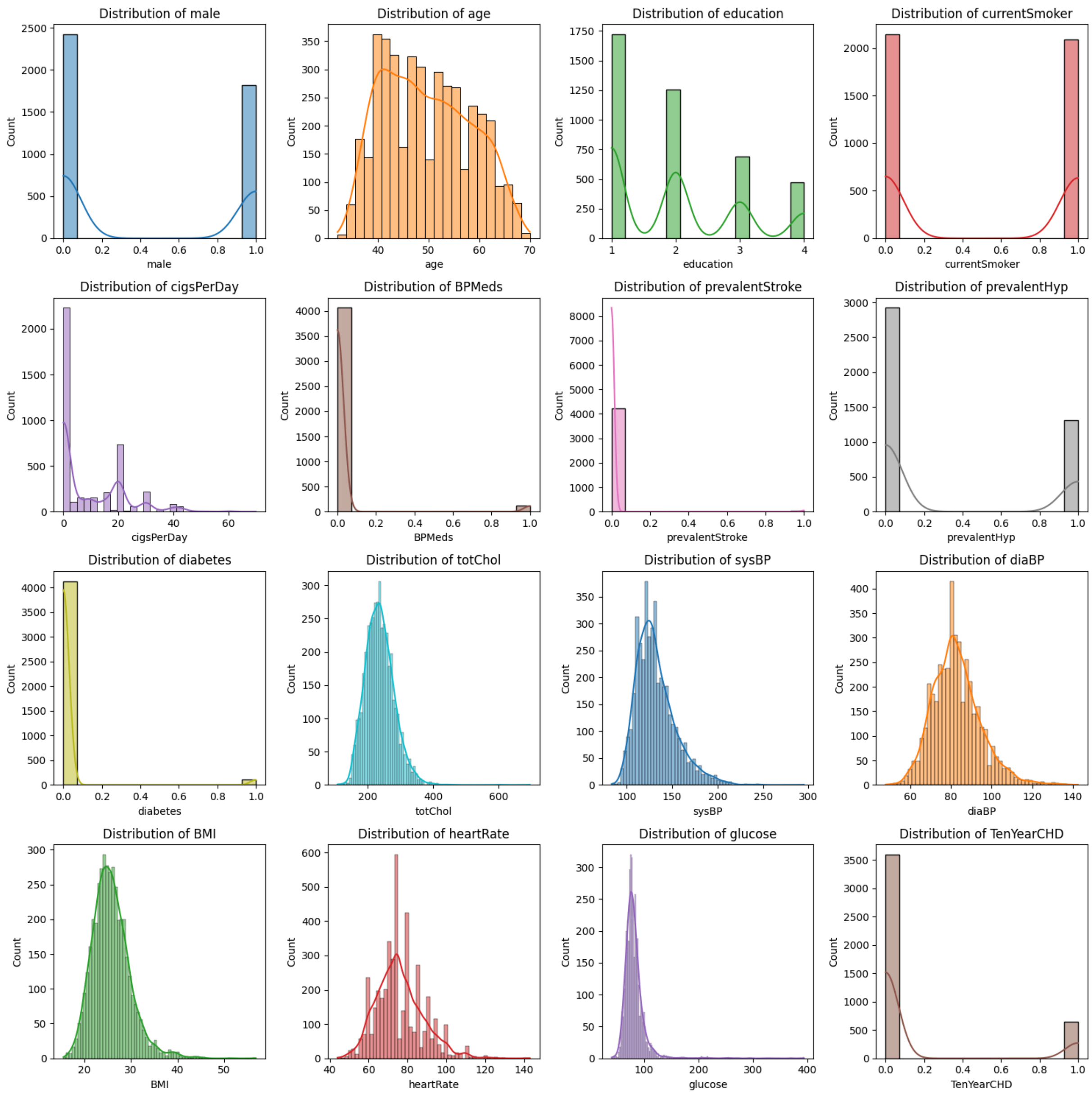
```
'male', 'age', 'education', 'currentSmoker', 'cigsPerDay', 'BPMeds',
       'prevalentStroke', 'prevalentHyp', 'diabetes', 'totChol', 'sysBP',
       'diaBP', 'BMI', 'heartRate', 'glucose', 'TenYearCHD'
```

---

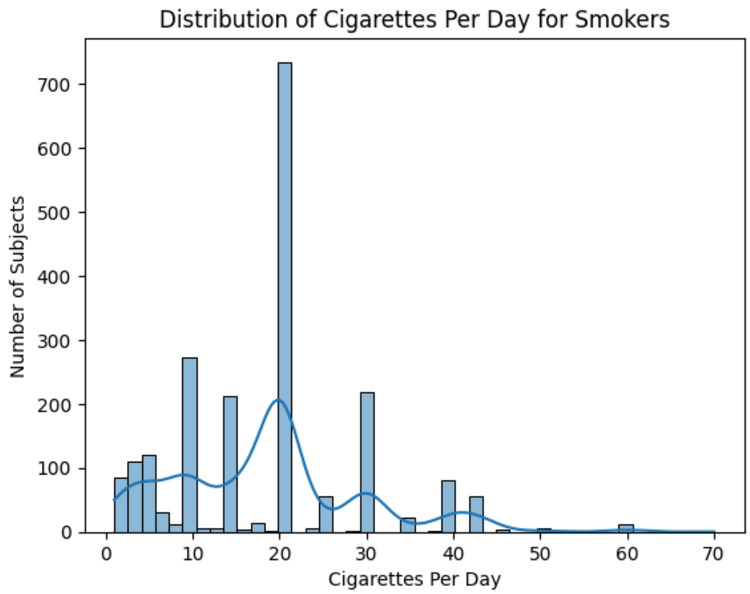
df_visualize


Distribution of male
Distribution of age
Distribution of education
Distribution of currentSmoker
Distribution of cigsPerDay
Distribution of BPMeds
Distribution of prevalentStroke
Distribution of prevalentHyp
Distribution of diabetes
Distribution of totChol
Distribution of sysBP
Distribution of diaBP
Distribution of BMI
Distribution of heartRate
Distribution of glucose
Distribution of TenYearCHD
Count
male
age
education
currentSmoker
cigsPerDay
BPMeds
prevalentStroke
prevalentHyp
diabetes
totChol
sysBP
diaBP
BMI
heartRate
glucose
TenYearCHD

▼ df original



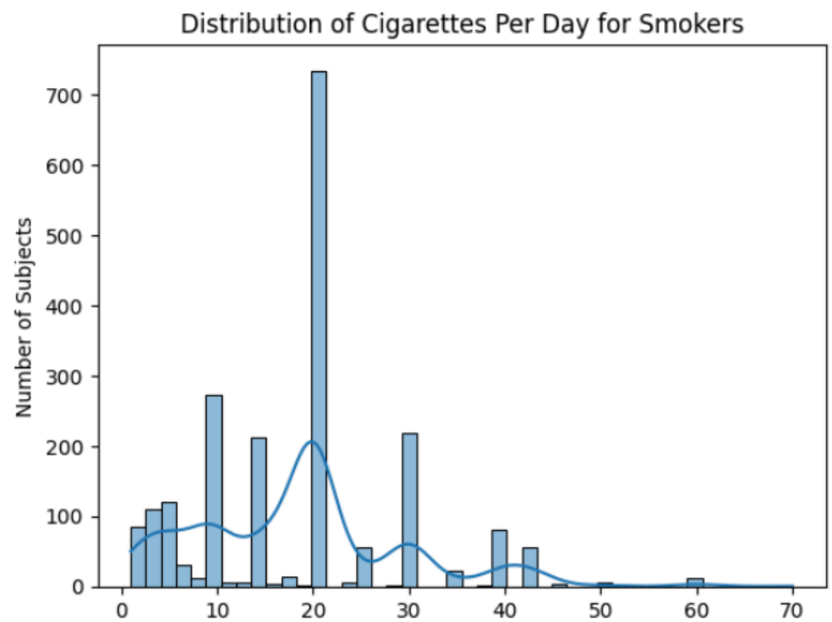
▼ Smokers: 2095

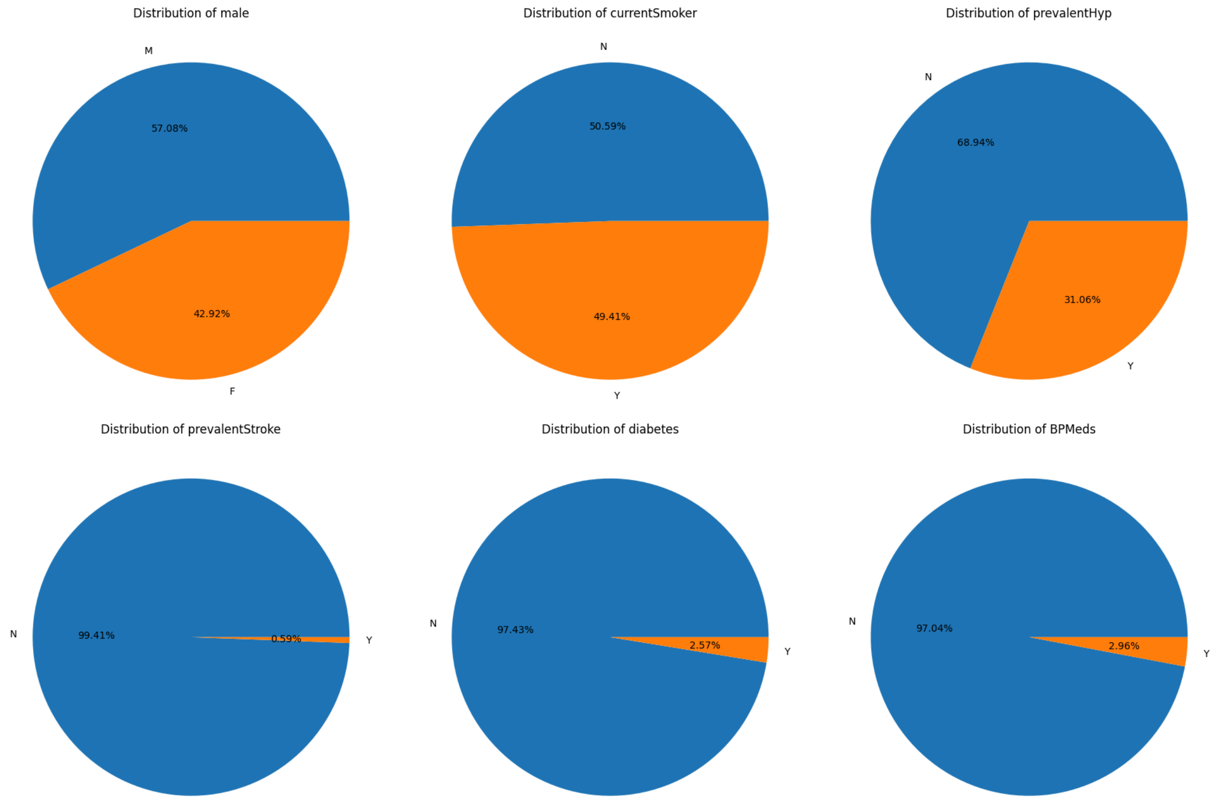

Distribution of Cigarettes Per Day for Smokers
Number of Subjects
Cigarettes Per Day
0
100
200
300
400
500
600
700
0
10
20
30
40
50
60
70

```python
df_smoker = df_visualize[df_visualize['currentSmoker'] == 'Y']
df_smoker.info()

# Plot the distribution of cigsPerDay for those records
sns.histplot(df_smoker['cigsPerDay'], kde=True)
plt.title("Distribution of Cigarettes Per Day for Smokers")
plt.xlabel("Cigarettes Per Day")
plt.ylabel("Number of Subjects")
plt.show()
```

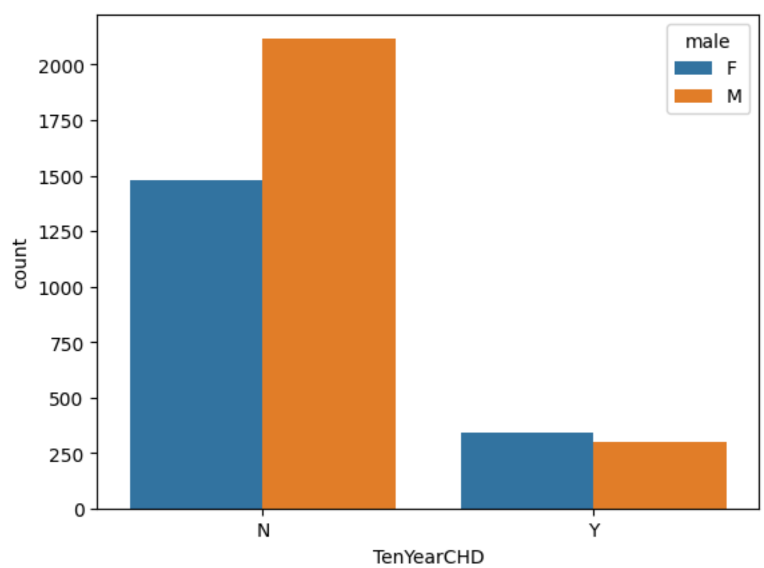
```
<class 'pandas.core.frame.DataFrame'>
Index: 2095 entries, 2 to 4239
Data columns (total 16 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   male             2095 non-null   object
 1   age              2095 non-null   int64
 2   education        2046 non-null   float64
 3   currentSmoker    2095 non-null   object
 4   cigsPerDay       2066 non-null   float64
 5   BPMeds           2072 non-null   float64
 6   prevalentStroke  2095 non-null   object
 7   prevalentHyp     2095 non-null   object
 8   diabetes         2095 non-null   object
 9   totChol          2064 non-null   float64
 10  sysBP            2095 non-null   float64
 11  diaBP            2095 non-null   float64
 12  BMI              2088 non-null   float64
 13  heartRate        2094 non-null   float64
 14  glucose          1890 non-null   float64
 15  TenYearCHD       2095 non-null   object
dtypes: float64(9), int64(1), object(6)
memory usage: 278.2+ KB
```

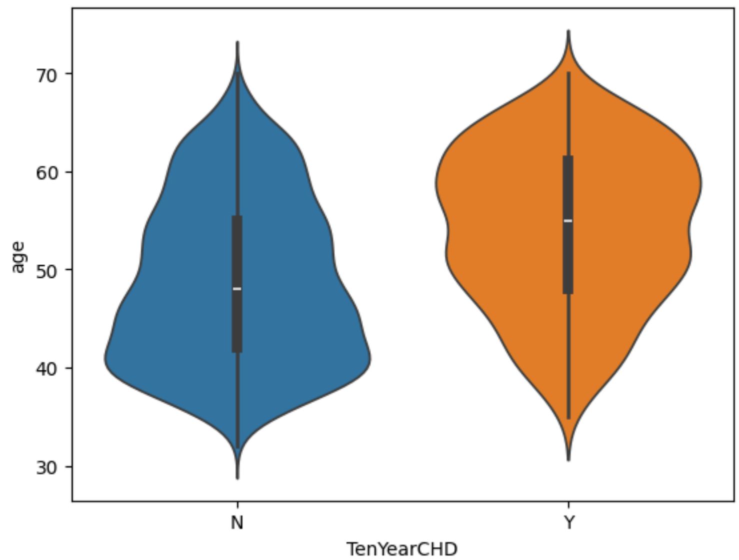


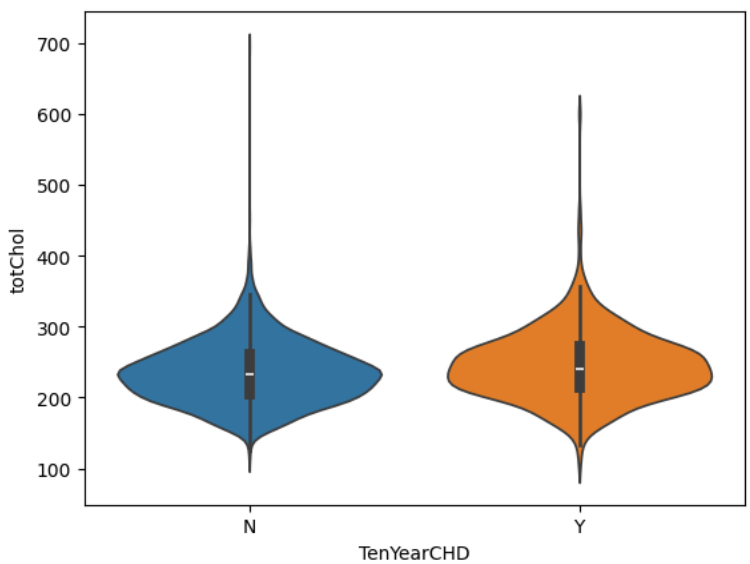


Violin Plot

```
sns.violinplot(x=df_visualize["age"])
sns.countplot(x=df_visualize["TenYearCHD"],hue=df_visualize["male"])
```







Logistic Regression

1. Data Encoding

```
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.model_selection import train_test_split

# Encode all columns with LabelEncoder (this converts categorical values to numeric)
df = df.apply(LabelEncoder().fit_transform)

# Split data into features (X) and target (y)
```

```
X = df.drop(columns=['TenYearCHD'])  # All columns except the target
y = df['TenYearCHD']  # Target column
```

2. Logistic Regression Model

```
# Split the data into train and test sets (stratified to preserve target class proportions)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42, stratify=y)

# Standardize the features for logistic regression (helps the model converge)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

3. Training, Predicting & Evaluating Logistic Regression

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, roc_curve, auc
import plotly.express as px

# Initialize and train logistic regression with increased iterations if needed
log_model = LogisticRegression(max_iter=1000, random_state=42)
log_model.fit(X_train_scaled, y_train)

# Make predictions on the test set
y_pred_log = log_model.predict(X_test_scaled)

# Print the classification report
print("Logistic Regression Classification Report:")
print(classification_report(y_test, y_pred_log))

# ROC-AUC Calculation for Logistic Regression
fpr, tpr, _ = roc_curve(y_test, log_model.predict_proba(X_test_scaled)[:, 1])
roc_auc = auc(fpr, tpr)
print("Logistic Regression ROC-AUC:", roc_auc)

# Plot ROC Curve using Plotly Express
roc_data = pd.DataFrame({'False Positive Rate': fpr, 'True Positive Rate': tpr})
fig = px.line(roc_data, x='False Positive Rate', y='True Positive Rate',
          title=f'Logistic Regression ROC Curve (AUC = {roc_auc:.4f})',
          labels={'False Positive Rate': 'False Positive Rate', 'True Positive Rate': 'True Positive Rate'})
# Add the reference line for a random classifier
fig.add_shape(type='line', x0=0, y0=0, x1=1, y1=1, line=dict(dash='dash', color='grey'))
fig.show()
```

```
Logistic Regression Classification Report:
          precision    recall  f1-score   support
```

```
           0       0.85      0.99      0.92       719
           1       0.47      0.05      0.10       129

    accuracy                           0.85       848
   macro avg       0.66      0.52      0.51       848
weighted avg       0.79      0.85      0.79       848

Logistic Regression ROC-AUC: 0.6995935353796724
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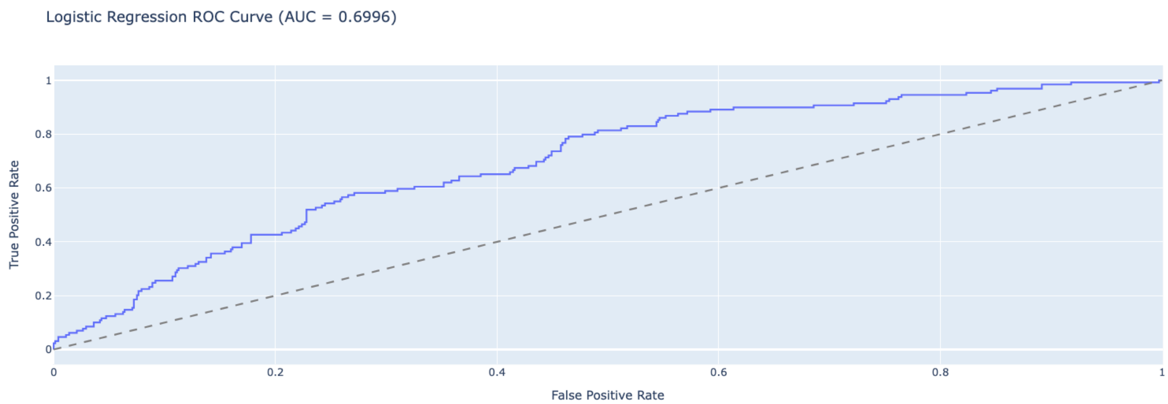

Decision Tree

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, roc_curve, auc

# Initialize and train the Decision Tree Classifier (limiting max_depth to control overfitting)
dt_model = DecisionTreeClassifier(max_depth=4, random_state=42)
dt_model.fit(X_train, y_train)

# Make predictions on the test set
y_pred_dt = dt_model.predict(X_test)

# Print the classification report
print("\nDecision Tree Classification Report:")
print(classification_report(y_test, y_pred_dt))

# ROC-AUC Calculation for Decision Tree (if predict_proba is available)
if hasattr(dt_model, "predict_proba"):
    fpr_dt, tpr_dt, _ = roc_curve(y_test, dt_model.predict_proba(X_test)[:, 1])
    roc_auc_dt = auc(fpr_dt, tpr_dt)
    print("Decision Tree ROC-AUC:", roc_auc_dt)
```

```
# Optional: Plot ROC Curve using Plotly Express for Decision Tree
roc_data_dt = pd.DataFrame({'False Positive Rate': fpr_dt, 'True Positive Rate': tpr_dt})
fig_dt = px.line(roc_data_dt, x='False Positive Rate', y='True Positive Rate',
                 title=f'Decision Tree ROC Curve (AUC = {roc_auc_dt:.4f})',
                 labels={'False Positive Rate': 'False Positive Rate', 'True Positive Rate': 'True Positive Rate'})
fig_dt.add_shape(type='line', x0=0, y0=0, x1=1, y1=1, line=dict(dash='dash', color='grey'))
fig_dt.show()
```

```
Decision Tree Classification Report:
              precision    recall  f1-score   support

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    accuracy                           0.84       848
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Decision Tree ROC-AUC: 0.6444135373203523
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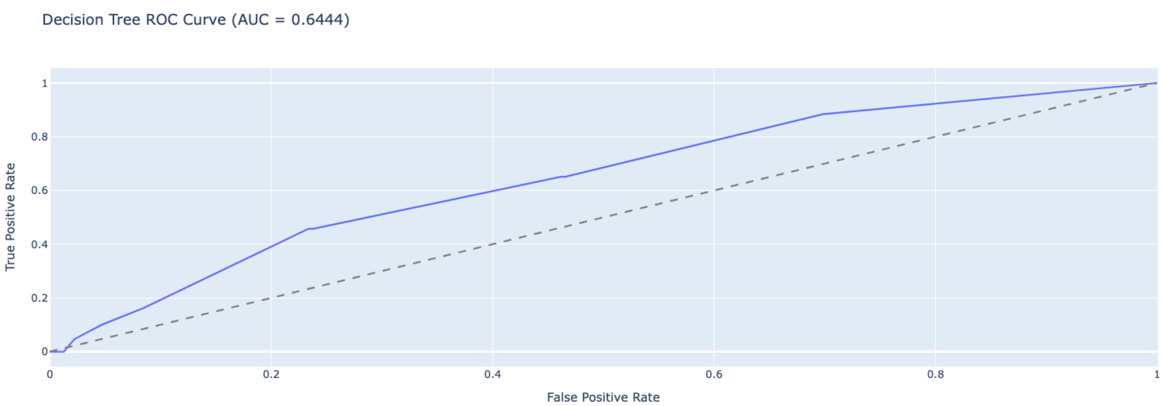

Decision Tree Classification Report:
precision recall f1-score support

0 0.85 0.98 0.91 719
1 0.27 0.05 0.08 129

accuracy 0.84 848
macro avg 0.56 0.51 0.49 848
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