Use the dataset 'credit_risk.csv'. Answer the following questions

1. Create the summary statistics of the variables in the dataset.

```
import pandas as pd
import statsmodels.api as sm
import numpy as np
```

```
df=pd.read_csv('/content/credit_risk.csv')
df.head(10)
```

	income	age	hh_size	employed	assets	loan_amount	credit_score	subsidy	urban	region	default	Unnamed: 11	Unnamed 1
0	38287.38793	49	3	1	74236.86907	24039.790710	573.162576	1	0	east	0	NaN	NaN
1	39160.62078	46	4	1	73994.39844	31725.607990	402.088091	0	0	west	1	NaN	NaN
2	69312.89512	49	5	1	125417.70620	21821.064210	669.369762	0	0	west	0	NaN	NaN
3	42764.90208	31	3	1	57848.19483	45202.512340	312.571074	0	1	east	0	NaN	NaN
4	71216.04434	22	4	1	68771.33000	24658.729830	592.562418	0	1	south	0	NaN	NaN
5	104762.86680	48	2	1	234536.67160	17051.171980	721.038992	1	1	east	0	NaN	NaN
6	62500.79316	27	5	1	57787.99628	28439.459090	509.618448	0	0	south	0	NaN	NaN
7	55338.15878	43	4	1	62948.97362	36138.663300	324.609154	1	0	north	1	NaN	NaN
8	48136.03000	28	1	1	85491.75712	7594.160674	646.566347	0	0	south	0	NaN	NaN
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

```
print("columns in dataset:",df.columns)
```

```
columns in dataset: Index(['income', 'age', 'hh_size', 'employed', 'assets', 'loan_amount',
       'credit_score', 'subsidy', 'urban', 'region', 'default', 'Unnamed: 11',
       'Unnamed: 12'],
      dtype='object')
```

```
x=sm.add_constant(df['loan_amount'])
y=df['credit_score']
```

```
model=sm.OLS(y,x).fit()
```

```
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:           credit_score   R-squared:                       0.747
Model:                            OLS   Adj. R-squared:                  0.747
Method:                 Least Squares   F-statistic:                 1.473e+04
Date:                Wed, 17 Sep 2025   Prob (F-statistic):               0.00
Time:                        17:57:39   Log-Likelihood:                -28565.
No. Observations:                5000   AIC:                         5.713e+04
Df Residuals:                    4998   BIC:                         5.715e+04
Df Model:                           1
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const         808.5481      2.451    329.870      0.000     803.743     813.353
loan_amount    -0.0097   8.03e-05   -121.375      0.000      -0.010      -0.010
==============================================================================
Omnibus:                       26.115   Durbin-Watson:                   2.007
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               26.478
Skew:                           0.178   Prob(JB):                     1.78e-06
Kurtosis:                       2.968   Cond. No.                     7.22e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 7.22e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

2. Build a decision tree tuning the features of maximum depth and minimum samples in each leaf.

Importing libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import random
from pprint import pprint
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, accuracy_score
from sklearn.model_selection import train_test_split, GridSearchCV
```

Loading the Dataset

```
df=pd.read_csv("/content/credit_risk.csv")
```

```
df.drop(["Unnamed: 11", "Unnamed: 12"], axis=1, inplace=True)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 11 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   income        5000 non-null   float64
 1   age           5000 non-null   int64  
 2   hh_size       5000 non-null   int64  
 3   employed      5000 non-null   int64  
 4   assets        5000 non-null   float64
 5   loan_amount   5000 non-null   float64
 6   credit_score  5000 non-null   float64
 7   subsidy       5000 non-null   int64  
 8   urban         5000 non-null   int64  
 9   region        5000 non-null   object 
 10  default       5000 non-null   int64  
dtypes: float64(4), int64(6), object(1)
memory usage: 429.8+ KB
```

```
df.head(100)
```

	income	age	hh_size	employed	assets	loan_amount	credit_score	subsidy	urban	region	default
0	38287.38793	49	3	1	74236.86907	24039.79071	573.162576	1	0	east	0
1	39160.62078	46	4	1	73994.39844	31725.60799	402.088091	0	0	west	1
2	69312.89512	49	5	1	125417.70620	21821.06421	669.369762	0	0	west	0
3	42764.90208	31	3	1	57848.19483	45202.51234	312.571074	0	1	east	0
4	71216.04434	22	4	1	68771.33000	24658.72983	592.562418	0	1	south	0
...	...	...	...	...	...	...	...	...	...	...	...
95	56462.77891	27	5	1	61709.67268	25537.20686	617.183372	0	0	north	1
96	68072.66303	24	3	1	102717.53870	36423.09396	503.717992	0	0	south	1
97	49953.37423	57	2	1	58544.51433	23412.75315	497.231945	0	1	east	0
98	12230.71431	65	2	0	27681.04103	10203.90760	687.906916	0	0	east	0
99	74844.52612	44	1	1	121206.07930	18879.99708	704.017152	0	1	east	0

100 rows × 11 columns

Data preparation

i. Define features (X) and Target (y)

```
X=df.drop("default", axis=1)
y=df["default"]
```

ii. Converting categorical variables into dummies

```
X = pd.get_dummies(X, drop_first=True)
```

Train, Test and Split

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Data pure ?

```
def check_purity(data):

    default_column = data[:, -1]
    unique_classes, counts = np.unique(default_column, return_counts=True)

    if len(unique_classes) == 1:
        return True
    else:
        return False
```

Classify

```
def classify_data(data):

    label_column = data[:, -1]
    np.unique(label_column, return_counts=True)

    unique_classes, counts_unique_classes = np.unique(label_column, return_counts=True)

    index = counts_unique_classes.argmax()
    classification = unique_classes[index]

    return classification
```

Potential splits

```
X_train.head()
```

	income	age	hh_size	employed	assets	loan_amount	credit_score	subsidy	urban	region_north	region_south	regior
4227	76022.11259	27	4	1	68774.93081	29732.33342	531.185298	0	0	False	False	
4676	41347.12048	28	5	1	74602.88985	36556.47732	322.796548	1	1	False	False	
800	28595.96309	24	3	1	67610.40990	38888.43572	360.203352	0	1	False	False	
3671	48381.58066	49	3	1	25070.89087	16947.28113	505.759584	0	0	True	False	
4193	45149.50982	41	4	1	28329.16749	19525.77309	505.682857	0	1	True	False	

```
def get_potential_splits(data):

    potential_splits = {}
    _, n_columns = data.shape
    for column_index in range(n_columns - 1):
        potential_splits[column_index] = []
        values = data[:, column_index]
        unique_values=np.unique(values)

        for index in range(len(unique_values)):
            if index != 0:
                current_value = unique_values[index]
                previous_value = unique_values[index-1]
                potential_split = (current_value + previous_value) / 2

                potential_splits[column_index].append(potential_split)
    return potential_splits
```

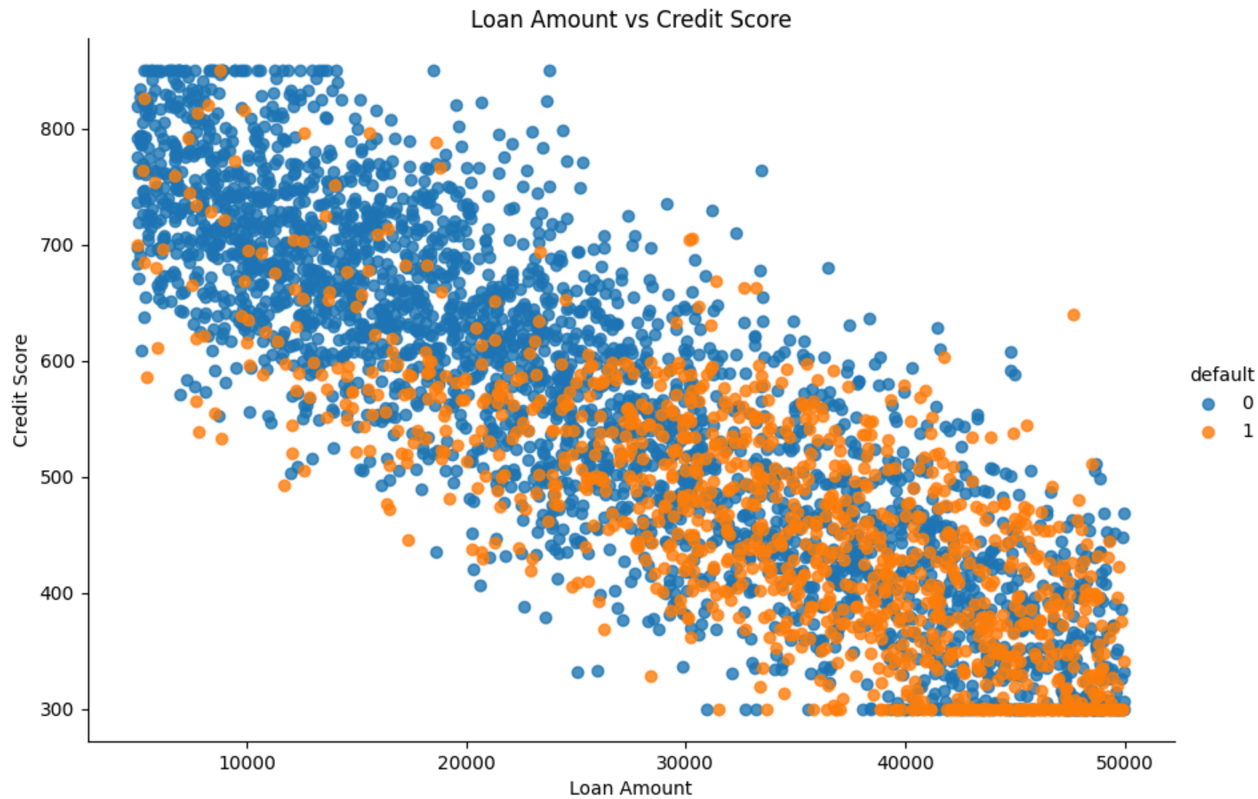
```python
train_df = pd.concat([X_train, y_train], axis=1)
potential_splits_result = get_potential_splits(train_df.values)
pprint(potential_splits_result)
```

```
{0: [5140.121337500001,
     5427.531654,
     5734.7848205,
     6384.4971105,
     7345.1692145,
     8072.938936500001,
     8440.130950499999,
     8744.379379,
     9023.888011,
     9199.586331499999,
     9461.8702175,
     9711.3486515,
     9960.1965015,
     10379.36968,
     10646.732335,
     10748.976934999999,
     10921.253004999999,
     11327.76362,
     11937.60306,
     12251.367975000001,
     12303.959455,
     12604.091315,
     12899.387050000001,
     13165.747735,
     13448.794695,
     13518.0788,
     13554.898165,
     13615.187275,
     13716.591260000001,
     13777.160035,
     13813.72028,
     13849.560249999999,
     13887.7128,
     13925.71725,
     13976.33632,
     14088.58465,
     14233.550500000001,
     14445.612335,
     14605.365415,
     14647.270845,
     14761.307424999999,
     14900.94087,
     14984.8743,
     15061.5769,
     15146.519035,
     15258.425094999999,
     15422.26972,
     15530.62301,
     15612.903545000001,
     15692.38199,
     15787.058255,
     15888.998220000001,
     16061.608905000001,
     16244.936590000001,
     16304.20145,
     16531.720275,
     16737.197399999997,
     16896.25888,
```

```python
train_plot_df = pd.concat([X_train, y_train], axis=1)

sns.lmplot(data=train_plot_df, x="loan_amount", y="credit_score", hue="default", fit_reg=False, height=6, aspect=1.5)
plt.xlabel("Loan Amount")
plt.ylabel("Credit Score")

plt.title("Loan Amount vs Credit Score")
plt.show()
```



Split Data

```
def split_data(data, split_column, split_value):

    split_column_values = data[:, split_column]
    data_below = data[split_column_values <= split_value]
    data_above = data[split_column_values > split_value]

    return data_below, data_above

split_column = 6
split_value = 537.06

train_np = pd.concat([X_train, y_train], axis=1).values
test_np = pd.concat([X_test, y_test], axis=1).values
data_below, data_above = split_data(train_np, split_column, split_value)
```

```
target_col = "default"

fig, axes = plt.subplots(1, 3, figsize=(16, 5))

sns.countplot(x=y_train, ax=axes[0])
axes[0].set_title("Original Class Distribution (Training Data)")
axes[0].set_xlabel(target_col)
axes[0].set_ylabel("Count")

sns.countplot(x=data_below[:, -1], ax=axes[1])
axes[1].set_title(f"{X_train.columns[split_column]} <= {split_value:.2f} (Training Data)")
axes[1].set_xlabel(target_col)
axes[1].set_ylabel("Count")

sns.countplot(x=data_above[:, -1], ax=axes[2])
axes[2].set_title(f"{X_train.columns[split_column]} > {split_value:.2f} (Training Data)")
axes[2].set_xlabel(target_col)
axes[2].set_ylabel("Count")


plt.tight_layout()
plt.show()
```

Lowest Overall Entrophy ?

```
def calculate_entropy(data):

    label_column = data[:, -1]
    _, counts = np.unique(label_column, return_counts=True)
    probabilities = counts / counts.sum()
    entropy = sum(probabilities * -np.log2(probabilities))
    print(f"Calculated Entropy: {entropy}")
    return entropy

def calculate_overall_entropy(data_below, data_above):
    n_data_points = len(data_below) + len(data_above)
    p_data_below = len(data_below) / n_data_points
    p_data_above = len(data_above) / n_data_points
    overall_entropy = (p_data_below * calculate_entropy(data_below) + p_data_above * calculate_entropy(data_above))
    print(f"Calculated Overall Entropy: {overall_entropy}")
    return overall_entropy
```

```
def determine_best_split(data, potential_splits):
    overall_entropy = 9999
    for column_index in potential_splits:
        for value in potential_splits[column_index]:
            data_below, data_above = split_data(data, split_column=column_index, split_value=value)
            current_overall_entropy = calculate_overall_entropy(data_below, data_above)

            if current_overall_entropy <= overall_entropy:
                overall_entropy = current_overall_entropy

                best_split_column = column_index
                best_split_value = value
    return best_split_column, best_split_value, overall_entropy
```

Decision Tree algorithm

Representation of decision tree

```
sub_tree = {"question": ["yes_answer", "no_answer"]}
```

algorithm

```
def determine_type_of_feature(df):
    feature_types = {}
    for col in df.columns:
```

```
        if df[col].dtype == 'object':
            feature_types[df.columns.get_loc(col)] = "categorical"
        else:
            feature_types[df.columns.get_loc(col)] = "continuous"
    return feature_types

def decision_tree_algorithm(df, counter=0, min_samples=2, max_depth=5):

    # data preparation
    if counter == 0:
        global COLUMN_HEADERS, FEATURE_TYPES
        COLUMN_HEADERS = df.columns
        FEATURE_TYPES = determine_type_of_feature(df)
        data = df.values
    else:
        data = df

    # base case
    if check_purity(data): # Corrected function name
        classification = classify_data(data)
        return classification

    # recursive part
    else:
        counter += 1

        # helper functions
        potential_splits = get_potential_splits(data)
        split_column, split_value, overall_entropy = determine_best_split(data, potential_splits)
        data_below, data_above = split_data(data, split_column, split_value)

        # instantiate sub-tree
        feature_name = COLUMN_HEADERS[split_column]
        type_of_feature = FEATURE_TYPES[split_column]
        if type_of_feature == "continuous":
            question = "{} <= {}".format(feature_name, split_value)
            sub_tree = {question: []}

        # recursive function calls
        yes_answer = decision_tree_algorithm(data_below, counter, min_samples, max_depth)
        no_answer = decision_tree_algorithm(data_above, counter, min_samples, max_depth)

        sub_tree[question].append(yes_answer)
        sub_tree[question].append(no_answer)

        return sub_tree
```

```
dtree = DecisionTreeClassifier(random_state=42)
```

```
param_grid = {
    "max_depth": [2, 4, 6, 8, 10, None],
    "min_samples_leaf": [1, 2, 5, 10, 20]
}
```

GridSearch Cv with cross-validation

```
grid_search = GridSearchCV(dtree, param_grid, cv=5, scoring="accuracy", n_jobs=-1)
grid_search.fit(X_train, y_train)
```

GridSearchCV

best_estimator_:
DecisionTreeClassifier

DecisionTreeClassifier

Best params and model

```
print("Best Parameters:", grid_search.best_params_)
best_model = grid_search.best_estimator_
```

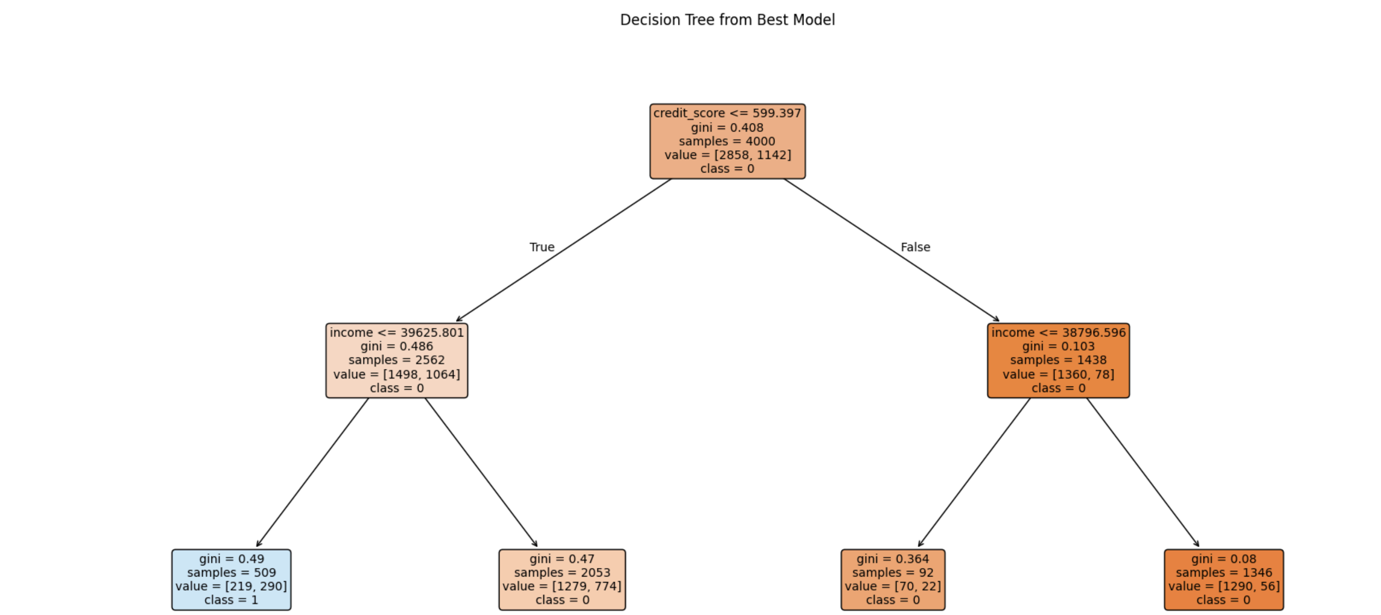
```
Best Parameters: {'max_depth': 2, 'min_samples_leaf': 1}
```

Decision Tree visualization

```
from sklearn.tree import plot_tree
import matplotlib.pyplot as plt

if hasattr(best_model, "estimators_"):
    estimator = best_model.estimators_[0]
else:
    estimator = best_model

plt.figure(figsize=(20,10))
plot_tree(estimator,
          feature_names=df.drop("default", axis=1).columns,
          class_names=df["default"].unique().astype(str),
          filled=True,
          rounded=True,
          fontsize=10)
plt.title("Decision Tree from Best Model")
plt.show()
```



Conclusion : Decision Tree tuned with GridSearchCV, optimizing max depth and min samples per leaf, yielding best parameters and improved accuracy.

2. Build a random forest model to predict credit card defaults for individuals tuning the features of number of features and max estimators.

```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
from collections import Counter
```

```
class RandomForest:

  def __init__(self, num_trees=25, min_samples_split=2, max_depth=5):
    self.trees=[]
    self.num_trees = num_trees
    self.min_samples_split = min_samples_split
    self.max_depth = max_depth
    self.decision_trees = []
    self.n_features = n_features
    self.trees_output = []
```

```
def fit(self, X, y):
  self.trees=[]
  for _ in range(self.num_trees):
    tree = DecisionTreeClassifier(min_samples_split=self.min_samples_split, max_depth=self.max_depth, n_features= self.n_features)

    x_sample, y_sample = bootstrap_sample(X, y)
    tree.fit(x_sample, y_sample)
    self.trees.append(tree)
```

```
X = df.drop("default", axis=1)
y = df["default"]
```

Bootstrapping

```
def bootstrap_sample(X, y):
  n_samples = X.shape[0]
  idxs = np.random.choice(n_samples, n_samples, replace=True)
  return X[idxs], y[idxs]
```

```
def predict(self, X):
  predictions=np.array([tree.predict(X) for tree in self.trees])
  tree_preds = np.swapaxes(predictions, 0, 1)
  predictions=np.array([self.most_common_label(tree_pred) for tree_pred in tree_preds])
  return predictions
```

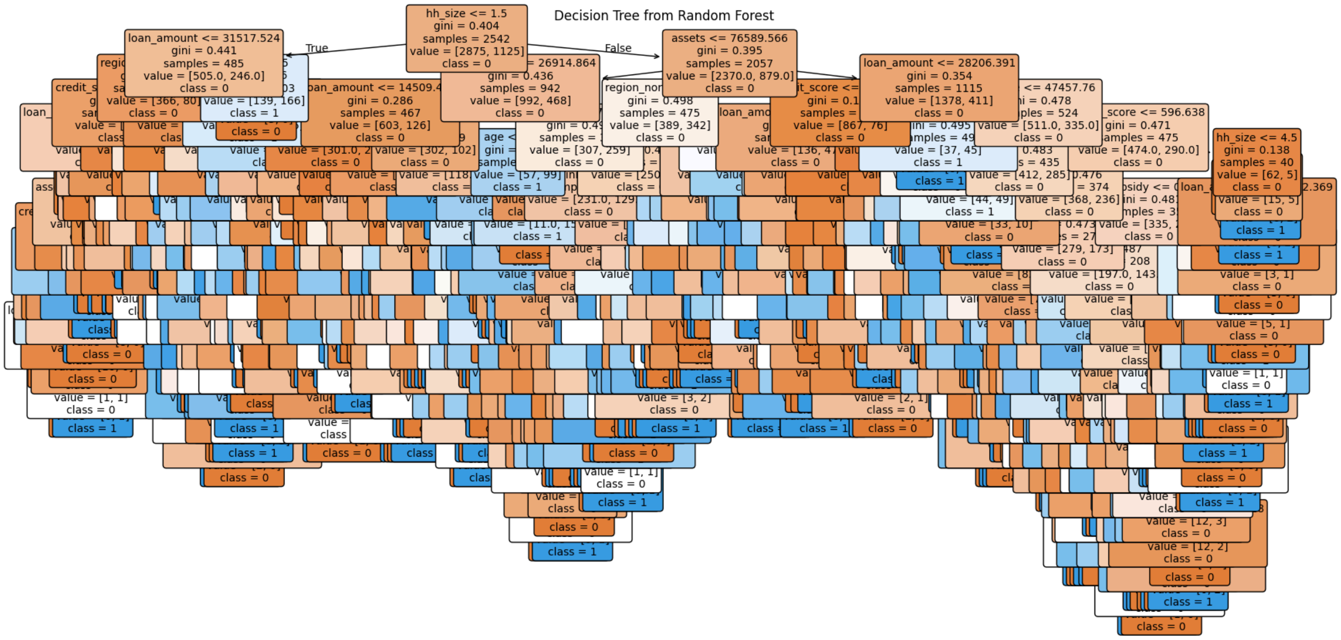
```
def most_common_label(self, tree_pred):
  counter = Counter(tree_pred)
  most_common = counter.most_common(1)[0][0]
  return most_common
```

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import plot_tree
import matplotlib.pyplot as plt

forest = RandomForestClassifier(random_state=42)
forest.fit(X_train, y_train)

tree_to_plot = forest.estimators_[0]

plt.figure(figsize=(20, 10))
plot_tree(tree_to_plot,
          feature_names=X_train.columns.tolist(),
          class_names=[str(c) for c in y_train.unique()],
          filled=True, rounded=True, fontsize=10)
plt.title("Decision Tree from Random Forest")
plt.show()
```



Train, Test and Split

```
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42)
```

Define Random Forest

```
rf = RandomForestClassifier(random_state=42)
```

Parameter grid for tuning

```
param_grid = {
    "n_estimators": [100, 200, 300, 500],
    "max_features": ["sqrt", "log2", None]
}
```

```
grid_search = GridSearchCV(
    rf, param_grid, cv=5, scoring="accuracy", n_jobs=-1
)
grid_search.fit(X_train, y_train)
```

```
GridSearchCV
best_estimator_:
RandomForestClassifier
RandomForestClassifier
```

Best parameters and model

```
print("Best Parameters:", grid_search.best_params_)
best_rf = grid_search.best_estimator_
```

```
Best Parameters: {'max_features': 'sqrt', 'n_estimators': 200}
```

Predictions on test set (Credit card defaults of individuals)

```
y_pred = best_rf.predict(X_test)

results = pd.DataFrame({
    "Actual": y_test.values[:10],
    "Predicted": y_pred[:10]
})
print(results)
```

```
   Actual  Predicted
0       1          1
1       0          0
2       0          1
3       1          0
4       0          0
5       0          0
6       1          0
7       0          0
8       0          0
9       0          0
```

3. Build a boosted decision tree (XGBoost or Boosted Gradient Trees) to predict credit card defaults.

```
import pandas as pd
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import classification_report, accuracy_score
from xgboost import XGBClassifier
```

```
X = df.drop("default", axis=1)
y = df["default"]
```

```
X = pd.get_dummies(X, drop_first=True)
```

Train, test and split

```
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42)
```

Define XGbosst classifier

```
xgb = XGBClassifier(
    objective="binary:logistic",
    eval_metric="logloss",
    use_label_encoder=False,
    random_state=42,
    min_child_weight=1
)
```

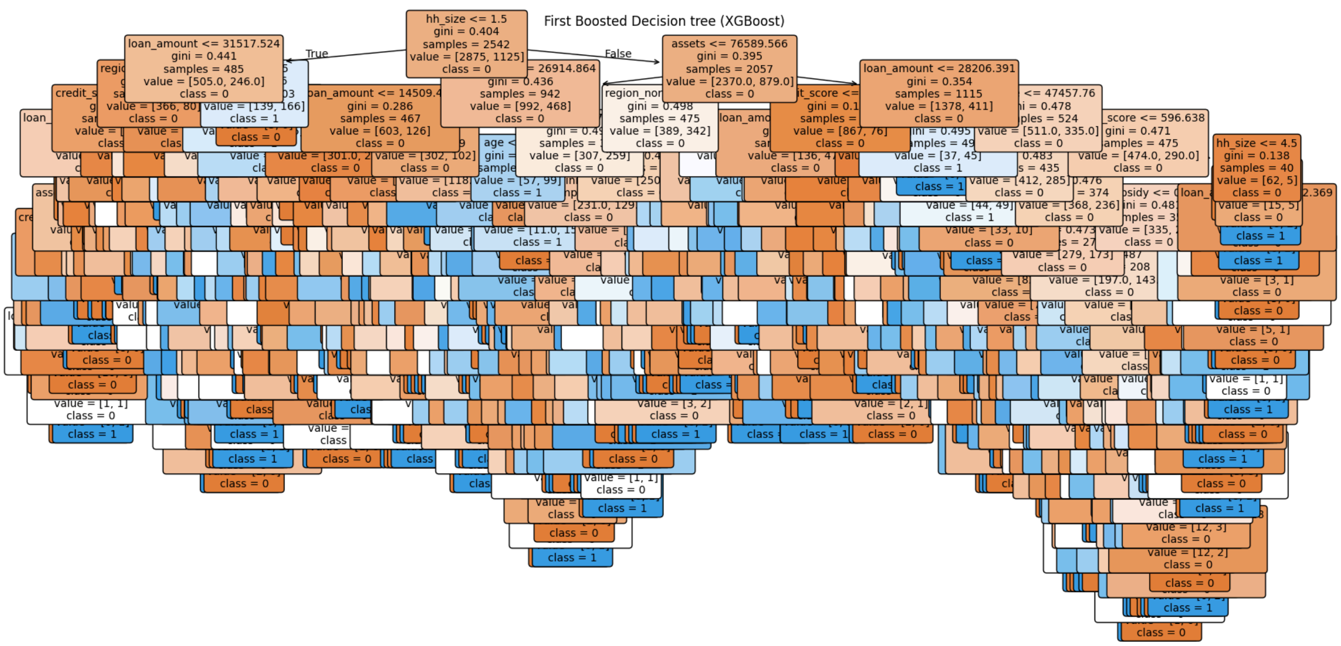
Parameter grid for tuning

```
param_grid = {
    "n_estimators": [100, 200, 300],
    "max_depth": [3, 5, 7],
    "learning_rate": [0.01, 0.1, 0.2],
    "subsample": [0.8, 1.0],
    "colsample_bytree": [0.8, 1.0],
    "min_child_weight": [1, 5, 10]
}
```

```
from sklearn.tree import plot_tree
import matplotlib.pyplot as plt

if hasattr(best_xgb, "estimators_"):
    estimator = best_xgb.estimators_[0]
else:
    estimator = best_xgb

plt.figure(figsize=(20,10))
plot_tree(estimator,
          feature_names=X_train.columns.tolist(),
          class_names=[str(c) for c in y_train.unique()],
          filled=True,
          rounded=True,
          fontsize=10)
plt.title("First Boosted Decision tree (XGBoost)")
plt.show()
```



Grid search

```
grid_search = GridSearchCV(
    estimator=xgb,
    param_grid=param_grid,
    cv=3,
    scoring="accuracy",
    verbose=1,
    n_jobs=-1
)

grid_search.fit(X_train, y_train)
```

```
Fitting 3 folds for each of 324 candidates, totalling 972 fits
/usr/local/lib/python3.12/dist-packages/xgboost/training.py:183: UserWarning: [21:04:42] WARNING: /workspace/src/learner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
```

▸ **GridSearchCV**

▸ **best_estimator_: XGBClassifier**

▸ XGBClassifier

Best Params and model

```
print("Best Parameters:", grid_search.best_params_)
best_xgb = grid_search.best_estimator_
```

```
Best Parameters: {'colsample_bytree': 1.0, 'learning_rate': 0.01, 'max_depth': 3, 'min_child_weight': 1, 'n_estimators': 200, 'subs
```

Evaluate model

```
y_pred = best_xgb.predict(X_test)
print("Accuracy:", accuracy_score(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test, y_pred))
```

```
Accuracy: 0.717
Classification Report:
               precision    recall  f1-score   support

           0       0.74      0.95      0.83       720
           1       0.48      0.12      0.20       280

    accuracy                           0.72      1000
   macro avg       0.61      0.54      0.51      1000
weighted avg       0.66      0.72      0.65      1000
```

```
y_pred = best_rf.predict(X_test)

results = pd.DataFrame({
    "Actual": y_test.values[:10],
    "Predicted": y_pred[:10]
})
print(results)
```

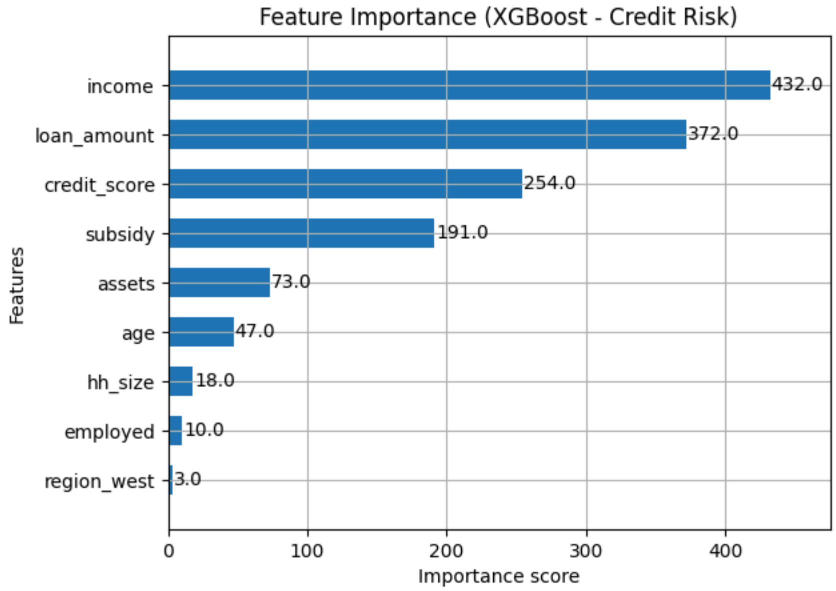
```
   Actual  Predicted
0       1          1
1       0          0
2       0          1
3       1          0
4       0          0
5       0          0
6       1          0
7       0          0
8       0          0
9       0          0
```

```
from xgboost import plot_importance

plt.figure(figsize=(12, 8))
plot_importance(best_xgb, importance_type="weight", max_num_features=15, height=0.6)
```

```
plt.title("Feature Importance (XGBoost - Credit Risk)")
plt.show()
```

```
<Figure size 1200x800 with 0 Axes>
```



Conclusiom: XGBoost tuned with GridSearchCV, optimizing depth, learning rate, estimators, and sampling, delivers high-accuracy predictions for credit card defaults.

4. For each model, report accuracy, precision, recall, F1-score, and ROC AUC on a held-out test set.

```
import pandas as pd
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_auc_score, classification_report
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
```

Train, test and split

```
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42)
```

Decision Tree

```
dtree = DecisionTreeClassifier(random_state=42)
param_grid_dt = {"max_depth": [2,4,6,8,10,None],
                 "min_samples_leaf": [1,2,5,10]}
grid_dt = GridSearchCV(dtree, param_grid_dt, cv=5, scoring="accuracy", n_jobs=-1)
grid_dt.fit(X_train, y_train)
best_dt = grid_dt.best_estimator_
```

Predictions

```
y_pred_dt = best_dt.predict(X_test)
y_prob_dt = best_dt.predict_proba(X_test)[:,1]
```

Random Forest

```
rf = RandomForestClassifier(random_state=42)
param_grid_rf = {"n_estimators": [100,200,300],
                 "max_features": ["sqrt","log2",None]}
grid_rf = GridSearchCV(rf, param_grid_rf, cv=5, scoring="accuracy", n_jobs=-1)
grid_rf.fit(X_train, y_train)
best_rf = grid_rf.best_estimator_
```

```
y_pred_rf = best_rf.predict(X_test)
y_prob_rf = best_rf.predict_proba(X_test)[:,1]
```

XGBoost

```
xgb = XGBClassifier(objective="binary:logistic", eval_metric="logloss", use_label_encoder=False, random_state=42)
param_grid_xgb = {
    "n_estimators": [100,200],
    "max_depth": [3,5],
    "learning_rate": [0.05,0.1],
    "subsample": [0.8,1.0],
    "colsample_bytree": [0.8,1.0]
}
grid_xgb = GridSearchCV(xgb, param_grid_xgb, cv=3, scoring="accuracy", n_jobs=-1)
grid_xgb.fit(X_train, y_train)
best_xgb = grid_xgb.best_estimator_

y_pred_xgb = best_xgb.predict(X_test)
y_prob_xgb = best_xgb.predict_proba(X_test)[:,1]
```

```
/usr/local/lib/python3.12/dist-packages/xgboost/training.py:183: UserWarning: [21:16:43] WARNING: /workspace/src/learner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
```

Evaluation function

```
def evaluate_model(name, y_test, y_pred, y_prob):
    print(f"\n{name} Results")
    print("Accuracy :", accuracy_score(y_test, y_pred))
    print("Precision:", precision_score(y_test, y_pred))
    print("Recall   :", recall_score(y_test, y_pred))
    print("F1-score :", f1_score(y_test, y_pred))
    print("ROC AUC  :", roc_auc_score(y_test, y_prob))
    print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

all models

```
evaluate_model("Decision Tree", y_test, y_pred_dt, y_prob_dt)
```

```

Decision Tree Results
Accuracy : 0.703
Precision: 0.4297520661157025
Recall   : 0.18571428571428572
F1-score : 0.2593516209476309
ROC AUC  : 0.6965376984126985

Classification Report:
               precision    recall  f1-score   support

           0       0.74      0.90      0.81       720
           1       0.43      0.19      0.26       280

    accuracy                           0.70      1000
   macro avg       0.59      0.54      0.54      1000
weighted avg       0.65      0.70      0.66      1000
```

```
evaluate_model("Random Forest", y_test, y_pred_rf, y_prob_rf)
```

```

Random Forest Results
Accuracy : 0.702
Precision: 0.44642857142857145
Recall   : 0.26785714285714285
F1-score : 0.33482142857142855
ROC AUC  : 0.7214335317460318

Classification Report:
               precision    recall  f1-score   support

           0       0.75      0.87      0.81       720
           1       0.45      0.27      0.33       280
```

```
    accuracy                           0.70      1000
   macro avg       0.60      0.57      0.57      1000
weighted avg       0.67      0.70      0.68      1000
```

```
evaluate_model("XGBoost", y_test, y_pred_xgb, y_prob_xgb)
```

```
XGBoost Results
Accuracy : 0.715
Precision: 0.4789915966386555
Recall   : 0.20357142857142857
F1-score : 0.2857142857142857
ROC AUC  : 0.7158630952380952

Classification Report:
              precision    recall  f1-score   support

           0       0.75      0.91      0.82       720
           1       0.48      0.20      0.29       280

    accuracy                           0.71      1000
   macro avg       0.61      0.56      0.55      1000
weighted avg       0.67      0.71      0.67      1000
```

5 .Use 5-fold cross validation for hyperparameter tuning

```
import pandas as pd
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import (
    accuracy_score, precision_score, recall_score,
    f1_score, roc_auc_score, classification_report)
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
```

Train, test and split

```
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42)
```

Decision tree

```
dtree = DecisionTreeClassifier(random_state=42)
param_grid_dt = {
    "max_depth": [2, 4, 6, 8, 10, None],
    "min_samples_leaf": [1, 2, 5, 10]
}
grid_dt = GridSearchCV(
    dtree, param_grid_dt, cv=5, scoring="accuracy", n_jobs=-1
)
grid_dt.fit(X_train, y_train)
best_dt = grid_dt.best_estimator_

y_pred_dt = best_dt.predict(X_test)
y_prob_dt = best_dt.predict_proba(X_test)[:, 1]
```

Random Forest

```
rf = RandomForestClassifier(random_state=42)
param_grid_rf = {
    "n_estimators": [100, 200, 300],
    "max_features": ["sqrt", "log2", None]
}
grid_rf = GridSearchCV(
    rf, param_grid_rf, cv=5, scoring="accuracy", n_jobs=-1
)
grid_rf.fit(X_train, y_train)
best_rf = grid_rf.best_estimator_
```

```
    y_pred_rf = best_rf.predict(X_test)
    y_prob_rf = best_rf.predict_proba(X_test)[:, 1]
```

XGBoost

```
    xgb = XGBClassifier(
        objective="binary:logistic",
        eval_metric="logloss",
        use_label_encoder=False,
        random_state=42
    )
    param_grid_xgb = {
        "n_estimators": [100, 200],
        "max_depth": [3, 5],
        "learning_rate": [0.05, 0.1],
        "subsample": [0.8, 1.0],
        "colsample_bytree": [0.8, 1.0]
    }
    grid_xgb = GridSearchCV(
        xgb, param_grid_xgb, cv=5, scoring="accuracy", n_jobs=-1
    )
    grid_xgb.fit(X_train, y_train)
    best_xgb = grid_xgb.best_estimator_

    y_pred_xgb = best_xgb.predict(X_test)
    y_prob_xgb = best_xgb.predict_proba(X_test)[:, 1]
```

```
/usr/local/lib/python3.12/dist-packages/xgboost/training.py:183: UserWarning: [21:24:38] WARNING: /workspace/src/learner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
```

Evaluation metrics

```
    def evaluate_model(name, y_test, y_pred, y_prob):
        print(f"\n{name} Results")
        print("Accuracy :", accuracy_score(y_test, y_pred))
        print("Precision:", precision_score(y_test, y_pred))
        print("Recall   :", recall_score(y_test, y_pred))
        print("F1-score :", f1_score(y_test, y_pred))
        print("ROC AUC  :", roc_auc_score(y_test, y_prob))
        print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

all models

```
    evaluate_model("Decision Tree", y_test, y_pred_dt, y_prob_dt)
    evaluate_model("Random Forest", y_test, y_pred_rf, y_prob_rf)
    evaluate_model("XGBoost", y_test, y_pred_xgb, y_prob_xgb)
```

```

Decision Tree Results
Accuracy : 0.703
Precision: 0.4297520661157025
Recall   : 0.18571428571428572
F1-score : 0.2593516209476309
ROC AUC  : 0.6965376984126985

Classification Report:
               precision    recall  f1-score   support

           0       0.74      0.90      0.81       720
           1       0.43      0.19      0.26       280

    accuracy                           0.70      1000
   macro avg       0.59      0.54      0.54      1000
weighted avg       0.65      0.70      0.66      1000


Random Forest Results
Accuracy : 0.702
Precision: 0.44642857142857145
Recall   : 0.26785714285714285
F1-score : 0.33482142857142855
ROC AUC  : 0.7214335317460318
```

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

           0       0.75      0.87      0.81       720
           1       0.45      0.27      0.33       280

    accuracy                           0.70      1000
   macro avg       0.60      0.57      0.57      1000
weighted avg       0.67      0.70      0.68      1000


XGBoost Results
Accuracy : 0.715
Precision: 0.4789915966386555
Recall   : 0.20357142857142857
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ROC AUC  : 0.7158630952380952

Classification Report:
              precision    recall  f1-score   support

           0       0.75      0.91      0.82       720
           1       0.48      0.20      0.29       280

    accuracy                           0.71      1000
   macro avg       0.61      0.56      0.55      1000
weighted avg       0.67      0.71      0.67      1000
```
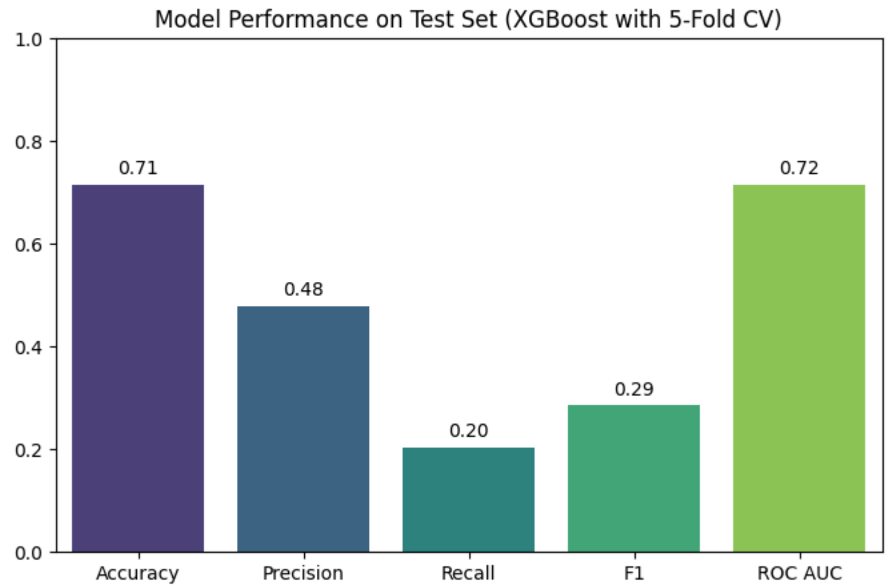
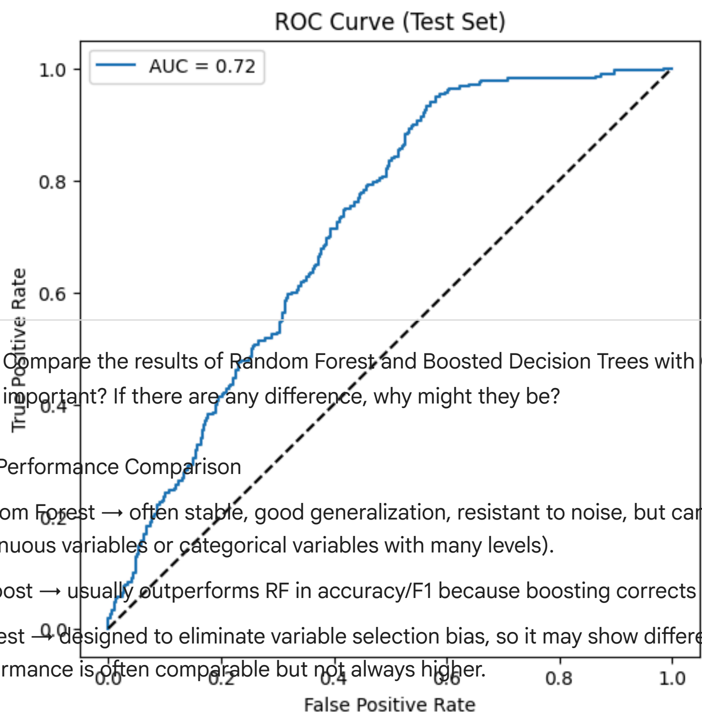

```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_auc_score, roc_curve

y_pred = best_xgb.predict(X_test)
y_proba = best_xgb.predict_proba(X_test)[:, 1]

metrics = {
    "Accuracy": accuracy_score(y_test, y_pred),
    "Precision": precision_score(y_test, y_pred, pos_label=1),
    "Recall": recall_score(y_test, y_pred, pos_label=1),
    "F1": f1_score(y_test, y_pred, pos_label=1),
    "ROC AUC": roc_auc_score(y_test, y_proba)
}

plt.figure(figsize=(8, 5))
sns.barplot(x=list(metrics.keys()), y=list(metrics.values()), palette="viridis", hue=list(metrics.keys()), legend=False)
plt.title("Model Performance on Test Set (XGBoost with 5-Fold CV)")
plt.ylim(0, 1)
for i, v in enumerate(metrics.values()):
    plt.text(i, v + 0.02, f"{v:.2f}", ha="center", fontsize=10)
plt.show()

# 4. ROC Curve
fpr, tpr, _ = roc_curve(y_test, y_proba, pos_label=1)
plt.figure(figsize=(6, 6))
plt.plot(fpr, tpr, label=f"AUC = {metrics['ROC AUC']:.2f}")
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve (Test Set)")
plt.legend()
plt.show()
```





7. Compare the results of Random Forest and Boosted Decision Trees with Conditional Inference Forest. Are the same features important? If there are any difference, why might they be?

---> Performance Comparison

Random Forest → often stable, good generalization, resistant to noise, but can give biased feature importance (especially toward continuous variables or categorical variables with many levels).

XGBoost → usually outperforms RF in accuracy/F1 because boosting corrects previous errors, but can overfit if not tuned.

CForest → designed to eliminate variable selection bias, so it may show different importance rankings compared to RF/XGBoost. Performance is often comparable but not always higher.

Feature Importance Differences

Random Forest & XGBoost (CART-based)

Feature importance usually based on Gini impurity (RF) or gain / split frequency (XGBoost).

Bias: features with many categories or continuous variables tend to look more important.

For example: “Age” or “Income” might appear more influential than “Marital Status” even if predictive power is similar.

Conditional Inference Forest

Uses permutation importance based on statistical significance tests.

Reduces bias, so categorical features with fewer levels (like “Education” or “Gender”) may be shown as important when RF/XGBoost understate them.

Often highlights different predictors because it tests associations more rigorously.