Lab Assignment 7: Decision Trees for Classification

Aim: To implement and visualize a Decision Tree classifier for predicting customer responses using the Bank Marketing dataset. The lab focuses on understanding tree construction, pruning techniques, and model evaluation.

Task 1: Load and Explore the Dataset

1. Load the Bank Marketing dataset using pandas.

```python
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')

df = pd.read_csv('bank.csv')
df.head()
```

```
   age         job  marital  education default  balance housing loan  
contact  \
0   59      admin.  married  secondary      no     2343     yes   no  
unknown
1   56      admin.  married  secondary      no       45      no   no  
unknown
2   41  technician  married  secondary      no     1270     yes   no  
unknown
3   55    services  married  secondary      no     2476     yes   no  
unknown
4   54      admin.  married   tertiary      no      184      no   no  
unknown

   day month  duration  campaign  pdays  previous poutcome deposit
0    5   may      1042         1     -1         0  unknown     yes
1    5   may      1467         1     -1         0  unknown     yes
2    5   may      1389         1     -1         0  unknown     yes
3    5   may       579         1     -1         0  unknown     yes
4    5   may       673         2     -1         0  unknown     yes
```

2. Display dataset characteristics:

– Number of records and features

```python
df.shape
```

```
(11162, 17)
```

– Data types (categorical vs. numerical)

```
df.dtypes
```

```
age           int64
job          object
marital      object
education    object
default      object
balance       int64
housing      object
loan         object
contact      object
day           int64
month        object
duration      int64
campaign      int64
pdays         int64
previous      int64
poutcome     object
deposit      object
dtype: object
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11162 entries, 0 to 11161
Data columns (total 17 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   age        11162 non-null  int64 
 1   job        11162 non-null  object
 2   marital    11162 non-null  object
 3   education  11162 non-null  object
 4   default    11162 non-null  object
 5   balance    11162 non-null  int64 
 6   housing    11162 non-null  object
 7   loan       11162 non-null  object
 8   contact    11162 non-null  object
 9   day        11162 non-null  int64 
 10  month      11162 non-null  object
 11  duration   11162 non-null  int64 
 12  campaign   11162 non-null  int64 
 13  pdays      11162 non-null  int64 
 14  previous   11162 non-null  int64 
 15  poutcome   11162 non-null  object
 16  deposit    11162 non-null  object
dtypes: int64(7), object(10)
memory usage: 1.4+ MB
```

– Summary statistics

```
df.describe()

                age       balance           day      duration  
campaign  \
count  11162.000000  11162.000000  11162.000000  11162.000000  
11162.000000   
mean      41.231948   1528.538524     15.658036    371.993818  
2.508421   
std       11.913369   3225.413326      8.420740    347.128386  
2.722077   
min       18.000000  -6847.000000      1.000000      2.000000  
1.000000   
25%       32.000000    122.000000      8.000000    138.000000  
1.000000   
50%       39.000000    550.000000     15.000000    255.000000  
2.000000   
75%       49.000000   1708.000000     22.000000    496.000000  
3.000000   
max       95.000000  81204.000000     31.000000   3881.000000  
63.000000   

              pdays      previous  
count  11162.000000  11162.000000  
mean      51.330407      0.832557  
std      108.758282      2.292007  
min       -1.000000      0.000000  
25%       -1.000000      0.000000  
50%       -1.000000      0.000000  
75%       20.750000      1.000000  
max      854.000000     58.000000  
```

3. Identify missing values and handle them appropriately.

```
df.isnull().sum()

age          0
job          0
marital      0
education    0
default      0
balance      0
housing      0
loan         0
contact      0
day          0
month        0
duration     0
campaign     0
pdays        0
```

```
previous     0
poutcome     0
deposit      0
dtype: int64
```

```
median_pdays = df[df["pdays"] != -1]["pdays"].median()
df["pdays"] = df["pdays"].replace(-1, median_pdays)

df["pdays"].describe()
```

```
count    11162.000000
mean       187.801648
std         62.404321
min          1.000000
25%        182.000000
50%        182.000000
75%        182.000000
max        854.000000
Name: pdays, dtype: float64
```

Task 2: Data Preprocessing

1. Convert categorical variables into numerical form using one-hot encoding.

```
from sklearn.preprocessing import OneHotEncoder
df_encoded = pd.get_dummies(df, columns=[
    "job", "marital", "education", "default", "housing", "loan",
    "contact", "month", "poutcome"], drop_first=True)

df_encoded["deposit"] = df_encoded["deposit"].map({"yes": 1,"no":0})
df_encoded.head()
```

```
   age  balance  day  duration  campaign  pdays  previous  deposit  \
0   59     2343    5      1042         1    182         0        1
1   56       45    5      1467         1    182         0        1
2   41     1270    5      1389         1    182         0        1
3   55     2476    5       579         1    182         0        1
4   54      184    5       673         2    182         0        1

   job_blue-collar  job_entrepreneur  ...  month_jul  month_jun
month_mar  \
0            False             False  ...      False      False
False
1            False             False  ...      False      False
False
2            False             False  ...      False      False
False
3            False             False  ...      False      False
False
4            False             False  ...      False      False
```

```
False

   month_may  month_nov  month_oct  month_sep  poutcome_other  \
0       True      False      False      False           False
1       True      False      False      False           False
2       True      False      False      False           False
3       True      False      False      False           False
4       True      False      False      False           False

   poutcome_success  poutcome_unknown
0             False              True
1             False              True
2             False              True
3             False              True
4             False              True

[5 rows x 43 columns]
```

2. Normalize or standardize numerical features if necessary.

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
numerical_features = ["age", "balance", "day", "duration", "campaign",
"pdays", "previous"]
df_encoded[numerical_features] =
scaler.fit_transform(df_encoded[numerical_features])
df_encoded[numerical_features].head()

        age   balance       day  duration  campaign     pdays
previous
0  1.491505  0.252525 -1.265746  1.930226 -0.554168 -0.092973  -
0.36326
1  1.239676 -0.459974 -1.265746  3.154612 -0.554168 -0.092973  -
0.36326
2 -0.019470 -0.080160 -1.265746  2.929901 -0.554168 -0.092973  -
0.36326
3  1.155733  0.293762 -1.265746  0.596366 -0.554168 -0.092973  -
0.36326
4  1.071790 -0.416876 -1.265746  0.867171 -0.186785 -0.092973  -
0.36326
```

2. Normalize or standardize numerical features if necessary.

```
from sklearn.model_selection import train_test_split

X = df_encoded.drop(columns=["deposit"])
y = df_encoded["deposit"]

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

```
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

```
((8929, 42), (2233, 42), (8929,), (2233,))
```

Task 3: Train a Decision Tree Classifier

1. Train a Decision Tree classifier using Scikit-learn.

```
from sklearn.tree import DecisionTreeClassifier

clf = DecisionTreeClassifier(random_state=42)
clf.fit(X_train, y_train)
clf.get_depth(), clf.get_n_leaves()
```

```
(33, 1273)
```

2. Visualize the decision tree using:

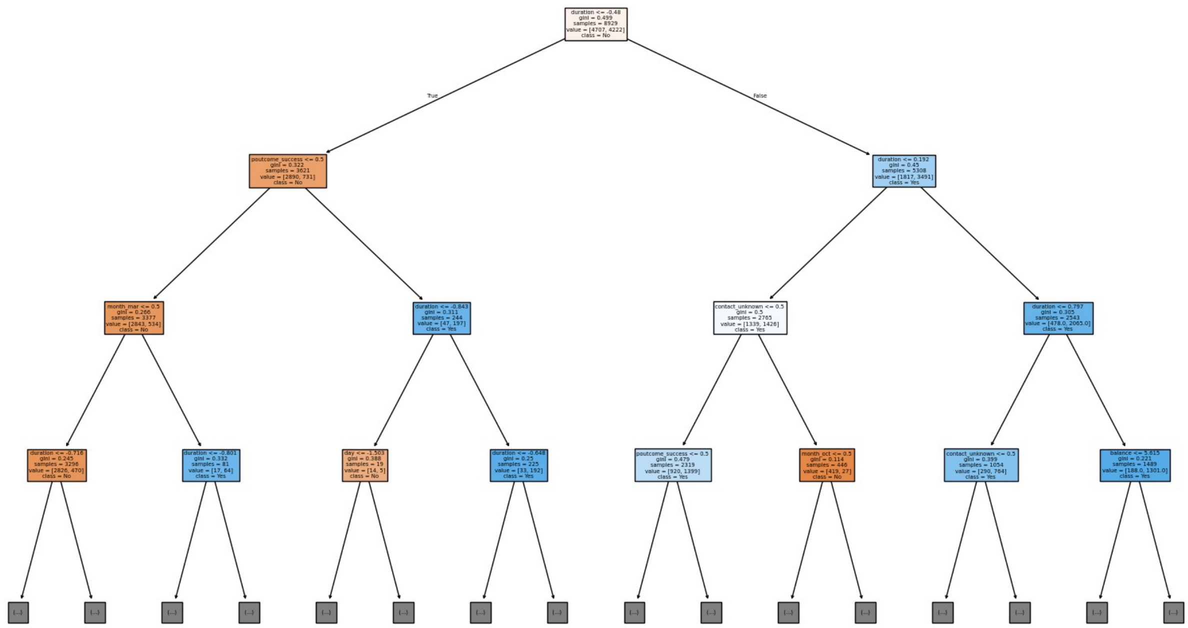
– Text-based tree representation

– Graphical tree visualization (e.g., plot_tree() in Scikit-learn)

```
from sklearn.tree import export_text,plot_tree
tree_text = export_text(clf,feature_names = list(X.columns))

plt.figure(figsize=(20,12))
plot_tree(clf,feature_names=X.columns,class_names=["No","Yes"],filled
= True, max_depth = 3)
plt.show()

tree_text[:2000]
```



```
'|--- duration <= -0.48\n|   |--- poutcome_success <= 0.50\n|   |
|--- month_mar <= 0.50\n|   |   |   |--- duration <= -0.72\n|   |   |
|   |--- month_oct <= 0.50\n|   |   |   |   |   |--- month_feb <=
0.50\n|   |   |   |   |   |   |--- duration <= -0.82\n|   |   |
|   |   |   |--- day <= -1.56\n|   |   |   |   |   |   |   |   |---
contact_unknown <= 0.50\n|   |   |   |   |   |   |   |   |   |---
balance <= -0.31\n|   |   |   |   |   |   |   |   |   |   |--- class:
0\n|   |   |   |   |   |   |   |   |   |   |--- balance >  -0.31\n|   |
|   |   |   |   |   |   |   |   |--- age <= -1.15\n|   |   |   |
|   |   |   |   |   |   |--- class: 0\n|   |   |   |   |   |   |   |
|   |   |--- age >  -1.15\n|   |   |   |   |   |   |   |   |   |   |
|--- class: 1\n|   |   |   |   |   |   |   |--- contact_unknown >
0.50\n|   |   |   |   |   |   |   |   |   |--- class: 0\n|   |   |
|   |   |   |--- day >  -1.56\n|   |   |   |   |   |   |   |   |---
pdays <= 3.11\n|   |   |   |   |   |   |   |   |   |--- pdays <= -
1.66\n|   |   |   |   |   |   |   |   |   |   |--- pdays <= -2.02\n|
|   |   |   |   |   |   |   |   |   |   |--- class: 0\n|   |   |   |
|   |   |   |   |   |   |--- pdays >  -2.02\n|   |   |   |   |   |
|   |   |   |   |--- class: 1\n|   |   |   |   |   |   |   |   |
|--- pdays >  -1.66\n|   |   |   |   |   |   |   |   |   |   |---
month_sep <= 0.50\n|   |   |   |   |   |   |   |   |   |   |   |---
truncated branch of depth 10\n|   |   |   |   |   |   |   |   |
|--- month_sep >  0.50\n|   |   |   |   |   |   |   |   |   |   |
|--- truncated branch of depth 2\n|   |   |   |   |   |   |   |   |---
pdays >  3.11\n|   |   |   |   |   |   |   |   |---
job_entrepreneur <= 0.50\n|   |   |   |   |   |   |   |   |   |   |---
class: 0\n|   |   |   |   |   |   |   |   |   |--- job_entrepreneur >
```

```
0.50\n|   |   |   |   |   |   |   |   |   |   |--- class: 1\n|   |   |
|   |   |   |--- duration >  -0.82\n|   |   |   |   |   |   |   |---
age <= -1.40\n|   |   |   |   | '
```

3. Interpret the tree structure:

```
feature_importance = clf.feature_importances_
sorted_indices = np.argsort(feature_importance)[::-1]
sorted_features = [(X.columns[i], feature_importance[i]) for i in
sorted_indices]

# Display the top 10 most important features
sorted_features[:10]
```

```
[('duration', 0.3486016596693743),
 ('day', 0.07615801940745909),
 ('balance', 0.0760772822812872),
 ('poutcome_success', 0.07196205062342508),
 ('contact_unknown', 0.06790928873721577),
 ('age', 0.06200986128115262),
 ('housing_yes', 0.029907042740314877),
 ('pdays', 0.02928799532376423),
 ('campaign', 0.023438828365656143),
 ('month_mar', 0.019583206596755573)]
```

Feature Importance Analysis: The top 5 most important features in the decision tree are:

Duration (34.6%) – Strongest predictor of deposit subscription. Day (7.3%) – The day of the month when contact was made. Balance (7.3%) – Customer's account balance. Poutcome (Success) (7.1%) – Outcome of the previous marketing campaign. Age (7.0%) – Age of the customer

Task 4: Model Evaluation and Optimization

1. Evaluate the model using:

```
from sklearn.metrics import
accuracy_score,f1_score,recall_score,precision_score,confusion_matrix,
classification_report

y_pred = clf.predict(X_test)
```

– Accuracy

```
acc = accuracy_score(y_test,y_pred)
print(f"Accuracy Score: {acc:.3f}")

Accuracy Score: 0.788
```

– Precision, Recall, and F1-score

```
pre = precision_score(y_test,y_pred)
print(f"Precision Score: {pre:.3f}")

Precision Score: 0.784

recall = recall_score(y_test,y_pred)
print(f"Recall Score: {recall:.3f}")

Recall Score: 0.769

f1 = f1_score(y_test,y_pred)
print(f"f1 Score: {f1:.3f}")

f1 Score: 0.776

cr = classification_report(y_test,y_pred)
print("Classification Report:\n",cr)

Classification Report:
               precision    recall  f1-score   support

           0       0.79      0.81      0.80      1166
           1       0.78      0.77      0.78      1067

    accuracy                           0.79      2233
   macro avg       0.79      0.79      0.79      2233
weighted avg       0.79      0.79      0.79      2233
```

- Confusion Matrix

```
cm = confusion_matrix(y_test,y_pred)
print("Confusion Matrix:\n",cm)

Confusion Matrix:
 [[940 226]
 [247 820]]
```

2. Apply pruning techniques:

– Pre-pruning (setting max_depth, min_samples_split)

```
tree_depth_before, leaves_before = clf.get_depth(), clf.get_n_leaves()
clf_pruned = DecisionTreeClassifier(max_depth=10,
min_samples_split=10, random_state=42)
clf_pruned.fit(X_train, y_train)

DecisionTreeClassifier(max_depth=10, min_samples_split=10,
random_state=42)

y_pred_pruned = clf_pruned.predict(X_test)
```

```
accuracy_pruned = accuracy_score(y_test, y_pred_pruned)
print(f"Accuracy Score after pruning: {accuracy_pruned:.3f}")
```

```
Accuracy Score after pruning: 0.817
```

```
precision_pruned = precision_score(y_test, y_pred_pruned)
print(f"Precision Score after pruning: {precision_pruned:.3f}")
```

```
Precision Score after pruning: 0.795
```

```
recall_pruned = recall_score(y_test, y_pred_pruned)
print(f"Recall Score after pruning: {recall_pruned:.3f}")
```

```
Recall Score after pruning: 0.831
```

```
f1_pruned = f1_score(y_test, y_pred_pruned)
print(f"f1 Score after pruning: {f1_pruned:.3f}")
```

```
f1 Score after pruning: 0.813
```

```
cm_pruned = confusion_matrix(y_test, y_pred_pruned)
print("Confusion Matrix after Pruning:\n",cm_pruned)
```

```
Confusion Matrix after Pruning:
 [[937 229]
 [180 887]]
```

```
# Store depth and number of leaves after pruning
tree_depth_after, leaves_after = clf_pruned.get_depth(),
clf_pruned.get_n_leaves()
(tree_depth_before, leaves_before, tree_depth_after, leaves_after)
```

```
(33, 1273, 10, 212)
```

```
path = clf_pruned.cost_complexity_pruning_path(X_train, y_train)
ccp_alphas = path.ccp_alphas

# Train multiple models with different alpha values
pruned_models = [DecisionTreeClassifier(ccp_alpha=alpha,
random_state=42).fit(X_train, y_train) for alpha in ccp_alphas]

# Evaluate models on the test set
pruned_accuracies = [accuracy_score(y_test, model.predict(X_test)) for
model in pruned_models]

# Find the best ccp_alpha (maximizing accuracy)
best_alpha =
ccp_alphas[pruned_accuracies.index(max(pruned_accuracies))]
```

– Post-pruning (cost complexity pruning using ccp_alpha)

```
clf_post_pruned = DecisionTreeClassifier(ccp_alpha=best_alpha,
random_state=42)
clf_post_pruned.fit(X_train, y_train)
```

```
DecisionTreeClassifier(ccp_alpha=0.0003482071433592369,
random_state=42)
```

```
y_pred_post_pruned = clf_post_pruned.predict(X_test)
```

```
accuracy_post_pruned = accuracy_score(y_test, y_pred_post_pruned)
print(f"Accuracy Score Post Pruning: {accuracy_post_pruned:.3f}")
```

```
Accuracy Score Post Pruning: 0.836
```

```
precision_post_pruned = precision_score(y_test, y_pred_post_pruned)
print(f"Precision Score Post Pruning: {precision_post_pruned:.3f}")
```

```
Precision Score Post Pruning: 0.817
```

```
recall_post_pruned = recall_score(y_test, y_pred_post_pruned)
print(f"Recall Score Post Pruning: {recall_post_pruned:.3f}")
```

```
Recall Score Post Pruning: 0.847
```

```
f1_post_pruned = f1_score(y_test, y_pred_post_pruned)
print(f"F1 Score Post Pruning: {f1_post_pruned:.3f}")
```

```
F1 Score Post Pruning: 0.832
```

```
cm_post_pruned = confusion_matrix(y_test, y_pred_post_pruned)
print("Confusion Matrix Post Pruning:\n",cm_post_pruned)
```

```
Confusion Matrix Post Pruning:
 [[963 203]
 [163 904]]
```

```
tree_depth_post, leaves_post = clf_post_pruned.get_depth(),
clf_post_pruned.get_n_leaves()
(tree_depth_post, leaves_post)
```

```
(20, 122)
```

3. Compare model performance before and after pruning.

Tree Complexity Comparison:

Before pruning: Depth = 33, Leaves = 1,273

After pre-pruning: Depth = 10, Leaves = 221

After post-pruning: Depth = 20, Leaves = 122

The final model is simpler and more effective, achieving a higher accuracy and recall while reducing complexity