Decision tree classification

Supevised non-parametric machine learning to classify a bivariate categorical variable.

In [1]:
```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import cross_val_score
import seaborn as sns
import matplotlib.pyplot as plt
```

Dataset

The *Heart Disease* dataset from the Cleveland database contains 14 variables from patients to classify the presence or absence of heart disease in a patient (https://archive.ics.uci.edu/dataset/45/heart+disease).

In [2]:
```
#load the data
df = pd.read_csv("https://raw.githubusercontent.com/dswede43/ML-methods/main/data/heart.csv")
df.head()
```

Out[2]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
0	52	1	0	125	212	0	1	168	0	1.0	2	2	3	0
1	53	1	0	140	203	1	0	155	1	3.1	0	0	3	0
2	70	1	0	145	174	0	1	125	1	2.6	0	0	3	0
3	61	1	0	148	203	0	1	161	0	0.0	2	1	3	0
4	62	0	0	138	294	1	1	106	0	1.9	1	3	2	0

In [3]:
```
#check for null values
df.isna().sum()
```

Out[3]:
```
age         0
sex         0
cp          0
trestbps    0
chol        0
fbs         0
restecg     0
thalach     0
exang       0
oldpeak     0
slope       0
ca          0
thal        0
target      0
dtype: int64
```

Feature variables (13)

1. age (continuous): Age of subject

2. sex (nominal): Gender of subject: 0 = female, 1 = male

3. cp = chest-pain type (nominal): Type of chest-pain experienced by the individual: 0 = typical angina, 1 = atypical angina, 2 = non-angina pain, 3 = asymptomatic angina

4. trestbps = Resting Blood Pressure (continuous): Resting blood pressure in mm Hg

5. chol = Serum Cholesterol (continuous): Serum cholesterol in mg/dl

6. fbs = Fasting Blood Sugar (ordinal): Fasting blood sugar level relative to 120 mg/dl: 0 = fasting blood sugar <= 120 mg/dl, 1 = fasting blood sugar > 120 mg/dl

7. restecg = Resting ECG (nominal): Resting electrocardiographic results 0 = normal, 1 = ST-T wave abnormality, 2 = left ventricle hyperthrophy

8. thalach = Max Heart Rate Achieved (continuous): Max heart rate of subject

9. exang = Exercise Induced Angina (nominal): 0 = no, 1 = yes

10. oldpeak = ST Depression Induced by Exercise Relative to Rest (continuous): ST Depression of subject

11. slope = Peak Exercise ST Segment (nominal): 0 = Up-sloaping, 1 = Flat, 2 = Down-sloaping

12. ca = Number of Major Vessels (0-3) Visible on Flouroscopy (continuous): Number of visible vessels under flouro

13. thal = Form of thalassemia (nominal): 0 = normal, 1 = fixed defect, 2 = reversible defect

Target variable (1)

14. target = Diagnosis of Heart Disease: Indicates whether subject is suffering from heart disease or not 0 = absence, 1 = heart disease present

Dataset preparation

Define target and feature variable datasets.

In [4]:
```
#define target and feature variables
target = 'target'
features = [col for col in df.columns if col != target]

#subset data to target and feature datasets
y = df[target]
X = df[features]
```

Apply one-hot encoding to multivariate features to remove ordinal patterns.

In [5]:
```
#define multivariate feature variables
multivariates = ['cp',
                 'restecg',
                 'slope',
                 'thal']

#apply one-hot encoding to multivariate features
X_encoded = pd.get_dummies(X, columns = multivariates)
X_encoded.head()
```

Out[5]:

	age	sex	trestbps	chol	fbs	thalach	exang	oldpeak	ca	cp_0	...	restecg_0	restecg_1	restecg_2	slope_0	slope_1	slope_2	thal_0
0	52	1	125	212	0	168	0	1.0	2	1	...	0	1	0	0	0	1	0
1	53	1	140	203	1	155	1	3.1	0	1	...	1	0	0	1	0	0	0
2	70	1	145	174	0	125	1	2.6	0	1	...	0	1	0	1	0	0	0
3	61	1	148	203	0	161	0	0.0	1	1	...	0	1	0	0	0	1	0
4	62	0	138	294	1	106	0	1.9	3	1	...	0	1	0	0	1	0	0

5 rows × 23 columns

Objective

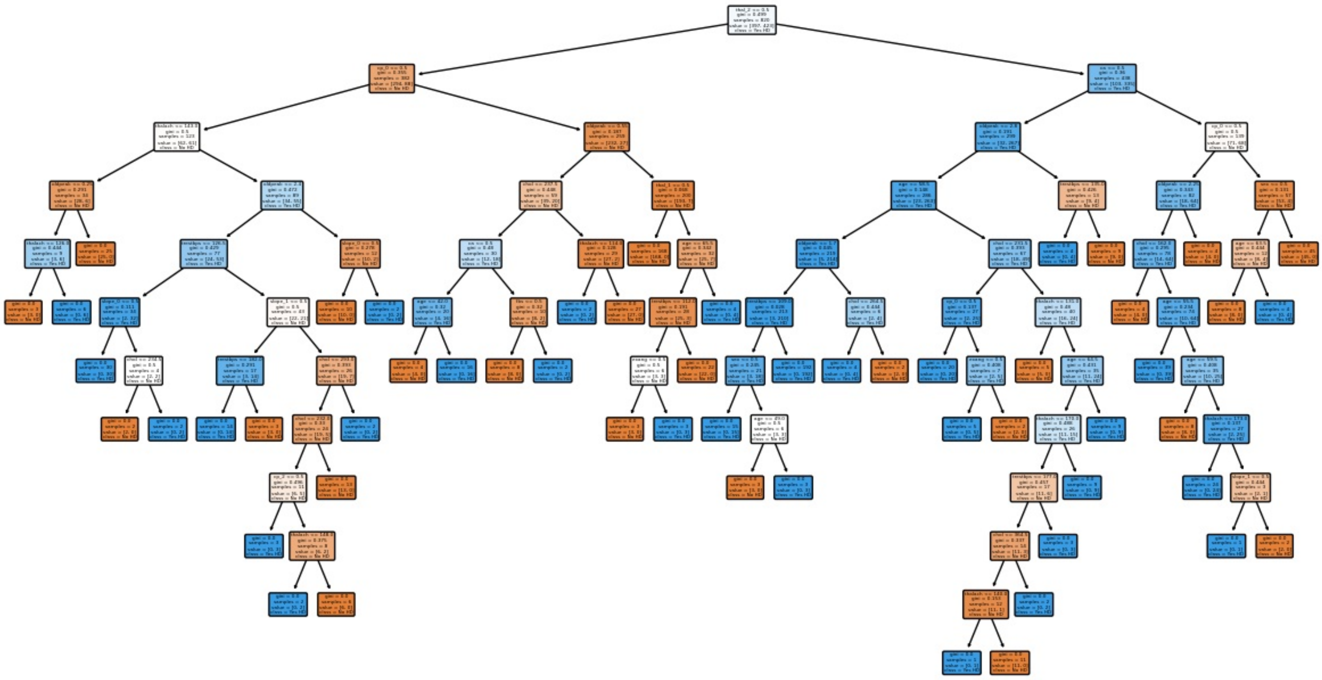
Create a decision tree classifier ML model to classify the precense of heart disease in a patient.

Build preliminary classification tree

Create a classification tree using all feature variables.

In [6]:
```
#split data into train and test datasets
X_train, X_test, y_train, y_test = train_test_split(X_encoded, y, test_size = 0.2, random_state = 42)

#build the preliminary decision tree classifier
prelim_tree = DecisionTreeClassifier(random_state = 42)
prelim_tree = prelim_tree.fit(X_train, y_train)
```

In [7]:
```
#visualize the decision tree
plt.figure(figsize = (15, 8))
plot_tree(prelim_tree,
          filled = True,
          rounded = True,
          class_names = ["No HD","Yes HD"],
          feature_names = list(X_encoded.columns))
plt.show()
```

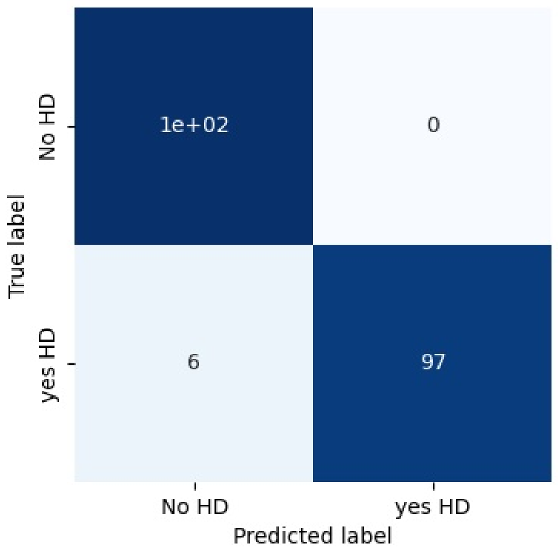


Confusion matrix for preliminary tree

Visualize the preliminiary model tree performance using a confusion matrix.

In [8]:

```
#make model predictions
y_pred = prelim_tree.predict(X_test)

#create the confusion matrix
cm = confusion_matrix(y_test, y_pred)

#plot the confusion matrix
plt.figure(figsize = (4,4))
sns.heatmap(cm, annot = True, cmap = 'Blues', cbar = False)
plt.xticks([0.5,1.5], ['No HD','yes HD'])
plt.yticks([0.5,1.5],['No HD','yes HD'])
plt.xlabel('Predicted label')
plt.ylabel('True label')
plt.show()
```



The preliminary model correctly classified **102/102 (100%)** patients with **no heart disease** and **97/103 (94.2%)** patients with **heart disease**.

Cost-complexity tree pruning

To simplify the tree model and prevent overfitting of training data.

In [9]:

```
#determine potential values for alpha
path = prelim_tree.cost_complexity_pruning_path(X_train, y_train)
ccp_alphas = path.ccp_alphas[:-1]
ccp_alphas
```

Out[9]:
```
array([0.        , 0.00162602, 0.00223577, 0.00225836, 0.00229555,
       0.00238334, 0.0028907 , 0.00311914, 0.00326655, 0.00351336,
       0.00372002, 0.00390244, 0.00406504, 0.00446403, 0.00453573,
       0.00454163, 0.00459691, 0.00487805, 0.00497125, 0.00602582,
       0.00675422, 0.00682927, 0.0071736 , 0.00743715, 0.00756177,
       0.00770296, 0.00819272, 0.01014212, 0.01026827, 0.01135529,
       0.01169648, 0.03120598, 0.03955513])
```

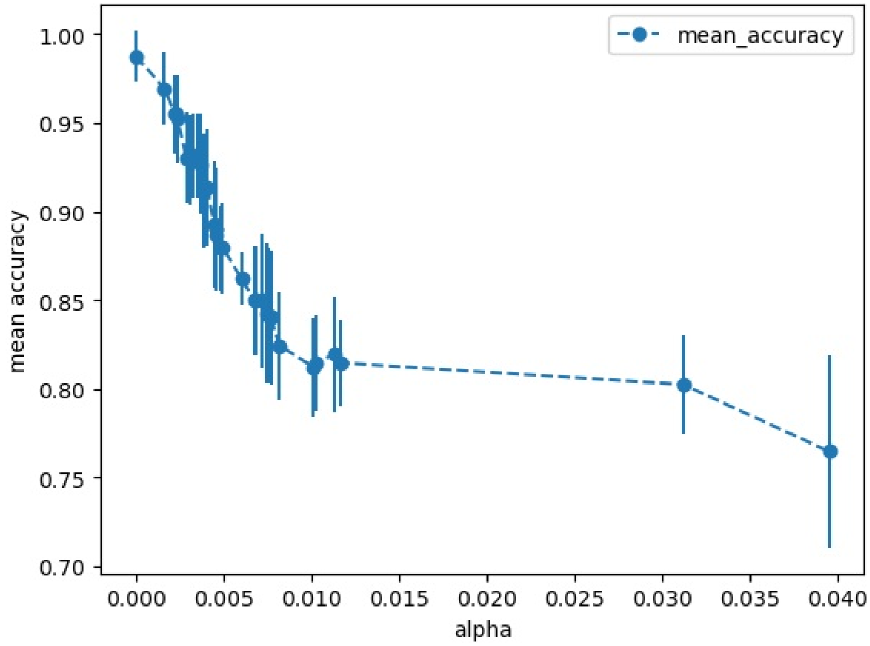
10-fold cross-validation to determine the optimal value for alpha

In [10]:
```
k = 10 #number of cross-validation folds

#10-fold cross-validation to determine the optimal value for alpha
alpha_values = []
for ccp_alpha in ccp_alphas:
    #create tree model
    tree_model = DecisionTreeClassifier(random_state = 42, ccp_alpha = ccp_alpha)

    #calculate accuracy scores using cross-validation
    scores = cross_val_score(tree_model, X_train, y_train, cv = k)

    #store accuracy results
    alpha_values.append([ccp_alpha, scores.mean(), scores.std()])

alpha_results = pd.DataFrame(alpha_values, columns = ['alpha','mean_accuracy','std_accuracy'])
alpha_results.head()
```

Out[10]:

	alpha	mean_accuracy	std_accuracy
0	0.000000	0.987805	0.014429
1	0.001626	0.969512	0.020588
2	0.002236	0.954878	0.022520
3	0.002258	0.954878	0.022520
4	0.002296	0.954878	0.022520

In [11]:
```
#plot the results
alpha_results.plot(x = 'alpha',
                   y = 'mean_accuracy',
                   yerr = 'std_accuracy',
                   marker = 'o',
                   linestyle = '--')
plt.ylabel('mean accuracy')
plt.show()
```



In [12]:
```
#set the optimal value for alpha
optimal_alpha = ccp_alphas[0]
optimal_alpha
```

Out[12]:
```
0.0
```

The optimal value for alpha is 0, which shows the greatest predictive accuracy on average. Therefore, no tree pruning is necessary.

Conclusion

The best performing tree model is the preliminary model with no tree pruning. The average accuracy from cross-validation with this model was 98.8%.