- Study Gini Index
- Compute the toy example using Gini Index
- Change criterion in the imported library, using Gini Index
- Compare Gini Index vs Entropy
- Use another dataset (data.csv)
- Play with parameters: max_depth min_samples_split min_samples_leaf
- Explain your understanding after trying these different parameters

```
# Write your code here
import numpy as np
import pandas as pd
```

```
df = pd.read_csv('toy_data.csv')
df
```

	age	income	student	credit rating	buys computer
0	<=30	high	no	fair	no
1	<=30	high	no	excellent	no
2	31-40	high	no	fair	yes
3	>40	medium	no	fair	yes
4	>40	low	yes	fair	yes
5	>40	low	yes	excellent	no
6	31-40	low	yes	excellent	yes
7	<=30	medium	no	fair	no
8	<=30	low	yes	fair	yes
9	>40	medium	yes	fair	yes
10	<=30	medium	yes	excellent	yes
11	31-40	medium	no	excellent	yes
12	31-40	high	yes	fair	yes
13	>40	medium	no	excellent	no

```
#compute toy data using gini index
def gini_index(data, attribute):
    freq = data.groupby(attribute)[attribute].count() / len(data)
    gini = 1 - (freq**2).sum()
    return gini
```

```
gini_index(df, 'buys computer')
```

```
np.float64(0.4591836734693877)
```

```
def conditional_gini_index(data, attribute, target, return_gis = False):
    freq_target = data.groupby(target)[target].count() / len(data)
    gis = pd.Series(dict([(k, gini_index(data[data[target] == k], attribute)) for k in data[
    if return_gis:
        return (freq_target * gis).sum(), gis
    return (freq_target * gis).sum()
```

```
conditional_gini_index(df, 'buys computer', 'age', return_gis = True)
```

```
(np.float64(0.34285714285714286),
 <=30     0.48
 31-40    0.00
 >40      0.48
 dtype: float64)
```

```
print("gini indices for each attribute")
pd.Series(dict([(k, conditional_gini_index(df, 'buys computer', k)) for k in df.columns]))
```

```
gini indices for each attribute
age              0.342857
income           0.440476
student          0.367347
credit rating    0.428571
buys computer    0.000000
dtype: float64
```

Create Dicision tree using gini index

```
def DecisionTree(df, target_attribute, features = []):
    if len(features) == 0:
        features = df.columns.values
        features = np.delete(features, np.where(features == target_attribute))

    tree = {}
    gis = pd.Series(dict([(k, conditional_gini_index(df, target_attribute, k)) for k in feat

    best_attribute = gis.idxmin()
    tree[best_attribute] = {}
    for k in df[best_attribute].unique():
        tree[best_attribute][k] = {}
        subtable = df[df[best_attribute] == k].drop(best_attribute, axis = 1)
        if len(subtable[target_attribute].unique()) == 1:
            tree[best_attribute][k] = subtable[target_attribute].unique()[0]
        else:
```

```
            subtree = DecisionTree(subtable, target_attribute, features = np.delete(features
            tree[best_attribute][k] = subtree

    return tree


import json
print(json.dumps(DecisionTree(df, 'buys computer'), indent = 4))
```


```
{
    "age": {
        "<=30": {
            "student": {
                "no": "no",
                "yes": "yes"
            }
        },
        "31-40": "yes",
        ">40": {
            "credit rating": {
                "fair": "yes",
                "excellent": "no"
            }
        }
    }
}
```


Using sklean (entropy)

```
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report


def encode_data(df):
    le = LabelEncoder()
    for col in df.columns:
        df[col] = le.fit_transform(df[col])
    return df

df = encode_data(df)


def fit_decision_tree(df, target_attribute, criterion = 'entropy', max_depth = None, min_sam
    X = df.drop(target_attribute, axis = 1)
    y = df[target_attribute]

    clf = DecisionTreeClassifier(
        criterion = criterion, random_state = 42,
```

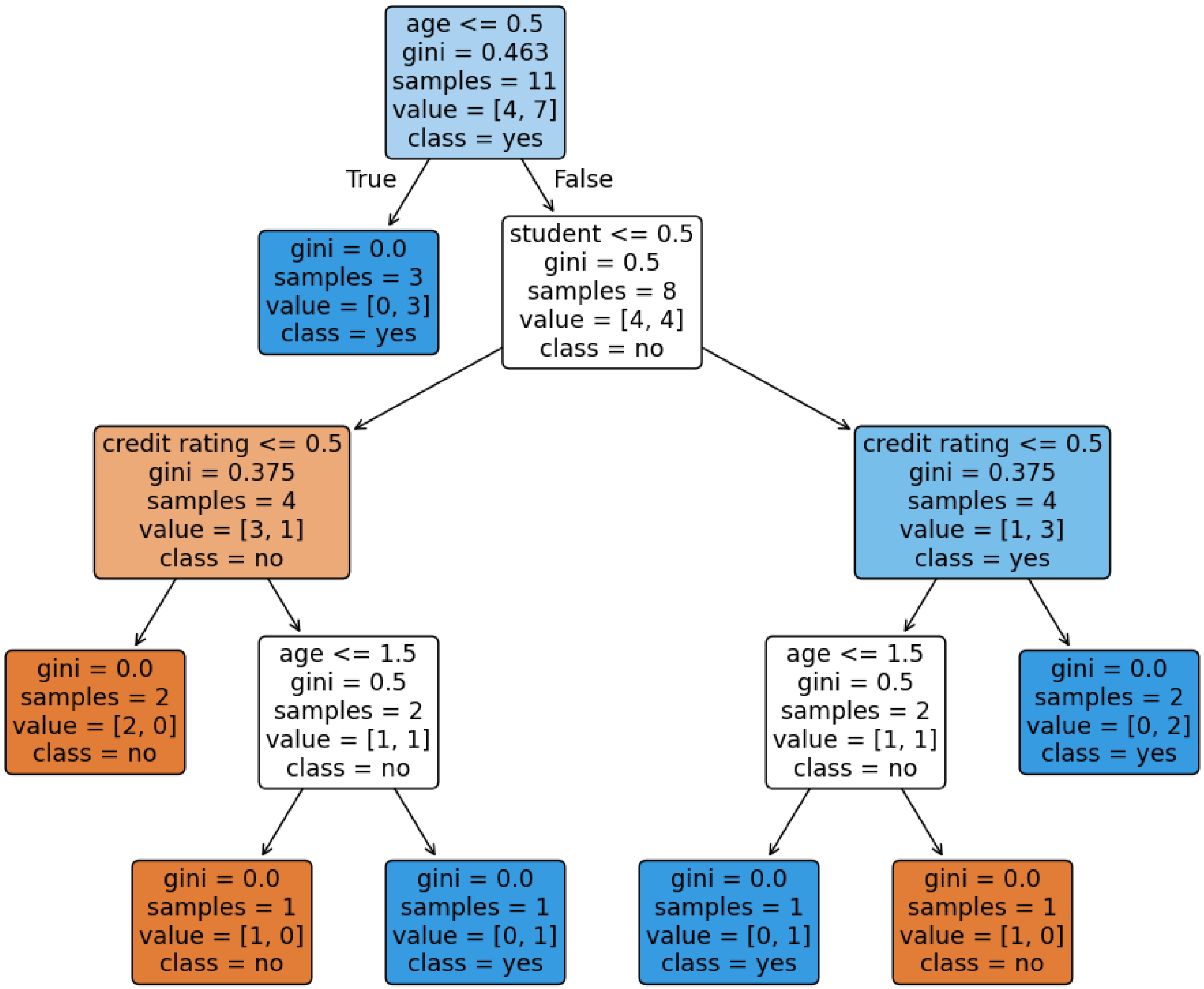
```
        max_depth = max_depth,
        min_samples_split = min_samples_split,
        min_samples_leaf = min_samples_leaf
    )
    clf.fit(X, y)
    return clf


def find_performance(y_test, y_pred):
    accuracy= accuracy_score(y_test, y_pred)
    print(f"Accuracy: {accuracy:.2f}")

    print("classification report:")
    print(classification_report(y_test, y_pred))

    print("confusion matrix:")
    print(confusion_matrix(y_test, y_pred))


def plot_decision_tree(clf, features, target_attribute):
    plt.figure(figsize=(12,10))
    plot_tree(clf, filled=True, feature_names=features, class_names=['no', 'yes'], rounded=1
    plt.show()
```

Put them all together version

```
df = pd.read_csv('toy_data.csv')

#encode data
df = encode_data(df)

#seperate features and target
X = df.drop('buys computer', axis = 1)
y = df['buys computer']

#split data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

#fit decision tree
clf = DecisionTreeClassifier(criterion='gini', random_state = 42)

#fit the model
clf.fit(X_train, y_train)

#predict
y_pred = clf.predict(X_test)

#find performance
print(f"Accuracy: {accuracy_score(y_test, y_pred):.2f}")
```

```
#classification report
print("classification report: ")
print(classification_report(y_test, y_pred))

#confusion matrix
print("confusion matrix: ")
print(confusion_matrix(y_test, y_pred))

#plot decision tree
plt.figure(figsize=(12,10))
plot_tree(clf, filled=True, feature_names=X.columns, class_names=['no', 'yes'], rounded=True
plt.show()
```

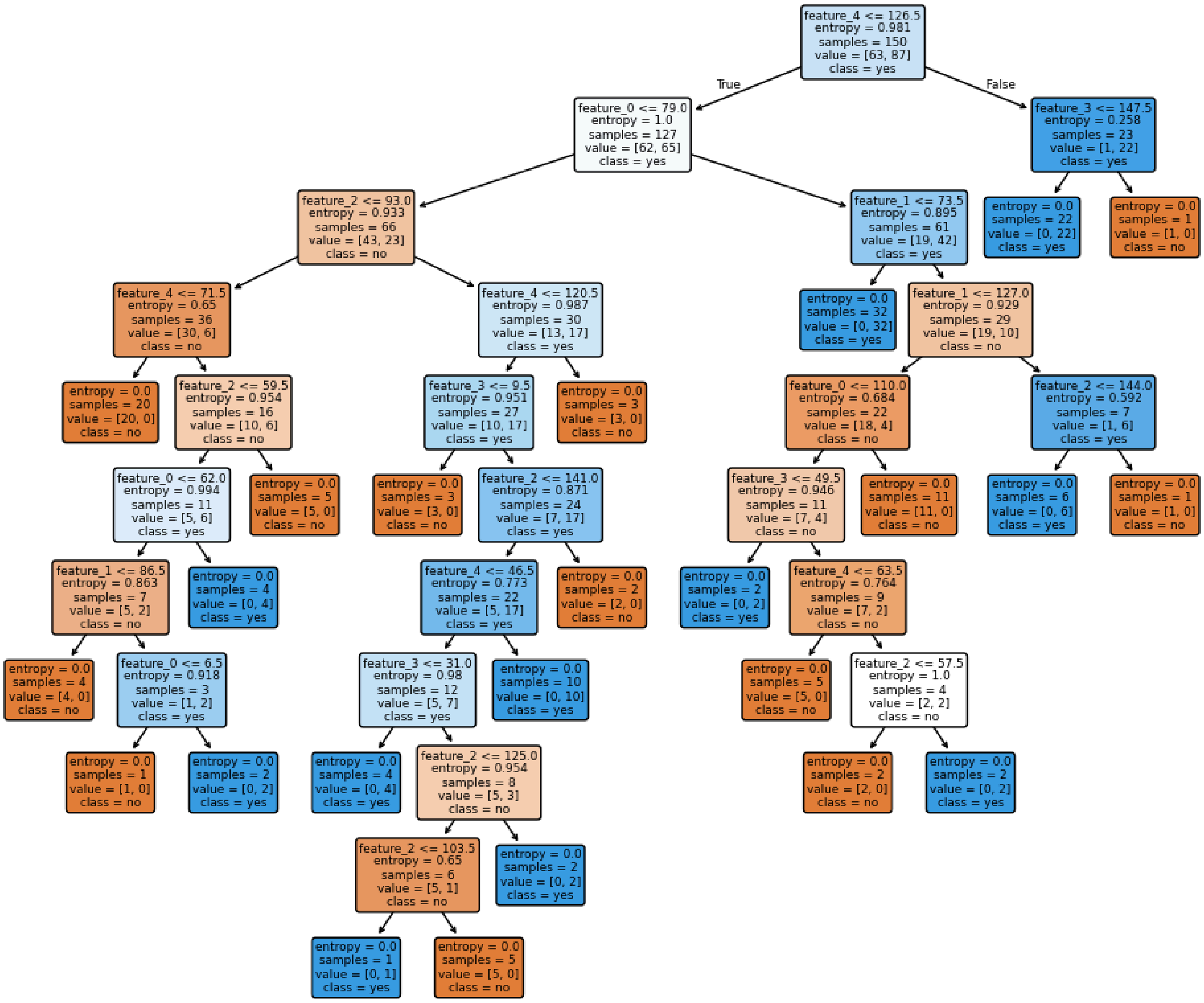
```
Accuracy: 1.00
classification report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00         1
           1       1.00      1.00      1.00         2

    accuracy                           1.00         3
   macro avg       1.00      1.00      1.00         3
weighted avg       1.00      1.00      1.00         3

confusion matrix:
[[1 0]
 [0 2]]
```



new Dataset

Entropy Version

```
df = pd.read_csv('dataset.csv')

#Create entropy tree

#encode data
df = encode_data(df)

#seperate features and target
X = df.drop('target', axis = 1)
y = df['target']

#split data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

#fit decision tree
clf = fit_decision_tree(df, 'target', criterion = 'entropy')

plot_decision_tree(clf, X.columns, 'target')
```



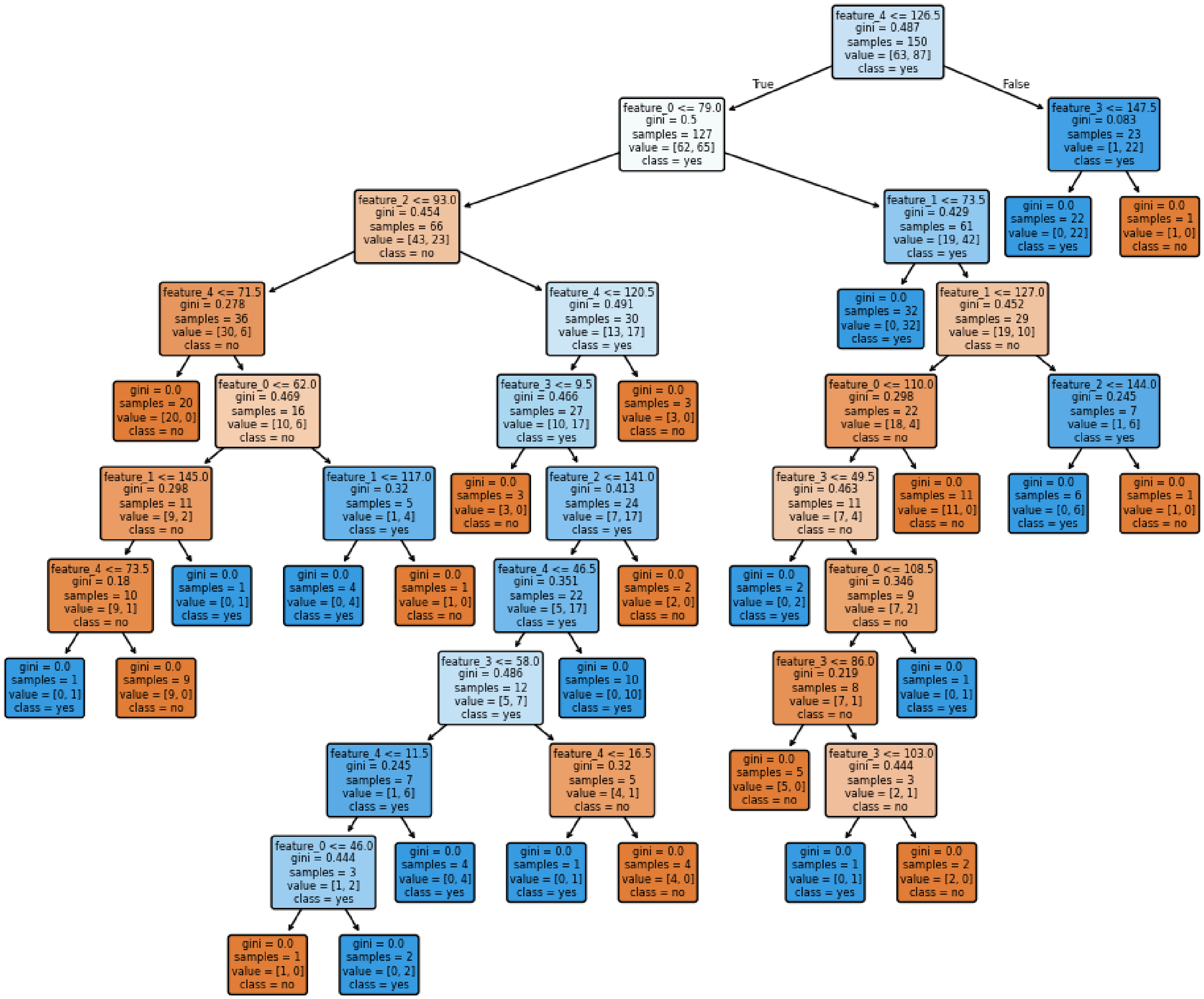

```
# evaluate the model
y_pred = clf.predict(X_test)

find_performance(y_test, y_pred)
```

```
Accuracy: 1.00
classification report:
              precision    recall  f1-score   support
```

```
              0       1.00      1.00      1.00        12
              1       1.00      1.00      1.00        18

       accuracy                           1.00        30
      macro avg       1.00      1.00      1.00        30
   weighted avg       1.00      1.00      1.00        30

confusion matrix:
[[12  0]
 [ 0 18]]
```

gini index

```
# Create gini tree

#fit decision tree
clf = fit_decision_tree(df, 'target', criterion = 'gini')

plot_decision_tree(clf, X.columns, 'target')
```




```
# evaluate the model

y_pred = clf.predict(X_test)

find_performance(y_test, y_pred)
```

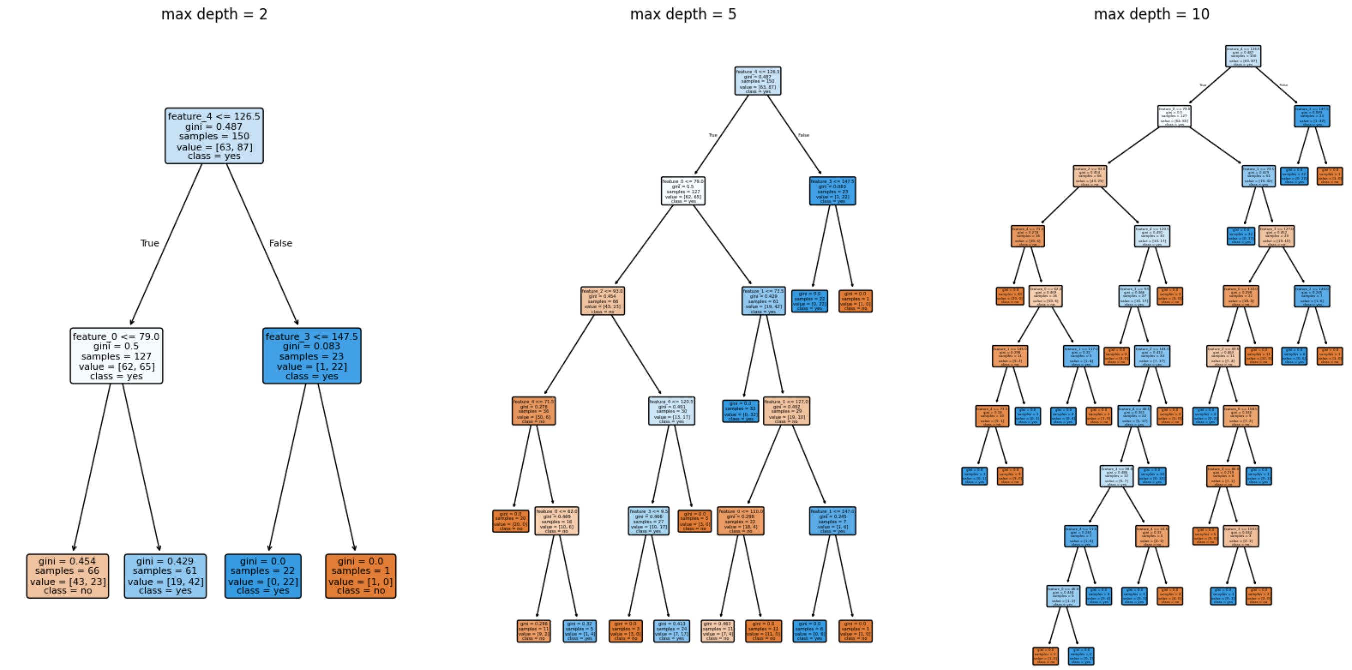
```
Accuracy: 1.00
classification report:
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        12
           1       1.00      1.00      1.00        18

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30

confusion matrix:
[[12  0]
 [ 0 18]]
```

Playing with Parameters

max_depth

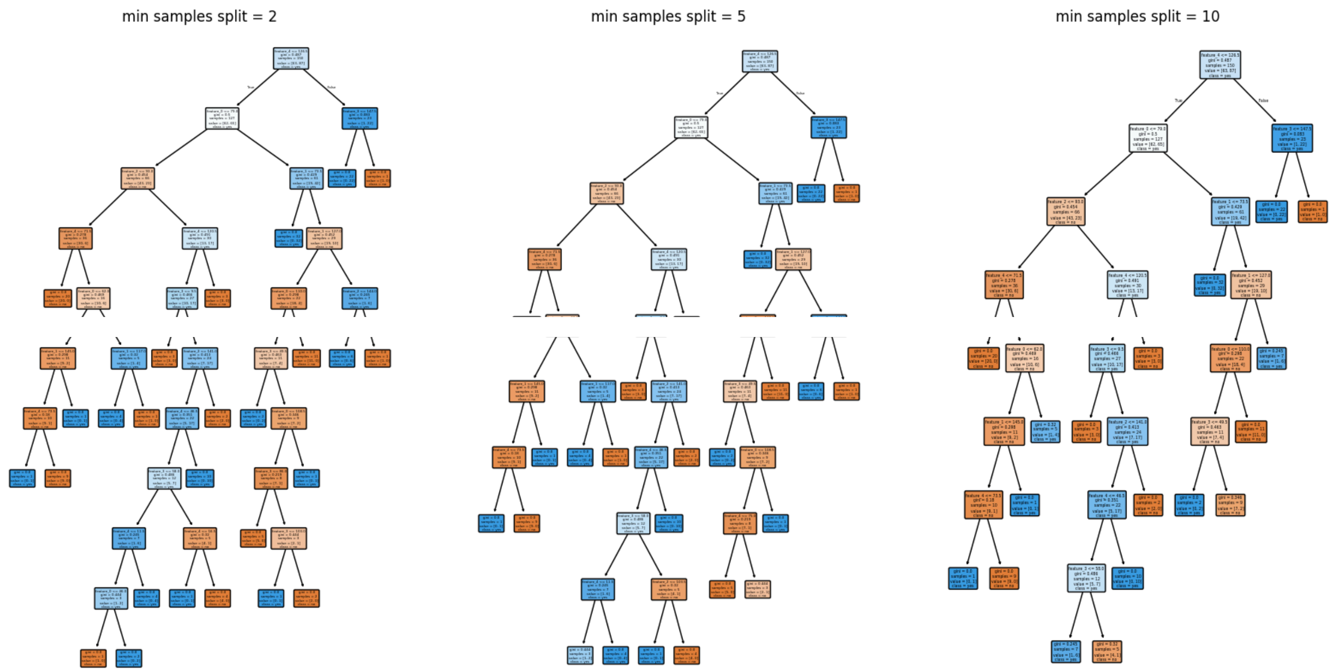
```
# Create gini tree with max depth

fig , ax = plt.subplots(1, 3, figsize=(20, 10))

max_depths = [2, 5, 10]

for md, ax in zip(max_depths, ax):
    clf = fit_decision_tree(df, 'target', criterion = 'gini', max_depth = md)
    plot_tree(clf, filled=True, feature_names=X.columns, class_names=['no', 'yes'], rounded=
    ax.set_title(f"max depth = {md}")

plt.show()
```



min_samples_split

```
# create gini tree with min samples split

fig , ax = plt.subplots(1, 3, figsize=(20, 10))

min_samples_splits = [2, 5, 10]

for mss, ax in zip(min_samples_splits, ax):
    clf = fit_decision_tree(df, 'target', criterion = 'gini', min_samples_split = mss)
    plot_tree(clf, filled=True, feature_names=X.columns, class_names=['no', 'yes'], rounded=
```

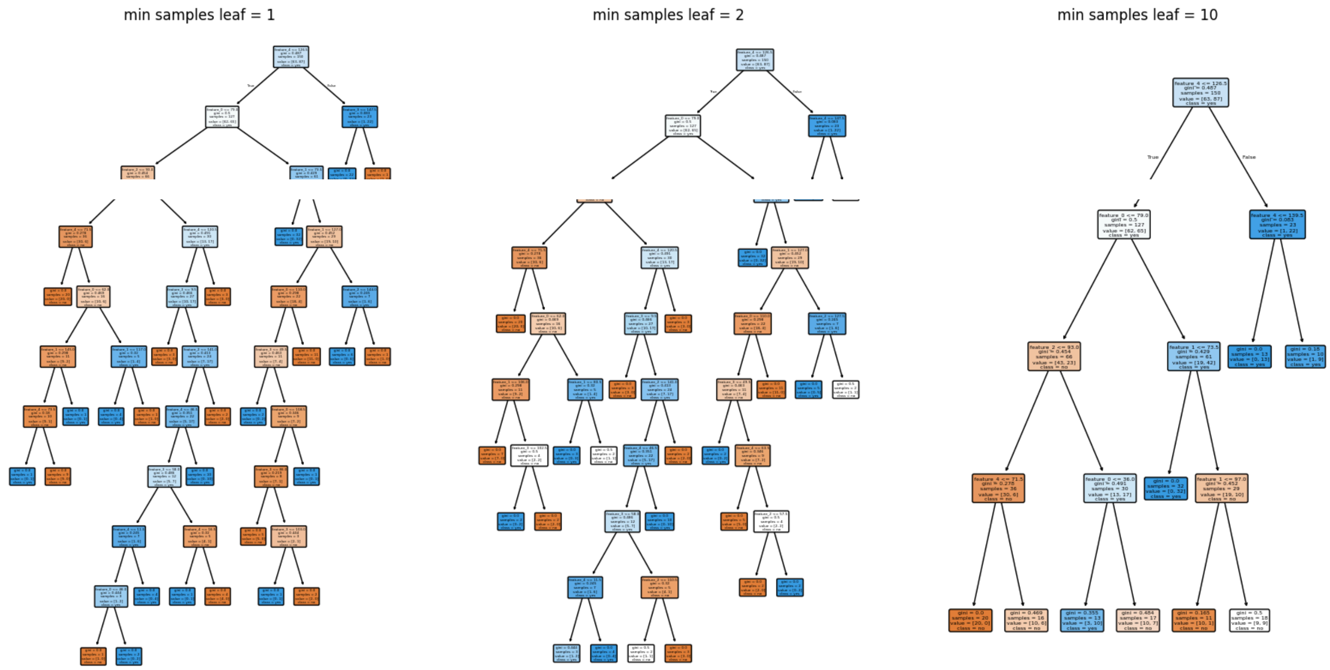
```
    ax.set_title(f"min samples split = {mss}")

plt.show()
```



min_samples_leaf

```
# create gini tree with min samples leaf

fig , ax = plt.subplots(1, 3, figsize=(20, 10))

min_samples_leafs = [1, 2, 10]
```

```
for msl, ax in zip(min_samples_leafs, ax):
    clf = fit_decision_tree(df, 'target', criterion = 'gini', min_samples_leaf = msl)
    plot_tree(clf, filled=True, feature_names=X.columns, class_names=['no', 'yes'], rounded=
    ax.set_title(f"min samples leaf = {msl}")

plt.show()
```



Conclusion Gini index VS Entropy Gini and Entropy are both impurity measures used in decision trees to determine the best attribute for splitting data. While Entropy quantifies impurity directly, Gini is computationally more efficient, making it the default criterion in sklearn's

DecisionTreeClassifier. Entropy is preferable when constructing multiway trees, whereas Gini is more suitable for creating balanced trees.

Parameters max_depth, min_samples_split, and min_samples_leaf help prevent overfitting and fine-tune the model to achieve optimal performance. Proper tuning of these parameters ensures a well-generalized decision tree.