```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sn
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.tree import DecisionTreeClassifier
from sklearn.tree import plot_tree
from sklearn import metrics
```

Decision Tree -- (drug200) dataset:

load the drug dataset for classification:

```python
drugs = pd.read_csv('drug200.csv', encoding='utf-8')
drugs.head()
```

	Age	Sex	BP	Cholesterol	Na_to_K	Drug
0	23	F	HIGH	HIGH	25.355	drugY
1	47	M	LOW	HIGH	13.093	drugC
2	47	M	LOW	HIGH	10.114	drugC
3	28	F	NORMAL	HIGH	7.798	drugX
4	61	F	LOW	HIGH	18.043	drugY

```python
#explore the data:
drugs.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 6 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   Age          200 non-null    int64
 1   Sex          200 non-null    object
 2   BP           200 non-null    object
 3   Cholesterol  200 non-null    object
 4   Na_to_K      200 non-null    float64
 5   Drug         200 non-null    object
dtypes: float64(1), int64(1), object(4)
memory usage: 9.5+ KB
```

```python
print(drugs['Cholesterol'].unique(),' -- ',drugs['Drug'].unique())
```

```
['HIGH' 'NORMAL']  --  ['drugY' 'drugC' 'drugX' 'drugA' 'drugB']
```

```python
#change the string to numric for the model:
drugs['Sex'] = drugs['Sex'].replace({'F' : 1, 'M' : 0})
drugs['BP'] = drugs['BP'].replace({'HIGH' : 2, 'NORMAL' : 1, 'LOW' :
```

```
0})
drugs['Cholesterol'] = drugs['Cholesterol'].replace({'HIGH' : 1,
'NORMAL' : 0})
drugs['Drug'] = drugs['Drug'].replace({'drugA' : 4, 'drugB' : 3,
'drugC' : 2 , 'drugX' : 1, 'drugY' : 0})

drugs.head()
```

	Age	Sex	BP	Cholesterol	Na_to_K	Drug
0	23	1	2	1	25.355	0
1	47	0	0	1	13.093	2
2	47	0	0	1	10.114	2
3	28	1	1	1	7.798	1
4	61	1	0	1	18.043	0

Build the model:

steps:

- split the data.
- standarizing the data.
- create the model.
- train the model.
- evaluate the model.
- visualize the model.

```
# split the data:
x = drugs.drop(columns=['Drug'])
y = drugs['Drug']

x_train, x_test, y_train, y_test = train_test_split(x, y,
test_size=0.3, random_state=23)

print(f'train shape: {x_train.shape} -- test shape: {x_test.shape}')

train shape: (140, 5) -- test shape: (60, 5)

# standraize the data:
standard = StandardScaler()
x_train_std = standard.fit_transform(x_train)
x_test_std = standard.transform(x_test)

# build the model then train it:

tree_model = DecisionTreeClassifier(max_depth=5, min_samples_leaf=5)
tree_model.fit(x_train_std,y_train)

DecisionTreeClassifier(max_depth=5, min_samples_leaf=5)
```

```
#predicate the values(classes) and evaluate the accuarcy:
y_pred = tree_model.predict(x_test_std)

print(f'Accuaracy: {metrics.accuracy_score(y_test, y_pred)}')
```

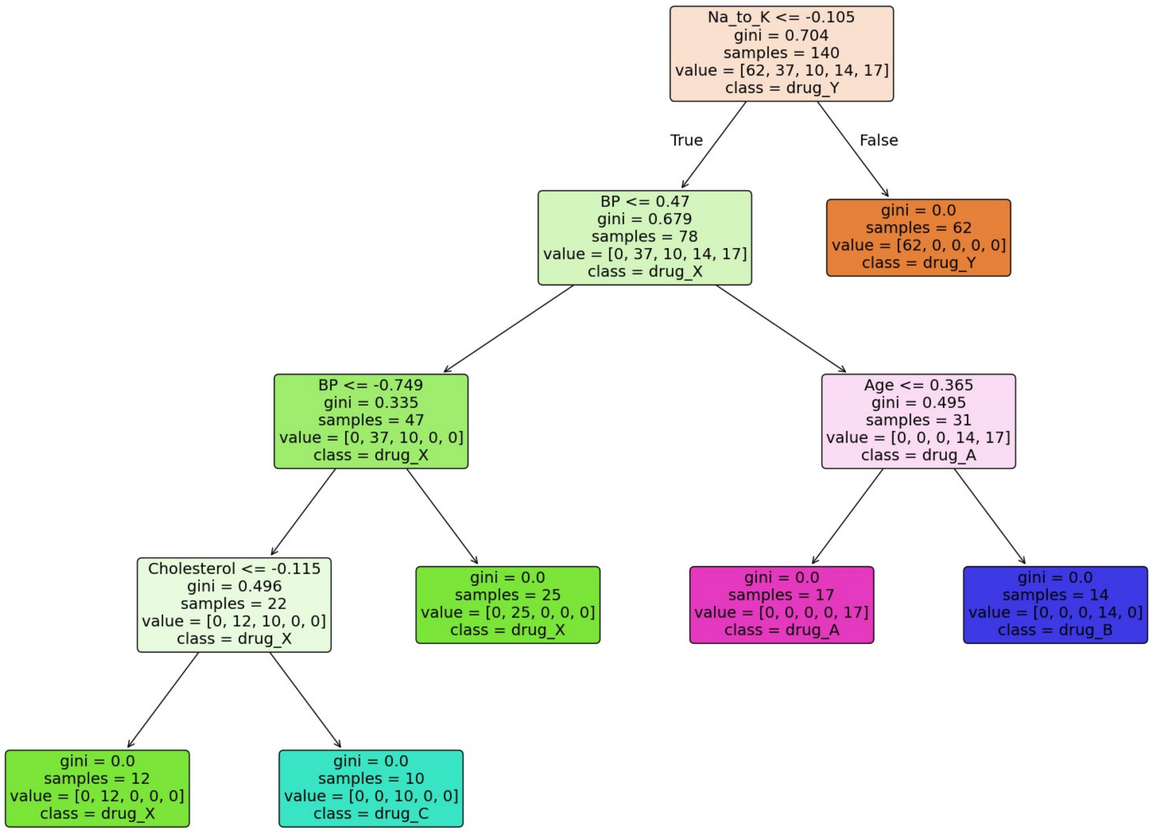
```
Accuaracy: 1.0
```

```
# to see the arrange of classes
tree_model.classes_
```

```
array([0, 1, 2, 3, 4])
```

```
# visualizing the model:
'''
Remamber:
{'drugA' : 4, 'drugB' : 3, 'drugC' : 2 , 'drugX' : 1, 'drugY' : 0}
'''

plt.figure(figsize=(20,15))
plot_tree(decision_tree=tree_model,feature_names=list(x_test.columns),
class_names=['drug_Y','drug_X','drug_C', 'drug_B','drug_A'],
          filled=True,rounded=True,fontsize=14)
plt.show()
```



insights:

- From the graph, we see that our model predict the classes well, the gini index in the graph gave small values, which mean the misclassification in the model is little.

Random Forest -- new dataset (Load Boston):

Load and store the dataset for Regression:

```
# import:
from sklearn.datasets import fetch_california_housing
from sklearn.ensemble import RandomForestRegressor

# store dataset:
california_house = fetch_california_housing()

# check from data:
california_house
```

```
{'data': array([[   8.3252    ,   41.        ,    6.98412698, ...,
2.55555556,
           37.88      , -122.23      ],
        [   8.3014    ,   21.        ,    6.23813708, ...,
2.10984183,
           37.86      , -122.22      ],
        [   7.2574    ,   52.        ,    8.28813559, ...,
2.80225989,
           37.85      , -122.24      ],
        ...,
        [   1.7       ,   17.        ,    5.20554273, ...,
2.3256351 ,
           39.43      , -121.22      ],
        [   1.8672    ,   18.        ,    5.32951289, ...,
2.12320917,
           39.43      , -121.32      ],
        [   2.3886    ,   16.        ,    5.25471698, ...,
2.61698113,
           39.37      , -121.24      ]]),
 'target': array([4.526, 3.585, 3.521, ..., 0.923, 0.847, 0.894]),
 'frame': None,
 'target_names': ['MedHouseVal'],
 'feature_names': ['MedInc',
  'HouseAge',
  'AveRooms',
  'AveBedrms',
  'Population',
  'AveOccup',
  'Latitude',
  'Longitude'],
 'DESCR': '.. _california_housing_dataset:\n\nCalifornia Housing
dataset\n--------------------------\n\n**Data Set Characteristics:**\
n\n:Number of Instances: 20640\n\n:Number of Attributes: 8 numeric,
predictive attributes and the target\n\n:Attribute Information:\n    -
MedInc        median income in block group\n    - HouseAge      median
house age in block group\n    - AveRooms      average number of rooms
per household\n    - AveBedrms     average number of bedrooms per
household\n    - Population    block group population\n    - AveOccup
average number of household members\n    - Latitude      block group
latitude\n    - Longitude     block group longitude\n\n:Missing
Attribute Values: None\n\nThis dataset was obtained from the StatLib
repository.\nhttps://www.dcc.fc.up.pt/~ltorgo/Regression/cal_housing.h
tml\n\nThe target variable is the median house value for California
districts,\nexpressed in hundreds of thousands of dollars ($100,000).\
n\nThis dataset was derived from the 1990 U.S. census, using one row
per census\nblock group. A block group is the smallest geographical
unit for which the U.S.\nCensus Bureau publishes sample data (a block
group typically has a population\nof 600 to 3,000 people).\n\nA
household is a group of people residing within a home. Since the
average\nnumber of rooms and bedrooms in this dataset are provided per
```

```
household, these\ncolumns may take surprisingly large values for block groups with few households\nand many empty houses, such as vacation resorts.\n\nIt can be downloaded/loaded using the\n:func:`sklearn.datasets.fetch_california_housing` function.\n\n.. rubric:: References\n\n- Pace, R. Kelley and Ronald Barry, Sparse Spatial Autoregressions,\n  Statistics and Probability Letters, 33 (1997) 291-297\n'}
```

Train the model:

steps:

- split the data.
- stadraizing the data.
- duild and train the model.
- evaluate the model.
- visualizing the model.

```
# split:
x_california = california_house.data
y_california = california_house.target

x_california_train, x_california_test, y_california_train,
y_california_test = train_test_split(x_california, y_california,
test_size=0.3, random_state=23)

print(f'train shape: {x_california_train.shape} -- test shape:
{x_california_test.shape}')
```

```
train shape: (14448, 8) -- test shape: (6192, 8)
```

```
# standarize the data:
standard2 = StandardScaler()
x_california_train_std = standard2.fit_transform(x_california_train)
x_california_test_std = standard2.transform(x_california_test)

# build and train the model:
randomForest_model = RandomForestRegressor(n_estimators=100,
random_state=23)

randomForest_model.fit(x_california_train_std,y_california_train)
```

```
RandomForestRegressor(random_state=23)
```

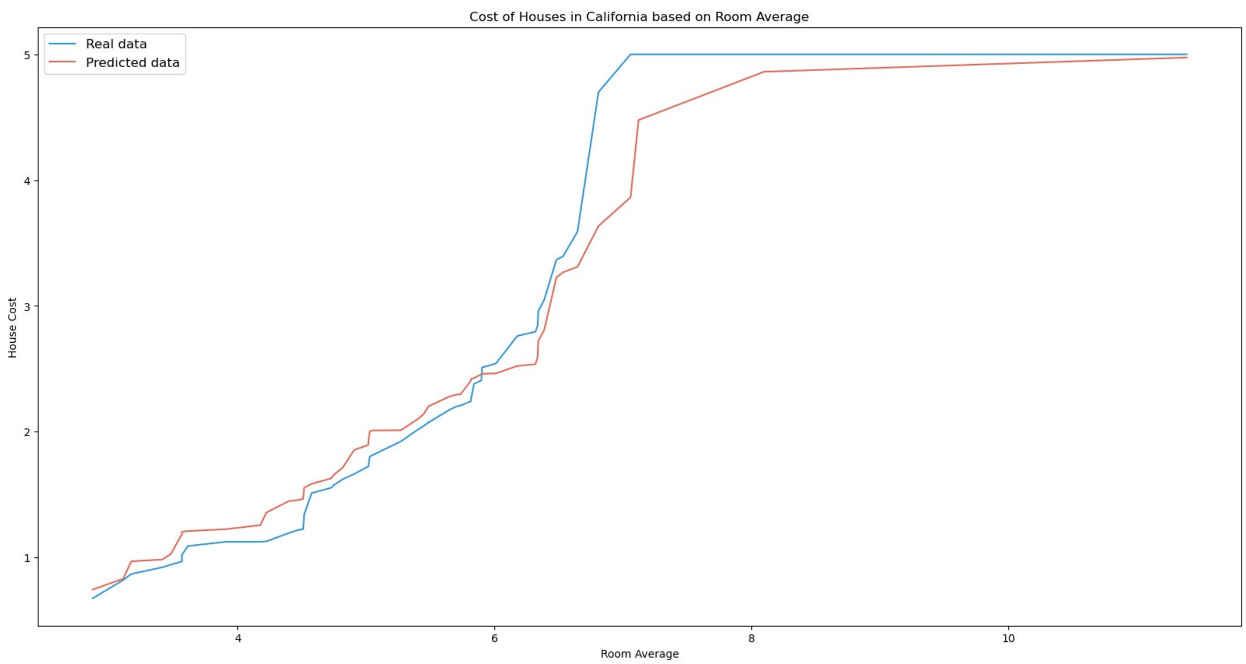
```
# predict the values and evaluate the R2 score(accuracy score for
regression):
y_california_predict =
randomForest_model.predict(x_california_test_std)
```

```
print(f'Accucarcy: {metrics.r2_score(y_california_test,
y_california_predict)}')
```

```
Accucarcy: 0.8107395747196504
```

```
# visualiseing the result:

plt.figure(figsize=(20,10))
plt.plot(sorted(x_california_test[0:50, 2]),
sorted(y_california_test[0:50]), color='#3498db', label = 'Real data')
plt.plot(sorted(x_california_test[0:50, 2]),
sorted(y_california_predict[0:50]), label = 'Predicted data',
color='#e26b5d')
plt.legend(fontsize=12)
plt.title('Cost of Houses in California based on Room Average')
plt.xlabel('Room Average')
plt.ylabel('House Cost')
plt.show()
```



insights:

- From the graph, we see that them model predict the house prices approximately 80% correctly.
- At 'Room-avg' between 6.5 and 7.7 it has a bigger gap than other periods.
- To have more accurate, we can use another model, such as svm.SVR, LinearRegression, or tunnig the same model. Also we can check from data, or add more data to data training.