Decision Trees - Decision Trees - 2

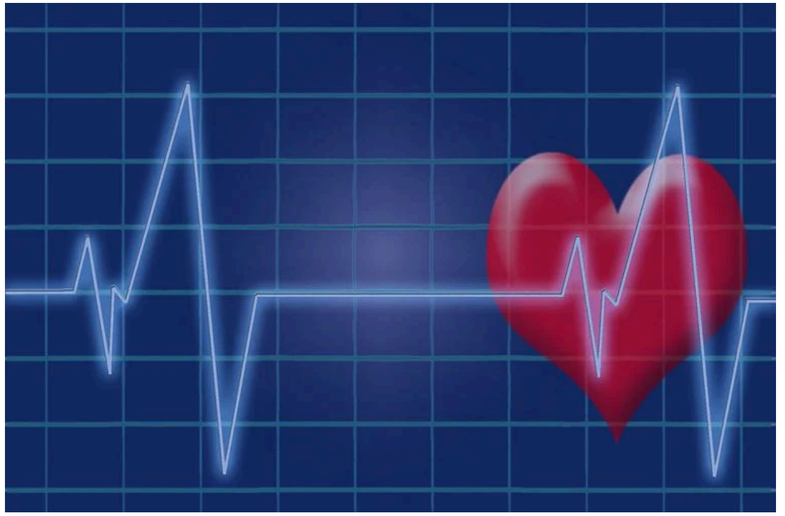
One should look for what is and not what he thinks should be. (Albert Einstein)

Module completion checklist

Objectives	Complete
Transform data in order to use Decision Trees	
Implement the Decision Tree algorithm on a small subset	

Stroke Prediction survey: case study

- According to the World Health Organization (WHO), stroke is the 2nd leading cause of death globally
- ***Click here*** to see a dataset showing the results of a clinical trial of a heart-disease drug survey on a sample of US adults
- Each row in the data provides relevant information about the adult, including whether they had a stroke or not
- We would like to use this data to predict whether a patient is likely to have a stroke based on their demographic information and medical history



Dataset

- In order to implement what you learn in this course, we will be using the `healthcare-dataset-stroke-data.csv` dataset
- We will be working with columns from the dataset such as:
  - `stroke`
  - `gender`
  - `age`
  - `hypertension`
  - `heart_disease`
  - `ever_married`

- We will be using different columns of the dataset to predict `stroke` as the target variable

Loading packages

Let's load the packages we will be using:

```
import os
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import pickle
from pathlib import Path
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
from sklearn.model_selection import GridSearchCV

#import graphviz
from sklearn import tree
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import cross_val_score
from matplotlib.legend_handler import HandlerLine2D
```

- To install `graphviz` through Anaconda, run the following code in the terminal:

```
conda install graphviz
```

- Then, install `python-graphviz`, which is a Python library for `graphviz`

```
conda install python-graphviz
```

Directory settings

- In order to maximize the efficiency of your workflow, you should encode your directory structure into `variables`
- We will use the `pathlib` library
- Let the `main_dir` be the variable corresponding to your `course` folder
- Let `data_dir` be the variable corresponding to your `data` folder

```
# Set 'main_dir' to location of the project folder
home_dir = Path(".").resolve()
main_dir = home_dir.parent.parent
print(main_dir)
```

```
data_dir = str(main_dir) + "/data"
print(data_dir)
```

```
plot_dir = str(main_dir) + "/plots"
if not os.path.exists(plot_dir):
    os.makedirs(plot_dir)
print(plot_dir)
```

Load the dataset

- Let’s load the entire dataset

```
df = pd.read_csv(str(data_dir)+"/"+ 'healthcare-dataset-stroke-data.csv')
print(df.head())
```

```
      id  gender   age  ...   bmi   smoking_status stroke
0   9046    Male  67.0  ...  36.6  formerly smoked      1
1  51676  Female  61.0  ...   NaN     never smoked      1
2  31112    Male  80.0  ...  32.5     never smoked      1
3  60182  Female  49.0  ...  34.4           smokes      1
4   1665  Female  79.0  ...  24.0     never smoked      1

[5 rows x 12 columns]
```

Subset data

- Remove any columns from the dataframe that are not numeric or categorical as we will not be using them in our models

```
df = df[['age', 'avg_glucose_level', 'heart_disease', 'ever_married', 'hypertension',
'Residence_type', 'gender', 'smoking_status', 'work_type', 'stroke', 'id']]
print(df.head())
```

```
    age  avg_glucose_level  heart_disease  ...       work_type  stroke     id
0  67.0             228.69              1  ...         Private       1   9046
1  61.0             202.21              0  ...   Self-employed       1  51676
2  80.0             105.92              1  ...         Private       1  31112
3  49.0             171.23              0  ...         Private       1  60182
4  79.0             174.12              0  ...   Self-employed       1   1665

[5 rows x 11 columns]
```

Data prep: check for NAs

- We now check for NAs and there are multiple methods to deal with them

```
 # Check for NAs.
print(df.isnull().sum())
```

```
age                     0
avg_glucose_level       0
heart_disease           0
ever_married            0
hypertension            0
Residence_type          0
gender                  0
smoking_status       1544
work_type               0
stroke                  0
id                      0
dtype: int64
```

- If we do have NAs, we could replace them with a mean or 0

```
percent_missing = df.isnull().sum() * 100 /
len(df)
print(percent_missing)
```

```
age                    0.000000
avg_glucose_level      0.000000
heart_disease          0.000000
ever_married           0.000000
hypertension           0.000000
Residence_type         0.000000
gender                 0.000000
smoking_status        30.215264
work_type              0.000000
stroke                 0.000000
id                     0.000000
dtype: float64
```

Data prep: check for NAs

```
# Delete columns containing either 50% or more
than 50% NaN Values
perc = 50.0
min_count =  int(((100-perc)/100)*df.shape[0] +
1)
df = df.dropna(axis=1,
               thresh=min_count)
print(df.shape)
```

```
(5110, 11)
```

```
# Function to impute NA in both numeric and
categorical columns
def fillna(df):
    numeric_columns =
df.select_dtypes(include='number').columns
    df[numeric_columns] =
df[numeric_columns].fillna(df[numeric_columns].mea

    categorical_columns =
df.select_dtypes(exclude='number').columns
    df[categorical_columns] =
df[categorical_columns].fillna(df[categorical_colu

    return df

df = fillna(df)
```

Data prep: target

- The next step of our data cleanup is to ensure the target variable is binary and has a label
- Let's look at the `dtype` of `stroke`

```
print(df['stroke'].dtypes)
```

```
int64
```

- We want to convert this to `bool` so that is a binary class

```
# Identify the the two unique classes
threshold = df['stroke'].mean()
df['stroke'] = np.where(df['stroke'] > threshold, 1,0)
```

```
unique_values = sorted(df['stroke'].unique())
df['stroke'] = np.where(df['stroke'] == unique_values[0],  False,True)
# Check class again.
print(df['stroke'].dtypes)
```

```
bool
```

Summarize the data

- Let's use the `.describe()` function within Pandas to summarize our data

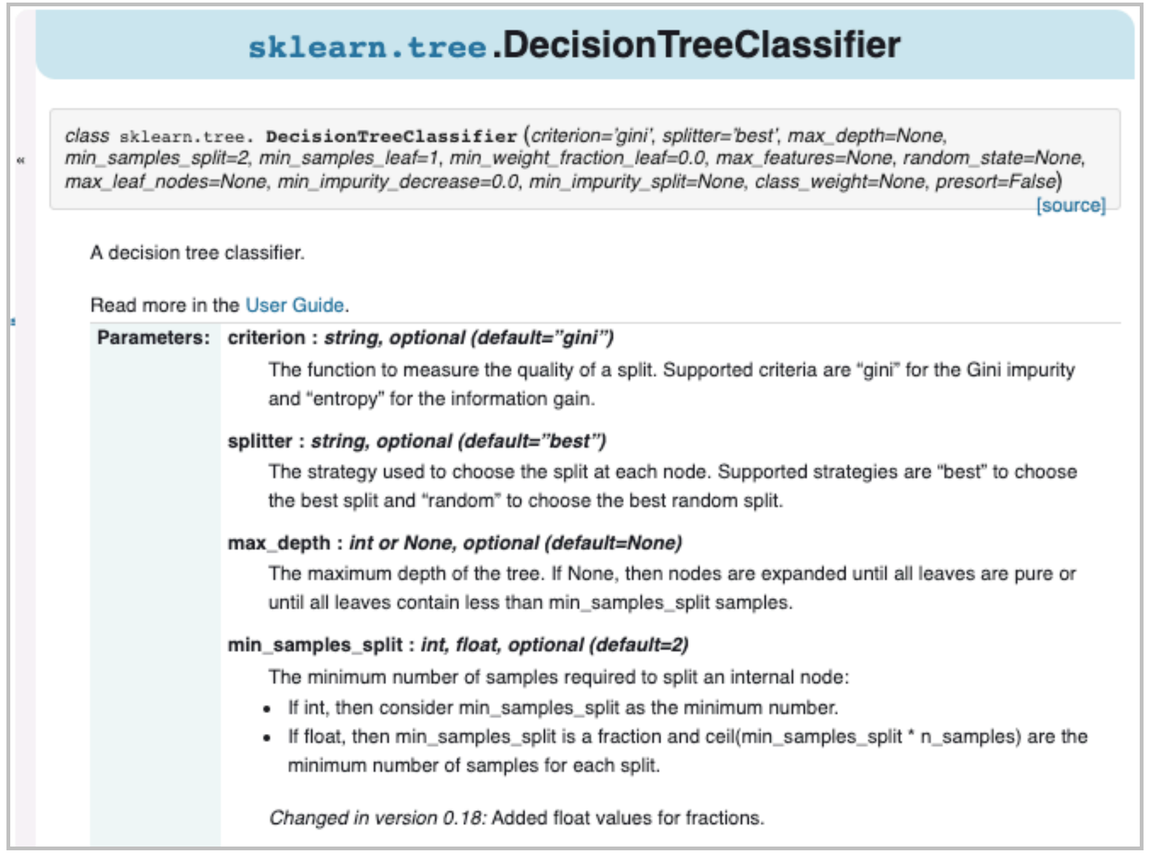
```
print(df.describe())
```

```
                age  avg_glucose_level  ...  hypertension             id
count  5110.000000        5110.000000  ...   5110.000000   5110.000000
mean     43.226614         106.147677  ...      0.097456  36517.829354
std      22.612647          45.283560  ...      0.296607  21161.721625
min       0.080000          55.120000  ...      0.000000     67.000000
25%      25.000000          77.245000  ...      0.000000  17741.250000
50%      45.000000          91.885000  ...      0.000000  36932.000000
75%      61.000000         114.090000  ...      0.000000  54682.000000
max      82.000000         271.740000  ...      1.000000  72940.000000

[8 rows x 5 columns]
```

scikit-learn: tree

- We will be using the `DecisionTreeClassifier` library from `scikit-learn`



sklearn.tree.DecisionTreeClassifier

class sklearn.tree. **DecisionTreeClassifier** (*criterion='gini', splitter='best', max_depth=None, min_samples_split=2, min_samples_leaf=1, min_weight_fraction_leaf=0.0, max_features=None, random_state=None, max_leaf_nodes=None, min_impurity_decrease=0.0, min_impurity_split=None, class_weight=None, presort=False*) [source]

A decision tree classifier.

Read more in the User Guide.

Parameters:

criterion : *string, optional (default="gini")*

The function to measure the quality of a split. Supported criteria are "gini" for the Gini impurity and "entropy" for the information gain.

splitter : *string, optional (default="best")*

The strategy used to choose the split at each node. Supported strategies are "best" to choose the best split and "random" to choose the best random split.

max_depth : *int or None, optional (default=None)*

The maximum depth of the tree. If None, then nodes are expanded until all leaves are pure or until all leaves contain less than min_samples_split samples.

min_samples_split : *int, float, optional (default=2)*

The minimum number of samples required to split an internal node:

- If int, then consider min_samples_split as the minimum number.
- If float, then min_samples_split is a fraction and ceil(min_samples_split * n_samples) are the minimum number of samples for each split.

Changed in version 0.18: Added float values for fractions.

- For all the parameters of the `tree` package, visit ***scikit-learn's documentation***

Trees: pre-processing steps

- Now that we know the problem and have our `df` dataset loaded, it's time to get the data ready to model
- Let's start with data pre-processing.
  - We don't need to scale data since trees are not sensitive to unscaled data
  - We don't need to look at the number of NAs because we already did this and have loaded the cleaned dataset
- **However, on your own data, these are steps you must walk through before modeling**

Module completion checklist

Objectives	Complete
Transform data in order to use decision trees	✔
Implement the decision tree algorithm and predict on test	

Decision Tree: splitting the data

- Let's split our dataset `df` into `X` and `y`
- `X` will contain the predictors
- `y` will contain the target variable

```
# Split the data into X and y
columns_to_drop_from_X = ['stroke'] + ['id']
X = df.drop(columns_to_drop_from_X, axis = 1)
y = np.array(df['stroke'])
```

Data prep: numeric variables

- In `Decision Trees`, we use **numeric data** as predictors
- We can **convert categorical data to integer values**

```
X = pd.get_dummies(X, columns = ['heart_disease', 'ever_married', 'hypertension', 'Residence_type',
'gender', 'smoking_status', 'work_type'], dtype=float, drop_first=True)
print(X.dtypes)
```

```
age                                float64
avg_glucose_level                  float64
heart_disease_1                    float64
ever_married_Yes                   float64
hypertension_1                     float64
Residence_type_Urban               float64
gender_Male                        float64
gender_Other                       float64
smoking_status_never smoked        float64
smoking_status_smokes              float64
work_type_Never_worked             float64
work_type_Private                  float64
work_type_Self-employed            float64
work_type_children                 float64
dtype: object
```

Decision Tree: running the algorithm

- Now let's run our tree on the entire `X` dataset

```
# Implement the decision tree on X.
clf = tree.DecisionTreeClassifier()
clf_fit = clf.fit(X, y)

# Look at our generated model:
print(clf_fit)
```

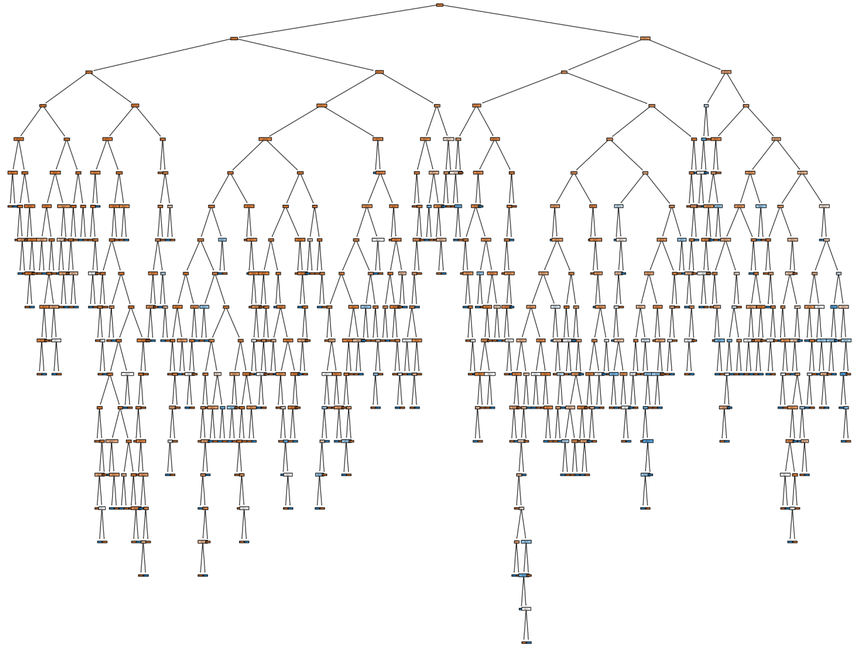
```
DecisionTreeClassifier()
```

Visualize: plot_tree

- We can visualize trees by using `sklearn.tree.plot_tree`
- You can read more about it ***here***
- We will use it in this module to illustrate the tree we are building

```
# Set figure size
fig = plt.figure(figsize=(25,20))
# Visualize `clf_fit_small`
tree.plot_tree(clf_fit,
               feature_names= X.columns,
               filled=True)
# Save figure
plt.savefig(str(plot_dir)+'/tree.png',format='png',bbox
= "tight")
```

```
plt.show()
```



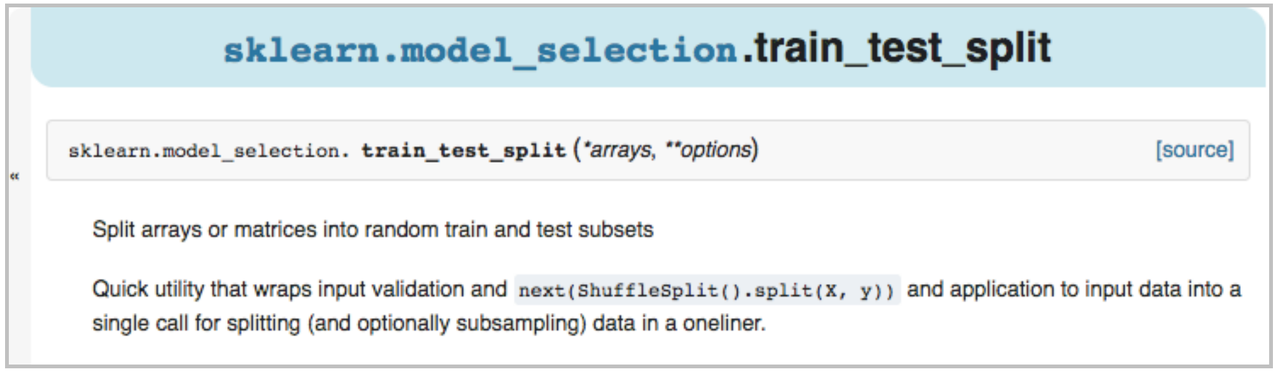
Decision Tree:

`healthcare-dataset-stroke-data.csv`

- Now, let's run the tree on the full `healthcare-dataset-stroke-data.csv` dataset
- **We will evaluate the model and add the results to our `model_final` dataframe**

scikit-learn: train_test_split

- We will be using the `train_test_split` library from `scikit-learn`



sklearn.model_selection.train_test_split

`sklearn.model_selection.` **`train_test_split`** (**arrays*, ***options*) [source]

Split arrays or matrices into random train and test subsets

Quick utility that wraps input validation and `next(ShuffleSplit().split(X, y))` and application to input data into a single call for splitting (and optionally subsampling) data in a oneliner.

- Inputs are:
  - Lists, NumPy arrays, scipy-sparse matrices, or Pandas DataFrames
- For all the parameters of the `tree` package, visit ***scikit-learn's documentation***

Split into train and test sets

- Split the cleaned data into a train set and test set
- Remember, we already imported the package at the start of this lesson
- Otherwise, we would have to import it now

```
# Split into train and test.
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3)

print(X_train.shape, y_train.shape)
```

```
(3577, 14) (3577,)
```

```
print(X_test.shape, y_test.shape)
```

```
(1533, 14) (1533,)
```

Fit Decision Tree and predict

- Now we will run `tree` on `X_train` and `y_train` and then predict on `X_test`

```
# Implement the decision tree on X_train.
clf = tree.DecisionTreeClassifier()
clf_fit = clf.fit(X_train, y_train)

# Predict on X_test.
y_predict = clf_fit.predict(X_test)
```

- The result is an **array of predictions**

```
y_predict[:20]
```

```
array([False, False, False, False, False, False, False, False, False,
       False, False, False, False, False, False, False, False, False,
       False,  True])
```

- We can determine the accuracy by comparing the predictions against `y_test`

Knowledge check

Module completion checklist

Objectives	Complete
Transform data in order to use decision trees	✔
Implement the decision tree algorithm and predict on test	✔

Congratulations on completing this module!

You are now ready to try Tasks 1-6 in the Exercise for this topic