Importing important libraries and classes

```
import pandas as pd
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import cross_val_score, KFold
from sklearn.ensemble import BaggingClassifier, AdaBoostClassifier
import seaborn as sns
import matplotlib.pyplot as plt
```

Loading the datasets

```
df1 = pd.read_csv('/content/sample_data/Iris.csv')
df1
```

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	1	5.1	3.5	1.4	0.2	Iris-setosa
1	2	4.9	3.0	1.4	0.2	Iris-setosa
2	3	4.7	3.2	1.3	0.2	Iris-setosa
3	4	4.6	3.1	1.5	0.2	Iris-setosa
4	5	5.0	3.6	1.4	0.2	Iris-setosa
...	...	...	...	...	...	...
145	146	6.7	3.0	5.2	2.3	Iris-virginica
146	147	6.3	2.5	5.0	1.9	Iris-virginica
147	148	6.5	3.0	5.2	2.0	Iris-virginica
148	149	6.2	3.4	5.4	2.3	Iris-virginica
149	150	5.9	3.0	5.1	1.8	Iris-virginica

150 rows × 6 columns

```
df2 = pd.read_csv('/content/sample_data/winequalityN (1).csv')
df2
```

	type	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
0	white	7.0	0.270	0.36	20.7	0.045	45.0	170.0	1.00100	3.00	0.45	8.8	6
1	white	6.3	0.300	0.34	1.6	0.049	14.0	132.0	0.99400	3.30	0.49	9.5	6
2	white	8.1	0.280	0.40	6.9	0.050	30.0	97.0	0.99510	3.26	0.44	10.1	6
3	white	7.2	0.230	0.32	8.5	0.058	47.0	186.0	0.99560	3.19	0.40	9.9	6
4	white	7.2	0.230	0.32	8.5	0.058	47.0	186.0	0.99560	3.19	0.40	9.9	6
...	...	...	...	...	...	...	...	...	...	...	...	...	...
6492	red	6.2	0.600	0.08	2.0	0.090	32.0	44.0	0.99490	3.45	0.58	10.5	5
6493	red	5.9	0.550	0.10	2.2	0.062	39.0	51.0	0.99512	3.52	NaN	11.2	6
6494	red	6.3	0.510	0.13	2.3	0.076	29.0	40.0	0.99574	3.42	0.75	11.0	6
6495	red	5.9	0.645	0.12	2.0	0.075	32.0	44.0	0.99547	3.57	0.71	10.2	5

Checking for any null values in the datasets

```
df1.isna().sum()
```

	0
Id	0
SepalLengthCm	0
SepalWidthCm	0
PetalLengthCm	0
PetalWidthCm	0
Species	0

dtype: int64

```
df2.isna().sum()
```

	0
type	0
fixed acidity	10
volatile acidity	8
citric acid	3
residual sugar	2
chlorides	2
free sulfur dioxide	0
total sulfur dioxide	0
density	0
pH	9
sulphates	4
alcohol	0
quality	0

dtype: int64

Handling the null values

```
# Handle potential NaN values
df1.fillna(0, inplace = True) # Replace NaN with 0 or another suitable value
df2.fillna(0, inplace = True)
```

```
df1.isna().sum()
```

	0
Id	0
SepalLengthCm	0
SepalWidthCm	0
PetalLengthCm	0
PetalWidthCm	0
Species	0

dtype: int64

```
df2.isna().sum()
```

	0
type	0
fixed acidity	0
volatile acidity	0
citric acid	0
residual sugar	0
chlorides	0
free sulfur dioxide	0
total sulfur dioxide	0
density	0
pH	0
sulphates	0
alcohol	0
quality	0

dtype: int64

Creating a function to evaluate classifier performance and create their heatmap

```
def evaluate_classifier(classifier, X, y, classifier_name):
# def is a Python keyword used to define a function.
# evaluate_classifier is the name of the function.
# The function takes four arguments:
#   classifier: The machine learning model (e.g., Decision Tree, Random Forest) you want to evaluate.
#   X: The input features of your dataset (often a pandas DataFrame).
#   y: The target variable or labels you're trying to predict.
#   classifier_name: A string representing the name of the classifier (for display purposes).

    kfold = KFold(n_splits=10, shuffle=True, random_state=42)
    scores = cross_val_score(classifier, X, y, cv=kfold, scoring='accuracy')
    print(f"{classifier_name} Accuracy: {scores.mean():.4f} (+/- {scores.std() * 2:.4f})")
    # KFold: This creates a strategy for splitting your data into 10 folds (groups) for cross-validation.
    #   n_splits=10: Divides the data into 10 folds.
    #   shuffle=True: Randomly shuffles the data before splitting.
    #   random_state=42: Sets a seed for reproducibility.
    # cross_val_score: This function applies the classifier to the data using the k-fold strategy,
    # calculates the model's accuracy for each fold, and stores the results in the scores variable.
    # print: This line displays the average accuracy and standard deviation of the
    # classifier's performance across all folds.

    try:
        numerical_cols = X.select_dtypes(include=['number']).columns
        if len(numerical_cols) > 0:
            plt.figure(figsize=(8, 6))
            sns.heatmap(X[numerical_cols].corr(), annot=True, cmap="coolwarm")
            plt.title(f"Heatmap for {classifier_name} (Numerical Features)")
            plt.show()
        else:
            print("No numerical features found for heatmap visualization.")
    except (ValueError, TypeError) as e:
        print(f"Heatmap visualization not possible for this data: {e}")
    # try...except: This block is used to handle potential errors during heatmap creation.
    # numerical_cols: This line identifies the columns in your dataset (X) that contain numerical data.
    # if len(numerical_cols) > 0:: If numerical features are found, the code proceeds to create the heatmap.
    # sns.heatmap: This function from the seaborn library generates the heatmap.
    #    X[numerical_cols].corr(): Calculates the correlation between numerical features.
    #    annot=True: Displays the correlation values on the heatmap.
    #    cmap="coolwarm": Sets the color scheme of the heatmap.
    # plt.title, plt.show: These lines set the title of the heatmap and display it.
    # If no numerical features are found or an error occurs, informative messages are printed.
```

Seperating the attributes based on input features and target feature

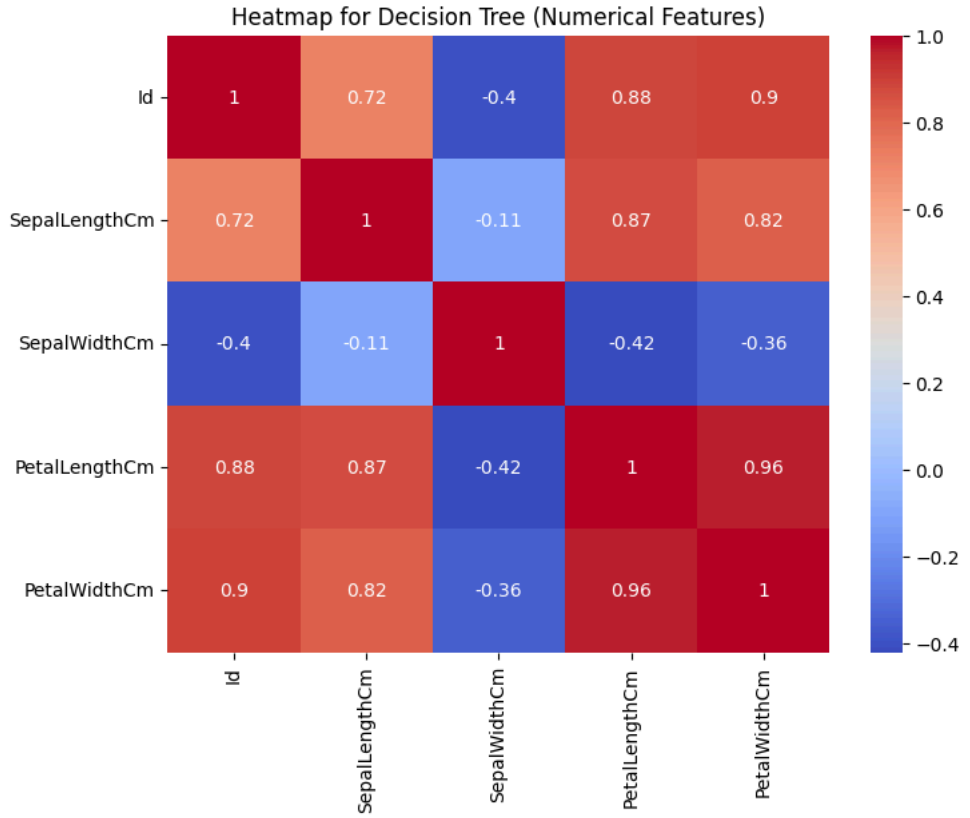
```
# Dataset 1
try:
    X1 = df1.drop('Species', axis=1)
    y1 = df1['Species']
except KeyError:
    print("Error: 'Species' column not found in dataset1.csv. Please check your data.")
    exit()
```

```
# try:: This begins a try...except block. It's used for error handling. The code within the try
# block is executed, and if a KeyError occurs, the code within the except block is executed instead.
# X1 = df1.drop('Species', axis=1):
#   X1: This variable is assigned the features (input data) for the machine learning model.
#   df1: This is the Pandas DataFrame containing data loaded from dataset1.csv.
#   .drop('Species', axis=1): This line removes the column named 'Species' from the DataFrame df1.
#       'Species' is the name of the column to be dropped.
#        axis=1 specifies that we are dropping a column (axis=0 would drop a row).
#        The result (DataFrame without the 'Species' column) is assigned to X1.
# y1 = df1['Species']:
#    y1: This variable is assigned the target variable (what we want the model to predict).
#    df1['Species']: This selects the 'Species' column from the DataFrame df1. This column
#    likely contains the labels or categories you want to predict.
# except KeyError:: If a KeyError occurs during the execution of the try block (specifically,
# if the 'Species' column is not found in df1), the code inside the except block will be executed.
# A KeyError typically happens when you try to access a column that doesn't exist in a DataFrame.
# print("Error: 'Species' column not found in dataset1.csv. Please check your data."): This line prints
# an error message to the console, informing the user that the 'Species' column is missing and suggesting
# they check their data file.
# exit(): This line terminates the program's execution because if no tareget attribute in dataset how we predict


# Dataset 2
try:
    X2 = df2.drop('type', axis=1)
    y2 = df2['type']
except KeyError:
    print("Error: 'type' column not found in dataset2.csv. Please check your data.")
    exit()

# THis is the same code as the above just for dataset2 oe df2
```

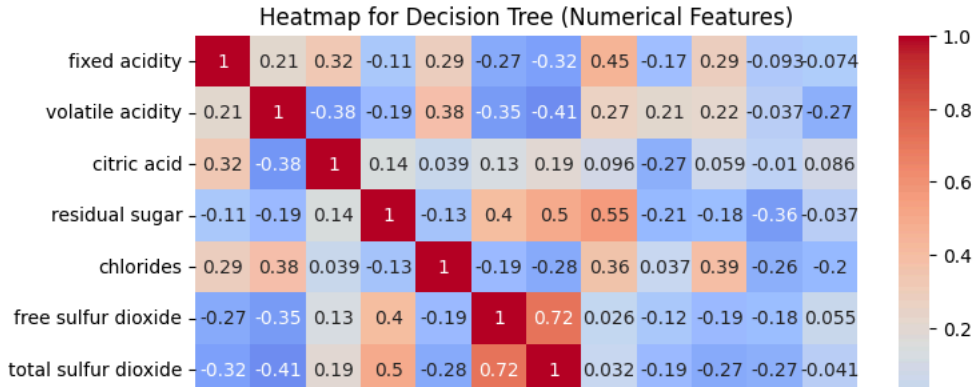
Applying the Decision Tree classifier

```
# Decision Tree Classifier
dt_classifier = DecisionTreeClassifier(random_state=42)
# dt_classifier = DecisionTreeClassifier(random_state=42): This line is where the
# Decision Tree model is created.
#     dt_classifier: This is a variable that will hold our Decision Tree model.
#       Think of it as a container for the model.
#     DecisionTreeClassifier(): This is the function from the sklearn.tree library
#       that actually creates the Decision Tree model.
#     random_state=42: This sets a seed for the random number generator used within
#       the Decision Tree algorithm. Setting a seed ensures that if you run the code
#       multiple times, you'll get the same results (which is important for reproducibility).

print("Dataset 1:")
evaluate_classifier(dt_classifier, X1, y1, "Decision Tree")
# This line calls the evaluate_classifier function (which was defined earlier in the code) to
# assess the performance of the Decision Tree model on the first dataset.
#     dt_classifier: The Decision Tree model we created.
#     X1: The features (input data) for the first dataset.
#     y1: The target variable (what we want to predict) for the first dataset.
#     "Decision Tree": A string representing the name of the classifier (used for display purposes).

print("\nDataset 2:")
evaluate_classifier(dt_classifier, X2, y2, "Decision Tree")
# Same with dataset2 or df2
```

```
Dataset 1:
Decision Tree Accuracy: 0.9933 (+/- 0.0400)
```




```
Dataset 2:
Decision Tree Accuracy: 0.9865 (+/- 0.0066)
```



Comparing the Decision Tree Classifiers with "Bagging" and "AdaBoost" with different estimators

```
# Ensemble methods - Bagging and AdaBoost (combined loop for brevity)
for classifier_type in ["Bagging", "AdaBoost"]:
    for n_estimators in [3, 5, 7, 9]:
        if classifier_type == "Bagging":
            classifier = BaggingClassifier(DecisionTreeClassifier(), n_estimators=n_estimators, random_state=42)
        else:
            classifier = AdaBoostClassifier(DecisionTreeClassifier(), n_estimators=n_estimators, random_state=42

        print(f"\nDataset 1 - {classifier_type} ({n_estimators} estimators):")
        evaluate_classifier(classifier, X1, y1, f"{classifier_type} ({n_estimators})")

        print(f"\nDataset 2 - {classifier_type} ({n_estimators} estimators):")
        evaluate_classifier(classifier, X2, y2, f"{classifier_type} ({n_estimators})")
# Nested Loops:
#     The code uses two nested for loops to iterate through different configurations:
#         The outer loop (for classifier_type in ["Bagging", "AdaBoost"]) selects either "Bagging" or
#           "AdaBoost" as the ensemble method.
#         The inner loop (for n_estimators in [3, 5, 7, 9]) iterates through different numbers of
#           estimators (weak learners) to be used in the ensemble.

# Creating the Ensemble Classifiers:
#   Inside the loops, an if statement checks the classifier_type:
#     If it's "Bagging", a BaggingClassifier is created using BaggingClassifier(DecisionTreeClassifier(),
#       n_estimators=n_estimators, random_state=42).
#        This means it will create an ensemble of Decision Trees using the Bagging technique.
```

```
#        n_estimators controls the number of Decision Trees in the ensemble.
#        random_state=42 ensures consistent results.
#     If classifier_type is "AdaBoost", an AdaBoostClassifier is created using AdaBoostClassifier
#       (DecisionTreeClassifier(), n_estimators=n_estimators, random_state=42).
#           This creates an ensemble of Decision Trees using the AdaBoost technique.
#           Similar to Bagging, n_estimators and random_state have the same roles.

# Evaluating the Classifiers:
#     After creating the classifier, the code calls the evaluate_classifier function
#       (defined earlier) to assess its performance on both datasets (X1, y1, X2, y2).
```

```
Dataset 1 - Bagging (3 estimators):
Bagging (3) Accuracy: 0.9867 (+/- 0.0800)
```