Question No. 1: Decision Tree & Random Forest

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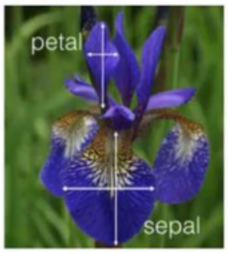
a) What is motivation behind ensemble methods? (3p)
b) How Random Forest training and inference works? Give pseudo code. (7p)

c) Iris dataset has 50 samples for each of three different species of Iris flower (total number of samples is 150). For each data sample, you have sepal length, sepal width, petal length and petal width and a species name (class/label). Figure below shows Iris flower and features in dataset:




```
5.1,3.8,1.9,0.4,Iris-setosa
4.8,3.0,1.4,0.3,Iris-setosa
5.1,3.8,1.6,0.2,Iris-setosa
4.6,3.2,1.4,0.2,Iris-setosa
5.3,3.7,1.5,0.2,Iris-setosa
5.0,3.3,1.4,0.2,Iris-setosa
7.0,3.2,4.7,1.4,Iris-versicolor
6.4,3.2,4.5,1.5,Iris-versicolor
6.9,3.1,4.9,1.5,Iris-versicolor
5.5,2.3,4.0,1.3,Iris-versicolor
6.5,2.8,4.6,1.5,Iris-versicolor
5.7.2.8.4.5.1.3.Iris-versicolor
```

Iris flower: sepal length, sepal width, petal length and width

Perform the following tasks:

- Load the given Iris dataset
- Split it into a training set and a test set
- Preprocess the data
- Build a Decision Tree classifier
- Then train a Random Forest classifier
- How much better does it perform compared to the Decision Tree classifier? (10p)

PART A

a) Motivation behind ensemble

Ensemble methods are a type of machine learning technique that involves combining multiple models to improve the accuracy and robustness of a single model. The motivation behind ensemble methods is that no single model is perfect, and there is always some degree of error or bias in any model. By combining multiple models, the errors and biases of individual models can be reduced, resulting in a more accurate prediction overall.

Another motivation behind ensemble methods is that they can be used to improve the performance of machine learning models on complex datasets. By combining multiple models with different strengths and weaknesses, ensemble methods can be designed to capture more of the complexity of the data and make more accurate predictions.

Ensemble methods are used in a wide variety of machine learning applications, including classification, regression, and anomaly detection. Some popular ensemble methods include bagging, boosting, and stacking.

PART B

b) How Random Forest training and inference works? Give pseudo code.

```
Training a Random Forest:

Function
TrainRandomForest(training_data, num_trees, max_depth, max_features):
    forest = []  # Create an empty list to hold the trees
    for i = 1 to num_trees:
        # Randomly select a subset of the training data
```

```
        # Randomly select a subset of the training data
        subset = RandomSubset(training_data)
        # Build a decision tree with the selected subset
        tree = BuildDecisionTree(subset, max_depth, max_features)
        # Add the tree to the forest
        forest.append(tree)
    return forest
End Function
```

```
Making Predictions with the Random Forest:

Function PredictWithRandomForest(forest, new_data_point):
    class_votes = {}  # Create a dictionary to store class votes
    for tree in forest:
        prediction = PredictWithDecisionTree(tree, new_data_point)
        if prediction in class_votes:
            class_votes[prediction] += 1
        else:
            class_votes[prediction] = 1
    best_class = FindClassWithMostVotes(class_votes)
    return best_class
End Function
```

PART C

Load the given Iris dataset

```
import numpy as np
import pandas as pd
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
from sklearn.ensemble import RandomForestClassifier
```

```
df = pd.read_csv("Iris.csv")
```

```
df.head(5)
```

	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

```
df.tail(5)
```

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
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

```
output = df["Species"].values
```

```
output
```

```
array(['Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica'], dtype=object)
```

```
type(output)
```

```
numpy.ndarray
```

```
# Create a mapping for the replacement
mapping = {'Iris-setosa': 0, 'Iris-versicolor': 1, 'Iris-virginica': 2}

# Use the 'replace' function to create the new column
df['Encoded_Species'] = df['Species'].replace(mapping)
```

```
df
```

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species	Encoded_Species
0	1	5.1	3.5	1.4	0.2	Iris-setosa	0

```
# Remove the 'Species' column
df = df.drop('Species', axis=1)
df = df.drop('Id', axis=1)
```

```
df
```

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

150 rows × 5 columns

```
Target = df["Encoded_Species"].values
```

```
Target
```

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

```
df = df.sample(frac=1, random_state=42) # Shuffle the DataFrame
```

```
df
```

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Encoded_Species
73	6.1	2.8	4.7	1.2	1
18	5.7	3.8	1.7	0.3	0
118	7.7	2.6	6.9	2.3	2
78	6.0	2.9	4.5	1.5	1
76	6.8	2.8	4.8	1.4	1
...	...	...	...	...	...
71	6.1	2.8	4.0	1.3	1
106	4.9	2.5	4.5	1.7	2
14	5.8	4.0	1.2	0.2	0
92	5.8	2.6	4.0	1.2	1
102	7.1	3.0	5.9	2.1	2

150 rows × 5 columns

Split it into a training set and a test set

```
# Split the data into feature (X) and target (Target)
feature = df.drop('Encoded_Species', axis=1)
Target = df['Encoded_Species']


# Define the split ratio
train_ratio = 0.8  # 80% for training, 20% for testing
test_ratio = 0.2

# Calculate the number of rows for training and testing
total_rows = len(df)
train_rows = int(train_ratio * total_rows)
test_rows = total_rows - train_rows

# Split the DataFrame into training and test DataFrames
train_df = df.iloc[:train_rows, :]
test_df = df.iloc[train_rows:, :]

# Reset the index for the new DataFrames
train_df = train_df.reset_index(drop=True)
test_df = test_df.reset_index(drop=True)

# Define features (X) and target (y) for training and test sets
X_train = train_df.drop('Encoded_Species', axis=1)
y_train = train_df['Encoded_Species']
X_test = test_df.drop('Encoded_Species', axis=1)
y_test = test_df['Encoded_Species']
```

```
train_df
```

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Encoded_Species
0	6.1	2.8	4.7	1.2	1
1	5.7	3.8	1.7	0.3	0
2	7.7	2.6	6.9	2.3	2
3	6.0	2.9	4.5	1.5	1
4	6.8	2.8	4.8	1.4	1
...	...	...	...	...	...
115	6.9	3.1	5.4	2.1	2
116	5.9	3.0	4.2	1.5	1
117	6.5	3.0	5.2	2.0	2
118	5.7	2.6	3.5	1.0	1
119	5.2	2.7	3.9	1.4	1

120 rows × 5 columns

```
test_df
```

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Encoded_Species
0	6.1	3.0	4.6	1.4	1
1	4.5	2.3	1.3	0.3	0
2	6.6	2.9	4.6	1.3	1
3	5.5	2.6	4.4	1.2	1
4	5.3	3.7	1.5	0.2	0
5	5.6	3.0	4.1	1.3	1
6	7.3	2.9	6.3	1.8	2
7	6.7	3.3	5.7	2.1	2
8	5.1	3.7	1.5	0.4	0
9	4.9	2.4	3.3	1.0	1
10	6.7	3.3	5.7	2.5	2
11	7.2	3.0	5.8	1.6	2
12	4.9	3.1	1.5	0.1	0
13	6.7	3.1	5.6	2.4	2
14	4.9	3.0	1.4	0.2	0
15	6.9	3.1	4.9	1.5	1
16	7.4	2.8	6.1	1.9	2
17	6.3	2.9	5.6	1.8	2
18	5.7	2.8	4.1	1.3	1
19	6.5	3.0	5.5	1.8	2

Preprocess the data

22 5.6 2.8 4.9 2.0 2

```
# Calculate the mean and standard deviation of each feature in the training set
mean = np.mean(X_train, axis=0)
std = np.std(X_train, axis=0)

# Perform feature scaling by subtracting the mean and dividing by the standard deviation
X_train_scaled = (X_train - mean) / std
X_test_scaled = (X_test - mean) / std
```

```
X_train_scaled.head(5)
```

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
0	0.358536	-0.621797	0.579953	0.036562
1	-0.124883	1.646156	-1.107866	-1.124820
2	2.292213	-1.075388	1.817687	1.456028
3	0.237681	-0.395002	0.467432	0.423689
4	1.204520	-0.621797	0.636214	0.294647

```
X_test_scaled.head(5)
```

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
0	0.358536	-0.168207	0.523693	0.294647
1	-1.575141	-1.755774	-1.332908	-1.124820
2	0.962810	-0.395002	0.523693	0.165604
3	-0.366593	-1.075388	0.411171	0.036562
4	-0.608303	1.419361	-1.220387	-1.253862

Build a Decision Tree classifier

```
# Create a Decision Tree classifier
clf = DecisionTreeClassifier(max_depth=5)  # You can set the maximum depth as desired

# Fit the classifier on the training data
clf.fit(X_train_scaled, y_train)

# Make predictions on the test data
y_pred = clf.predict(X_test_scaled)

# Calculate the accuracy of the classifier
accuracy = accuracy_score(y_test, y_pred)

print(f"Accuracy: {accuracy :.2f}")
print(f"Accuracy: {accuracy * 100:.2f}%")
```

```
Accuracy: 0.93
Accuracy: 93.33%
```

*Then train a Random Forest classifier *

```
# Create a Random Forest classifier
rf_clf = RandomForestClassifier(n_estimators=1000, random_state=42)  # You can adjust the number of trees (n_estimators)

# Fit the Random Forest classifier on the training data
rf_clf.fit(X_train_scaled, y_train)

# Make predictions on the test data
rf_y_pred = rf_clf.predict(X_test_scaled)

# Calculate the accuracy of the Random Forest classifier
rf_accuracy = accuracy_score(y_test, rf_y_pred)

print(f"Random Forest Accuracy: {rf_accuracy :.2f}")
print(f"Random Forest Accuracy: {rf_accuracy * 100:.2f}%")
```

```
Random Forest Accuracy: 0.97
Random Forest Accuracy: 96.67%
```

How much better does it perform compared to the Decision Tree classifier?

```
# Accuracy of the Decision Tree classifier
decision_tree_accuracy = accuracy

# Accuracy of the Random Forest classifier
random_forest_accuracy = rf_accuracy

# Calculate the performance improvement
performance_improvement = (random_forest_accuracy - decision_tree_accuracy) * 100

print(f"Decision Tree Accuracy: {decision_tree_accuracy * 100:.2f}%")
print(f"Random Forest Accuracy: {random_forest_accuracy * 100:.2f}%")
print(f"Performance Improvement: {performance_improvement:.2f}%")
```

```
Decision Tree Accuracy: 93.33%
Random Forest Accuracy: 96.67%
Performance Improvement: 3.33%
```