decisionTrees

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TD1 Machine Learning - MMVAI

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The goal of this parctical lab is to implement a decision tree classifier

Import

[ ]:
```
import numpy as np
import matplotlib.pyplot as plt
from matplotlib.colors import ListedColormap

# This one are used to compare our decision tree with the one of sklearn-learn
from sklearn import tree
from sklearn.tree import DecisionTreeClassifier

from sklearn.datasets import load_iris
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split
```

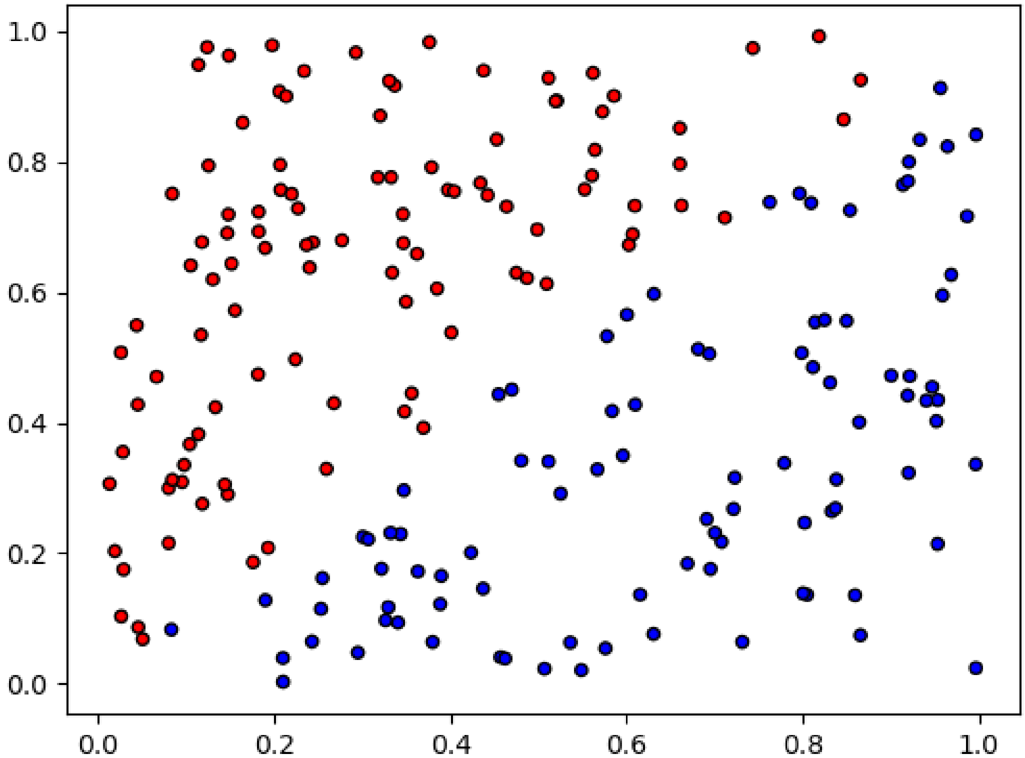
Generate and visualize the data

[ ]:
```
# Generate 200 2d feature points and their corresponding binary labels.
X = np.random.rand(200, 2)
y = np.zeros(200)
y[np.where(X[:,0]<X[:,1])] = 1

rows = np.column_stack((X, y))
```

[ ]:
```
# Create color maps
cmap_light = ListedColormap(['#AAAAFF', '#FFAAAA'])
cmap_bold = ListedColormap(['#0000FF', '#FF0000'])
```

[ ]:
```
# Plot also the training points
plt.scatter(X[:, 0], X[:, 1], c=y, cmap=cmap_bold,
            edgecolor='k', s=20)
```

[ ]:
```
<matplotlib.collections.PathCollection at 0x7f642515afd0>
```



TODO

Write a python class called Question used to partition the dataset

The training data could be seen as a table composed of 3 columns [X, Y] and 200 rows

[ ]:
```python
class Question:
    """
    A Question is used to partition a dataset.
    """
    def __init__(self, column, value):
        self.column = column
        self.value = value

    def match(self, example):
        # Compare the feature value in an example to the
        # feature value in this question.
        val = example[self.column]
        return val <= self.value
```

For each row in the dataset, check if it matches the question. If so, add it to 'true rows', otherwise, add it to 'false rows'.

[ ]:
```python
def split(rows, question):
    true_rows, false_rows = [], []
    for row in rows:
        if question.match(row):
            true_rows.append(row)
        else:
            false_rows.append(row)
    return true_rows, false_rows
```

Calculate the gini Impurity or the Entropy

[ ]:
```python
def class_counts(rows):
    """Counts the number of each type of example in a dataset."""
    counts = {}
    for row in rows:
        label = row[-1]
        if label not in counts:
            counts[label] = 0
        counts[label] += 1
    return counts
```

[ ]:
```python
def gini(rows):
    """
    Calculates the Gini impurity for a set of rows.

    Parameters:
    - rows (list): A list of data rows where each row's last element is the␣
 ↪class label.

    Returns:
    - float: The Gini impurity score for the set of rows.

    Formula:
    Gini impurity = 1 - Σ (p_i)^2

    where p_i is the probability of an item with label i in the set of rows.
    """
    counts = class_counts(rows)
    impurity = 1
    for label in counts:
        prob_of_label = counts[label] / float(len(rows))
        impurity -= prob_of_label ** 2
    return impurity
```

Compute the information gain as The uncertainty of the starting node, minus the weighted impurity of two child nodes.

[ ]:
```python
def infomation_gain(left, right, current_uncertainty):
    p = float(len(left)) / (len(left) + len(right))
    return current_uncertainty - p * gini(left) - (1 - p) * gini(right)
```

Find the best question to ask by iterating over every feature / value and calculating the information gain

[ ]:
```python
def find_best_split(rows):
    best_gain = 0
    best_question = None
    current_uncertainty = gini(rows)
    n_features = len(rows[0]) - 1

    for col in range(n_features):
        values = set([row[col] for row in rows])

        for val in values:
            question = Question(col, val)

            # try splitting the dataset
            true_rows, false_rows = split(rows, question)

            # Skip this split if it doesn't divide the
            # dataset.
            if len(true_rows) == 0 or len(false_rows) == 0:
                continue

            # Calculate the information gain from this split
            gain = infomation_gain(true_rows, false_rows, current_uncertainty)

            if gain >= best_gain:
                best_gain, best_question = gain, question

    return best_gain, best_question
```

Building the decision tree

[ ]:
```python
def decision_tree(rows):
    gain, question = find_best_split(rows)

    # Stopping condition
    if gain == 0:
        return Leaf(rows)

    true_rows, false_rows = split(rows, question)

    # Recursively build the true branch.
    true_branch = decision_tree(true_rows)
```

```
    # Recursively build the false branch.
    false_branch = decision_tree(false_rows)

    # Return a Question node.
    return DecisionNode(question, true_branch, false_branch)

class Leaf:
    """A Leaf node classifies data."""

    def __init__(self, rows):
        self.predictions = class_counts(rows)

class DecisionNode:
    """A Decision Node asks a question."""

    def __init__(self, question, true_branch, false_branch):
        self.question = question
        self.true_branch = true_branch
        self.false_branch = false_branch
```

Define function to predict with the decision tree

[ ]:
```
def predict_single(node, row):
    """Predict the class label for a single row using the given decision tree.
    ↪"""
    # If we reach a leaf node, return the predictions
    if isinstance(node, Leaf):
        return max(node.predictions, key=node.predictions.get)

    # If the question is satisfied, go to the true branch; otherwise, go to the␣
    ↪false branch
    if node.question.match(row):
        return predict_single(node.true_branch, row)
    else:
        return predict_single(node.false_branch, row)

def predict(tree, data):
    """Predict the class labels for a dataset using the given decision tree."""
    return [predict_single(tree, row) for row in data]
```

[ ]:
```
my_tree = decision_tree(rows)
my_predictions = predict(my_tree, X)

# Calculate accuracy using scikit-learn's accuracy_score
accuracy = accuracy_score(y, my_predictions)
print("Your decision tree accuracy:", accuracy)
```

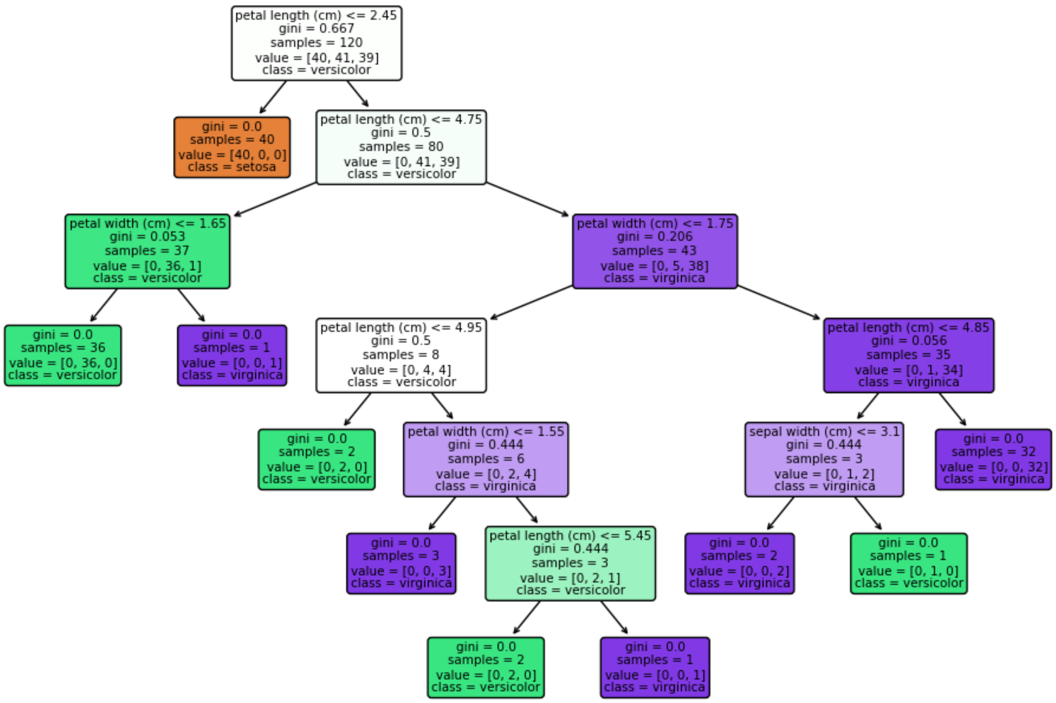
```python
# Compare with scikit-learn's decision tree

# Train scikit-learn's decision tree
sklearn_tree = DecisionTreeClassifier()
sklearn_tree.fit(X, y)

# Use scikit-learn's predict method
sklearn_predictions = sklearn_tree.predict(X)

# Calculate accuracy using scikit-learn's accuracy_score
sklearn_accuracy = accuracy_score(y, sklearn_predictions)
print("Scikit-learn decision tree accuracy:", sklearn_accuracy)
```

```
Your decision tree accuracy: 1.0
Scikit-learn decision tree accuracy: 1.0
```

Bonus

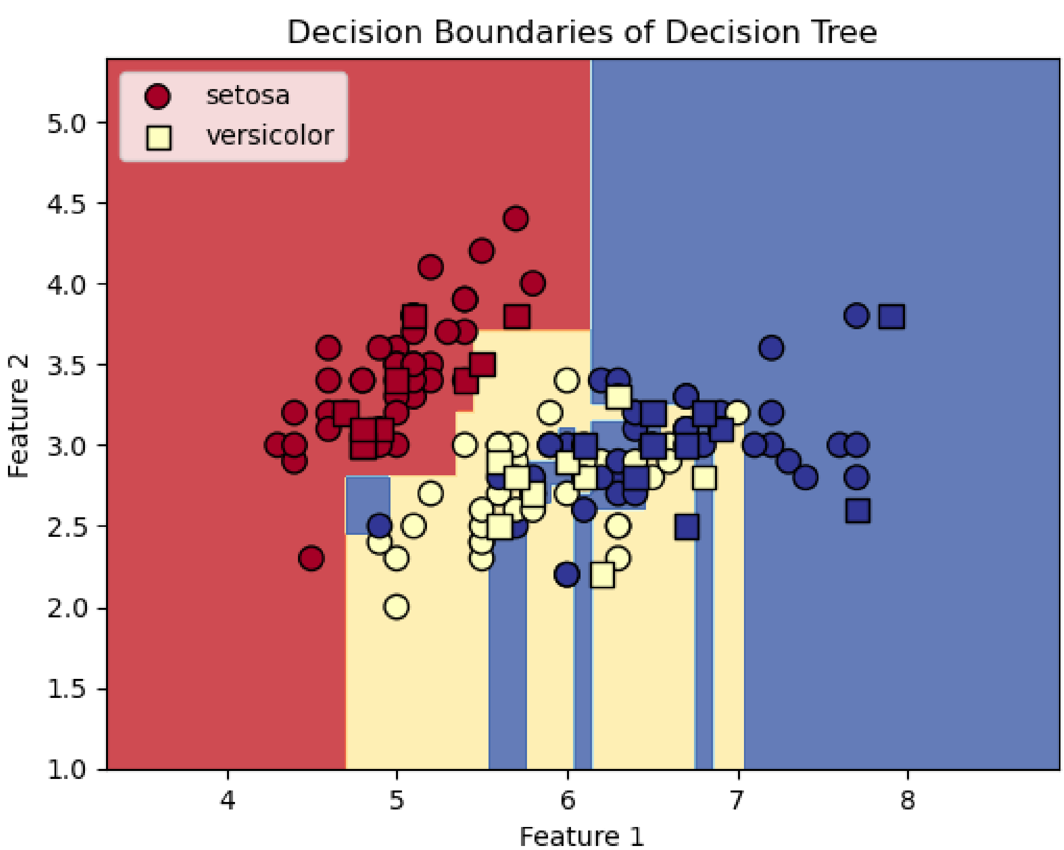
Using sklearn the idea is to plot the decision boundaries and the also trying to visualize the decision tree (node and leaf)

[ ]:
```python
# Charger un jeu de données, par exemple, iris
data = load_iris()
X = data.data
y = data.target

# Convertir le tableau numpy en une liste de chaînes
class_names = [str(cls) for cls in data.target_names]

# Diviser les données en ensembles d'entraînement et de test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)

# Initialiser le modèle d'arbre de décision
model = DecisionTreeClassifier()

# Entraîner le modèle sur les données d'entraînement
model.fit(X_train, y_train)

# Afficher l'arbre de décision
plt.figure(figsize=(12, 8))
tree.plot_tree(model, filled=True, feature_names=data.feature_names,␣
 ↪class_names=class_names, rounded=True)
plt.show()
```



[ ]:
```python
X = data.data[:, :2]  # Utiliser seulement les deux premières caractéristiques pour faciliter la visualisation
y = data.target

# Diviser les données en ensembles d'entraînement et de test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Initialiser le modèle d'arbre de décision
model = DecisionTreeClassifier()

# Entraîner le modèle sur les données d'entraînement
model.fit(X_train, y_train)

# Définir la plage des valeurs pour les deux caractéristiques
x_min, x_max = X[:, 0].min() - 1, X[:, 0].max() + 1
y_min, y_max = X[:, 1].min() - 1, X[:, 1].max() + 1

# Créer une grille de points pour la prédiction
xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.01),
                     np.arange(y_min, y_max, 0.01))

# Prédire la classe pour chaque point de la grille
```

```
Z = model.predict(np.c_[xx.ravel(), yy.ravel()])
Z = Z.reshape(xx.shape)

# Afficher les frontières de décision
plt.contourf(xx, yy, Z, alpha=0.8, cmap=plt.cm.RdYlBu)

# Afficher les points d'entraînement
scatter_train = plt.scatter(X_train[:, 0], X_train[:, 1], c=y_train,␣
  ↪edgecolors='k', cmap=plt.cm.RdYlBu, marker='o', s=80, label='Training Data')
scatter_test = plt.scatter(X_test[:, 0], X_test[:, 1], c=y_test,␣
  ↪edgecolors='k', cmap=plt.cm.RdYlBu, marker='s', s=80, label='Testing Data')

# Ajouter des étiquettes et une légende
plt.xlabel('Feature 1')
plt.ylabel('Feature 2')
plt.title('Decision Boundaries of Decision Tree')
plt.legend(handles=[scatter_train, scatter_test], labels=class_names,␣
  ↪loc='upper left')

# Afficher le graphique
plt.show()
```



```
[ ]:
```