Machine Learning Course

Assignment 2: Decision Trees and K-nn

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p1

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[37]:
```
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
from sklearn import tree
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split

import warnings

# Suppress SettingWithCopyWarning
warnings.filterwarnings("ignore", category=pd.errors.SettingWithCopyWarning)
```

[38]:
```
data = pd.read_csv("drug.csv")

# Check whether there are missing values
missing_values = data.isnull().sum()
print('Missing values:\n', missing_values)

print('----------------------')
```

```
Missing values:
 Age            0
Sex            0
BP             2
Cholesterol    2
Na_to_K        1
Drug           0
dtype: int64
----------------------
```

[39]:
```
# Check the type of each feature (categorical or numerical)
data_types = data.dtypes
print('Data types:\n', data_types)

print('----------------------')
print('First experiment:')
```

```
Data types:
```

```
 Age              int64
Sex              object
BP               object
Cholesterol      object
Na_to_K         float64
Drug             object
dtype: object
----------------------
First experiment:
```

[40]:
```python
# Records containing missing values are filled
data.loc[:, ["Age", "Na_to_K"]] = data[["Age", "Na_to_K"]].fillna(data[["Age",␣
↪"Na_to_K"]].mean())



# For categorical columns
for column_name in data.columns:
    if data[column_name].dtype == 'object':
        data[column_name].fillna(data[column_name].mode()[0], inplace=True)
```

[42]:
```python
# categorical features and targets are encoded
label_encoder = LabelEncoder()
for column_name in data.columns:
    if data[column_name].dtype == 'object':
        data.loc[:, column_name] = label_encoder.fit_transform(data.loc[:,␣
↪column_name])

x = data.drop(columns=['Drug'])
y = data['Drug']  # Update to use a Series for the target

y=label_encoder.fit_transform(y)
```

[43]:
```python
# Number of experiments
num_experiments = 5

# Initialize lists to store accuracy values and size of trees
accuracy_values = []
tree_sizes = []
```

[44]:
```python
#First experiment
for i in range(num_experiments):
    # Split the data into training and testing sets with different random states
    x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.3)

    # train the Decision Tree
    model = tree.DecisionTreeClassifier(criterion="gini")
    model.fit(x_train, y_train)
```

```python
    # Get the size of the decision tree
    tree_size = model.tree_.node_count
    tree_sizes.append(tree_size)
    print(f"Experiment {i + 1} - Decision Tree Size: {tree_size}")

    # Make predictions
    y_pred = model.predict(x_test)

    # Calculate accuracy
    accuracy = model.score(x_test, y_test)
    accuracy_values.append(accuracy)
    print(f"Experiment {i + 1} - accuracy: {accuracy:.4f}")
```

```
Experiment 1 - Decision Tree Size: 11
Experiment 1 - accuracy: 0.9667
Experiment 2 - Decision Tree Size: 15
Experiment 2 - accuracy: 0.9833
Experiment 3 - Decision Tree Size: 15
Experiment 3 - accuracy: 0.9833
Experiment 4 - Decision Tree Size: 15
Experiment 4 - accuracy: 0.9167
Experiment 5 - Decision Tree Size: 15
Experiment 5 - accuracy: 0.9667
```

[45]:
```python
# Find the index of the experiment with the Max accuracy
best_experiment_index = np.argmax(accuracy_values)
best_accuracy = accuracy_values[best_experiment_index]
best_tree_size = tree_sizes[best_experiment_index]

# Print results
print(f"\nBest Model (Experiment {best_experiment_index + 1}):")
print(f"Max accuracy: {best_accuracy:.4f}")
print(f"Decision Tree Size: {best_tree_size}")

print('----------------------')
```

```

Best Model (Experiment 2):
Max accuracy: 0.9833
Decision Tree Size: 15
----------------------
```

[46]:
```python
print('Second experiment:')


mean_accuracies = []
```

```
mean_trees_size = []
split_ratios = np.arange(0.3, 0.8, 0.1)
columns = ['split_ratio','mean_accuracy', 'max_accuracy',␣
↪'min_accuracy','mean_tree_size', 'max_tree_size', 'min_tree_size']
report_df = pd.DataFrame(columns=columns)
```

Second experiment:

[47]:
```
#Second experiment
for split_ratio in split_ratios:
    # Initialize lists to store results for each ratio
    accuracy_values = []
    tree_sizes = []

    for i in range(num_experiments):
        # Split the data into training and testing sets
        x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=1 -␣
↪split_ratio)

        # train the Decision Tree
        model = tree.DecisionTreeClassifier(criterion="gini")
        model.fit(x_train, y_train)

        # Get the size of the decision tree
        tree_size = model.tree_.node_count
        tree_sizes.append(tree_size)

        # Calculate accuracy
        accuracy = model.score(x_test, y_test)
        accuracy_values.append(accuracy)

    #Calculate the mean, maximum, and minimum accuracy at each training set␣
↪size.
    mean_accuracy=np.mean(accuracy_values)
    max_accuracy=max(accuracy_values)
    min_accuracy = min(accuracy_values)

    #Measure the mean, maximum, and minimum tree size.
    mean_tree_size = np.mean(tree_sizes)
    max_tree_size = max(tree_sizes)
    min_tree_size = min(tree_sizes)

    #Save mean_accuracy and mean_tree_size
    mean_accuracies.append(mean_accuracy)
    mean_trees_size.append(mean_tree_size)

    #Add Data to report
```

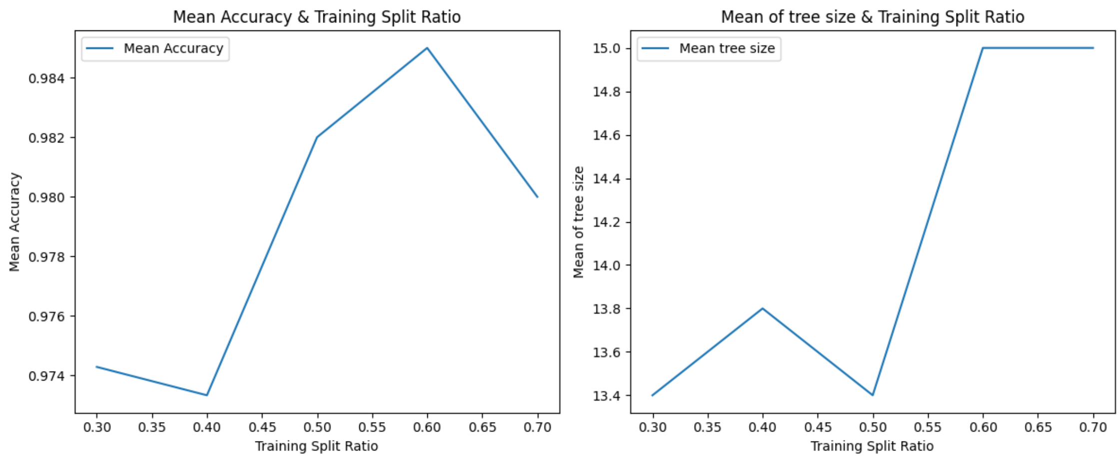
```
    record = pd.DataFrame({
        'split_ratio': [split_ratio],
        'mean_accuracy':[mean_accuracy],
        'max_accuracy':[max_accuracy],
        'min_accuracy':[min_accuracy],
        'mean_tree_size':[mean_tree_size],
        'max_tree_size':[max_tree_size],
        'min_tree_size':[min_tree_size]
    })
    if report_df.empty:
        report_df = record.copy()
    else:
        report_df = pd.concat([report_df, record], ignore_index=True)
```

[48]:

```
#print report
print(report_df)

# Create two plots
plt.figure(figsize=(12, 5))

# Plot accuracy against set size
plt.subplot(1, 2, 1)
plt.plot(split_ratios, mean_accuracies, label='Mean Accuracy')
plt.title('Mean Accuracy & Training Split Ratio')
plt.xlabel('Training Split Ratio')
plt.ylabel('Mean Accuracy')
plt.legend()


# Plot number of nodes in the final tree against set size
plt.subplot(1, 2, 2)
plt.plot(split_ratios, mean_trees_size, label='Mean tree size')
plt.title('Mean of tree size & Training Split Ratio')
plt.xlabel('Training Split Ratio')
plt.ylabel('Mean of tree size')
plt.legend()

plt.tight_layout()
plt.show()
```

```
   split_ratio  mean_accuracy  max_accuracy  min_accuracy  mean_tree_size  \
0          0.3       0.974286      0.992857      0.942857            13.4
1          0.4       0.973333      0.983333      0.950000            13.8
2          0.5       0.982000      0.990000      0.960000            13.4
3          0.6       0.985000      0.987500      0.975000            15.0
4          0.7       0.980000      1.000000      0.950000            15.0
```

	max_tree_size	min_tree_size
0	15	11
1	17	11
2	15	11
3	15	15
4	15	15



[ ]:

p2

December 7, 2023

[2]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
import warnings

# Suppress SettingWithCopyWarning
warnings.filterwarnings("ignore", category=pd.errors.SettingWithCopyWarning)
```

[3]:
```
# Load the "diabetes.csv" dataset.
data = pd.read_csv('diabetes.csv')

# The features and targets are separated
x = data.drop(columns=['Outcome'])
y = data[['Outcome']]
```

[4]:
```
# The data is shuffled and split into training and testing sets
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.3,␣
↪random_state=100)
```

[5]:
```
# Features are Normalized using Min-Max Scaling.
x_train_max = x_train.max()
x_train_min = x_train.min()
range_x_train = x_train_max - x_train_min
x_test_scaled = (x_test - x_train_min) / range_x_train
x_train_scaled = (x_train - x_train_min) / range_x_train
```

[6]:
```
# Convert data to Numpy array
x_train_np = x_train_scaled.to_numpy().reshape((-1, 8))
x_test_np = x_test_scaled.to_numpy().reshape((-1, 8))
y_train_np = y_train.to_numpy().reshape((-1, 1))
y_test_np = y_test.to_numpy().reshape((-1, 1))
```

[7]:
```
# Function to calculate Euclidean Distance
def euclidean_distance(point1, point2):
    return np.sqrt(np.sum((point1 - point2) ** 2))

# Function for Distance-Weighted Voting
```

```
def distance_weighted_vote(distances):
    weights = 1 / (distances + 1e-10)  # Adding a small constant to avoid␣
 ↪division by zero
    return weights / np.sum(weights)

# Function to predict the class using KNN
def knn_predict(train_data, train_labels, test_instance, k):
    distances = np.array([euclidean_distance(test_instance, train_instance) for␣
 ↪train_instance in train_data])
    sorted_indices = np.argsort(distances)

    # Break ties using Distance-Weighted Voting
    vote_weights = distance_weighted_vote(distances[sorted_indices[:k]])
    class_votes = np.zeros(np.max(train_labels) + 1)

    for i in range(k):
        class_votes[train_labels[sorted_indices[i]]] += vote_weights[i]

    predicted_class = np.argmax(class_votes)
    return predicted_class

# Function to evaluate KNN for a given k value
def knn_evaluate(train_data, train_labels, test_data, test_labels, k):
    correct_count = 0

    for i in range(len(test_data)):
        predicted_class = knn_predict(train_data, train_labels, test_data[i], k)
        if predicted_class == test_labels[i]:
            correct_count += 1

    accuracy = correct_count / len(test_data) * 100
    return correct_count, len(test_data), accuracy
```

[ ]:
```
# Set the range of k values for iterations
k_values = [2, 3, 4 ,7 ,23]
accuracies=[]
# Perform iterations and print results
for k in k_values:
    correct, total, accuracy = knn_evaluate(x_train_np, y_train_np, x_test_np,␣
 ↪y_test_np, k)
    print(f"k value: {k}")
    print(f"Number of correctly classified instances: {correct}")
    print(f"Total number of instances: {total}")
    print(f"Accuracy: {accuracy:.2f}%\n")
    accuracies.append(accuracy)
```

```
k value: 2
```

```
Number of correctly classified instances: 163
Total number of instances: 231
Accuracy: 70.56%

k value: 3
Number of correctly classified instances: 167
Total number of instances: 231
Accuracy: 72.29%

k value: 4
Number of correctly classified instances: 164
Total number of instances: 231
Accuracy: 71.00%

k value: 7
Number of correctly classified instances: 170
Total number of instances: 231
Accuracy: 73.59%
```

[ ]:

```

```