Machine Learning

Assignment 8: Decision Tree

Code: import pandas as pd import numpy as np import math # Define the dataset data = {'A1': [True, True, False, False, False, True, True, True, False, False], 'A2': ['Hot', 'Hot', 'Hot', 'Cool', 'Cool', 'Cool', 'Hot', 'Hot', 'Cool', 'Cool'], 'A3': ['High', 'High', 'High', 'Normal', 'Normal', 'High', 'High', 'Normal', 'Normal', 'High'], 'label': ['No', 'No', 'Yes', 'Yes', 'Yes', 'No', 'No', 'Yes', 'Yes', 'Yes']} df = pd.DataFrame(data) print(df) # Define a function to calculate entropy def entropy(labels): _, counts = np.unique(labels, return_counts=True) probabilities = counts / len(labels) entropy_val = sum([-p * math.log2(p) for p in probabilities]) print(entropy_val) return entropy_val # Define a function to calculate information gain def information_gain(data, split_attribute_name, target_attribute_name): total_entropy = entropy(data[target_attribute_name]) _, counts = np.unique(data[split_attribute_name], return_counts=True)

probabilities = counts / len(data[split_attribute_name])

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weighted_entropy = sum(probabilities * \
    [entropy(data.where(data[split_attribute_name]==value).dropna()[target_attribute_name]) \
    for value in np.unique(data[split_attribute_name])])
  information_gain = total_entropy - weighted_entropy
  return information_gain
  print(total_entropy)
# Define a function to get the best attribute for splitting
def get_best_attribute(data, target_attribute_name):
  information_gains = [(attribute, information_gain(data, attribute, target_attribute_name)) \
              for attribute in data.columns if attribute != target_attribute_name]
  best_attribute = max(information_gains, key=lambda x: x[1])[0]
  return best_attribute
# Define a recursive function to build the decision tree
def build_decision_tree(data, target_attribute_name, default_class=None):
  # If all the instances belong to the same class, return that class
  if len(np.unique(data[target_attribute_name])) == 1:
    return np.unique(data[target_attribute_name])[0]
  # If the dataset is empty, return the default class
  elif len(data) == 0:
    return default_class
  # If there are no more attributes to split, return the most common class
  elif len(data.columns) == 1:
    return default_class
  else:
    # Get the best attribute for splitting
    best_attribute = get_best_attribute(data, target_attribute_name)
    # Create a new decision tree node with the best attribute
    tree = {best_attribute: {}}
    # Get the unique values of the best attribute
    unique_values = np.unique(data[best_attribute])
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# Recursively build the subtree for each unique value
    for value in unique_values:
       subtree = build_decision_tree(data.where(data[best_attribute] == value).dropna(),
                        target_attribute_name, default_class)
       # Add the subtree to the tree
      tree[best_attribute][value] = subtree
    return tree
# Build the decision tree
tree = build_decision_tree(df, 'label')
print(tree)
# Define a function to make predictions using the decision tree
def predict(instance, tree, default_class=None):
  attribute = next(iter(tree))
  if instance[attribute] in tree[attribute]:
    result = tree[attribute][instance[attribute]]
    print(tree)
```

Output:

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A1 A2 A3 label
A1 Tue Hot High No
True Hot Normal Yes
Talse Cool Normal Yes
Talse Cool Normal Yes
The Normal Yes
True Hot High No
True Hot Normal Yes
False Cool Normal Yes
False Cool Normal Yes
False Cool Normal Yes
False Cool High No
True Hot Normal Yes
False Cool High No
0.9709505944546686
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Submitted By:

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