

Data Mining

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Lab - 10

Implement Decision Tree(ID3) in python

Uses Information Gain to choose the best feature to split.

Recursively builds the tree until stopping conditions are met.

1. Calculate Entropy for the dataset.

- 2. Calculate Information Gain for each feature.
- 3. Choose the feature with maximum Information Gain.
- 4. Split dataset into subsets for that feature.
- 5. Repeat recursively until:

All samples in a node have the same label.

No features are left.

No data is left.

Step 2. Import the dataset from this address.

import Pandas, Numpy

```
order id quantity
                                                        item name \
0
                                    Chips and Fresh Tomato Salsa
1
                       1
                                                             Izze
2
             1
                       1
                                                Nantucket Nectar
3
             1
                       1
                          Chips and Tomatillo-Green Chili Salsa
             2
                        2
                                                     Chicken Bowl
           . . .
          1833
                       1
                                                    Steak Burrito
4617
          1833
4618
                       1
                                                    Steak Burrito
4619
          1834
                       1
                                              Chicken Salad Bowl
                       1
                                              Chicken Salad Bowl
4620
          1834
4621
          1834
                       1
                                              Chicken Salad Bowl
                                      choice description item price
0
                                                              $2.39
                                                      NaN
1
                                             [Clementine]
                                                              $3.39
2
                                                  [Apple]
                                                              $3.39
3
                                                              $2.39
                                                      NaN
4
      [Tomatillo-Red Chili Salsa (Hot), [Black Beans...
                                                             $16.98
. . .
                                                                 . . .
     [Fresh Tomato Salsa, [Rice, Black Beans, Sour ...
                                                             $11.75
4617
4618
     [Fresh Tomato Salsa, [Rice, Sour Cream, Cheese...
                                                             $11.75
     [Fresh Tomato Salsa, [Fajita Vegetables, Pinto...
                                                             $11.25
4620
     [Fresh Tomato Salsa, [Fajita Vegetables, Lettu...
                                                              $8.75
     [Fresh Tomato Salsa, [Fajita Vegetables, Pinto...
                                                              $8.75
[4622 rows x 5 columns]
```

Create Following Data

```
In [10]:
    data = pd.DataFrame({
        'Outlook': ['Sunny', 'Sunny', 'Overcast', 'Rain', 'Rain', 'Cool', 'Cool', 'Sunny', 'Sunny', 'Sunny', 'Sunny', 'Overcast'
        'Temperature': ['Hot', 'Hot', 'Mild', 'Cool', 'Cool', 'Cool', 'Mild', 'Cool', 'Mild', 'Mild', 'Mild', 'Mild', 'Mild'
        'Humidity': ['High', 'High', 'High', 'Normal', 'Normal', 'Normal', 'Normal', 'Normal', 'Normal', 'Normal', 'Normal', 'Weak', 'Weak', 'Strong', 'Strong', 'Strong', 'Strong', 'Strong', 'Yeak', 'Yeak', 'Yeak', 'Yes', 'Yes
```

Now Define Function to Calculate Entropy

```
In [13]: def entropy(y):
    unique_labels, counts = np.unique(y, return_counts=True)
    probabilities = counts / counts.sum()
    entropy_value = -np.sum(probabilities * np.log2(probabilities))
    return entropy_value
```

Testing of Above Function -

```
y = np.array(['Yes', 'No', 'Yes', 'Yes'])
Function Call - > entropy(y))
output - 0.8112781244591328

In [15]: y = np.array(['No', 'No', 'Yes', 'Yes','No','No','Yes','Yes'])
print(entropy(y))
0.9709505944546686
```

Define function to Calculate Information Gain

```
In [21]: def information_gain(data, split_attribute, target):
    # Calculate total entropy of the target
    total_entropy = entropy(data[target])
```

```
# Find unique values of the splitting attribute
values, counts = np.unique(data[split_attribute], return_counts=True)

# Calculate weighted entropy after splitting
weighted_entropy = 0
for value, count in zip(values, counts):
    subset = data[data[split_attribute] == value]
    weighted_entropy += (count / len(data)) * entropy(subset[target])

# Information Gain formula
info_gain = total_entropy - weighted_entropy
return info_gain
```

Testing of Above Function-

```
data = pd.DataFrame({ 'Weather': ['Sunny', 'Sunny', 'Rain', 'Rain'], 'Play': ['Yes', 'No', 'Yes', 'Yes'] })
Function Call - > information_gain(data, 'Weather', 'Play')
Output - 0.31127812445913283

In [24]: data = pd.DataFrame({
        'Weather': ['Sunny', 'Sunny', 'Rain', 'Rain'],
        'Play': ['Yes', 'No', 'Yes', 'Yes']
})
print("Information Gain:", information_gain(data, 'Weather', 'Play'))
```

Implement ID3 Algo

Information Gain: 0.31127812445913283

```
In [27]: def id3(data, target, features):
    # If all examples are same class → leaf node
    if len(np.unique(data[target])) == 1:
```

```
return np.unique(data[target])[0]

# If no more features left → return majority class
if len(features) == 0:
    return data[target].mode()[0]

# Choose feature with max IG
gains = [information_gain(data, f, target) for f in features]
best_feature = features[np.argmax(gains)]

# Create tree dict
tree = {best_feature: {}}
for value in np.unique(data[best_feature]):
    subset = data[data[data[best_feature] == value].drop(columns = [best_feature])
    subtree = id3(subset, target, [f for f in features if f != best_feature])
    tree[best_feature][value] = subtree
```

Use ID3

```
In [30]: # Test dataset
                            # data = pd.DataFrame({
                                              'Weather': ['Sunny', 'Sunny', 'Rain', 'Overcast'],
                                              'Temperature': ['Hot', 'Mild', 'Hot', 'Mild', 'Hot'],
                                              'Play': ['No', 'Yes', 'Yes', 'Yes', 'Yes']
                            # })
                            data = pd.DataFrame({
                                        'Outlook': ['Sunny', 'Sunny', 'Overcast', 'Rain', 'Rain', 'Overcast', 'Sunny', 'Sunny', 'Rain', 'Overcast'
                                        'Temperature': ['Hot', 'Hot', 'Hot', 'Mild', 'Cool', 'Cool', 'Cool', 'Mild', 'Cool', 'Mild', 'Mild', 'Mild', 'Hot', 'Mild'
                                        'Humidity': ['High', 'High', 'High', 'High', 'Normal', 'Normal', 'High', 'Normal', 'Normal', 'Normal', 'High',
                                        'Wind': ['Weak', 'Strong', 'Weak', 'Weak', 'Strong', 'Strong', 'Weak', 'Weak', 'Weak', 'Strong', 'Weak', 'Weak', 'Strong', 'Weak', 'Weak', 'Strong', 'Weak', 'Weak', 'Strong', 'Weak', 'Weak', 'Weak', 'Strong', 'Weak', 'Weak
                                        'PlayTennis': ['No', 'No', 'Yes', 'Yes', 'Yes', 'No', 'Yes', 'No', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'No']
                            })
                            features = ['a1', 'a2', 'a3']
                            tree = id3(bookdata, 'class', features)
                            print(tree)
                        {'a1': {'f': 'y', 't': {'a3': {'hi': 'n', 'nor': 'y'}}}}
```

Print Tree

Extra: Create Predict Function

Extra: Predict for a sample

sample = {'Outlook': 'Sunny', 'Temperature': 'Cool', 'Humidity': 'High', 'Wind': 'Strong'}

Your Answer?