

Machine Learning (SS24)

Assignment 01: Preprocessing and K-Nearest Neighbors

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1. Preprocessing

Final result:

ID	Age	Income	Owns_Car
1.0	25.0	0.3333333333333335	1.0
2.0	33.75	0.0	0.0
3.0	35.0	0.5	1.0
4.0	45.0	1.0000000000000002	1.0
5.0	30.0	0.6666666666666667	0.0

Number of Vehicles	Preferred Transport Mode_Bike	Preferred Transport Mode_Car	Preferred Transport Mode_Public Transport
2.0	0.0	1.0	0.0
0.0	0.0	0.0	1.0
1.0	0.0	1.0	0.0
0.0	0.0	1.0	0.0
0.0	1.0	0.0	0.0

Codes:

```
assignment1.py x
1 import pandas as pd
2 from sklearn.preprocessing import MinMaxScaler
3 import matplotlib.pyplot as plt
4
5
6 # Specify the file path
7 file_path = "D:\\A1_ITECH\\12_ML\\Assignments_github\\ML_assignment\\assignment1\\transportation_preference.csv"
8
9 # Read the CSV file into a DataFrame
10 df = pd.read_csv(file_path)
11
12 print(df.head())
13
14 #question_a
15 # Identify columns with missing values
16 missing_cols = df.columns[df.isnull().any()]
17
18 # Impute missing values
19 for col in missing_cols:
20     if col == 'Age':
21         mean_age = df['Age'].mean()
22         df[col].fillna(mean_age, inplace=True)
23     elif col == 'Income':
24         median_income = df['Income'].median()
25         df[col].fillna(median_income, inplace=True)
26     elif col == 'Number of Vehicles':
27         mode_vehicles = df['Number of Vehicles'].mode()[0]
28         df[col].fillna(mode_vehicles, inplace=True)
29
30 print(df)
31
32 #question_b
33 # Initialize the MinMaxScaler
34 scaler = MinMaxScaler()
35
36 # Apply Min-Max scaling to the "Income (K$)" column
37 df['Income'] = scaler.fit_transform(df[['Income']])
38
39 print(df['Income'])
40
41 #question_c
42 # Binary encoding for "Owns_Car" column
43 df['Owns_Car'] = df['Owns_Car'].map({'Yes': 1, 'No': 0})
44
45 # One-hot encoding for "Preferred Transport Mode" column
46 df = pd.get_dummies(df, columns=['Preferred Transport Mode'], dtype=int)
47
48 print(df['Preferred Transport Mode_Car'], df['Preferred Transport Mode_Bike'],
49       df['Preferred Transport Mode_Public Transport'])
50
51 # Plotting the DataFrame
52 plt.figure(figsize=(40, 30)) # Adjust the figure size as needed
53 plt.table(cellText=df.values,
54          colLabels=df.columns,
55          loc='center')
56 plt.axis('off') # Turn off the axis
57 plt.savefig("args: 'table_image.png', bbox_inches='tight', pad_inches=0.05) # Save as image
58 plt.show()
59
```

2. K-Nearest Neighbors

```
dataset = np.array([
    [1, 2, 3, 0],
    [2, 3, 1, 1],
    [3, 1, 2, 0],
    [4, 5, 1, 1],
    [3, 3, 4, 0]
])
```

(a) Distance Calculation

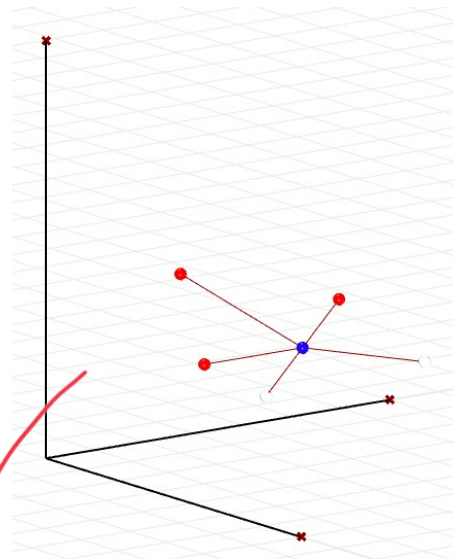
The nearest 3 neighbors for K=3:

Neighbor Index: 1, Distance: 1.4142, Class Label: 1

Neighbor Index: 2, Distance: 2.0000, Class Label: 0

Neighbor Index: 4, Distance: 2.0000, Class Label: 0

Assigned class for K=3: 0



(b) Impact of K

Assigned class for K=1: 1

Assigned class for K=5: 0

Small K Value:

- > Benefits: (1) Very sensitive to the local variation of the data set;
(2) Can deal with the situation where there are many small groups of data.
- > Drawbacks: (1) over-fitting, which means the model will be specific to the training data and cannot fit the new data very well;
(2) Will be disturbed by abnormal data, if the new observation is surrounded by some wrong data, the model will make the wrong decision;
(3) The model cannot have a very good „understanding“ of the global data set.

Big K Value:

- > Benefits: (1) Will not be disturbed by wrong data, when there is a relatively big data set, a big K value will lead to a more average result;
(2) Have a better understanding of the whole data set.
- > Drawbacks: (1) lack of precision, which means some small groups will be ignored;
(3) Oversimplified.

(c) Distance Weighting

Some type of distance-weighted voting:

Inverse Distance Weighting - In this type of voting, the closer the data is, the more impossible for the new observation to be the same. It will **reverse the result**, which means when K=3, the new observation (X1=3, X2=3, X3=2) will be classified as **Class Label: 1**.

Gaussian Weighting - In this type, the weight will be calculated based on the distance using a Gaussian function like $w_i = e^{-\alpha \times d_i^2}$. So when K=3, the nearest three neighbors are at indices 1, 2, and 4 in the data set, their new distance will be:

Neighbor 2 (index 1): New_distance = $1.4142 \times 0.1353 = 0.1913$

Neighbor 3 (index 2): New_distance = $2 \times 0.0183 = 0.1353$

Neighbor 5 (index 4): New_distance = $2 \times 0.0183 = 0.1353$

New class label will 1.

Code

```
1 import numpy as np
2 from scipy.spatial import distance
3
4 dataset = np.array([
5     [1, 2, 3, 0],
6     [2, 3, 1, 1],
7     [3, 1, 2, 0],
8     [4, 5, 1, 1],
9     [3, 3, 4, 0]
10 ])
11
12 new_observation = np.array([3, 3, 2])
13
14 def knn_classification(K):
15     distances = []
16     for idx, obs in enumerate(dataset):
17         euclidean_distance = distance.euclidean(new_observation, obs[:3])
18         distances.append((euclidean_distance, obs[3], idx))
19
20     distances.sort(key=lambda x: x[0])
21     nearest_neighbors = distances[:K]
22
23     classes = [neighbor[1] for neighbor in nearest_neighbors]
24     majority_class = max(set(classes), key=classes.count)
25
26     return majority_class, nearest_neighbors
27
28 def knn_classification_weight(K):
29     distances = []
30     for idx, obs in enumerate(dataset):
31         euclidean_distance = distance.euclidean(new_observation, obs[:3])
32         distances.append((euclidean_distance, obs[3], idx))
33
34     distances.sort(key=lambda x: x[0])
35     nearest_neighbors = distances[:K]
36
37     classes = [neighbor[1] for neighbor in nearest_neighbors]
38     majority_class = max(set(classes), key=classes.count)
39
40     return majority_class, nearest_neighbors
41
42
43 def print_nearest_neighbors(nearest_neighbors, K):
44     print(f"\nThe nearest {K} neighbors for K={K}:")
45     for neighbor in nearest_neighbors:
46         distance, label, index = neighbor
47         print(f"Neighbor Index: {index}, Distance: {distance:.4f}, Class Label: {label}")
48
49 class_k1, nearest_neighbors_k1 = knn_classification(1)
50 class_k3, nearest_neighbors_k3 = knn_classification(3)
51 class_k5, nearest_neighbors_k5 = knn_classification(5)
52
53 print(f"Assigned class for K=1: {class_k1}")
54 print(f"Assigned class for K=3: {class_k3}")
55 print(f"Assigned class for K=5: {class_k5}")
56
57 print_nearest_neighbors(nearest_neighbors_k1, 1)
58 print_nearest_neighbors(nearest_neighbors_k3, 3)
59 print_nearest_neighbors(nearest_neighbors_k5, 5)
```

