

```

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.metrics import accuracy_score

raw_data = pd.read_csv('Q1_data.csv')
feature_matrix = raw_data.drop('class', axis=1).values
label_vector = np.where(raw_data['class'] == 'normal', 0, 1)

print(raw_data.head());

```

	duration	src_bclasstes	dst_bclasstes	count	srv_count
error_rate \					
0	0	520	0	428	428
0.0					
1	0	0	0	131	18
0.0					
2	0	0	0	20	8
1.0					
3	0	1235	404	1	4
0.0					
4	0	224	1415	1	1
0.0					

	srv_error_rate	error_rate	srv_error_rate	
same_srv_rate ... \				
0	0.0	0.0	0.0	1.00 ...
1	0.0	1.0	1.0	0.14 ...
2	1.0	0.0	0.0	0.40 ...
3	0.0	0.0	0.0	1.00 ...
4	0.0	0.0	0.0	1.00 ...

	dst_host_srv_count	dst_host_same_srv_rate	dst_host_diff_srv_rate
\			
0	255	1.00	0.00
1	18	0.07	0.06
2	68	0.27	0.02
3	179	0.72	0.12
4	48	1.00	0.00

	dst_host_same_src_port_rate	dst_host_srv_diff_host_rate	\
0	1.00	0.00	
1	0.00	0.00	
2	0.01	0.00	
3	0.04	0.02	
4	0.02	0.00	

	dst_host_serror_rate	dst_host_srv_serror_rate
0	0.0	0.00
1	0.0	0.00
2	1.0	1.00
3	0.0	0.01
4	0.0	0.00

	dst_host_srv_rerror_rate	class
0	0.0	anomalclass
1	1.0	anomalclass
2	0.0	anomalclass
3	0.0	normal
4	0.0	normal

[5 rows x 23 columns]

```
print(raw_data.info());
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 200 entries, 0 to 199
```

```
Data columns (total 23 columns):
```

#	Column	Non-Null Count	Dtype
0	duration	200 non-null	int64
1	src_bclasstes	200 non-null	int64
2	dst_bclasstes	200 non-null	int64
3	count	200 non-null	int64
4	srv_count	200 non-null	int64
5	serror_rate	200 non-null	float64
6	srv_serror_rate	200 non-null	float64
7	rerror_rate	200 non-null	float64
8	srv_rerror_rate	200 non-null	float64
9	same_srv_rate	200 non-null	float64
10	diff_srv_rate	200 non-null	float64
11	srv_diff_host_rate	200 non-null	float64

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12 dst_host_count          200 non-null    int64
13 dst_host_srv_count      200 non-null    int64
14 dst_host_same_srv_rate  200 non-null    float64
15 dst_host_diff_srv_rate  200 non-null    float64
16 dst_host_same_src_port_rate 200 non-null    float64
17 dst_host_srv_diff_host_rate 200 non-null    float64
18 dst_host_serror_rate    200 non-null    float64
19 dst_host_srv_serror_rate 200 non-null    float64
20 dst_host_rerror_rate    200 non-null    float64
21 dst_host_srv_rerror_rate 200 non-null    float64
22 class                   200 non-null    object
dtypes: float64(15), int64(7), object(1)
memory usage: 36.1+ KB
None

scaler = StandardScaler() # to normalize all the data
feature_matrix = scaler.fit_transform(feature_matrix)
print(feature_matrix); # feature_matrix has the training data without
class field from csv

[[-0.1180733 -0.07777228 -0.2117447 ... -0.67984097 -0.4467788
 -0.43567987]
 [-0.1180733 -0.07810672 -0.2117447 ... -0.67984097  2.41169081
  2.35177931]
 [-0.1180733 -0.07810672 -0.2117447 ...  1.47462258 -0.4467788
 -0.43567987]
 ...
 [-0.1180733 -0.07810672 -0.2117447 ...  1.47462258 -0.4467788
 -0.43567987]
 [-0.1180733 -0.07800703 -0.15243546 ... -0.65829634 -0.4181941
 -0.40780528]
 [-0.1180733 -0.07808743 -0.19969542 ... -0.67984097 -0.4467788
 -0.43567987]]

# split data
training_features, testing_features, training_labels, testing_labels =
train_test_split(
    feature_matrix,
    label_vector,
    test_size=0.3,
    stratify=label_vector,
    random_state=665
);

print(f"Training Set: Normal Count = {np.sum(training_labels == 0)}")
print(f"Training Set: Anomaly Count = {np.sum(training_labels == 1)}")
print(f"Testing Set: Normal Count = {np.sum(testing_labels == 0)}")
print(f"Testing Set: Anomaly Count = {np.sum(testing_labels == 1)}")

```

Training Set: Normal Count = 70
Training Set: Anomaly Count = 70
Testing Set: Normal Count = 30
Testing Set: Anomaly Count = 30

```
def activation(val):  
    # step function  
    if val >= 0: return 1;  
    return 0;  
  
def train_perceptron(features, labels, learning_rate=0.1,  
max_iterations=1000):  
    num_samples, num_features = features.shape  
  
    # init weights and threshold  
    weights = np.zeros(num_features)  
    bias = 0.0  
  
    for it in range(max_iterations):  
        for idx in range(num_samples):  
            curr_sample = features[idx];  
            true_label = labels[idx];  
  
            # fn = x0 * w0 + x1 * w1 + .... + bias  
            fn = np.dot(curr_sample, weights) + bias;  
            predicted_val = activation(fn);  
  
            # update weights  
            if true_label != predicted_val:  
                err = true_label - predicted_val;  
  
                weights = weights + (learning_rate * err *  
curr_sample);  
                bias = bias + (learning_rate * err);  
  
        return weights, bias  
  
def predict(features, weights, bias):  
    pred_list = [];  
    num_samples = len(features);  
  
    for idx in range(num_samples):  
        curr_sample = features[idx];  
  
        fn = np.dot(curr_sample, weights) + bias;  
        pred_val = activation(fn);  
  
        pred_list.append(pred_val);  
  
    return np.array(pred_list);
```

```

# training
trained_weights, trained_bias = train_perceptron(training_features,
training_labels)

predicted_test_labels = predict(testing_features, trained_weights,
trained_bias)
perceptron_accuracy = accuracy_score(testing_labels,
predicted_test_labels)

print(f"Perceptron Classification Accuracy: {perceptron_accuracy *
100:.2f}%")

Perceptron Classification Accuracy: 93.33%

best_k_value = 0
highest_training_accuracy = 0.0

# try different num of clusters
for num_clusters in [2, 3, 4]:

    # Initialize and fit K-Means
    kmeans_algorithm = KMeans(n_clusters=num_clusters,
random_state=665, n_init=10)
    kmeans_algorithm.fit(training_features)

    cluster_assignments = kmeans_algorithm.labels_

    print(f"\nanalysis for K = {num_clusters}:")

    # This map will store which class (0 or 1) each cluster represents
    id_class_map = {}

    for cluster_id in range(num_clusters):
        # get all points that belong to this cluster
        indices_in_cluster = np.where(cluster_assignments ==
cluster_id)
        true_labels_in_cluster = training_labels[indices_in_cluster]

        # calculate the num of elements in cluster
        normal_count = np.sum(true_labels_in_cluster == 0)
        anomaly_count = np.sum(true_labels_in_cluster == 1)
        total_count_in_cluster = normal_count + anomaly_count

        # make sure the cluster isn't empty
        if total_count_in_cluster == 0:
            continue;

        percent_normal = (normal_count / total_count_in_cluster) *
100;
        percent_anomaly = (anomaly_count / total_count_in_cluster) *

```

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100;

    print(f" cluster id {cluster_id}: normal={percent_normal:.1f}%
%, anomaly={percent_anomaly:.1f}%")

    # give the clutter the label of the majority
    if normal_count > anomaly_count:
        id_class_map[cluster_id] = 0 # normal
    else:
        id_class_map[cluster_id] = 1 # anomaly

    # calc accuracy
    predicted_labels_from_clustering = []
    for assigned_cluster in cluster_assignments:
        predicted_label = id_class_map[assigned_cluster]
        predicted_labels_from_clustering.append(predicted_label)

    current_accuracy = accuracy_score(training_labels,
predicted_labels_from_clustering)
    print(f" classification accuracy (on train set):
{current_accuracy * 100:.2f}%");

    # Keep track of the best K
    if current_accuracy > highest_training_accuracy:
        highest_training_accuracy = current_accuracy;
        best_k_value = num_clusters;

print(f"\noptimal number of clusters (K): {best_k_value}");

analysis for K = 2:
    cluster id 0: normal=0.0%, anomaly=100.0%
    cluster id 1: normal=71.4%, anomaly=28.6%
    classification accuracy (on train set): 80.00%

analysis for K = 3:
    cluster id 0: normal=25.0%, anomaly=75.0%
    cluster id 1: normal=0.0%, anomaly=100.0%
    cluster id 2: normal=86.5%, anomaly=13.5%
    classification accuracy (on train set): 88.57%

analysis for K = 4:
    cluster id 0: normal=25.0%, anomaly=75.0%
    cluster id 1: normal=0.0%, anomaly=100.0%
    cluster id 2: normal=86.3%, anomaly=13.7%
    cluster id 3: normal=100.0%, anomaly=0.0%
    classification accuracy (on train set): 88.57%

optimal number of clusters (K): 3

```