lab_2_kaggle

March 28, 2024

[3]:
```
import os
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from functools import partial as partial_func
from sklearn.cluster import KMeans
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.neighbors import NearestNeighbors
from sklearn.preprocessing import MinMaxScaler
import matplotlib.pyplot as plt
import seaborn as sns
```

1 Data preprocessing

1.0.1 Generating taining and testing data

[78]:
```
path = "/kaggle/input/daily-and-sports-activities/data"
```

[79]:
```
print(os.listdir("/kaggle/input/daily-and-sports-activities/data/a03/p1"))
```

```
['s18.txt', 's31.txt', 's15.txt', 's03.txt', 's10.txt', 's20.txt', 's40.txt',
's09.txt', 's12.txt', 's50.txt', 's53.txt', 's25.txt', 's55.txt', 's33.txt',
's43.txt', 's39.txt', 's19.txt', 's23.txt', 's44.txt', 's49.txt', 's04.txt',
's08.txt', 's29.txt', 's47.txt', 's30.txt', 's48.txt', 's22.txt', 's32.txt',
's07.txt', 's21.txt', 's26.txt', 's45.txt', 's34.txt', 's60.txt', 's36.txt',
's17.txt', 's57.txt', 's54.txt', 's28.txt', 's05.txt', 's11.txt', 's37.txt',
's16.txt', 's38.txt', 's52.txt', 's56.txt', 's13.txt', 's06.txt', 's02.txt',
's24.txt', 's01.txt', 's59.txt', 's46.txt', 's14.txt', 's27.txt', 's58.txt',
's51.txt', 's35.txt', 's42.txt', 's41.txt']
```

[80]:
```
def read_file(filename):
  """
    Return list of all 125 rows (125 * 45)
  """
  data = []
  with open(filename, 'r') as file:
    for line in file:
```

```
        row = [float(value) for value in line.strip().split(',')] # Converting to␣
↪float
        data.append(row)
    return data
```

[81]:
```
def approach_2_generator(list_of_rows):
    return [item for row in list_of_rows for item in row]
```

[82]:
```
def approach_1_generator(list_of_rows):
    n = len(list_of_rows)
    mean_sample = [0 for _ in range(len(list_of_rows[0]))]
    for row in list_of_rows:
        for i in range(len(row)):
            mean_sample[i] += row[i]
    return [x / n for x in mean_sample]
```

[83]:
```
def generate_data(approach):
    """
        This function generates and splits tainging and tesing data condering␣
↪the approach desired.
        approach = 1 -> Taking the mean of each column in each segment␣
↪resulting in 45 features for each data point.
        approach = 2 -> Flattening all the features together in 45 x 125 = 5625␣
↪features for each data point.
    """
    training_data, training_labels, testing_data, testing_labels = [], [], [],␣
↪[]

    for activity in sorted(os.listdir(path)):
        label = int(activity[1:]) - 1   # To make it zero-based
        subjects_path = os.path.join(path, activity)
        # subject_path = path + '/' + activity
        for subject in sorted(os.listdir(subjects_path)):
            segments_path = os.path.join(subjects_path, subject)

            for segment in sorted(os.listdir(segments_path)):
                file_name =  os.path.join(segments_path, segment)
                data_sample = []

                if approach == 1:
                    data_sample = approach_1_generator(read_file(file_name))
                elif approach == 2:
                    data_sample = approach_2_generator(read_file(file_name))

                if int(segment[1:3]) <= 48: # Belongs to training data
                    training_data.append(data_sample)
                    training_labels.append(label)
```

```
                else:
                    testing_data.append(data_sample)
                    testing_labels.append(label)
    return  training_data , training_labels , testing_data , testing_labels
```

1.0.2 Data generated by taking the mean of each column in each segment

[84]:
```
training_data_1 , training_labels_1 , testing_data_1 , testing_labels_1 =␣
 ↪generate_data(1)
```

1.0.3 Data generated by flattening all the features together

[86]:
```
training_data_2 , training_labels_2 , testing_data_2 , testing_labels_2 =␣
 ↪generate_data(2)
```

1.0.4 Testing the data

[87]:
```
print(f"Training data in approach-1 is considered to be (7296 * 45) but it's␣
 ↪({len(training_data_1)} * {len(training_data_1[0])})")
```

```
Training data in approach-1 is considered to be (7296 * 45) but it's (7296 * 45)
```

[88]:
```
print(f"Training data in approach-2 is considered to be (7296 * 5625) but it's␣
 ↪({len(training_data_2)} * {len(training_data_2[0])})")
```

```
Training data in approach-2 is considered to be (7296 * 5625) but it's (7296 *
5625)
```

1.0.5 Normalizing featrues

[89]:
```
scaler = MinMaxScaler()
# Normalizing approach 1
# TODO: remove
normalized_training_data_1 = training_data_1
normalized_testing_data_1 = testing_data_1

# Normalizing approach 2
scaler.fit(training_data_2)
normalized_training_data_2 = scaler.transform(training_data_2)
normalized_testing_data_2 = scaler.transform(testing_data_2)
```

1.0.6 Applying dimensionality reduction using PCA

[90]:
```
# pca = PCA(n_components=0.95)
pca = PCA(n_components=0.95)
pca.fit(normalized_training_data_2)
reduced_training_data_2 = pca.transform(normalized_training_data_2)
reduced_testing_data_2 = pca.transform(normalized_testing_data_2)
```

1.0.7 Showing the effect of PCA

[91]:
```
print(f"The dimensions of reduced flattened training data :␣
↪{len(reduced_training_data_2)} * {len(reduced_training_data_2[0])}")
print(f"The dimensions of reduced flattened testing data :␣
↪{len(reduced_testing_data_2)} * {len(reduced_testing_data_2[0])}")
```

```
The dimensions of reduced flattened training data : 7296 * 299
The dimensions of reduced flattened testing data : 1824 * 299
```

2 Clustering evaluation

2.0.1 External evaluation

[250]:
```
def contingency_table(cluster_ids, labels):
    """
        Computes contingency_table given cluster ids (zero-based), labels␣
↪(zero-based).
        returns contingency_table of size: |unique cluster_ids| * |unique␣
↪labels|
    """
    assert len(cluster_ids) == len(labels)
    n = int(max(cluster_ids) + 1)
    m = int(max(labels) + 1)
    contingency_table = np.zeros((n, m))
    for cluster, label in zip(cluster_ids, labels):
        contingency_table[cluster][label] += 1
    return contingency_table
```

[251]:
```
def match_cluster_label(contingency_table):
    """The index of the list is the cluster id, whereas list element is the␣
↪corresponding label"""
    return np.argmax(contingency_table, axis = 1) # 0-based index labels if you␣
↪want to match the real label add plus
```

[252]:
```
def true_positive(contingency_table):
    tp = 0
    for row in contingency_table:
        for elem in row:
            tp += (elem * (elem - 1) / 2)
```

```
    return tp
```

[253]:
```
def false_positive(contingency_table):
    fp = 0
    for row in contingency_table:
        for i in range(len(row)):
            for j in range(i + 1, len(row)):
                fp += (row[i] * row [j])
    return fp
```

[254]:
```
def confusion_matrix(contingency_table):
    """
        Calculates confusion matrix from contingency table
        return: True positive, True negative, False positive, False negative
    """
    tp, tn, fp, fn = 0 ,0 ,0 ,0
    # True positive
    tp  = true_positive(contingency_table)

    # False positive
    fp = false_positive(contingency_table)

    # False negative
    fn = false_positive(contingency_table.T)


    # True negative
    tn = np.sum(contingency_table) - (tp + fp + fn)

    return tp, tn, fp, fn

```

[255]:
```
def precision(contingency_table, number_of_samples):
    return sum(np.max(contingency_table, axis=1)) / number_of_samples
```

[256]:
```
def precision_confusion(tp, tn, fp, fn):
    return tp / (tp + fp)
```

[257]:
```
def recall(tp, tn, fp, fn):
    return tp / (tp + fn)
```

[258]:
```
def f_measure(contingency_table):
    purity, recall, f_score = 0, 0, 0
    col_sum_list = np.sum(contingency_table, axis=0)
    number_of_samples = np.sum(contingency_table)
    for row in contingency_table:
        max_element = np.max(row)
```

```
        max_ind = np.argmax(row)

        number_of_elements_in_cluster = np.sum(row)
        # Only calculate the purity and recall for a cluster if it's not empty
        if number_of_elements_in_cluster != 0:
            purity = (max_element / number_of_elements_in_cluster)
            recall = (max_element / col_sum_list[max_ind])
        if purity != 0:
            f_score += 2 * ((purity * recall) / (purity + recall))
    return f_score / len(contingency_table)
```

[259]:

```
def conditional_entropy(contingency_table, number_of_samples):
    entropy = 0
    for row in contingency_table:
        num_elements_of_cluster = np.sum(row)
        if num_elements_of_cluster != 0:
            cluster_entropy = 0
            for col in row:
                p = col / num_elements_of_cluster
                if p != 0:
                    cluster_entropy -=  (p * np.log2(p))
            entropy += ((num_elements_of_cluster / number_of_samples) *␣
↪cluster_entropy)
    return entropy
```

[260]:

```
def perform_external_measures(contingency_table, number_of_samples):
    tp, tn, fp, fn = confusion_matrix(contingency_table)
    print(f"Precision is {precision(contingency_table, number_of_samples)}")
    print(f"Recall is {recall(tp, tn, fp, fn)}")
    print(f"F-score is {f_measure(contingency_table)}")
    print(f"Conditional entropy is {conditional_entropy(contingency_table,␣
↪number_of_samples)}")
    return [precision(contingency_table, number_of_samples), recall(tp, tn, fp,␣
↪fn), f_measure(contingency_table), conditional_entropy(contingency_table,␣
↪number_of_samples)]
```

3 K-means

3.1 Work flow

[261]:

```
def kmeans(data, k, max_iter=1000, tol=1e-6):
    # Convert data to numpy array
    data = np.array(data)

    # Initialize centroids randomly
```

```
    centroids = [data[i] for i in np.random.choice(range(len(data)), k,␣
↪replace=False)]

    # Initialize cluster assignments as integers
#     clusters = np.zeros(len(data), dtype=int)
    clusters = np.array([int(0) for i in range(len(data))])

    for _ in range(max_iter):
        # Assign each data point to the nearest centroid
        for i, point in enumerate(data):
            distances =  np.linalg.norm(np.array(point) - np.array(centroids),␣
↪axis=1)
            clusters[i] = np.argmin(distances)

        # Update centroids
        new_centroids = np.array([np.mean(data[np.where(clusters == i)],␣
↪axis=0) for i in range(k)])

        # Check convergence
        if np.linalg.norm(new_centroids - centroids) < tol:
            break

        centroids = new_centroids

    return clusters, centroids
```

[262]:
```
def predict(data, centroids):
    clusters = np.zeros(len(data), dtype=int)
    for i, point in enumerate(data):
        distances = np.linalg.norm(point - centroids, axis=1)
        clusters[i] = np.argmin(distances)
    return clusters
```

[263]:
```
def get_accuracy(clusters, labels, cluster_assignments):
    correct = 0
    for i in range(len(clusters)):
        if cluster_assignments[int(clusters[i])] == labels[i]:
            correct += 1
    return correct / len(labels)
```

[264]:
```
def run_kmeans(training_data, testing_data, training_labels, testing_labels, k):
    training_predictions, centroids = kmeans(training_data, k)
    testing_predictions = predict(testing_data, centroids)

    contegncy_table_training = contingency_table(training_predictions,␣
↪training_labels)
```

```
    contegncy_table_testing = contingency_table(testing_predictions,␣
↪testing_labels)

    cluster_assignments = match_cluster_label(contegncy_table_training)
    return get_accuracy(training_predictions, training_labels,␣
↪cluster_assignments), get_accuracy(testing_predictions, testing_labels,␣
↪cluster_assignments), contegncy_table_training, contegncy_table_testing
```

[265]:
```
k_list = [8, 13, 19, 28, 38]
```

3.2 Approach 1

[266]:
```
evaluation_k_mean_training_app_1 = []
evaluation_k_mean_testing_app_1 = []
```

[279]:
```
for k in k_list:
    print(f"\033[92m K : {k} \033[0m")
    training_accuracy1, testing_accuracy1, contengency_table_training_1,␣
↪contengency_table_testing_1 = run_kmeans(normalized_training_data_1,␣
↪normalized_testing_data_1, training_labels_1, testing_labels_1, k)

    # Evaluate clustering (training)
    print("\033[91m \nTraining evaluation\n \033[0m")
    evaluation_k_means_app_training_1 =␣
↪perform_external_measures(contengency_table_training_1,␣
↪len(normalized_training_data_1))
    evaluation_k_mean_training_app_1.append(evaluation_k_means_app_training_1)

    # Evaluate clustering (testing)
    print("\033[91m \nTesting evaluation\n \033[0m")
    evaluation_k_means_app_testing_1 =␣
↪perform_external_measures(contengency_table_testing_1,␣
↪len(normalized_testing_data_1))
    evaluation_k_mean_testing_app_1.append(evaluation_k_means_app_testing_1)

    print(f"\033[94m \ntraining accuracy: {training_accuracy1}\t testing␣
↪accuracy: {testing_accuracy1} \033[0m")
    print('-' * 80)
```

```
 K : 8


Training evaluation


Precision is 0.29509320175438597
Recall is 0.5464498591452521
F-score is 0.44447680057792
```

```
Conditional entropy is 2.538216266869179

Testing evaluation

Precision is 0.2905701754385965
Recall is 0.5500692520775623
F-score is 0.44445407491983563
Conditional entropy is 2.504626589055863

training accuracy: 0.29509320175438597   testing accuracy: 0.2905701754385965

--------------------------------------------------------------------------------
 K : 13

Training evaluation

Precision is 0.4805372807017544
Recall is 0.5865333413494572
F-score is 0.5901100732326381
Conditional entropy is 1.972892807251191

Testing evaluation

Precision is 0.48464912280701755
Recall is 0.5850184672206833
F-score is 0.6090553104568841
Conditional entropy is 1.973360379997946

training accuracy: 0.4805372807017544    testing accuracy: 0.48464912280701755

--------------------------------------------------------------------------------
 K : 19

Training evaluation

Precision is 0.4662828947368421
Recall is 0.4384318743987907
F-score is 0.4510738280884972
Conditional entropy is 1.9679370268399887
```

Testing evaluation

Precision is 0.4555921052631579
Recall is 0.43130193905817177
F-score is 0.44213615771854076
Conditional entropy is 1.9689911943297114

training accuracy: 0.4662828947368421   testing accuracy: 0.4512061403508772

K : 28

Training evaluation

Precision is 0.5046600877192983
Recall is 0.3404791351747515
F-score is 0.3906072370607719
Conditional entropy is 1.7197003408819658

Testing evaluation

Precision is 0.4994517543859649
Recall is 0.3381117266851339
F-score is 0.385290151920176
Conditional entropy is 1.6831424981068788

training accuracy: 0.5046600877192983   testing accuracy: 0.4994517543859649

K : 38

Training evaluation

Precision is 0.5860745614035088
Recall is 0.3196271929824561
F-score is 0.36990305979929966
Conditional entropy is 1.375612770240433

```
Testing evaluation


Precision is 0.5899122807017544
Recall is 0.3176708217913204
F-score is 0.37241630973856354
Conditional entropy is 1.324497837135152

training accuracy: 0.5860745614035088	testing accuracy: 0.5838815789473685

--------------------------------------------------------------------------------
```

3.3 Approach 2

[280]:
```
evaluation_k_mean_training_app_2 = []
evaluation_k_mean_testing_app_2 = []
```

[281]:
```
for k in k_list:
    training_accuracy2, testing_accuracy2,  contengency_table_training_2,␣
 ↪contengency_table_testing_2 = run_kmeans(reduced_training_data_2,␣
 ↪reduced_testing_data_2, training_labels_2, testing_labels_2, k)
    print(f"\033[92m K : {k} \033[0m")
    # Evaluate clustering (training)
    print("\033[91m \nTraining evaluation\n \033[0m")
    evaluation_k_means_app_training_2 =␣
 ↪perform_external_measures(contengency_table_training_2,␣
 ↪len(reduced_training_data_2))
    evaluation_k_mean_training_app_2.append(evaluation_k_means_app_training_2)

    # Evaluate clustering (testing)
    print("\033[91m \nTesting evaluation\n \033[0m")
    evaluation_k_means_app_testing_2 =␣
 ↪perform_external_measures(contengency_table_testing_2,␣
 ↪len(reduced_testing_data_2))
    evaluation_k_mean_testing_app_2.append(evaluation_k_means_app_testing_2)

    print(f"\033[94m \ntraining accuracy: {training_accuracy2}\t testing␣
 ↪accuracy: {testing_accuracy2} \033[0m")
    print('-' * 80)
```

```
 K : 8


Training evaluation
```

```
Precision is 0.36554276315789475
Recall is 0.6062415544409326
F-score is 0.5472439909004391
Conditional entropy is 2.307936620452125

Testing evaluation

Precision is 0.36896929824561403
Recall is 0.6115766389658357
F-score is 0.5548398373756382
Conditional entropy is 2.3031069766361574

training accuracy: 0.36554276315789475   testing accuracy: 0.36896929824561403

--------------------------------------------------------------------------------
 K : 13

Training evaluation

Precision is 0.4634046052631579
Recall is 0.571289107232834
F-score is 0.5532666494238739
Conditional entropy is 1.922288902958042

Testing evaluation

Precision is 0.46765350877192985
Recall is 0.5667128347183749
F-score is 0.564126284937241
Conditional entropy is 1.917889788450215

training accuracy: 0.4634046052631579    testing accuracy: 0.46765350877192985

--------------------------------------------------------------------------------
 K : 19

Training evaluation

Precision is 0.5685307017543859
Recall is 0.5695999954193578
F-score is 0.5305721998487009
```

```
Conditional entropy is 1.5172462451403177

Testing evaluation

Precision is 0.5668859649122807
Recall is 0.5677631578947369
F-score is 0.5298250533002303
Conditional entropy is 1.5297417487687825

training accuracy: 0.5685307017543859    testing accuracy: 0.5668859649122807

--------------------------------------------------------------------------------
 K : 28

Training evaluation

Precision is 0.6546052631578947
Recall is 0.4542851907837479
F-score is 0.5010147056124514
Conditional entropy is 1.215713111492446

Testing evaluation

Precision is 0.6611842105263158
Recall is 0.46200369344413666
F-score is 0.5066826050314196
Conditional entropy is 1.1508248153330836

training accuracy: 0.6546052631578947    testing accuracy: 0.6611842105263158

--------------------------------------------------------------------------------
 K : 38

Training evaluation

Precision is 0.6676260964912281
Recall is 0.39374055242545003
F-score is 0.40906343385906824
Conditional entropy is 1.1724097056472444
```

```
Testing evaluation


Precision is 0.6869517543859649
Recall is 0.3980493998153278
F-score is 0.42788007316303944
Conditional entropy is 1.1107845891588408

training accuracy: 0.6676260964912281    testing accuracy: 0.6754385964912281

--------------------------------------------------------------------------------
```

Spectral clustering

3.4 Work flow

[282]:
```python
def RBF_kernel(v1, v2, gamma):
    d = np.linalg.norm(v1 - v2)
    return np.exp(-gamma * d**2)
```

[283]:
```python
def knn_similarity_k(k):
    def knn_similarity(D):
        model = NearestNeighbors(n_neighbors=k, metric='euclidean')
        model.fit(D)

        # Compute k-NN indices
        distances, indices = model.kneighbors(D)

        n = len(D)
        # Create an empty adjacency matrix
        A = np.zeros((n, n))

        # Fill in the similarity matrix
        for i in range(n):
            for j in indices[i]:
                A[i, j] = 1
                A[j, i] = 1  # For symmetry: j is also a neighbor of i

        return A
    return knn_similarity
```

[284]:
```python
def spectral_clustering(D, k, sim_func):
  epsilon = 1e-10
  # Compute similarity matrix
  A = sim_func(D)
```

```
    # Compute degree matrix
    degrees = np.sum(A, axis=1)
    degree_mat = np.diag(degrees)

    # Compute Laplacian asymetric matrix
    la = np.eye(len(D)) - np.linalg.inv(degree_mat) @ A

    eigenvalues, eigenvectors = np.linalg.eig(la)

    # Sort eigenvalues and eigenvectors in ascending order
    sorted_indices = np.argsort(eigenvalues)
    sorted_eigenvalues = eigenvalues[sorted_indices]
    sorted_eigenvectors = eigenvectors[:, sorted_indices]

    # Choose the smallest K eigenvectors
    smallest_eigenvectors = sorted_eigenvectors[:k, :]

    # Normalize each row
    reduced_data  = (np.real(smallest_eigenvectors).T)

    for i in range(len(reduced_data)):
          reduced_data[i] = reduced_data[i] / (np.linalg.norm(reduced_data[i]) +␣
 ↪epsilon)
    return reduced_data
```

Applying spectral clustering to app. 1

[285]:
```
# State init
gamma_list = [0.0001] # Don't ever use gamma = 1
k = 19
evaluation_spectral_app_1 = []
evaluation_spectral_app_2 = []
# Function init
knn_sim = knn_similarity_k(10)
sim_func_list = [knn_sim, cosine_similarity, np.corrcoef]
```

[287]:
```
number_of_samples_spectral_app_1 = len(normalized_training_data_1)
for sim_func in sim_func_list:
    print(f"Evaluation of spectral clustering using similarity measure :␣
 ↪\033[94m{sim_func.__name__.upper()}\033[0m")
    reduced_training_data_spectral_cosine_app_1 =␣
 ↪spectral_clustering(normalized_training_data_1, k, sim_func) # Replace test

    # Cluster traing data using k-means and return cluster id for each training␣
 ↪sample
    kmeans = KMeans(n_clusters=k)
```

```
    kmeans.fit(reduced_training_data_spectral_cosine_app_1)
    cluster_ids_spectral_app_1 = kmeans.labels_

    # Create contingency table matrix for matching training data clusters
    contingency_table_spectral_app_1 =␣
↪contingency_table(cluster_ids_spectral_app_1, training_labels_1)

    # Evaluate clustering
    evaluation_spectral_app_1.
↪append(perform_external_measures(contingency_table_spectral_app_1,␣
↪number_of_samples_spectral_app_1))
    print("-" * 80)
```

```
Evaluation of spectral clustering using similarity measure :
KNN_SIMILARITY

/opt/conda/lib/python3.10/site-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(

Precision is 0.05688048245614035
Recall is 0.9893686157299253
F-score is 0.013728379374446674
Conditional entropy is 4.227989754914487
--------------------------------------------------------------------------------
Evaluation of spectral clustering using similarity measure :
COSINE_SIMILARITY

/opt/conda/lib/python3.10/site-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(

Precision is 0.4233826754385965
Recall is 0.3372190062296734
F-score is 0.4373339052798815
Conditional entropy is 2.160124760886055
--------------------------------------------------------------------------------
Evaluation of spectral clustering using similarity measure : CORRCOEF

/opt/conda/lib/python3.10/site-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(

Precision is 0.39035087719298245
Recall is 0.3119123894920068
F-score is 0.39551971878686243
```

```
Conditional entropy is 2.2882931895631167
--------------------------------------------------------------------------------
```

3.5 Applying spectral clustering to app. 2

[288]:
```python
number_of_samples_spectral_app_2 = len(reduced_training_data_2)
for sim_func in sim_func_list:
    print(f"Evaluation of spectral clustering using similarity measure :␣
↪\033[94m{sim_func.__name__.upper()}\033[0m")
    reduced_training_data_spectral_cosine_app_2 =␣
↪spectral_clustering(reduced_training_data_2, k, sim_func) # Replace test

    # Cluster traing data using k-means and return cluster id for each training␣
↪sample
    kmeans = KMeans(n_clusters=k)
    kmeans.fit(reduced_training_data_spectral_cosine_app_2)
    cluster_ids_spectral_app_2 = kmeans.labels_

    # Create contingency table for matching training data clusters
    contingency_table_spectral_app_2 =␣
↪contingency_table(cluster_ids_spectral_app_2, training_labels_2)

    # Evaluate clustering
    evaluation_spectral_app_2.
↪append(perform_external_measures(contingency_table_spectral_app_2,␣
↪number_of_samples_spectral_app_2))
    print("\n")
```

```
Evaluation of spectral clustering using similarity measure :
KNN_SIMILARITY

/opt/conda/lib/python3.10/site-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(

Precision is 0.3782894736842105
Recall is 0.3170591704456965
F-score is 0.3990549744528832
Conditional entropy is 2.4099442893838408


Evaluation of spectral clustering using similarity measure :
COSINE_SIMILARITY

/opt/conda/lib/python3.10/site-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
```

```
  warnings.warn(

Precision is 0.36101973684210525
Recall is 0.34510486807750446
F-score is 0.37460186562657344
Conditional entropy is 2.116355272332628


Evaluation of spectral clustering using similarity measure : CORRCOEF

/opt/conda/lib/python3.10/site-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(

Precision is 0.41296600877192985
Recall is 0.3618005931931657
F-score is 0.42840550354072304
Conditional entropy is 1.9978442184442002
```

Comparision

[ ]:
```python
measure_list = ["Precision", "Recall", "F-score", "Conditional entropy"]
```

3.6 Approach 1

[293]:
```python
# K means evaluation
k_mean_training_eval_1 = np.mean(evaluation_k_mean_training_app_1, axis=0)
print(k_mean_training_eval_1)
# spectral evaluation
spectral_training_eval_1 =  np.mean(evaluation_spectral_app_1, axis=0)
print(spectral_training_eval_1)
```

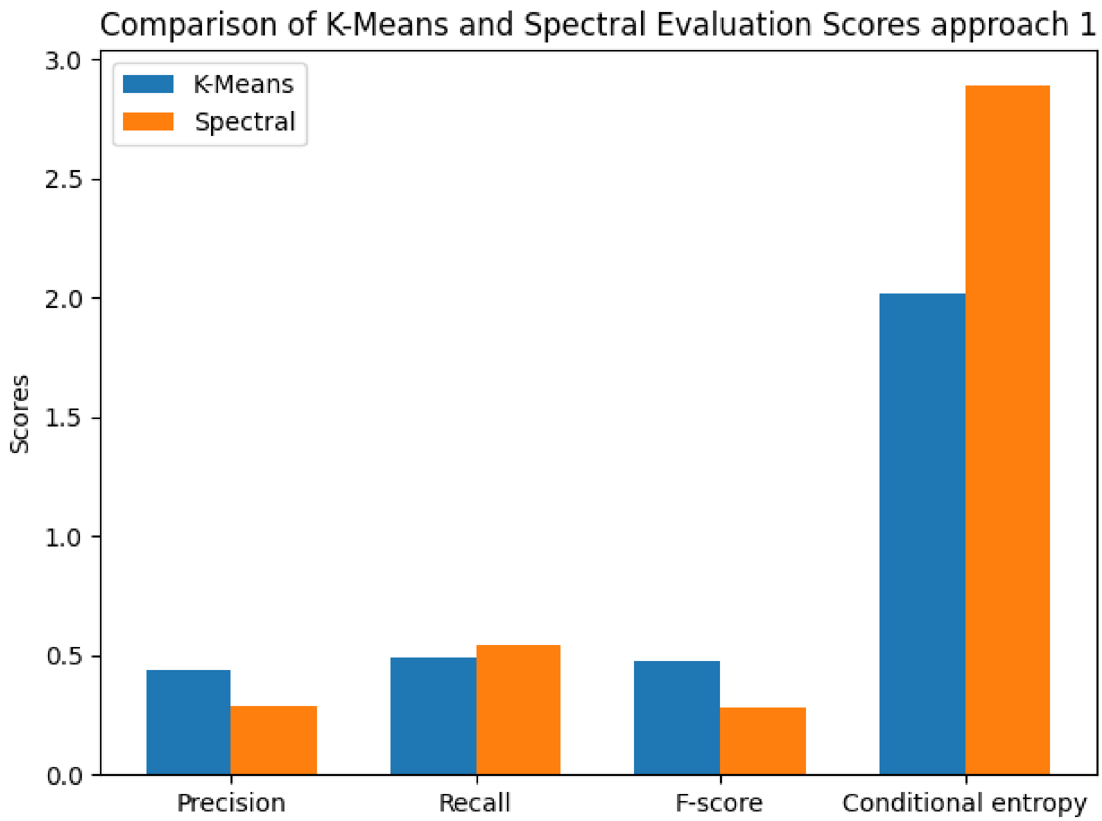
```
[0.43925732 0.48841205 0.47353378 2.01440082]
[0.29020468 0.54616667 0.282194   2.8921359 ]
```

3.6.1 Plot

[294]:
```python
x = np.arange(len(measure_list))
width = 0.35
```

[295]:
```python
fig, ax = plt.subplots()
rects1 = ax.bar(x - width/2, k_mean_training_eval_1, width, label='K-Means')
rects2 = ax.bar(x + width/2, spectral_training_eval_1, width, label='Spectral')

ax.set_ylabel('Scores')
ax.set_title('Comparison of K-Means and Spectral Evaluation Scores approach 1')
ax.set_xticks(x)
```

```
ax.set_xticklabels(measure_list)
ax.legend()

fig.tight_layout()

plt.show()
```



3.7 Approach 2

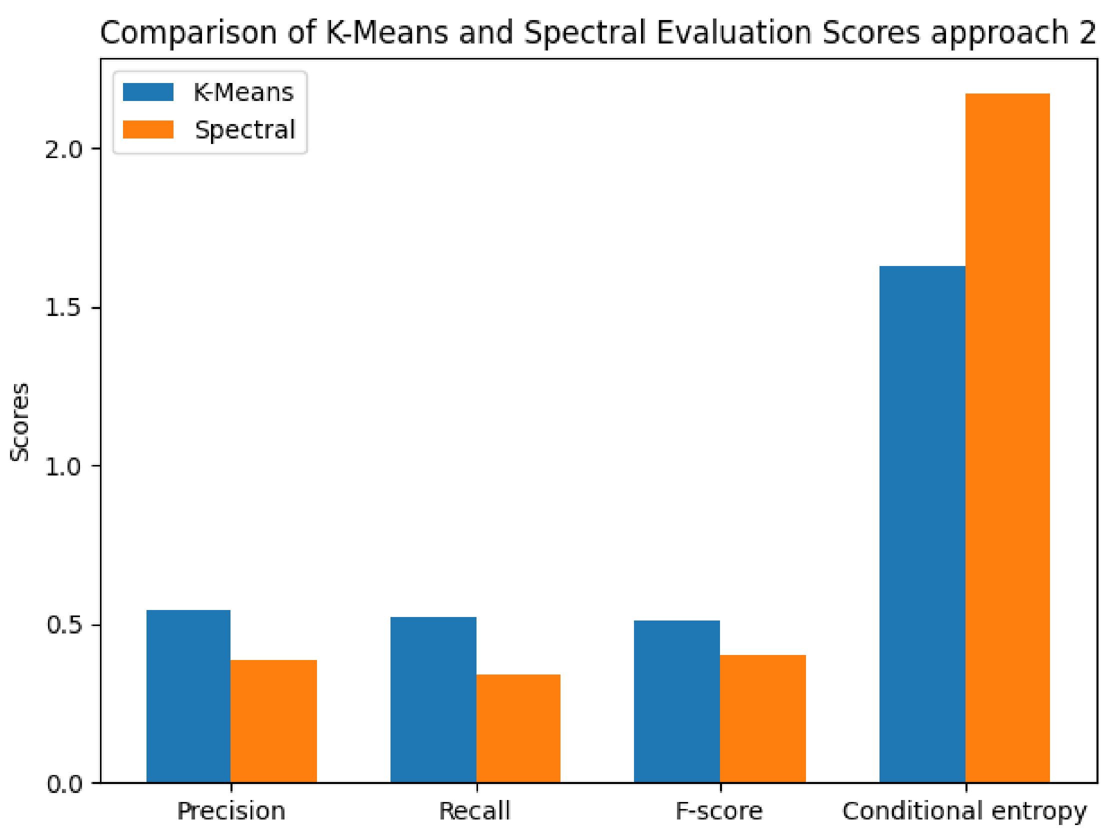
[297]:
```
# K means evaluation
k_mean_training_eval_2 = np.mean(evaluation_k_mean_training_app_2, axis=0)
print(k_mean_training_eval_2)
# spectral evaluation
spectral_training_eval_2 =  np.mean(evaluation_spectral_app_2, axis=0)
print(spectral_training_eval_2)
```

```
[0.54394189 0.51903128 0.5082322  1.62711892]
[0.38409174 0.34132154 0.40068745 2.17471459]
```

3.7.1 Plot

[298]:
```
x = np.arange(len(measure_list))
width = 0.35
```

[299]:
```
fig, ax = plt.subplots()
rects1 = ax.bar(x - width/2, k_mean_training_eval_2, width, label='K-Means')
rects2 = ax.bar(x + width/2, spectral_training_eval_2, width, label='Spectral')

ax.set_ylabel('Scores')
ax.set_title('Comparison of K-Means and Spectral Evaluation Scores approach 2')
ax.set_xticks(x)
ax.set_xticklabels(measure_list)
ax.legend()

fig.tight_layout()

plt.show()
```



4 DBSCAN Clustering

[301]:
```
# Helper method to find the neighbors of a given data point
def find_neighbors(data, index, eps):
    # Calculate the Euclidean distance between the current data point and all␣
 ↪other data points
    distances = np.linalg.norm(data - data[index], axis=1)

    # Find the indices of the neighbors within the specified epsilon radius
    neighbors = np.where(distances <= eps)[0]

    return neighbors

# Helper method to grow a new cluster or expand an existing one
def expand_cluster(data, labels, index, neighbors, cluster_id, eps,␣
 ↪min_samples):
    # Assign the cluster label to the current data point
    labels[index] = cluster_id

    # Iterate over each neighbor of the current data point
    for neighbor in neighbors:
        # Skip if the neighbor is already assigned to a cluster
        if labels[neighbor] != 0:
            continue

        # Find the neighbors of the current neighbor
        neighbor_neighbors = find_neighbors(data, neighbor, eps)

        # If the number of neighbors is greater than or equal to min_samples,␣
 ↪add them to the current cluster
        if len(neighbor_neighbors) >= min_samples:
            neighbors = np.concatenate((neighbors, neighbor_neighbors))

        # Assign the cluster label to the current neighbor
        labels[neighbor] = cluster_id

def dbscan(data, eps, min_samples):
    # Initialize the cluster labels
    labels = np.zeros(len(data), dtype=int)
    cluster_id = 0

    # Iterate over each data point
    for i in range(len(data)):
        # Skip if the data point is already assigned to a cluster
        if labels[i] != 0:
            continue
```

```
        # Find the neighbors of the current data point
        neighbors = find_neighbors(data, i, eps)

        # If the number of neighbors is less than min_samples, mark the data␣
↪point as noise
        if len(neighbors) < min_samples:
            labels[i] = -1
        else:
            # Expand the cluster starting from the current data point
            cluster_id += 1
            expand_cluster(data, labels, i, neighbors, cluster_id, eps,␣
↪min_samples)

    labels = [label if label != -1 else 0 for label in labels]

    return labels
```

5 Applying DBSCAN app. 1

6 Training

[310]:
```
eps_values = np.arange(1, 4, 0.5).tolist()
num_samples_values = np.arange(3, 6, 1).tolist()

# Initialize lists to store the values
precision_values = []
recall_values = []
f_measure_values = []
entropy_values = []

for num in num_samples_values:
    print("For num =", num)
    for eps in eps_values:
        print("For eps =", eps)
        cluster_labels = dbscan(np.array(normalized_training_data_1), eps, num)

        # Create confusion matrix for matching training data clusters
        confusion_mat = contingency_table(cluster_labels, training_labels_1)

        # Evaluate clustering
        number_of_samples = len(normalized_training_data_1)
        measures = perform_external_measures(confusion_mat, number_of_samples)

        # Append the measures to the respective lists
        precision_values.append(measures[0])
        recall_values.append(measures[1])
```

```python
        f_measure_values.append(measures[2])
        entropy_values.append(measures[3])
        print()
```

```
For num = 3
For eps = 1.0
Precision is 0.7741228070175439
Recall is 0.19376760684347946
F-score is 0.0336132466171751
Conditional entropy is 0.9743540341663073

For eps = 1.5
Precision is 0.8952850877192983
Recall is 0.13795391301360452
F-score is 0.0477726937821018
Conditional entropy is 0.4685865022582791

For eps = 2.0
Precision is 0.912828947368421
Recall is 0.1342643488617104
F-score is 0.06323471793012035
Conditional entropy is 0.3572272360413257

For eps = 2.5
Precision is 0.8736293859649122
Recall is 0.12578872932985205
F-score is 0.07425809154275535
Conditional entropy is 0.4486678260115638

For eps = 3.0
Precision is 0.8201754385964912
Recall is 0.11513587329943659
F-score is 0.07550901699110744
Conditional entropy is 0.5970654837818341

For eps = 3.5
Precision is 0.782483552631579
Recall is 0.11962203975997435
F-score is 0.077240034158346
Conditional entropy is 0.738338365102837

For num = 4
For eps = 1.0
Precision is 0.7420504385964912
Recall is 0.21778090788328525
F-score is 0.0379687563131295
Conditional entropy is 1.1111632340128552
```

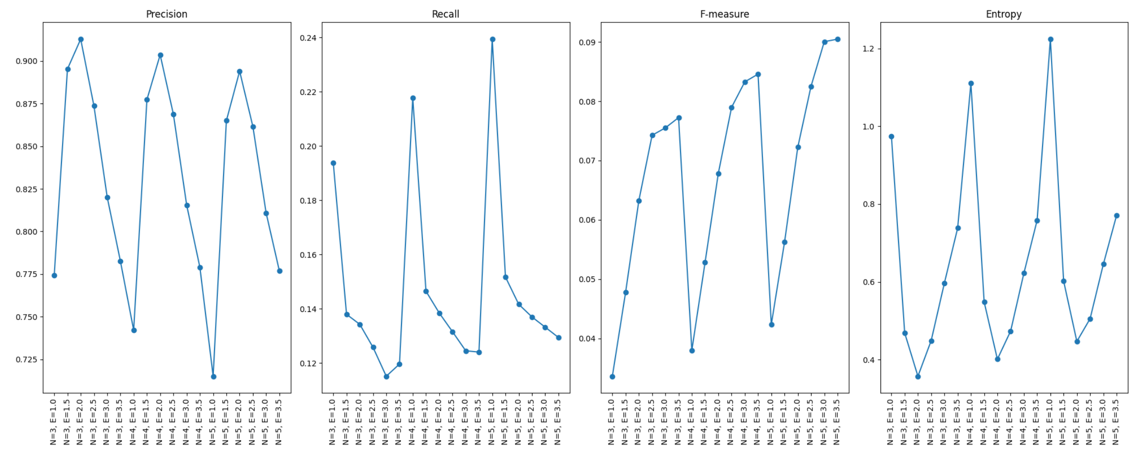
```
For eps = 1.5
Precision is 0.8773300438596491
Recall is 0.14645243575649305
F-score is 0.05282042593580049
Conditional entropy is 0.5483059259733518

For eps = 2.0
Precision is 0.9036458333333334
Recall is 0.13844346914937475
F-score is 0.06783146193203032
Conditional entropy is 0.4010094277978601

For eps = 2.5
Precision is 0.8686951754385965
Recall is 0.13154459255187578
F-score is 0.0789679334262579
Conditional entropy is 0.4733977480465809

For eps = 3.0
Precision is 0.815515350877193
Recall is 0.12451330676560854
F-score is 0.08327325490335054
Conditional entropy is 0.6221327476233027

For eps = 3.5
Precision is 0.7789199561403509
Recall is 0.12403878086207687
F-score is 0.08457474231754425
Conditional entropy is 0.7582646235818347

For num = 5
For eps = 1.0
Precision is 0.7150493421052632
Recall is 0.2393636056525125
F-score is 0.04233147128616215
Conditional entropy is 1.224246086499617

For eps = 1.5
Precision is 0.8649945175438597
Recall is 0.1517015654344739
F-score is 0.056222642386285424
Conditional entropy is 0.6021260178860264

For eps = 2.0
Precision is 0.8940515350877193
Recall is 0.14165278159497963
F-score is 0.07223890305235686
Conditional entropy is 0.446725996265183
```

```
For eps = 2.5
Precision is 0.8615679824561403
Recall is 0.1369905466996473
F-score is 0.08252428921923625
Conditional entropy is 0.5052385251449419

For eps = 3.0
Precision is 0.8108552631578947
Recall is 0.1332143797810453
F-score is 0.09004853774267595
Conditional entropy is 0.6453559189132921

For eps = 3.5
Precision is 0.7768640350877193
Recall is 0.12942246690486006
F-score is 0.09047748086232082
Conditional entropy is 0.7709193859645253
```

[311]:

```
# Create x values for the plot
x_values = [f'N={num}, E={eps}' for num in num_samples_values for eps in␣
 ↪eps_values]

# Create the plots
plt.figure(figsize=(20, 8))

plt.subplot(1, 4, 1)
plt.plot(x_values, precision_values, marker='o')
plt.title('Precision')
plt.xticks(rotation=90)

plt.subplot(1, 4, 2)
plt.plot(x_values, recall_values, marker='o')
plt.title('Recall')
plt.xticks(rotation=90)

plt.subplot(1, 4, 3)
plt.plot(x_values, f_measure_values, marker='o')
plt.title('F-measure')
plt.xticks(rotation=90)

plt.subplot(1, 4, 4)
plt.plot(x_values, entropy_values, marker='o')
plt.title('Entropy')
plt.xticks(rotation=90)
```

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



7 Testing

[312]:

```
eps_values = np.arange(1, 4, 0.5).tolist()
num_samples_values = np.arange(3, 6, 1).tolist()

# Initialize lists to store the values
precision_values = []
recall_values = []
f_measure_values = []
entropy_values = []

for num in num_samples_values:
    print("For num =", num)
    for eps in eps_values:
        print("For eps =", eps)
        cluster_labels = dbscan(np.array(normalized_testing_data_1), eps, num)

        # Create confusion matrix for matching training data clusters
        confusion_mat = contingency_table(cluster_labels, testing_labels_1)

        # Evaluate clustering
        number_of_samples = len(normalized_testing_data_1)
        measures = perform_external_measures(confusion_mat, number_of_samples)

        # Append the measures to the respective lists
        precision_values.append(measures[0])
        recall_values.append(measures[1])
```

```
        f_measure_values.append(measures[2])
        entropy_values.append(measures[3])
        print()
```

```
For num = 3
For eps = 1.0
Precision is 0.762609649122807
Recall is 0.23119806094182827
F-score is 0.10451451103888988
Conditional entropy is 0.9865302388584883

For eps = 1.5
Precision is 0.8793859649122807
Recall is 0.17289935364727607
F-score is 0.12561276837460233
Conditional entropy is 0.49657426734613036

For eps = 2.0
Precision is 0.899671052631579
Recall is 0.16605493998153278
F-score is 0.15043939922791105
Conditional entropy is 0.3760265366086436

For eps = 2.5
Precision is 0.8722587719298246
Recall is 0.1608264081255771
F-score is 0.1623001807664169
Conditional entropy is 0.4331859114909499

For eps = 3.0
Precision is 0.8157894736842105
Recall is 0.14511772853185595
F-score is 0.16512123630374656
Conditional entropy is 0.5840951801931605

For eps = 3.5
Precision is 0.7648026315789473
Recall is 0.14544090489381348
F-score is 0.16829218634472895
Conditional entropy is 0.7938397548864838

For num = 4
For eps = 1.0
Precision is 0.7099780701754386
Recall is 0.27130655586334257
F-score is 0.12072511884063515
Conditional entropy is 1.2183228891624955
```

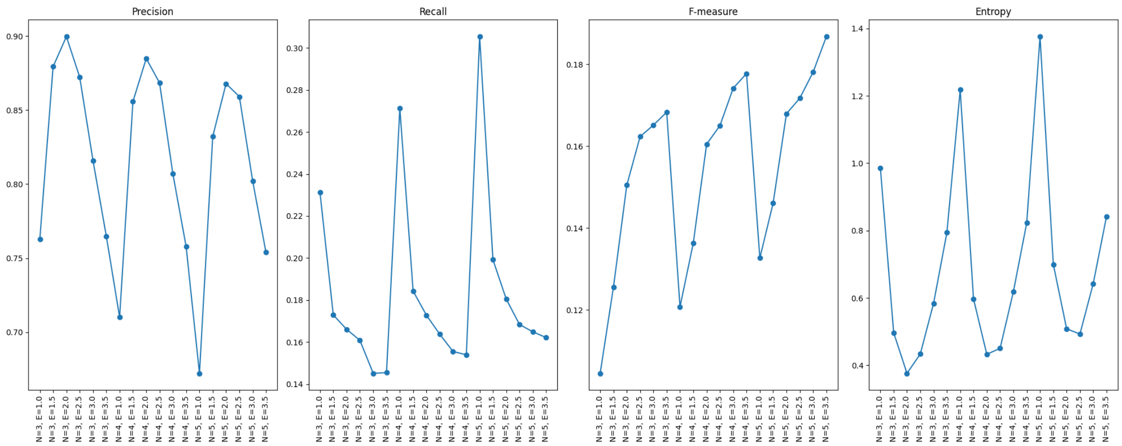
```
For eps = 1.5
Precision is 0.8558114035087719
Recall is 0.1842566943674977
F-score is 0.13634482355693942
Conditional entropy is 0.5972948861653294

For eps = 2.0
Precision is 0.8848684210526315
Recall is 0.17278393351800553
F-score is 0.16046017772678492
Conditional entropy is 0.43250495683191875

For eps = 2.5
Precision is 0.868421052631579
Recall is 0.16372345337026778
F-score is 0.1649909146053473
Conditional entropy is 0.45025451860186566

For eps = 3.0
Precision is 0.8070175438596491
Recall is 0.15549399815327794
F-score is 0.17413193055727744
Conditional entropy is 0.6189268035046808

For eps = 3.5
Precision is 0.7576754385964912
Recall is 0.15394736842105264
F-score is 0.17771135070099062
Conditional entropy is 0.8226059156195612

For num = 5
For eps = 1.0
Precision is 0.6721491228070176
Recall is 0.30541320406278855
F-score is 0.1326520249848196
Conditional entropy is 1.3761851766215656

For eps = 1.5
Precision is 0.8322368421052632
Recall is 0.19918051708217913
F-score is 0.14608841243903578
Conditional entropy is 0.6994057034183107

For eps = 2.0
Precision is 0.8678728070175439
Recall is 0.1804478301015697
F-score is 0.16790317829240187
Conditional entropy is 0.5082496755682107
```

```
For eps = 2.5
Precision is 0.8591008771929824
Recall is 0.1683287165281625
F-score is 0.17167345301448259
Conditional entropy is 0.4926767782650118

For eps = 3.0
Precision is 0.8020833333333334
Recall is 0.16486611265004616
F-score is 0.17803225518789356
Conditional entropy is 0.6427638944172658

For eps = 3.5
Precision is 0.7538377192982456
Recall is 0.1621191135734072
F-score is 0.18673356123072132
Conditional entropy is 0.8420832703406579
```

[313]:

```python
# Create x values for the plot
x_values = [f'N={num}, E={eps}' for num in num_samples_values for eps in␣
 ↪eps_values]

# Create the plots
plt.figure(figsize=(20, 8))

plt.subplot(1, 4, 1)
plt.plot(x_values, precision_values, marker='o')
plt.title('Precision')
plt.xticks(rotation=90)

plt.subplot(1, 4, 2)
plt.plot(x_values, recall_values, marker='o')
plt.title('Recall')
plt.xticks(rotation=90)

plt.subplot(1, 4, 3)
plt.plot(x_values, f_measure_values, marker='o')
plt.title('F-measure')
plt.xticks(rotation=90)

plt.subplot(1, 4, 4)
plt.plot(x_values, entropy_values, marker='o')
plt.title('Entropy')
plt.xticks(rotation=90)
```

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



8 Applying DBSCAN app. 2

9 Training

[314]:
```
eps_values = [4.5]
num_samples_values = [3]

# Initialize lists to store the values
precision_values = []
recall_values = []
f_measure_values = []
entropy_values = []

for num in num_samples_values:
    for eps in eps_values:
        cluster_labels = dbscan(np.array(reduced_training_data_2), eps, num)

        # Create confusion matrix for matching training data clusters
        confusion_mat = contingency_table(cluster_labels, training_labels_2)

        # Evaluate clustering
        number_of_samples = len(reduced_training_data_2)
        measures = perform_external_measures(confusion_mat, number_of_samples)

        # Append the measures to the respective lists
        precision_values.append(measures[0])
        recall_values.append(measures[1])
```

```
        f_measure_values.append(measures[2])
        entropy_values.append(measures[3])
```

```
Precision is 0.8758223684210527
Recall is 0.15065517498053227
F-score is 0.05600960003999893
Conditional entropy is 0.4438129607159361
```

10 Testing

[307]:
```
eps_values = np.arange(3.5, 5.5, 0.5).tolist()
num_samples_values = np.arange(2, 5, 1).tolist()

# Initialize lists to store the values
precision_values = []
recall_values = []
f_measure_values = []
entropy_values = []

for num in num_samples_values:
    print("For num =", num)
    for eps in eps_values:
        print("For eps =", eps)
        cluster_labels = dbscan(np.array(reduced_testing_data_2), eps, num)

        # Create confusion matrix for matching training data clusters
        confusion_mat = contingency_table(cluster_labels, testing_labels_2)

        # Evaluate clustering
        number_of_samples = len(reduced_testing_data_2)
        measures = perform_external_measures(confusion_mat, number_of_samples)

        # Append the measures to the respective lists
        precision_values.append(measures[0])
        recall_values.append(measures[1])
        f_measure_values.append(measures[2])
        entropy_values.append(measures[3])
        print()
```

```
For num = 2
For eps = 3.5
Precision is 0.8771929824561403
Recall is 0.14509464450600185
F-score is 0.07908661680202861
Conditional entropy is 0.48399378453004405

For eps = 4.0
```

```
Precision is 0.8832236842105263
Recall is 0.15011542012927054
F-score is 0.09223327730481551
Conditional entropy is 0.42027373935067963

For eps = 4.5
Precision is 0.8766447368421053
Recall is 0.16608956602031394
F-score is 0.10799038594024757
Conditional entropy is 0.43039321017590704

For eps = 5.0
Precision is 0.8415570175438597
Recall is 0.20507848568790396
F-score is 0.11964940502005288
Conditional entropy is 0.5447122519852038

For num = 3
For eps = 3.5
Precision is 0.8053728070175439
Recall is 0.18297553093259464
F-score is 0.09233267705008917
Conditional entropy is 0.7742810227897531

For eps = 4.0
Precision is 0.8388157894736842
Recall is 0.1762465373961219
F-score is 0.1020366929855264
Conditional entropy is 0.5858313100832429

For eps = 4.5
Precision is 0.84375
Recall is 0.1930747922437673
F-score is 0.11886685508898251
Conditional entropy is 0.5425903026583686

For eps = 5.0
Precision is 0.8157894736842105
Recall is 0.23310249307479225
F-score is 0.13166708632082236
Conditional entropy is 0.6169063566256989

For num = 4
For eps = 3.5
Precision is 0.7324561403508771
Recall is 0.23664589104339798
F-score is 0.10264594042961836
Conditional entropy is 1.0821743513762627
```

```
For eps = 4.0
Precision is 0.787828947368421
Recall is 0.20226223453370268
F-score is 0.11315321766667377
Conditional entropy is 0.7933679805236229

For eps = 4.5
Precision is 0.805921052631579
Recall is 0.20975300092336102
F-score is 0.1306741705410216
Conditional entropy is 0.6949821120220602

For eps = 5.0
Precision is 0.7944078947368421
Recall is 0.24793397968605724
F-score is 0.14020909628828207
Conditional entropy is 0.7052182001294203
```

[308]:

```python
# Create x values for the plot
x_values = [f'N={num}, E={eps}' for num in num_samples_values for eps in␣
 ↪eps_values]

# Create the plots
plt.figure(figsize=(20, 8))

plt.subplot(1, 4, 1)
plt.plot(x_values, precision_values, marker='o')
plt.title('Precision')
plt.xticks(rotation=90)

plt.subplot(1, 4, 2)
plt.plot(x_values, recall_values, marker='o')
plt.title('Recall')
plt.xticks(rotation=90)

plt.subplot(1, 4, 3)
plt.plot(x_values, f_measure_values, marker='o')
plt.title('F-measure')
plt.xticks(rotation=90)

plt.subplot(1, 4, 4)
plt.plot(x_values, entropy_values, marker='o')
plt.title('Entropy')
plt.xticks(rotation=90)
```

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